



## Optimizing reliability and cost of system for aggregate production planning in a supply chain

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### KEYWORDS

Aggregate production planning;  
Supply chain management;  
Reliability;  
Multi-objective harmony;  
NSGA-II & NRG A.

**Abstract.** In this paper, the researchers present a multi-objective model for multi-product, multi-site aggregate production planning model in a supply chain. The goals are to minimize the total cost of the supply chain, including inventory costs, manufacturing costs, work force costs, hiring and firing costs, and also to maximize the minimum of suppliers' reliability by considering probabilistic lead times to simultaneously improve the system performance. Since the problem is NP-Hard, a Pareto-based multi-objective harmony search algorithm is proposed. To demonstrate the performance of the presented algorithm, a Non-dominated Sorting Genetic Algorithm (NSGA-II) and a Non-dominated Ranking Genetic Algorithm (NRGA) are applied. The results demonstrate the robustness of the proposed algorithm to probe the Pareto solutions.

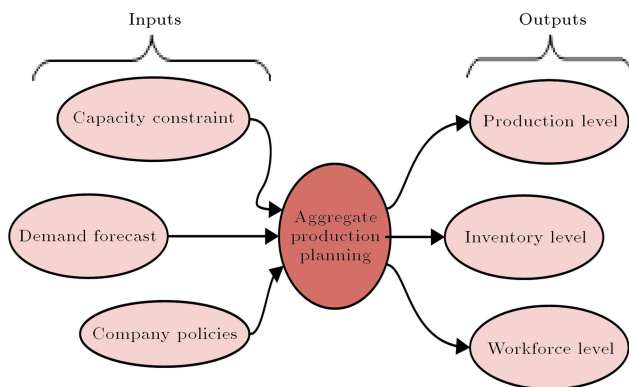
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### 1. Introduction

A supply chain is a set of different parties, including suppliers, manufacturers, people, distribution centers, transportation channels, etc. in which each firm has a specific role in transforming raw materials to end products with regard to costumers' demand. In recent years, improvement in globalization, competition, integration, etc. has channelized firms to concentrate on the entire members involved in the supply chain, in addition to their individual production plans. Connecting all members of a supply chain together and providing production planning based on the relationships

between the firms is one of the most important issues which can be conducted by Supply Chain Management (SCM). In other words, SCM should be able to plan all the activities involved in producing a product from suppliers to costumers in a supply chain. Inappropriate management of a supply chain leads to the bankruptcy of the members and failure in global competitions. One of the medium-range planning in the SCM, which includes a time horizon from 3 to 18 months, is Aggregate Production Planning (APP) in which aggregated products are considered instead of individual products. APP, as a technical level planning, attempts to determine the optimal quantity of production, inventory level, workforce, etc. in each period with regard to some constraints to satisfy the uncertain demand of all products [1]. The result of APP can be used as a base for other plans such as Capacity Requirements Planning (CRP), Master Production Schedule (MPS), and Material Requirements Planning (MRP) [2]. In a systematic view of APP, one can introduce capacity

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**Figure 1.** Inputs and outputs of APP process.

constraints, demands, and firm's policies and strategies as inputs of APP and determine the production levels, inventory levels, workforce levels, subcontracting, etc. as outputs of the system depicted in Figure 1.

Based on a number of the objective function, considered in the models, the APP models can be classified into two following categories: single-objective function problems and multi-objective function problems. A common objective function in the APP models is to minimize the total cost of the system. In addition, maximization of service level, minimization of changing of work force level, and minimization of the risk are other objective functions which can be considered.

Over the last decades, numerous single-objective APP models have been studied in the research studies. Various models have been developed to solve the APP problem since Holt et al. [3] presented HMMS (Holt, Modigliani, Muth and Simon) rule. Bergstrom and Smith [4] generalized the HMMS approach for multi-product system. Oh and Karimi [5] developed a multi-product supply chain planning model with a drawback. Guillen et al. [6] discussed a mixed-integer linear programming model for tactical planning of multi-product supply chains.

All the above mentioned research studies discussed a single-objective APP model which tried to minimize the total cost, while the other objective functions can be considered in APP models. In other words, in the practical APP model, conflicting objective functions can be considered [7]. Wang and Liang [8] proposed a multi-objective APP model including minimizing the total costs, carrying and backordering costs, and changing workforce level in a fuzzy environment. Leung and Chan [9] proposed a multi-objective APP model which attempted to maximize profit, minimize repairing costs, and maximize machine utilization regarding different operational constraints. Baykasoglu and Gocken [10] used a direct solution method based on ranking methods of fuzzy numbers and Tabu search to solve fuzzy multi-objective aggregate production planning problem. Mirzapour Al-e-Hashem et al. [1] proposed a multi-objective mixed integer nonlinear

programming model to deal with APP considering two conflicting objectives simultaneously as well as the uncertain nature of the supply chain. Mirzapour Al-e-Hashem et al. [11] introduced a multi-objective model, including minimizing the total cost, maximizing the service level, and maximizing workers' productivity, to deal with a multi-period, multi-product and multi-site aggregate production planning problem under uncertainty. Sadeghi et al. [12] considered minimizing the total costs, carrying and backordering costs, and rate of changes in workforce level simultaneously by a multi-objective model for aggregate planning and used a goal programming approach to solve the proposed model. Rodger [13] used real-world data to determine the structure of a Bayesian network. In this research, stochastic simulation based on Markov blankets was used to determine the distribution of backorders and customer wait time in supply chains. Fuzzy logic was employed to produce a funnel diagram, demonstrating that the Acquisition Advice Code, Acquisition Method Suffix Code, Acquisition Method Code, and Controlled Inventory Item Code backorder performance metric of a trigger group dimension might change dramatically with variations in ALT, PLT, unit price, quantity ordered, and stock. Rodger et al. [14] reported on the results of fuzzy induced linguistic ordered weighted averaging for group decision support evaluation of backorder risk triggers to ensure that equipment is available and fully operational when needed. Risk factors were identified, the impact importance and probability metric performance ratings were determined via induced linguistic ordered weighted averaging, and a risk mitigation strategy was used to identify and predict Supply Chain Backorder Risk Triggers (SCBORT). Finally, they presented supply chain risk as a probability/impact matrix. Ramanathan [15] studied several supply chain management initiatives such as vendor-managed inventory, continuous replenishment, and Collaborative Planning Forecasting and Replenishment (CPFR) that had been previously proposed in the literature to improve the performance of supply chains. In this research, collaborative performance measurement acts as a testing tool to identify a helping environment to collaborate by pinpointing areas requiring improvements before initializing collaboration. Gholamian et al. [16] proposed a fuzzy multi-objective mixed-integer nonlinear programming (FMOMINLP) to address a comprehensive multi-site, multi-period and multi-product Aggregate Production Planning (APP) problem under uncertainty. They developed a fuzzy programming method to solve the presented model. Finally, the efficiency of the model was investigated by a real industry SC case study. Pasandideh et al. [17] proposed a bi-objective optimization of a multi-product, multi-period three-echelon supply-chain-network problem. To bring the problem

