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Meta-heuristic Algorithms for an Integrated Production-Distribution Planning Problem in a Multi-Objective Supply Chain

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Abstract

In today's global marketplace, an effective integration of production and distribution plans into a unified framework is crucial for attaining competitive advantages. This paper, therefore, addresses an integrated multi-product and multi-time period production-distribution planning problem for a two-echelon supply chain subject to the real-world constraints. It is assumed that all transportations are outsourced to third-party logistics providers and all-unit quantity discounts on transportation costs are taken into consideration. The problem is formulated as a multi-objective mixed-integer linear programming model which attempts to simultaneously minimize the total delivery time and total transportation costs. Due to the complexity of the considered problem, the genetic algorithm (GA) and particle swarm optimization (PSO) algorithm are developed within the LP-metric method and desirability function framework for solving the real-sized problems in a reasonable computational time. As the performance of meta-heuristic algorithms is significantly influenced by the calibration of their parameters, Taguchi methodology is used to tune the parameters of the developed algorithms. Finally, the efficiency and applicability of the proposed model and solution methodologies are demonstrated through several problems of different sizes.
Keywords: Supply chain; Production-distribution planning; Multi-objective optimization; Meta-heuristic algorithms; Transportation costdiscount.

1. Introduction

Intense competitions in today's global marketplace, shorter product life cycles, changes in demand patterns, and heightened expectations of customers have obliged companies to pay more attention to their supply chains. As companies have become aware of their supply chain performance and the importance of their operational performance improvement, coordination and integration of the production and distribution operations have been recognized as the source of competitive advantage. Technically, the integrated production and distribution planning makes an effort to find a solution which is better than the result of two separate optimizations in production and distribution plans.

In traditional supply chain management, the focus of the integration of production-distribution planning is often on the single objective function. In this regard, Park (2005) presented the solutions for integrated production and distribution planning and investigated the effectiveness of this integration through a computational study in a multi-plant, multi-retailer, multi-item and multi-period logistic environment where the objective was to maximize the total net profit. Park et al. (2007) developed a new genetic algorithm for the integration of production and distribution planning in supply chain where minimizing total costs was the key objective. Computational results of this study showed the efficiency of the proposed genetic algorithm for a number of test problems with various sizes. Based on the integration of production and distribution plans, Fahimnia et al. (2012) proposed a mixed integer non-linear formulation for a two-echelon supply network and employed a genetic algorithm for solving the problem where the goal was to minimize the total production, inventory holding, transportation and shortage costs.

Recently, a number of studies have been devoted to multi objective optimization in the field of integration of production-distribution planning in supply chains. Altiparmak et al. (2006) presented a mixed-integer non-linear programming model and employed a new approach based on a genetic algorithm for solving the model. In their study, the objectives were the minimization of total costs, the maximization of customer services in terms of acceptable delivery times, and the maximization of capacity utilization balance for distribution centers. In another study, Zanjirani Farahani and Elahipanah (2008) investigated a three-echelon distribution network including multiple suppliers, wholesalers, and retailers

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and proposed a mixed-integer linear programming model. They took advantage of a hybrid non-dominated sorting genetic algorithm for solving the proposed model, where the objectives were minimizing the total costs of supply chain and minimizing the sum of backorders and surpluses of products in all periods. Kamali et al. (2011) extended a multi-objective mixed-integer non-linear programming model to integrate the system of a single buyer and multiple vendors under an all-unit quantity discount policy for the vendors. Their proposed model minimizes the total system cost, the total number of deficient items, as well as the total number of late delivered items and maximizes the total purchasing value. More recently, Liu and Papageorgiou (2013) addressed production, distribution and capacity planning of global supply chains considering cost, responsiveness and customer service level simultaneously. The problem was formulated as a mixed-integer programming model and the ε-constraint method and Lexicographic mini max method were provided to tackle the multi objective problem.

Although many studies have been carried out to minimize total delivery time and total transportation costs, to our knowledge, no one has considered the lead time required for producing demand of customers and quantity discount on transportation costs with regard to the above-mentioned objectives. This paper, therefore, deals with a multi-product and multi-time period integrated production-distribution planning problem. The problem is formulated as a multi-objective mixed-integer linear programming model which intends to simultaneously minimize the total delivery time and total transportation costs. The production lead time and all-unit quantity discount on transportation costs as the main contributions of the paper are included in the first and second objective functions, respectively. Moreover, in addition to the unit transportation cost, the fixed cost of using transportation vehicles which refers to the minimization of total transportation costs to come closer to the real-world supply chain situations is added to the objective function. Concerning the complexity of the considered problem, meta-heuristic algorithms, the GA and PSO algorithm are developed to tackle the problem. Furthermore, to integrate the two objective functions, the LP-metric method and disierability function approach are employed and a heuristic method is proposed for generating feasible problems. The parameters of the developed algorithms are then calibrated using the concept of Taguchi methodology to increase the accuracy of solutions. Finally, the effectiveness of the proposed model and solution methodologies are illustrated via different generated test problems in different sizes.

The remainder of the paper is as organized as follows: Section 2 presents the problem description and formulation in detail. Section 3 is devoted to introducing multi-objective optimization techniques, namely LP-metric method and desirability function approach. In Section 4, solution methodologies consisting of the GA and PSO along with their steps are explained and a parameter tuning approach is applied to calibrate the algorithms. In order to illustrate the application of the proposed model and examine the performance of the solution methodologies, different problems in various sizes are solved in Section 5. Finally, conclusions and future research directions are provided in Section 6.

2. Statement of the Problem

This paper deals with a production-distribution planning problem in a two-echelon supply chain, as illustrated in Figure 1. There are multiple manufacturers and distributors in this supply chain which provide various products for customers. Manufacturers and distributors outsource transportations to the third-party logistics providers. All demands have to be satisfied and transportation costs, demands and delivery lead times are known and deterministic.

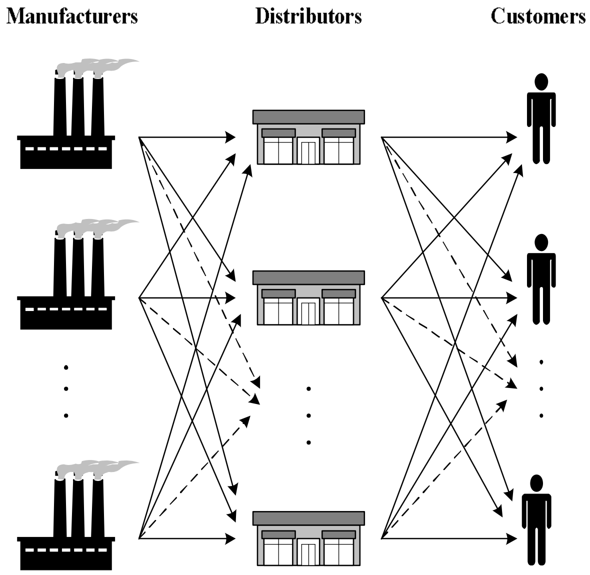

Fig. 1. General schema for supply chain structure

Before formulating the multi-objective model, we first define the set of assumptions, indices, parameters and decision variables that will be used throughout the paper.

The assumptions

- All-unit quantity discounts on transportation costs are taken into consideration.
- All transportations are outsourced to the third-party logistics providers.
- All products can be produced by all manufacturers.
- The direct transport of products from manufacturers to consumers is not possible.
- Each distributor can serve more than one customer.

