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Abstract A supply chain is a complex network which involves the products, services and information flows between suppliers and customers. A typical supply chain is composed of different levels, hence, there is a need to optimize the supply chain by finding the optimum configuration of the network in order to get a good compromise between the multi-objectives such as cost minimization and lead-time minimization. There are several multi-objective optimization methods which have been applied to find the optimum solutions set based on the Pareto front line. In this study, a swarm-based optimization method, namely, the bees algorithm is proposed in dealing with the multi-objective supply chain model to find the optimum configuration of a given supply chain problem which minimizes the total cost and the total lead-time. The supply chain problem utilized in this study is taken from literature and several experiments have been conducted in order to show the performance of the proposed model; in addition, the results have been compared to those achieved by the ant colony optimization method. The results show that the proposed bees algorithm is able to achieve better Pareto solutions for the supply chain problem.

1. Introduction

Nowadays, the complexity of the business environment is rapidly increasing [1]. This is due to several factors such as the expansion of the market, a wide range of suppliers, increased competition and customers demands on the performance of a company, in particular, the waiting time, cost and quality of the product [2]. Among these factors, if we consider the range of suppliers to the market, it is necessary to design an optimized supply chain model [3]. The supply chain is a complex network from suppliers to customers, which involves people, technologies, activities, information and resources. Its design and management has the purpose of obtaining the best global performances under unions operating criteria [4]. A typical supply chain is composed of the following elements: suppliers, manufacturing plants, warehouses, distribution centres (DCs), customers/final markets.

The optimization of a supply chain is related to selecting the optimum resource options in order to satisfy the objective function / functions. The single objective-based supply chain models are mostly aimed at finding the minimum total cost [5, 6]. However, the modelling of a supply chain requires more than a single-objective such as lead-time minimization, inventory level minimization, service level maximization, environmental impact maximization and so on [7]. Sometimes these objectives may cause conflicts such as increasing the service level usually causes a growth in costs. Therefore, the aim must be to find trade-off solutions to satisfy the conflicting objectives.

In multi-objective optimization problems there is no single optimum solution, but there is a solution set which creates Pareto optimal solutions. Pareto optimal solutions are a set of trade-offs between different objectives and are non-dominated solutions, i.e., there is no other solution which would improve an objective without causing a worsening in at least one of the other objectives [8].

In the literature, several models have been proposed to solve supply chain design problems to get the Pareto optimal solutions. Most of these models are based on genetic algorithms and the fuzzy logic approach. Work has been done on the facility location problem of a four echelons supply chain (suppliers, plants, DCs and customers) [9]. The objectives of this work are to minimize the total cost, maximize customer services and the capacity utilization balance for DCs using a genetic algorithm-based approach.

Another reported work on supply chains is based on the supplier selection, product assembly and distribution system using a modified Pareto genetic algorithm to minimize the total cost and delivery time, and maximize the quality [10].

A multi-objective location-inventory problem has been investigated using a multi-objective evolutionary algorithm based on the non-dominated sorting genetic algorithm II (NSGAII) in order to minimize total costs and maximize the volume fill rate and the responsiveness level [11].

An optimum mathematical planning model for green partner selection, which involves four objectives which are cost, time, product quality and green appraisal score, has been developed in [12]; this model employed two types of genetic algorithms to solve multi-objectives and then to find the set of Pareto optimal solutions. In this study, the weighted sum approach that can generate a greater number of solutions has been proposed.

In [13], the authors have developed a multi-objective fuzzy mathematical programming model for a forward/reverse supply chain minimizing the total cost and the environmental impact. This approach is composed of two parts: in the first phase the method of Jimenez et al. [14] is applied to convert the proposed multi-objective probability mixed integer programming model into an

equivalent auxiliary crisp model, and in the second phase a fuzzy solution method based on the e-constraint method to find the final preferred compromise solution has been proposed.

A multi-product, multi-stage and multi-period scheduling model is proposed in [15] to deal with multiple incommensurable goals for a multi-echelon supply chain network with uncertain market demands and product prices; a two-phase fuzzy decision-making method is presented to maximize the participants' expected profits, average safe inventory levels, average customer service levels and robustness of selected objectives to demand uncertainties.