closer to reality, the majority of the parameters in this network were considered stochastic. The problem was first formulated into the framework of a single-objective stochastic mixed integer linear programming model. Then, it was reformulated into a bi-objective deterministic mixed-integer nonlinear programming model. To solve the complicated problem, a Non-dominated Sorting Genetic Algorithm (NSGA-II) was utilized and Non-dominated Ranking Genetic Algorithm (NRGA) was used to validate the results obtained. Pasandideh et al. [18] investigated a bi-objective optimization of a multi-product multi-period three-echelon supply chain network consisting of manufacturing plants, Distribution Centers (DCs) with uncertain services for each one and customer nodes. The two objectives were the minimization of the total cost, while minimization of the average number of products dispatched to customers was followed by considering reliability indices assumed for the distribution centers. Rooeinfar et al. [19] proposed a new Supply Chain Network, and two novel hybrid algorithms were developed to solve the model. Each hybrid algorithm integrates the simulation technique with two metaheuristic algorithms, including the Genetic Algorithm (GA) and the Simulated Annealing Algorithm (SAA), namely HSIM-META. Computational results show that the proposed HSIM-META has suitable accuracy and speed for use in real-world applications. Entezaminia et al. [20] proposed a multi-objective, multi-period, multi-product and multi-site Aggregate Production Planning (APP) model in a green supply chain considering a Reverse Logistic (RL) network. In this model, minimizing the total losses and maximizing total environmental scores of products were the objective functions. They demonstrated the trade-off between the conflicting objective functions by a set of Pareto-optimal solutions as generated by the LP-metrics method.

It is obvious that in a chain with various suppliers, producing the raw material for manufacturers can be done in different ways. But, delivery time of the suppliers is not precise, and it is possible that delays occur in shipment of materials from suppliers to manufacturers. Hence, considering probabilistic lead time is more realistic. This lead time can be a measure for defining the reliability of suppliers, and consideration of their reliability can influence manufacturers' production. In other words, the selection of suppliers that maximizes the reliability of the whole system can be considered as another objective function in this paper.

Based on the complexity of the APP problems and the proposed problem associated with non-linear mixed integer programming models, using the exact or hard-computing methods will be time-consuming, especially when the problem size increases [21]. This is proof of why we propose a meta-heuristic algorithm method to solve the proposed problem. Among multi-objective

algorithms, a widely used Pareto-based algorithm is an extended version of a Genetic Algorithm (GA) for multi-objective problems, called Non-dominated Sorting Genetic Algorithm (NSGA-II) proposed by Deb et al. [22]. This algorithm can be used in different scopes of operational management. Harmony Search Algorithm (HSA), as a music-inspired algorithm, is simple in concept and has just a few parameters. It is easy to be implemented and has been successfully applied to different problems including the mechanical structure design [23], pipe network optimization [24], and inventory models [25].

In this paper, a multi-objective model considering a multi-period, multi-product, and multi-site aggregate production planning problem is developed. The first objective function is minimizing the sum of the total cost in the supply chain, and the second one, considered as a contribution, includes improving the performance of the system through maximizing the minimum suppliers' reliability by considering probabilistic lead times not discussed in the literature of multi-objective APP models. With regard to the complexity of the proposed APP model, we present a Multi-Objective Harmony Search Algorithm (MOHSA) and compare its results with those of the Non-dominated Sorting Genetic Algorithm (NSGA-II) and Non-dominated Ranking Genetic Algorithm (NRGA) as the best-developed Pareto-based approaches in the literature.

The rest of this paper is organized as follows: A mathematical formulation of the proposed multi-objective APP problem is presented in Section 2. The solution procedure and parameter tuning are proposed in Sections 3 and 4, respectively. Section 5 provides the result analysis and comparisons. Finally, conclusion and suggestion for future research are presented in Section 6.

## 2. Problem formulation

The proposed APP problem in a supply chain can be described as follows: there are  $S$  suppliers,  $J$  manufacturers, and  $C$  customers, as shown in Figure 2. Each supplier can produce several items with regard to its capacity constraint and transport them to the manufacturers. Each manufacturer is able to produce several products according to the needed raw materials provided by suppliers and subcontracting is allowed for the manufacturer. There is a restricted available time for manufacturing. For each supplier and manufacturer, the production cost of each item can be different. The warehouse capacity of manufacturers for raw materials and end products is limited. The produced end products are transported to costumers' zones regarding their demands. Based on geographical distribution of supply chain's members, including suppliers, manufacturers, and costumers in an area, the

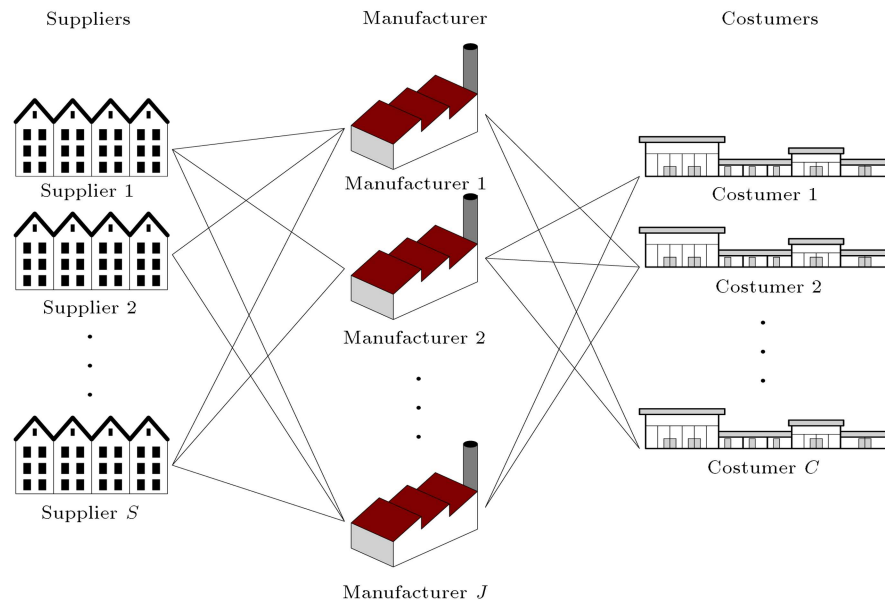


Figure 2. Supply chain configuration.

transportation time between them can vary. Shortage can occur for each product. The probabilistic lead time for transporting raw materials from suppliers to manufacturers is considered, and the reliability of suppliers in delivering materials can be computed based on this definition. In other words, a supplier is reliable if he can transport the needed raw materials to a manufacturer in a predefined duration time.

This paper models the APP problem as a bi-objective programming with the following objective functions:

1. Minimizing the total cost of supply chain;
2. Maximizing performance level by maximizing reliability in supplier selection process.