- Manufacturers, distributors and third-party logistics providers have a limited capacity which depends on the product and time period.

The indices

i The index for manufacturers; $(i = 1, 2, \dots, I)$

j The index for distributors; $(j = 1, 2, \dots, J)$

k The index for customers; $(k = 1, 2, \dots, K)$

l The index for third-party logistics providers; $(l = 1, 2, \dots, L)$

h The index for price levels; $(h = 1, 2, \dots, H)$

p The index for product types; $(p = 1, 2, \dots, P)$

t The index for planning time periods; $(t = 1, 2, \dots, T)$

The parameters

d_{kpt} The demand of customer k for product p in time period t;

a_{pit} The production capacity of product p at manufacturer i in time period t;

b_{pjt} The distribution capacity of product p at distributor j in time period t;

c_{pijlt} The transportation capacity of third-party logistics provider l for transporting product p from manufacturer i to distributor j in time period t;

s_{pjklt} The transportation capacity of third-party logistics provider l for transporting product p from distributor j to customer k in time period t;

CP_{pijlht} The transportation cost per unit of product p from manufacturer i to distributor j by third-party logistics provider l at price level h in time period t;

CD_{pjklht} The transportation cost per unit of product p from distributor j to customer k by third-party logistics provider l at price level h in time period t;

lm_{kpt} The production lead time per unit of demand of customer k for product p in time period t;

lp_{pijlt} The delivery lead time required for transporting product p from manufacturer i to distributor j by third-party logistics provider l in time period t;

ld_{pjklt} The delivery lead time required for transporting product p from distributor j to customer k by third-party logistics provider l in time period t;

r_{pijlht} The maximum number of product p transported from manufacturer i to distributor j by third-party logistics provider l at price level h in time period t;

z_{pjklht} The maximum number of product p transported from distributor j to customer k by third-party logistics provider l at price level h in time period t;

fc The fixed cost of using a transportation vehicle;

vc The capacity of a transportation vehicle;

M A large positive number.

The decision variables

NP_{pijlt} The amount of product p transported from manufacturer i to distributor j by third-party logistics provider l in time period t;

ND_{pjklt} The amount of product p transported from distributor j to customer k by third-party logistics provider l in time period t;

QP_{pijlht} The quantity of product p transported from manufacturer i to distributor j by third-party logistics provider l at price level h in time period t;

QD_{pjklht} The quantity of product p transported from distributor j to customer k by third-party logistics provider l at price level h in time period t;

V_{pit} If product p is produced at manufacturer i in time period t, 1; otherwise, 0;

W_{pjt} If product p is distributed by distributor j in time period t, 1; otherwise, 0;

WP_{pijlt} If product p is transported from manufacturer i to distributor j by third-party logistics provider l in time period t, 1; otherwise, 0;

WD_{pjklt} If product p is transported from distributor j to customer k by third-party logistics provider l in time period t, 1; otherwise, 0;

XP_{kpit} If demand of customer k for product p is produced at manufacturer i in time period t, 1; otherwise, 0;

XD_{pijt} If product p produced at manufacturer i is distributed by distributor j in time period t, 1; otherwise, 0;

X_{pijlht} If product p is transported from manufacturer i to distributor j by third-party logistics provider l at price level h in time period t, 1; otherwise, 0;

Y_{pjklht} If product p is transported from distributor j to customer k by third-party logistics provider l at price level h in time period t, 1; otherwise, 0.

The mathematical model of the problem

Then the problem is formulated as follows:

$$Min\ (LT) = \sum_k \sum_p \sum_i \sum_t XP_{kpit}\, lm_{kpt}\, d_{kpt} + \sum_p \sum_i \sum_j \sum_l \sum_t WP_{pijlt}\, lp_{pijlt} + \sum_p \sum_j \sum_k \sum_l \sum_t WD_{pjklt}\, ld_{pjklt} \quad (1)$$

$$Min\ (TC) = \sum_p \sum_i \sum_j \sum_l \sum_h \sum_t QP_{pijlht}\, cp_{pijlht} + \sum_p \sum_j \sum_k \sum_l \sum_h \sum_t QD_{pjklht}\, cd_{pjklht} + fc(U + \tau) \quad (2)$$

subject to:

$$\sum_j \sum_l ND_{pjklt} = d_{kpt}; \qquad \forall\ k, p, t \quad (3)$$

$$\sum_j \sum_l NP_{pijlt} \le V_{pit}\, a_{pit}; \qquad \forall\ p, i, t \quad (4)$$

$$\sum_k \sum_l ND_{pjklt} \le W_{pjt}\, b_{pjt}; \qquad \forall\ p, j, t \quad (5)$$

$$\sum_l WP_{pijlt} \le 1; \qquad \forall\ p, i, j, t \quad (6)$$

$$\sum_l WD_{pjklt} \le 1; \qquad \forall\ p, j, k, t \quad (7)$$

$$\sum_i XP_{kpit} = 1; \qquad \forall\ k, p, t \quad (8)$$

$$\sum_j XD_{pijt} \le 1; \qquad \forall\ i, p, t \quad (9)$$

$$\sum_k \sum_i XP_{kpit} = \sum_i \sum_j XD_{pijt}; \qquad \forall\ p, t \quad (10)$$

$$\sum_h QP_{pijlht} \le WP_{pijlt}\, c_{pijlt}; \qquad \forall\ p, i, j, l, t \quad (11)$$

$$\sum_h QD_{pjklht} \le WD_{pjklt}\, s_{pjklt}; \qquad \forall\ p, j, k, l, t \quad (12)$$

$$\sum_{n \in J} lp_{pinlt} WP_{pinlt} \leq (lp_{pijlt} - M) W_{pjt} + M \; ; \qquad \forall\; p, i, j, l, t \tag{13}$$

$$\sum_{h} QP_{pijlht} = NP_{pijlt} \; ; \qquad \forall\; p, i, j, l, t \tag{14}$$

$$\sum_{h} QD_{pjklht} = ND_{pjklt} \; ; \qquad \forall\; p, j, k, l, t$$

(15)

$$X_{pijlht} r_{pijlh-1t} \leq QP_{pijlht} \; ; \qquad \forall\; p, i, j, l, h, t \tag{16}$$

$$QP_{pijlht} < X_{pijlht} r_{pijlht} \; ; \qquad \forall\; p, i, j, l, h, t \tag{17}$$

$$Y_{pjklht} z_{pjklh-1t} \leq QD_{pjklht} \; ; \qquad \forall\; p, j, k, l, h, t \tag{18}$$

$$QD_{pjklht} < Y_{pjklht} z_{pjklht} \; ; \qquad \forall\; p, j, k, l, h, t \tag{19}$$

Where R_{pijl0t} and Z_{pjkl0t} are equal to zero for all third party logistic providers.

