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RESEARCH PAPER

Modeling The Make-to-Order Problem Considering The Order Queuing System Under Uncertainty

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ABSTRACT

In this paper, the modeling of a make-to-order problem considering the order queue system under the robust fuzzy programming method is discussed. Considering the importance of timely delivery of ideal demand, a four-level model of suppliers, production centers, distribution centers, and customers has been designed to reduce total costs. Due to the uncertainty of transportation costs and ideal demand, the robust fuzzy programming method is used to control the model. The analysis of different sample problems with the League Championship Algorithm (LCA), Particle Swarm Optimization (PSO), and Salp Swarm Algorithm (SSA) methods shows that with the increase in the uncertainty rate, the amount of ideal demand has increased, and this has led to an increase in total costs. On the other hand, with the increase of the stability coefficients of the model, contrary to the reduction of the shortage costs, the total costs of the model have increased due to transportation. Also, the analysis showed that with the increase in the number of servers in the production and distribution centers, the average waiting time for customers' order queues has decreased. By reducing the waiting time, the total delivery time of customer demand decreases, and the amount of actual demand increases. On the other hand, due to the lack of significant difference between the Objective Function Value (OBF) averages among the solution methods, they were prioritized, and SSA was recognized as an efficient algorithm. By implementing the model in a real case study in Iran for electronic components, it was observed that 4 areas of the Tehran metropolis (8-18-16-22) were selected as actual distribution centers. Also, the costs of the whole model were investigated in the case study and the results show the high efficiency of the solution methods in solving the make-to-order supply chain problem.

KEYWORDS: *Make to order; Order queuing system; Uncertainty; Robust fuzzy programming; Meta-heuristic algorithm.*

1. Introduction

In traditional manufacturing companies, goods were stored in warehouses and other places after production, which made the supply chain more complicated. If the company uses a make-to-order (MTO) business model, there is no need to stock the manufactured products. But at the same time, there will be a need to store raw materials and components. Therefore, it is clear that supply chains depend on the nature of the company. The concept of the MTO model is based on assembling immediately after receiving the order. This model requires the effective management of component inventories and delivery of the required supplies during the supply chain. A solution to overcome this need is the multi-purpose use of devices to produce goods. One of the main advantages of this type of model is the perception that each customer can visualize the product they need. In addition, every customer receives their goods quickly [1].

MTO supply chain (MTOSC) is one of the types of supply chain, and the impact of products produced according to the order on the environment and society is considered an important and main issue. The use of made-to-order engineering in manufacturing systems to provide customized products is progressing and expanding [2]. These companies have to find

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better ways to integrate the capacities of engineers, manufacturers, and suppliers to deal with the backlog [3]. In these environments, the selection of products is done by the customer and based on the existing plans. In such an environment, factories are forced to strive to rationalize their activities, focus on competencies, and competitive advantages, provide business services, outsource as many upstream processes as possible, and perform non-core activities for their supply chain partners. Products produced in this way are often used to meet the needs of small customers with low circulation and a wide range of technology. The main business activities in such companies include quotation, design, construction, assembly, as well as facility planning. With the increasing intensity of competition in producing and supplying goods and services, companies have faced multiple competition in their performance goals, such as quality, price, responsiveness, flexibility, and reliability. In such a situation, mass production has become the main goal of many companies. Accordingly, companies have focused on deploying and developing MTOSC, which has good flexibility and responsiveness. Using this strategy has become a competitive weapon to gain more market share in the global market as well [4]. In MTOSC, after receiving the order, the supply of materials, manufacturing of parts, and the final product are carried out. As soon as the order is received, the products are assembled in the factory and sent to the retailers through distribution centers, and if the distance between the retailers and the factories is close enough, they are delivered to the retailers directly from the factory [5]. Among the incoming orders to MTO manufacturing companies, only some of them are selected for production, and the rest are rejected. Therefore, these companies should accept orders that increase their profit and share in the competitive market. The MTO strategy can quickly and standardly manufacture or customize products based on automation and without any inventory forecast or purchase delays [6]. Such systems provide the opportunity to customize products based on the needs of customers, and the organization, which is faced with an increase in demand on the one hand, will face operational problems on the other hand, including the limitation of the production line capacity. In the past, according to the state of free-market capacity, the producers told the customer what product to buy. The customer's desire and taste were formed according to the state of the goods in the market. The companies started production in this system according to the supply state and available capacities. they paid and any company that had more capacity took more market share [7]. Today, with the competitive market and the customer's demand and taste development, what the customer wants should be produced.