A bi-objective optimization approach to the designing and planning of a supply chain is proposed in [16] in order to maximize the annual profit and minimize the environmental impact; profit and environmental impacts are balanced using an optimization approach adapted from symmetric fuzzy linear programming, while the supply chain is modelled as a mixed integer linear programming optimization problem using the resource-task-network methodology.

In [17], a multi-objective evolutionary algorithm called the fuzzy logic non-dominated sorting genetic algorithm II (FL-NSGAII) is used to solve a multi-objective optimization problem of vehicle routing in which multiple depots, multiple customers and multiple products are considered; the travelling distance and the total travelling time are the two objective functions to be minimized.

A random fuzzy multi-objective mixed-integer non-line-

ar programming model for the supply chain design problem has been proposed in [18], with a spanning tree-based genetic algorithm in order to minimize the total cost and maximize customers service level.

The model in [19] deals with the planning of a multi-product, multi-period and multi-echelon supply chain network that consists of several existing plants at fixed places, some warehouses and distribution centres at undetermined locations, and a number of given customer zones. The supply chain planning model is constructed as a multi-objective mixed-integer linear program to satisfy several conflicting objectives, such as minimizing the total cost, raising the decision robustness in various product demand scenarios, lifting the local incentives, and reducing the total transport time. A two-phase fuzzy decision-making method has been proposed.

In [20], the proposed method is a bi-objective mathematical programming formulation which minimizes the total costs and the expected transportation costs after failures of facilities of a logistics network; a new hybrid solution methodology is introduced by combining the robust optimization approach, queuing theory and fuzzy multi-objective programming.

In addition to the above genetic algorithm and fuzzy logic-based supply chain models, several other models have also been proposed in particular based on the swarm-based optimized models. One of the swarm-based model has been proposed on an inventory model for an assembly supply chain network which has fuzzy demand for single products and a fuzzy reliability of external suppliers effect on determination of inventory policy [21]. The performance of the supply chain is assessed by two criteria including total cost and fill rate. To solve this bi-criteria model, hybridization of multi-objective particle swarm optimization and simulation optimization is considered. In [22], an optimization mathematical model integrating cost and time criteria has been solved using a modified particle swarm optimization method (MEDPSO) for solving a multi-echelon unbalanced supply chain planning problem. The results indicated that the MEDPSO method can obtain a better quality solution compared to classical GA and PSO.

Furthermore, another swarm-based optimization model is proposed for a resource options selection problem in a bulldozer supply chain design in [23]. The model is based on the ant colony optimization technique to solve the multi-objective problem and to find the Pareto solution set where the aim is to find the best combination of the resource options by minimizing the total cost and the total lead-time.

In this work, the optimization of the bulldozer supply chain problem given in [23] has been selected because of the complexity of the supply chain network and its general combinatorial nature that makes it suitable for various supply chain problems, and the bees algorithm (BA), which is another swarm-based optimization technique, is proposed to solve this problem [24]. The algorithm is based on the food foraging behaviour of a swarm of bees combining a random search with a neighbourhood search. The BA has been successfully applied to several optimization problems [25–42].

There is no single algorithm which can find the best solution for all types of optimization problems according to the no-free lunch theorem [43]. In previous work, the BA has been shown to have better performance compared to the following optimization algorithms tested for continuous type benchmark functions; simplex method, stochastic simulated annealing, genetic algorithm, ant colony optimization [44]. Hence, the BA has been selected for the bulldozer supply chain problem. Note that the results found by the ant colony optimization in [23] were not global optimum. The aim of this study is to improve on the previously reported results using a multi-objective optimization approach based on the BA. The bees algorithm has also been proven to be a valid approach to get the Pareto optimal set for multi-objective problems [45–47]. In [45], the BA has been tested on the classical environmental/economic dispatch problem (EEDP). The EEDP was amended in conjunction with the bees algorithm to identify the best design in terms of energy performance and carbon emission reduction by adopting zero and low carbon technologies. This computer-based tool supports the decision-making process in the design of a low-carbon city. The algorithm is also tested on a welded beam design problem which involves two non-linear objective functions and seven constraints [46, 47]. The BA results have been compared with those obtained with the non-dominated sorting genetic algorithm (NGSA) and the NGSAII, and it has been shown that the bees algorithm is able to find more non-dominated solutions.