$$\sum_{h} X_{pijlht} \leq 1 \; ; \qquad \forall\; p, i, j, l, t \tag{20}$$

$$\sum_{h} Y_{pjklht} \leq 1 \; ; \qquad \forall\; p, j, k, l, t \tag{21}$$

$$\frac{\sum_{\forall QP_{pijlht} \neq 0} QP_{pijlht} + \sum_{\forall QD_{pjklht} \neq 0} QD_{pjklht}}{vc} \geq U \tag{22}$$

$$\frac{\sum_{\forall QP_{pijlht} \neq 0} QP_{pijlht} + \sum_{\forall QD_{pjklht} \neq 0} QD_{pjklht}}{vc} - U = \varsigma \tag{23}$$

$$\varsigma \leq \tau \leq \varsigma \times M \tag{24}$$

$$\tau \in \{0,1\}, \quad \varsigma \geq 0, \quad U \geq 0 \;\&\; Integer \tag{25}$$

$$WP_{pijlt}, WD_{pjklt}, XP_{kpit}, XD_{pijt}, V_{pit}, W_{pjt}, X_{pijlht}, Y_{pjklht} \in \{0,1\}; \forall p, i, j, k, l, h, t \tag{26}$$

$$NP_{pijlt}, ND_{pjklt}, QP_{pijlht}, QD_{pjklht} \geq 0 \;\&\; Integer; \; \forall\; p, i, j, k, l, h, t \tag{27}$$

The first objective function (1) aims to minimize the total delivery time of supply chain including the lead time required for producing demands of customers, the delivery lead time required for transporting products from manufacturers to distributors and the delivery lead time required for transporting products from distributors to customers. The second objective function (2) attempts to minimize the total transportation costs including the unit transportation cost and the fixed cost of using transportation vehicles, incurred in transporting products from manufacturers to distributors and from distributors to customers.

Constraint set (3) guarantees that the demand of each customer is totally satisfied. Constraint sets (4) and (5) are the capacity constraints for the manufacturers and distributors, respectively. The two constraint sets (6) and (7) show that a manufacturer or distributor, whenever selected, can only deliver products by a single third-party logistics provider to distributors and customers, respectively. Constraint set (8) ensures that each customer demand for each product is produced by only one manufacturer. Constraint set (9) guarantees that the product produced at each manufacturer is only transported to a single distributor. Constraint set (10) states that the total amount of customer demands assigned to the manufacturers should be equal to the total amount of manufacturer products assigned to the distributors. Constraint sets (11) and (12) ensure that the total amount of products transported from manufacturers to distributors and from distributors to customers cannot exceed the capacity of the third-party logistics providers. Constraint set (13) implies that the nearest distributor to the manufacturer is selected for products distribution. Constraint sets (14) and (15) are the balance equations related to the quantity of transported products. Constraint sets (16) and (17) describe that how the quantity of products transported from manufacturers to distributors falls into one of the intervals offered by the selected third-party logistics provider. Constraint sets (18) and (19) are similar to constraint sets (16) and (17) but applied for the quantity of products transported from distributors to customers. Constraint sets (20) and (21) impose that a third-party logistics provider, whenever selected, should only transport products at one price level. Constraint sets (22)-(25) are used to overcome the non-linearity of the second objective function. Particularly, constraint set (22) denotes the number of transportation vehicles used by all third-party logistics providers to transport products in all time periods. Finally, constraint set (26) shows the binary restrictions while constraint set (27) specifies non-negative integer conditions.

3. Multi-Objective Optimization Techniques

Today, considering the dynamic situation of real-world optimization problems, most of the researches in the field of optimization pursue more than one goal; the goals are often in conflict with each other and improvements in one of them make other goals worse. Multi-objective optimization techniques are ideally suited for dealing with such problems. The two main approaches to multi-objective optimization problems are preference-based methods which are only useful if a relative preference factor of the objectives is known in advance and generating methods which generate non-dominated solutions and one objective is not preferable to other objectives (Cohon, 1985). In the classical techniques of multi-objective optimization problems which are based on preference-based methods, the process of finding multiple solutions in a multi-objective optimization problem changes into the process of obtaining a single solution in a single-objective optimization problem (Deb, 2001).

In this research work, as all transportations are outsourced to the third-party logistics providers and they offer all-unit quantity discounts on transportation costs, transportation costs are the lowest when lthe arge quantities of products are shipped between the stages of the supply chain. However, the total delivery time of the supply chain which is made up of the time devoted to producing and transporting products from manufacturers to customers through distributors often can be reduced if products are shipped immediately after they are produced at manufacturers. Therefore, there is a tradeoff between holding products until enough of them are accumulated to reduce transportation costs and shipping them immediately to reduce delivery time. Accordingly, since our proposed model consists of two objectives conflicting in nature, we have taken advantage of the classical methods of multi-objective optimization, namely LP-metric methodology and desirability function approach to transform the two objective functions into a single one.

3.1. LP-metric method

LP-metric method is one of the most widely used classical techniques to handle multi-objective problems involving multiple objectives conflicting in nature. In this method, the weighted LP distance measure of any solution x from the ideal solution z^* can be minimized as follows:

Minimize LP(x) =

$$\left(\sum_{m=1}^{M}\left[w_m \left|f_m(x)-z_m^*\right|^p\right]\right)^{1/p} \qquad P\in[1,\ \infty) \qquad (28)$$

where $w_m \in [0, 1]$ is the non-negative weight of the m-th objective function determined by the decision maker while the relation $\sum_{m=1}^{M} w_m = 1$ is satisfied and the P shows the importance of the deviation of each objective function from its ideal value. When $P=1$ is applied, the resulting problem reduces to the weighted sum of the deviations. When $P=2$ is considered, the weighted Euclidean distance of any point in the objective space from the ideal point is minimized. When $P=\infty$ is used, the largest deviation $w_m(\left|f_m(x)-z_m^*\right|)$ is minimized as follows:

$$\text{Minimize } LP(x) = \left\{\underset{m}{Max}\ \ w_m(\left|f_m(x)-z_m^*\right|)\right\} \qquad P=\infty \qquad (29)$$

In Eq. (28), it is supposed that objective functions have the same scale. But, if they do not have the same scale, each objective function could be made scale-less through the following formula:

Minimize LP(x) =

$$\left(\sum_{m=1}^{M}\left[\frac{w_m \left|f_m(x)-z_m^*\right|^p}{z_m^*}\right]\right)^{1/p} \qquad P\in[1,\ \infty) \qquad (30)$$

3.2. Desirability function method

The desirability function approach is another method of transforming multiple objectives into a single one in a given optimization problem. This method allocates a desirability function $d_m(Y_m)$ to each response Y_m. It is useful to mention that $d_m(Y_m)=0$ represents a completely undesirable value of Y_m and $d_m(Y_m)=1$ shows a completely desirable response value. Then, the overall desirability D is obtained by integrating individual desirability values by applying the geometric mean as follows

$$Maximize \quad D(x)$$

$$D(x) = (d_1(Y_1) \times d_2(Y_2) \times \ldots \times d_M(Y_M))^{1/M} \tag{31}$$

$$d_m(Y_m) = \left[\frac{u_m - Y_m}{u_m - l_m}\right]^q; \quad 0 \le d_m(Y_m) \le 1, \quad m = 1, 2, \ldots, M \tag{32}$$

where l_m, u_m and Y_m represent the lower bound, upper bound and target value, respectively, that are desired for response Y_m. Also, the exponent q determines how strictly the target value is desired. For $q=1$, the desirability function increases linearly towards l_m, for $q<1$ the function is convex, and for $q>1$ the function is concave.

4. Solution Methodologies

Considering the numerous constraints which make the supply chain problem more complicated and since Burk et al. (2008) proved that problems under quantity discount policies are NP-hard, we have developed meta-heuristic algorithms, the genetic algorithm (GA) and the particle swarm optimization (PSO) algorithm, to tackle the considered problem.

