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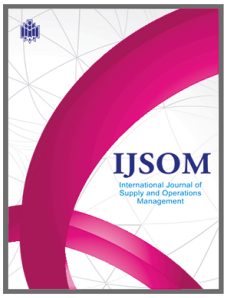

Presenting a multi objective model for Supplier selection in order to reduce green house gas emission under uncertion demand

Habibollah Mohamadi[a], Ahmad Sadeghi[a*]

[a]*Department of industrial Engineering, Science and Research Branch, Islamic Azad University, Qazvin, Iran*

Abstract

Recently, much attention has been given to Stochastic demand due to uncertainty in the real - world. In the literature, decision-making models and suppliers' selection do not often consider inventory management as part of shopping problems. On the other hand, the environmental sustainability of a supply chain depends on the shopping strategy of the supply chain members. The supplier selection plays an important role in the green chain. In this paper, a multi-objective nonlinear integer programming model for selecting a set of suppliers considering Stochastic demand is proposed. while the cost of purchasing including the total cost, holding and stock out costs, rejected units, units that have been delivered sooner, and total green house gas emissions are minimized, while the obtained total score from the supplier assessment process is maximized. It is assumed that the purchaser provides multiple products from the number of predetermined supplier to a Stochastic demand and the uniform probability distribution function. The product price depends on the order quantity for each product line that is intended. Multi-objective models using known methods, such as Lp-metric have become an objective function and then using genetic algorithms and simulated annealing meta-heuristic is solved.

Keywords: Stochastic Demand; green house gas emission; genetic algorithm; simulated annealing; L-p metric.

1. Introduction

Supply chain management (SCM), includes manufacturers, suppliers, distribution centers and retailers, and in order to ensure efficient flow of raw materials, it works in process inventory and finished goods through the facility. The Supply chain management is a coordinator of production activities, inventory, supply chain positioning and transportation between participants, striving to achieve greater efficiency and to meet the expectations of customers

* Corresponding email address: a.sadeghi@qiau.ac.ir

(Hugos, 2006). One of the most discussed methods in Supply Chain Management is purchasing the needed items. Purchase in an organization usually includes all activities associated with the purchase process. These activities include determining the need for the supplier selection, setting the conditions for issuance of a contract to order and ensuring it is sent (Weijum and Zhiming, 2007). Among the various activities a company is involved in, purchase is one of the most important strategies, which creates considerable opportunities to reduce costs and increase the quality of provided raw materials. Therefore, shopping has a key role in the success of company strategies through the proper selection of suppliers that can support their competition and long-term strategies (Mendoza and Ventura, 2012). Consequently, choosing and determining the most appropriate suppliers in the supply chain is considered an important issue that should be considered strategically. The objective of supplier selection is to identify the supplier that has the highest potential in order to meet the company's needs or, simply, to offer a more acceptable cost (Wang and Yang, 2009). Acceptable suppliers, cause a reduction in procurement costs and production time, and also increase customer satisfaction and strengthen the company's competitiveness. The main objective of evaluating suppliers is to allocate desirable and optimal quotas to them at the time of an order.

On the other hand, one of the favorite topics in the supply chain management is the issue related to the supply chain management environment. Green supply chain management, integrating supply chain management with environmental requirements at all stages of product design, raw materials, production processes, distribution and transmission, choosing green suppliers and delivering them to the customer and finally, recycling management to maximize the amount of energy and resource efficiency goes side by side with improved performance of the entire supply chain (Sarkis, 2006). The area includes or displays the suppliers based on their environmental performance and the distinctive function of a particular supplier (for example, requirements and legal requirements) or an advanced one (as the green joint product design) (Rao, 2002). Since all human activities, directly or indirectly, contribute to greenhouse gas emissions, all producers should pay attention to their share in emissions and consider the economic consequences it may have. The amount of carbon in a product will affect the greenhouse gas emissions. These gases are produced during the process of manufacturing, marketing and using the product. Most of the earlier models have concentrated on cost, quality and delivery time issues, but have not allocated enough importance to greenhouse gas emissions in evaluating suppliers. An interesting survey conducted by a consulting firm (Tru cost, 2009) showed that only 19 percent of the total greenhouse gas (GHG) emission in the supply chain is generated by direct operational activities of the company, and the rest of the 81 percent emission is generated by other indirect activities such as emission from first tier supplier, electricity supplier and emission from the other supply chain members. In this scenario, supplier selection plays an important role in minimizing carbon emission in the supply chain. Therefore, the supplier tendency to minimize greenhouse gas emissions is becoming one of the supplier selection factors. The environmental sustainability of the supply chain depends on the purchase strategy of the supply chain members. As a result, supplier selection plays an important role in the green

chain (Shaw et al., 2012). The main objective of this paper is to propose a multi objective model for order allocation and supplier selection when the buyer of goods is faced with random demands. Also, in this model, in addition to reducing the amount of returned product and late delivered units, environmental issues and an overall reduction in greenhouse gas emissions are intended as a criterion for the selection of suppliers. In this study, we seek to answer the question that. How is the issue of supplier selection and order quantity allocation with simultaneous consideration of issues of timely delivery, the quality, supplier's scores, environmental matters and procurement costs when the customer is faced with random demand for products dealt with. The remainder of the study is as follows: Section 2 is devoted to a review of the literature. Section 3 is the notation and the problem formulation of the issue. The solution algorithms are presented in Section 4. Section 5 is concerned with some computational results in order to evaluate the performance of proposed heuristic algorithms. Section 6 concludes and presents ideas for further research in these fields.

