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Research Article

A New Bi-objective Mathematical Model to Optimize Reliability and Cost of Aggregate Production Planning System in a Paper and Wood Company

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Abstract

In this research, a bi-objective model is developed to deal with a supply chain including multiple suppliers, multiple manufacturers, and multiple customers, addressing a multi-site, multi-period, multi-product aggregate production planning (APP) problem. This bi-objective model aims to minimize the total cost of supply chain including inventory costs, manufacturing costs, work force costs, hiring, and firing costs, and maximize the minimum of suppliers' and producers' reliability by considering probabilistic lead times to improve the performance of the system and achieve a more reliable production plan. To solve the model in small sizes, a ε-constraint method is used. A numerical example, by utilizing the real data from a paper and wood industry, is designed and the model performance is assessed. With regard to the fact that the proposed bi-objective model is NP-hard, one multi-objective harmony search algorithm is used for large-scale problems and its results are compared with the NSGA-II algorithm. The results demonstrate the capability and efficiency of the proposed algorithm in finding Pareto solutions.

Keywords: Multi-objective; Aggregate Production Planning; Supply Chain, Reliability; Harmony search; NSGA-II

1. Introduction

Nowadays, supply chain management (SCM) which covers production planning for the entire supply chain from the raw material supplier to the end customer has become the foundation for operations management. Since SCM has become the core of the enterprise management in the 21st century, there is considerable interest to exploit the full potential of SCM in enhancing organizational competitiveness. SCMexertsa tremendous impact on organizational performance in terms of competing based on price, quality, dependability, responsiveness, and flexibility in the global market and it is becoming a more matured discipline. Hence, this requires a more defined organizational structure, performance measures, etc. One of the problems that should be addressed in this scope is the aggregate production planning (APP), which is addressed in this research study along with the broader topics of SCM. The SCM has ledmanagers and analysts to shift their focuses from only manufacturing plants to entities plants; for example, suppliers, warehouses, and customers. Baykasoglu (2001) has defined APP as medium-term capacity planning over 3–18 months planning horizon and its 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 Production planning plays a crucial role in imposing costs onthe organization. Therefore, a good APP facilitates supply chain management.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) (Ozdamar et al., 1998). In a systematic view of APP, one can introduce capacity constraints, demands and firm's policies and strategies as theinputs of APP and determine the production levels, inventory levels, workforce levels, subcontractinglevels, etc., as theoutputs of the system.

Considering the real world conditions for the aggregate production planning problem, in a manner that the general framework of the problem, including inputs, and outputsis well considered, has always been studied in the research.The inputs and outputs are based on some parameters with uncertain value. Uncertainties might arise in lead time, and so forth; thus,the reliability of the production plan isvery important. Reliability can be defined as the probability that a system or a product will perform in a satisfactory manner for a given period of time when used under specified operating conditions (Blanchard and Benjamin, 2004). Our researchconsiders a bi-objective model for APP in multi-echelon supply chain considering input constraints that achieve outputs withthe minimum imposed cost as well as maximum system reliability.

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The rest of thispaper is organized as follows: in Section 2, the literature review is presented. A mathematical formulation of proposed multi-objective APP problem is presented in Section 3. The solution procedure is proposed in Section 4.In Section 5, a case study fromthepaperand woodindustry is considered in order to investigate the validity and practicality of the proposed model.Section 6 provides the result analysis and comparisons. Finally, the conclusion and suggestions for future research are presented.

2. Literature Review

Numerous APP models with varying degrees of sophistication have been introduced in the last decades. Since Holt et al. (1995) proposed the approach for the first time, scholars have developed numerous models to help solving the APP problems, each with their own supporters and detractors. Hanssman and Hess (1960) developed a model based on the linear programming approach using a linear cost structure of the decision variables. Their model was extended for multi-product, multi-stage production systems in which optimal disaggregation decisions can be made under capacity constraints (Lanzenauer, 1970; Guillen et al., 2005). Masud and Hwang (1980) presented three MCDM methods to solve the APP problem. Logendran and Nam (1992) reviewedthe APP models from 140 journal articles and 14 books, and categorized the models into optimal and near-optimal classifications.

Based on thenumber 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 (Wang and Liang, 2004). A common objective function in the APP models is to minimize the total cost of the system. In addition, maximization of theservice level, minimization of changing thework force level, and minimization of the risk are other objective functions which can be considered (Baykasoglu, 2001; MirzapourAl-e-Hashem et al., 2011; Masud and Hwang, 1980; Wang and Liang, 2004; Wang and Liang, 2005; Leung and Chan, 2009; Sadeghi et al., 2013; Gholamian et al., 2015). Vahdani et al. (2012) developed a novel mathematical model that integrates the network design decisions in both forward and reverse supply chain networks. The model also utilizes an effective reliability approach to find a robust network design. Vahdani et al. (2015) presented a model for designing a reliable network of facilities in closedloop supply chain under uncertainty. For this purpose, a bi-objective mathematical programming formulation is developed which minimizes the total costs and the expected transportation costs after failures of a logistics network facilities. Pasandideh et al. (2015) 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, as well asmaximization of the average number of products dispatched to customers, which was followed by considering the reliability indices assumed for the distribution centers. Rahmani and Mahoodian (2017) applied a robust approach to formulate a model to overcome the uncertain parameters. Moreover, they predicted the risk of facilities' disruption under different scenarios and presented a reliable model. The Benders decomposition algorithm was proposed to solve the presented model considering several acceleration methods to acceleratethe convergence of the algorithm. Chunghu et al. (2018) proposed a concise and definite mathematical definition of supply chain reliability and, derived related functions such as hazard function, cumulative hazard function, availability, and mean residual capacity at component level based on the definition. Additionally, they provided selected structural reliability models such as series, parallel, parallel-series, series–parallel, and *k*-out-of-*n* system on the system level by utilizing the original reliability theory.

In spite of many research studies in APP literature considering different objectives, reliability has been rarely discussed as an effective index in production planning. In a large number of research studies, the APP problem has been investigated with various objectives and conditions; however, there is not any study which investigating how much the reliability of production plans can affect decision making. Recently, Ramyar et al. (2017) presented a multi-objective model for aggregate production planning model in a supply chain net work systems. The goals were to minimize the total cost of the supply chain and also to maximize the minimum of suppliers' reliability. In this paper, reliability has to be regarded as an effective indicator of integrated production planning along with a cost index for decision making with more reliability.

Obviously, in a chain with various suppliers and manufacturers, supplying raw materials from suppliers to producers and producing goods from producers to shopping centers are accomplished with different suppliers and producers as a supply chain includes different suppliers and producers. Presenting appropriate schedulingfor goods by manufacturers is difficult and uncertain. This is due to theuncertainty in lead time of suppliers and producers and occurrence of delay in shipping raw materials from suppliers to manufacturers and manufacturers to shopping centers. Therefore, possible lead times of suppliers and manufacturers are considered as a measurement index to evaluate the reliability of APP in the supply chain in this research. Hence, the selection of suppliers and manufacturers that maximizes the reliability of the whole system can be considered as another objective function.

As a result, a bi-objective model is designed to deal with a supply chain including multiple suppliers, multiple manufacturers and multiple customers, addressing a multi-site, multi-period, multi-product aggregate production planning problem in this research. 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 maximizing the minimum of

suppliers', and producers' reliability by considering probabilistic lead times, to enhance the performance of the system and achieve a more reliable production plan lead times.
According to the complexity of APP problem, it is NP-hard (Fahimnia et al., 2006). Therefore, a lot of research studies have applied the meta-heuristic algorithms to resolvetheAPP problem (Fahimnia et al., 2006; Jiang and Kong, 2008; Ramezanian et al., 2012; Chakraborthty and AkhtarHasin, 2013; Wang and Yeh, 2014; Chakrabortty and Hasin 2013). Among multi-objective algorithms, the 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). This algorithm can be used in different scopes of operational management (Chambari et al., 2012; Deb et al., 2002). In addition, another meta-heuristic algorithm called Harmony search algorithm (HSA) has been presented which can demonstrate acceptable results for complex problems (Geem et al., 2001). Considering the performance of harmony search algorithm for single-objective problem, the multi-objective harmony search algorithm version was developed (Geem, 2007; Rahmati et al., 2013). In this article, to solve the APP problem, a multi-objective harmony search algorithm (MOHSA) is used. Finally, considering the performance of the MOHSA algorithm, its results are compared with the NSGA-II algorithm.

