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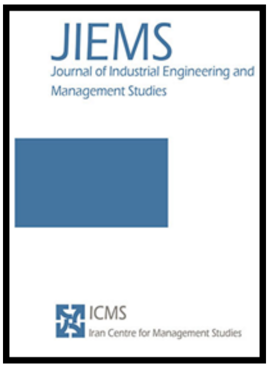

Integrated sourcing and inventory decisions considering sources' disruptions with a hybrid simulation-MOPSO-TOPSIS approach: A Pharmaceutical case study

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Abstract

In this research, the integrated sourcing and inventory policy problem in a pharmaceutical distribution company is investigated. In order to select the superior solution, a new tool is introduced. Sourcing is one of the most critical issues in pharmaceutical industry. In addition, drug inventory shortages can cause irreparable humanitarian crises. However, only a limited number of studies has been focused on integrated sourcing and inventory policy of drugs so far. In real-world problems, it is difficult to calculate the exact cost of inventory shortage such as company reputation and humanitarian crises. To overcome this obstacle, in this study, the number of shortage is considered as a separate objective. Likewise, demands of the distributors and breakdowns of suppliers are stochastic, and due to the complicated nature of the problem is difficult to calculate the objective function by using classic methods. So, simulation is used for estimating the objectives of the problem. It's been proved that the problem of this study is NP-Hard. Therefore, a metaheuristic multi-objective particle swarm optimization (MOPSO) method is used to find the optimal solution. To test the reliability of the model and the proposed algorithm, a real drug distributing problem is used and after estimating a Pareto front, the best answer is chosen by The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method.

Keywords: Sourcing and inventory control policy; MOPSO; TOPSIS; Pharmaceutical industry.

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1. Introduction

As pressure to improve supply chain cost performance increases for many companies, the evaluation and selection of competent suppliers becomes a key concern (Keskin et al., 2010). On the other hand, much of the company's capital is maintained in the form of inventory. So far, most research has examined two problem of sourcing and inventory policy separately, in which the results will not be the global optimal response.

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Supplier selection and inventory policy are two dependent decisions, and if these two decisions are seamlessly taken, the response is more optimal than the separate one. Firouz et al. (2017). Furthermore, over the last century, there has been a significant increase in drug shortage reported by the US Central Statistics Office, which has been reported as supply disruptions (Lücker and Seifert, 2017). Therefore, our focus is on an integrated choice of supplier selection and inventory control in a drug distributing company. In this research, a drug distributor company wants to simultaneously optimize the supplier selection process and inventory decisions of its branches. In this problem, each drug distributing branch of company is faced to a specific stochastic demand. To respond timely to the customers, each distributor's branch maintains a certain amount of inventory and acts in accordance with a specific (r, Q) policy to fill its inventory from the supplier to whom it is assigned. In other words, inventory policy seeks to answer both questions about how much and when each branch is ordering. In addition, any unsatisfied demand at the distributor's branch level is a deferred order with a specific expense. Hence, holding costs, shortages, and replenishments are considered for inventory in distributors. The focus of this study is not on the supplier's assessment, though. In fact, the main focus is to obtain a relationship between the supplier selection and inventory decisions in a quantitative manner. Most of the previous research has merely created a conceptual model for selecting the supplier. The contributions of this paper are as follows: First, unlike the most previously proposed models, we take into account uncertainty on both demand and supply sides. Second, we propose a new multi-objective model and a simulation optimization method for integrated sourcing and inventory control problem. In this research, after describing the research background, an integrated mathematical model of integrated supplier selection and inventory policy will be designed and then a new multi-objective simulation optimization tool will be developed and introduced to solve the problem. Finally, the superior solution will be chosen using TOPSIS technique and the results will be analyzed.

2. Literature review

Supplier selection is considered a strategic decision in the field of supply chain management. Sustainable supplier selection is the process of identifying the appropriate supply partners of an organization with the most beneficial monetary value (Moheb-Alizadeh, 2019).The current experiences of supply chain management encourage distributing branches to reduce the number of suppliers. This leads to long-term commitment and close relationships with suppliers (Shin et al. 2009).
Determining a purchase strategy for the company has three main steps:

1) Creating a supplier reference set.

2) Selecting suppliers from the references set that accept orders from the company.

3) Determining the quantity of goods for ordering from each of the selected supplier (Burke et al. 2007).

The first step involves selecting suppliers which have a predetermined set of criteria. These criteria include price, quality, delivery performance, order completion and flexibility, financial position, and so on. A significant part of the purchase and sourcing literature is dedicated to this decision. Keskin et al. (2010) considered an integrated choice of supplier selection with similar details to this study. They formulated the problem as a nonlinear mixed integer programming model and developed an efficient decomposition-oriented approach to solve it. The results of their paper, while highlighting the relationship between inventory and supplier selection, did not consider the effect of stochastic demand. Freeman et al. (2018) investigated sourcing strategies for a capacitated firm subject to supply and demand uncertainty problem.