### 2.1. Notations

The parameters in this model are as follows:

$D_{ict}$	Demand of product $i$ ( $1, 2, \dots, I$ ) in demand point $c$ ( $1, 2, \dots, C$ ) in period $t$ ( $1, 2, \dots, T$ )
$C_{qj}$	Production cost per hour in regular time ( $q = 1$ ), overtime ( $q = 2$ ), and subcontracting ( $q = 3$ ) at factory $j$ ( $1, 2, \dots, J$ )
$L_{jt}$	Manpower cost of labors at factory $j$ in period $t$
$a_{ij}$	Production time of product $i$ at factory $j$
$F_{jt}$	Firing cost of workers at factory $j$ in period $t$
$H_{jt}$	Hiring cost of workers at factory $j$ in period $t$

$I_{1mjt}$	Inventory holding cost for raw material $m$ ( $1, 2, \dots, M$ ) at factory $j$ in period $t$
$I_{2ij t}$	Inventory holding cost for finished product $i$ at factory $j$ in period $t$
$I_{3ict}$	Inventory holding cost for finished product $i$ in customer's zone $c$ in period $t$
$T_{1sjt}$	Transportation cost for supplier $s$ ( $1, 2, \dots, S$ ) to factory $j$ in period $t$
$T_{2ict}$	Transportation cost from factory $j$ to demand point $c$ in period $t$
$Cr_{smt}$	Cost of raw material $m$ provided by supplier $s$ in period $t$
$\gamma_{im}$	Number of units of raw material $m$ required for each unit of product $i$
$\alpha_t$	Fraction of the workforce variation allowed in period $t$
$\nu$	Productivity of labors ( $0 \leq \nu \leq 1$ )
$TI_{qjt}$	Available regular time ( $q = 1$ ), overtime ( $q = 2$ ), and capacity of subcontracting ( $q = 3$ ) in terms of time unit at factory $j$ in period $t$
$P_{1j}$	Raw material storage capacity at factory $j$
$P_{2j}$	End product storage capacity at factory $j$
$P_{3c}$	End product storage capacity in customer's zone $c$
$P_{4smt}$	Maximum number of raw material $m$ supplier $s$ could be provided in period $t$

$LT_{sj}$  : Probabilistic lead time for shipping raw material from supplier  $s$  to factory  $j$

$\varphi_{LT}$  : Maximum acceptable lead time of supplier for being reliable

$LT_{jc}$  : Lead time required for shipping end products from factory  $j$  to demand point  $c$

$\pi_{ict}$  : Shortage cost of product  $i$  in customer's zone  $c$  in period  $t$

$TC$  : Total Cost of supply chain

$r_{sj} = P(LT_{sj} < \varphi_{LT})$ : Reliability of supplier  $s$  for providing required raw materials of factory  $j$

### Decision variables

$X_{ijqt}$  : Number of product  $i$  produced at factory  $j$  using method  $q$  in period  $t$

$XL_{jt}$  : Number of workers at factory  $j$  in period  $t$

$XF_{jt}$  : Number of workers at factory  $j$  fired in period  $t$

$XH_{jt}$  : Number of workers at factory  $j$  hired in period  $t$

$XM_{mjt}$  : Inventory level of raw material  $m$  at factory  $j$  at the end of period  $t$

$XP_{ijt}$  : Inventory level of end product  $i$  at factory  $j$  in period  $t$

$XI_{ict}$  : Inventory level of end product  $i$  in customer's zone  $c$  in period  $t$

$XS_{smjt}$  : Number of units of raw material  $m$  shipped from supplier  $s$  to factory  $j$

$YS_{ijct}$  : Number of units of end product  $i$  provided by factory  $j$  for demand point  $c$  in period  $t$

$z_{sjt}$  : One if supplier  $s$  provides at least one of the raw materials for factory  $j$  in period  $t$ ; 0 otherwise

$B_{ict}$  : Shortage of product  $i$  in demand point  $c$  in period  $t$

$O$  : One if the total cost of the supply chain is violated from a pre-specified value ( $\Omega$ ); 0 otherwise.

### 2.2. Multi-objective APP model

The multi-objective APP model can be stated as follows:

$$\begin{aligned} \text{Min } Z_1 = TC = & \sum_{i,j,q,t} a_{ij} C_{qj} X_{ijqt} \\ & + \sum_{s,m,j,t} C_{rsm} XS_{smjt} + \sum_{j,t} L_{jt} XL_{jt} \end{aligned}$$

$$\begin{aligned} & + \sum_{j,t} F_{jt} XF_{jt} + \sum_{j,t} H_{jt} XH_{jt} \\ & + \sum_{m,j,t} I_{1mj} XM_{mjt} + \sum_{i,j,t} I_{2ij} XP_{ijt} \\ & + \sum_{i,c,t} I_{3ict} XI_{ict} + \sum_{s,m,j,t} T_{1sj} XS_{smjt} \\ & + \sum_{i,j,c,t} T_{2ict} YS_{ijct} + \sum_{i,c,t} \pi_{ict} B_{ict}, \end{aligned} \quad (1)$$

$$\text{Max } Z_2 = \text{Min}_{s,j,t} (r_{sj} z_{sjt}), \quad (2)$$

$$XP_{ijt} = XP_{ij(t-1)} + \sum_q X_{ijqt} - \sum_c YS_{ijct} \quad \forall i, j, t, \quad (3)$$

$$\begin{aligned} XM_{mjt} = & XM_{mj(t-1)} + \sum_s XS_{smj(t-\mu_{LT_{sj}})} \\ & - \sum_{q,i} x_{ijqt} \cdot \gamma_{im} \quad \forall m, j, t, \end{aligned} \quad (4)$$

$$XL_{jt} = XL_{j(t-1)} + XH_{jt} - XF_{jt} \quad \forall j, t, \quad (5)$$

$$\begin{aligned} XI_{ict} = & XI_{ic(t-1)} + \sum_j YS_{ijc(t-\mu_{LT_{sj}})} - D_{ict} \\ & - B_{ic(t-1)} \quad \forall i, c, t, \end{aligned} \quad (6)$$

$$XL_{jt} \nu (TI_{1jt} + TI_{2jt}) \geq \sum_{i,q \in \{1,2\}} x_{ijqt} \cdot a_{ij} \quad \forall j, t, \quad (7)$$

$$\sum_i x_{ij3t} \cdot a_{ij} \leq TI_{3jt} \quad \forall j, t, \quad (8)$$

$$\sum_m XM_{mjt} \leq P_{1j} \quad \forall j, t, \quad (9)$$

$$\sum_i XP_{ijt} \leq P_{2j} \quad \forall j, t, \quad (10)$$

$$\sum_m XI_{ict} \leq P_{3c} \quad \forall c, t, \quad (11)$$

$$(XF_{jt} + XH_{jt}) \leq \alpha_{(t-1)} (XL_{j(t-1)}) \quad \forall j, t, \quad (12)$$

$$\sum_j XS_{smjt} \leq P_{4smt} \quad \forall s, m, t, \quad (13)$$

$$XS_{smjt} \leq M \cdot z_{sjt} \quad \forall m, s, j, t, \quad (14)$$

$$z_{sjt} \in \{0, 1\}, \quad (15)$$

$$XF_{jt}, XH_{jt}, XL_{jt} \geq 0 \text{ and integer} \quad \forall j, t, \quad (16)$$

$$X_{ijqt}, X_{S_{jsmt}}, X_{M_{mjt}}, X_{P_{ijt}}, Y_{S_{ijct}}, B_{ict}, X_{F_{jt}}, \\ XH_{jt}, XL_{jt} \geq 0 \quad \forall i, j, c, s, m, t. \quad (17)$$