4.1. The constraint handling technique

In this study, given a large number of constraints, particularly capacity constraints related to the manufacturers, distributors and third-party logistics providers, the test problems generated are not always feasible. Hence, we propose a heuristic method to produce feasible problems. In this technique, customers' demands will never exceed the capacity limitations. To this end, the total demand of customers for a special product in a time period is less than or equal to the lowest maximum capacity of manufacturers, maximum capacity of distributors and maximum capacity of third-party logistics providers. In this case, there will be at least one manufacturer, one distributor and one third-party logistics provider that can satisfy the total demand of all customers for a special product in a time period. It should be noted that the proposed procedure, depicted in Figure 2, is not the only technique for generating feasible problems.

Procedure of Generating Feasible Problems

For each Planning Time Period *t* ***do***

  For each Product Type *p* ***do***

C1= ***Find*** (Maximum Capacity of Manufacturers)

C2= ***Find*** (Maximum Capacity of Distributor centers)

C3= ***Find*** (Maximum Capacity of Third-party logistics providers)

V= ***Find*** (Minimum among ***C1, C2, C3***)

Generate Random Total Demand in [**1, V**]

Assign Total Demand to every Customer

End for

  End for

Fig. 2. Procedure of generating feasible problems

4.2. The genetic algorithm

The genetic algorithm (GA) is an optimization and search technique based on the evolutionary process of biological organisms in nature. The theoretical foundations of GAs were originally developed by Holland (1975) and popularized by Goldberg (1989). In the past decade, GA has been widely adopted by many researchers for solving various problems in the field of supply chain (Syarif et al., 2002; Gen and Syarif, 2005; Altiparmak et al., 2006; Park et al., 2007; Kannan et al., 2009; Fahimnia et al., 2012). The main reasons behind the success of GAs are their good performance in large-scale problems, their resistance to becoming trapped in local optima, and their applicability to a wide variety of optimization problems (Goldberg, 1989).

In GA, a population of individuals (called chromosomes), which encode potential solutions to a specific optimization problem, evolves toward better solutions through successive generations. The evolution usually starts with a population of randomly generated individuals to ensure that the search is robust and unbiased. In each generation, the fitness of every individual in the population is evaluated with respect to a given objective function. The best-fit individuals are selected from the current population for reproduction, and merged or modified through crossover and mutation operators to form a new population which shares some characteristics taken from both parents. The new population is then used in the next iteration of the algorithm. The fitness of new individuals is evaluated and the least-fit population is replaced with new individuals. In general, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been found.

Initialization

The required basic information to start the GA including the population size (*Pop Size*), crossover probability (P_c), mutation probability (P_m), reproduction probability (P_r) and number of iterations (*nIt*) are determined. Furthermore, an initial population of solutions is randomly generated.

Representation

Although GA is known as a problem-independent algorithm, designing a suitable representation scheme is one of the most important steps when it is employed for some optimization problems (Syarif et al., 2002). A chromosome should be able to reflect the characteristics of a problem and include information about the solution which it renders. In this paper, the proposed representation scheme consists of two parts:

(I) The first part which is a $1 \times I$ vector, specifies the priority of manufacturers for producing products. Each member of this vector is a random number between zero and one.

(II) The second part is a three-dimensional matrix ($L \times P \times T$) which represents the third-party logistics provider's priority for transporting products from manufacturers to distributors and from distributors to customers in each time period.

Now, here is a numerical example to provide further explanation. Suppose that six manufacturers and four third-party logistics providers are available. As illustrated in Figure 3, vector I with six genes is generated in which each gene contains a number between zero and one and considering the particular product and time period, the second part of solution scheme involves four genes with numbers between zero and one. Then, the genes of vector I and L are sorted in ascending order while reserving their positions. As it is shown in Figure 4, the priority of manufacturers and third-party logistics providers can be determined. When a customer order is larger than the capacity of the manufacturer which is our first priority for producing products (the fifth manufacturer), this customer order will be allocated to the manufacturer which is in the next priority (the third manufacturer). Similarly, if the capacity of the third-party logistics provider as the first priority is not enough, transportations will be assigned to the next third-party logistics provider which has the higher priority.

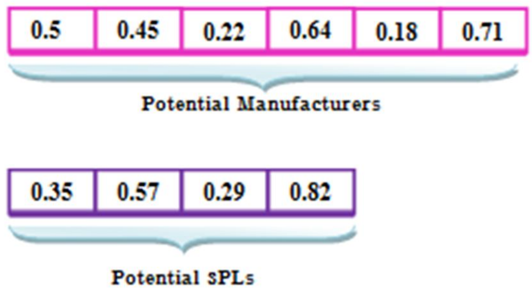

Fig. 3. Generated vector I and L

Fig. 4. Sorted vector I and L

Evaluation

An essential issue in multi-objective optimization problems is how to determine the fitness value of the solutions. The fitness value of each solution reflects the relative strength of a solution to others in terms of its achievement of objectives. Here, to evaluate the fitness function, we have used the LP-metric method and desirability function approach that transform the two objective functions into one. The LP-metric method is applied for $P = 1$ where $w = [0.4, 0.6]$. Also, in the desirability function method considering the minimization of objective functions, we set l_1 and l_2 to zero and u_1 and u_2 to a large number.

Since various constraints may generate infeasible solutions, there exist several methods of handling these infeasibilities such as rejecting or repairing the infeasible solutions and penalizing the objective function (Naraharisetti et al., 2007). In this paper, applying a heuristic method to generate feasible problems (see Subsection 4.1) results in solutions which are always feasible. Therefore, there is no need for the common techniques of rejecting, repairing or penalizing while facing with the problem's constraints.

Parent selection mechanism

Parent selection is the task of choosing individual solutions to be parents through a fitness-based process, where the higher the fitness function is, the better chance an individual has to be selected. There exist a number of selection operators that can be used to select the parents. Roulette wheel selection operator which is utilized in this study is a form of fitness-proportionate selection in which the probabilities of individuals being selected are calculated as proportional to their fitness values.

Crossover operator

The parent selection phase does not create new individuals. Hence, the GA benefits from crossover and mutation as two main operators to create new solutions by combining or altering the current solutions that have shown to be good temporary solutions. The crossover is employed to investigate the new solution space and to see if the crossover operator corresponds to the exchanging information between the selected parents with the hope that it creates better offspring (Altiparmak et al., 2006). There are many crossover operators in the GA literature. In this paper, we have used a two-point crossover operator which is applied to both parts of the chromosomes. In the two-point crossover operator, a pair of chromosomes is selected at random for mating in the selection phase. Then, two random numbers are generated along the string length as the crossover cutting points and the position values are swapped between the two chromosomes following the crossover cutting points to produce two offspring. A graphical representation of the two-point crossover for the first part of the chromosome is depicted in Figure 5.