3. Problem Formulation

The proposed multi-objective multi-product multi-site APP problem in a supply chain can be described as follows:

There are *J* sites, *S* suppliers and *C* customers (Figure1). Each site produces several product items assembled from some parts supplied by suppliers, regarding consumption rates. The production cost of a certain item at different sites and raw material cost in different suppliers can be different. Eachis site characterized by its own raw material,end product inventory capacities and the available time for its production which is limited to its number of *k*-level workers well asthe allowed amount of regular and overtime. Every site could subcontract an allowed proportion of its product to subcontractors. All sites, suppliers and customers' zones aregeographically spread, and then the transportation cost from suppliers to sites and from sites to customers' zones can vary. Being aware ofthe fact that storing the end products in customers' zones is impossible, the shortage can occur for each product. The probabilistic lead time for transporting raw materials from suppliers to manufacturers and transporting products from manufacturers to costumers is considered, and the reliability of suppliers and manufacturers in delivering materials and products can be computed based on this definition. In other words, a supplier is reliable if he can transport the required raw materials to a manufacturer, and a manufacturer is reliable if he can transport the needed products to a customer at predefined timeduration. The problem is to determine: (1) the quantity of product *i* manufactured at site *j* to fulfill thedemand of customer'szone *c* in each period of time by *k*-level workers; (2) the quantity of raw material *m* provided by supplier *s* in all periods to fulfill the net requirements of site *j* regarding to the consumption rates and the lead times; (3) the quantity of raw material *m* and end product *i* stored at site *j* in each period; (4) the amount of demand in each customer's zone is not met in each period.

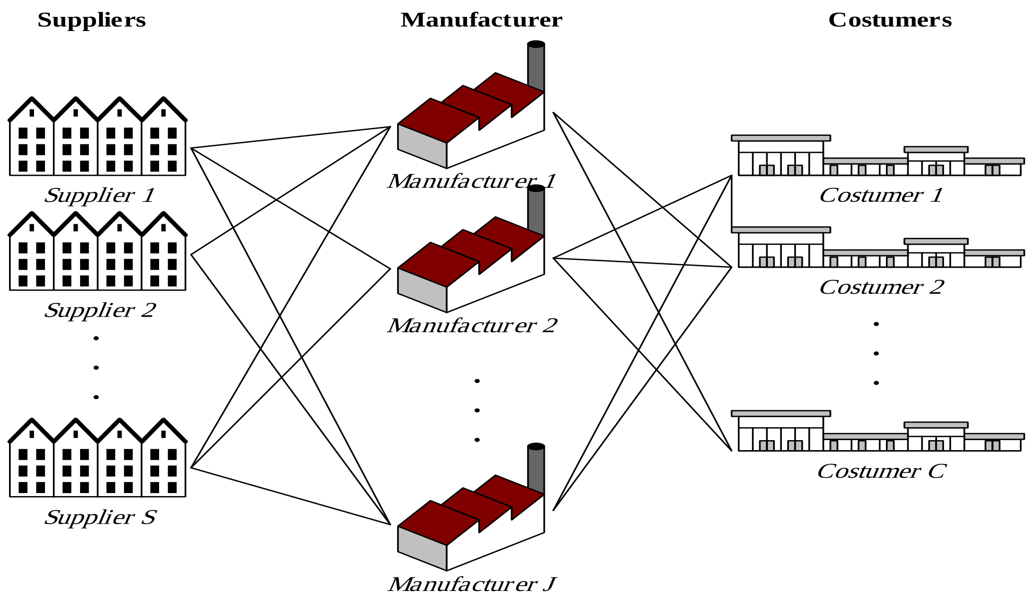

Fig. 1. Supply chain configuration

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 theperformance level by maximizing reliability in supplier and manufacturer selection process.

3.1. Denominations

The notations including indices, parameters, and decision variables are:

Indices:

s index used for a supplier, $s= 1, 2, ...,S$
m index used for araw material, $m =1, 2, …, M$
j index used for a factory, $j=1, 2, …….J$
k index used for a k-level labor, $k= 1, 2, ..., K$
q index used for a production at the regular time ($q=1$), overtime ($q=2$), and subcontracting ($q=3$)
c index for a customer, $c= 1, 2, ..., C$
i index for a finished product, $i= 1, 2, ..., I$
t index used for a period with a fixed length of τ, $t = 1, 2, ..., T$

Parameters:

D_{ict}	Demand of product i in demand point c in period t
C_{qj}	Production cost per hour at regular time ($q=1$), overtime ($q=2$), and subcontracting ($q=3$) at factory j
L_{kjt}	Manpower cost of k-level labors at factory j in period t
a_{ij}	Production time of product i at factory j
F_{kjt}	Firing cost of k-level worker at factory j in period t
H_{kjt}	Hiring cost of k-level worker at factory j in period t
I_{1mjt}	Inventory holding cost for raw material m at factory j in period t
I_{2ijt}	Inventory holding cost for finished product i at factory j in period t
I_{3ijt}	Inventory holding cost for finished product i in costumer’s zone c in period t
T_{1sjt}	Transportation cost for supplier s to factory j in period t
T_{2jct}	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
γ_{im}	Number of units of raw material m required for each unit of product i
α_t	Fraction of the workforce variation allowed in period t
V_k	Productivity of k-level labors ($0 \leq V_k \leq 1$)
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_{3j}	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_{smjt}	Probabilistic lead time for shipping raw material m from supplier s to factory j in period t
$f_{smjt}(LT_{smjt})$	Probability distribution function LT_{smjt}
$\mu_{LT_{smjt}}$	Mean lead time for shipping raw material m from supplier s to factory j in period t
$\varphi_{LT_{smjt}}$	Maximum acceptable lead time of raw material m supplier s to factory j in period t for being reliable
LT_{ijct}	Probabilistic lead time required for shipping end product i from factory j to demand point c in period t
$\mu_{LT_{ijct}}$	Mean lead time required for shipping end product i from factory j to demand point c in period t
$f_{ijct}(LT_{ijct})$	Probability distribution function LT_{ijct}
$\varphi_{LT_{ijct}}$	Maximum acceptable lead time of end product i factory j to demand point c in period t for being reliable
π_{ict}	Shortage cost of product i in customer’s zone c in period t
TC	Total cost of supply chain

$r_{smjt} = P\left(LT_{smjt} < \varphi_{LT_{smjt}}\right) = \int_0^{\varphi_{LT_{smjt}}} f_{smjt}(LT_{smjt}).d\left(LT_{smjt}\right)$: Reliability of supplier s for providing required raw materials m to factory j in period t

$r_{ijct} = P\left(LT_{ijct} < \varphi_{LT_{ijct}}\right) = \int_0^{\varphi_{LT_{ijct}}} f_{ijct}(LT_{ijct}).d\left(LT_{ijct}\right)$: Reliability of factory j for shipping end product i to demand point c in period t

Decision variables:

X_{ijqt}	Number of product i produced at factory j using method q in period t
XL_{kjt}	Number of k-level workers at factory j in period t
XF_{kjt}	Number of k-level workers at factory j fired in period t
XH_{kjt}	Number of k-level 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 in period t