In this model, Eq. (1) denotes the first objective function aiming to minimize the total cost of the supply chain including production cost of manufacturers and suppliers, workforce hiring and firing costs, inventory costs, transportation costs, and shortage costs. The second objective function (Eq. (2)) attempts to improve performance level through maximizing the minimum of suppliers' reliability. In this function, it should be considered that the minimization operator is defined for  $\{s, j | z_{sjt} = 1\}$ . By this consideration, the system tries to confirm a balance in supplier selection problems. Eqs. (3) and (4) are balance constraints for inventory of end product and raw material, respectively. Eq. (5) ensures the workforce level balance. An inventory balance equation of demand point  $c$  is considered in Eq. (6). Eq. (7) guarantees that for each manufacturer, the sum of regular time and overtime with regard to productivity of workforce limits the available production time. Eq. (8) is a subcontracting constraint. Eqs. (9) to (11) limit the raw material, end product inventory levels of manufacturers, and costumer zones' to their related inventory storage capacities, respectively. Eq. (12) limits the change in workforce level by the proportion of workers in the previous period. Eq. (13) restricts the amount of shipments from supplier  $s$  by the supplier capacity. Eq. (14) ensures that if supplier  $s$  provides at least one of the raw materials for factory  $j$  in period  $t$ , its related binary variable ( $z_{sjt}$ ) must be one. Eqs. (15)–(17) denote variable types.

### 3. The solution procedures

Pareto-based approaches have been widely used in research studies, especially in order to solve complicated models. Based on NP-hardness of aggregate production planning, we present a multi-objective Pareto-based meta-heuristic algorithm called MOHSA and compare it with two based-developed ones in the literature, NSGA-II and NREGA, which are described in this section.

A multi-objective problem consists of some conflicting objectives  $f(\vec{x}) = [f_1(\vec{x}), \dots, f_m(\vec{x})]$  with regard to some constraints  $g_i(\vec{x}) \leq 0$ ,  $i = 1, 2, \dots, c$ ,  $\vec{x} \in X$  where  $\vec{x}$  denotes  $n$ -dimensional vectors and  $X$  is the feasible region. For a minimization model, we say that solution  $\vec{a}$  dominates solution  $\vec{b}$  ( $\vec{a}, \vec{b} \in X$ ) if:

1.  $f_i(\vec{a}) \leq f_i(\vec{b})$ ,  $\forall i = 1, 2, \dots, m$  and;
2.  $\exists i \in \{1, 2, \dots, m\} : f_i(\vec{a}) < f_i(\vec{b})$ .

There are some solutions that cannot dominate each other. The set of these solutions is called Pareto solutions set or Pareto front. Pareto-based algorithms

try to find the optimal front during the evolution process, which is achieved in the last iteration of algorithm. This front is expected to have the most convergence and the highest diversity [22].

#### 3.1. The MOHSA

In HSA, the objective function is interpreted as harmony, and aesthetic estimation of the player helps him/her to find good state of the harmony. Indeed, in this algorithm, the qualitative improvisation process is turned into quantitative optimization process. Therefore, in this paper, multi-objective version of HSA is developed and presented to the literature of APP. The details of MOHSA are described in the following subsections.

##### 3.1.1. Solution representation

To code the solutions, we presented a bi-part solution representation structure. A  $1 \times S$  random vector specifies the priority of suppliers for transporting materials into the manufacturer, and a  $1 \times J$  random vector specifies the priority of manufacturers for producing the products. Figure 3 schematically represents an example of this structure. In this structure, each gene of vectors is a random number between zero and one. Besides, customers' demands will never exceed the capacity limitations throughout the supply chain. In this figure,  $S = 4$ ; so, the random numbers are generated as  $1 \times 4$  vector; their positions are kept, and then sorted in an ascending order. Based on our capacity, two of the first genes are selected. The positions of these numbers are selected as suppliers (suppliers numbers 3 and 1 are selected based on the corresponding capacity). Moreover, the continuous decision variables, including  $X_{ijqt}$ ,  $X_{S_{jsmt}}$ ,  $X_{M_{mjt}}$ ,  $X_{P_{ijt}}$ ,  $Y_{S_{ijct}}$ ,  $B_{ict}$ ,  $X_{F_{jt}}$ ,  $XH_{jt}$ , and  $XL_{jt}$ , are encoded based on upper bounds and are randomly generated between zero and its upper bound.

To prevent violation of constraints, a penalty function approach method is applied to penalize them [26]. Penalty values are considered for all of the two-objective functions through an additive function.

##### 3.1.2. Improvising process

In an improvisation of the process of a musician, when a musician improvises with an instrument, he or she faces three possible options of:

- (I) Playing from his/her memory (with probability  $P_{HMCR}$ );


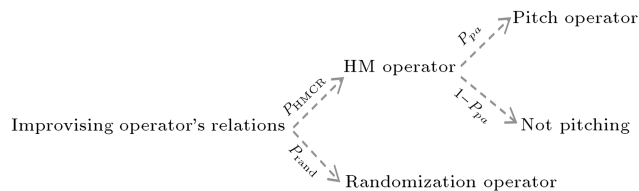
Generated vector	0.39	0.90	0.23	0.45
Sorted vector	0.23 (3)	0.39 (1)	0.45 (4)	0.90 (2)
Selected suppliers				

Figure 3. An instance of DCs encoding.

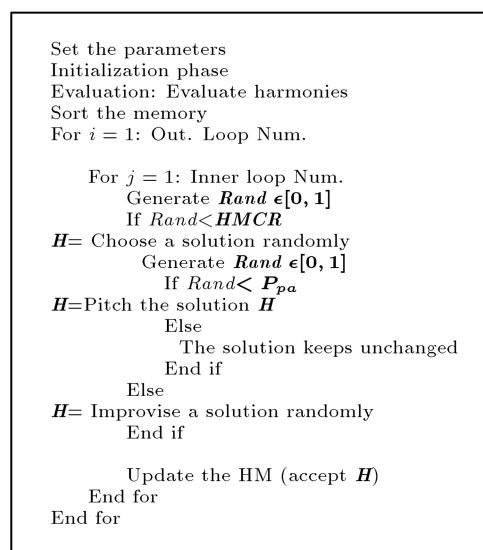
- (II) Adjusting the pitches slightly (with probability  $P_{pa}$ );
- (III) Composing randomly (with probability  $P_{rand}$ ).

These options are formalized into three quantitative operators in HSA called harmony memory, pitch adjusting, and randomization [27]. Therefore, the improvising process of the HSA is the combination of these three operators. Accordingly, the main steps of the HSA are explained in the next subsections. To apply the improvising process in different iterations, a random solution is selected first, and then one/two operator(s) of the HSA (based on their probabilities) is/are used to improvise the selected solution. After improvising a new solution, the HSM is updated by replacing the worse solution with the new solution. Interested readers should refer to Geem et al. [24], Geem [28], and Rahmati et al. [29] for additional information. Figure 4 presents a schematic view of the relationship between different HSA probabilities.

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 pitch adjusting operator of MOHSA is designed similar to the mutation operator of the GA as a swap strategy [27,29]. We also represent the Pseudo-code of HSA as well in Figure 5.



