Original Research

A comparative study of meta-heuristic algorithms in supply chain networks

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Abstract

Today, with the development of Information Technology (IT) and economic globalization, the suppliers' selection has been emphasized in supply chain systems. Accordingly, artificial intelligence-based methods have attracted much attention. Hence, in this research, the selection of appropriate suppliers with respect to the multi-resource supply policy, and the implementation of lateral transshipment have been studied, and meta-heuristic algorithms have been employed to solve the problem. In the proposed method, the supply chain network is improved by minimizing the inventory shortages through utilizing lateral transshipment between different factories. In order to efficiently solve the problem, a hybrid meta-heuristic algorithm based on population-based genetic algorithm (GA) and single-solution simulated annealing (SA), named GASA, is propose, in order to simultaneously gain with the advantages of both algorithms, i.e., global search ability of GA and local search ability of SA. In order to compare the results of the proposed GASA, it is compared with GA and SA, to find the best solution. Given the parameters' optimization and conducted analyses and comparisons of primary and hybrid algorithms' performance, the hybrid GASA algorithm has been identified as the most efficient algorithm to solve the problem, compared to the other algorithms, emphasizing cost reduction and shortage volume.

Keywords - Supply chain management; Multi-resource supplier selection; Lateral transshipment; Genetic algorithm; Simulated annealing

1. INTRODUCTION

Several decades have passed since the emergence of supply chain concepts. So far, many research efforts have been devoted to the realization and clarification of its attributions in order to promote this phenomenon and expand the industries and trade domains to a global level. One of the primary issues of supply chains, which are of the main concerns of its managers, is the decision-making process. The necessity of a proper decision and selecting an appropriate supplier among other suppliers, the best distributor, and the best region to attract customers and best business partners for the formation of integrated partnerships and many other issues are among the critical problems raised in the decision-making of supply chain management. These decisions include minor and macro problems, and in many cases, the wrong decision would impose a high cost. There by signifying the importance of proper decision making. In most of the decision-making problems, many objectives and factors are involved, and the decision-maker opts to select the best possible option among multiple solutions.

It is crucial to consider different factors to apprise the suppliers, which are basically input data for the evaluation, and their outputs would be the suppliers' rankings used to select suppliers. This could be important in many different aspects. For example, the employment of the best suppliers, reducing the final product's total production cost, decreasing the suppliers' management costs, the utilization of all of the suppliers' facilities, enabling the suppliers' appraisal, and selecting suppliers (Ravindran et al, 2010).

Some of the utilized suppliers' selection methods are known as non-exact (approximate) methods, including the Analytical Hierarchy Process (AHP). Scoring the selection criteria and determining their importance and placement is one of the AHP approach's problems. However, as an advantage of the AHP approach, one can determine the relative importance of suppliers' selection criteria, qualitatively and orally. The more advanced version of this approach for selecting the suppliers is Analytical Network Process (ANP) (Chan et al, 2008). One of the advantages of non-exact methods is that there is no need to assign exact numerical values as the criteria' weights. Fuzzy Sets is another non-exact (approximate) method. Moreover, the Total Cost of Ownership is another approach for selecting the best suppliers. This approach would be utilized once the entire model's costs, including quality, delivery, and service costs, can be expressed as the profit and loss in terms of the unit price (Ramanathan, 2007).

Our primary objective in this study is to minimize the total cost of the supply chain networks including the purchase cost, ordering cost, contract cost, holding cost, transportation cost, and shortage cost, and minimize the inventory shortages. Therefore, in this research, in addition to applying the genetic algorithm, the simulated annealing algorithm, and the hybrid algorithm, a comparative analysis among these three algorithms would be conducted. Using the comparisons conducted in this study, the esteemed readers seeking an appropriate algorithm can easily select their desired algorithm among the proposed algorithms considering their advantages and disadvantages.

There are various global and local search metaheuristics in literature, e.g., evolutionary, swarm intelligence, and nature-inspired algorithms (Sabet et al., 2016). Among them, genetic algorithm (GA) and simulated annealing (SA) are the most common global and local metaheuristics, which have been widely used to solve different optimization problems. Generally, the whole search space is preferred to be globally explored at the early iterations (Shokouhifar & Jalali, 2017), while exploitation through local search operators is more preferred at the last iterations when the algorithm encounters with near-optimal solutions (Naderi et al., 2021). Therefore, to obtain a better trade-off between speed and solution quality, we present a hybrid metaheuristic approach for supply chain problems based on the GA and SA (called GASA). Our motivation is to gain with the benefits of the both algorithms into the hybrid GASA algorithm, i.e., global search (exploration) of the GA and local search (exploitation) of the SA.