The main question of the research can be stated as follows: How can a model be designed for the MTOSC, in which the total supply chain network costs can be minimized under conditions of uncertainty.

2. Literature Review

Due to the competitive environment, supply chain systems are increasingly moving from a make-to-stock (MTS) system to an MTO system. Traditional supply chain strategies are not efficient enough to deal with uncertainties. While customers are impatient with long lead times, companies should pay more attention to order-to-delivery time and find sustainable solutions to minimize order-to-delivery time. The number of companies using supply chain strategy, which leads to shorter production time by manufacturers, is increasing [8].

Lin et al. [9] designed an integrated supply-side, manufacturing and demand-side operations network to minimize the total expected operating cost. They modeled it in a deterministic equivalent formulation. An L-shaped decomposition with an additional decomposition step in the master problem is proposed. Lalmazloumian et al. [4] considered a supply chain planning problem of an agile manufacturing company operating in a build-to-order environment under various kinds of uncertainty. An integrated optimization approach of procurement, production and distribution costs associated with the supply chain members has been taken into account. A robust optimization scenario-based approach used to absorb the influence of uncertain parameters and variables. Ocampo et al. [10] present a real case application of a newly developed game theory model in the analysis of a multiple, multi-period, single manufacturer-supplier custom supply chain, with fuzzy parameters. They modeled the vertical interaction in the supply chain as a Stackelberg game in which the manufacturer was considered the leader and the suppliers were the followers.

Shi et al. [11] presented a Lagrange-based MTO supply chain network design algorithm under order-to-delivery time-dependent demand. The main objective of their proposed mathematical model is to minimize the total cost of the designed supply chain network consisting of factories, distribution centers, and retailers. Ma et al. [12] presented a collaborative cloud service platform to develop a new MTO apparel supply chain model. They designed a meta-heuristic model to select suppliers according to each received demand optimally. The multi-agent-based simulation was used to construct the proposed platform and evaluate the new sustainable supply chain model. An experiment was conducted to compare the new model with the custom model of traditional clothing with an outsourcing mechanism. Based on the simulation results, a significant improvement was shown in terms of the stability of the proposed platform and the corresponding supply chain model.

Chuna et al. [13] presented a game theory approach to analyze a supply chain consisting of a manufacturer with several suppliers, which has a dynamic nature. Because it considers the interactions and decisions of companies in multiple periods. These interactions are related to the MTO environment, market elasticity, price, and supply time. In order to test the applicability of the proposed model, they presented a case study of a local advertising supply chain in the central Philippines. Finally, the results were interpreted to provide key managerial insights and conclusions. Szmelter-Jarosz et al. [14] studied how the material flow in the supply chain affects its information flow and vice versa. They considered a model in which mathematical modeling creates coordinated information and material flow patterns. The parameters were studied, and the effects of each one on the other parameters were investigated. Relations were extracted, and the studied system was transformed into a mixed integer nonlinear programming model. Xu [15] presented a study aimed at introducing a web-based test system to minimize the effect of ripples caused by operational risks in the field of MTO. For this purpose, he used the design science research method to identify system requirements, business process design, and implement and evaluate a web-based test system. The results showed that the developed system has the potential to reduce the negative impact of the ripple effect caused by operational risks in the MTO supply chain in terms of material shortage, late delivery, and subsequent additional costs associated with the acceleration of MTO actions.

Holweg & Miemczyk [16] presented a strategic framework for MTO automotive procurement and pointed out that the proposed framework significantly impacts the automotive supply chain network. Rahmaniani et al. [17] presented a mixed-integer linear programming model in the MTOSC network, where customer returns are separated from components and eligible items are transferred to factories. They minimized the total cost and environmental impact. Alnahhal et al. [18] investigated the temporal integration process at a central integration center in an MTOSC. They used simulation to investigate the impact of a new and specific time integration on response time in outbound logistics and used Arena software for supply chain modeling. The results showed that when the order preparation time is more varied, time integration can be more effective.