2. Literature review

The widespread nature and supplier selection process modeling complexity is heavily reliant on multi-criteria and multi-objective decision making. Supplier selection process has recently (in the past decade) begun to utilize different aspects of the environment (Herva and Roca, 2013). Over the past decades, many models have been developed in the field of purchasing and supply. These models are often developed using mathematical theories such as linear programming, decision theory, game theory and expert systems, nonlinear programming and multiple objectives linear and non-linear mathematical models. The models are employed in various domains such as initial evaluation and selection of suppliers, decisions about purchasing, the allocation of orders to suppliers, the supplier relationship management, and procurement cost analysis. Since the literature review is extensive, we focus on the problem of assigning orders to green suppliers in which the techniques of multi-objective decision-making are used. Weber et al. (2000) presented a multi-objective programming approach and data envelopment analysis (DEA) to determine the number of suppliers in the environment purchase with multiple sellers and a single product. Ghodsypour and O'Brien (2001) have presented the mixed integer linear programming model to solve the multiple criteria supplier selection problem. This model was presented to determine the optimal allocation of products to suppliers in order to reduce the procurement costs. Amid et al. (2006) introduced a fuzzy multi-objective linear programming model for supplier selection. This model deals with the ambiguity and imprecision of input data, and to helping the decision-makers determine the optimal order quantities of each supplier. Furthermore, Narasyman et al. (2006) presented a multi-objective programming model concerning the suppliers selection problem in multi-product and discounts, while bidding mechanisms for the selection of suppliers were considered. Concerning the suppliers model, with a certain amount of uncertainty in the input data, Lee et al. (2009) conducted a research on the choice of contract suppliers under demand and price uncertainty in a dynamic market. Mendoza and Ventura (2010) proposed a two-step approach for supplier selection and order quantity allocation simultaneously. In the first step, Analytical Hierarchy Process (AHP) was introduced for ranking and reducing the number of suppliers to an acceptable amount. In the second phase, they offered an integer linear

programming model to find the optimal order. For Ozkok and Tiryaki (2011) a compensatory fuzzy approach with multiple items is used for the problem of multi-objective linear supplier selection. Fuzzy operators were used in this study. Lee and Zabynsky (2011) announced that the uncertainty combination in demand and the supplier capacity in the optimization model could result in a robust selection of suppliers. They suggested contingency planning (SP) potential disruption planning (CCP) models in order to determine the minimal set of suppliers and the optimal order quantity by taking business courses that offered discounts. Both of the above-mentioned models are an attempt to create a balance between a small number of suppliers, with the risk of failure to respond to the demand. Fahimnia et al. (2013) presented a case study on the impact of carbon pricing on closed-loop supply chain. This study is the first assessment of the effects of forward and reverse supply chain on the carbon footprint. major researches are displayed in table (1).

Table1. Related literatures of supplier selection

Author	Year	Description
Yang et al.	2011	Multi-product supplier selection model provided with Stochastic demands and budget constraints and the level of service.
Shaw et al.	2012	Supplier selection using fuzzy AHP and fuzzy multi-objective linear programming to reduce carbon emissions in the supply chain for a single product.
Arikan	2013	Multi-objective linear programming for supplier selection problem with three objective functions to minimize the cost and maximize the quality and delivery time maximization.
Shen et al.	2013	Fuzzy Multi Criteria approach for evaluating the performance of green suppliers in the supply chain green with verbal performance. Fuzzy set theory for understanding the human mind and using fuzzy TOPSIS to generate an overall performance score for each suppliers applies.
Dou et al.	2013	Green supplier evaluation model using the methodology of network analysis in Grey environment.
Zhang and Chen	2013	Supplier selection problem with random demand and fixed selection costs and quantity discounts. In addition, the maintenance costs for excess inventory and shortage costs are also considered.
Zhan g and Zhang	2011	The supplier selection and the purchase of a single product or multiple objectives are addressed under stochastic demand. The goal is to select the suppliers and the allocation of the purchase order, to minimize the maintenance costs and shortages.
Esfandiari and Seifbarghy	2013	Multi-objective supplier selection model with stochastic demand, in this model, the price depends on the quantity ordered.

In this study, the supplier selection problem is addressed by considering the purchasing problem under stochastic demand and reducing the emissions of carbon by multiple suppliers and multiple products. In this study, we propose a multi-objective model to minimize the cost of purchase, returned units, delivered late units and the overall reduction of the greenhouse gas emissions as well as maximizing the process of evaluating suppliers. It is assumed that the customer buys various products from a number of preset suppliers, as provided. Stochastic demands provide the purchaser of the product from the supplier with a

predetermined number. The uniform probability distribution function for each sample product demand is considered. It should be noted that the stochastic demand functions are independent of the probability distribution of various products. Since the demand is stochastic, the buyer may incur holding or shortage costs. This cost is considered as the cost of purchase. In this study, raw material supply prices of suppliers are considered depending on the order quantity for each product linearly. Selection and rate allocation problem with suppliers, and also considering the issues with timely delivery, quality, rating assessment of suppliers and procurement costs in terms of environmental issues, random application of innovation research, are considered the genesis of the process.

3. Presentation and Discussion of the proposed model

In this study, a multi-objective model is proposed, in which it is attemped to minimize the cost of purchase, returned units and units delivered late and greenhouse gas emissions and bring the total score of the supplier evaluation form to maximum. The proposed model can be used for companies that buy a number of products (parts) from a selected number of suppliers including refrigerator manufacturers, suppliers of cloth and etc. The proposed model has five different objective functions: minimizing the total operating cost of the purchase including purchase costs, maintenance costs and the costs of inventory shortages, to minimize the number of returned units, to minimize the total units delivered late, to minimize greenhouse gas emissions, while the five functions are intended to maximize the total score of the supplier evaluation. Objective functions, respectively, are expressed by equations (1) - (5).