The key contributions in this paper can be summarized as follows:

- Improving the supply chain network by minimizing the inventory shortages through utilizing lateral transshipment between different factories.
- Presenting a hybrid meta-heuristic algorithm based on population-based GA and single-solution SA (named GASA), to simultaneously gain with the advantages of both algorithms, i.e., global search ability of GA and local search ability of SA.
- Performing GA, SA, and GASA, to solve the supply chain management problem under lateral transshipment between factories.
- Evaluating the advantages and disadvantages of the different algorithms including GA, SA, and GASA, according to the obtained results.

The rest of the paper is organized as follows: Existing techniques in literature are reviewed in Section 2. Our methodology is presented in Section 3. The simulation results of GA, SA, and GASA, for the optimization of the supply chain problem are provided in Section 4, and finally, the paper is concluded in Section 5.

2. THEORETICAL FOUNDATIONS AND RESEARCH BACKGROUND

The suppliers' selection is a process that the suppliers, as a component of the supply chain, would be analyzed, appraised, and selected. The suppliers' selection problem was considered by many academics since the 1960s (Asgharizadeh et al, 2015). A quick review of the conducted research on supplier selection literature shows that suppliers' selection literature can be categorized into two divisions:

In the conducted research, the scholars either addressed the different criteria of suppliers' selection or proposed a paradigm for evaluating and selecting suppliers by using different decision-making methods. In a few researches, both of the aforementioned subjects were covered, and in addition to the identification and customization of criteria, the researchers proposed an applied paradigm by using those criteria in organization evaluations. For the final stage of the suppliers' selection, many models can be found in which the weighing models are among the commons. In these models, each one of the available criteria would be assigned a weight so that the most important criterion would be assigned the highest weight. Then, each criterion's weight would be multiplied in its score, and finally, their outputs would be summed up. The supplier with the highest credit would be selected (Liu & Zhang, 2011).

The timely procurement of goods is one of the most crucial problems many factories faced. Concretely, the proper selection of suppliers is a high priority in the supply chain management realm, and developing appropriate solution techniques to solve the suppliers' selection problem is of utmost importance. Therefore, many research efforts have been devoted to proposing approaches to cope with the customers' orders appropriately and in addition to better procurement of required materials and goods, prevent wasting time, budget, and workforce. One category of these approaches is the employment of meta-heuristic algorithms, including Tabu search, simulated annealing, genetic, and particle swarm optimization algorithms, which are capable of providing relatively good solutions (Samouei & Fattahi, 2017).

Moreover, Saputro et al. (2019) investigated the supplier selection and inventory management. In this research, the multi-resource strategy has been considered for selecting the supplier, demand disruption, and stochastic supply, and the problem has been solved using a hybrid discrete-event simulation and genetic algorithm. Rao (2017), have conducted a comparative study between GA and SA in an e-commerce supply chain network and searched for the best possible path for supplying the manufacturers' demands by acquiring the shortest path and comparing it with its neighboring solution. Firouz et al. (2017) investigated the supplier selection and lateral transshipment problem considering the multi-resource strategy. The order assignment was determined based on the inventory level, and the demand was decided based on the (Q, R) model. Kuhpfahl and Bierwirth, (2016) studied six local neighbor search approaches for the scheduling problems in supply chain in order to minimize the weighted tardiness. Akram et al. (2016) also proposed a fast simulated annealing algorithm to solve supply chain network problem.

Ataee (2015), proposed a new approach for selecting the suppliers portfolio using the combination of DEMATEL multiple-attribute decision making method and data envelopment analysis, and in the end, they answered this question that selecting this kind of portfolio would lead to agility or leaning of a supply chain. Sawik (2017), investigated the flexible supply portfolio selection under disruption risks and proposed a mixed-integer programming approach for risk evaluation. This model has been utilized for selecting and maintaining suppliers under disruptions and assigning the order volume and emergency inventory.

There are many researches which applied meta-heuristic algorithms for the supply chain management problems. Rostami et al. (2020) developed a GA for the integrating virtual cellular manufacturing with supply chain management considering new product development. Fathi et al. (2021) proposed an integrated queuing-stochastic optimization based on GA for the location-inventory management in supply chain networks. Dzalbs and Kalganova (2020) developed an accelerating supply chain using ant colony optimization (ACO) across a range of hardware solutions. Jiang et al. (2019) utilized a complex network-oriented technique based on artificial bee colony (ABC) for the global bi-objective optimization in three-echelon supply chains.

Shokouhifar et al. (2021) proposed a whale optimization algorithm (WOA) for the inventory management in blood supply chains. Atabaki et al. (2019) presented a firefly algorithm (FA) for the network design of a closed-loop supply chain with price-sensitive demand. Luan et al. (2019) applied a hybrid algorithm based on GA and ACO (GAACO) to solve the supplier selection problem. Buhayenko et al. (2018) utilized variable neighborhood search (VNS) for the supply chain coordination using dynamic price discounts. Mohammed and Duffuaa (2020) proposed a tabu search (TS) for the optimal design of the multi-objective multi-product supply chain networks. Fathollahifard et al. (2019) utilized SA to solve a bi-objective location-allocation routing problem in green home healthcare supply chains.