They analyzed the robustness of the five most frequently occurring sourcing strategies as key problem parameters vary; the value of each of the available sourcing tactics individually; and the impact of limited capacity on the optimal sourcing strategy.

The complexity of addressing conflicting objectives such as minimizing costs and maximizing service levels in real inventory control problems mainly stems from the fact that more accurate optimizers can be used to produce more varied and better non-dominated solutions (r, Q). Moslemi and Zandieh (2011) compared some of the new strategies for mass optimization of multi-objective particles swarm in a permanent review inventory control system. In Burcu et al. (2010) a general problem of supplier selection for a company with several stores was investigated.

Multi-period inventory control problems are mainly studied by considering two assumptions. Firstly, a permanent review, which depends on the level of inventory and the order which may occur at any time. Secondly, a period, which order is placed at the beginning of each period. Taleizadeh et al. (2013) neglected these two aforementioned restricting assumptions and assumed that the times between two replenishments are independent and random variables. For their problem, the decision variables (the maximum inventory of several products) were integer values. In their research, while demands were in the form of fuzzy numbers, a combination of the order deferred trade and lost sales was considered for shortages. They showed that the model of this problem was non-linear integer programming and presented a combination of fuzzy simulation and genetic algorithm for solving the problem. Then, the performance of the proposed method in three numerical examples was compared with the current methods by using a combined fuzzy simulation and simulation annealing (SA) approach. The numerical results indicated the better performance of the proposed approach compared to the current methods. In the research of Duan and Warren Liao (2013), the optimal policies for replenishments of decent supply chains that operate under two different control strategies (centralized and decentralized) and have diverse demands were identified. They developed a new metaheuristic algorithm for optimization and an evaluation module based on supply chain inventory model. In this research, a system with a decent distributor and a number of retailers were carefully studied. They tested ten different demand patterns, four levels of capacity constraints, and two different control strategies, and found that capacity constraints may change the order patterns for high demand with high deviations. . In a study by Badri et al. (2013), a mathematical model was developed to make simultaneous strategic and tactical decisions. In this model, issues such as deployment of equipment were considered as strategic and long-term decisions, and production planning and distribution were considered as tactical decisions

It has been widely acknowledged that simulation is a powerful computer-based tool that enables decision-makers to improve operational efficiency through the ability to integrate the inherent uncertainty of complex real systems (Glover et al. 1999). Simulation has been extensively implemented for modeling large supply chains (Joines et al., 2002; Tarzi & Cavalieri, 2004; Kochel & Nielander, 2005). Simulation models are able to simulate the behavior of complex systems, although they may require large amounts of development and runtime which make them inadequate to solve optimization problems. This situation is resolved by using the simulation optimization approach. In this way, the best combination of problem parameters is effectively searched and identified via using intelligent search techniques. The present study develops a simulation-optimization algorithm for the integrated choice of supplier selection. One of the most popular commercial software packages using metaheuristic algorithms is OptQuest. This software uses a combination of scattering, tabu search, and neural networks to solve large multi-scenario optimization problems with linear programming model (Fu et al., 2005).

Without proper optimization of replenishment policies, the supply chain system will incur an unnecessarily high cost. The use of centralized control for supply chains with unsustainable demand patterns was also beneficial (Duan and Warren Liao, 2013). The simulation optimization approach for efficient control of the multi-location inventory system along with the shipping has been of great interest of researchers. Existing models can be analytically solved only by simplifying assumptions, though. There are many heuristics available to find the estimated optimal solutions, but the internal relationships between ordering and shipping decisions for continuous time are not included in these methods. Hochmuth and Kochel (2012) designed a model to overcome this gap and identified its validity with a case study. In their model, to meet the demands, each location on a given time horizon was able to both order to the external supplier and deliver goods from another location to satisfy the demands. Mandal et al. (2005) used a geometric programming approach to solve multi-objective fuzzy inventory model to find demand, inventory levels and inventory level for each commodity. Tsou (2009) used a number of metaheuristics methods such as MOPSO, multi-objective electromagnetic optimization (MOEMO), and Strength Pareto Evolutionary Algorithm (SPEA) to solve the multi-objective inventory system (r, Q). He used MOPSO to solve the inventory system and then used a Multiple Attribute Decision-making (MADM) called The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to rank Pareto front. In another study in 2008, he used the electromagnetic algorithm to optimize the multi-objective inventory system. In Arreola-Risa (2011) study, a heuristic optimization method for the production and inventory system was presented. The presented heuristic used the simulation benefits and simultaneously reduces the negative effect by regression analysis. In Burcu et al. (2010) a general problem of supplier selection for a company with several stores was investigated. The purpose of their research was, first of all, the simultaneous determination of the suppliers that the company must work with. Determining the order quantity of each store from the selected suppliers was another goal of their research. In the proposed model, in addition to the general costs of choosing the supplier and delivering the goods between the supplier and the assigned store, the costs associated with inventory and store decisions were also considered. Then, they proposed an integrated model of supplier selection and inventory. They considered output, shipping capacity, and capacity constraints in their model, and they achieved the solutions by using the Generalized Benders Decomposition (GBD) method. Tsai and Zheng (2013) presented a simulation optimization algorithm for solving the problem of two-echelon inventory system with service level constraints. The purpose of their research was to determine the optimum inventory levels to minimize the cost of inventory so that the expected response time is satisfied. Golini and Kalchschmidt (2011) addressed the sourcing at a global level with high physical distances and examined their relationships with inventory levels.