3.1.Model Assumptions

1. It is assumed that the buyer obtains multiple products from a number of predetermined suppliers.
2. Because the demand is stochastic the buyer incurs shortage and maintenance costs in addition to the purchase cost.
3. It is assumed that the buyer assumes minimum and maximum order quantity per supplier.
4. It is assumed that the price of commodity suppliers linearly depend on the order quantity for each product.
5. The stochastic demand functions are independent of the probability distribution of various products.

3.2. Notations

i: Supplier Index.
j: product index.
P_{ij} : Price of product j offered by supplier i is dependent on the order quantity.
W_i : Supplier evaluation score i is obtained by the purchaser.
t_{ij} : Percentage of late delivered units of product j by supplier i.
q_{ij} : Percentage of returned units of product j that i have been delivered by suppliers.

Q_j : Highest acceptable percentage of (authorized) returns of the units of product j.
T_j : Highest acceptable percentage (permissible) of late delivered units of product j.
D_j : Demand random variable of product j in the planning horizon.
G_{ij}: Carbon emissions for product j from supplier i.
C^{cup}: Maximum carbon emitted for different products.
$F(D_j)$: Probability distribution function.
H_j : Holding cost per unit of product j that remains at the end of the planning horizon.
π_j : Penalty cost per unit of lost demand for product j.
L_{ij} : The least amount of product j which should be ordered to supplier i.
U_{ij} : The maximum amount of product j which should be ordered to supplier i.
LD_j : Low demand for product j.
UD_j : High demand for product j.

Decision variables:

X_{ij}: Order quantity of product j is assigned to supplier i.

The final model is as follows:

$$Min\ Z_1 = \text{Min } Z_1 = \sum_i \sum_j p_{ij} X_{ij} + \sum_j h_j \int_{D_j=LD_j}^{\sum_i X_{ij}} (\sum_i X_{ij} - D_j) f(D_j) + \sum_j \pi_j \int_{\sum_i X_{ij}}^{UD_j} (D_j - \sum_i X_{ij}) f(D_j) \quad (1)$$

$$\text{Min } Z_2 = \sum_i \sum_j q_{ij} X_{ij} \quad (2)$$

$$\text{Min} Z_3 = \sum_i \sum_j t_{ij} X_{ij} \quad (3)$$

$$\text{Max} Z_4 = \sum_j \sum_i W_i X_{ij} \quad (4)$$

$$\text{Min } Z_5 = \sum_i \sum_j G_{ij} X_{ij} \quad (5)$$

Constraints of the model are expressed by equations (6) – (10)

$$L_{ij} \le X_{ij} \le U_{ij} \qquad \forall\ i,j \quad (6)$$

$$\sum_i \sum_j q_{ij} X_{ij} \le Q_j \sum_i X_{ij} \qquad \forall\ j \quad (7)$$

$$\sum_i \sum_j t_{ij} X_{ij} \le T_j \sum_i X_{ij} \qquad \forall\ j \quad (8)$$

$$\sum_i \sum_j G_{ij} X_{ij} \le C_j^{cap} \qquad \forall j \quad (9)$$

$$D_j = [LD_j, UD_j] \qquad \forall j \quad (10)$$

$$Xij \ge 0\ , INTGE \qquad \forall\ i,j \quad (11)$$

Equation (1) is composed of three parts. In the first part, $\sum_i \sum_j p_{ij} X_{ij}$, represents the total purchase cost which the sum of price of any product is offered by any supplier product multiplied by the order quantity of each product assigned to each supplier. In the second part

$\sum_j h_j \int_{D_j=LD_j}^{\sum_i X_{ij}} (\sum_i X_{ij} - D_j) f(D_j)$, indicates the total cost of inventory. Holding cost per unit of product j is shown by h_j. The remaining second part of the inventory equation describes the remaining expected parts at the end of the planning horizon. Which is zero when($\sum_i X_{ij} < D_j$).The third part $\sum_j \pi_j \int_{\sum_i X_{ij}}^{UD_j} (D_j - \sum_i X_{ij}) f(D_j)$, represents the cost of inventory shortages. π_j is the shortage cost per unit of product j in the planning horizon.

In this paper, the random variable of product demand j is considered a uniform probability distribution. Considering different symbols, $f(D_j)$ into equation (12) is defined as:

$$f(D_j) = \frac{1}{UD_j - LD_j} \quad (12)$$

In this paper it is assumed that the suppliers' prices depend on the linear size of the order that equation (13) is obtained from:

$$P_{ij} = a_{ij} - b_{ij} X_{ij} \quad (13)$$

The parameters a_{ij} and b_{ij} represent the slope of the curve order price in Figure 1.