As mentioned above, there are many meta-heuristic algorithms to solve supply chain problems. The existing meta-heuristic algorithms are either population-based with proper global search mechanism (i.e., exploration), or single-population with high local search capabilities (i.e., exploitation). Our motivation is to simultaneously gain with the both advantages into the combined GASA algorithm. Comparison of the proposed method with the existing meta-heuristic algorithms for supply chain management can be seen in Table 1.

3. METHODOLOGY

In this study, a mathematical model has been employed to select the supplier for procuring the required raw materials of a manufacturing company, and different procurement approaches have been considered. The factory's demand is random, and its supplies would be fulfilled by several suppliers selected based on a number of criteria, including price, capacity, quality, and disruption. In this study, we have considered a two-stage supply chain network in which its first stage is factories with $N \geq 2$, and in its second stage are suppliers with $M \geq 2$. Each factory's demand would be randomly generated on a daily basis, and we have assumed that the suppliers and factories would face some disruptions in the manufacturing process and the demand. Further, the model would be solved and analyzed using the genetic algorithm, simulated annealing algorithm, and the hybrid genetic-simulated annealing algorithms

TABLE 1
COMPARISON OF THE PROPOSED GASA ALGORITHM WITH THE EXISTING META-HEURISTIC ALGORITHMS

Reference	Algorithm	Global Searching	Local Searching
Rostami et al. (2020)	GA	Yes	No
Fathi et al. (2021)	GA	Yes	No
Dzalbs & Kalganova (2020)	ACO	Yes	No
Jiang et al. (2019)	ABC	Yes	No
Shokouhifar et al. (2021)	WOA	Yes	No
Atabaki et al. (2019)	FA	Yes	No
Luan et al. (2019)	GAACO	Yes	No
Buhayenko et al. (2018)	VNS	No	Yes
Mohammed & Duffuaa (2020)	TS	No	Yes
Fathollahifard et al. (2019)	SA	No	Yes
Proposed method	GASA	Yes	Yes

.
In general, the system's costs would be categorized into three distinct types:

- The costs of suppliers' selection and their respecting contract costs.
- Factory's inventory costs including the costs of holding, ordering, shortages, and procurements.
- Transportation costs between suppliers and factories.

The model is formulated in the following. As all objectives have the same type of cost, we convert the multiple objectives into a single-objective function by means of simple summation, as:

$$min\, S = \sum_{t\in T}\sum_{i\in I} s_i[MAX(0,(+D_{it} - PW_{it})]$$

$$min\, G(X,Y,Q,R) = \sum_{t\in T}\sum_{i\in I}\sum_{j\in J} c_j Q_{ij} Y_{ij}\, B_{ijt} + \sum_{j\in J} f_j X_j \;+\; \sum_{t\in T}\sum_{i\in I}\Big[\sum_{j\in J,Q_{ij}\neq 0}\Big\{\big(p_{ij} + r_{ij} d_{ij}\big) Y_{ij} B_{ijt}\left[\frac{Q_{ij}}{M}\right]\Big\} + \sum_{k\in I,Q_{ik}^T\neq 0}\Big\{(p_{ik}^T + r_{ik}^T d_{ik}^T) Y_{ik}^T B_{ikt}^T\left[\frac{Q_{ik}^T}{M}\right]\Big\}\Big] + \sum_{t\in T}\sum_{i\in I}\Big[\sum_{j\in J,Q_{ij}\neq 0} K_i Y_{ij} B_{ijt} + \sum_{k\in I,Q_{ik}^T\neq 0} K_i^T Y_{ik}^T B_{ikt}^T\Big] + \sum_{t\in T}\sum_{i\in I} h_i\Big[PW_{i0} - \sum_{t\in T} D_{it} - \sum_{k\in I,k\neq i}\sum_{t\in t} Q_k^T B_{kit}^T Y_{ki}^T + \sum_{t\in T}\sum_{j\in J,Q_{ij}\neq 0} Q_i Y_{ij} B_{ijt} + \sum_{k\in I,k\neq i}\sum_{t\in t} Q_k^T B_{iKt}^T Y_{ik}^T\Big] + \sum_{i\in I} WC_i * \frac{max(PW_{it})}{W-cap_i} + \sum_{t\in T}\sum_{i\in I} s_i[MAX(0,(+D_{it} - PW_{it})] \quad (1)$$

St:

$$\sum_{t\in T}\Big(\sum_{j\in J} Y_{ij} + \sum_{k\in I,k\neq i} Y_{ik}^T - \sum_{l\in I,l\neq i} Y_{li}^T\Big) = E(D_i) \quad (2)$$

