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A Multi-objective Evolutionary Approach for Integrated Production-Distribution Planning Problem in a Supply Chain Network

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Abstract

Integrated production-distribution planning (PDP) is one of the most important approaches in supply chain networks. We consider a supply chain network (SCN) consististing of multi suppliers, plants, distribution centers (DCs), and retailers. A bi-objective mixed integer linear programming model for integrating production-distribution designed here aim to simultaneously minimize total net costs in supply chain and transfer time of products for retailers. From different terms of evolutionary computations, this paper proposes a Pareto-based meta-heuristic algorithm called multi-objective simulated annealing (MOSA) to solve the problem. To validate the results obtained, a popular algorithm, namely non-dominated sorting genetic algorithm (NSGA-II) is utilized as well. Since the solution-quality of proposed meta-heuristic algorithm severely depends on their parameters, the Taguchi method is utilized to calibrate the parameters of the proposed algorithm. Finally, in order to probe the validity of the proposed model, a numerical example is solved and conclusions are discussed.
Keywords: Supply chain network (SCN), Integrated production-distribution planning (PDP), Multi-objective simulated annealing (MOSA), Non-dominated sorting genetic algorithm (NSGA-II), Taguchi method.

1. Introduction

The traditional production management approaches that are less integrated in the following processes will lose their effectiveness. Supply chain (SC) as an integrated approach for the proper management of materials, products, information, and financial is capable (Chen and Lee, 2004). In this regard, a close relationship exists between design and management of flows (materials, information, financial) and success of a chain. A SC is defined as a network of facilities in order to supply products to final customers at the appropriate time and location. Thus, SC as well as transfer of the final good to customers will deliver it of the proper lead time. So, in addition to the total costs of chain which are minimized, the needs of the customers with high service level are also met (Simchi-Levi et al., 2000). The main problem in SC is the integrated PDP. The problem of production planning is decision making about the products produced by manufacturers (Lee and Kim, 2002; Park et al., 2007). Decisions related to finding a channel to deliver products from a manufacturer to a distributor or customer is distribution planning problem. These problems are mutually dependent; therefore, they should be simultaneously considered in an integrated approach (Lee and Kim, 2002; Rizk et al., 2005; park et al., 2007; Selim et al., 2008).

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Modeling and analysis of integrated PDP problems in SCNs have been an active area of research for many years. Fahimnia et al. (2013) presented a whole set of integrated PDP model of SCNs in different categories, one of which has solving methodology. The search space to find the optimal solution in integrated SC problems may contain long CPU time. For this reason, selecting an effective optimization technique to solve SC optimization models is so prominent and has always been a key subject in literature. To do this, a brief related literature review of the aforementioned solving methodologies in both of the single-objective and multi-objective models is presented.

In this regard, Haq et al. (1991) proposed an integrated production-inventory-distribution model incorporating many realistic conditions to determine optimal production and distribution as well as inventory level. A mixed integer linear programming (MILP) is formulated for minimizing the total cost of system. Barbarosoglu and Ozgur (1999) used Lagrangian relaxation method in hierarchical design of an integrated production-distribution in a 2-echelon system. A MILP is presented to minimize the total fixed and variable costs. Chen and lee (2004) presented a multi-product, multi-stage, and multi-period model with multiple incommensurable goals of a multi-echelon SCN as a mixed-integer nonlinear programming (MINLP) problem. The fuzzy sets are considered to describe the uncertain demands and product prices in this model. Selim et al. (2008) developed a multi-objective linear programming (LP) model to collaborate PDP problem in a SC. A fuzzy goal programming is considered to incorporate decision maker's imprecise aspiration levels. Ferrio and Wassick (2008) proposed a multi-product chemical supply network include production sites, an arbitrary number of DCs, and customer zones (CZs). This problem was formulated as a MILP model for redesigning and optimizing of network. Their model was analyzed by GAMS/CPLEX mathematical programming solver. Tuzkaya and Onut (2009) presented an integrated model to determine the best strategy of distribution the sub-products between supplier, warehouses and manufacturers. The objective function is minimizing total costs of the inventory, warehouse, manufacturer, and penalty cost for supplier, manufacturers and warehouses. Jolayemi (2010) presented an integrated MILP model with factories, DCs, and retailers for determining the optimal quantities of products to be produced, optimum inventory holding in factories, optimal transportation quantities to DCs, optimal inventory holding in DCs, and optimal quantities transported to retailers in each period. The model is introduced as production-distribution and transportation planning problem that two versions as the fully optimized version (FOV) and the less fully optimized (LFOV) is considered to solve it. Pishvaee and Razmi (2012) presented an interactive fuzzy solution approach to solve a multi-objective fuzzy mathematical programming model for an environmental supply chain network design (SCND) with objectives of the minimizing total cost and minimization of the total environmental impact. Bashiri et al. (2012) presented a new multi-product mathematical model with strategic and tactical planning and different time resolution decisions for a multi-echelon network. This model was categorized in small, medium, and large scales and was solved by CPLEX solver in small and medium size, and some heuristics to decrease solution time. Sadjadi and Davoudpour (2012) proposed an efficient Lagrangian to solve a two-echelon SCND problem. The problem is designed in both strategic and tactical levels of SC planning in deterministic, single period, and multi-commodity contexts, and is formulated as a mixed integer programming (MIP) model to minimize total costs of the network. Badri et al. (2013) developed a new multi-commodity SCND model with different time resolutions for strategic and tactical decisions. The objective function is maximizing the total net income over the time. A mathematical technique based on the Lagrangian Relaxation method was developed to solve the problem. Liu and Papageorgiou (2013) proposed a multi-objective production-distribution and capacity planning model by considering costs, response, and service level in a universal SC. Their model is solved by means of the ε-constraints and Lexicographic mini-max methods.