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

Z_{smjt} One, if supplier *s* provides raw material *m* for factory *j* in period *t*; 0 otherwise

Z_{ijct} One, if factory *j* provides end-product *i* for demand point *c* in period *t*; 0 otherwise

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

3.2. Multi-objective APP model

$$Min\ Z_1 = TC = \sum_{i,j,q,t} a_{ij}C_{qj}X_{ijqt} + \sum_{s,m,t} Cr_{smt}.(\sum_{j} XS_{smjt}) + \sum_{k,j,t} L_{kjt}XL_{kjt} + \sum_{k,j,t} F_{kjt}XF_{kjt} + \sum_{k,j,t} H_{kjt}XH_{kjt} + \sum_{m,j,t} I_{1mjt}XM_{mjt} + \sum_{i,j,t} I_{2mjt}XP_{ijt} + \sum_{i,c,t} I_{3ict}XI_{ict} + \sum_{s,j,t} T_{1sjt}.(\sum_{m} XS_{smjt}) + \sum_{j,c,t} T_{2jct}.(\sum_{i} YS_{ijct}) + \sum_{i,c,t} \pi_{ict}B_{ict} \quad (1)$$

$$Max\ Z_2 = Min_{s,m,j,i,c,t}\{r_{smjt} + (1 - Z_{smjt})M, r_{ijct} + (1 - Z_{ijct})M\} \quad (2)$$

S. T.

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

$$XM_{mjt} = XM_{mj(t-1)} + \sum_{s} XS_{smj(t-\mu_{LT_{smjt}})} - \sum_{q,i} x_{ijqt}.\gamma_{im} \qquad \forall\, m,j,t \quad (4)$$

$$XL_{kjt} = XL_{kj(t-1)} + XH_{kjt} - XF_{kjt} \qquad \forall\, k,j,t \quad (5)$$

$$XI_{ict} = XI_{ic(t-1)} + \sum_{j} YS_{ijc(t-\mu_{LT_{ijct}})} - D_{ict} - B_{ic(t-1)} \qquad \forall\, i,c,t \quad (6)$$

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

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

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

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

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

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

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

$$XS_{smjt} \leq M.Z_{smjt} \qquad \forall\, m,s,j,t \quad (14)$$

$$Z_{smjt} \leq M.XS_{smjt} \qquad \forall\, m,s,j,t \quad (15)$$

$$YS_{ijct} \leq M.Z_{ijct} \qquad \forall\, i,c,j,t \quad (16)$$

$$Z_{ijct} \leq M.YS_{ijct} \qquad \forall\, i,c,j,t \quad (17)$$

$$Z_{smjt} \in \{0,1\} \qquad \forall\, m,s,j,t \quad (18)$$

$$Z_{ijct} \in \{0,1\} \qquad \forall\, i,c,j,t \quad (19)$$

$$XF_{kjt}, XH_{kjt}, XL_{kjt} \geq 0\ and\ integer \qquad \forall\, k,j,t \quad (20)$$

$$X_{ijqt}, XS_{jsmt}, XI_{ict}, XM_{mjt}, XP_{ijt}, YS_{ijct}, B_{ict}, XF_{kjt}, XH_{kjt}, XL_{kjt} \geq 0 \qquad \forall\, i,j,c,s,k,m,t \quad (21)$$

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 the improve performance level through maximizing the minimum of suppliers' and manufacturers' reliability. In this function, it should be considered that the minimization operator is defined for $\{s, m, j, t | Z_{smjt} = 1\}, \{i, j, c, t | Z_{ijct} = 1\}$. By this consideration, the system attempts to confirm a balance in supplier and manufacturer selection problems. Eq. (3) and Eq. (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 the sum of regular time and overtime with regards to productivity of workforce limit the available production times for each manufacturer. 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 the workforce level by the proportion of workers in previous period. Eq. (13) restricts the amount of shipments from supplier *s* by the supplier capacity. Eq. (14) ensures that if supplier *s* provides raw material m for factory *j* in period *t*, its related binary variable (Z_{smjt}) must be one. Eq. (15) ensures that if supplier *s* does not provide any raw materials for factory *j in* period *t*, its related binary variable (Z_{smjt}) must be zero.Eq. (16) ensures that if factory *j* provides end-product *i* for demand point *c* in period *t*, its related binary variable (z_{ijct}) must be one. Eq. (17) ensures that if factory *j* does not provide any end-products for demand point *c* in period *tin* period *t*, its related binary variable (Z_{ijct}) must be zero. Eqs. (18)- (21) denote variable types.

4. The Solution Procedures

In this section, a Pareto-based meta-heuristic algorithm called MOHS is presented to solve the proposed APP model. Moreover, NSGA-II is utilized to validate the results obtained. However, some required multi-objective backgrounds are first defined in the following subsection.

4.1. Fundamental concept of multi-objective algorithms

Consider a multi-objective model with a set of conflicting objectives $f(\vec{x}) = [f_1(\vec{x}), \ldots, f_m(\vec{x})]$subject to $g_i(\vec{x}) \leq 0, i = 1, 2, \ldots, c$ $\vec{x} \in X$, where $\vec{x}$ denotes n -dimensional vectors that can get real, integer, or even Booleans and *X* is the feasible region. Then, for a minimization model, we say that solution $\vec{a}$ dominates solution $\vec{b}$ ($\vec{a}, \vec{b} \in X$) if:

1) $f_i(\vec{a}) \leq f_i(\vec{b}), \forall i = 1,2, \ldots, m$ and

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

Moreover, a set of solutions that cannot dominate each other is called Pareto solutions set or Pareto front. A good Pareto front has two features: (1) good convergence, and (2) good diversity of the solutions. Accordingly, Pareto-based algorithms aim to achieve the Pareto optimal front during the evolution process. The Pareto optimal front is called to the front of the last iteration of the algorithms. This front is expected to have the most convergence and the highest diversity (Deb et al., 2002).

4.2. The MOHSA

Harmony search (HS) is a population-based meta-heuristic algorithm that works on the basis of the improvisationof musicians.In other words, the qualitative optimization process of this algorithm mimics the qualitative improvisation process of musicians. In comparison with genetic algorithm (GA), as a common and popular algorithm, harmony vector is equivalent to chromosome; whereas, harmony of improvising is equivalent to the fitness function.

Sivasubramani and Swarup (2011) have developed a multi-objective version of HS for continuous optimization cases. This version utilizes operators of the NSGA-II algorithm to guide its evolution process.As mentioned above, in thispaper, a multi-objective version of HSA is presented to solve the proposed APP model. The details of MOHSA are described in the following subsections.

4. 2. 1. Solution representation

To code the solutions, a five-fold solution representation structure is presented (Figure 2) in the form of the following descriptions:

Part (I)	**1**	**2**	**………**	**S**
Part (II)	**1**	**2**	**………**	**M**
Part (III)	**1**	**2**	**……….**	**J**
Part (IV)	**1**	**2**	**………**	**I**
Part (V)	**1**	**2**	**………**	**C**

Fig.2. Scheme of solution representation structure

I. The first part: *1×S* random vector specifies the priority of the suppliers for transporting materials into the manufacturer;
II. The second part: *1×M* random vector specifies the priority of materials for transporting into the manufacturer;
III. The third part: *1×J* random vector specifies the priority of manufacturers for producing the products;
IV. The fourth part: random vector specifies the priority of producing the products;
V. The fifth part: *1×C* random vector specifies the priority of customers for transporting the products to the customers.