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

$$\sum_{i\in I} Y_{ij} \le W_j X_j\,; \quad \forall j\in J \quad (4)$$

$$Y_{ij} \le E(D_i)\,; \quad \forall i\in I, \forall j\in J \quad (5)$$

$$Y_{ik}^T \le E(D_i)\,; \quad \forall i,k\in I, i\neq k \quad (6)$$

$$q_j X_j \ge q_i^{min}\,; \quad \forall i\in I, \forall j\in J \quad (7)$$

$$Q_i \ge Q_j^{min}\,; \quad \forall i\in I, \forall j\in J \quad (8)$$

$$X_j \in \{0,1\}\,; \quad \forall j\in J \quad (9)$$

$$Y_{ij} \in \{0,1\}\,; \quad \forall i\in I, \forall j\in J \quad (10)$$

$$Y_{ik}^T \in \{0,1\}\,; \quad \forall i\in I, \forall k\in I \quad (11)$$

$$B_{ijt} \in \{0,1\}\,; \quad \forall i\in I, \forall j\in J, \forall t\in T \quad (12)$$

$$B_{ikt}^T \in \{0,1\}\,; \quad \forall i\in I, \forall k\in I, \forall t\in T \quad (13)$$

where i,k={1,2,…,N} is factory index, and j={1,2,…,M} is supplier index, and superscript T represents the lateral transshipment between factories. f_j is the annual contractual cost for supplier j, q_j is the percentage of acceptable-quality products by supplier j, W_j is the annual capacity of supplier j, $E(D_i)$ is the expected demand of factory i, and K_i (K_i^T) is the fixed setup cost of factory i when sourced by the suppliers (other factories). Q_{ij} (Q_{ik}^T) is the order quantity of factory i

from suppliers (other factories). Moreover, B_{ijt} (B^T_{ikt}) is a binary variable, which is equal to 1, if any product is transferred from supplier *j* (factory *k*) to factory *i* at time *t*; and otherwise, is 0.

I. The problem's variable definition

Seven decision variables have been introduced to express a potential solution. These variables are as follows:

- X_j: The selected suppliers would be defined as a binary vector (array) with length M. Therefore, based on equation 14, if the j^{th} supplier would be selected for procuring the factory's raw materials, the variable would be one, otherwise would be zero:

$$X_j = \begin{cases} 1 & \text{if the } j^{th} \text{ supplier is selected} \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

1	2	3	4	5	. . .	M
0	1	1	0	1	. . .	1

- Y_{ij}: The transportation between suppliers and factories in different periods would be defined as a binary $N \times M$ matrix. According to equation 15, if the transportation is occurred from j^{th} supplier to i^{th} factory, the array would be equal to one; otherwise, it would be zero. It should be mentioned that If all variables in column *j* in Y are 0, it means that supplier *j* has not been selected (even if X(*j*)=1). In this case, the elements of X is updated as X(*j*)=X(*j*)*sum(Y(:,*j*)). However, we use the vector X for the wise versa case, in which, for a supplier *j*, X(*j*)=0, but there is any factory *i* with Y(*i*,*j*)=1, which means factory *i* selects supplier *j*. In this case, factory *i* cannot purchase any product from supplier *j*, because X(*j*)=0.

$$Y_{ij} = \begin{cases} 1 & \text{if the transportation is required from } j^{th} \\ & \text{supplier to } i^{th} \text{ factory} \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

	1	2	3	4	5	. . .	M
1	1	0	1	0	1	. . .	0
2	1	1	0	1	1	. . .	1
:	:	:	:	:	:	:	:
N	0	1	1	0	1	. . .	1

- Y^T_{ik}: The transportation between different factories in different periods would be defined as a binary $N \times N$ matrix. According to equation 16, if the transportation is occurred from k^{th} factory to i^{th} factory, the array would be equal to one, otherwise would be zero:

$$Y^T_{ij} = \begin{cases} 1 & \text{if the transportation is required from } k^{th} \\ & \text{factoryto } i^{th} \text{ factory} \\ 0 & \text{otherwise} \end{cases} \tag{16}$$

	1	2	3	4	5	. . .	N
1	1	0	1	0	1	. . .	0
2	1	1	0	1	1	. . .	1
:	:	:	:	:	:	:	:
N	0	1	1	0	1	. . .	1

- R: Determining the inventory threshold level of each factory to order from suppliers in different periods, which would be defined as a discrete $1 \times N$ vector:

1	2	3	4	5	. . .	N
1000	638	834	456	281	. . .	548

- Q: Determining the order volume for each factory to order from suppliers in different periods, which would be defined as a discrete $1 \times N$ vector:

1	2	3	4	5	. . .	N
1070	2638	834	1456	3281	. . .	1548

- R^T: Determining the inventory threshold level of each factory to order from other factories in different periods which would be defined as a discrete $1 \times N$ vector according to equation 17:

$$R^T = R_{tind} \times R \tag{17}$$

- R_{tind}: Inventory level in the lateral transshipment that would be defined with 0.1 resolutions.