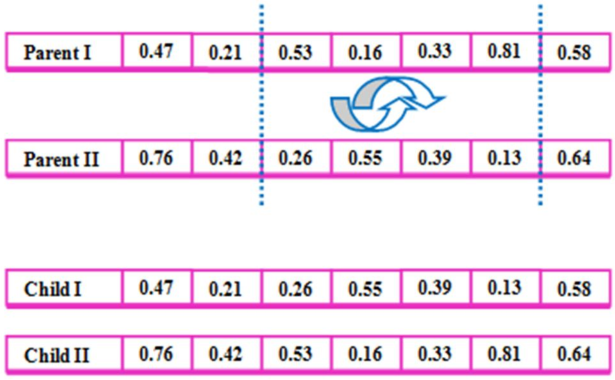

Fig. 5. A sample of two-point crossover

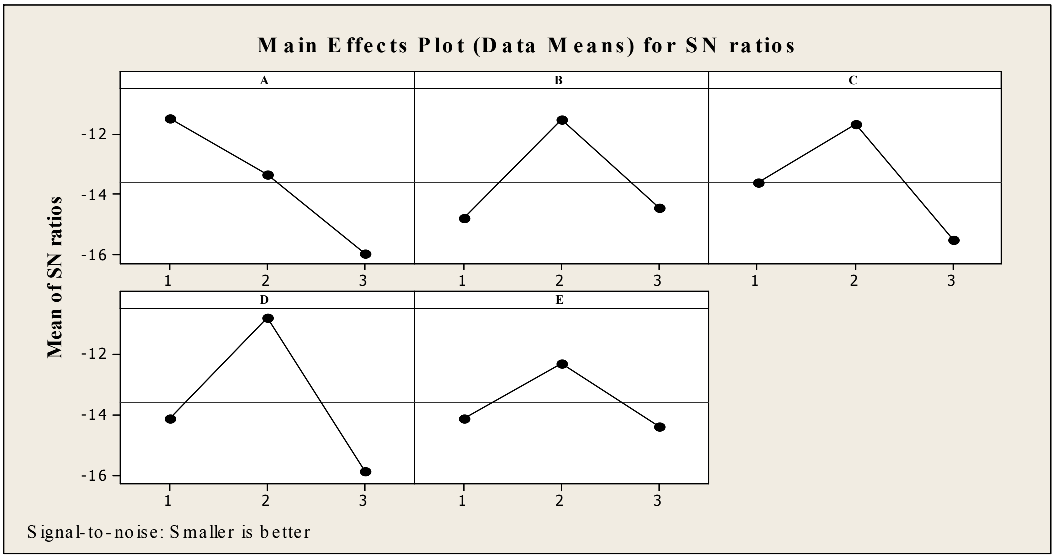

Fig. 6. Average S/N ratio levels for GA's parameters

Mutation operator

The mutation operator helps with the exploration of the whole search space and is to prevent the algorithm from being trapped in local optima. This operator introduces diversity into the population whenever the population tends to become homogeneous due to the repeated use of the selection and crossover operator. Among different forms of mutation operator, we have taken advantage of the swap mutation to modify the gene of an existing chromosome for increasing the variability of the population. In this mutation operator which is considered to be employed for both parts of the chromosomes, a single chromosome is selected at random from the population. Then, the positions of its two randomly selected genes are exchanged with each other.

Termination condition

The evolution process is repeated until a termination condition has been satisfied. In this paper, the stopping criterion is set as a fixed number of iterations. When the algorithm reaches a predefined number of iterations, it will be stopped.

4.3. Performance improvement of the GA

To improve the performance of the proposed GA, we have used two local search algorithms. In these local search algorithms, all the chromosomes in the population (including the initial population, the mutated population, and the offspring) are evaluated and sorted in descending order according to their integrated objective function values in each generation. Then, N_L individuals and N_B individuals which are the least-fit and the best-fit solutions in the population respectively are selected, local search based on the swap mutation is carried out on them, and the fitness values are calculated for the new solutions.

If the implementation of local search algorithms results in new solutions which are better than previous solutions, the new solutions replace the previous ones. Finally, the better solutions are transferred to the next generation and the remaining solutions will be omitted.

4.4. The particle swarm optimization algorithm

The particle swarm optimization (PSO) is an evolutionary computation algorithm introduced by Kennedy and Eberhart (1995). The development of the PSO algorithm was inspired by some social behavior of animals such as bird flocking, fish schooling, and swarm theory. Like the genetic algorithm (GA), the PSO is a population-based optimization approach, has fitness values to evaluate the population, updates the population, and searches for the optimum with random techniques. However, unlike the GA, the PSO has no evolution operators such as crossover and mutation (Haq and Kannan, 2006). During recent years, the PSO algorithm has been successfully used to cope with many optimization problems in supply chains (Kadadevaramath, 2009; Jolai et al., 2011; Kamali et al., 2011; Kadadevaramath et al., 2012) due to its ease of implementation, its fast convergence in comparison with many global optimization algorithms like GAs and SA (Umarani and Selvi, 2010), and its hybridization and specialization ability.

The PSO algorithm is initialized with a population of random solutions called particles, and each potential solution is initialized with a randomized position and velocity. These particles fly about in a virtual search space by following the current optimum particles. The particle motion is mainly influenced by three factors (Sha and Hsu, 2008): the velocity of the particle in the latest iteration, the *Pbest* position which is the best solution found by each particle itself so far, and the *Gbest* position which is the best solution found by the whole swarm so far. At each iteration, the position and velocity of each particle *i* toward its *Pbest* and *Gbest* positions are updated using Eqs. (33) and (34), respectively. Then, the position of particle *i* in the solution space is mapped, its fitness value according to the optimization fitness function is assessed, and the *Pbest* and *Gbest* positions are changed if necessary. This process would repeat until the termination condition is met.

$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{33}$$

$$V_i^{t+1} = \omega\, V_i^t + \varphi_1 r_1 (Pbest_i^t - X_i^t) + \varphi_2 r_2 (Gbest^t - X_i^t) \tag{34}$$

where V_i^t is called the velocity of particle *i* which represents the distance to be traveled by this particle from its current position, X_i^t is the current position of particle *i*, ω is the inertia weight which controls the momentum of the particle, φ_1 and φ_2 are the balance factors between the influence of individual's knowledge and social knowledge in moving the particle towards the target, and r_1 and r_2 are uniformly distributed random numbers which are used to maintain diversity of the population.

In this paper, the representation scheme of solutions, objective function evaluation, and stopping criterion of the PSO algorithm are set as those of the GA dealt with in Subsection 4.2.

4.5. Algorithms parameter tuning

The performance of meta-heuristic algorithms depends largely on its parameters. Therefore, it is essential to choose the parameters of these algorithms carefully to increase the precision of solutions. There are several methodologies in the design of experiments (DOE) that can be used to adjust the algorithms. An alternative would be a full factorial experiment in which all levels of a given factor are combined with all levels of every other factor in the experiment (Montgomery, 2005). In a full factorial experiment as the number of investigated factors goes up, the number of level combinations increases very quickly and this leads to very large computational efforts. Taguchi (1986) proposed a number of designs to examine a large number of factors with a very small number of observations. In order to specify the best level of each factor, Taguchi's methodology considers the signal-to-noise (S/N) ratio as a measure of variation as follows:

$$\text{S/N ratio} = -10 \log_{10} (RPD)^2 \tag{35}$$

In the proposed GA and PSO algorithm there are five and four parameters respectively that should be tuned. These parameters and their levels are described in Tables 1 and 2. Considering three levels for manufacturers (I=7, 10, 14), two levels for distributors (J=4, 8), two levels for third-party logistics providers (L=3, 5), and four levels for customers (K=15, 20, 25, 30), we generate 3*2*2*4=48 test problems and run the GA and PSO algorithm for each problem under Taguchi plans. It should be noted that here the response is a combination of two objective functions using the LP-metric method and the L_{27} and L_9 are selected for the GA and PSO algorithm as the fittest orthogonal array design. Moreover, we have applied the relative percentage deviation (RPD) as a common performance measure to assess the algorithms. The RPD shows that how much an algorithm is different from the best obtained solution on average and is computed according to the following relation:

$$RPD = \frac{Sol - Min_{Sol}}{Min_{Sol}} \tag{36}$$

where the *Sol* is the solution found by a given algorithm for an instance and the Min_{Sol} represents the best solution obtained for each instance. Obviously, lower values for the RPD are preferred.