Recently, Tsai and Chen (2016) presented a multi-objective model for minimizing inventory costs, inventory levels, and shortage rates, and solved it through a simulation-based ranking and selection method. In addition, they proposed another method in which the members to the Pareto front were converted into a single utility by the AHP method. Their problem did not include factors such as simultaneous supplier selection and transportation and side transportation. Cárdenas-Barrón et al. (2016) presented a method based on reduction and improvement for solving a hybrid MILP model of supplier selection and order size for a multiple product and multiple period problem. They proved the superior performance of their method by solving problems in different dimensions. Their model did not include multiple objectives, probabilities, shortages, and transportation. Firouz et al. (2017) solved the supplier selection and sourcing model with lateral transshipments, but their model was single-objective and did not provide a solution for choosing a superior solution from the Pareto Front.

Research into healthcare issues especially on the pharmaceutical supply chain (PSC) has increased rapidly. The availability, accessibility, affordability, and safety of drugs form the four main aspects that are valued by the consumers in the context of PSC (Nematollahi et al., 2018). Priyan and Uthayakumar (2014) presented a fuzzy inventory model for possibilistic conditions in a pharmaceutical company and solved the problem by Lagrange coefficients approach.

By reviewing previous researches, one can easily understand that no significant research has yet been made on multi-objective integrated sourcing and inventory policy despite its importance in the pharmaceutical industry. This research seeks to bridge this gap.

3. Methodology

This is a developmental and applied research. A large part of the material in this article has been gathered from library sources including books, theses, and articles. In order to test the proposed algorithms, a drug distributing company's data are used.

3.1. Formulating the model

Before describing the system, the defined symbols are presented as follows:

A. Parameters

Parameter	Definition
I	Set of distributors' branches
J	Set of predetermined Suppliers
C_j	Cost of purchasing each unit from the distributor branch j
f_i	Fixed contract cost with supplier i
d_{ij}	Distance between distributor branch i and supplier j
K_i	Fixed ordering cost of distributor branch i
θ_j	Frequency rate of breakdowns
$Demand_i$	Demand of distributor branch i
s_i	Cost of each deferred ordering unit at the distributor branch i
W_j	Annual output capacity of supplier j
$TrSize$	Truck Capacity
h_i	Holding cost of each unit in the distributor branch i
LT_{ij}	Delivery time of the supplier i to distributor branch j
$Q_j^{\min}$	The minimum order quantity from supplier j
$q_j^{\min}$	Minimum accepted quality level for distributor branch i
q_j	The percentage of good quality products of supplier j
p_{ij}	Fixed shipping cost of order from the supplier j to the distributor branch i by each truck
r_{ij}	Variable shipping cost of inventory from supplier j to distributor branch i by each truck

B. Decision variables:

Variable	Definition
X_j	If the supplier j is chosen, it is equal to 1 and otherwise equals to zero.
Y_{ij}	If the supplier j is assigned to distributor branch i, it is equal to 1, otherwise it is zero.
Q_i	Quantity of each order of distributor branch i
R_i	Reorder point of distributor branch i

In this research, unlike the usual approaches of supplier selection, a big distributing company with multiple branches is considered, all of which are geographically dispersed. Figure 1 represents the structure of the problem.

