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A hybrid GA-TLBO Algorithm for Optimizing a Capacitated Three-Stage Supply Chain Network

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KEYWORDS

Supply chain network design;
Teaching-learning-based optimization;
Genetic algorithm;
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ABSTRACT

A teaching-learning-based optimization (TLBO) algorithm is a new population-based algorithm applied to some applications in the literature successfully. In this paper, a hybrid genetic algorithm (GA)-TLBO algorithm is proposed for the capacitated three-stage supply chain network design (SCND) problem. To escape infeasible solutions emerged in the problem of interest due to realistic constraints, a combination of a random key and priority-base encoding scheme is proposed. To assess the quality of the proposed hybrid GA-TLBO algorithm, some numerical examples are conducted. Then, the results are compared with those of GA, TLBO and exact algorithms.

1. Introduction

Today's organizations are looking for opportunities that improve their supply chain network to compete in global markets efficiently. A supply chain network design (SCND) problem is an attempt at the same way and one of the most important decisions in supply chain management (SCM) which affects key factors of success of a supply chain, such as responsiveness, transportation costs, and establishment costs of facilities. Typically, a SCND problem is an extended form of a two-stage transportation problem, in which in the first stage, the number and location of facilities are determined and, in the second stage, the flow of materials and products is determined [1]. While the former is specified as strategic decision level, the latter is recognized as tactical decision level. The first and second stage decisions are usually modelled via binary and continuous variables, respectively. Thus, a mixed-integer linear programming (MILP) model is used for the problem. A supply chain network (SCN) includes supplier, production, distribution centers as the nodes of the network and connections between these facilities as the edges of the network with the aim of buying raw materials, converting them to finished products, and distributing final products in a good way to customer zones [2]. Generally, the SCND problem includes the problem of determining the numbers, locations and capacities of facilities and the amount of shipments between them [3].

According to the supply chain planning matrix [4], integration of raw material suppliers, production centers, and distribution centers is categorized as horizontal integration while integration of tactical and/or operational inventory levels when addressing strategic level decision is referred to as vertical integration. In this paper, both strategic and tactical level decisions are integrated in a two-stage scheme so that the strategic level decisions are taken into

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account in the first stage, while the tactical level decisions are considered in the second stage of the problem.

The SCND problem is a computationally complex problem and is categorized as a non-deterministic polynomial-time hard (NP-hard) class [1]. For now, many researchers and practitioners have tried to find optimum solution to the SCND problem through developing heuristic, metaheuristic and exact algorithms. Exact algorithms, such as Lagrangian Relaxation (see [3]) and Benders decomposition (see [5]), provide global optimum solutions, meanwhile their computational efficiency is dramatically reduced in real large-sized problems. In addition, implementing exact solution methods in many problems is a really hard task and their successful implementation needs strong knowledge of mathematics. In contrast, heuristic or meta-heuristic algorithms provide local optimum solutions in a very low computational time. Many researchers have reported the efficiency of heuristic-based algorithms in achieving good quality solutions in reasonable time [22, 23]. Accordingly, the efficiency of meta-heuristic algorithms is dependent upon a solution representation method [6]. An appropriate solution representation method has two main features: (1) it is feasible; (2) its feasibility is not violated when applying the operators of different meta-heuristic algorithms. The better solution representation approach leads to speedy convergence of the algorithm to optimal or near-optimal solutions and decreases the used memory. The SCND problem is subject to many realistic constraints (e.g., demand satisfaction, material flow balance and capacity). Therefore, the emerging infeasible solutions in this problem are inherent when evolutionary algorithms are applied. To deal with the infeasible solutions, three methods, including repairing, discarding, and penalty approaches, have been proposed in the literature [1]. These methods increase computational time and use memory in solution procedure of the problem.