Since most of the realistic SCs are complex in nature with a high number of variables and constraints involved, mathematical optimization methods such as LP and MIP may not be very effective in solving real world SCN problems (Fahimnia et al., 2013). Furthermore, due to the exponential growth of the problem size and complexity, the model would become NP-Hard and long CPU time is required in order to process complex mathematical algorithms (Park et al., 2007; Jolai et al., 2011). Hence, heuristic and meta-heuristic algorithms are used to solve the problems. In this regard, Syarif et al. (2002) designed a multi-echelon SCN in order to select of the plants and DCs to be opened and the distribution network design to satisfy the demand, which was solved using a spanning-tree-based Genetic algorithm (GA). Altiparmak et al. (2009) presented a multi-objective network structure of manufacturers and CZs in which shortage is forbidden. The minimization of total costs and delivery time and balancing the capacity of the factories were objective functions in this problem. The objectives' weights are determined by using an analytic hierarchy process (AHP) and utilized a GA to solve the problem. Park et al. (2007) proposed a multi-period SC model, including supplier, factory, and DC with multi-product for minimizing the total cost, and presented a GA to solve the problem. Kazemi et al. (2009) proposed a multi-level SC with two scenarios for making their production-distribution decisions. A multi-agent system based on GA for each level by considering interplay of the levels is proposed to solve the problem. Chang (2010) designed a multi-echelon SCN including suppliers, factories, DCs and retailers for minimizing the total costs of chain including purchasing and transportation cost of raw materials and products, manufacturing of products in factories, and storage cost of products in DCs. In order to help in finding rapidly a solution, a GA is utilized with optimum search features combined with a co-evolutionary mode and constraint-satisfaction. Amrani et al. (2011) presented a multi-commodity production-distribution network with alternative facility configuration. The problem formulated as a MIP model, and solved by using a variable neighborhood search (VNS) method. Jolai et al. (2011) developed a linear multi-objectives production-distribution model in a SCN with several products, levels, and periods. The decision maker's imprecise aspiration levels of goals are incorporated into the model using a fuzzy goal programming approach and solved by considering three meta-heuristic algorithms with a new fitness function in GA and particle swarm optimization (PSO), and an improved hybrid GA as well. Mehdizadeh and Afrabandpei (2012) presented a multi-stage and multi-product logistic network with minimizing the total cost of supply chain and solved it by a hybrid priority-based genetic algorithm (pb-GA) and SA in two phases to find the optimal solution. Taherkhani and Seifbarghy (2012) proposed a multi-echelon supply chain to minimize the total cost of supply chain consists of purchasing, assembling, and transportation costs between levels. Then, the model is solved by a SA based heuristic. Kadadevaramath al. (2012) presented the modeling and optimization of a three echelon SCN using the PSO / intelligence algorithms.

Regarding the above literature review, as the problem in large size is shown strongly NP-hard, a little variety of solving methodology including meta-heuristic algorithms have been utilized to find Pareto solution sets of different multi-criteria SCN models. Therefore, in this paper, a bi-objective model of an integrated PDP in a multi-echelon SCN is presented in which in addition to minimizing the total costs of the chain, service level is also considered. In this model, in order to improve the service level, the transfer time of products is optimized. Two parameter-tuned Pareto-based algorithms are also proposed to find non-dominated solutions of solving the problem. The rest of the paper is organized as follows: problem definition and mathematical formulation are presented in section 2. Section 3 presents the proposed meta-heuristic algorithms proposed. Section 4 presents the Taguchi method to tune the parameters. Experimental data and analysis of results also demonstrated different problems of various sizes in this section. Finally, conclusion and directions for future research appear in section 5.

2. Description of the Model

A SC with some suppliers, plants, DCs, and retailers are considered in fixed locations. In SC of this study, the used raw materials of products are supplied from suppliers to plants, and various products produced by each plant if produced in the related period, are transferred to various distributors. Here, a distributor can be understood as a logistics warehouse delivering finished products from a plant to a retailer. In this research, the allocation between DCs and retailers in order to obtain suitable quantity of distribution is investigated. Minimization of total chain costs, and transfer time of products to retailers are the objective functions of the model. Furthermore, in case of retailer demands in each period are not met, the shortage as lost sale is different concept that is considered in the model's first objective function. In this model there is one objective function on time and one objective function on cost. It is worth mentioning that, on one hand, we want to decrease lead time of products to retailers and, on the other hand, minimization of costs of all the echelons altogether is also required. Therefore, minimizing transfer times in SC may lead to an increase in the total cost of the supply chain. These are the reasons for choosing such conflicting objectives in this research. The proposed SCN is illustrated in Figure 1. The assumptions, notations and mathematical formulation for this SC are presented in the following section.

2.1. Assumptions

In the formulation of the problem, the following assumptions are considered:

- A SC with several suppliers, plants, DCs and retailers is considered.
- All decisions are made within multi periods.
- There is a transportation capacity constraint for all periods.
- Each plant can produce various products, and can produce all the products within each period.
- The shortage as lost sale is considered for retailers.

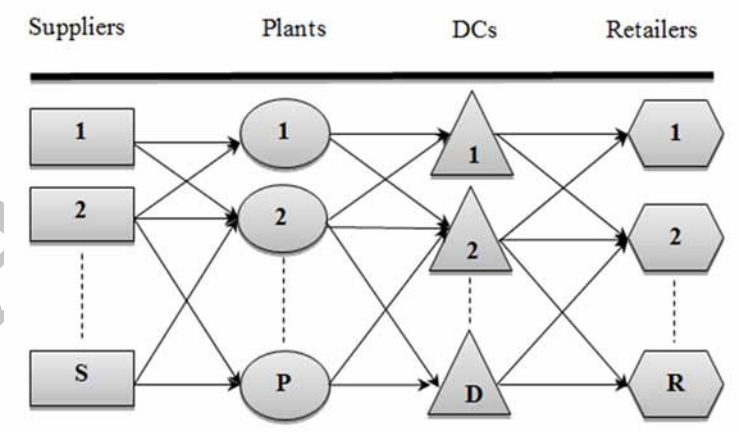

Fig. 1. The studied SCN

2.2. Indices

s: index of suppliers (s=1, 2, …, S)
p: index of plants (p=1, 2, …, P)
d: index of DCs (d=1, 2, …, D)
c: index of retailers (r=1, 2, …, R)
i: index of products (i=1, 2, …, I)
t: index of time periods (t=1, 2, …, T)

2.3. Parameters

DE_{rit}: Amount of product i demanded by retailer r in period t

CSM_{spt}: Supply and transportation cost per unit of raw material from supplier s to plant p in period t

CSE_{pit}: Production preparation cost of product i at plant p in period t

CP_{pit}: Production cost of product i at plant p in period t

CH_{pit}: Inventory holding cost of product i at plant p in period t

CT_{pdit}: Transportation and purchase cost of product i from plant p to DC d in period t

CH_{dit}: Inventory holding cost of product i at DC d in period t

CT_{drit}: Transportation and purchase cost of product i from DC d to retailer r in period t

CPT_{spt}: Transportation capacity of raw material from supplier s to plant p in period t

CPT_{pdt}: Transportation capacity of products from plant p to DC d in period t

CPT_{drt}: Transportation capacity of products from DC d to retailer r in period t

CPP_{pit}: Production capacity of product i at plant p in period t

CPD_{pit}: Inventory capacity of product i at plant p in period t

CPD_{dit}: Inventory capacity of product i at DC d in period t

TSM_{spt}: Time required to ship of raw material from supplier s to plant p in period t

TP_{pit}: Time required to produce and holding of product i at plant p in period t

TT_{pdit}: Time required to ship of product i from plant p to DC d in period t

TT_{drit}: Time required to ship of product i from DC d to retailer r in period t

CLS_{rit}: Cost of lost sale of product i for retailer r in period t

2.4. Decision variable

QSM_{spt}: Supply quantity per unit of raw material from supplier s to plant p in period t