Dohale et al. [19] conducted cross-case and cross-case analyses of four MTO-based Sari manufacturing companies to determine the intensity of SCR considering the pandemic and identify appropriate strategies to mitigate the SCR shock. Zhai & Cheng [20] presented an analytical model that shows how production lead time coverage affects the decision, the retailer's promised delivery time, and supply chain performance. They considered models for four scenarios: thecentralized model, Nash model, manufacturer-led Stackelberg model, and retailer-led Stackelberg model. Gholami et al. [21] in a study investigated the problem of order acceptance and scheduling of customized products in MTO. For this purpose, they proposed a new mixed integer programming mathematical model to optimize order acceptance, production planning, maintenance, and transportation decisions, and to confirm its effectiveness, they tested the model with a four-layer supply chain. The results showed that integrated order acceptance and proposed scheduling can save up to 30% in supply chain costs. According to the literature review, there is no comprehensive model of MTOSC under uncertainty that considers the order queuing system. Also, most of the conducted research is deterministic, and in this research, the FRP method is used to control non-deterministic parameters. On the other hand, in this research, various meta-innovative methods have been used to solve and implement the model in Iran's electronic components industry.

3. Definition of the Problem

In this part of the paper, the modeling of an MTOSC problem considering the queuing system is discussed. The considered SC consists of suppliers ($s \in S$), production centers ($i \in I$), distribution centers ($j \in J$) and customers ($k \in K$). According to Figure (1), customers announce their product demand to the distribution centers, which must be provided at time 0. In this department, customer order registration of various products is based on an M/M/C queue system. After that, the distribution centers send the recorded demand to the production centers. The production centers also produce products and send them to customers according to the orders from the distribution centers, which are considered an M/M/C system. Each distribution and production center has a number of servers with different distribution and production rates, which leads to different waiting times for customers' orders in the order queue. The waiting time for customers' orders in the queue of distribution and production centers, along with other transportation times for product preparation, leads to achieving the maximum time for sending orders from production centers to customers. In the presented model, the actual demand is calculated based on the maximum delivery time of the orders from the production centers to the customers, which is usually less than the ideal demand of the customers. Finally, each production center also needs raw materials ($r \in R$) to produce the products required by the customer, which is estimated through suppliers.

The main purpose of presenting the above model in the MTOSC problem is to select points for establishing distribution centers and assign the best combination of suppliers, production centers, distribution centers, and customers to each other to obtain the lowest network design cost. In this model, due to the indeterminacy of the ideal demand and transportation costs, the RFP method controls the indeterminate parameters and provides maximum customer demand in a steady state.

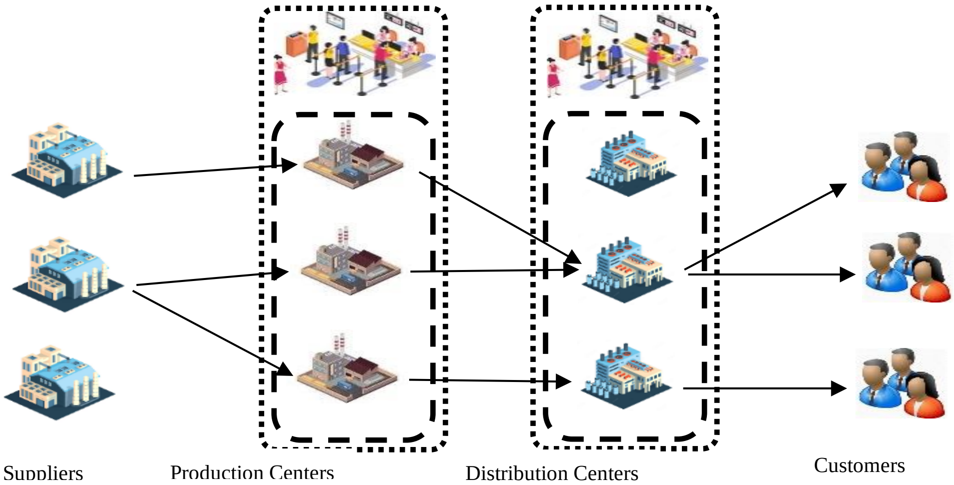


Fig. 1. Proposed MTOSC network

According to the explanations provided, the assumptions of the problem are considered as follows:

- In MTOSC, each manufacturing facility has sufficient capacity to meet the demand.
- Each customer can place an order to only one production center.
- The number of service providers and the rate of each service provider are specific for the centers.
- The ideal demand for non-deterministic customers is triangular fuzzy numbers.
- The actual demand depends on the delivery time of the products.
- Each production center can be assigned to only one distribution center.

The decision parameters and variables of the MINLP model of the investigated problem are as follows.

Parameters

$\tilde{d}_k$	Ideal customer demand k when "delivery time" equals 0.
tp_i	The time required to prepare products in the production center $i \in I$
td_j	Time required to prepare products in distribution center $j \in J$
ts_{rs}	Time required to prepare raw material $r \in R$ at supplier $s \in S$
ti_{si}	Transportation time of products from supplier $s \in S$ to production center $i \in I$
tpd_{ij}	Transportation time of products from production center $i \in I$ to distribution center $j \in J$
tpr_{jk}	Transportation time of products from distribution center $j \in J$ to customer $k \in K$
cp_{rs}	The cost of choosing a supplier $s \in S$ to supply raw material $r \in R$

$\widetilde{ci}_{rsi}$	The cost of transporting the raw material $r \in R$ from the supplier $s \in S$ to the production center $i \in I$
$\widetilde{cpd}_{ij}$	The cost of transporting products from the production center $i \in I$ to the distribution center $j \in J$
$\widetilde{cdr}_{jk}$	The cost of transporting products from the distribution center $j \in J$ to the customer $k \in K$
f_j	The cost of choosing a distribution center in location $j \in J$
b_r	The amount of raw material $r \in R$ required to produce one unit of product
B_j	The maximum number of servers in the distribution center $j \in J$
C_i	The maximum number of attendants in Production center $i \in I$
$\vartheta_j \le B_j$	The number of servers in the distribution center $j \in J$
$\tau_i \le C_i$	The number of servers in production center $i \in I$
μ_j	Distribution rate of products by distribution center $j \in J$
δ_i	Production rate of products by production center $i \in I$
θ_j	Probability of registering more than n orders in the order queue of distribution center $j \in J$
γ_i	Probability of registering more than n orders in the order queue of production center $i \in I$

Decision variables

de_{ijk}	Deliverable demand to customer $k \in K$ from production center $i \in I$ and through distribution center $j \in J$
S_{ijk}	1 If customer $k \in K$ is assigned to production center $i \in I$ through distribution center $j \in J$; 0 otherwise.
Z_j	1 If the distribution center is selected in location $j \in J$; 0 otherwise.
U_{irs}	1 if the raw material $r \in R$ is provided by the supplier $s \in S$ for the production center $i \in I$; 0 otherwise.
X_{jk}	1 if distribution center $j \in J$ is assigned to customer $k \in K$; 0 otherwise.
W_{ij}	1 If the production center $i \in I$ is assigned to the distribution center $j \in J$; 0 otherwise.
V_{rs}	1 if the raw material $r \in R$ is provided by the supplier $s \in S$; 0 otherwise.
T_{ijk}	The maximum time to transfer products from the production center $i \in I$ to the customer $k \in K$ through the distribution center $j \in J$
λ_j	Total amount of product distributed by distribution center $j \in J$
σ_i	The total amount of product produced by production center $i \in I$
Tw_i	The waiting time for a customer's order in the queue of production center $i \in I$
Tv_j	The waiting time for a customer's order in the queue of the distribution center $j \in J$
π_{0j}	Probability of having 0 orders in the order queue of distribution center $j \in J$
π_{0i}	Probability of having 0 orders in the order queue of production center $i \in I$
ω	The coefficient of production of products according to the delivery time