1	2	3	4	5	. . .	N
0.2	0.2	0.2	0.2	0.2	. . .	0.2

- Q^T: Determining the order volume for each factory to order from other factories in different periods which would be defined as a discrete $1 \times N$ vector according to equation 18:

$$Q^T = Q_{tind} \times Q \tag{18}$$

- Q_{tind}: Lateral transshipment order volume, that would be defined with 0.1 resolutions.

1	2	3	4	5	. . .	N
0.4	0.4	0.4	0.4	0.4	. . .	0.4

II. Utilized Algorithms

- *Genetic Algorithm*

In the genetic algorithm, a searching mechanism would be initiated using a randomized population of chromosomes. A chromosome would be encoded. In the proposed approach, to generate an initial solution (i.e., chromosome), binary structures including X_j, Y_{ij} and Y_{ij}^T, are randomly filled with 0 or 1. Moreover, integer structures (e.g., R and Q), and continuous structures (e.g., R_{tind} and Q_{tind}) are considered via random values, according to the type (integer or continuous) and allowable range of variables. Once the initial population has been generated, the main GA iteration loop would be launched, which includes two stages: The first stage is the evaluation of generated solutions' penalties and the second stage is the population update mechanism. The stages would be repeated sequentially until the stopping condition, which is the maximum number of iterations, is met. The chromosomes' penalty evaluation would be calculated based on equation 6.

Population updating in GA encompasses three phases: recombination, crossover, and mutation, which would generate P_R%, P_C%, and P_M% of the next-generation, respectively. In this study, these values are set as P_R=10%, P_C=50%, and P_M=40%. In the Recombination phase, P_R% of the best chromosomes in the current population, would be directly carried out to the next generation. Moreover, P_C% and P_M% of the population are updated using crossover and mutation operators. In order to generate an offspring in the crossover phase, at first, two parents are selected using roulette wheel selection (RWS), and then, uniform crossover operator is performed on them. In this method, each decision variable of the offspring is transferred from one of the parents randomly. Moreover, to generate an offspring in the mutation phase, a single parent is selected using RWS, and then, binary, integer, or continuous mutation operator (based on the definition of each decision variable) is performed on a randomly selected variable of the parent.

- *Simulated Annealing*

Given that each local search operator is capable of escaping local optimal, in each iteration of the simulated annealing algorithm, the local search operator would be applied to one to seven randomly selected structures to generate a new solution in the current solution proximity. In this research, two local search processes, namely the binary swap and binary change, for each of the three binary structures have been employed. Moreover, two local search operators, namely the double swap and double change operator, have been exploited for double structures.

If the binary structure is selected for local search, one of the binary swap or binary change would be applied to it randomly. However, if the double structure is selected, one of the double swap or double change operators would be used. Given the problem's formulation, sometimes changing one genome would not improve the solutions; in these cases, swapping two genomes would be more effective.

In each iteration, if the neighboring solution is better than the current solution, the algorithm would definitely consider it as the new solution. Otherwise, the algorithm would accept it as the new solution with the probability of $e^{\frac{-\Delta E}{T}}$. In this equation, $\Delta E = E^{new} - E^{old}$ would be the difference between the current objective function value and the neighboring solution objective function value, and T is the temperature parameter. Initially, the temperature would be extremely high to increase the probability of accepting bad solutions. By decreasing the temperature, the probability of accepting bad solutions would be reduced, and consequently, the algorithm would be converted to a good solution. In this study, the temperature would be reduced linearly based on equation 19, from the initial temperature $T_{initial}$ in the first iteration to the final temperature T_{final} in the last iteration:

$$T = T_{initial} + \frac{t}{I_{SA}} \times \left(T_{final} - T_{initial}\right) \quad (19)$$

where t is the current iteration number of the simulated annealing algorithm, and I_{SA} is the total number of iterations on the simulated annealing algorithm.

- *Hybrid Genetic-Simulated Annealing*

Generally, optimization methods for NP-hard problems can be divided into exact, heuristic, and metaheuristics. An exact algorithm obtains the optimal solution, but it is not possible to use these methods for the real-world networks, because of the required running time (Naderi et al., 2021). As a result, heuristics or metaheuristics must be applied. Although heuristics are fast in term of the running time, they don’t investigate the whole search space effectively, and thus, metaheuristics should be used to achieve the best performance (Sorensen, 2015). There are various global and local metaheuristic algorithms in literature. Among them, GA and SA have been widely used to solve different combinatorial NP-hard optimization problems.