QP_{pit}: Production quantity of product i at plant p in period t

QS_{pdit}: Supply quantity of product i from plant p to DC d in period t

QS_{drit}: Supply quantity of product i from DC d to retailer r in period t

I_{pit}: Inventory of product i at plant p in period t

I_{dit}: Inventory of product i at DC d in period t

W_{pit}: 1, if plant p produces product i in period t, 0 otherwise

Y_{drt}: 1, if DC d is assigned to retailer r in period t, 0 otherwise

2.5. Objective functions

The first objective function of the proposed model given in Eq. (1) minimizes total costs in supply chain including supply and transportation of raw material from suppliers to plants, production preparation and production in plants, inventory holding of products in plants, transportation and purchase of products to DCs, inventory holding of products in DCs, transportation and purchase of products to retailers, and lost sale of products. The second objective function given in Eq. (2) minimizes transfer time of products to retailers.

$$\begin{aligned} Min\, Z_1 = &\sum_{s=1}^{S}\sum_{p=1}^{P}\sum_{t=1}^{T} CSM_{spt} \times QSM_{spt} + \sum_{p=1}^{P}\sum_{i=1}^{I}\sum_{t=1}^{T} CSE_{pit} \times W_{pit} + \sum_{p=1}^{P}\sum_{i=1}^{I}\sum_{t=1}^{T} CP_{pit} \times QP_{pit} \\ &+ \sum_{p=1}^{P}\sum_{i=1}^{I}\sum_{t=1}^{T} CH_{pit} \times I_{pit} + \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{i=1}^{I}\sum_{t=1}^{T} CT_{pdit} \times QS_{pdit} + \sum_{d=1}^{D}\sum_{i=1}^{I}\sum_{t=1}^{T} CH_{dit} \times I_{dit} \\ &+ \sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{i=1}^{I}\sum_{t=1}^{T} CT_{drit} \times QS_{drit} + \sum_{r=1}^{R}\sum_{i=1}^{I}\sum_{t=1}^{T} CLS_{rit} \times \left(DE_{rit} - \sum_{d=1}^{D} QS_{drit}\right) \end{aligned} \tag{1}$$

$$\begin{aligned} Min\, Z_2 = &\sum_{s=1}^{S}\sum_{p=1}^{P}\sum_{t=1}^{T} TSM_{spt} \times QSM_{spt} + \sum_{p=1}^{P}\sum_{i=1}^{I}\sum_{t=1}^{T} TP_{pit} \times QP_{pit} + \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{i=1}^{I}\sum_{t=1}^{T} TT_{pdit} \times QS_{pdit} \\ &+ \sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{i=1}^{I}\sum_{t=1}^{T} TT_{drit} \times QS_{drit} \end{aligned} \tag{2}$$

Subject to

$$\sum_{d=1}^{D} Y_{drt} \geq 1 \qquad \forall\ r,t \tag{3}$$

$$QSM_{spt} \leq CPT_{spt} \qquad \forall\ s,p,t \tag{4}$$

$$\sum_{i=1}^{I} QS_{pdit} \leq CPT_{pdt} \qquad \forall\ p,d,t \tag{5}$$

$$\sum_{i=1}^{I} QS_{drit} \leq CPT_{drt} \times Y_{drt} \qquad \forall\ d,r,t \qquad (6)$$

$$QP_{pit} \leq CPP_{pit} \times W_{pit} \qquad \forall\ p,i,t \qquad (7)$$

$$\sum_{d=1}^{D} QS_{drit} \leq DE_{rit} \qquad \forall\ r,i,t \qquad (8)$$

$$I_{pit} - I_{pit-1} = QP_{pit} - \sum_{d=1}^{D} QS_{pdit} \qquad \forall\ p,i,t \qquad (9)$$

$$I_{dit} - I_{dit-1} = \sum_{p=1}^{P} QS_{pdit} - \sum_{r=1}^{R} QS_{drit} \qquad \forall\ d,i,t \qquad (10)$$

$$\sum_{s=1}^{S} QSM_{spt} - \sum_{i=1}^{I} QP_{pit} = 0 \qquad \forall\ p,t \qquad (11)$$

$$I_{pit} \leq CPD_{pit} \qquad \forall\ p,i,t \qquad (12)$$

$$I_{dit} \leq CPD_{dit} \qquad \forall\ d,i,t \qquad (13)$$

$$QSM_{spt}, QP_{pit}, QS_{pdit}, QS_{drit}, I_{pit}, I_{dit} \geq 0 \qquad \forall\ s,p,d,r,i,t \qquad (14)$$

$$W_{pit}, Y_{drt} \in \{0,1\} \qquad \forall\ p,d,r,i,t \qquad (15)$$

$$I_{pi0}, I_{di0} = 0 \qquad \forall\ p,d,i \qquad (16)$$

Constraint (3) ensures that each retailer can be supplied more than one DC in each period. Constraint (4) indicates transportation capacity of raw material to procurement for plants in each period. Also, constraints (5) and (6) show transportation capacity of products to ship from plants to DCs and from DCs to retailers among periods. Constraint (7) shows that if the product i produce by plant p in period t; it limits by production capacity. In constraint (8), the shipment quantity of each product to each retailer by DCs during each time period should not exceed the retailer demand. Equations (9) and (10) indicate inventory levels of products in plants and DCs in each time period. For instance, constraint (10) indicates that inventory of product i in DC d is equal to the inventory of product i in the previous period plus the quantity of product i received from plants in period t minus quantity of product i shipped to retailers in period t. Eq. (11) ensures that production quantity of products by each plant in each period is equal to the total supply quantity of raw material by suppliers. Constraints (12) and (13) state that inventory of product i in each period should not exceed the inventory capacity in plants and DCs, respectively. Finally, constraints (14) and (15) is the condition of non-negatively and binary integer of all variables. Note that the initial states of the inventories are as (16).

3. Solving Methodology

According to complexity of the problem in literature and proof by Kazemi (2009) and Joali et al. (2011), two Pareto-based multi-objective meta-heuristic algorithms, namely, the multi-objective simulated annealing (MOSA) and NSGA-II are implemented to solve the problem. Actually, we aim to introduce MOSA to the literature of the integrated PDP problems and NSGA-II is used to evaluate the performance of the MOSA. To do so, first some required multi-objective backgrounds are defined in the following.

3.1. Preliminary concepts of multi-objective algorithms

Consider a multi-objective model with a set of conflict objectives $f(\tilde{x}) = [f_1(\tilde{x}), \dots, f_m(\tilde{x})]$ subject to $g_i(\tilde{x}) \leq 0$, i=1, 2, …, k, in which $\tilde{x} \in X$ denotes n-dimensional vector that can get real, integer, or even Boolean value and X is the feasible region, domination concept for a minimization problem is defined as follows (Deb, 2001):

1) $f_i(\tilde{a}) \leq f_i(\tilde{b}), i = 1,2,\dots,m$

2) $\exists\ i \in \{1,2,\dots,m\}: f_i(\tilde{a}) < f_i(\tilde{b})$

According to these conditions, solution $\tilde{a}$ dominates solution $\tilde{b}$ under the simultaneously existing of the two mentioned conditions. Based on this definition, Pareto optimal front is called to a set of solutions that cannot dominate each other. This front has two main features which are known as 1) good convergence and 2) good diversity within the solutions of the Pareto front (Deb, 2001).