The most suitable solution representation for different meta-heuristic algorithms is the one represented considering the problem structure so that infeasibility of the solution is avoided in all iterations when different operators of the algorithm are applied. Considering the structure of the SCND problem, five solution representation methods, including matrix-based representation [7], basic feasible solution representation [8], direct transportation tree representation [9], spanning tree-based representation by a Prüfer number [10], and priority-based representation [1], have been proposed. Advantages and disadvantages of these methods were concisely discussed by Lotfi and Tavakkoli-Moghaddam [6]. Notably, the superiority of the priority-based encoding scheme compared to other mentioned methods has been investigated in the literature by researchers and practitioners [6, 11, 12].

In this paper, a new hybrid meta-heuristic algorithm, namely TLBO combined with the GA, is proposed to solve the capacitated three-stage SCND problem. The TLBO algorithm is a new population-based algorithm proposed by Rao et al. [13]. It encompasses two determinant phases, namely ‘teacher phase’ and ‘student phase’. The students are considered as solutions and evaluated by their grades. The teacher phase of the algorithm includes leading the average solutions toward the best solution assumed as teacher. In the student phase, the algorithm tries to escape from local optimal solutions by considering interaction between students. Indeed, interaction between students helps them to improve their knowledge and move toward the best one. This algorithm has been successfully applied to constrained mechanical design optimization problems and multi-objective heat exchanger problems [14]. Moreover, the algorithm has less parameters, which should be set before running with respect to other evolutionary algorithms. In addition, we modify the priority-base encoding scheme in such a way that it can be used in the proposed evolutionary algorithms for continuous search space. For this end, we combine the random key representation with the priority-based encoding representation method. Indeed, the algorithm searches the continuous space by a random key representation and then solution is altered into a priority-based representation.

To the best of our knowledge, there is no research work in the literature applying the hybrid GA-TLBO by using a combination of the random key and priority-based representation to the SCND problem. Therefore, our innovation basically lies in the used hybrid GA-TLBO approach and the used solution representation (i.e., combination of random key and priority-based methods) in designing feasible solutions that need no repair mechanism, unlike the spanning tree-based representation method, whose implementation is usual in the literature. In this way, the generated solutions would be feasible when all operators of

TLBO and GA are employed. Therefore, the efficiency of the proposed hybrid GA-TLBO is improved. The performance of the proposed hybrid GA-TLBO is compared with respect to GA, TLBO, and exact algorithms.

The body of this paper is organized as follows. In the next section, the related studies are surveyed. In Section 3, the mathematical formulation of the problem is presented. In Section 4, the solution representation method and the structure of the proposed hybrid GA-TLBO are described. In Section 5, computation results are presented and discussed. Finally, Section 6 presents the concluding remarks.

2. Related Studies

In this section, the related literature in this field is briefly reviewed. Gen et al. [1] proposed a priority-based GA for two-stage transportation problem to escape from infeasible solutions resulted due to realistic constraints embedded in the problem. They report the efficiency of the priority-based encoding representation with respect to spanning-based representation [10] in three factors: 1) achieving the optimal solutions in many test problems experienced, 2) easy to implementation, and 3) achieving feasible solutions after applying genetic operators. Meanwhile, the priority-based encoding scheme needs a two-digit memory more than spanning tree-based encoding representation in each stage of the problem. Lotfi and Tavakkoli-Moghaddam [6] applied a modified priority-based encoding representation to a fixed-charge transportation problem. Computational complexity of this problem is due to discrete space of objection function and constraints. In their proposed algorithm, the fixed and variable costs are altered to a cost, and then the priority-based encoding scheme is applied. Syarif et al. [15] developed a GA based on a spanning tree-base encoding representation for the three-stage logistic network design problem. They designed the feasibility measures and presented the repairing mechanism for the infeasible solution so that it can be applied to real world problems.

Jayaraman and Ross [16] developed a simulated annealing (SA) algorithm for the supply chain network problem incorporating cross-docking centers. Their model considers cross-docking centers at the intermediate between distribution centers (DCs) and customer centers to improve the responsiveness of the supply chain network. Altiparmak et al. [11] extended a GA for the multi-objective SCND problem that minimizes establishing and flow material costs between different echelons in the first objective function, maximizes responsiveness of the throughput network, and minimizes the equity of capacity utilization ratio to balance the capacity utilization. They used a priority-base representation for generating feasible solutions and utilized the weighted sum method to deal with multiple objectives. Pishvaee et al. [12] developed a memetic algorithm based on a modified priority-based encoding method for the bi-objective closed-loop supply chain network design problem. Their model determines the location, number and capacity of facilities in the forward and reverse sides simultaneously.