The bees algorithm-based supply chain optimization model is implemented on a resource options selection problem which has been taken from the literature in order to minimize the total cost and the total lead-time of the supply chain. Several numerical experiments have been conducted in order to show the performance of the algorithm on a Pareto solutions set and later compare them to those achieved by the ant colony optimization.

This study is organized as follows: the description of the bees algorithm is given in section 2, the multi-objective optimization with the bees algorithm is given in section 3, the supply chain case study model is given in section 4, the experimental study is given in section 5, the results are given in section 6 and finally conclusions are given in section 7.
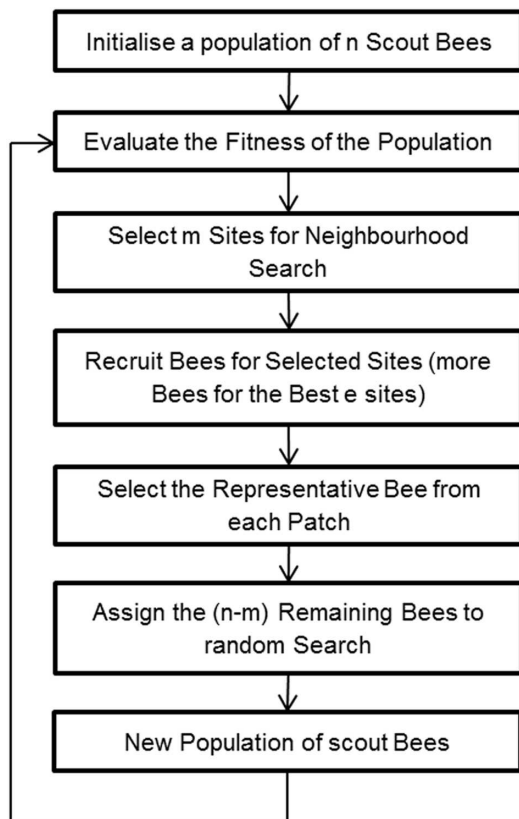
2. The bees algorithm optimization

2.1. Bees foraging process in nature

During the harvesting season, a bee colony employs part of its population to scout [48, 49] the fields surrounding the hive. Scout bees move randomly looking for food sources. When they return to the hive, scout bees deposit the nectar (or pollen) that they have collected during the search process. Then they start to do a ritual called the "waggle dance" to communicate with other bees and give them information about the food source [50]. The waggle dance is performed on a particular area of the hive called the "dance floor", and communicates three basic pieces of information regarding the flower patch: the direction in which it is located, its distance from the hive, and its quality rating [49, 51]. After the waggle dance, the dancer bee goes back to the flower patch with its followers, called recruited bees. The number of recruited bees depends on the quality rating of the patch. Flower patches that contain rich and easily available nectar or pollen sources attract the largest number of followers (foragers) [50, 52]. Once a recruited forager returns to the hive, it will in turn waggle dance to direct other idle bees towards the food source.

2.2. The bees algorithm

The bees algorithm is an optimization algorithm inspired by the natural foraging behaviour of honey bees to find the optimal solution. The flow chart of the algorithm is shown in Figure 1.

The algorithm requires a number of parameters to be set, which are given as follows: the number of the sites (n), the number of sites selected for neighbourhood search among n sites (m), the number of top-rated (elite) sites among m selected sites (e), the number of bees recruited

Figure 1. The flow chart of the bees algorithm

for the best *e* sites (*nep*), the number of bees recruited for the other (*m-e*) selected sites (*nsp*), the neighbourhood size of each selected patch for neighbourhood (local) search (*ngh*), and the stopping criterion. The algorithm starts with the *n* scout bees being placed randomly in the search space. The fitness of the sites visited by the scout bees is evaluated.

Then the *m* fittest sites are designated as selected sites and chosen for neighbourhood search. The algorithm conducts a local search process around the selected sites by assigning more bees to the best *e* sites and fewer bees to the non-elite best sites. Selection of the best sites is made according to their associated fitness value. Finally, the remaining sites (*n-m*) will be searched randomly, which is the global search stage of the bees algorithm. During the global search stage one bee will be recruited for each (*n-m*) site. The algorithm will run until the stopping criteria are met.