Table 1
Factors and their levels for GA

Factors	Symbol	Levels		
		Level 1	Level 2	Level 3
Pop Size	(A)	100	200	300
P_c	(B)	0.80	0.85	0.90
P_m	(C)	0.005	0.01	0.015
N_L	(D)	5	10	15
N_B	(E)	10	15	20

Table 2
Factors and their levels for PSO algorithm

Factors	Symbol	Levels		
		Level 1	Level 2	Level 3
ω	(A)	0.75	1.0	1.25
φ_1	(B)	1.0	1.5	2.0
φ_2	(C)	1.0	1.5	2.0
Pop Size	(D)	100	200	300

The developed algorithms are coded in MATLAB 7.10 (2010) and all test problems are run on a laptop with Core i7 GHz CPU and 6.0 GB of RAM in a Microsoft Windows 7 environment. After obtaining the results of Taguchi experiment, the RPDs are transformed into the S/N ratio. The average S/N ratios for different levels of the parameters of GA and PSO algorithm are depicted in Figures 6 and 7 respectively, and the optimum levels of the tuned parameters and other parameters of the proposed algorithms are presented in Table 3.

5. Computational Results and Comparisons

The integrated objective function value through the LP-metric method and desirability function approach and the computational time are taken into account as measures for evaluating the performance of the developed algorithms. In this regard, various test problems in different sizes are generated as presented in Table 4.

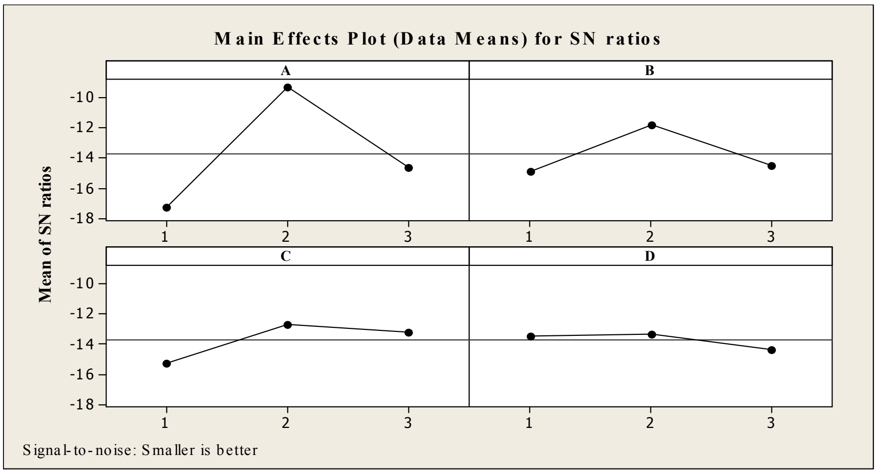

Fig. 7. Average S/N ratio levels for PSO's parameters

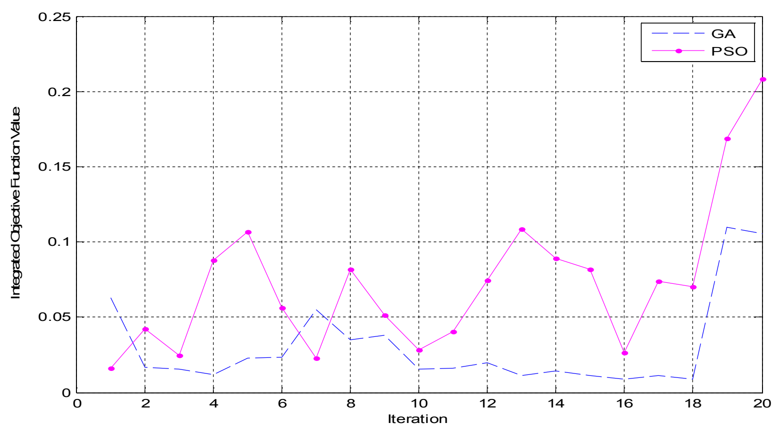

Fig. 8. Integrated objective function values of algorithms within LP-metric method

Table 3
Optimum parameter levels

Solving methods	Parameters	Optimum amount
GA	$Pop\ Size_{GA}$	100
	P_c	0.85
	P_m	0.01
	P_r	0.14
	nIt	100
	N_L	10
	N_B	15
PSO	$Pop\ Size_{PSO}$	200
	ω	1
	φ_1	1.5
	φ_2	1.5

Table 4
Generated test problems

Test problem number	*I*	*J*	*K*	*L*	*P*	*T*	*H*
1	4	3	15	2	2	2	2
2	6	3	20	2	3	2	2
3	7	4	25	3	3	3	2
4	9	6	30	4	3	4	2
5	10	7	35	5	4	4	2
6	12	7	40	6	4	5	2
7	12	8	45	7	5	6	3
8	14	10	50	9	5	6	3
9	15	12	55	10	6	8	3
10	17	13	60	12	7	9	3
11	20	15	70	12	7	10	3
12	22	18	80	14	8	12	3
13	24	20	90	15	8	12	4
14	25	21	100	18	8	12	4
15	28	25	110	20	9	15	4
16	30	27	125	23	9	15	4
17	30	28	140	25	10	16	4
18	32	29	155	27	10	17	4
19	35	30	180	28	10	18	4
20	40	35	200	30	10	18	4

Considering the following assumptions, the test problems are solved by the GA and PSO. To eliminate the uncertainties of the resulting solutions, each test problem is run two times under different random environments. Then, the average of these two runs is considered as the final response. The computational results are reported in Tables 5 and 6.

- Lead times required for producing demands and delivery lead times of third-party logistics providers follow a uniform distribution ~ *Uniform* [10, 100].
- Transportation cost per unit of product from manufacturers to distributors and from distributors to customers follows a uniform distribution ~ *Uniform* [700, 800] for the first interval, a uniform distribution ~ *Uniform* [500, 650] for the second interval, a uniform distribution ~ *Uniform* [300, 450] for the third interval and a uniform distribution ~ *Uniform* [100, 250] for the forth interval.
- The capacity of manufacturers, distributors and third-party logistics providers follow a uniform distribution as ~ *Uniform* [100, 240], ~ *Uniform* [70, 180] and ~ *Uniform* [90, 280], respectively.
- The upper bound of the discount interval offered by the third-party logistics providers follows a uniform distribution ~ *Uniform* [100, 1000].
- Capacity of a transportation vehicle and the fixed cost of using a transportation vehicle are equal to 1000 and 100, respectively.