3.2. Multi-objective simulated annealing algorithm

Simulated annealing (SA) was first introduced by Kirkpatrick et al. (1983) to solve the large combinatorial optimization problems. This algorithm simulates the annealing process. In this algorithm, initially, a matter to melt is heated and then gradually cooled, whose structural properties of cold matter depend on the cooling rate. In this process, until the system reaches a frozen steady state, changes of energy are simulated. So, this idea is used to search the feasible solution of an optimization problem with the convergence goal to an optimal solution.

SA by beginning from a current solution (X_1) generates another solution (X_2) by taking a stochastic step in some neighbourhood of X_1. If the new solution improves the value of the objective function, it replaces as the new current solution. Otherwise, the new solution is accepted with a given probability. The possibility of moving to solutions with a higher cost characterizes, and enables it to away from local optimum. The probabilistic acceptance of the worst solution depends on the cost difference between the two solutions and it also decreases during the search. Eq. (17) inspired from thermodynamics models, and this probability often defines:

$$Probability\,(i, X, X_i) = exp^{\frac{-\Delta f_i}{T_i}}\ ; \quad \Delta f_i = \frac{f(X_i) - f(X)}{f(X_i)} \times 100 \qquad (17)$$

Where T_i is the temperature at stage *i*. The temperature is kept unchanged during each stage, which consists of a constant number of iterations. After each stage, the temperature is decreased by a factor $\beta \in (0,1)$ that T_i is obtained based on eq. (18) (Kirkpatrick et al, 1983). SA differs from each other with respect to the various factors such as neighbourhood search, cooling (annealing) schedule and termination criterion.

$$T_i = \beta \times T_{i-1}; \quad i \geq 2, \quad 0 \leq \beta \leq 1 \qquad (18)$$

3.2.1. Solution representation

In this section, to represent solution, structure variables are used. In this representation, each of the structures created as part of the solution is expression of a feature of the solution. The structure of chromosome consists of three parts. The first part consists of two vectors with dimension of $P \times I \times T$ and $D \times R \times T$ that represents assignment of production in each period, and allocation between DCs and retailers in each period that are generated with uniform distribution as binary numbers. Quantity of supply, and amount of production and distribution of products are decisions that should be determined in the second part; these variables are generated based on the transportation capacity of all echelons and production capacity to produce of products. The third part also shows the inventory of the plants and DCs in each period.

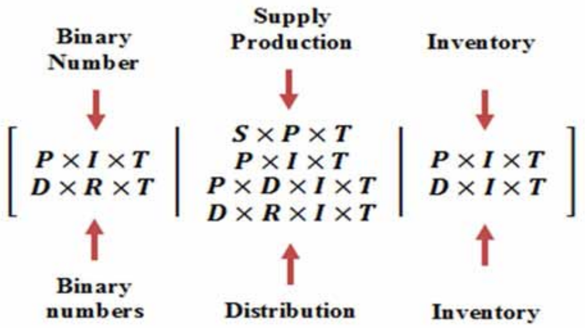

Fig. 2. The solution representation

In the presented chromosome, if all constraints are satisfied, then an initial generated solution is feasible. Hence, a heuristic policy is determined for all the variables. For instance, about a typical $D \times R \times I \times T$ structure of the solution in second part the following strategy is taken:

If DC d is assigned to retailer r in period t, then, product i from DC d is shipped to retailer r in period t based on the corresponding transportation capacity. In this case, the number of products provided to retailer r in period t should be less than the transportation capacity of the DC in that period. Now, until the sum of products shipped from DC d to retailer r is more than the transportation capacity, a product order is selected randomly. Then, this difference is calculated (δ). This process continues until the maximum difference among (δ) and the amount of selected randomly product that is shipped from DC d to retailer r in period t, which is shown (Δ), does not reach less than zero ($\max(0, \Delta)$). In fact, zero is considered in order to prevent minimum amount of shipped product gets negative and to avoid solutions keep infeasible. This guarantees to generate feasible solutions.

In the third part of a chromosome, the inventory balance constraints must be satisfied. To do this, the following strategy is employed for typical $D \times I \times T$ structure:

- If the inventory of product *i* for plant *p* in period *t* becomes negative, until this value is negative, this inventory (Ϫ) is obtained. Then, a uniform random number in (0, 1) is first generated. If the random number is less than a predetermined value between (0, 1), a product order is selected randomly and as for production capacity, will be incorporated into production value. This process continues until the inventory of product *i* in plant *p* to in period *t* get out of negative. Otherwise, if the random number is more than the predetermined value, a DC is randomly selected to ship product until the quantity of product *i* shipped from plant *p* to the selected DC in period *t* is equal to the maximum difference among the shipped quantity to the selected DC along with Ϫ and zero.

3.2.2. Neighborhood structure

A new solution is generated by altering the elements of current solution. In this step, two elements of one variable are selected and their positions swap together (Haupt and Haupt, 2004). Figure 4 illustrates this operation on the quantity of product *i* produced by plant *p* in period *t*. Note that the feasibility of solutions must be checked in accordance with the utilized policies when this operation is applied on all the variables.

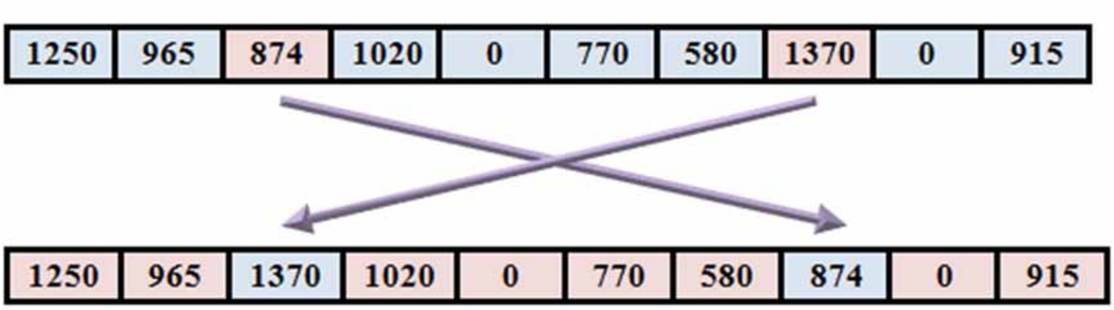

Fig. 3. An example of the neighbourhood structure

3.2.3. Multi-objective process of MOSA

Since designing the Pareto-based MOSA is desired and that the simple SA is not a population based algorithm, a parallel mechanism is used to increase the efficiency of the single objective SA. This mechanism of MOSA starts with setting of the initial parameters including, population size (popsize), Temperature (T), iteration number (itr), number of the implementation of the neighborhood structure on each solution of the population (num.struct), temperature reduction rate (β), and archive size (Archsize). Then, a population of the solutions is generated. In fact, in the multi-objective version of the SA algorithm, a number (equal to popsize) of the simple SA run simultaneously and create a population. During the iterations, Temperature (T) controls the possibility of the acceptance of deteriorating solutions. It means that, for high Temperature, specifically in the beginning of the search process, the algorithm is flexible to reach to weak solutions. However, at lower Temperature, which mostly happens in the final steps of the search process, this flexibility is more restricted and decreased.