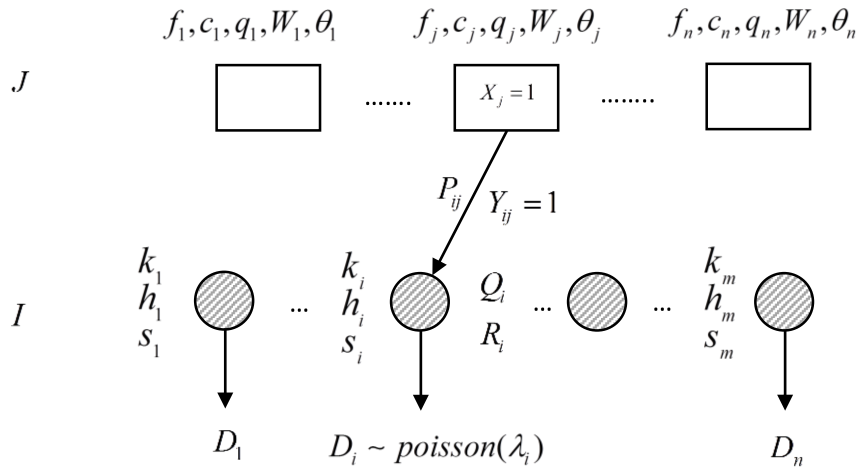

Figure 1. The graphic representation of the proposed integrated model

In this case, m number ($m \geq 2$) of distributors are to produce a drug to satisfy the demands of the distributor branch. The demand is based on the Poisson distribution with mean λ_i to each distributor branch i. Each supplier j has an annual output capacity of W_j. For each supplier j, the binary decision variable X_j is equal to one if the supplier j is selected. Otherwise, it will be zero. The second set of decision variables depends on the choice of suppliers. For the distributor's branch $i \in I$ and the supplier $j \in J$, the variable Y_{ij} is equal to 1 if the distributor branch i is assigned to the supplier j, otherwise its value will be zero. This problem is a single sourcing type, and each distributor branch will only be assigned to a supplier.

To reduce costs in the planning horizon, there must be a trade-off between the supplier selection and the inventory control policy of each distributor branch. The distributor branch inventory level is continuously reviewed by (r, Q) policy and when it is lower than R, Q is ordered. The placed order from the supplier j arrives at the distributor's branch i after the delivery time LT_{ij}.

The orders are carried by trucks with $TrSize$ capacity. Since the quality of the supplied order from supplier of j is equal to q_j, the stock of the distributor branch i increases by $Q_i \times q_j$. Shipping costs from distributor branch i to supplier j is comprised of two parts. then one of the its members Variable shipping cost Per unit by Truck (r_{ij}) which is calculated based on the distance between distributor branch i and supplier j, therefore, the $r_{ij} \times d_{ij}$ relationship is used to calculate the total cost of the variable shipment between distributor branch i and supplier j. d_{ij} is the distance between distributor branch i and supplier j. Euclidean distance was used to calculate the distance between distributor branch i and supplier j.

In general, costs of the system are divided into three categories:

1- The cost of selecting suppliers and contracting them:

Contract cost is $\sum_{j\in J} f_i X_j$.

2. Costs of the distributor branch's inventory system including holding costs, ordering, shortages, and purchases:

The holding costs Equal to:

$$\sum_{i\in I}\sum_{j\in J} h_i \left[\frac{Q_i}{2} + R_i - E\left[LT \times \frac{1}{\lambda_i} \right] \right] Y_{ij} \tag{1}$$

The order cost equals to:

$$\sum_{i\in I} \frac{K_i E[D_i]}{Q_i} \tag{2}$$

The purchase cost equals to:

$$\sum_{i\in I}\sum_{j\in J} c_j E[D_i] Y_{ij} \tag{3}$$

The computable part of the shortage cost is

$$\sum_{i\in I}\sum_{j\in J} \frac{s_i n_j(R_i) E[D_i] Y_{ij}}{Q_i} \tag{4}$$

In which $n_j(R_i)$ is the loss function incurred by shortage and is calculated by relation (5). F is the reciprocated Poisson function.

$$n_j(R_i) = E\left[LTD_{ij} \right] \bar{F}(R_i) - R_i \bar{F}(R_i + 1) \tag{5}$$

3. Shipping costs between the distributor branch and the suppliers:

The total shipping cost is equal to:

$$\sum_{i\in I}\sum_{j\in J}\left\{\frac{\left(p_{ij}+r_{ij}d_{ij}\right)E[D_i]Y_{ij}}{M}\right\} \tag{6}$$

Relationship (8) shows the total cost of the system. Calculating the exact cost of shortage including Company reputation and human casualties is unrealistic in the real world, though. Therefore, minimizing the number of shortages in accordance with equation (7) along with the minimizing the cost is considered. According to (9), each distributor branch will be allocated to only one supplier. According to equation (10), each distributor branch is assigned to a supplier that has been selected. Based on Equation (11), the distributor branch's demand should not exceed the supplier's capacity. According to equation (12), the minimum quality required by the distributor branch should be satisfied. Based on the relationship (13), the order quantity of the distributor branch must be higher than the minimum acceptable order of the supplier. Equation 14 states that the order quantity must be positive. Also, according to equation (15), the variables X_j and Y_{ij} are binary.