In this structure, each gene of vectors is a random number between zero and one. Besides, thecustomers' demands will never exceed the capacity limitations.To clarify the trend of encoding the problem, Figure 3 indicates an example of manufacturer selection in which *J* = 5. In this figure, the random numbers are generated; their positions are kept and then sorted in an ascending order. Based on our capacity, three of the first genes are selected. The positions of these numbers are selected by manufacturers (manufacturers' numbers, 3, 5, and 4, are selected based on corresponding capacity). Moreover, the Continuous decision variables including $X_{ijgt}, XS_{jsmt}, XI_{ict}, XM_{mjt}, XP_{ijt}, YS_{ijct}, B_{ict}, XF_{kjit}, XH_{kjt}, XL_{kjt}$ are encoded based on upper bounds and are randomly generated between zero and its upper bound.

To preventthe violation of constraints, a penalty function approach method is applied to penalize them (Yeniay and Ankare, 2005). Penalty values are considered for all of the two objective functions through an additive function.

Generated Vector	**0.46**	**0.73**	**0.23**	**0.42**	**0.35**
Sorted Vector	**0.23 (3)**	**0.35 (5)**	**0.42 (4)**	**0.46 (1)**	**0.73 (2)**

$\underbrace{\textbf{0.23 (3)} \quad \textbf{0.35 (5)} \quad \textbf{0.42 (4)}}_{\textbf{Selected Manufacturers}}$

Fig. 3. An instance of Manufacturers encoding

4. 2. 2. Improvising process

In an improvising process of a musician, three common options are used:

1) Playing from memory
2) Adjusting the pitches slightly
3) Composing randomly

HS mimics these options to designthe search operators called harmony memory (*HM*) to adjust pitches, and to randomize (Geem, 2001). To employ these operators, a solution israndomlyselected and one/two operator(s) of the HS is/are used to improvise the selected solution based on operators' probabilities in Eq. (22) to Eq. (24).

$$P_{HMCR} = HMCR \tag{22}$$

$$P_{pa} = HMC \tag{23}$$

$$P_{rand} = 1 - HMCR \tag{24}$$

The *HM* operator is used to control elitism in HS by means of a rate called harmony memory considering rate (*HMCR*). To exploit the best performance of this algorithm, *HMCR* is generally set between 0.75 and 0.95 (Geem, 2001). Since the pitch adjusting is employed in improvising environment to change frequencies slightly, a similar operator is used in the optimization process of an HS algorithm to generate slightly different solutions called neighbor solution. To control this operator, a rate called pitch-adjusting rate (r_{pa}) is used. This rate is usually set between 0.1 and 0.5, where its probability (P_{pa}) is obtained using Eq. (23). Subsequently, the pitch-adjusting operator of the HS algorithmrandomly selects one (or more) vector(s) in the chromosome and employs a swap strategy. The mechanism of this strategy is depicted in Figure 4. This operator is the distinctive part of the HS algorithm proposed in this research with the one given in (Sivasubramani and Swarup, 2011).

Harmony Vector1	0.56	0.23	0.45	0.68	0.94	0.33	0.87
Harmony Vector2	0.56	0.23	0.87	0.68	0.94	0.33	0.45

Fig.4. The pitch-adjusting operator

Finally, the randomization operator is utilized to increase diversity during the search process by entering new random solution within the population. The probability of using this operator (*P rand*) is obtained using Eq (24).

In the next subsection, a multi-objective version of the HS algorithm (MOHS) is developed to find a near-optimum front of the multi-objective problem at hand.

4. 2. 3. Multi-objective operators of the MOHS

To use HS algorithm in multi-objective functions problems, the comparison of the solutions should be considered with regard to all objective functions. To this end, Fast Non-Dominated Sorting (FNDS) and Crowding Distance (CD), as the two basic concepts of multi-objective meta-heuristics, are used. In FNDS, initial population (R) is evaluated. In this regard, all solutions are selected via the domination theory (Debet et al., 2002). Throughthis process, all solutions are divided into different fronts. After sorting the populations based on

FNDS, the solutions in the same fronts (equal non-dominated rank) are evaluated based on the CD measure. The procedure of CD calculation is computed based on (Hajipour et al., 2014). A selection operator should be applied to select individuals of the next generation;therefore, in this paper a crowded tournament selection operator is employed(Coello et al., 2007). In this regard, n individuals are randomly chosen. The combination of FNDS and CD measures providesthe solution's rank in Pareto fronts. The solutions with the least ranks are better and selected sooner in the new population. Afterwards, in order to assure the elitism, the parents and offspring populations are hybridized, and again, the non-domination sorting is executed until the population size becomes N. 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 (Debet al., 2002). By means of the proposed selection method, the population of the next iteration P_{t+1} is chosen to have a predetermined size.

Figure 5illustrates the Pseudo code of MOHS algorithm based on the basic operators of an HS algorithm and the described multi-objective operators. The main multi-objective parts are shown in a different color.

```
Set the parameters:Phcr, Paj,Pop. Size,Outer and Inner Loop size
Initialization: Generating harmonies as size as HM size
Evaluation: Evaluate harmonies
Performnon-dominated sorting and calculate ranks
Calculate Crowding distance (CD)
Sort population according to ranks and CDS

For i=1: Out. Loop Num.
Pt= population
    For j=1:  Inner loop Num.
        Generate Rand ϵ [0,1]
        If Rand<HMCR
H = Choose a solution randomly
            Generate Rand ϵ [0,1]
              If Rand<Ppa
H =Pitch the solution H
                Else
                  The solution keeps unchanged
                End if
        Else
H = Improvise a solution randomly
        End if
Update the HM (accept H, if dominates final Pareto solution of HM)
    End for
Qt= new population
Rt=Pt∪Qt
Performnon-dominated sorting onRt and calculate ranks
Calculate Crowding distance (CD) ofRt
Sort population according to ranks and CDS  on Rt
Create  Pt+1 as size as population size (population= Pt+1)
End for
```

Fig. 5. MOHSA Pseudo code (Rahmati et al., 2013)

4.3. Non-dominated sorting genetic algorithm (NSGA-II)

NSGA-II is a modified version of NSGA, which was presented by Srinivas and Deb (1995). To overcome the disadvantages of NSGA, such as the lack of elitism and the complexity of calculations, Deb et al. (2002) proposed NSGA-II as a Pareto-based algorithm in which both fast non-dominating sorting and CD concepts are considered.In this paper, an NSGA-II approachis applied to solve the proposed APP model and compare the results with those of the presented MOHSA approach. The crossover and mutation operators of NSGA-II are uniform crossover and swap operators, respectively (Haupt and Haupt, 2004). Further, binary tournament selection strategic method is applied in NSGA-II.The flowchart of NSGA-IIis presented in Figure 6.