In Pareto-based multi-objective algorithms, the domination concept is utilized for ranking, while in a single-objective algorithm the objective function value is used to rank the solutions. In the NSGA-II algorithm, proposed by Deb et al. (2002), two new mechanisms are inserted to the simple GA. One of these mechanisms calculates ranks for each solution of the population according to the number of the dominated solutions by that solution. This mechanism classifies and dedicates solutions of the population into different fronts and is called fast non-dominated sorting (FNDS). To search the second goal named diversity, another operator named crowing distance (CD) was considered in NSGA-II to estimate the density of similar rank solutions lay surrounding a particular solution. Bigger values of CD show better solutions lying in a less crowded area. Then, a binary tournament selection is performed according to the above two operators, in which if solutions are from different ranks, the one with smaller rank is selected. Otherwise, the one with the more value of CD is selected.

After generating a population of the solutions, solutions are evaluated and their objective functions are determined. In this step, similar to NSGA-II, ranks and CDs of the solutions are calculated. Then, by repetitive implementation of the neighbourhood structure on each solution of the sorted population (P_t), a new population (S_t) is developed. For solutions of S_t, ranks and CDs are calculated and a comparison is performed. In this comparison, if a member of S_t , $S_t(i)$, dominates the corresponding same ranked solution of P_t , $P_t(i)$, it is replaced with that. Otherwise, it is replaced if a randomly generated uniform number between 0 and 1 becomes less than $e^{\frac{-\Delta f_i}{T_i}}$. In this step, a new population, called Q_t , is generated. This replacement is mimicked from the single objective SA. However, instead of comparing the objective function values, domination is implemented.

Now, a process like the NSGA-II evolution process is used to face with the multi-objective environment of the problem. During this mimicked process, the new generated population (Q_t) is combined with the beginning population (P_t) and create a new population named R_t ($R_t = P_t \cup Q_t$). Then, ranks and CDs are calculated and R_t is sorted. In this step, population of the next iteration (P_t) is chosen based on popsize. In the last step of this (and each) iteration, this population is added to the archive (A_t), where the archive is ranked and sorted again. Of course, in case the number of members of the archive exceeds the determined size of the archive (Archsize), the redundant worst members are omitted. P_t is the starting population of the next iteration. The comprehensive pseudo code of the MOSA is illustrated in Fig. 9.

3.3. The employed NSGA-II algorithm

The main difference of NSGA-II algorithm with the MOSA is the evolution process of the algorithm from P_t to Q_t. In MOSA algorithm, single objective SA is employed as process evolution; while, in NSGA-II, the evolution process of a GA is used. Furthermore, NSGA-II uses a binary tournament selection strategy of selection operator. Accordingly, after generating or modifying populations by means of single-objective operators of the algorithms (GA or SA), the population is dealt in multi-objective way in a similar fashion in all algorithms. Besides, to minimize the impact of using different operators on the performance comparison process of the algorithms, operators are designed identically. To do so, the neighbourhood structure of the MOSA is designed similar to the mutation operator of NSGA-II. Other parameters such as the population size of all algorithms, and all parameters of NSGA-II are also set identically. Moreover, in NSGA-II the crossover operator is also designed similarly using a uniform crossover operator (Bate and Jones, 2008).