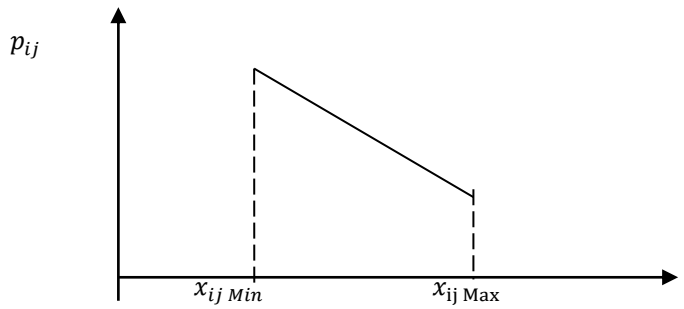

Figure1. curve order – price Product j of supplier i

Equation (2) is an attempt to minimize the amount of total returned products. Usually, the buyer intends to reduce the number of defective items to improve product quality, reduce costs associated with returned product quality and reduce warranty costs. This minimization can also lead to the satisfaction of the buyers and clients. To ensure the model structure, the number of items returned should be kept at a low level. Equation (3) corresponds to minimizing the total amount of late delivered units. In order to reduce the total ordering time from suppliers, the cost of maintenance and to prevent adverse effects resulting from late delivery of items purchased and the whole supply chain, we will seek to minimize their number. Although the number of products that are delivered late to the buyer cannot be known precisely before they occur, it is possible to estimate the values by using previously acquired documents about their performance and prediction methods. Equation (4) is intended to maximize the total scores for supplier evaluation. Using MADM techniques like AHP, ANP, ANP Fuzzy, AHP Fuzzy, Topsis, etc., buyers can use intangible criteria to make decisions in the selection of suppliers. According to the procurement strategy, various criteria, such as service level of organization, communication, etc. can be included in the

decision making process. Obviously, some of these buyers can, in accordance with the company policies, can be in some of these criteria. That is why using MADM methods (are) mentioned above for each of the suppliers'gains weight. Using the results obtained, the buyers use suppliers that have their total weight maximized. The objective function of equation (5) is to minimize the total amount of greenhouse gas emissions supplied, and provide for product j by supplier i. Greenhouse gases spread in the case of raw materials and transportation of raw materials for delivery to customers and clients. Carbon footprints of products can be traced in the available profile (PAS) 2050, by a measure developed by the Institute of standard of Great Britain. The buyer could consider the fixed rate cap carbon emissions as a constraint on models. Equation (6) ensures that the order quantity of product j is assigned to supplier between the minimum and maximum values. Equation (7) ensures that the total number of rejected units is less than or equal to the maximum permissible level. Equation (8) ensures that the total number of late delivered units of each product is below the permitted level. Equation (9) is the maximum amount of carbon emissions for product j. Equation (10) consists of upper and lower limit for the demand of any product. Equation (11) is stated to be an integer.

In order to solve multi-objective supplier selection problem in this study, use of LP-metric method for p is equal to one which implies that the late optimized (Z_1^*, Z_2^*, Z_3^*, Z_4^*, Z_5^*) of the model, and then to combine the min to the single objective function in equation (14) are listed. It should be noted that the objective function (14), minimizes the (6) – (11) constraints.

$$Z=b1[\frac{[Z_1-Z_1^*]}{Z_1^*}]+b2[\frac{Z_2-Z_2^*}{Z_2^*}]+b3[\frac{Z_3-Z_3^*}{Z_3^*}]+b4[\frac{Z_4-Z_4^*}{Z_4^*}]+b5[\frac{Z_5^*-Z_2}{Z_5^*}] \quad (14)$$

b1, b2, b3, b4, b5 weight and the importance of each objective stated by the decision maker will be offer.

Lp-metric method, is a method of combining the multiple objectives into a single unit. For non-negative weights as coordination spaces L_p any solution X of Z can be the ideal solution to minimalizing equation (15):

$$\text{Minimize } L_p(x) = (\sum_{i=1}^{m}[W_m \ |f_m(x) - Z_m^*|^p])^{\frac{1}{p}} \qquad p\in[1,\infty) \quad (15)$$

Equation (15) W_m represents goal weight of M and $\sum_{i=1}^{m} W_m = 1$, $W_m \in [0,1]$ is established. P = 1 indicates that it is equally important for all deviations from the targets considered. P = 2 indicates that any variation is in accordance with their own weight, so that the largest deviation would be attributed to the greatest weight of the assignment. When p tends to infinity, it tends to minimize the sum of the deviations of the maximum single deviation from the target (Lai and Hwang, 1996).

4. The proposed solving techniques.

The proposed model is considered a non-linear planning model in which the number of decision variables and constraints increase severely when the size of the problem increases. In these models, large scale problems cannot be solved using software environments such as

Lindau, Lingo, and etc, which are based on traditional methods such as simplex, branch and bound and similar methods. solving time is an important parameter in dealing with optimization problems, yet major issues in the proposed model using exact methods cannot be solved in a reasonable time, therefore this is a NP-hard problem. On the other hand, With respect to the equation (14), we can conclude that the model is in a non-linear and integer condition. These features make the model hard enough to solve. Under such circumstances, meta-heuristic algorithms can be used (Gen, 1997). Since the objective function of (1) is nonlinear, therefore the objective function of Z of equation (14) is non-linear and includes integer variables. As a result, the same model Z with respect to the constraints (6) – (11) belongs to the minimum function of a nonlinear integer programming (NIP). in their study, Costa and Oliveira (2001) suggest that evolutionary strategies such as genetic and simulated annealing algorithms are currently the best algorithms to solve the problem of integer nonlinear programming.