Cardona-Valdés et al. [17] developed a tabu search (TS) algorithm for a two-layer production-distribution planning problem in which conditions, such as multiple manufacturing centers, distribution centers, and a set of potential locations of warehouses are modeled under uncertainty. Devika et al. [18] considered sustainability issues in the structure of the SCND problem through developing mixed-integer linear programming (MILP) model to design a sustainable supply chain network. They considered three aspects of sustainability including economic, environmental, and social objectives in their study. Then, to solve the proposed multi-objective model in large-scales, metaheuristic algorithms based on adapted imperialist competitive algorithms and variable neighborhood search are developed. Govindan et al. [19] addressed the integrated dynamic location and routing problem for a two-layer supply chain network. In their model, economic and environmental objectives are optimized, simultaneously. In addition, they applied the proposed model in a perishable food supply chain. Finally, to solve the proposed model, efficient multi-objective particle swarm optimization and adapted multi-objective variable neighborhood search algorithms are implemented.

Govindan et al. [24] proposed a hybrid multi-objective algorithm based on the adapted multi-objective electromagnetism mechanism algorithm and adopted multi-objective variable neighborhood search to solve a sustainable supply chain network design problem under a stochastic demand condition. Nasiri et al. [25] proposed a cuckoo optimization algorithm to determine the optimum location-allocation decisions in a *p*-center hub location problem. Grangier et al. [26] proposed a heuristic solution method based on large neighborhood search for the vehicle routing problem with cross docking. Their proposed algorithm improves the best-known solution in 19 of 35 instances from the literature.

3. Proposed Mathematical Model

In the proposed model, three stages, including production centers, DCs, and customers, are considered. The aim is to determine the optimum number and location of facilities in different echelons among candidate locations and optimum material flow between facilities of the configured SCN. The capacities of facilities are limited, and the number of facilities that can be established in different echelons is restricted due to budget limitation.
The nomenclature used in formulation of the mathematical model is as follows:

Indices

i	Set of plants (i=1,.., I)
j	Set of distribution centers (j=1,.., J)
k	Set of customers (k=1,.., K)

Parameters

d_k	Demand of customer zone k
Q_i	Fixed cost of opening plant i
F_j	Fixed cost of opening DC j
γ_{ij}	Transportation cost of unit product shipment from plant i to DC j
δ_{jk}	Transportation cost of unit product shipment from DC j to customer k
cap_i	Capacity of plant i
ca_j	Capacity of DC j
W	Maximum number of DCs which can be established
Z	Maximum number of plants which can be established

Decision variables

x_{ij}	Amount of products transported from plant i to DC j
y_{ik}	Number of products transported from DC j to customer zone k
z_i	1 if plant i is established at potential location i; 0 otherwise
w_j	1 if DC j is established at potential location j; 0 otherwise

According to the above-mentioned descriptions, the mathematical model can be presented as follows:

$$\text{Min } Z = \sum_i Q_i z_i + \sum_j F_j w_j + \sum_i \sum_j \gamma_{ij} x_{ij} + \sum_j \sum_k \delta_{jk} y_{jk} \tag{1}$$

s.t.