Table 5
Computational results of proposed GA

Test problem number	Proposed GA		LP-metric method		Desirability function method	
	OFV1	OFV2	Integrated OFV	Time (Sec)	Integrated OFV	Time (Sec)
1	90341	799.8613	0.062941	95.311	0.985433	98.254
2	116477	3250.441	0.016790	105.142	0.963998	110.056
3	239386	3073.115	0.015620	130.978	0.903088	134.742
4	223061	8219.773	0.011703	245.206	0.937806	252.327
5	297681	6356.773	0.022513	350.025	0.886562	356.149
6	345378	12508.71	0.023273	537.148	0.853041	534.286
7	563594	21235.84	0.054748	733.059	0.793596	737.340
8	636879	29269.22	0.034824	856.197	0.761105	864.053
9	834818	47433.45	0.037777	964.937	0.712066	969.152
10	1223706	395308.2	0.015598	1141.886	0.665860	1152.396
11	1267879	94316.85	0.015826	1463.619	0.662315	1481.877
12	1690781	131566.3	0.019676	1925.431	0.623558	1956.150
13	1646775	138639.2	0.011446	2355.268	0.639842	2379.466
14	1918700	209528.3	0.014356	2977. 532	0.596038	3245. 162
15	2382557	282050.3	0.010951	3512.760	0.571815	3520.938
16	2571514	343895.7	0.008814	4132.854	0.567038	4161.036
17	2913080	353594.8	0.010951	4697.437	0.531965	4713.435
18	3051531	479975.1	0.008967	5361.881	0.511352	5372.926
19	3069117	494982.3	0.110002	6721.755	0.504693	6715.611
20	3553510	545561.2	0.105712	8296.429	0.474649	8308.225

Table 6
Computational results of proposed PSO

Test problem number	Proposed PSO		LP-metric method		Desirability function method	
	OFV1	OFV2	Integrated OFV	Time (Sec)	Integrated OFV	Time (Sec)
1	85112	788.1534	0.016077	59.145	0.995696	61.224
2	169053	4817.82	0.042567	76.763	0.881272	75.918
3	316904	3141.859	0.024374	126.871	0.843873	129.204
4	284611	8520.74	0.087642	192.749	0.861751	198.545
5	481757	6992.031	0.106882	229.577	0.805274	235.164
6	549562	13497.53	0.056458	366.542	0.791477	370.613
7	566134	21493.06	0.022978	420.681	0.760235	428.799
8	1084295	30392.84	0.081619	529.934	0.712694	541.565
9	153076	49525.23	0.051604	720.505	0.615211	718.257
10	1260528	399201.9	0.028126	911.994	0.659856	924.359
11	1443563	98453.35	0.040615	1030.807	0.620445	1039.855
12	2116915	135138.0	0.074315	1409.602	0.579526	1414.706
13	1836397	148789.4	0.108661	1714.645	0.593412	1728.350
14	2172932	213522.2	0.089135	2085.490	0.571263	2088.196
15	2834295	306947.1	0.081632	3183.328	0.517730	3197.110
16	3012584	388117.8	0.026484	3650.846	0.495984	2656.544
17	3988086	356538.3	0.074138	4072.248	0.399846	4061.385
18	3344457	484150.7	0.069981	5216.719	0.488961	5221.116
19	3693741	523984.5	0.168521	6523.147	0.418175	6530.592
20	5315311	705423.3	0.208137	7807.851	0.326630	7819.527

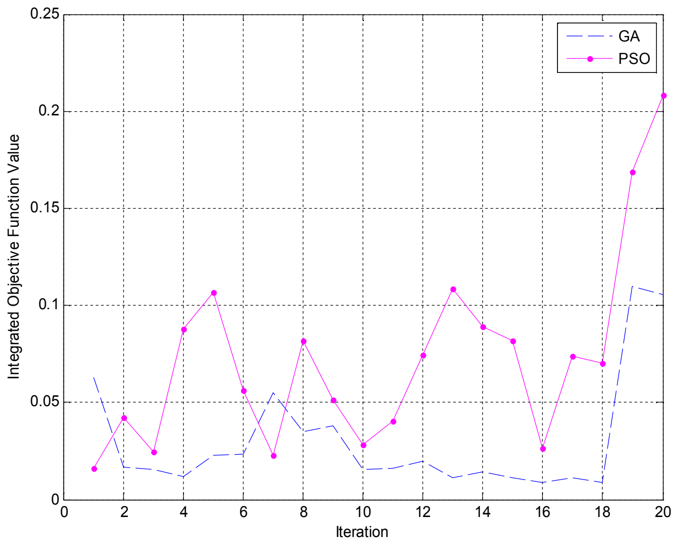

Fig. 8. Integrated objective function values of algorithms within LP-metric method

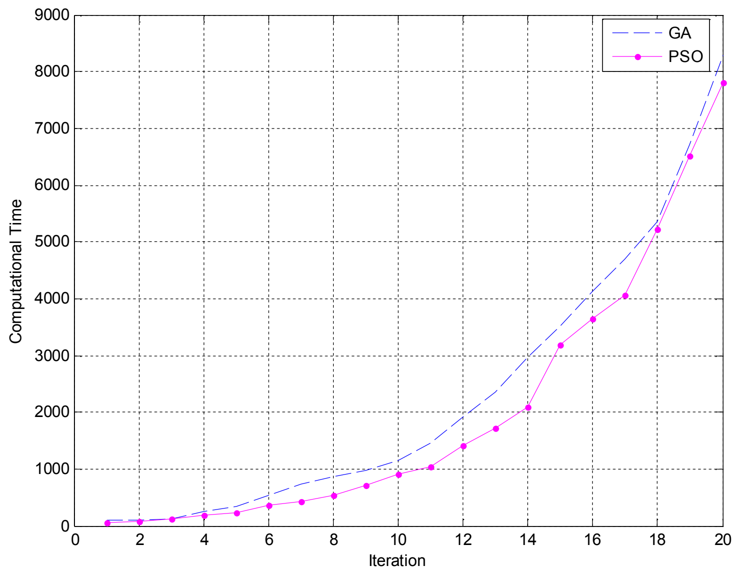

Fig. 9. Computational times of algorithms within LP-metric method

As is shown in Figure 8, the GA gives a good performance in comparison with the PSO in terms of the quality of solutions obtained from the LP-metric method. However, unlike the GA, the PSO leads to a better computational time as illustrated in Figure 9. Furthermore, the two algorithms produce identical performances in terms of their solutions within the desirability function method.

Besides, to compare the effectiveness of the proposed algorithms in terms of integrated objective function and computational time, we conduct a one-way analysis of variance through the Minitab 14.1 software (2003). According to the ANOVA results presented in Tables 7 and 8, since the three p-values are more than α = 0.05, we can conclude that there is no statistically significant difference between the two algorithms in terms of the integrated objective function value through the desirability function method and computational times at a 95% confidence limit. However, it is proved that there is a significant difference between the algorithms in terms of the integrated objective function value through the LP-metric method. The ANOVA results are graphically illustrated in Figures 10 and 11.