4.1.Genetic Algorithm

Genetic algorithms are among the random technique based components based on the mechanism of natural selection and genetic evolution of the model, and they provide procedures to resolve the issue. The usual form of the algorithm was introduced by Goldberg (1989), starting with the initial set of random solutions called population, somewhat different from classical search techniques. This feature causes the place to find the perfect spot, right on the boundary of the identified variable, and the possibility of finding the optimal spot size increases. In the genetic algorithm, each individual in the population is called a chromosome, representing a solution to the problem. Chromosomes through successive iterations, called generations, evolve and during each generation, the fitness using certain criteria is evaluated. To create the next generation, new chromosomes, called offspring will be created through the conjunction of two chromosomes from current generation using a crossover operator or modifying a chromosome using a mutation operator. New generation, by selecting operator based on the fitness values of the parents and children, and removing some of the rest of them in order to maintain a constant population size, are formed (Esfandiari and Seifbarghy, 2013). After several generations, the algorithm will converge to the best chromosome. Before presenting the general form of the genetic algorithm we describe some of the icons below.

Pop size: initial population size of the late.
Max It: a predetermined number of iterations.
PC: crossover rate (probability of selected chromosomes in each generation to Junction).
Pm: the mutation rate (probability of a bit of a leap for answers).
Fitness function: The fitness function.

The general form of the proposed genetic algorithm is as follows:

Step 1: Initialize the population size, a predetermined number of iterations, crossover rate and mutation rate.

Step 2: Randomly generate an initial population with respect to the initial population size.

Step 3: repeat until a predetermined number of iterations (Max It).

3-1: Apply the reproduction operator to select a set of late Eligible uses roulette wheel selection method.

3-2: Selection of parent chromosomes of the new population with probability Pc.

3-3: Crossover:

(A): the combination of pairs of parents among the parent chromosomes.

(B): applying a two-point crossover operator to produce two offspring chromosomes from the initial two parent chromosomes.

I: replacing each chromosome in the population with offspring chromosome.

3-4: Apply the random mutations in a population with a probability Pm.

3-5: Calculate the fitness value for each chromosome, and saving the highest value, if it would be better than the value.

Step 4: The Best of Print.

4.2.Simulated Annealing Algorithm

In 1953, the metropolis algorithm proposed changes for evaluating the solid temperature. Later in 1983, Patrick simulated an algorithm to minimize the cost function and a cold object unit lit reaches the ground energy state, and it can be used to solve optimization problems with this operation. He and his colleagues proposed this algorithm called Simulated Annealing. Simulated Annealing Algorithms, which are a stochastic search algorithm based on the Monte Carlo model, are widely used in the field. In each iteration of the algorithm, the annealing process being at any stage, there will be a small amount of displaced atoms that this will lead to a change in energy show, that is ΔE in that system. If $\Delta E \leq 0$, the movement and position of the two accepted atoms and solid structure, with the displaced atom will used as the starting point for the next stage. In cases where $\Delta E > 0$, there is likely an encounter to occur. This means that the probability that a solid structure is adopted, using equation (16) is determined where:

$$P(\Delta E)=e^{\frac{\Delta E}{k_b \cdot T}} \quad (16)$$

T: initial temperature

k_b: Boltzmann constant

In this case, in order to accept or reject the new position of atoms, in fact, a random number with uniform distribution in the interval (0, 1) is selected and compared with P(ΔE). If the number obtained is less than P(ΔE), the exposition is then accepted and is used to start the next stage. Otherwise the new structure will be rejected. This process continues until one finds the equilibrium level (Esfandiari and Seifbarghy 2013).

The simulated annealing algorithm is as follows:

1. Choosing first solutions I from the set of possible solutions.
2. Selecting the initial temperature T_0 and the number of repetitions at each temperature.
3. Determining the process of temperature drop.

4. Select function of the number of substitution at each temperature.
5. Equalizing the counters related to temperature change to zero.
6. Repetition of the freezing process loop.
7. Calculate the new temperature (temperature reduction).
8. Repeating loop till establishing a stop condition.

4.3.Coding framework

Methods of defining a structure to illustrate the results are among the most influential factors in increasing the performance of optimization algorithms. Presenting the obtained solutions is the most important part in designing better meta-heuristic algorithms. Since each chromosome is providing a solution to the problem, the chromosome must be able to properly display the characteristics of the problem. The chromosome should be designed in such a way that be able to create an extensive range of possible answers. To obtain an answer, we should create a matrix containing all of the decision variables. Chromosomes contain m * n genes which, with respect to the range, form a m * n matrix of integers for each variable; where m is the number of suppliers and n is the number of products. In this study, two meta-heuristic algorithms for each solution are presented using a matrix with m rows and n columns of integers, with respect to the defined range, for each variable; where m is the number of suppliers and n is the number of products.

5. Computational results

In this section we designed a few numerical in order to investigate and examine the performance of the proposed model and given heuristics. An example is provided in the original problem by changing the parameters of the first issue of numerical examples as provided. Initially, we have designed a basic problem as example 1; other problems are generated by varying the values of selected parameters of the basic problem. In the first example, assume that we have three suppliers and three products that we grade evaluating for suppliers to supply one, two and three of a total score of 100, respectively 80, 70 and 90 that obtained the MCDM techniques like ANP, AHP or Topsis. Weight of each of the goals is b1 = b2 = b3 = b4 = b5 = 0.2. The maximum percentage of acceptance of the returned units, the maximum percentage of units by late deliveries, maintenance costs, shortage costs, limiting the demand and the maximum amount of carbon emissions per unit of product are presented below:

Q_1 =0.15, Q_2 =0.12, Q_3= 0.14, T_1= 0.13, T_2= 0.12, T_3=0.14, h_1=5, h_2= 4, h_3=6, π_1= 3, π_2= 5, π_3= 4, ${C_1}^{cap}$= 2000, ${C_2}^{cap}$= 2000, ${C_3}^{cap}$= 2000, LD_1=54, LD_2 =65 , LD_3= 35, UD_1=260, UD_2 =250, UD_3=246