$$\sum_j y_{jk} \geq d_k \qquad \forall k \tag{2}$$

$$\sum_i x_{ij} = \sum_k y_{jk} \qquad \forall j \tag{3}$$

$$\sum_j x_{ij} \leq cap_i z_i \qquad \forall i \tag{4}$$

$$\sum_k y_{jk} \leq ca_j w_j \qquad \forall j \tag{5}$$

$$\sum_j w_j \leq W \tag{6}$$

$$\sum_i z_i \leq Z \tag{7}$$

$$x_{ij}, y_{jk} \geq 0 \tag{8}$$

$$z_i, w_j \in \{0,1\} \tag{9}$$

Objective function (1) minimizes the establishing costs of plants and DCs and transportation (material flows) costs from plants to DCs and then from DCs to customers. Constraint (2) ensures that demand of customers is fulfilled and shortage is not permissible. Constraint (3) is a balance constraint at DCs. Constraints (4) and (5) consider capacity limitations for plants and DCs, respectively. Constraints (6) and (7) satisfy that the established plants and DCs do not violate their upper bounds. These constraints may be emerged due to budget limitations. Constraints (8) and (9) express non-negative and binary limitations for variables.

4. Solution Procedure

In this section, the TLBO algorithm is first described from [13, 14]. Then, the encoding scheme of solutions through priority-based algorithm and random key is presented.

4-1. TLBO algorithm

For now, many efficient single and population-based metaheuristic algorithms have been developed and applied to various real-world problems. TLBO is a population-based algorithm, proposed by Rao et al. [13]. TLBO has been inspired from teaching-learning process of educational organizations. Through this process, learners or students increase their knowledge or capabilities to become useful and eligible. In other words, they change from unskilled level to better skilled level through teaching process. Therefore, teacher and learners are two key elements of this algorithm in which the influence of teacher quality on the output of students is considered. Indeed, learners and teachers are considered as the solutions to the problem so that teachers are better solutions than students and try to improve their quality. It should be noted that students usually learn from their teacher or through interaction and discussion among themselves. In this algorithm, these two types of learning are considered. Teaching-learning process is iteratively performed to meet the stopping conditions of the algorithm.

Suppose that there are two different teachers (i.e., $T1$ and $T2$) that teach the same subject to learners with the same levels in two different classes. A good teacher efficiently teaches the learners, and therefore the mean or average of grades of his or her class is better than other one. For example, if $T1$ is better than $T2$, then the mean of his or her class ($M1$) will be better than $M2$. Teachers will try to increase the mean of grades of class. The efficiency of students is assessed according to the mean value of the class (i.e., population).

The group of beginner learners constitutes the population of the algorithm. Moreover, decision variables play the role of different subjects assigned to learners. For example, in a SCND problem, different binary and continuous variables are considered as the subjects offered to students. The objective function value is considered as a criterion for evaluating the results of learners. In a population, the learner with the best value of objective function (i.e., the best solution) is considered as the teacher. This algorithm includes two phases: 'teacher phase' and 'learner phase'. The learning process of students through the teacher is simulated in teacher phase. In this phase, the teacher teaches learners and tries to improve the average result of the class (i.e., population).

Assume that there are 'm' number of matters (i.e., decision variables) assigned to 'n' number of students. That is, the population size is equal to 'n' and each learner's result is considered as a solution. At any iteration i, $M_{j,i}$ is the average result of the students in a special subject 'j' (j=1, …, m).

In addition, in any iteration, each student with the best result is considered as a teacher.

Assume that the result of the best student in each cycle is illustrated by $X_{total\text{-}kbest,i}$ for all assigned matters. In each iteration, the best student is recognized as a teacher. A teacher will strongly attempt to improve the knowledge level of the all students; however, improving knowledge level of a student is dependent upon the quality of teaching process and the quality of presentations of other students.