3. Multi-objective optimization with the bees algorithm

The multi-objective optimization falls into the area of the multiple criteria decision-making.

In the multi-objective optimization there is no single solution to satisfy each objective, therefore there exists a possible solution set called Pareto optimal solutions which are the non-dominated solutions [53]. A solution in the feasible solution space is called Pareto optimal (or non-dominated solution) if there is no other feasible solution in the solution space that reduces at least one objective function without increasing another. As shown

1 Initialize population with random solutions.
2 Evaluate fitness of the population.
3 While (stopping criterion not met)
  Forming new population.
4 Select sites for neighbourhood search.
5 Recruit bees for selected sites and evaluate fitnesses.
6 Select the representative bee from each patch.
7 Assign remained bees for global search (randomly) and evaluate their fitness values.
8 Create / Amend the Pareto optimal set.
9 End While.

Table 1. Multi-objective bees algorithm pseudo code

in Figure 2, the black points are dominated solutions while dotted points are non-dominated solutions.

In this study, the multi-objective bees algorithm parameters are set similar to the bees algorithm for a single objective optimization problem. In addition, there is a Pareto optimal set for the proposed method. The pseudo code for the multi-objective bees algorithm is given in Table 1.

According to Table 1, the algorithm starts with *n* scout bees randomly distributed in the search space. The fitness of the sites (i.e., the performance of the candidate solutions) visited by the scout bees are evaluated in step 2.

In step 4, after sorting the sites according to their fitness, the first *m* sites (selected sites) are chosen for neighbourhood search.

In step 5, the algorithm searches around the selected sites. In step 6, the representative bee will be the it is dominated by one of the recruited bees; in that case the representative will be the new non-dominated bee.

In step 7, the remaining bees in the population are placed randomly around the search space to scout for new potential solutions.

Step 8 is the new stage added to the basic bees algorithm to allow the algorithm to deal with multi-objective optimization problems. If the fitness value of the

Figure 2. Pareto solutions example

representative is a non-dominated solution, it will be added to the Pareto optimal set. In addition, if this solution is dominating the other solutions in the created Pareto optimal set, the dominated solutions will be removed from the set.

The process will be repeated until a stopping criterion is met.

4. Supply chain design case study using the multi-objective bees algorithm

In this study, the multi-objective bees algorithm has been used to solve a resource options selection problem for the supply chain design of a bulldozer, taken from [23]. The supply chain design problem is a general problem that concerns the optimal choice of resource options across a supply chain network in order to minimize the total cost and the lead-time simultaneously for a product or a family of products.

In this study, the given supply chain is composed of N activities including the sourcing/supplying of each of the components, the assembling of each of the sub-assemblies and final products, and the delivering of each product to its destination market. Each activity can be performed by a different number of resource options(N_i), and each resource option has its own cost and processing lead-time.

The total supply chain cost can be calculated by Equation 1:

$$TC = \xi \sum_{i=1}^{N} \left(\mu_i \sum_{j=1}^{N_i} C_{ij} y_{ij} \right) \qquad (1)$$

where C_{ij} is the cost of the jth resource option for the activity i, y_{ij} is a binary variable equal to 1 if the resource option j is selected to perform the activity i and 0 otherwise, μ_i is the average demand per unit time at the activity i. Starting from the average demands at the delivery nodes (markets demand), it is possible to calculate average demand for all the supply chain activities. Finally, ξ denotes the period of interest depending on the unit time.

A supply chain can be represented by nodes connected by links representing supply-demand relationships between activities. The activity at a particular node cannot start until all inputs to the node are available, until all preceding activities are completed. For this reason, the cumulative lead-time at a node, expressed by Equation 2, is the sum of the processing lead-time of the node and the maximum delivery lead-time of all input components:

$$LT_i = \sum_{j=1}^{N_i} T_{ij} y_{ij} + \max_{a_k \in S_i}(LT_k) \qquad (2)$$

where T_{ij} is the processing lead-time of the jth resource option for the node i, S_i is the set of nodes that input to node i, a_k are the activities belonging to S_i and LT_k is the cumulative lead-time of node k. For the sourcing activities, there is no preceding input, so the second term of Equation 2 will be zero.