Table 7

ANOVA results for GA and PSO within LP-metric method

Integrated Objective Function Value					
Source	**DF**	**SS**	**MS**	**F-Test**	**P-Value**
Factor	1	0.01795	0.01795	10.85	0.002
Error	38	0.06288	0.00165		
Total	39	0.08083			
Computational Time					
Factor	1	984520	984520	0.18	0.677
Error	38	211771691	5572939		
Total	39	212756210			

Table 8

ANOVA results for GA and PSO within desirability function method

Source	DF	SS	MS	F-Test	P-Value
Integrated Objective Function Value					
Factor	1	0.0364	0.0364	1.20	0.279
Error	38	1.1485	0.0302		
Total	39	1.1849			
Computational Time					
Factor	1	1452582	1452582	0.26	0.611
Error	38	210045629	5527517		
Total	39	211498211			

```
       Individual 95% CIs For Mean Based on
       Pooled StDev

        Integrated Objective Function Value

       ----+---------+---------+---------+-----
GA     (--------*---------)
PSO                         (---------*----------)
       ----+---------+---------+---------+-----
         0.020     0.040     0.060     0.080


                 Computational Time

       ------+---------+---------+---------+---
GA           (--------------*---------------)
PSO        (--------------*--------------)
       ------+---------+---------+---------+---
           1400      2100      2800      3500
```

Fig. 10. Graphical representation of ANOVA results for algorithms within LP-metric method

```
Individual 95% CIs For Mean Based on
Pooled StDev

Integrated Objective Function Value

-----+---------+---------+---------+----
GA                (------------*------------)
PSO       (------------*------------)
-----+---------+---------+---------+----
0.600     0.660     0.720     0.780


Computational Time

-------+---------+---------+---------+--
GA              (---------------*---------------)
PSO        (---------------*---------------)
-------+---------+---------+---------+--
1400      2100      2800      3500
```

Fig. 11. Graphical representation of ANOVA results for algorithms within desirability function method

6. Concluding Remarks and Future Research Directions

In this study, we developed a multi-objective mixed-integer linear programming model for solving an integrated multi-product and multi-time period production-distribution planning problem. The goal of the proposed optimization model was to determine the quantity of transported products, allocation of the customers' demands to the manufacturers and distributors, as well as the allotment of the products transportations to the third-party logistics providers such that the total delivery time and total transportation costs are minimized. Due to the complexity of the considered problem, the GA and PSO algorithm were hired along with the LP-metric method and desirability function approach to find the near optimal solutions consistent with decision makers' opinion. The Taguchi method was then used to tune the parameters of the proposed algorithms. Finally, the efficiency and the efficacy of the proposed model and the solution methodologies were demonstrated through a set of generated problems in different sizes.

Some directions for further studies are recommended as follows:

- Multi-objective meta-heuristic solution methodologies can be employed and the performance of the new solution methodology can be examined.
- Uncertainty of demands, transportation costs and delivery lead times may be considered in the model, and new solution methodologies to handle uncertainty and fuzziness can be developed.
- Parameter analysis can be performed to study the effects of the model's parameter changes on the results obtained by the proposed solution methodologies.
- The robustness of the solution methodologies may be amended by changing the solution representation scheme.

7. References

[1] Altiparmak, F., Gen, M., Lin, L. and Paksoy, T. (2006). A genetic algorithm approach for multi-objective optimization of supply chain networks. Computers & Industrial Engineering, 51(1), 196-215.

[2] Burke, G.J., Carrillo, J. and Vakharia, A.J. (2008). Heuristics for sourcing from multiple suppliers with alternative quantity discounts. European Journal of Operational Research, 186(1), 317–329.

[3] Cohon, J.L. (1985). Multicriteria programming: Brief review and application. In J.S.Gero (Ed.), Design Optimization, 163-191. New York: Academic Press.

[4] Deb, K. (2001). Multi-objective optimization using evolutionary algorithms. Chichester, UK: Wiley.

[5] Fahimnia, B., Luong, L. and Marian, R. (2012). Genetic algorithm optimization of an integrated aggregate production–distribution plan in supply chains. International Journal of Production Research, 50(1), 81-96.

[6] Gen, M. and Syarif, A. (2005). Hybrid genetic algorithm for multi-time period production/distribution planning. Computers & Industrial Engineering, 48(4), 799-809.

[7] Goldberg, D. (1989). Genetic algorithms in search: Optimization and machine learning. Reading, MA: Addison-Wesley.

[8] Haq, A.N. and Kannan, G. (2006). Effect of forecasting on the multi-echelon distribution inventory supply chain cost using neural network, genetic algorithm and particle swarm optimization. International Journal of Services Operations and Informatics, 1(1-2), 1–22.

[9] Holland, J.M. (1975). Adaption in natural and artificial systems. Ann Arbor, MI: The University of Michigan.

[10] Jolai, F., Razmi, J. and Rostami, N.K.M. (2011). A fuzzy goal programming and meta heuristic algorithms for solving integrated production/distribution planning problem. Central European Journal of Operations Research, 19(4), 547-569.

[11] Kadadevaramath, R.S. (2009). Performance analysis of multi-echelon supply chain network through new DSS optimizer. International Journal of Computer Applications in Technology, 36(3-4), 233-246.

[12] Kadadevaramath, R.S., Chen, J.C.H., Shankar, B.L. and Rameshkumar, K.. (2012). Application of particle swarm intelligence algorithms in supply chain network architecture optimization. Expert Systems with Applications, 39(11), 10160-10176.

[13] Kamali, A., Fatemi Ghomi, S.M.T. and Jolai, F. (2011). A multi-objective quantity discount and joint optimization model for coordination of a single-buyer multi-vendor supply chain. Computers & Mathematics with Applications, 62(8), 3251-3269.

[14] Kannan, G., Noorul Haq, A. and Devika, M. (2009). Analysis of closed loop supply chain using genetic algorithm and particle swarm optimization. International Journal of Production Research, 47(5), 1175-1200.

[15] Kennedy, J. and Eberhart, R. (1995). Particle swarm optimization. Proceedings of the 1995 IEEE International Conference on Neural Network, IV, 4, 1942–1948.

[16] Liu, S. and Papageorgiou, L.G. (2013). Multiobjective optimization of production, distribution and capacity planning of global supply chains in the process industry. Omega, 41(2), 369-382.

[17] MATLAB, Release 7.10.0.499. (2010). The MathWorks Inc. Natick, Massachusetts, USA.

[18] MINITAB, Release 14.1., (2003), The Minitab Inc., Canada.

[19] Montgomery, D.C. (2005). Design and Analysis of Experiments. Sixth edition, John Wiley & Sons, New York.

[20] Naraharisetti, P.K., Karimi, I.A. and Srinivasana, R. (2007). Optimal Supply Chain Redesign using Genetic Algorithm. 17th European Symposium on Computer Aided Process Engineering – ESCAPE17.

[21] Park, Y.B. (2005). An integrated approach for production and distribution planning in supply chain management. International Journal of Production Research, 43(6), 1205-1224.

[22] Park, B.J., Choi, H.R. and Kang, M.H. (2007). Integration of Production and Distribution Planning Using a Genetic Algorithm in Supply Chain Management. Advances in Soft Computing, 41, 416-426.

[23] Sha, D.Y. and Hsu, C.Y. (2008). A new particle swarm optimization for the open shop scheduling problem. Computers & Operations Research, 35(10), 3243-3261.

[24] Syarif, A., Yun, Y. and Gen, M. (2002). Study on multi-stage logistic chain network: a spanning tree-based genetic algorithm approach. Computers & Industrial Engineering, 43(1-2), 299-314.

[25] Taguchi, G. (1986). Introduction to Quality Engineering: Designing Quality into Products and Processes. White Plains: Asian Productivity Organization/UNIPUB, Tokyo, Japan.

[26] Umarani, R. and Selvi, V. (2010). Particle Swarm Optimization-Evolution, Overview and Applications. International Journal of Engineering Science and Technology, 2(7), 2802-2806.

[27] Zanjirani Farahani, R. and Elahipanah, M. (2008). A genetic algorithm to optimize the total cost and service level for just-in-time distribution in a supply chain. International Journal of Production Economics, 111(2), 229-243.