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Parameter setting: Popsize, iteration, num.struct, Archsize, T, β
Initialization: generate initial solutions
Evaluation: evaluate initial solution
Perform non-dominated sorting and calculate ranks
Calculate crowding distance (CD)
Sort population according to ranks and CDs
P_t=population
For it=1:iteration
      For i=1:popsize
          For j=1:num.struct
               S_t(i)= perform neighborhood structure on the solution i of the population P_t(i)
          End
      End
      Perform non-dominated sorting and calculate ranks (S_t)
      Calculate crowding distance (CD) (S_t)
      Sort population according to ranks and CDs (S_t)
      For i= 1:popsize
           If dominates (S_t(i) , P_t(i))
              Q_t(i)= S_t(i)
          Else
              P = exp^(-Δf_i / T_i)
              If rand < P
              Q_t(i)= S_t(i)
             End
          End
      End
      R_t = P_t ∪ Q_t
      Perform non-dominated sorting and calculate ranks (R_t)
      Calculate crowding distance (CD) (R_t)
      Sort population according to ranks and CDs (R_t)
      P_t = choose popsize number of the solution of the R_t
      A_t = A_t ∪ P_t
      Perform non-dominated sorting and calculate ranks (A_t)
      Calculate crowding distance (CD) (A_t)
      If size of A_t > Archsize
      A_t = select frontmax number of the solution
     Else
  Update T (T = β × T_0)
end
```

Fig. 4. Pseudo code of the multi-objective simulated annealing algorithm

4. Computational Results

This section presents experimental outputs of the algorithms. To do so, first, some popular multi-objective metrics are introduced. After that, the parameters of the algorithms are tuned via Taguchi method. Finally, defined metrics are calculated on the outputs of the metrics and outputs are compared on different statistical tests.

4.1. Multi-objective metrics

In order to evaluate the performances of the two multi-objective meta-heuristic algorithms five metrics are used as follows.

1- Diversity: is used for evaluating the spread of the front (Zitzler and Thiele, 1998). 2- Spacing: measures the standard deviation of the distances among solutions of the Pareto front (Zitzler, 1999). 3- Mean ideal distance (MID): measures the convergence rate of Pareto fronts to a certain point (0, 0) (Zitzler and Thiele, 1998). 4- Number of found solutions (NOS): measures the number of the Pareto solutions in Pareto optimal front. 5- The CPU time of running the algorithms to reach near optimum solutions.

4.2. Parameter Setting

This section is divided into two sections to present parameter settings of both the model and the algorithms. Table 1 presents generated scenario of the input data which are used during the experimental results.

Table 1
Inputs of the model

Parameter	Range	Parameter	Range
DE_{rit}	Uniform (1500,2000)	CT_{drit}	Uniform(100,110)
CP_{pit}	Uniform(20,30)	TSM_{spt}	Uniform(5,7)
CSE_{pit}	Uniform(5,10)	CPD_{pit}	Uniform(9000,10000)
CSM_{spt}	Uniform(25,35)	TP_{pit}	Uniform(8,16)
CT_{pdit}	Uniform(70,80)	CPT_{spt}	Uniform(5000,8000)
CH_{pit}	Uniform(10,15)	CPT_{pdt}	Uniform(2000,3000)
CLS_{rit}	Uniform(10,15)	CPT_{drt}	Uniform(2000,3000)
CH_{dit}	Uniform(10,15)	TT_{pdit}	Uniform(5,7)
TT_{drit}	Uniform(3,5)	CPP_{pit}	Uniform(8000,10000)
CPD_{dit}	Uniform(10000,12000)		

To assess the model, 15 test problems are generated. These problems are investigated in three sizes and each of the five problems as (S= 3, …, 7; P= 5, …, 9; D= 6, …, 10; R= 9, …, 13) in the first size, (S= 8, …, 12; P= 10, …, 14; D= 11, …, 15; R= 14, …, 18) in the second size, and (S= 13, …, 17; P= 15, …, 19; D= 16, …, 20; R= 19, …, 23) in the third size. Besides, 5 product types at 6 time periods are considered in test problems.

In order to calibrate the parameters of the proposed algorithms, the Taguchi method is utilized. This method is an experimental design methodology. Optimization of process parameters is the key step in the Taguchi method in order to achieve high quality without increasing cost. The greatest advantage of this method is to save the experimental time as well as the cost by finding out the significant factors by analysis (Fraley et al. 2006). One of the important steps involved in Taguchi's method is selection of an orthogonal array (OA). The OA estimates the effects of factors on the response mean and variation and also allows investigating each effect independently from the others and may reduce the cost and time associated with the experiment when fractionated designs are used. To obtain optimum process parameters setting, Taguchi proposed a statistical measure of performance named the signal to noise ratio (S/N). This ratio considers both the mean and the variability. In addition to S/N ratio, ANOVA is used to indicate the influence of process parameters on performance measures. Taguchi proposed three categories of performance characteristics in the analysis of the S/N ratio: the higher-the-better, the nominal-the-better, and the smaller-the-better (Ross, 1996). Then, the aim of the method is to maximize the S/N ratio. In this paper, due to minimization nature of the objective functions of this research, the smaller-the-better type of the response is used. Eq. (19) formulates S/N of this type of response, where Y denotes the response and n shows the number of OAs.