$$min\,S\left(\boldsymbol{X},\boldsymbol{Y},\boldsymbol{Q},\boldsymbol{R}\right)=\sum_{i\in I}\sum_{j\in J}\frac{n_j\left(R_i\right)E\left[D_i\right]Y_{ij}}{Q_i} \tag{7}$$

$$min\,G\left(\boldsymbol{X},\boldsymbol{Y},\boldsymbol{Q},\boldsymbol{R}\right)=\sum_{i\in I}\sum_{j\in J}c_jE\left[D_i\right]Y_{ij}+\sum_{j\in J}f_iX_j+\sum_{i\in I}\sum_{j\in J}\left\{\frac{\left(p_{ij}+r_{ij}d_{ij}\right)E[D_i]Y_{ij}}{M}\right\}$$
$$+\sum_{i\in I}\frac{K_iE\left[D_i\right]}{Q_i}+\sum_{i\in I}\sum_{j\in J}h_i\left[\frac{Q_i}{2}+R_i-E\left[LTD\right]\right]Y_{ij}+\sum_{i\in I}\sum_{j\in J}\frac{s_in_j\left(R_i\right)E\left[D_i\right]Y_{ij}}{Q_i}+ \tag{8}$$

$St:$

$$\sum_{j\in J}Y_{ij}=1,\forall i\in I \tag{9}$$

$$Y_{ij}\le X_j,\forall i\in I,\forall j\in J \tag{10}$$

$$\sum_{i\in I}E\left[D_i\right]Y_{ij}\le W_jX_j\;,\forall i\in I,\forall j\in J \tag{11}$$

$$q_jX_j\ge q_i^{min}Y_{ij}\;,\forall i\in I,\forall j\in J \tag{12}$$

$$Q_i\ge Q_j^{min}Y_{ij}\;,\forall i\in I,\forall j\in J \tag{13}$$

$$Q_i\ge 0\;,\forall i\in I \tag{14}$$

$$X_j,Y_{ij}\in\left\{0,1\right\},\forall i\in I,\forall j\in J \tag{15}$$

3.2. Solving the model

The proposed model is a Mixed Integer Nonlinear Programming (MINLP). In addition, due to the NP-hard nature of the problem, solving the model with conventional methods by increasing the number of variables and dimensions is not possible. To overcome this impediment, the metaheuristic methods were implemented for optimization. It's been proved that the problem of this study is NP-Hard. Therefore, a metaheuristic multi-objective particle swarm optimization (MOPSO) method is used to find the optimal solution. On the other hand, some of the variables are stochastic, and conventional methods cannot be used to obtain the compatibility of each solution. Therefore, simulation is used to address this aspect of the problem. The structure of the utilized technique in this study, according to Figure 2, consists of two parts that are repeated to find the near optimal solution. The simulation section depicts a complex scenario and calculates the objective functions. The optimization section, on the other hand, seeks to create and select the optimal vector of the selected suppliers, and then determine the optimal Y and (r,Q) according to the selected suppliers.

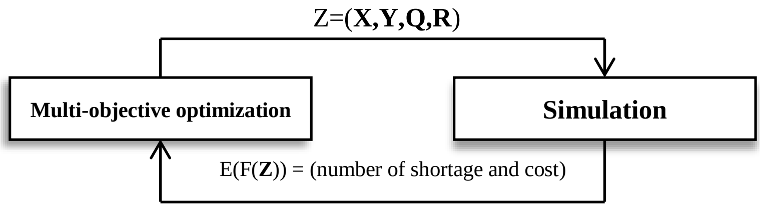

Figure 2. The structure of simulation optimization

After creating a binary vector $\bar{X}_j$, it is necessary to determine the optimal associated $\bar{Y}_{ij}$. The optimal answer $\bar{Y}_{ij}$ is obtained by solving the following problem. This problem minimizes transport costs in accordance with equation (16) and constraint from equation (17) to (20).

$$\min_{Y} \sum_{i\in I}\sum_{j\in J}\left(p_{ij}+r_{ij}d_{ij}\right)\frac{E\left[D\right]_i}{TrSize}Y_{ij} \tag{16}$$

$s.t.$

$$\sum_{j\in J} Y_{ij} = 1, \forall i \in I \tag{17}$$

$$Y_{ij} \le \bar{X}_j, \forall i \in I, \forall j \in J \tag{18}$$

$$\sum_{i\in I} E\left[D_i\right] Y_{ij} \le W_j \bar{X}_j \quad, \forall i \in I, \forall j \in J \tag{19}$$

$$X_j \ , Y_{ij} \in \left\{0,1\right\}, \forall i \in I, \forall j \in J \tag{20}$$