When applying a metaheuristic algorithm, the whole search space should be globally explored at the early iterations of the algorithm, while exploitation via local searching is more useful when the algorithm encounters with near-optimal solutions at the last iterations (Baliarsingh et al., 2021). To obtain a better trade-off between speed and performance, we propose a hybrid approach to solve the supply chain management problem based on the GA and SA algorithms (called GASA) with local and global search capabilities.

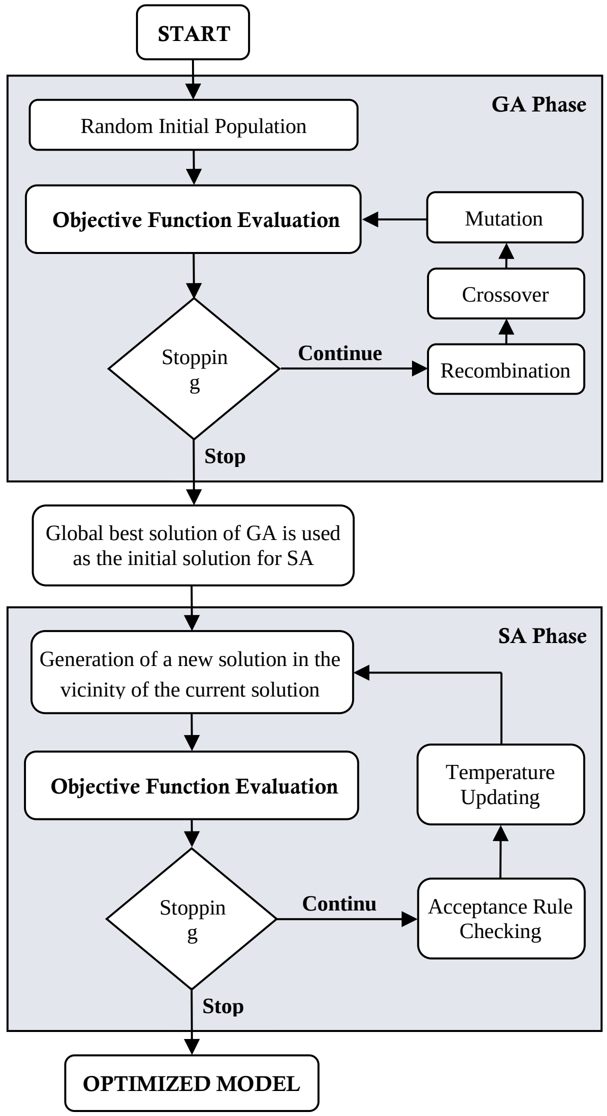

FIGURE 1
FLOWCHART OF THE COMBINED GASA ALGORITHM

Overall flowchart of the combined GASA algorithm can be seen in Figure 1. In the combined GASA, at first, an initial population is randomly generated to be fed to the GA as its input. After the global search process of the GA, the global best solution found by the GA would be fed to the SA as its input, in order to utilize the local search capability of the SA to obtain a better solution.

4. SIMULATION RESULTS

Tuning of the controllable parameters of the meta-heuristic algorithms is of utmost importance, when designing these algorithms to solve an optimization problem. To tune the controllable parameters of the GASA in both GA and SA phases, evaluation-based parameter setting method (Fanian et al., 2018; Naderi et al., 2021; Shokouhifar, 2021) is used. The controllable parameters of the GASA in both GA and SA phases ae summarized in Table 2.

TABLE 2
SETTING THE CONTROLLABLE PARAMETERS OF GASA

Parameter	Value
Number of iterations in GA phase	400
Population size of GA	50
Recombination rate (P_R)	10%
Crossover rate (P_R)	50%
Mutation rate (P_R)	40%
Number of iterations in SA phase	20,000
Initial temperature in SA	10
Cooling rate	0.1

As mentioned above, the multi-resource model with lateral transshipment is considered to find the best meta-heuristic to solve the model. In the multi-resource state, in which the lateral transshipment among factories is acceptable, we have computed the different costs including holding, ordering, transportation, purchase contract, and shortage cost, using the three algorithms of SA, GA, and GASA and calculated the objective function value by adding the shortage volume to the costs. To generalize the obtained results, we have executed the aforementioned model in different states and by using different numbers of factories (5, 10, and 20) and different numbers of suppliers (5, 10, and 20).

Comparison of the objective value and running time for different cases can be seen in Tables 3 and 4, respectively. According to the average objective values in Table 3, the GASA managed to acquire the lowest cost compared to the GA and SA algorithms with the average objective function value of 6.41e+06. However, according to Table 4, as the GASA utilizes both GA and SA algorithms sequentially, it requires more CPU running time, approximately twice than the GA and SA (on average).

The value of the different objectives obtained by GA, SA, and GASA are provided in Tables 5, 6, and 7, respectively. Moreover, convergence of the GA, SA, and the combined GASA, can be seen in Figures 2, 3, and 4, respectively.