$$\frac{S}{N}\ ratio = -10 \times \log\left(\frac{S(Y^2)}{n}\right) \tag{19}$$

To conduct the Taguchi method more comprehensively, a response is considered in this research. As mentioned earlier, in Pareto based algorithms, two main goals including (1) good convergence and (2) diversity are sought. Among the introduced metrics in Section 4.1, CPU time and MID are the ones that measure the convergence rate of the algorithms and the others are used for modelling the diversity of the algorithms. Hence, MID metric is considered as a response.

In order to utilize the Taguchi method, the levels of the factors are first determined in Table 2. As observed above, factors are presented in two ways, including their actual names along with their coded names. Moreover, three levels are considered for each factor involved in the algorithms. Then, using Minitab 14 Software, the L9 design is used for NSGA-II. Meanwhile, the L27 design is employed for MOSA. The OAs of these designs along with experimental results are presented in Table 3 (for NSGA-II) and Table 4 (for MOSA).

Table 2
Factor levels of the parameters of the algorithms

Multi-Objective Algorithms	Algorithm Parameters	Parameters Range	Low (1)	Medium (2)	High (3)
NSGA-II	nPop (A)	25-75	25	50	75
	P_c (B)	0.8-0.9	0.8	0.85	0.9
	P_m (C)	0.05-0.15	0.05	0.1	0.15
	nIter (D)	100-300	100	200	300
MOSA	Temprature (A)	500-1000	500	750	1000
	Redurate (B)	0.9-0.99	0.9	0.95	0.99
	MaxA (D)	100-200	100	150	200
	nPop (E)	5-15	5	10	15
	MaxIt (F)	100-300	100	200	300
	nMove (G)	5-10	5	8	10

Table 3
Computational results to tune NSGA-II

Run Order	Algorithm Parameters				Response Value of NSGA-II
	A	B	C	D	MID
1	1	1	1	1	330535843.07
2	1	2	2	2	341198969.88
3	1	3	3	3	326321596.91
4	2	1	2	3	360311604.79
5	2	2	3	1	320715432.77
6	2	3	1	2	327413623.79
7	3	1	3	2	360916813.15
8	3	2	1	3	324634080.34
9	3	3	2	1	322107772.79

Table 4
Computational results to tune MOSA

Run Order	Algorithm Parameters						Response Values of MOSA
	A	B	C	D	E	F	*MID*
1	1	1	1	1	1	1	336668659.08
2	1	1	1	1	2	2	355611801.44
3	1	1	1	1	3	3	332629067.17
4	1	2	2	2	1	1	367578473.88
5	1	2	2	2	2	2	328843998.64
6	1	2	2	2	3	3	354415379.90
7	1	3	3	3	1	1	322762686.96
8	1	3	3	3	2	2	33836353.67
9	1	3	3	3	3	3	316023983.29
10	2	1	2	3	1	2	371646175.10
11	2	1	2	3	2	3	315233329.54
12	2	1	2	3	3	1	364480480.06
13	2	2	3	1	1	2	319295760.23
14	2	2	3	1	2	3	348984328.52
15	2	2	3	1	3	1	309936723.24
16	2	3	1	2	1	2	343529243.33
17	2	3	1	2	2	3	340698595.17
18	2	3	1	2	3	1	323403919.07
19	3	1	3	2	1	3	303096525.30
20	3	1	3	2	2	1	321236506.70
21	3	1	3	2	3	2	315396631.64
22	3	2	1	3	1	3	327456159.79
23	3	2	1	3	2	1	339262330.25
24	3	2	1	3	3	2	340125537.13
25	3	3	2	1	1	3	330154421.12
26	3	3	2	1	2	1	355056801.90
27	3	3	2	1	3	2	334207892.15

For each algorithm, the effect plot for S/N ratio is presented in Fig. 5. In this figure, for each parameter the higher value of the S/N ratio is the factor of choosing the best level of that parameter in the experiment. Using the above results, the proper values of the parameters are determined and highlighted in Table 2.

4.3. Outputs of the algorithms on the metrics

Table 5 presents experimental outputs of the algorithms on the mentioned metrics. The statistical outputs of the metrics are summarized in Table 6. These algorithms are programmed by MATLAB software on a PC with 4-GB RAM and 2.4-GHz CPU.

In this section, the performances of the proposed tuned multi-objective solving methodologies are evaluated and compared using the multi-objective metrics given in Section 4.1. Table 5 illustrates the computational results of employing the algorithms on the 15 test problems introduced in Section 4.2. Furthermore, to eliminate uncertainties of the solutions obtained, each problem is implemented five times under different random environments. Then, the averages of these five runs are treated as the ultimate responses. Moreover, the algorithms are statistically compared based on the properties of their obtained solutions via the 2-sample t-test. The P-values of these tests on each metric are summarized in Table 6. We note that while in terms of the diversity and NOS metrics, bigger values are desired, for spacing, MID and CPU time, smaller values are better. Then, in general, based on the average of outputs in the last row of Table 5, it is clear for NSGA-II has better performance in terms of diversity and CPU time. Meanwhile, for other metrics, in a total view, MOSA has better performances. However, when the metrics are statistically compared, in terms of spacing, NOS, and CPU Time, the algorithms have significant differences. This conclusion is also confirmed at 95% confidence level based on the results given in Table 6. Furthermore, Figs. 6 and 7 support this conclusion as graphical and interval plots for two spacing and NOS.