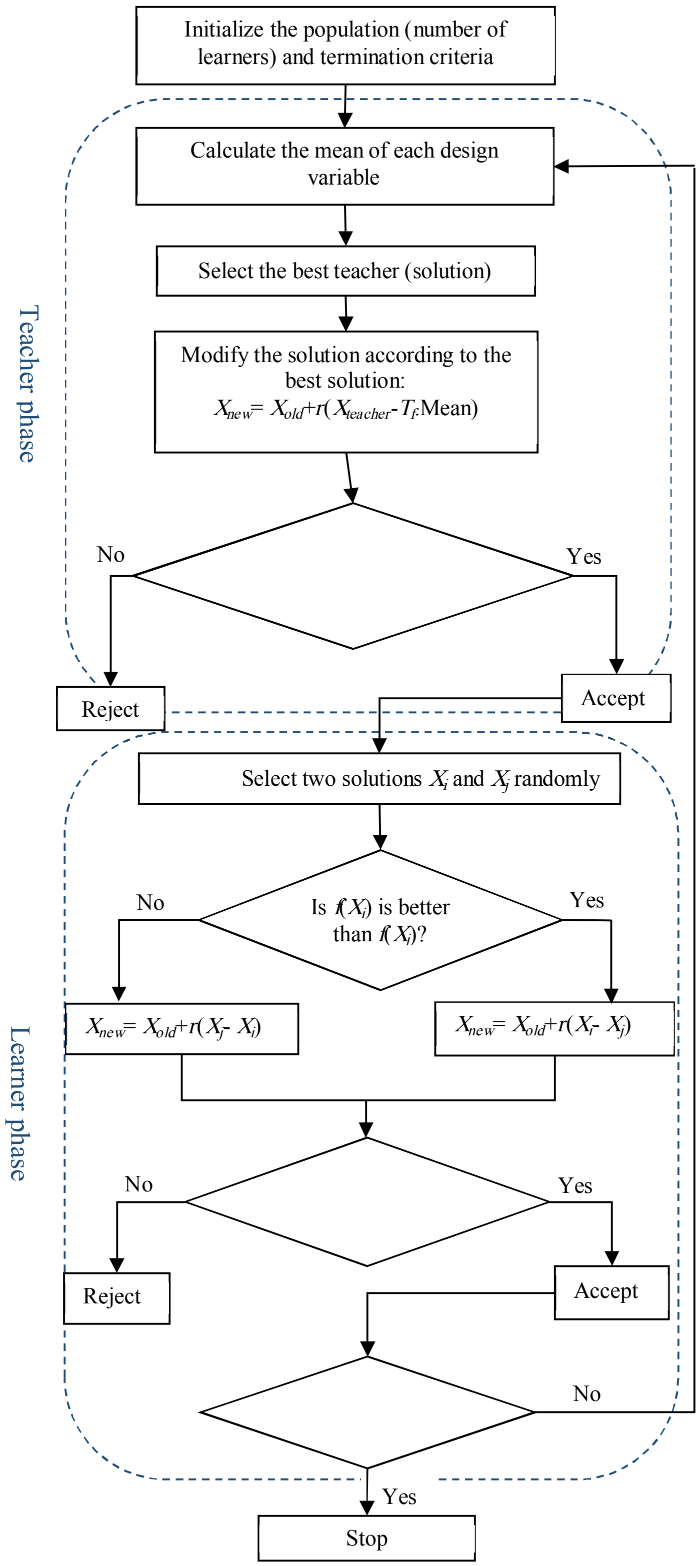

Fig. 1. Flowchart of TLBO algorithm

Therefore, the difference between the result of the teacher and mean result of the students in each matter can be represented as Equation (10):

$$Difference\_Mean_{j,i} = r_i\ (X_{j,kbest,i} - T_F M_{j,i}) \qquad (10)$$

where $X_{j,kbest,i}$ is the result of the best student, which is considered as a teacher in matter j. T_F represents the teaching factor which leads to alteration of mean value, and r_i is the random number specified in the range [0, 1]. The value of T_F is equal to 1 or 2, which is determined through equation (11) decided randomly as follows.

$$T_F = round\ [1+rand[0,1](2-1)] \qquad (11)$$

Note that the value of T_F is not entered as an input into the start of the algorithm, but its amount is randomly calculated within the structure of the algorithm, randomly. Therefore, T_F is not a parameter of the algorithm. According to the value of $Difference\_Mean_{j,k,i}$, the achieved solution is revised in the teacher phase as follows:

$$X'_{j,k,i} = X_{j,k,i} + Difference\_Mean_{j,k,i} \qquad (12)$$

where $X'_{j,k,i}$ illustrates the updated amount of $X_{j,k,i}$. $X'_{j,k,i}$ is kept if it has better objective function value. All the accepted maintained solutions in the teacher phase are considered as the input values to the learner phase.