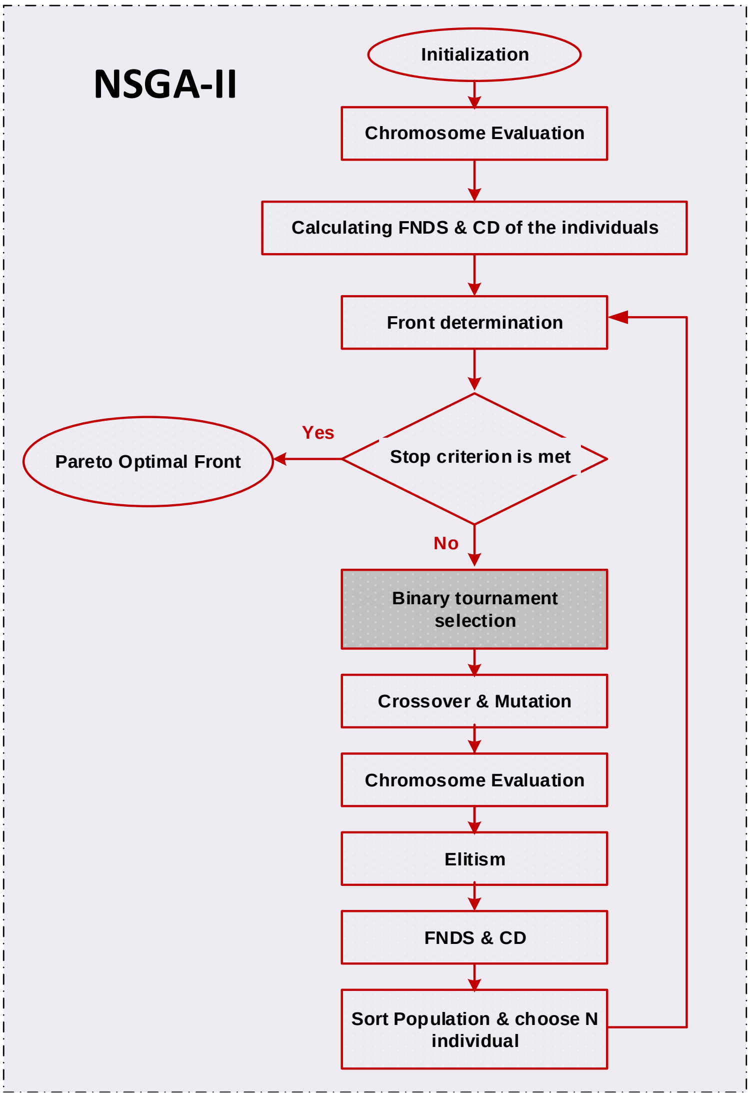

Fig. 6. NSGA-II flowchart

4. 4. Parameter tuning

In order to calibrate the parameters of the proposed algorithms, the Taguchi method is utilized in this research. In NSGA-II, the parameters are the numbers of population, crossover probability, mutation probability, and the maximum number of iteration. In this researchstudy, the numbers of population and the maximum number of iteration are 50 and 300, respectively. Optimal values of crossover probability (Pc) and mutation probability (Pm) are determined via the Taguchi method.

Three levels are considered for each parameter and the L9 design is used. In order to tune the parameters, the mean ideal solution (*MID*) is selected as the main response in Taguchi analysis. According to the main effects plots of Figure 7, the optimal value of crossover probability and mutation probability are 0.8 and 0.25, respectively forthetest problem No. 8. In MOHSA the parameters are the numbers of population, Inner Loop (Loop1), Outer Loop (Loop2), Pitch adjusting operator (Paj), and Harmony memory operator (Phcr) that the numbers of population, Inner Loop (Loop1), Outer Loop (Loop2) are 50, 40, and 60, respectively. Optimal values of Pitch adjusting operator (Paj) and Harmony memory operator (Phcr) are determined through the Taguchi method. Three levels are considered for each parameter and the L9 design is used. In order to tune the parameters, the mean ideal solution (*MID*) is selected as the main response in Taguchi analysis. According to the main effects plots of Figure 8, the optimal value of Pitch adjusting operator (Paj) and Harmony memory operator (Phcr)are 0.5 and 0.7, respectively forthe test problem No.8 (Table 4).

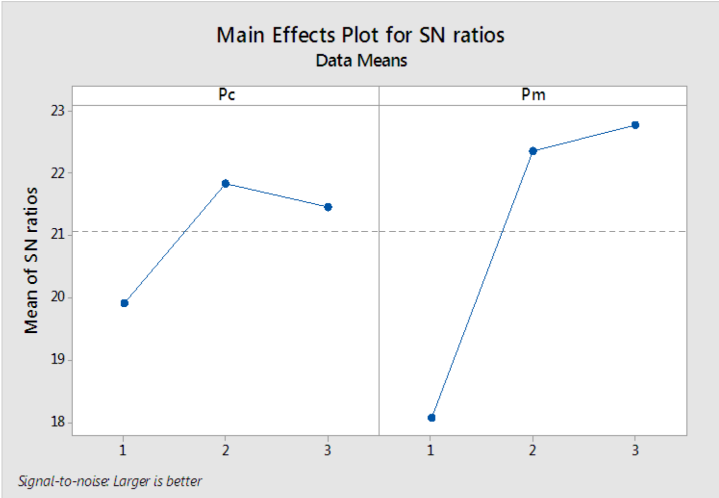

Fig. 7. Setting the NSGA-II parameters by Taguchi

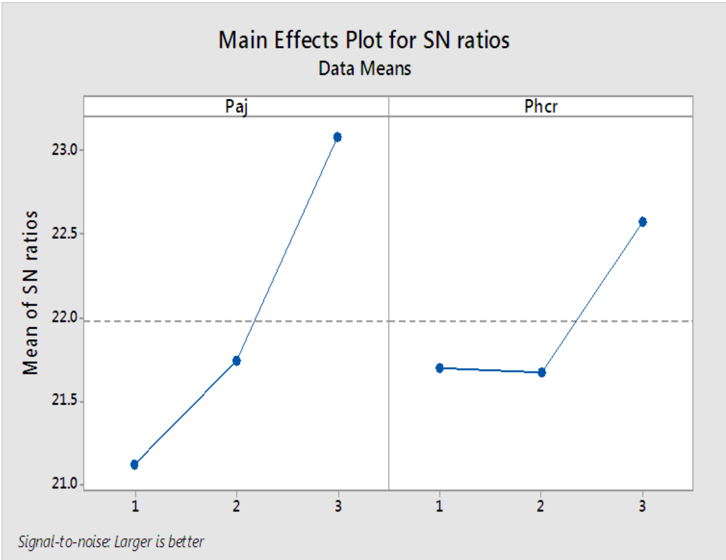

Fig. 8. Setting the MOHSA parameters by Taguchi

5. A Case Study in a Paper and Wood Industry

In this section, as a real-world industrial case a data set is provided from a paper and wood industry to illustrate the applicability of the proposed model to practical problems.

5. 1. Case description

At present, the factories belonging to the company under study cover an areaofabout 500,000 hectares altogether in the form of 73 comprehensive forest and farm management plans. Among the most important tasks of the company the protection, reforestation, development and exploitation by considering the social-economic conditions can be mentioned. Additionally, providing and executing comprehensive forest and farm management plans, establishing thousands of kilometers of ramp networks in order to access natural resources, silviculture and reforestation operations and finally, proper and substantial exploitation of the forests with the goal of continuous output, wood production increment and providing a part of the country's cellulose industrial needs are some of the other tasks thecompany supervisionseeks.

The expansion of the company in the recent decade and the existence of other factoriespressed wooden board, wood fiber and varied kinds of paper processing workshops haveboosted thedaily demand for various types of raw materials that should be provided from different locations nearbythe relevant suppliers and customers.

There are five types of end products which the desired case has sold during the recent years:

I. Printing and writing typical specifications: 50 g/m^2
II. Newsprint typical specifications (HB)
III. Fluting typical specifications 113–127 g/m^2
IV. Newsprint typical specifications 48.8g/m^2

V. Printing and writing typical specifications 70 g/m^2

There are ten substances supplied as the combinations ofthefollowing cellulosic sources:

I. Bombast stem, Hempseed and Cotton which have a long yarn (about 1.2–6 mm).
II. Plant stems like Wheat, Grain, Cane, Hemp, etc.
III. Pine trees (with long yarn) or plane tree (with short yarn about 0.5–1.2 mm).
IV. Types of discarded papers or scrap cartons.

The planning horizon of monitored time is assumed to be 12 periods. According to Figure 9, there are 3 sites eachlocated nearthe customers' and suppliers' zone. Suppliers are spread geographically throughthe entire country and also near the woods. The values of parameters can be provided upon request.