**Figure 4.** The relationship among different probabilities of HAS.



**Figure 5.** HSA Pseudo-code [29].

### 3.1.3. Multi-objective operators of the MOHS

While the objective function value was used to rank the solutions in a single-objective algorithm, the domination concept was utilized for ranking Pareto-based multi-objective algorithms. In the NSGA-II algorithm, as proposed by Deb et al. [22], the Fast Non-Dominated Sorting (FNDS) operator was employed for inserting the dominance concept by searching the first goal called convergence. Smaller values of FNDS indicate better ranks. To search the second goal named diversity, another operator named Crowding Distance (CD) was considered in NSGA-II to estimate the density of similar rank solutions placed surrounding a particular solution. Larger 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 a smaller rank is selected. Otherwise, the one with the more value of CD is selected.

The process is initiated by initializing the initial population of harmony vectors,  $P_t$ . Then, the new operators, including HM, migration, and mutation, are implemented on  $P_t$  to create a new population,  $Q_t$ . The combination of  $P_t$  and  $Q_t$  creates  $R_t$  for keeping elitism in the algorithm. In this step, vectors of  $R_t$  are sorted in several fronts based on FNDS and CD [22]. Using the proposed selection method, population of the next iteration,  $P_{t+1}$ , is chosen to have a predetermined size. Figure 6 demonstrates the evolution process of the proposed MOHS, schematically.

To demonstrate performance of the proposed MOHSA, two well-developed Pareto-based multi-objective evolutionary algorithms, called NSGA-II and NREGA, are applied, described in the following subsection.

### 3.2. The NSGA-II and NREGA

Non-dominated Sorting Genetic Algorithm (NSGA) is one of the most popular evolutionary algorithms, used to solve multi-objective problems. This non-dominated based meta-heuristic algorithm, which is an extension of the Genetic Algorithm (GA), was proposed by Srinivas and Deb [30]. The main criticisms of the NSGA, such as lack of elitism, the need for specifying the sharing parameter, and high computational complexity of non-dominated sorting, lead to introducing an extension of NSGA, called NSGA-II, proposed by Deb et al. [22].

In this paper, we apply an NSGA-II approach to solve the proposed APP model and compare the results with those of the presented MOHSA approach. As another Pareto-based evolutionary algorithm, NREGA is another multi-objective evolutionary algorithm introduced by Al Jaddan et al. [31] to solve multi-objective optimization problems. The crossover and mutation operators of NSGA-II and NREGA are uniform crossover

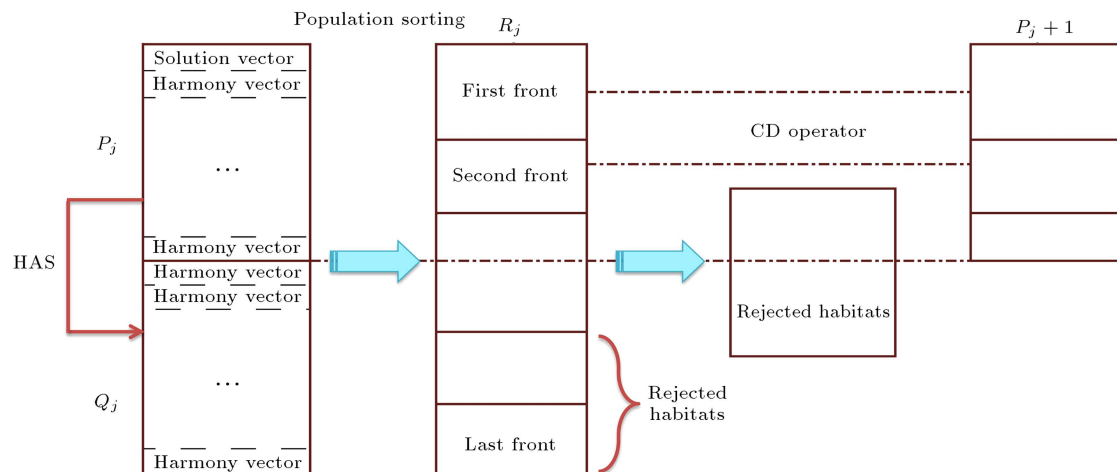


Figure 6. MOHSA evolution process.

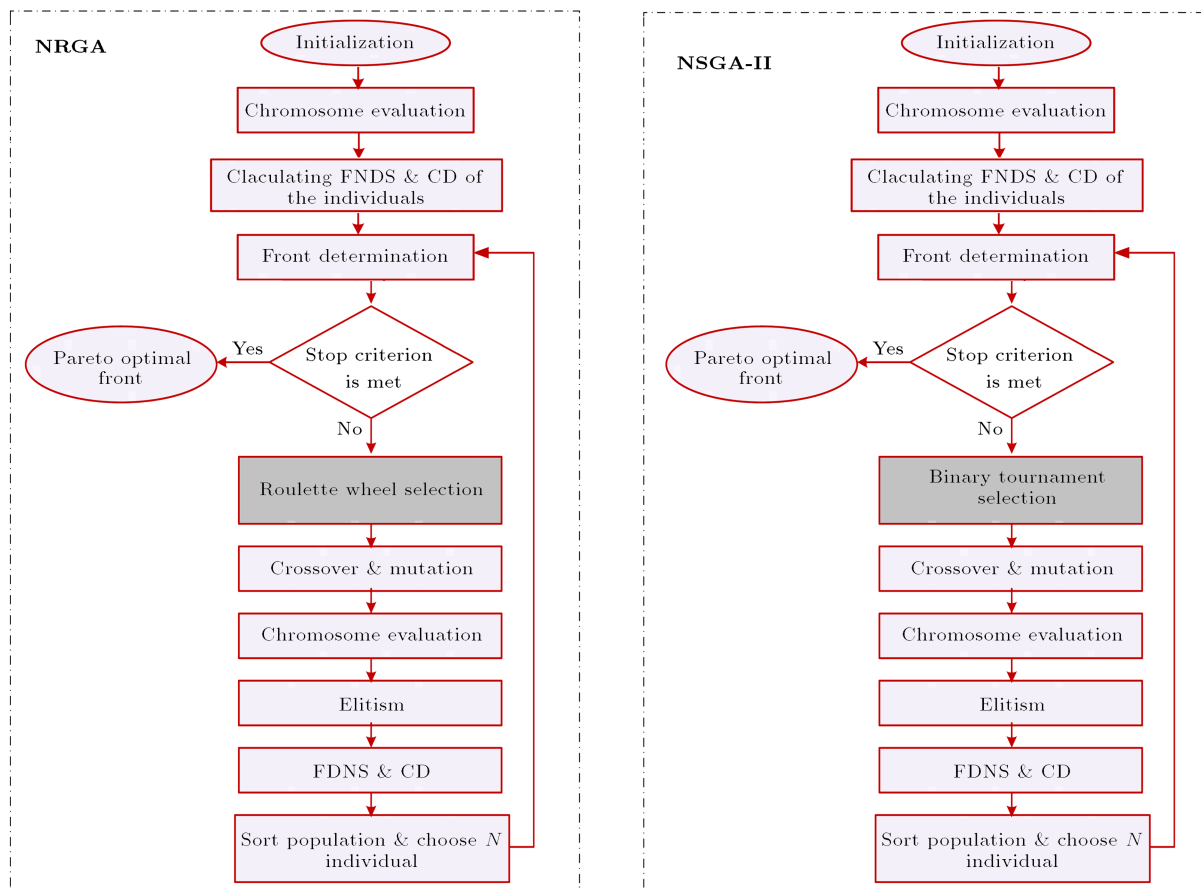


Figure 7. NSGA-II and NPGA flowcharts.

and swap operators, respectively [32]. Further, binary tournament selection and roulette wheel selection strategies methods are applied in NSGA-II and NPGA, respectively. The flowcharts of NSGA-II and NPGA are plotted in Figure 7.