In the learner phase of the TLBO algorithm, the learning process of students through interaction and discussion among themselves is simulated. A learner will increase his or her knowledge level through discussion with other students if they have more knowledge than him or her. Equations (13) and (14) model the learner phase of the algorithm. Two students P and Q are randomly determined, such that $X'_{total-P,i} \neq X'_{total-Q,i}$, where $X'_{total-P,i}$ and $X'_{total-Q,i}$ are the updated amounts of $X_{total-P,i}$ and $X_{total-Q,i}$, respectively, at the end of teacher phase.

$$X''_{j,P,i} = X'_{j,P,i} + r_i\ (X'_{j,P,i} - X'_{j,Q,i}), \qquad (13)$$
$$\text{If } X'_{total-P,i} > X'_{total-Q,i}$$
$$X''_{j,P,i} = X'_{j,P,i} + r_i\ (X'_{j,Q,i} - X'_{j,P,i}), \qquad (14)$$
$$\text{If } X'_{total-Q,I} > X'_{total-P,i}$$

$X''_{j,P,i}$ is kept if it leads to a better objective function value. Figure 1 demonstrates the flowchart of TLBO algorithm.

Considering the structure of TLBO algorithm, we have implemented the well-known GA operators (i.e., crossover and mutation) within TLBO algorithm to make use of the advantages of hybrid evolutionary algorithms. Therefore, the final solution is achieved through the hybrid GA-TLBO algorithm.

4-2. Priority-based encoding scheme

As mentioned previously, a solution representation method has great influence on the performance of the evolutionary algorithm. The solution representation method is different for different problems. A priority-based solution representation method proposed by [20] is so compatible with the structure of the supply chain network optimization problem. Indeed, by this method, the produced solutions remain feasible under applying different operators of evolutionary algorithms. Although matrix-based representation and spanning tree methods have been used for encoding the network problem, there will be a need for repairing mechanism and special operators for obtaining feasible solutions [6].

Gen et al. [1] proposed a new encoding scheme entitled priority-based encoding to escape from different repairing methods in the search process of algorithm. This method has been employed on the shortest path problem and project scheduling problem successfully [10]. The main difference of this method compared to the matrix-based and spanning tree method emerges from the particular decoding and encoding mechanisms for transportation trees.

In this method, solutions are encoded as arrays of size $|I|+|J|$, in which the location of each cell within the structure of the solution represents the sources and depots and the value of each cell indicates the priority of the node for making a tree among candidates. In the proposed supply chain network design model, assume that there are two plants, three distribution centers, and four customer zones, then Figure 3 is used for a solution representation using a priority-based method. Note that only a grey color section represents the solution. It should be noted that in the SCND problem studied by Gen et al. [1], only DCs location and material flows within a supply chain network are determined. In our problem, locations of plants, DCs, and material flows are optimized, simultaneously. In addition, the number of facilities that can be established in different echelons is restricted due to a budget limitation. Therefore, the SCND problem studied here has a higher degree of complexity than the problem studied by Gen et al. [1].

The priorities in a solution are randomly generated. To do so, we use a random key method [21], which has a high degree of key randomness. In this method, firstly, random keys are generated in continuous space, and then their integer positions are used as priorities in the solution. For more description of the priority-based method, interested readers are referred to [1]. Figure 2 illustrates how the decision variables related to material flow of the second segment of the SCN are calculated through this representation method. This procedure is repeated for calculating the decision variables of the first segment. Algorithm 1 is used for decoding solutions by the use of the priority-based method.

$$\begin{bmatrix} 9 & 17 & 15 & 16 \\ 14 & 12 & 16 & 13 \\ 13 & 14 & 17 & 11 \end{bmatrix}$$

Transportation costs of the second segment (3× 4)