Values of the parameters, the percentage of reject, percentage of late deliveries, carbon emissions in Tables (2), the values of intercept a_{ij} and the slope of the curve price- order b_{ij} for each supplier and each product in Table (3) and the values of the maximum and the minimum order quantity for each supplier, in table (4) are presented. Considering the values

of basic question, changing the value of the returned units of each product q_{ij} are two, in table (5), as an example. Concerning the basic question of values, Table (5), changes the values of the percentage of late deliveries for each product t_{ij} as shown in three examples. The fourth example is taking a major issue for t_{ij} and q_{ij} and also change the parameters in Table (5), and weight supplier one, two and three respectively 85, 95 and 92 are considered. With considering the first issue of values, by changing the percentage of late deliveries, the percentage of returned units (Table5), the maximum percentage change in the reception of the returned units per product, one, two and three respectively 0.13, 0.13 and 0.15, the maximum percentage of acceptance of late delivered units per product, one, two and three respectively, 0.14, 0.13 and 0.13, five examples are considered. Table (6) changes in the values of the parameters a_{ij} intercept and the slope of the price curve- order b_{ij} for each supplier and the parameters of each product for the first issue to consider is the six the example. Example seven, changes the values of parameters intercepted and the slope of the curve in Table (6), along with changes in the fifth example. Example eight, for each changed parameter (Table6) amounts intercept a_{ij} and the slope of the curve prices–ordering b_{ij} changes in carbon emissions (Table5), with the maximum amount of carbon emissions C^{cup} for one, two and three respectively in 1400, 1300, 1500. It also changes the parameters and the rate of maintenance cost and lack of demand for each product respectively h_1= 13, h_2=10, h_3=12, π_1= 10, π_2= 8, π_3= 14, LD_1=60, LD_2 =75, LD_3= 70, UD_1=248, UD_2 =240, UD_3=260. The ninth example accounts for changes q_{ij} and t_{ij} parameters mentioned in table (5), the weight of suppliers one, two and three respectively 85, 95 and 92, and for changes in intercept and slope of the price curve-order Table (6). Changes in the seventh example, account for Carbon foot print of each production in table 4, the maximum amount of carbon emissions C^{cup} for one, two and three respectively in 1400, 1300 and 1500; weights Supplier one, two and three respectively 85, 95 and 92, and as an example, 10 is considered.

Table2. The values of the q_{ij} and t_{ij} and G_{ij} in numerical example 1

$\mathbf{q_{ij}}$	j= 1	j= 2	j= 3	$\boldsymbol{t_{ij}}$	j= 1	j= 2	j= 3	$\boldsymbol{G_{ij}}$	j= 1	j= 2	j= 3
i= 1	0.01	0.05	0.04	i= 1	0.05	0.04	0.02	i= 1	1.3	1.5	1.4
i= 2	0.06	0.03	0.02	i= 2	0.06	0.01	0.05	i= 2	1.7	1.3	1.2
i= 3	0.04	0.03	0.07	i= 3	0.03	0.04	0.02	i= 3	1.6	1.6	1.3

Table3. The values of the a_{ij} and b_{ij} in numerical example 1

$\boldsymbol{a_{ij}}$	j= 1	j= 2	j= 3	$\mathbf{b_{ij}}$	j= 1	j= 2	j= 3
i= 1	259	284	266	i= 1	5/12	5/12	2/3
i= 2	286	287	262	i= 2	6/11	½	10/11
i= 3	291	280	259	i= 3	15/29	5/12	25/34

Table4. The values of the L_{ij} and U_{ij} in numerical example 1

$\boldsymbol{L_{ij}}$	j= 1	j= 2	j= 3	$\mathbf{U_{ij}}$	j= 1	j= 2	j= 3

i= 1	32	25	17	i= 1	104	85	92
i= 2	10	33	19	i= 2	65	83	74
i= 3	20	24	12	i= 3	78	84	80

Table5. The values of the q_{ij} and t_{ij} and G_{ij} in numerical example 2

$\mathbf{q_{ij}}$	j= 1	j= 2	j= 3	$\boldsymbol{t_{ij}}$	j= ١	j= ٢	j= ٣	$\boldsymbol{G_{ij}}$	j= 1	j= 2	j= 3
i= 1	0.03	0.02	0.06	i= 1	0.04	0.01	0.05	i= 1	1.8	1.9	2.1
i= 2	0.05	0.04	0.01	i= 2	0.03	0.02	0.07	i= 2	1.4	1.3	1.5
i= 3	0.03	0.08	0.02	i= 3	0.01	0.04	0.06	i= 3	2.3	1.6	1.7

Table6. The values of the a_{ij} and b_{ij} in numerical example 1

$\boldsymbol{a_{ij}}$	j= 1	j= 2	j= 3	$\mathbf{b_{ij}}$	j= 1	j= 2	j= 3
i= 1	209	197	207	i= 1	5/18	2/3	2/5
i= 2	204	167	211	i= 2	4/11	4/5	6/11
i= 3	207	156	206	i= 3	10/29	2/3	15/34