5. 2. Optimal decisions

In this sub-section, first, to show the conflict between the objective functions, the mathematical model of the problem under study is solved using the GAMS softwarewith each objective function separately (in absence of the other objective function); the results are presented in Table 1. The results revealthat two functions are in conflict with each other. Moreover, to obtain the Pareto solutions, the problem is solved separately once via the ε-constraint method and another time using the MOHS algorithm; the results are presented in Table 2. Finally, according to expert viewpoints, Pareto solution 2(Table 2) (for ε-constraint method) is selected as the ultimate optimal response.

Table 1
Investigation of the conflict between the objective functions of the problem

Objective function	The results of solving the model with different objective functions	
	With $f_1(x)$	With $f_2(x)$
$f_1(x)$	879133.010	2930127.246
$f_2(x)$	0.204	1.000

Table 2
The comparison of the Pareto responses of the ε-constraint and MOHSA methods

Objective Function	MOHSA			ε-constraint		
	Pareto solution no.			Pareto solution no.		
	1	2	3	1	2	3
$f_1(x)$	905670.88	1136587.19	1292267.03	934652.35	1213079.51	1387636.34
$f_2(x)$	0.364	040.6	0.844	0.342	0.592	0.832

5.3. Sensitivity analysis

In this sub-section, model parameters areinitially categorized into lead time parameters and parameters related to cost objective function. Afterwards, the effect of parameters' value changes is checked for the Pareto solution 2 (for ε-constraint method); the results are presented in Table 3. For example, the results show that by decreasing 20% of the parameters' values, 33.14% of the value of the cost function ($f_1(x)$) reduces with the same reliabilitylevel ($f_2(x)$) or by decreasing 20% of the mean leadtimes, 4.2% of the value of the cost function decreases with thesame reliabilitylevel.Additionally, once20% of the value of the parameters other than the mean lead timesincreases, 1.35 of reliabilitylevel reduces and 33% of the value of the cost function increases.

Table 3
Computation results of the sensitivity analysis

Objective function	Change the value of the parameters other than the mean lead times		Change the mean lead times		Change the value of the parameters		Increase the mean lead times	Decrease the mean lead times
	Increase	Decrease	Increase	Decrease	Increase	Decrease	Decrease the value of other the parameters	Increase the value of other the parameters
$f_1(x)$	1440747.44	779617.08	13046090.3	1033558.8	1881801	720184	808060.5	1374620.4
$f_2(x)$	0.607	0.615	0.643	0.615	0.666	0.615	0.603	0.615

6. Result Analysis and Comparisons

In this section, the performance comparisons of two meta-heuristic algorithms are investigated. The proposed algorithms are coded in MATLAB software (Version, R2013a) environment, and the experiments are performed on two GHz laptop with eight GB RAMto estimate the response functions. To evaluate and compare the performances of the solution methodologies under different environments, the experiments are implemented on 12 problems which are reported in Table 4. Then, these instance problems are solved by MOHSA and NSGA-II. Moreover, the following information is also presentedin Table 5.

Table 4
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	15	6	3
7	10	20	12	4
8	10	30	12	4
9	10	40	12	5
10	20	40	18	5
11	20	50	24	10
12	35	50	24	10

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

1. *Quality Metric (QM)*: The ratio of the number of non-dominated solutions 'algorithm to total number of archives non-dominated solutions 'algorithm
2. *Diversity*: measures the extension of the Pareto front (Zitzler and Thiele, 1998).
3. *Spacing*: measures the standard deviation of the distances among solutions of the Pareto front (Zitzler and Thiele, 1998).
4. *Mean ideal distance (MID*): measures the convergence rate of Pareto fronts to a certain point (Zitzler and Thiele, 1998).
5. The CPU *time* of running the algorithms to reach near optimum solutions.

The result 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 to Figures 9-13.

Table 5
Input parameters' values of the numerical examples

$D_{ict} \sim U\ (100, 500)$	$T_{1sjt} \sim U\ (10, 30)$
$C_{qj} \sim U\ (10, 40)$	$T_{2ict} \sim U\ (10, 30)$
$L_{kjt} \sim U\ (1000, 3000)$	$Cr_{smt} \sim U\ (80, 120)$
$a_{ij} \sim U\ (0.1, 0.2)$	$\gamma_{im} \sim U\ (3, 9)$
$F_{kjt} \sim U\ (2000, 4000)$	$\alpha_t \sim U\ (0, 1)$
$H_{kjt} \sim U\ (6000, 10000)$	$TI_{1,jt} \sim U\ (7, 9)$
$I_{1mjt} \sim U\ (100,200)$	$TI_{2,jt} \sim U\ (0, 4)$
$I_{2ijt} \sim U\ (150, 250)$	$TI_{3,jt} \sim U\ (0, 4)$
$I_{3ict} \sim U\ (150, 250)$	$PM_{mj} \sim U\ (1, 20)$
$\pi_{ict} \sim U\ (100, 400)$	$PP_{ic} \sim U\ (1,20)$
$Lt_{smjt} \sim U\ (0, b_{smjt})$	$P_{1j} \sim U\ (1000,2000)$
$b_{smjt} \sim U\ (2\ , 5)$	$P_{2j} \sim U\ (500,1000)$
$LT_{ijtc} \sim U\ (0, b\ f_{ijct})$	$P_{3c} \sim U\ (800,1400)$
$bf_{ijct} \sim U\ (2,5)$	$P_{4smt} \sim U\ (1000,5000)$
$\mu_{LT_{smjt}} = b_{smjt}/2$	$\varphi_{LT_{ijct}} = 1$
$\mu_{LT_{ijct}} = bf_{ijct}/2$	$m = 1,2, \ldots\ldots, 10$
$\varphi_{LT_{smjt}} = 1$	$s = 1,2,3,4,5$

Table 6
Computational results of multi-objective metrics comparisons for two algorithms

Problem	**Proposed MOHSA**					**NSGA-II**				
No	*QM*	*MID*	*Spacing*	*Diversity*	*Time*	*QM*	*MID*	*Spacing*	*Diversity*	*Time*
1	0.0143	5.67E+06	5.67E+07	73250153	47.21	0.0128	4.53E+07	4.34E+07	736451436	96.56
2	0.0134	5.71E+06	9.23E+05	776348122	52.23	0.0084	1.43E+07	1.53E+06	732457355	110.73
3	0.0288	6.64E+07	8.43E+06	72345681	60.78	0.0295	9.21E+07	5.21E+07	734653213	150.13
4	0.036	5.83E+07	8.73E+05	63578532	101.42	0.0169	3.24E+08	6.53E+07	478543213	250.67
5	0.0424	1.23E+08	4.21E+07	763421566	324.32	0.0003	3.23E+08	6.21E+06	84384783	501.52
6	0.0345	2.07E+08	9.83E+06	787432189	403.56	0.0132	6.58E+08	2.67E+07	684375474	1004.78
7	0.0043	2.14E+08	5.67E+05	298743215	1254.67	0.0136	9.23E+08	5.67E+06	387543316	2500.90
8	0.0123	3.67E+08	7.87E+06	384521854	1546.56	0.0042	1.55E+09	1.43E+08	88739452	3587.87
9	0.0035	4.43E+08	6.94E+07	356743219	1875.47	0.0023	8.23E+08	4.23E+07	89765432	4279.34
10	0.0298	5.67E+08	5.78E+07	2243754172	5783.32	0.0234	9.67E+08	3.41E+07	98743215	10764.57
11	0.0243	2.41E+09	3.23E+08	465321786	8785.78	0.0005	2.41E+09	5.68E+06	87645321	18734.12
12	0.0298	3.59E+09	8.53E+07	564324187	9625.32	0.0242	5.63E+09	3.11E+07	754321767	32567.34