The cumulative lead-time at a delivery node will be the total lead-time for delivery of a product to its destination. In the case of a single product-single destination, the total supply chain lead-time is the cumulative lead-time at node N, expressed by Equation 3.

$$TLT = LT_N \qquad (3)$$

In the case of a network with multiple products and multiple delivery destinations there will be more delivery nodes, each with their own cumulative lead-time. There are different ways to calculate the total supply chain lead-time, for instance, according to the average of delivery nodes' lead-times, the average of lead-times of delivery nodes weighted according to the importance of each customer destination or the longest lead-time amongst delivery nodes expressed by Equation 4 which is used in this work:

$$TLT = \max_{a_d \in D} LT_d \qquad (4)$$

where D is the set of delivery nodes, a_d a delivery activity and LT_d the cumulative at a delivery node.

The problem is composed of two objective functions (Equation 1 and Equation 4), a decision variable y_{ij} (Equation 5), and two constraints. Equation 6 ensures that the lead-time relationships between nodes are correct and Equation 7 ensures that only one resource option is selected for each activity (a single sourcing policy is assumed). Furthermore, resources are assumed with unlimited capacity.

$$y_{ij} = \begin{cases} 1 & \text{if j is selected} \\ 0 & \text{otherwise} \end{cases} \qquad \text{for } i \in N \qquad (5)$$

$$\sum_{j=1}^{N_i} T_{ij} y_{ij} + \max_{a_k \in S_i}(LT_k) - LT_i = 0 \qquad \text{for } i \in N \qquad (6)$$

$$\sum_{j=1}^{N_i} y_{ij} = 1 \qquad \text{for } i \in N \qquad (7)$$

As mentioned earlier, the case study utilized in this study is taken from [23]. This model is a multi-product problem with three final products sent to four different market regions in different quantities depending on the monthly demand. The network is composed of 38 activities and 105 resource options for a total possible solutions of $\prod_{i=1}^{38} N_i = 1.284 \times 10^{16}$, where N_i is the number of resource options available at activity i. Starting from the monthly demand of delivery nodes, the monthly demands for all the nodes of the network are calculated. The period of interest ξ is set for 12 months.

The supply chain configuration is given in Figure 3. Nodes 27, 28 and 29 represent the activities to get the three final products sent to the markets illustrated by dotted nodes from 30 to 38 according to the monthly demand μ. Numbers inside the circles correspond to the numbers of resource options available at each activity, while the arrows represent the input-output relationships between the nodes. The costs C_{ij} and the processing lead-time T_{ij} of resource options, and more details on each activity and component, can be found in [23].

Parameter	Symbol	Comb. 1	Comb. 2	Comb. 3	Comb. 4
Population	n	10	25	50	100
Number of selected sites	m	3	8	15	30
Number of elite sites	e	1	2	5	10

Table 2. Combinations of n, m and e tested

Parameter	Symbol	Comb. 1	Comb. 2	Comb. 3	Comb. 4
Number of Bees recruited for elite sites	neb	2	5	10	20
Number of Bees recruited for selected sites	nsb	1	3	6	12