The above model is linear and can be solved by classical methods. In this case, the order quantity $\bar{Q}$ must be specified for each distributor branch. After determining X and Y, determining optimal (R,Q) requires making a balance in inventory replenishment, holding, shortage, and transportation costs. The determination of optimal (R,Q) requires the simultaneous solution of equations (21) and (22).

$$Q_i = \sqrt{\frac{2E\left[D_i\right][K_i + s_i n_j\left(R_i\right)+\left(p_{ij}+r_{ij}d_{ij}\right)]Y_{ij}}{h_i}} \quad , \forall i \in I, \forall j \in J \tag{21}$$

$$R_i = F^{-1}\left(1-\frac{Q_i h_i}{s_i E\left[D_i\right]}\right), \forall i \in I \tag{22}$$

The two mentioned relationships are repeated in a loop to reach the necessary convergence. We also obtain the initial value for Q_i from the following equation:

$$Q_i = \sqrt{\frac{2K_i.E\left[D_i\right]}{h_i}} \quad ,\forall i \in I \tag{23}$$

3.3. MOPSO algorithm

In the proposed methodology, a multi-objective optimization algorithm is used to solve the problem in accordance with Fig. 2. In this research multi-objective particle swarm optimization algorithm was selected to use. This algorithm was introduced in 2002 by Coello and developed by him and his colleagues in 2004 and 2006. In this algorithm, the best non-dominated solutions are stored in an external memory (Moslemi and Zandieh, 2011).

Step 1: Creating an initial Population.

In the developed algorithm, the number of particles is 20 and the external archive size is 15.

Step 2: Separating non-dominated members and save them to external memory.

Step 3: Celling the discovered solution space.

Step 4: Selecting a Leader

After determining the probability of selecting cells using a roulette wheel mechanism, one of the cells is selected and then one of its members is randomly selected as the leader.

To conduct selection in this algorithm, after celling the solution space, with the help of the Boltzman relation, the probability of choosing each cell is determined according to (24). According to this, the cells with fewer members are more likely to be selected. ii is the cell's number.

$$Prob_{ii} = \frac{e^{-n_{ii}}}{\sum_j e^{-n_{ii}}} ,0 \le prob_{ii} \le 1 ,\sum_i p_i = 1 \tag{24}$$

Step 5: Implementing the operators of MOPSO algorithm

In the discrete version of PSO, speed should be converted to probability, which is the same chance of getting a value of 1 for a particle. The higher the probability is, the greater the probability that the particle will take the value of 1 (Kennedy and Eberhart, 2001). Here, relations (25), (26), and (27) were used to calculate the particle velocity. C_1 and C_2 are constant and equal numbers. $pBest_l$ is the best answer for each particle l and $nBest_t$ is the best overall answer (leader). $w = 0.5$ is the inertial constant. r_1 and r_2 are random numbers, V_{it} is the particle velocity, X_{it} is the position of the particle, $V_{\max}$ is 4 and sp_l is the probability between zero and one. Then a random number ρ is generated in $[0,1]$ and by equation (28) the new position of the particle is determined.

$$V_{it} = w.V_{l,t-1} + c_1.r_1.\left(pBest_l - x_{l,t} \right) + c_2.r_2.\left(nBest_t - x_{l,t} \right) \tag{25}$$

$$-V_{max} \le V_{l,t} \le V_{max} \tag{26}$$

$$sp_l = \frac{1}{1+e^{-V_{l,t}}} \tag{27}$$

$$x_{l,t} = \begin{cases} 1 & \rho \le sp_l \\ 0 & \text{otherwise} \end{cases} \tag{28}$$

In this algorithm, a random mutation rate of 0.2 was used.

Step 6: Updating the best personal experience of each particle.

If the new position dominates the best experience, then the new position will take the place of the best experience. If the new position is dominated by the best experience, no action will be taken. If none of these situations occur, and none of them dominate each other, one of the two positions is randomly considered as the best experience.

Step 7: Adding non-dominated members of the current population to the external memory.

Step 8: Removing non-dominated external memory members.

Step 9: Removing Members exceeding the capacity of external memory.

The probability of eliminating the answers beyond the capacity of the external memory according to (29) is obtained. ii is the cell’s number. After determining the probabilities, additional solutions are eliminated by using the roulette wheel method.

$$del\_prob_i = \frac{e^{n_{ii}}}{\sum_j e^{n_{ii}}} \quad ,0 \le del\_prob_{ii} \le 1, \sum_i q_{ii} = 1 \tag{29}$$

Step 10: If the end condition is fulfilled, stop and otherwise go to step three.