TABLE 3
COMPARISON OF OBJECTIVE FUNCTION VALUES IN MULTI-RESOURCE WITH LATERAL TRANSSHIPMENT STATE

Number of Factories	Number of Suppliers	GA	SA	GA-SA
5	5	3.5827e+06	3.5719e+06	3.5563e+06
10	10	6.4947e+06	7.0951e+06	6.2039e+06
10	20	6.8433e+06	6.6776e+06	6.5979e+06
20	10	1.6494e+07	1.8010e+07	1.5394e+06
20	20	1.5324e+07	7.5743e+09	1.4131e+07
Average Cost		9.75E+06	1.52E+09	6.41E+06

TABLE 4
COMPARISON OF CPU RUNNING TIME OF THE DIFFERENT ALGORITHMS FOR DIFFERENT TEST CASES (IN SECONDS)

Number of Factories	Number of Suppliers	GA	SA	GA-SA
5	5	17	19	35
10	10	20	22	42
10	20	24	28	51
20	10	25	30	53
20	20	32	38	66
Average Time		23.6	27.4	49.4

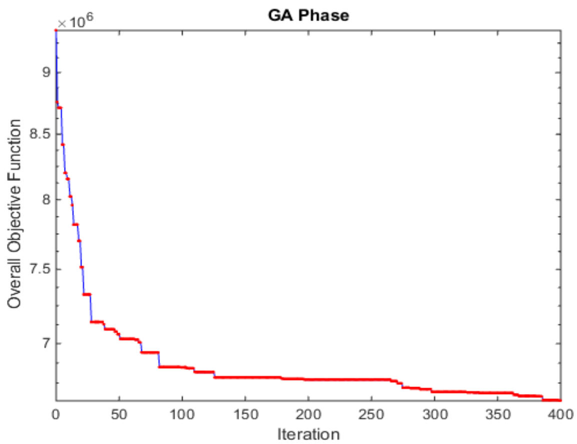

FIGURE 2
OVERALL OBJECTIVE FUNCTION VALUE FOR 10 FACTORIES AND 10 SUPPLIERS USING GA ALGORITHM

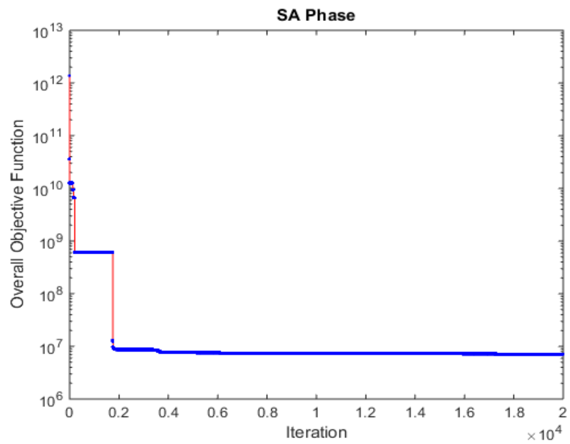

FIGURE 3
OVERALL OBJECTIVE FUNCTION VALUE FOR 10 FACTORIES AND 10 SUPPLIERS USING SA ALGORITHM

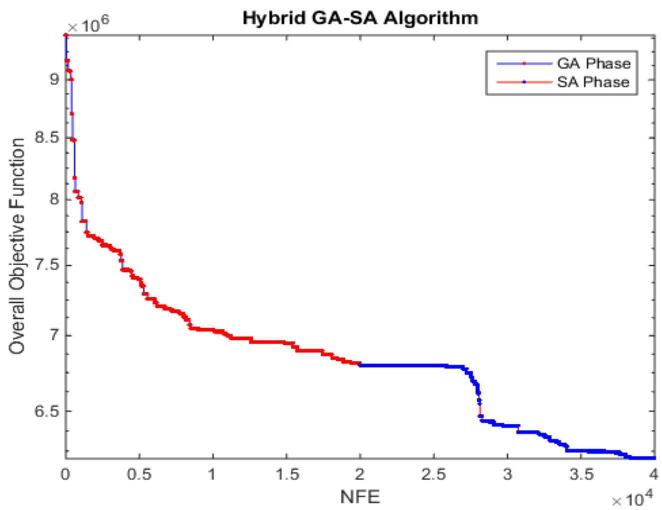

FIGURE 4
OVERALL OBJECTIVE FUNCTION VALUE FOR 10 FACTORIES AND 10 SUPPLIERS USING GASA ALGORITHM

TABLE 5
THE RESULTS OF THE MULTI-RESOURCE MODEL WITH LATERAL TRANSSHIPMENT USING THE GA ALGORITHM

Number of Factories	Number of Suppliers	Holding cost	Ordering cost	Transportation cost	Contract cost	Purchase cost	Shortage	Total cost	Objective function
5	5	2.63e+05	914962	6.7735e+05	3.2037e+05	1.4067e+06	0	3.5827e+06	3.5827e+06
10	10	6.1928e+05	2046319	1.0464e+06	6.6386e+06	2.2737e+06	0	6.6386e+06	6.6386e+06
10	20	5.91e+05	2369565	1.2137e+06	5.5563e+05	2.1134e+06	0	6.8433e+06	6.8433e+06
20	10	1.24e+06	5831294	2.5222e+06	1.4e+06	5.4978e+06	0	1.6494e+07	1.6494e+07
20	20	1.31e+06	5846750	2.5566e+06	1.3469e+06	4.2567e+06	0	1.5324e+07	1.5324e+07