#### 4. Parameter tuning

Since the quality of meta-heuristic algorithms largely

depends on the parameters and operators, Experiments designs are used to set the parameters. Experiments designs is an organized method to determine the relationship between input and output processes. In this section, parameters and operators of MOHSA are determined. Due to the large number of parameters in HSA, finding a suitable composition of parameters that improves the performance of algorithms is favorable. Since there are many parameters, using complete



factorial method is insufficient. To solve this problem, Taguchi method has been used. In this section, to set the parameters, several large-scale problems have been selected and are presented in Figures 8-10 by using major effect chart. In the cases where the number of agents and their levels is high, Taguchi method is more efficient than complete factorial method. For orthogonal array, L27 equaling 27 is much less than the number required for complete factorial method [33,29]. In order to tune the parameters, the Mean Ideal Distance (MID) is selected as the main response in Taguchi analysis.

According to the main effects plots of Figures 8-10, the optimal value of the algorithm's parameters for problem no. 10 is reported in Table 1.

## 5. Result analyses and comparisons

This section provides the application of the proposed methodology and the performance comparisons of the three meta-heuristic algorithms. The developed algorithms are coded in MATLAB software (Version 7.10.0.499, R2010a) environment, and the experiments

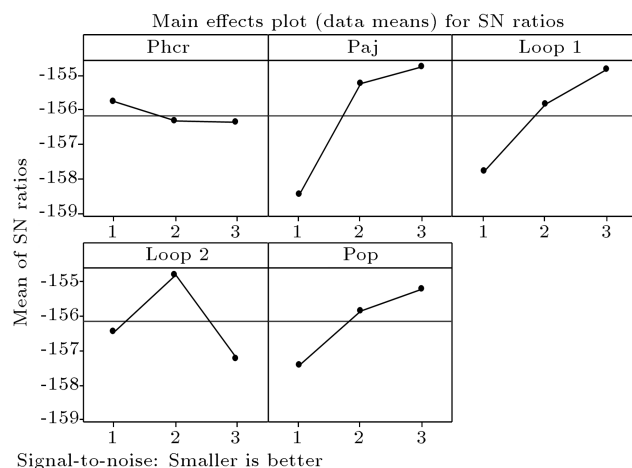


Figure 8. Setting the MOHSA parameters by Taguchi.

are performed on a two GHz laptop with eight GB RAM to estimate the response functions.

To evaluate and compare the performances of the

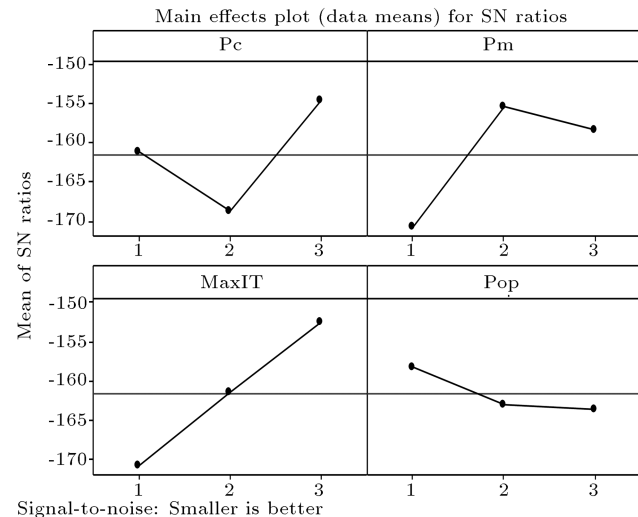


Figure 9. Setting the NRGa parameters by Taguchi.

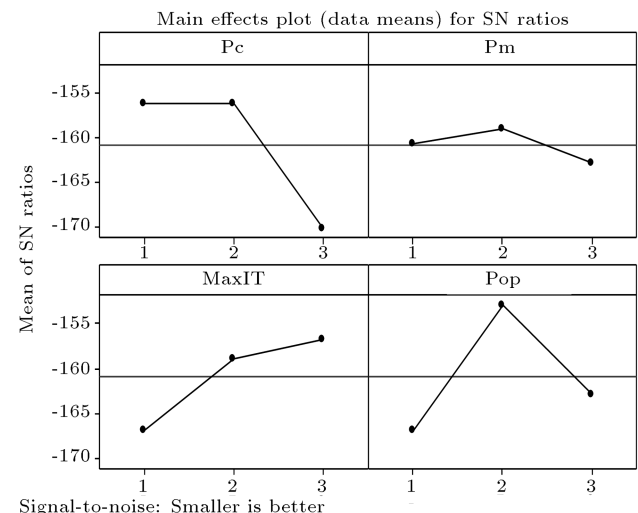


Figure 10. Setting the NSGA-II parameters by Taguchi.

Table 1. Optimal parameters for the algorithms.

Algorithms	Parameters	Leveling	Factor optimal
MOHSA	Population size (Pop)	{20,30,50}	50
	Inner Loop (Loop1)	{20,30,40}	40
	Outer Loop (Loop2)	{30,60,90}	60
	Pitch adjusting operator (Paj)	{0.1,0.3,0.5}	0.5
	Harmony memory operator (Phcr)	{0.7,0.8,0.9}	0.7
NRGA	Population size (Pop)	{25,50,100}	25
	Maximum of Iteration (MaxIT)	{100,200,300}	300
	Probability of crossover (Pc)	{0.7,0.8,0.9}	0.9
	Probability of mutation (Pm)	{0.1,0.25,0.4}	0.25
NSGA-II	Population size (Pop)	{25,50,100}	50
	Maximum of Iteration (MaxIT)	{100,200,300}	300
	Probability of crossover (Pc)	{0.7,0.8,0.9}	0.8
	Probability of mutation (Pm)	{0.1,0.25,0.4}	0.25

**Table 2.** Generated test problem.

Problem no.	$I$	$C$	$T$	$J$
1	2	2	2	1
2	2	5	2	1
3	3	5	3	2
4	3	10	3	2
5	5	10	6	3
6	5	10	6	3
7	10	20	12	4
8	10	20	12	4
9	10	40	12	5
10	20	40	18	5
11	20	50	24	10
12	35	50	24	10