Source \ Depot	300	350	300	350
550	300		250	
300		300		
450		50	50	350

Optimal material flow

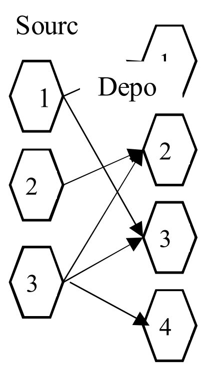

Fig. 2. Material flow calculation

First segment					Second segment						
Plants		DCs			DCs			Customers			
1	2	1	2	3	1	2	3	1	2	3	4
2	3	4	5	1	2	5	3	7	4	1	6

Fig. 3. Solution representation

***Algorithm* 1**

Inputs: K: set of sources

J: set of depots

b_j: demand on depot (source) j

CA_k: capacity of facility k

c_{kj}: transportation cost of one unit of product from source k to depot j

v ($|K| + |J|$): encoded solution

Outputs: g_{kj}: material flow between nodes k and j

Y_k: binary variable indicates the established facilities

While $\sum_j b_j \geq 0$

***Step* 1**: $g_{kj}=0 \;\; \forall j \in J, k \in K$

***Step* 2**: select a node based on l=argmax $v(1,t)$, $t \in |K|+|J|$

***Step* 3**: if $l \in K$, then a source is selected $k^*= l$

j^*=argmin$\{c_{kj}|\;\; v(1,j)\neq 0,\;\; k\in K\}$ Select a depot with minimum cost

else $j^*=l$ a depot is selected

k^*=argmin$\{c_{kj}|\;\; v(1,j)\neq 0,\;\; k\in K\}$ Select a source with minimum cost

***Step* 4**: $g_{k^*j^*}= \min(CA_{k^*}, bj^*)$

Update demands and capacities

$CA_{k^*}= CA_{k^*} - g_{k^*j^*}$, $b_{j^*}= b_{j^*} - g_{k^*j^*}$

***Step* 5**: if CA_k=0 then $v(1,k^*)=0$

if b_{j^*}=0 then $v(1,j^*)=0$

end of loop

***Step* 6**: for 1 to K

if $\sum_j g_{kj} \geq 0$

Y_k=1

End

The solution of the proposed model is represented as $|I|+|J|+|K|$ matrix. The solution includes two segments, in which each segment is related to one echelon of the considered supply chain network. To decode a solution, firstly, the second segment is decoded and then the first segment is decoded. In fact, decoding the first segment is impossible before the second segment is decoded [12].

In other words, at first, the second segment is considered as depots and sources. Then, after decoding the second segment, the first segment is again treated as depots and sources.

5. Computational Results

In this section, we conduct 10 numerical examples in small, medium, and large sizes to evaluate the performance of the proposed hybrid GA-TLBO algorithm. Because of adding some contributions to the proposed SCND problem (e.g., budget limitation and potential areas for plant establishing), there is no benchmark problem in the literature to compare the acquired results with them. Thus, we use the data randomly generated according to Table 1. Note that we have not assumed that the parameters in Table 1 have uniform distribution; however, the parameters are deterministic that have been randomly generated within the mentioned ranges in Table 1. The proposed hybrid GA-TLBO algorithm and other algorithms (i.e., GA and TLBO) are coded in Matlab 2012 optimization software. In addition, the proposed model is coded in GAMS 23.5 optimization software and solved by a CPLEX algorithm, which provides a global optimum solution. This solution is achieved under 30 minutes.

Tab. 1. Random generation of data

Parameter	Value
d_k	U [120, 500]
Q_i	U [2280000, 20820000]
F_j	U [228000, 2082000]
γ_{ij}	U [10, 50]
δ_{jk}	U [40, 90]
cap_i	U [500, 4500]
ca_j	U [150, 2000]
W	4
Z	8

Table 2 indicates the best results achieved by the proposed GA-TLBO algorithm and other meta-heuristics developed for comparing the results. The number of iterations of each algorithm is considered to be 30, and the best result of all iterations is reported for each algorithm. In addition, the number of population in each iteration is assumed to be 100.