$$\begin{aligned}\text{Min OBF} = &\sum_{j=1}^{J} f_j Z_j + \sum_{r=1}^{R}\sum_{s=1}^{S} cp_{rs} V_{rs} + \sum_{i=1}^{I}\sum_{r=1}^{R}\sum_{s=1}^{S}\sum_{j=1}^{J}\sum_{k=1}^{K} \widetilde{ci}_{rsi} U_{rsi} b_r \left(de_{ijk} S_{ijk}\right) \\ &+ \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(\widetilde{cpd}_{ij} + \widetilde{cdr}_{jk}\right) de_{ijk} S_{ijk}\end{aligned} \tag{1}$$

s.t.:

$$\sum_{j=1}^{J} X_{jk} = 1, \quad \forall k \in K \tag{2}$$

$$\sum_{i=1}^{I} W_{ij} = Z_j, \quad \forall j \in J \tag{3}$$

$$\sum_{s=1}^{S} U_{irs} = 1, \quad \forall i \in I, r \in R \tag{4}$$
$$S_{ijk} \le X_{jk} \le Z_j, \quad \forall j \in J, k \in K \tag{5}$$
$$S_{ijk} \le W_{ij} \le Z_j, \quad \forall i \in I, j \in J \tag{6}$$
$$S_{ijk} \ge X_{jk} + W_{ij} - 1, \quad \forall i \in I, j \in J, k \in K \tag{7}$$
$$U_{irs} \le V_{rs}, \quad \forall i \in I, r \in R, s \in S \tag{8}$$
$$\lambda_j = \sum_{k=1}^{K} \tilde{d}_k X_{jk}, \quad \forall j \in J \tag{9}$$
$$\sigma_i = \sum_{k=1}^{K}\sum_{j=1}^{J} \tilde{d}_k S_{ijk}, \quad \forall i \in I \tag{10}$$
$$\pi_{0i} = \left[\sum_{i'=0}^{\tau_i-1} \frac{1}{i'!}\left(\frac{\sigma_i}{\delta_i}\right)^{i'} + \frac{1}{\tau_i!}\left(\frac{\sigma_i}{\delta_i}\right)^{\tau_i}\left(\frac{\tau_i\delta_i}{\tau_i\delta_i - \sigma_i}\right)\right]^{-1}, \quad \forall i \in I \tag{11}$$
$$\left(\sum_{i'=0}^{\tau_i} \frac{\sigma_i^{i'}}{i'!\,\delta_i^{i'}} + \sum_{i'=\tau_i+1}^{\tau_i+C_i} \frac{\sigma_i^{i'}\tau_i^{\,i'-\tau_i}}{i'!\,\delta_i^{i'}}\right)\pi_{0i} \ge (1-\gamma_i), \quad \forall i \in I \tag{12}$$
$$\pi_{0j} = \left[\sum_{j'=0}^{\vartheta_j-1} \frac{1}{j'!}\left(\frac{\lambda_j}{\mu_j}\right)^{j'} + \frac{1}{\vartheta_j!}\left(\frac{\lambda_j}{\mu_j}\right)^{\vartheta_j}\left(\frac{\vartheta_j\mu_j}{\vartheta_j\mu_j - \lambda_j}\right)\right]^{-1}, \quad \forall j \in J \tag{13}$$
$$\left(\sum_{j'=0}^{\vartheta_j} \frac{\lambda_j^{j'}}{j'!\,\mu_j^{j'}} + \sum_{j'=\vartheta_j+1}^{\vartheta_j+B_j} \frac{\lambda_j^{j'}\vartheta_j^{\,j'-\vartheta_j}}{j'!\,\mu_j^{j'}}\right)\pi_{0j} \ge (1-\theta_j), \quad \forall j \in J \tag{14}$$
$$Tw_i = \left[\frac{\pi_{0i}}{\tau_i!}\left(\frac{\sigma_i}{\delta_i}\right)^{\tau_i!}\frac{\tau_i\delta_i}{(\tau_i\delta_i - \sigma_i)^2} + \frac{1}{\delta_i}\right], \quad \forall i \in I \tag{15}$$
$$Tv_j = \left[\frac{\pi_{0j}}{\vartheta_j!}\left(\frac{\lambda_j}{\mu_j}\right)^{\vartheta_j!}\frac{\vartheta_j\mu_j}{(\vartheta_j\mu_j - \lambda_j)^2} + \frac{1}{\mu_j}\right], \quad \forall j \in J \tag{16}$$
$$de_{ijk} = \tilde{d}_k e^{-\omega T_{ijk}}, \quad \forall i \in I, j \in J, k \in K \tag{17}$$
$$T_{ijk} = \left(\max_{\forall r \in R, s \in S}[(ts_{rs} + ti_{si})U_{irs}] + (tp_i + tw_i) + tpd_{ij} + td_{jk} + (tv_j + td_j)\right), \quad \forall i \in I, j \in J, k \in K \tag{18}$$
$$S_{ijk}, Z_j, U_{irs}, X_{jk}, W_{ij}, V_{rs} \in \{0,1\} \tag{19}$$
$$de_{ijk}, T_{ijk}, \lambda_j, \sigma_i, Tw_i, Tv_j, \pi_{0j}, \pi_{0i}, \omega \ge 0 \tag{20}$$