**Table 3.** Input Parameters' values of the numerical examples.

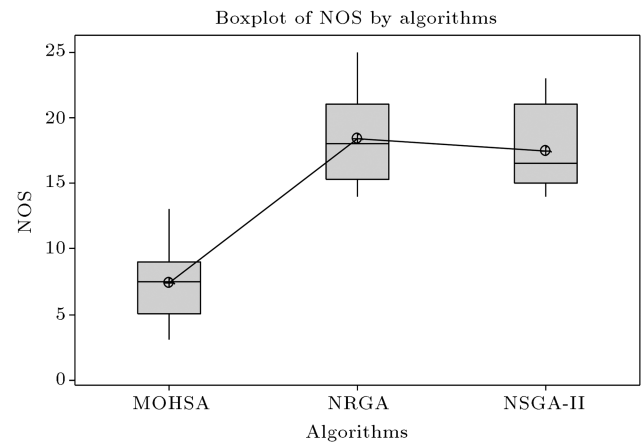
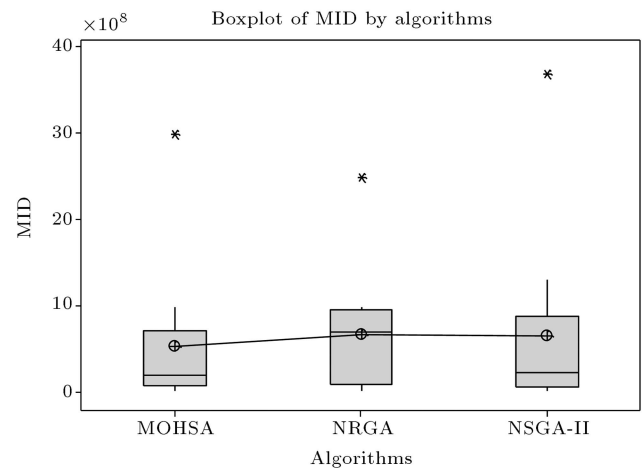
Parameters and their values	
$D_{ict} \sim U(100, 500)$	$T_{2ict} \sim U(10, 30)$
$C_{qj} \sim U(10, 40)$	$Cr_{smt} \sim U(80, 120)$
$L_{jt} \sim U(1000, 3000)$	$\gamma_{im} \sim U(3, 9)$
$a_{ij} \sim U(10, 20)$	$\alpha_t \sim U(0, 1)$
$F_{jt} \sim U(2000, 4000)$	$TI_{1,jt} \sim U(7, 9)$
$H_{jt} \sim U(6000, 10000)$	$TI_{2,jt} \sim U(0, 4)$
$I_{1mjt} \sim U(100, 200)$	$P_{1j} \sim U(1000, 2000)$
$I_{2ijt} \sim U(150, 250)$	$P_{2j} \sim U(500, 1000)$
$I_{3ict} \sim U(150, 250)$	$P_{3c} \sim U(800, 1400)$
$\pi_{ict}^n \sim U(100, 400)$	$P_{4smt} \sim U(1000, 5000)$
$LT_{sj}, LT_{jc} \sim \text{Uniform}(0, 4)$	$\varphi_{LT} = 1$
$T_{1s jt} \sim U(10, 30)$	

solution methodologies under different environments, the experiments are implemented on 12 problems, which are reported in Table 2. These problems are categorized based on the number of costumers ( $I$ ), the number of facilities ( $J$ ), and the maximum number of on-duty servers ( $P$ ). Moreover, the following information is also given in Table 3.

Then, these instance problems are solved by three algorithms. Furthermore, to eliminate uncertainties of the solutions obtained, each problem is used three times under different random environments. Then, the averages of these three runs are treated as the ultimate responses. The objective function values of problems nos. 8 and 11 are reported in Tables 4 and 5.

In order to evaluate the performances of the three multi-objective meta-heuristic algorithms, four metrics are used as Zitzler and Thiele [34]:

- (I) Number of Pareto Solution (NOS);
- (II) Mean Ideal Distance (MID);
- (III) Spacing;
- (IV) Diversity;
- (V) Computational time.

**Figure 11.** Box-plot comparisons of the algorithms in terms of NOS metric.**Figure 12.** Box-plot comparisons of the algorithms in terms of MID metric.

The results of comparisons in terms of all multi-objective metrics for all algorithms are reported in Table 6. Moreover, the algorithms are compared based on the properties of their obtained solutions. For these cases, all metrics are also plotted and graphically compared in Figures 11-15.

We note that while bigger values are desired in terms of the *diversity* and NOS metrics, smaller values are better for spacing, MID, and CPU time. Thus, according to the analysis of variance outputs in Tables 7-11 and  $p$ -values, MOHSA shows better performance in terms of CPU Time. However, in terms of MID, Diversity, and Spacing metrics, the algorithms almost work in a similar way. This conclusion is confirmed at a 95% confidence level.

## 6. Conclusion and future research

A multi-objective model for multi-product, multi-site aggregate production planning model in a supply chain was developed in this paper. The goals were to

**Table 4.** Pareto solutions of problem no. 8.

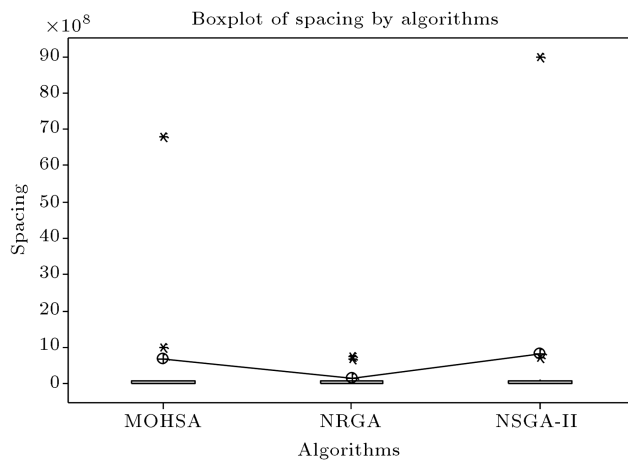
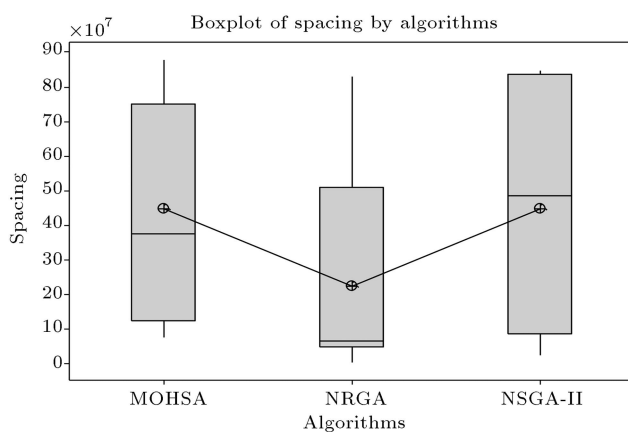
Pareto solution number	NSGA-II		NRGA		Proposed MOHSA	
	Objective 1	Objective 2	Objective 1	Objective 2	Objective 1	Objective 2
1	6.53E+07	0.5086	5.09E+07	0.3450	1.39E+07	0.3501
2	8.01E+07	0.6715	4.59E+07	0.2567	5.27E+07	0.6990
3	3.50E+07	0.1481	4.39E+07	0.2244	9.19E+07	0.9344
4	7.61E+07	0.6324	9.54E+07	0.8702	8.02E+07	0.8890
5	9.84E+07	0.8344	7.47E+07	0.6397	6.65E+07	0.8082
6	5.60E+07	0.4225	8.79E+07	0.7854	6.01E+07	0.7516
7	9.35E+07	0.8043	6.88E+07	0.5773	—	—
8	4.92E+07	0.3671	7.78E+07	0.6733	—	—
9	8.88E+07	0.7673	5.61E+07	0.4467	—	—
10	4.00E+07	0.2109	9.16E+07	0.8267	—	—
11	8.43E+07	0.7230	3.91E+07	0.1284	—	—
12	7.23E+07	0.5756	6.34E+07	0.5210	—	—
13	1.13E+08	0.8911	8.44E+07	0.7461	—	—
14	5.89E+07	0.4494	1.12E+08	0.8988	—	—
15	4.45E+07	0.3033	5.84E+07	0.4702	—	—
16	—	—	7.17E+07	0.6077	—	—