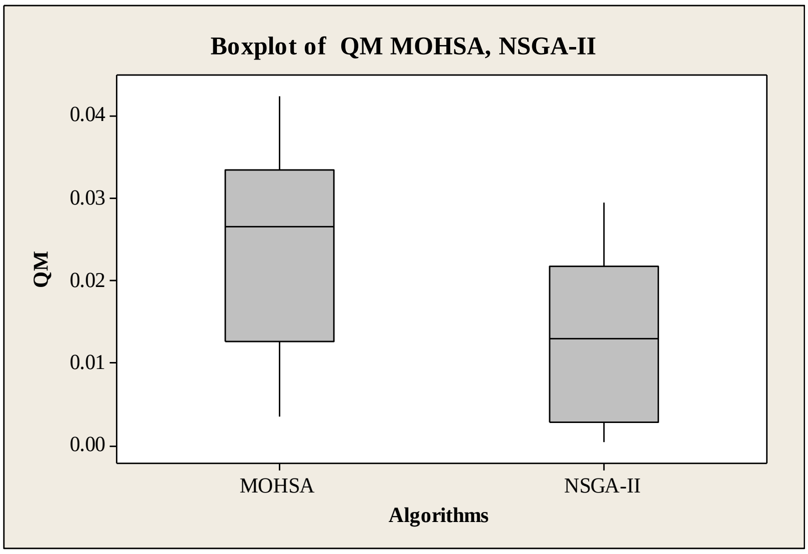

Fig. 9.Box-plotcomparisons of the algorithms in terms of *QM* metric

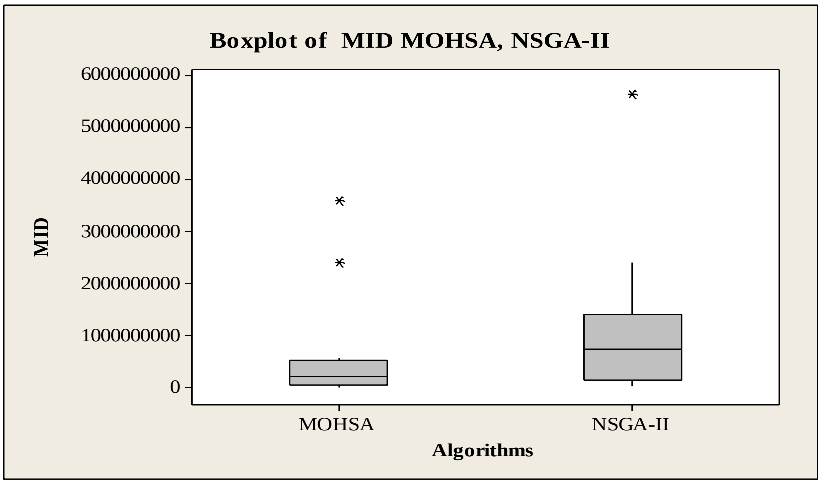

Fig. 10.Box-plotcomparisons of the algorithms in terms of *MID* metric

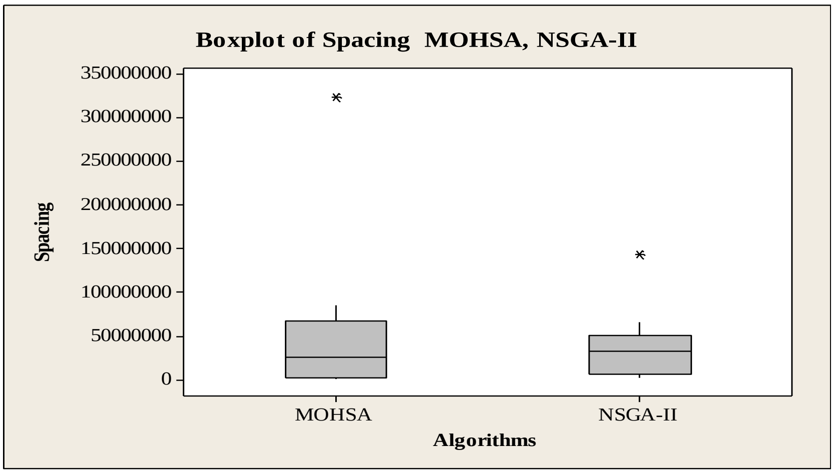

Fig. 11.Box-plotcomparisons of the algorithms in terms of *Spacing*metric

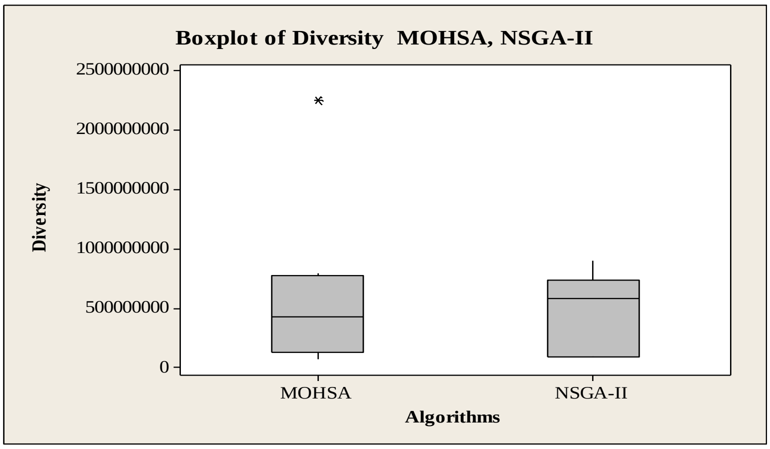

Fig. 12.Box-plot comparisons of the algorithms in terms of *Diversity* metric

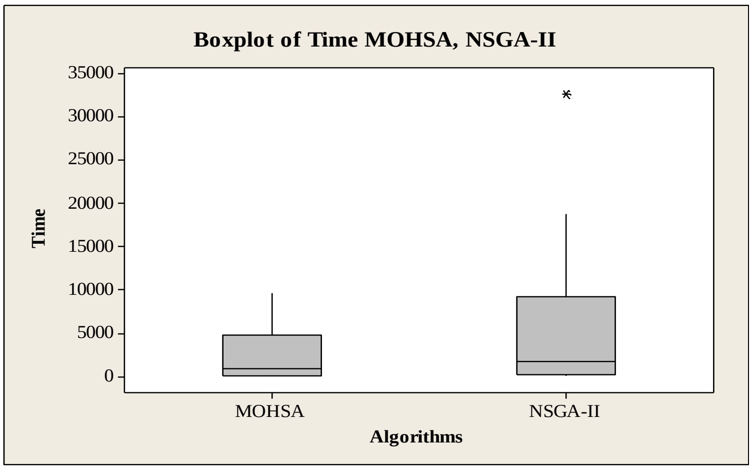

Fig. 13.Box-plot comparisons of the algorithms in terms of *Time* metric

The figures show that means *QM* metric of MOHSA is more than NSGA-II. Moreover, the mean of *MID*, *Diversity*, *Time* and *Spacing* metrics of NSGA-II is more than MOHSA.

It is worthy of notethat the bigger value is desired in terms of the *QM* metrics. Thus, according to an analysis of variance outputs in Table 7 and *p*-values, MOHSA shows better performance in terms of *QM*. However, in terms of *MID*, *Diversity*, *Time* and *Spacing* metrics, the algorithms almost function similarly. This conclusion is confirmed at a 95% confidence level.