This can be viewed as a validation signal of the test problems used. Besides, to clarify better performance of the proposed Pareto-based algorithms, the obtained Pareto solutions of both the algorithms on two test problem 2 and 12 are presented in Fig. 8.

Although the experimental results and comparisons above show that the proposed MOSA is a compatible algorithm with NSGA-II, for further explicitly and clarification, the outputs of the metrics are also integrated and the popular multi-criteria decision making method of TOPSIS is used here (Hwang and Yoon, 1981). Equal weight for all metrics is considered. Tables (7), (8), and (9) indicate steps of TOPSIS method to select the final alternative that according to the ranking obtained by TOPSIS, MOSA achieves the highest rank among the NSGA-II.

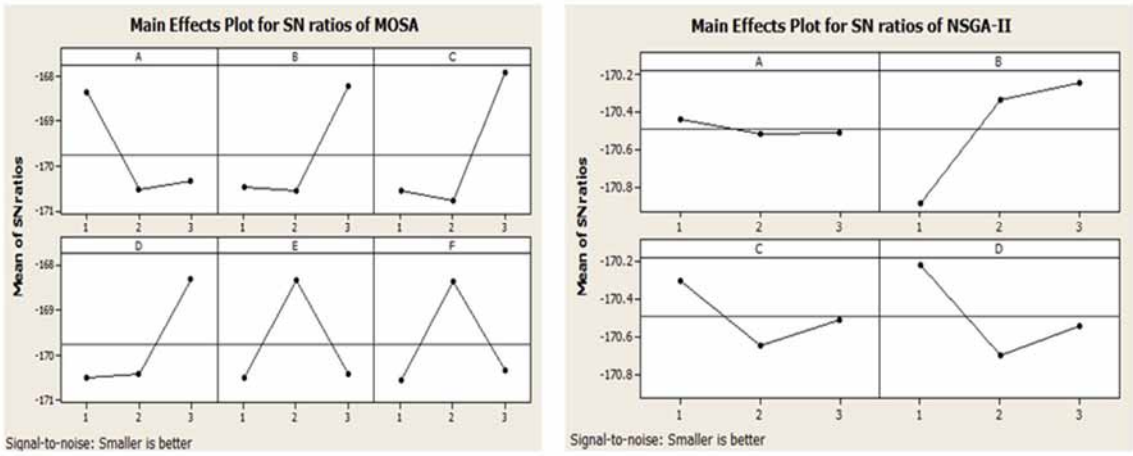

Fig. 5. S/N ratio of the Taguchi method for MOSA and NSGA-II

Table 5
Multi-objective metrics obtained for each algorithm

Num	Proposed NSGA-II					Proposed MOSA				
	Spacing	*Diversity*	*NOS*	*MID*	*Time*	*Spacing*	*Diversity*	*NOS*	*MID*	*Time*
1	303091.4	1226592.1	3	31398548.9	57.43	48229.1	266111.6	7	21773747.8	89.28
2	22708.9	930067.9	3	32274068.1	62.17	55386.5	622827.6	7	25424667.2	108.57
3	191708.9	476850.5	4	29109204.2	70.85	52158.4	411367.0	4	29016149.9	123.39
4	98112.7	775791.9	3	27370419.4	79.88	107004.5	551144.8	6	34089267.5	139.11
5	47050.8	581006.1	3	27510848.4	90.18	29718.5	558003.8	4	33283308.2	153.76
6	112724.7	1794512.1	5	188652252.3	120.47	103280.9	886899.2	3	121572228.6	225.57
7	170697.4	1214184.1	3	124905285.1	125.09	52555.1	2243829.7	6	123145010.8	239.75
8	423645.1	917000.9	3	144753365.6	144.67	51673.9	374100.8	3	108523755.5	261.05
9	884706.7	3543518.3	5	153156143.5	159.72	843136.6	2686184.9	3	157111489.9	288.22
10	790166.4	3239168.2	3	142023468.3	173.93	122322.3	1487229.9	5	147904766.9	307.69
11	1207687.1	3878825.3	4	413167497.0	278.44	692295.1	3965591.1	4	393822922.8	483.14
12	1729717.1	3719551.8	4	405743636.4	302.17	510498.4	8605121.1	8	398592413.4	524.63
13	4468780.5	9410892.5	3	445947404.3	328.04	119545.2	4551200.9	5	410113080.7	577.89
14	1760653.1	4386453.6	4	410707425.8	359.25	130208.9	1849278.3	3	391584469.1	614.64
15	1577897.4	4246539.1	3	412822999.1	380.51	860571.4	7658368.5	4	270618195.5	662.27
Ave	919289.88	2689396.96	3.53	199302838	182.19	258572.32	2447817.28	4.8	177705032	319.93

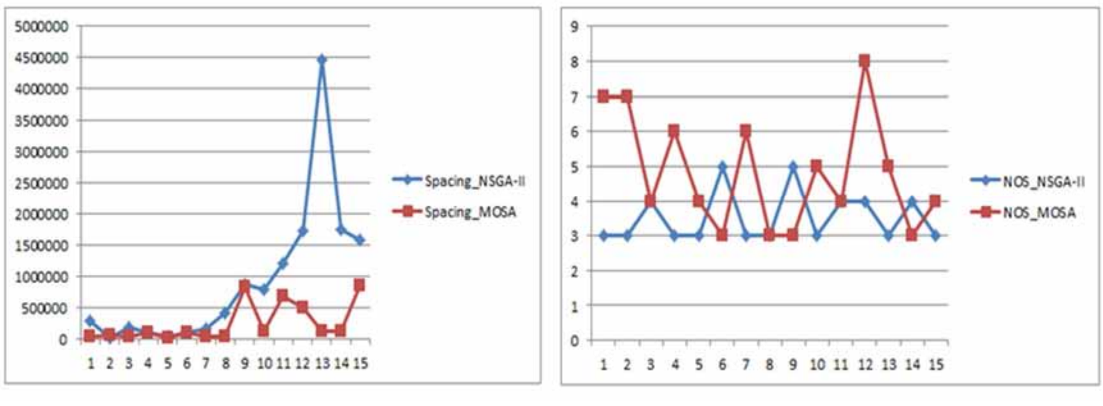

Fig. 6. Graphical summery of the performance of the algorithms on spacing and NOS metrics

Table 6
Statistical comparison of proposed MOSA with NSGA-II

	t-test	
	***P*-value**	**Result**
Diversity	0.795	H_0 is not rejected
MID	0.717	H_0 is not rejected
Time	0.03	H_0 is rejected
Spacing	0.049	H_0 is rejected
NOS	0.014	H_0 is rejected

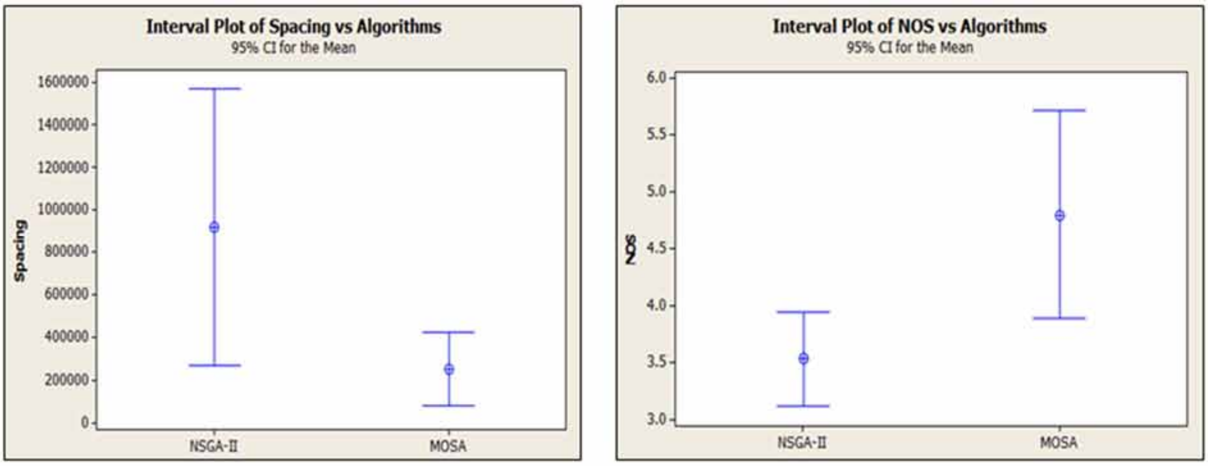

Fig. 7. Interval Plot of the statistical test on spacing and NOS metrics

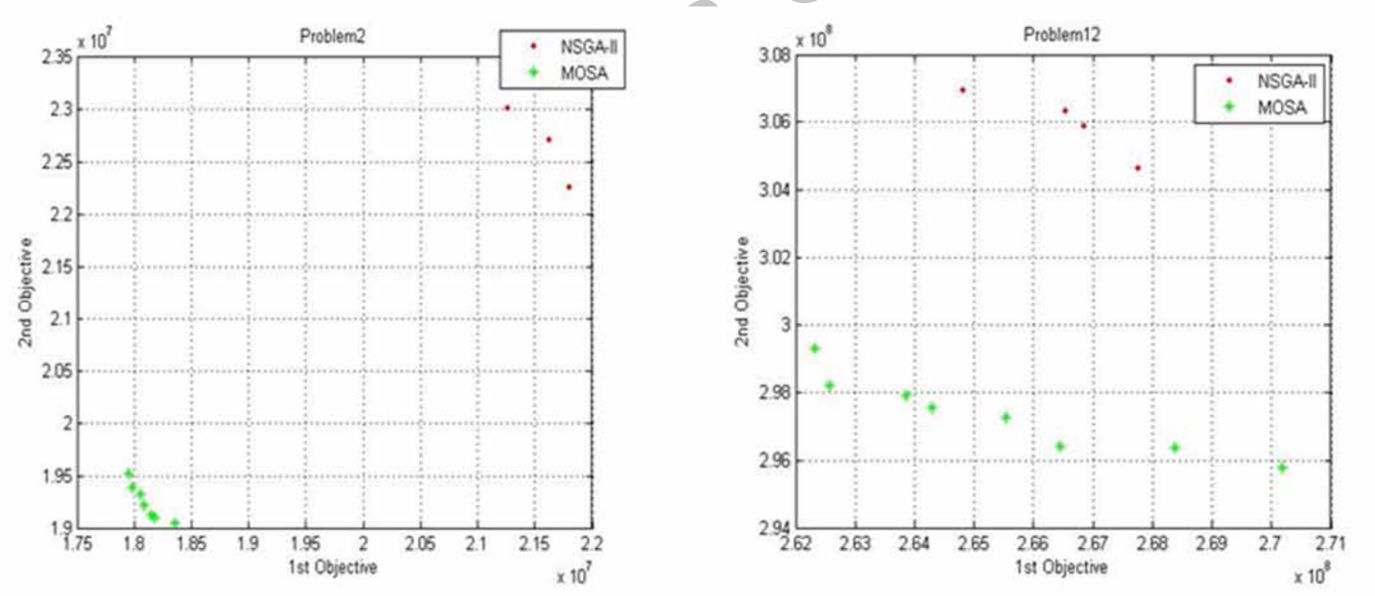

Fig. 8. Obtained Pareto-front of the algorithms on two test problem 2and 12

Table 7
Decision matrix of the problem

Algorithm	*Spacing*	*Diversity*	*NOS*	*MID*	*Time*
NSGA-II	182.19	199302838	3.53	2689396.96	919289.88
MOSA	319.93	177705032	4.8	2447817.28	258572.32

Table 8
Normalized weight matrix

Algorithm	*Spacing*	*Diversity*	*NOS*	*MID*	*Time*
NSGA-II	0.192528985	0.147908304	0.118490906	0.149278266	0.098970857
MOSA	0.054153393	0.134622188	0.161120778	0.133101462	0.173795194

Table 9
Distance of each option to ideal and not ideal solutions matrix and Final ranking of proportional distance of each option to ideal solution

Algorithm	d_1^+	d_1^-	CL	Ranking
NSGA-II	0.145694198	0.075994751	0.342799005	2
MOSA	0.075994751	0.145694198	0.657200995	1

5. Conclusion and Future Research

The aim of this paper is to study integrated PDP problem in a multi-echelon SCN with multiple products and at several time periods. Furthermore, if final products are not supplied for retailers, shortage costs as lost sale is considered in the model. In addition, minimizing total costs in SC, transfer time of products for retailers is considered within the bi-objective structure of the model. Since, the problem is NP-Hard, a Pareto-based algorithm called MOSA is proposed and compared with an existing algorithm of the literature called NSGA-II. Of course, first algorithms are tuned via the Taguchi method. Then, some multi-objective measures are used to compare the MOSA with the other algorithm. According to these results, it is proved that MOSA is a comparable alternative for the existing multi-objective Pareto-based algorithms of the literature. For future research, shortage cost as combined backorder and lost sales can be considered. Also, uncertainty of parameters such as costs, demands, transportation capacity, inventory capacity and production capacity of the problem can be extended as a fuzzy model and may be solved using fuzzy multi-objective meta-heuristic algorithms.

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