TABLE 6
THE RESULTS OF THE MULTI-RESOURCE MODEL WITH LATERAL TRANSSHIPMENT USING THE SA ALGORITHM

Number of Factories	Number of Suppliers	Holding cost	Ordering cost	Transportation cost	Contract cost	Purchase cost	Shortage	Total cost	Objective function
5	5	2.6972e+05	880195	6.8422e+05	3.2037e+05	1.4174e+06	0	3.5719e+06	3.5719e+06
10	10	6.1890e+05	2473852	1.1303e+06	7.0174e+05	2.1704e+06	0	7.0951e+06	7.0951e+06
10	20	4.9912e+05	2237492	1.1918e+06	5.6314e+05	2.1860e+06	0	6.6776e+06	6.6776e+06
20	10	1.2645e+06	7082844	2.6730e+06	1.3262e+06	5.6632e+06	0	1.8010e+07	1.8010e+07
20	20	1.2699e+06	8719513	3.8574e+06	1.4545e+06	6.2490e+06	350.2	2.1567e+07	7.5743e+09

TABLE 7
THE RESULTS OF THE MULTI-RESOURCE MODEL WITH LATERAL TRANSSHIPMENT USING THE GASA ALGORITHM

Number of Factories	Number of Suppliers	Holding cost	Ordering cost	Transportation cost	Contract cost	Purchase cost	Shortage	Total cost	Objective function
5	5	2.6931e+05	881679	6.7648e+05	3.2037e+05	1.4084e+06	0	3.5563e+06	3.5563e+06
10	10	6.0309e+05	1806223	9.6882e+05	7.0174e+05	2.1240e+06	0	6.2039e+06	6.2039e+06
10	20	4.5072e+05	2166898	1.2299e+05	5.5344e+05	2.1969e+06	0	6.5979e+06	6.5979e+06
20	10	1.1021e+06	5326172	2.6972e+05	1.1917e+06	5.4504e+06	0	1.5394e+06	1.5394e+06
20	20	1.0807e+06	5316360	2.4694e+06	1.1701e+06	4.0948e+06	0	1.4131e+07	1.4131e+07

5. Conclusion

In this paper, genetic algorithm, simulated annealing, and a hybrid genetic-simulated annealing algorithm have been employed to solve the supply chain network problem under lateral transshipment, and their results have been compared. The genetic algorithm is the most common population-based evolutionary algorithm. In addition to the strong global search strategy (using the crossover operator), this algorithm possesses the ability to escape local optimal (using the mutation operator). On the other hand, the simulated annealing is a single-solution algorithm with powerful local search ability. In general, to solve each optimization problem, we deal with randomized solution sets. Therefore, it is preferable to apply the global search mechanism more frequently in the first iterations of the algorithm. By progressing the algorithm, the quality of solutions would be improved, and the algorithm would deal with solutions closer to the optimal solution. In this situation, it is better to apply the local search mechanism around the solutions close to the optimal solution in order to increase the speed and accuracy of the algorithm. Therefore, to achieve a proper balance between speed and accuracy, first, the global search mechanism would be employed using the genetic algorithm. Once the near-optimal solutions have been acquired, to save time, and increase the speed and accuracy of the algorithm, the time-consuming algorithm would be terminated, and the single-population simulated annealing algorithm would be applied to the remaining process. Therefore, considering the cost reduction and inventory shortage reduction factors, the hybrid algorithm is much more efficient and effective. Besides the advantages of the proposed hybrid global-local metaheuristic algorithm requires more CPU running time to obtain the solution, as it sequentially run the genetic algorithm and simulated annealing. In this paper, some assumptions have been taken into account, which may be far from the reality. As a future work, more realistic assumption can be considered. Moreover, other combination of the global and local search-based metaheuristic algorithms could be utilized and evaluated for the supply chain management problem. Moreover, other techniques for the representation of feasible solutions can be tested. In this paper, simple swap mutation operators for binary, integer, and continuous variables have been used. To further improve the solution quality and convergence speed of the proposed algorithm, other mutation operators based on heuristic information of the problem model can be utilized.

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COMPETING INTEREST STATEMENT

The authors declare no conflict of interest.

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