3.4. TOPSIS technique

1. Calculating of the normalized decision matrix: The normalized value of n_{ij} is calculated as follows:

$$n_{ij} = \frac{a_{ij}}{\sum_{i=1}^{m} a_{ij}}, i = 1,...,m,\ j = 1,...,n \tag{30}$$

2. Calculating the normalized weighted decision matrix

$$v_{ij} = w_j n_{ij}, i = 1,...,m,\ j = 1,...,n \tag{31}$$

w_j is the weight of jth criterion, and $\sum_{j=1}^{n} w_j = 1$. These weights are determined by the decision maker.

3. Determining the positive and negative ideal solution:

$$A^+ = \left\{\left(v_1^+, v_2^+, \ldots, v_n^+\right)\right\} = \left\{\left(\max v_{ij} | i \in O\right), \left(\min v_{ij} | i \in I\right)\right\} \tag{32}$$

$$A^- = \left\{\left(v_1^-, v_2^-, \ldots, v_n^-\right)\right\} = \left\{\left(\min v_{ij} | i \in O\right), \left(\max v_{ij} | i \in I\right)\right\} \tag{33}$$

O is the corresponding profitable criteria, and I is the correspond costly criteria.

4. Calculating the distance from the ideal solutions

$$d_i^+ = \left[\sum_{j=1}^{n} \left(v_{ij} - v_j^+ \right) \right]^{\frac{1}{2}}$$ Distance from the ideal positive answer (32)

$$d_i^- = \left[\sum_{j=1}^{n} \left(v_{ij} - v_j^- \right) \right]^{\frac{1}{2}}$$ Distance from the negative ideal answer (33)

5. Calculating the relative proximity to the ideal solution

$$Re_i = \frac{d_i^-}{d_i^- + d_i^+} \tag{34}$$

6. Ranking the solutions

4. Data analysis

To test the proposed algorithms, the data provided by Burcu et al. (2010) are used and according to the parameters, six testing problem were described in Table (2). Then a real problem of a drug distributing company is solved. In the following section, the parameters and data, as well as the distributions of data generation are given. The parameters used in this problem are described in Table 1. Two combinational types of breakdowns were also considered for the supplier. In type one, repetition of breakdowns is high and the time between breakdowns is an exponential function with an average of 7, but their duration is short (an exponential function with an average of 1). In type two, the frequency between breakdowns is low, and the time between two breakdown points is an exponential function average of 45, but the length of breakdowns is long (an exponential function with an average of 7). The proposed algorithms and simulations were conducted by using MATLAB® 2016 software. The algorithms were run using a PC with a Core i3 processor and 4GB RAM with the Windows 10 operating system.

Table1. Data generation of the problem

Category	Number	parameter	symbol	function	unit
Distributor branch	1	Physical location	$P_i = (x_i, y_i)$	$[U(0.1,1.150), U(0.1,1.150)]$	-
	2	Average time between requests		$expo(\lambda_i), \lambda_i = U(0.05,0.25)$	h
	3	Ordering fee	K_i	U(5000,10000)	$/order
	4	Holding costs	h_i	U(0.5,3)	$/unit/year
	5	The cost of shortages	s_i	U(1,3)	$/unit/year
Supplier	6	Physical location	$P_j = (x_j, y_j)$	$[U(0.1,1.150), U(0.1,1.150)]$	-
	7	Contract cost	f_j	U(10000,30000)	$/vendor
	8	Unit cost of goods	c_j	U(0.4,20)	$/unit
	9	production capacity	PC_j	U(250,275)	Unit/day
	10	Quality	q_j	U(0.6,0.85)	-
General	11	The fixed cost of each truck	p_{ij}	U(250,275)	$/order
	12	Delay time	LT_{ij}	$U(1,25,3) \times d_{ij}$	h
	13	Shipping cost per kilometer	r_{ij}	U(0.75,3)	$/kilometer
	14	Truck capacity	TrSize	500	$

The size of the designed problems is described in Table 2.

Table 2. Size of test problems

Problem index	**1**	**2**	**3**	**4**	**5**	**6**
Number of Distributers	15	15	15	30	30	30
Number of Suppliers	10	20	40	10	20	40

After executing the algorithms for each problem size in a 5-year time frame and calculating the annual average cost and shortage number, results showed good performance of the algorithm. Each run provides an estimated Pareto front similar to Figure 1 as its output. Figure 1 shows a Pareto front for a problem with 15 distributor and 20 supplier.