Table 7

Statistical comparisons of algorithms based on five metrics

Metric	**Source**	**Degree of freedom**	**Sum squares**	**Mean squares**	**F**	**P-value**
	Algorithms	1	0.000569	0.0000898	280.70	0.046
QM	Error	22	0.0000003	0.0000003		
	Total	23	0.0008986			
	Algorithms	1	1.35499E+18	1.35499E+18	0.72	0.405
MID	Error	22	4.12980E+19	1.87718E+18		
	Total	23	4.26530E+19			
	Algorithms	1	1.76307E+15	1.76307E+15	0.37	0.550
Spacing	Error	22	1.05011E+17	4.77322E+15		
	Total	23	1.06774E+17			
	Algorithms	1	1.49178E+17	1.49178E+17	0.67	0.421
Diversity	Error	22	4.87150E+18	2.21432E+17		
	Total	23	5.02067E+18			
	Algorithms	1	83208646	83208646	1.48	0.237
Time	Error	22	1239908472	56359476		
	Total	23	1323117118			

Besides, to clarifythe better performance of the proposed Pareto-based algorithms, the obtained Pareto solutions of all algorithms on 2 test problems, 8 and 12, are presented in Figures14 and 15. In order to show the convergence objectives, the convergence plots of the two objectives are plotted inFigures 16 and 17.

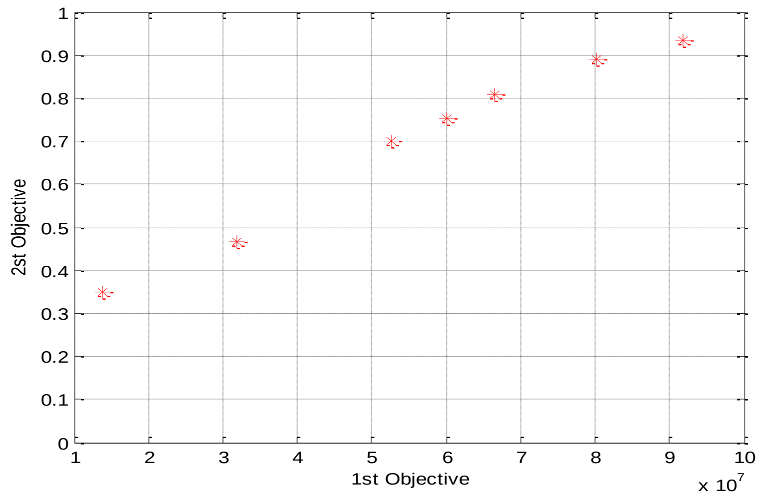

Fig. 14.Obtained Pareto-front of the proposed MOHSA on test problem 8

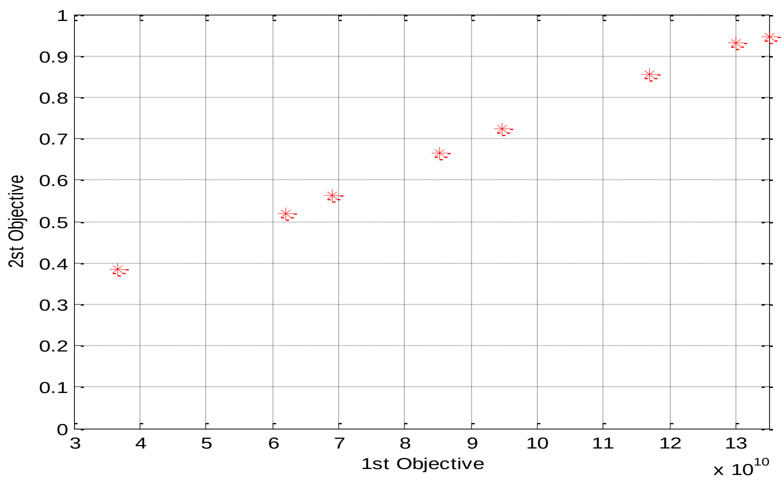

Fig. 15. Obtained Pareto-front of the proposed MOHSA on test problem 12

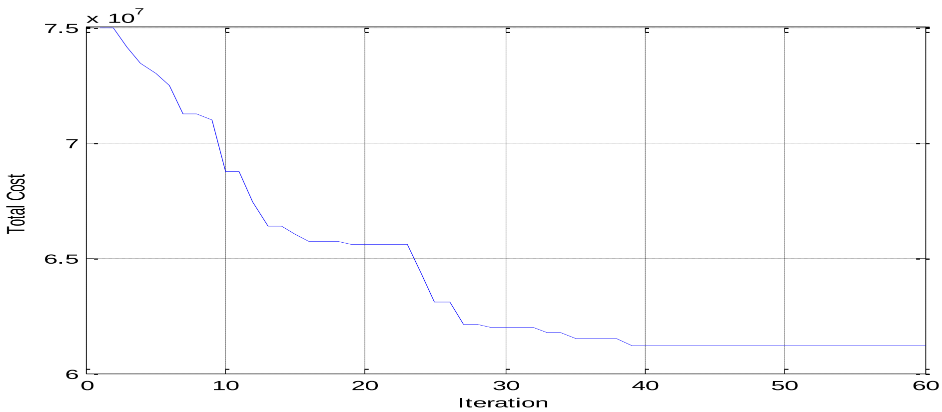

Fig. 16. The convergence plot of the cost function for problem 4based on the proposed MOHSA

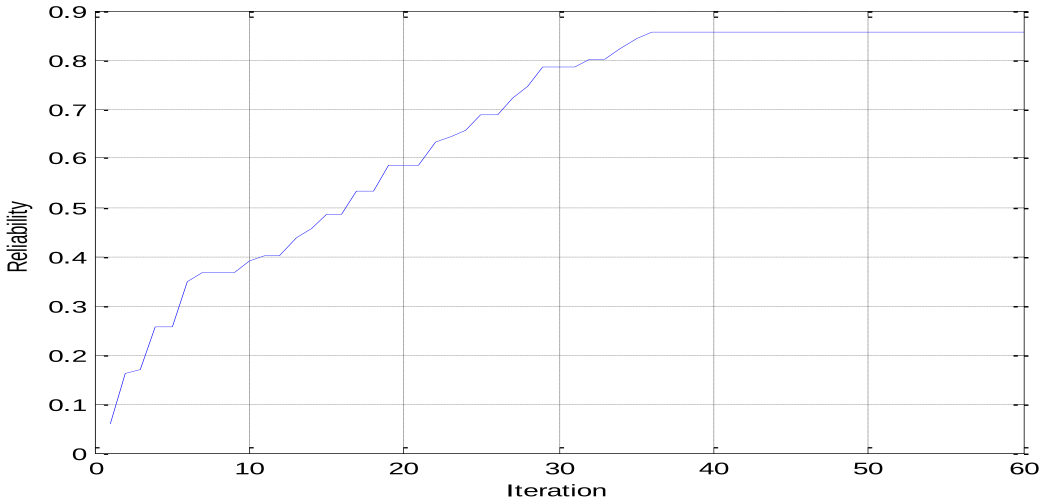

Fig. 17. The convergence plot of the reliability function for problem 4based on the proposed MOHSA

7. Conclusion and Future Research

A bi-objective model is developed to deal with a supply chain including multiple suppliers, multiple manufacturers, and multiple customers, addressing a multi-site, multi-period, multi-product aggregate production planning (APP) problem.This bi-objective model aims to minimize the total cost of supply chain including inventory costs, manufacturing costs, work force costs, hiring, and firing costs, and maximize the minimum of suppliers' and producers' reliability by considering probabilistic lead times to improve the performance of the system and achieve a more reliable production plan. The model is applied to an illustrative case study of the paper and wood industry and theε-constraint method is used to solvethe proposed bi-objective optimization model. With regardto the fact thatthe proposed bi-objective model is NP-Hard, for large-scale problems one multi-objective harmony search algorithm has been used. To demonstrate the performance of the presented algorithm, NSGA-IIis applied. The results reveal that MOHSA has better performance in terms of *QM*. However, in terms of *MID*, *Diversity*, *Time* and *Spacing* metrics, our proposed MOHSA has the same capability as the best-developed algorithms in the literature. For future investigations and developing the presented model, it is suggested that the function of the lead time of the products and raw materials be determined according to several factors including reliability of the warehouses for storing products and raw materials, the reliability of the transportation routes and the reliability of production machines.

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