The LP-metric method is to answer the main problem of the objective function (objective function,(Z_1 , Z_2, Z_3, Z_4, Z_5) consider them separately) according to the constraints (6) - (10), with the main problem to obtain the ideal solution being solved. The first problem is Z_1 nonlinear, and it is solved by the proposed meta-heuristic methods and considered best value solutions for each sample. Other problems are linear and convex. So we solve obtained optimal solutions for other objectives using Lingo software11. Table (7) shows the optimal values of the objective function. Having an ideal (Z_1^* , Z_2^*, Z_3^* , Z_4^* , Z_5^*) value of the objective function Z in equation (13) with respect to the constraints (6) - (10) is obtained using the two meta-heuristic proposed methods. Before applying the proposed algorithm, the algorithm parameters should be adjusted, so the first to be used Taguchi method has adjusted the parameters of the proposed algorithm, and has also been tested on three levels and 27 experiments design using Minitab software. An experiments design sequence off to test the change in the input variables or system parameters. Taguchi experimental design method was introduced in 1960 by Professor Taguchi. This approach provides optimal conditions using minimum number of experiments and dramatically reduces the time and cost required. In this method, after identifying important parameters of each algorithm, often three levels for each parameter is selected. Then, considering the number of parameters, a number of experiments are designed. Each one of these experiments, are the combination of the levels of the specified parameter. After conducting the experiment, the change agent which is called signal to noise ratio (S / N ratio), is introduced and experimental conditions which has the highest value in the signal-to-noise ratio, is selected as optimal. Values for a genetic algorithm to optimize the parameters of the initial population size, cross over rate, mutation rate and the number of iterations using the Taguchi method were 30, 0.8, 0.02 and100, respectively, and for simulated annealing algorithm for optimal activity .The initial temperature, the number of

iteration sat each temperature, rate of temperature change and the total number of iterations, were respectively 10, 5, 0.90 and 50. In Table (8) the obtained values for the10 examples are shown and listed by the proposed genetic and simulated annealing meta-heuristic algorithms. For coding meta-heuristic algorithms MATLAB.13 software is used. To gain a better understanding of the results, the solutions obtained by the proposed solution are described in the first example.

Table7. The optimal values of the objective function of 10 numerical examples.

No	Z_1^*	Z_2^*	Z_3^*	Z_4^*	Z_5^*
1	52230	6.58	6.62	271.60	59800
2	54026	7.30	6.72	277.60	59800
3	55626	6.58	6.55	271.60	59800
4	54030	7.30	6.84	277.60	67239
5	56496	7.31	6.76	227.10	59800
6	37046	6.58	6.62	271.60	59800
7	38123	7.31	6.76	271.60	59800
8	40304	6.58	6.62	331	59720
9	38625	7.30	6.84	277.60	59800
10	36893	7.31	6.76	338.70	67154

Table8. Integrated objective function value Z^* and time for each numerical example.

No	Z^*(GA)	Time (Ga)	Z^*(SA)	Time(SA)
1	0.2598	72.27	0.2214	80.45
2	0.2103	90.13	0.2239	95.90
3	0.2587	75.25	0.2366	81.67
4	0.27	73.92	0.2802	83.45
5	0.2183	85.40	0.2210	87.77
6	0.2301	75.82	0.2159	78.45
7	0.3216	69.39	0.2899	84.34
8	0.2462	68.15	0.2591	83.28
9	0.2193	73.57	0.2364	80.21
10	0.1955	76.53	0.2286	85.43
Mean	0.2043	76.04	0.2413	84.09

To solve the main problem using the proposed algorithm, first, the values of the Z^* objective functions are obtained separately. Values of (Z_2^* ،Z_3^*، Z_4^* , Z_5^*) are calculated using the software Lingo11, respectively being 6.58, 6.62, 271.60, and 59800, and (Z_1^*) , because of being a nonlinear integer, has been obtained by the proposed algorithm, which is equal to 52,230. The value of main problem, using genetic algorithms objective function is equal to 0.2598 and by using simulated annealing it would be equivalent to 0.2214. The average response for both genetic and simulated annealing algorithms solutions is approximately equal but time solvation for genetic is better than simulated annealing.

Because of the buyer, demand is randomly considered. Values of the random demand for the products of one, two and three are considered respectively as 77, 181 and 84. Order values assigned to the suppliers are obtained by genetic algorithm and simulated annealing, and are presented in Table (9). According to Table (9) it can be seen that the demand for product one, are the values 35, 10 and 21 using a genetic algorithm and the values of 32, 13 and 18 using the simulated annealing algorithm, in order to be allocated to supplier one, two and three. So

that criteria is intended to improve the quality, timely delivery, reduce procurement costs and greenhouse gas emissions and the maximum score for supplier evaluation of a product.

Table9. The values of Xij while utilizing GA and SA for numerical example 1.

X_{ij} GA	j= 1	j= 2	j= 3	X_{ij}SA	j= 1	j= 2	j= 3
i= 1	35	30	31	i= 1	32	25	30
i= 2	10	35	20	i= 2	13	36	22
i= 3	21	27	13	i= 3	18	25	12

6. Conclusions and Recommendations

In this paper, the multi-objective integer linear programming model for supplier selection problem is presented considering the purchase under stochastic demand with a uniform probability distribution and to reduce greenhouse gas emissions. The objectives are minimum procurement costs, the minimum unit of return, the minimum storage units delivered late, the minimum size of greenhouse gas emissions (carbon footprint) and the maximum total score of evaluating suppliers. The objectives listed by L-1-metric method with consideration of equal weights for each objective, convert to one objective. Integer nonlinear programming problem is solved using genetic and simulated annealing algorithms. After identifying the main parameters treated for each algorithm using Taguchi experimental design method, parameters are set. The performance of the proposed algorithm, is designed a numerical example. According to average solutions obtained by both the proposed algorithms, it can be concluded that almost the same answers are provided. In this paper we sought a model that can recognize orders to suppliers, when buyer demand because of uncertainty in the real world face products, and that be able to reduce costs and increase product quality, profitability and customer satisfaction. In addition, Environmental issues in the preceding note are achieved by selecting a supplier of timely delivery and reduce product returns to reduce the cost of purchasing. And with regard to product quality and reduce greenhouse gas emissions while providing supplies and transportation of products and increase the company's profitability will lead to customer satisfaction. In this study, using LP –metric objectives function has converted to one objective and then converting meta-heuristic methods have been resolved, Future research can be objective functions without converting one objective, using meta-heuristic multi-objective methods such as NSGA-II, MOPSO and similar algorithms that do not need to convert goals in to an objective function to be solved. Other future research that can be offered is that the supplier evaluation model presented with stochastic demand for various periods or models assign quotas for each of the suppliers using linguistic variables like high, very high, medium, low and very low provided or offering Model selection and allocation of orders to suppliers, the uncertainty in demand and order using robust optimization.