Table 3. Combinations of neb and nsb tested

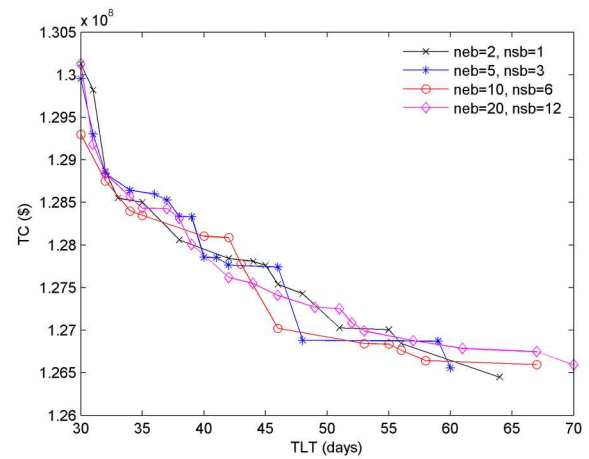| Activities							Network configurations		
1	3	4	3	3	1	4	3	1	1
2	3	1	1	2	2	2	1	1	2
3	2	2	3	1	1	4	3	2	1
4	2	2	2	1	4	2	3	2	1
5	2	2	1	3	3	3	1	3	1
6	2	2	1	1	1	1	1	1	1
7	3	3	1	2	2	1	2	1	3
8	1	1	2	1	2	2	1	3	3
9	1	2	2	1	2	1	1	1	2
10	5	5	5	5	5	1	5	1	5
11	3	2	2	2	3	2	3	3	1
12	2	3	1	2	3	2	1	3	2
13	1	1	1	1	2	1	1	2	2
14	2	1	3	2	2	1	1	2	1
15	2	1	1	1	1	1	2	2	1
16	2	3	3	3	1	3	2	1	1
17	3	3	2	2	2	3	2	1	3
18	3	3	3	3	2	3	2	3	3
19	2	2	2	1	1	1	1	1	1
20	4	4	1	4	4	4	4	2	4
21	2	4	3	4	1	3	4	1	1
22	1	2	2	2	2	2	2	1	1
23	2	2	1	1	1	1	1	2	2
24	2	2	2	2	2	1	1	1	1
25	3	1	1	3	3	1	1	1	3
26	2	1	2	3	1	1	3	1	1
27	3	2	2	1	3	2	1	1	3
28	2	2	2	2	2	2	1	2	1
29	2	2	2	2	2	1	1	1	1
30	2	2	1	1	2	1	1	1	1
31	2	2	2	2	2	1	1	1	1
32	1	2	1	1	1	1	1	1	1
33	2	2	2	2	1	1	1	1	1
34	2	1	1	2	1	1	1	1	1
35	2	1	1	1	1	1	1	1	2
36	2	2	2	2	1	2	1	1	1
37	2	2	2	2	1	1	1	1	1
38	2	2	2	2	1	2	2	1	2
w_1	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
w_2	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1
TLT (days)	30	31	34	36	46	54	58	70	60
TC ($)	129652620	129051300	128485608	128332908	127023480	126821568	126500100	126421236	126572640

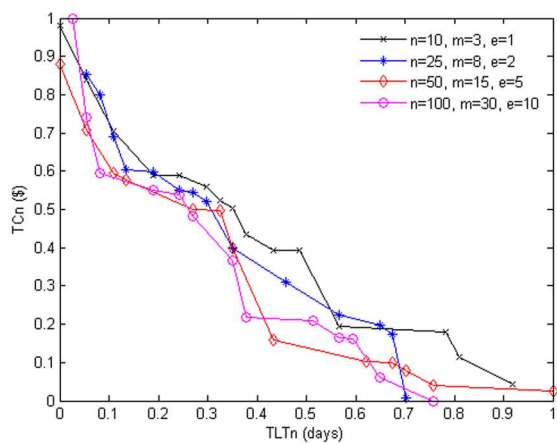**Table 4.** Network configurations for each couple of weights

Figure 3. Bulldozer supply chain configuration

(a)
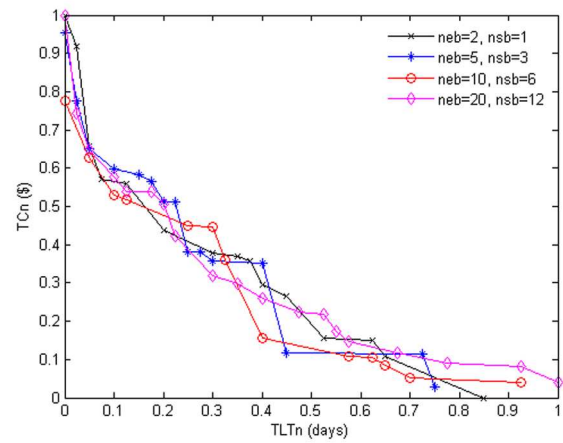

(b)

Figure 4. Pareto fronts (a) and Pareto normalized fronts (b) with different combinations of *n*, *m* and *e*

(a)

(b)

Figure 5. Pareto fronts (a) and Pareto normalized fronts (b) with different combinations of *neb* and *nsb*