Table 3 shows the mean absolute percentage error (MAPEs) achieved for different test problems. The MAPE used for error measurement is as follows:

$$MAPE = \frac{Best\ Solution - Optimal\ Solution}{Optimal\ Solution}$$

The achieved results illustrate that the all applied algorithms have admissible MAPEs for the proposed SCND problem. The good results of the applied algorithms could be explained due to using priority-based solution method which does not have any repairing mechanism when different operators are applied. The proposed GA-TLBO algorithm outperforms the GA and TLBO, except in one case (i.e., test problem 4×7×15). This observation is due to random nature of population generation in the applied algorithms. The MAPEs achieved for the hybrid GA-TLBO algorithm is significant with respect to the MAPEs of other algorithms, especially in large test problems. The performance of the GA is better than the TLBO algorithm in four test problems as well as the TLBO outperforms the GA in four cases. Since all algorithms run under several minutes, their time efficiency is not reported here. Obviously, in a SCND problem that is a strategic level decision-making problem, having several minutes is acceptable to solve the problem.

Tab. 2. The best results of the applied evolutionary and exact algorithms

	Problem size $\lvert I \times J \times K \rvert$	Hybrid GA-TLBO	GA	TLBO	CPLEX (Global optimum)
Small size	2×5×12	44216544	44216616	44216616	44215340
	2×4×10	43864645	43864645	43864645	43863090
	4×8×20	69589377	69598665	69598546	69585120
Medium size	3×10×18	60997040	61001456	61015737	60991940
	3×9×22	87339625	87364000	87357277	87327850
	4×7×15	52588724	52587936	52602483	52585730
Large size	5×10×30	103092399	103096230	103096196	103089700
	5×8×28	97258973	97261415	97261341	97255040
	5×7×25	88979576	88979558	88981569	88977260
	4×9×26	96717596	96719642	96723236	96711330

Tab. 3. MAPEs between evolutionary and exact algorithms

Problem size $\lvert I \times J \times K \rvert$	Hybrid GA-TLBO	GA	TLBO
2×5×12	2.72E-05	2.89E-05	2.89E-05
2×4×10	3.55E-05	3.55E-05	3.55E-05
4×8×20	6.12E-05	1.95E-04	1.93E-04
3×10×18	8.36E-05	1.56E-04	3.90E-04
3×9×22	1.35E-04	4.14E-04	3.37E-04
4×7×15	5.69E-05	4.20E-05	3.19E-04
5×10×30	2.61E-05	6.33E-05	6.30E-05
5×8×28	4.04E-05	6.55E-05	6.48E-05
5×7×25	2.58E-05	2.58E-05	4.84E-05
4×9×26	6.48E-05	8.59E-05	1.23E-04

5. Conclusion

In this paper, we have presented a hybrid GA-TLBO algorithm for a three-stage supply chain network design (SCND) problem. In this work, to produce values in a chromosome, first, we generate random solutions and then their positions are extracted to be used as integer values in a chromosome. This method is familiar to a random key method, which helps us to use different crossover and mutation operators defined in continuous space. We have used a combination of the random key and priority-base encoding scheme to escape from infeasible solutions emerged in the problem of interest due to realistic constraints. In order to assess the quality of the proposed algorithm, its performance has been compared with respect to the outcomes of the GA, TLBO, and exact algorithms. The acquired results show that the proposed hybrid GA-TLBO algorithm is superior to other applied algorithms. In the proposed hybrid GA-TLBO algorithm, crossover and mutation operators of the GA have been applied within the TLBO algorithm. Finally, the efficiency of the new TLBO algorithm has been justified for the SCND problem by this research.

For the current study, the following research directions can be addressed in the future. The problem can be developed under uncertainty and applied in a real case, such as the MDF wood supply chain. To deal with the uncertainty, stochastic methods, robust optimization approaches or fuzzy mathematical programming approaches can be applied. In addition, investigating parameter tuning methods and landscape analysis will determine the most suitable values of the parameters of the hybrid GA-TLBO algorithm. To justify the efficiency of the new TLBO algorithm, it should be applied to various optimization problems in different fields.

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