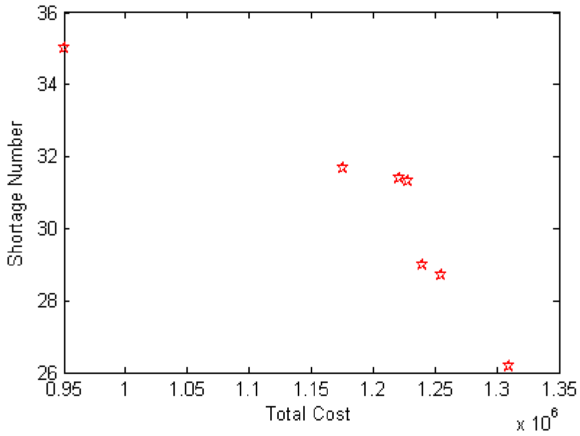

Figure 1. The estimated Pareto front of the algorithms

Then, TOPSIS technique was used to select the preferred solution from the estimated Pareto front. The 7 points of the obtained Pareto front for a problem with 30 distributor and 10 supplier were ranked according to Table 3.

Table 3. Ranking the estimated Pareto front by TOPSIS

Pareto front Index	Importance weight	1	2	3	4	5	6	7
Rank		7	3	2	1	4	5	6
Total Cost	70%	950152	1175391	1221036	1227972	1240176	1255265	1309962
Number of shortages	30%	35.00	31.68	31.40	31.32	29.01	28.70	26.20
Final weight		0.48	0.62	0.66	0.68	0.56	0.55	0.51

Results shows that the solution 4 is more preferred than the others considering the weight that managers have set. The results will be changed by changing the weight of managers selected.

Figure 2 also shows the percentage of each cost component of the system.

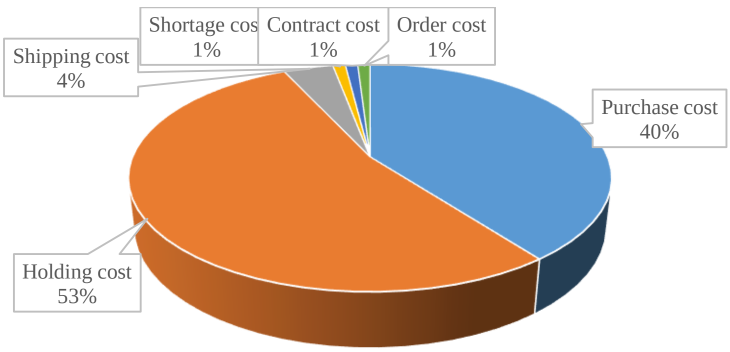

Figure 2. The percentages of integrated costs of system

In the case of non-failure, the average number of shortages of pareto solutions was 24.76 and, with the consideration of supplier's failures, it was 30.47. By performing the nonparametric hypothesis of the median number of shortages by SPSS® 22 and the rejection of the assumption zero, it was proved that the number of shortages is increased with the consideration of the supplier's failure. So, it is important to select suppliers without failure.

5. Conclusion and future research

In this research, an integrated model for supplier selection and inventory system for a drug distributing company in a stochastic environment was developed, while current models are often isolated and definite and have just one objective. Optimizing subsystems individually means that the whole system's objectives are not optimal. In this model, two objectives were to minimize, cost and number of shortages. Separating the number of shortages is due to the fact that a part of drug shortage cost is incalculable.

In this research, the problem was considered in a drug distributing system, but according to research literature, this model is also very useful for other systems. In Iran, many chain stores and distributing companies face this issue, but due to a lack of scientific and methodological solutions, their total cost is not optimal. The simulation part of this research can be used to calculate the cost and shortage of complex trading and industrial systems that cannot be calculated by conventional methods. The proposed MINLP model was solved by a MOPSO metaheuristic algorithm. Since the supplier breakdowns and the demand of the distributors are stochastic, the simulation is implemented to calculate the objective functions. Then, according to the weights of each objective, the superior solution was selected by TOPSIS technique. One of the limitations of this research is the high computational time of the integrated algorithm and the difficulty to calculate some of the model parameters in the real world. For example, it is difficult to calculate the exact amount of holding costs. Further research can focus on defining new objectives such as service level. Furthermore, the investigated problem was presented for a single drug system. For future work, the model can be developed for systems with several drugs and joint replenishment. Suppliers and distributors are facing with a lot of constraints in the real world. Also, new constraints such as inventory capacity of supplier and distributor branch, capital, capacity, and the number of truck deliveries between the supplier and the distributor branch can be added to the model. On the other hand, adding new operators to current algorithms or combining them with other algorithms can expedite the performance of the proposed algorithms as well as improving their accuracy. Likewise, other methods such as ELECTRE and AHP can be used to select a better solution than that of selected by TOPSIS. The parameters of the algorithms presented in this study are static. However, these parameters can be dynamically modified so as to change over time and provide better results.

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