5. Experimental tests

Several experimental tests have been conducted in order to show the performance of the multi-objective bees algorithm parameters on the solutions, and to find the combination of them that gives the best Pareto front. All the experiments are carried out with the number of iterations fixed to 1000 and a patch size *ngh* of 1. In all tests the algorithm is run 100 times and results are added after each run in order to get more robust solutions. The weighted sum approach has been used to evaluate the quality of the Pareto fronts. For each couple of normalized solutions of all combinations of the bees algorithm parameters, the Z (main objective) function is calculated, expressed by Equation 8:

$$Z = w_1 TCn + w_2 TLT_n \tag{8}$$

where *TCn* and *TLTn* are the normalized solutions and w_1 and w_2 are the weights where the summation is equal to 1. To minimize both the cost and lead-time simultaneously, it needs to find the minimum value of Z function according to the weight values which regulate the importance of each objective function as stipulated by the decision-maker. For this reason, in each test the Pareto front which contains the minimum of Z has been considered as the fittest.

During experiments, the parameters of the bees algorithm have been tuned by trial and error empirically to find the best combination of the parameters set.

In the first experimental attempt, the four different combination of *n*, *m* and *e* are tested given in Table 2, while *neb* and *nsb* are fixed to 10 and 6 respectively, and the equal weight values (0.5, 0.5) have been utilized for both cost and lead-time.

In the second experimental attempt, *n*, *m* and *e* are set to 50, 15 and 5 respectively and the weight values are selected equal (0.5, 0.5), then the best parameter sets for the *neb* and *nsb* are searched; the combination sets utilized in this study are given in Table 3.

According to the above experiments on parameter tuning, the best parameter combination of the bees algorithm has been utilized for the next section which will be based on finding the Pareto front lines according to the different combination of weights.

6. Results and discussion

6.1. Effect of n, m and e

The Pareto front line of each combination of *n*, *m* and *e* is given in Figure 4(a) and the normalized results are given in Figure 4(b).

According to the Figure 4, the first combination gives 15 points, and second, third and fourth give 14, 13 and 13 respectively. On the other hand, Z function values are lower using the last two combinations.

The minimum value of the Z function is 0.29600567 which corresponds to a total cost of 127023480 $ and

a total lead-time of 46 days was found with the third parameter combination set (*n*=50, *m*=15, *e*=5). For further analysis, this combination set has been utilized.
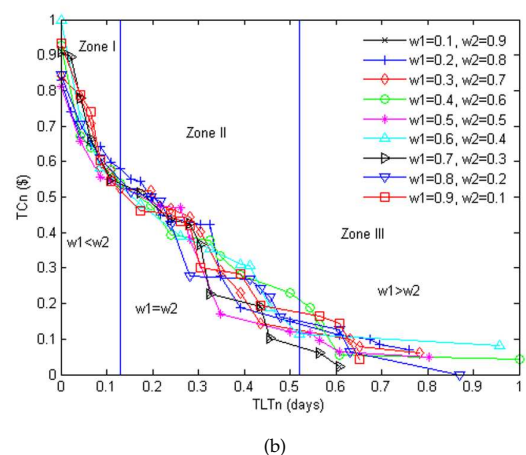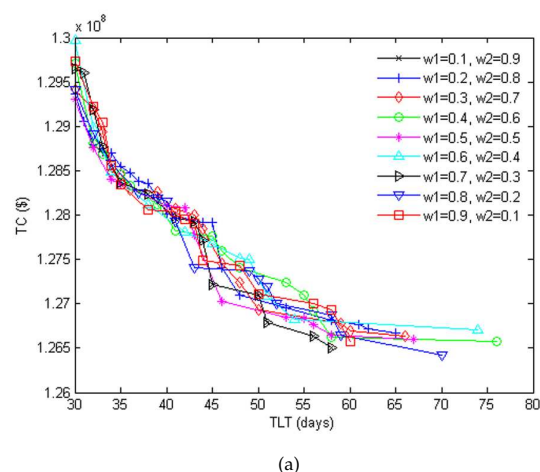
6.2. Effect of neb and nsb

The Pareto front line of each combination of the *neb* and *nsb* parameters are given in Figure 5(a) and the Pareto front line of the normalized results are given in Figure 5(b). According to Figure 5, the best combination of *neb* and *nsb* is (*neb*=10 and *nsb*=6). The minimum value of the Z function gives a total cost of 127023480 $ and a total lead-time of 46 days which indicates the Pareto front line of the red line in the Figure 5(a), i.e., *neb* and *nsb* are 10 and 6 respectively.