References

Amid A., Ghodsypour S.H. and O'Brien C. (2006). Fuzzy multi objective linear model for supplier selection in a supply chain, *Int. J. Prod. Econ*, 104 (2) -394-407.

Arikan F.(2013). A fuzzy solution approach for multi objective supplier selection. *Expert Systems with Applications*, 40 -947–952.

Dou Y., Zhu Q. and Sarkis J. (2013). Evaluating green supplier development programs with a grey-analytical network process-based methodology, *European Journal of Operational Research*.

Esfandiari N. and Seifbarghy M. (2013). Modeling a stochastic multi-objective supplier quota allocation problem with price-dependent ordering, *Applied Mathematical Modelling*.

Fahimnia B., Sarkis J., Dehghanian F., Banihashemi N. and Rahman. S. (2013). The impact of carbon pricing on a closed-loop supply chain: an Australian case study, *Journal of Cleaner Production*, 1-16.

Gen M. (1997). Genetic Algorithm and Engineering Design. John Wiley & sons.

Ghodsypour S.H. and O'Brien C. (2001). The total cost of logistics in supplier selection, under conditions of multiple sourcing, multiple criteria and capacity constraint, *Int. J. Prod. Econ*, 73 (1) -15–27.

Herva M. and Roca E. (2013). Ranking municipal solid waste treatment alternatives based on ecological footprint and multi-criteria analysis, *Ecological Indicators*, 25-77e84.

Hugos M. (2006). Essential of supply chain management (2nd ed.). John Wiley & Sons. Intergovernmental Panel on Climate Change (IPCC). Summary for Policy.

Lai Y.J. and Hwang C.L. (1996). fuzzy Multiple Objective Decision making, *Method and Application, Springer-Verlag.*

Li L. and Zabinsky B. Z. (2011). Incorporating uncertainty into a supplier selection problem, *Int. J. Production Economics*, 134 -344–356.

Li S., Murat A. and Huang. W. (2009). Selection of contract suppliers under price and demand uncertainty in a dynamic market, *European Journal of Operational Research*, 198 -830–847.

Mendoza A. and Ventura A. (2012). Analytical models for supplier selection and order quantity allocation, *Applied Mathematical Modelling*, 36 -3826–3835.

Mendoza V. and Ventura J.A. (2012). Analytical models for supplier selection and order quantity allocation, *Appl. Math. Model*, 36 (8) -3826–3835.

Narasimhan R., Talluri S. and Mahapatra S.K. (2006). Multiproduct multicriteria model for supplier selection with product life-cycle considerations, *Decis. Sci*, 37 (4) -577–603.

Ozkok B. A. and Tiryaki F. (2011). A compensatory fuzzy approach to multi-objective linear supplier selection problem with multiple-item, *Expert Systems with Applications*, 38 11363–11368.

Rao P. (2002). Green the supply chain: a new initiative in south East Asia, *International Journal of Operation and Production Management*, 22 (6), 632e655.

Sarkis J. (2006). Greening the supply chain. Springerlink-Ver lag Londen limited.

Shaw K., Shankar R., Yadav S. S. and Thakur L. S. (2012). Supplier selection using fuzzy AHP and fuzzy multi-objective linear programming for developing low carbon supply chain, *Expert Systems with Applications*, 39 -8182–8192.

Shen L., Olfat L., Govindan K., Khodaverdi R. and Diabat. A. (2013). A fuzzy multi criteria approach for evaluating green supplier's performance in green supply chain with linguistic preferences, *Resources, Conservation and Recycling*, 74, 170e17.

Wang T.Y. and Yang Y. H. (2009). A fuzzy model for supplier selection in quantity discount environments, *Expert Systems with Applications*, 36(10), 12179–12187.

Weber C.A., Current J. and Desai A. (2000). An optimization approach to determining the number of vendors to employ, Supply Chain Manage, *Int. J*, 5 (2)-90–98.

Weijum X.and Zhiming. W.(2007). Supplier selection with multiple criteria in volume discount environments, *The international jornal of management science, omega*, 35.494-504.

Yang P.C., Wee H.M., Pai S. and Tseng Y.F. (2011). Solving a stochastic demand multi-product supplier selection model with service level and budget constraints using Genetic Algorithm, *Expert Systems with Applications*, 38 - 14773–14777.

Zhang J. l. and Chen J. (2013). Supplier selection and procurement decisions with uncertain demand,fixed selection costs and quantity discounts, *Computers & Operations Research*, 40 2703–2710.

Zhang J. L. and Zhang M.Y. (2011). Supplier selection and purchase problem with fixed cost and constrained order quantities under stochastic demand, *Int.J.Prod. Econ*, 129 (1) -1-7.