**Table 5.** Pareto solutions of problem no. 11.

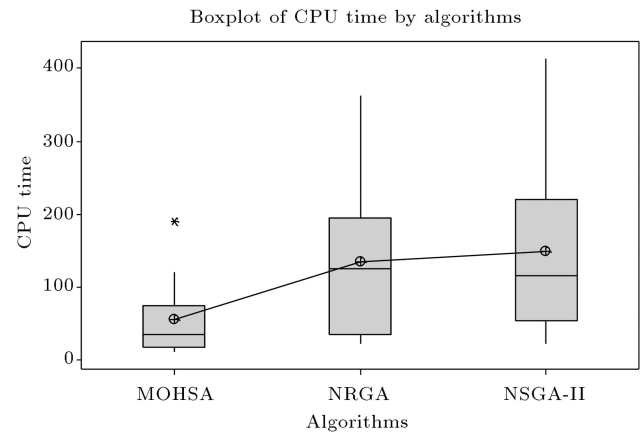
Pareto solution number	NSGA-II		NRGA		Proposed MOHSA	
	Objective 1	Objective 2	Objective 1	Objective 2	Objective 1	Objective 2
1	5.96E+10	0.5760	9.05E+10	0.8402	3.67E+10	0.3831
2	9.05E+10	0.8280	7.66E+10	0.7583	6.90E+10	0.5640
3	3.33E+10	0.3466	3.06E+10	0.4313	1.17E+11	0.8558
4	1.01E+11	0.9133	7.05E+10	0.7204	1.30E+11	0.9302
5	9.83E+10	0.8903	1.11E+11	0.9140	6.21E+10	0.5189
6	2.23E+10	0.1907	3.01E+10	0.4023	1.35E+11	0.9473
7	3.62E+10	0.3727	5.97E+10	0.6502	2.59E+10	0.2774
8	7.66E+10	0.7161	8.33E+10	0.7982	8.52E+10	0.6664
9	5.49E+10	0.5357	6.48E+10	0.6844	9.47E+10	0.7243
10	7.05E+10	0.6660	5.05E+10	0.5868	—	—
11	1.21E+11	0.9394	1.15E+11	0.9177	—	—
12	4.27E+10	0.4309	3.93E+10	0.5031	—	—
13	1.82E+10	0.1398	2.17E+10	0.3496	—	—
14	5.05E+10	0.4982	1.33E+10	0.2540	—	—
15	3.06E+10	0.3223	3.62E+10	0.4779	—	—
16	8.32E+10	0.7700	4.64E+10	0.5574	—	—
17	—	—	9.84E+10	0.8845	—	—

**Table 6.** Computational results of multi-objective metrics comparisons for three algorithms.

Problem no.	Proposed MOHSA					NSGA-II					NRGA				
	NOS	MID	Spacing	Diversity	Time	NOS	MID	Spacing	Diversity	Time	NOS	MID	Spacing	Diversity	Time
1	9	6E+06	7690	82465023	11.52	23	7E+06	7633	836454875	21.66	21	6E+07	7655	648729584	21.99
2	9	6E+06	8766	876348278	15.44	21	9E+06	8655	847638748	38.91	19	1E+07	6544	772354726	22.73
3	11	8E+07	7434	82736292	16.81	16	7E+07	5688	834768378	45.88	18	9E+07	9853	827368742	29.91
4	13	8E+07	4584	73492284	21.53	17	8E+07	8721	483784734	76.10	15	1E+08	9790	67485282	49.21
5	8	1E+08	18712	873684277	22.73	21	6E+07	87654	84384783	91.62	22	1E+08	87341	3642347	82.61
6	5	2E+08	87645	784268392	26.72	21	2E+08	77611	684348384	110.81	21	6E+08	98652	46234827	121.81
7	7	2E+08	89966	374920923	41.94	15	3E+08	54388	483784783	119.85	25	9E+08	67390	6348232	129.82
8	6	4E+08	123560	374928902	49.66	15	5E+08	876691	83847384	159.75	16	1E+09	897443	47835404	148.73
9	5	5E+08	6588799	374928980	61.87	17	8E+08	8544975	84384783	178.83	18	8E+08	8756532	65354504	171.91
10	9	8E+08	78767221	238476899	77.99	16	9E+08	87655501	87589979	233.70	17	8E+08	87996209	67374363	201.74
11	4	1E+09	984989893	562437223	121.10	14	1E+09	698212180	23720645	298.61	15	2E+09	678524489	87373583	278.53
12	3	3E+09	6798567589	647289022	189.81	14	4E+09	8974461871	837843878	412.87	14	1E+09	732434588	54353783	362.74

**Figure 13.** Box-plot comparisons of the algorithms in terms of Spacing metric.**Figure 14.** Box-plot comparisons of the algorithms in terms of Diversity metric.

minimize the total cost of supply chain, including inventory costs, manufacturing costs, work force costs, hiring, and firing costs, and to maximize the minimum of suppliers' reliability by considering probabilistic lead

**Figure 15.** Box-plot comparisons of the algorithms in terms of Time metric.**Table 7.** Statistical outputs of NOS metric.

Algorithm	DF	SS	MS	F	P-value
Algorithms	2	894.6	447.3	45.14	0.000
Error	33	326.83	9.90		
Total	35	1220.89			

times to simultaneously improve performance of the system. Since the problem is NP-Hard, a Pareto-based multi-objective harmony search algorithm is proposed. To demonstrate the performance of the presented algorithm, NSGA-II and NRGA are applied. The results show that MOHSA has better performance in terms of CPU Time. However, in terms of MID, Diversity, and Spacing metrics, our proposed MOHSA has the same capability as the best-developed algorithms in the literature. As for future research, one can develop the model by formulating the problem in competitive supply chains.

**Table 8.** Statistical outputs of MID metric.

Algorithm	DF	SS	MS	F	P-value
Algorithms	2	1.43865E+17	7.19323E+16	0.09	0.910
Error	33	2.49970E+19	7.57484E+17		
Total	35	2.51408E+19			

**Table 9.** Statistical outputs of Spacing metric.

Algorithm	DF	SS	MS	F	P-value
Algorithms	2	3.11980E+18	1.55990E+18	0.44	0.645
Error	33	1.15933E+20	3.51313E+18		
Total	35	1.19053E+20			

**Table 10.** Statistical outputs of Diversity metric.

Algorithm	DF	SS	MS	F	P-value
Algorithms	2	3.94541E+17	1.97270E+17	1.86	0.172
Error	33	3.50060E+18	1.06079E+17		
Total	35	3.89514E+18			

**Table 11.** Statistical outputs of CPU Time metric.

Algorithm	DF	SS	MS	F	P-value
Algorithms	2	62182	31091	3.35	0.047
Error	33	306463	9287		
Total	35	368644			

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