According to the above results, the best combination of the parameter sets are *n*=50, *m*=15, *e*=5, *neb*=10 and *nsb*=6. These values have been utilized to calculate the Pareto fronts according to the weights' values.

6.3. Effect of weights and comparison to ant colony optimization

In this section, the Pareto front line is calculated with different combinations of weights.

(a)

(b)

Figure 6. Pareto fronts lines (a) and Pareto normalized fronts lines (b) with nine combinations of weights

Figure 7. Boxplot of *Z* functions results for two samples obtained with the same parameters values of the bees algorithm-based approach

In Figure 6(a), nine different combinations of the weights have been utilized such as $(w_1, w_2) = (w_1, 1-w_1)$, where $w_1=0.1,0.2...0.9$. In Figure 6(b), the normalized results are given. For instance using $w_1=0.1$ and $w_2=0.9$, more importance is given to the minimization of the total lead-time instead of the total cost, using $w_1=0.5$ and $w_2=0.5$ the two objectives have the same importance, and finally in the case of $w_1=0.9$ and $w_2=0.1$, the minimization of the total cost is favoured.

It is clear that each point of each Pareto front line can be taken as a solution to the problem depending on the decision-maker. It is also possible to find a representative point for each curve according to the minimization of the *Z* function. Finally, the nine couples of the total cost and the total lead-time which give the minimum value of the *Z* function for all the combinations of weights are given in Table 4 with network configuration. The results show that, when $w_1 < w_2$ the *Z* function minimum value is located in the zone of the lower total lead-time and higher total cost (*I*), when $w_1 = w_2$ the *Z* function minimum value is located in a central zone (*II*), while when $w_1 > w_2$ the *Z* function minimum value is located in the zone of the higher total lead-time and lower total cost (*III*).

All results are compared with those obtained by the ant colony optimization in [23] where the Pareto front lines were calculated with three values of λ which regulates the importance of two objective functions; $\lambda = 0.1$ corresponds to $w_1=0.9$ and $w_2=0.1$, $\lambda = 0.5$ to $w_1=w_2=0.5$ and $\lambda = 0.9$ to $w_1=0.1$ and $w_2=0.9$. According to the results in [23], it shows that each value of λ covers only some portion of the Pareto front line. However, the results computed from the bees algorithm shows that each weight value covers more portions of the Pareto front line. For each couple of the weights, the minimum total lead-time value of 30 days has been found, while the minimum cost value depends on the weights. The minimum total cost found is 126421236 $ for $w_1=0.8$ and $w_2=0.2$. Thus, the bees algorithm found more Pareto non-dominated solutions than the ant colony approach and obtained lower costs. For instance, comparing the results using $\lambda = 0.5$ for the ant colony approach and $w_1=w_2=0.5$ for the bees algorithm approach, both of them found the minimum total lead-time of 30 days, but the first one

found a minimum total cost of 127193700 $ while the bees algorithm approach found 126595752 $.

The bees algorithm-based approach has been proven to give repeatable results as shown in Figure 7. Comparing the boxplots of two samples of results in terms of *Z* function obtained with the same weights and parameters, very similar distributions have been achieved, with means of 0.395 and 0.392, and variances of 0.0030 and 0.0025.

7. Conclusions

In this study, a multi-objective bees algorithm-based supply chain design model has been proposed and applied on a supply chain problem. This problem deals with the resource options' selection for a multi-product and multi-delivery supply chain in order to minimize two objective functions simultaneously, namely, total cost and total lead-time of the network. Several tests have been conducted to find the optimum parameters for the bees algorithm. Subsequently, Pareto front lines have been computed with different weight combinations. The results showed the efficiency of the proposed model. The Pareto solutions of the proposed model have been compared with those obtained by an ant colony optimization [23]. This showed that the bees algorithm is a more powerful tool for finding a better Pareto solution for supply chain problems.

Future work will consider increasing the complexity of the problem and testing it using the current version of the bees algorithm, in addition, an improved version of the bees algorithm will be researched.

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