Equation (1) minimizes the total costs of the MTOSC problem. These costs include the cost of choosing distribution centers, providing raw materials by suppliers, and transportation. Equation (2) guarantees that each customer is assigned to only one distribution center. Equation (3) guarantees that each production center should be assigned to only one distribution center. Equation (4) shows that each production center can get raw materials from only one supplier. Equations (5) to (7) show that the allocation between the customer and the production center occurs if the intermediary distribution center is selected. Equation (8) shows what type of raw material the supplier should supply. Equations (9) and (10) show the total amount of distribution and production by each selected center, respectively. These values are used as input rates to determine the queue length of distribution and production centers. Equations (11) to (14) show the probability of having 0 customers in the order queue of production and distribution centers and the probability of having more than n customers in the queue of these centers. Equations (15) and (16) show the waiting time for customers' orders in the queue of production and distribution centers. Equation (17) shows the maximum delivery time of products from production centers to customers. Equation (18) shows the actual demand of each customer in terms of the maximum calculated time. Equations (19) and (20) show binary and continuous variables.

Due to the indeterminacy of ideal demand parameters and transportation costs in the MTOSC model, the RFP method has been used to control the indeterminacy parameters. In this method, first, non-deterministic parameters are defined under the form of triangular fuzzy numbers and the following fuzzy model is defined:

Base model

$$\min \mathrm{Fy} + \mathrm{E}[\tilde{\mathrm{C}}]\mathrm{x}$$
$$\text{s.t.:}$$
$$\mathrm{NEC}\{\mathrm{Ax} \geq \tilde{\mathrm{D}}\} \geq \alpha$$
$$\mathrm{Ex} \leq \mathrm{Sy}$$
$$\mathrm{y} \in \{0,1\}, \qquad \mathrm{x} \geq 0$$

$\Rightarrow$

Defuzzy model

$$\min \mathrm{Fy} + \left(\frac{\mathrm{C^o} + 2\mathrm{C^m} + \mathrm{C^p}}{4}\right)\mathrm{x}$$
$$\text{s.t.:}$$
$$\mathrm{Ax} \geq [(1-\alpha)\mathrm{D^m} + \alpha \mathrm{D^p}] + \left[\left(\mathrm{h^m} + \frac{\upsilon_t + \upsilon'_t}{4}\right)(1-\varepsilon)\right] \tag{21}$$
$$\mathrm{Ex} \leq \mathrm{Sy}$$
$$\mathrm{y} \in \{0,1\}, \qquad \mathrm{x} \geq 0$$

In the above model, $\tilde{C} \sim (C^o, C^m, C^p)$ is the variable costs of the problem. $\tilde{D} \sim (D^o, D^m, D^p)$ is the demand of the problem, which are defined as non-deterministic parameters of the problem? Also, α as the minimum degree of certainty of establishing non-deterministic limits (uncertainty rate) and $\left[\left(\frac{\upsilon_t + \upsilon'_t}{4}\right)(1-\varepsilon)\right]$shows the flexibility of non-deterministic limits. The parameters $\upsilon_t$and υ'_t represent the distance between the lateral margins of the uncertain parameter with its most probable value. These parameters indicate the possible violation of soft constraints, which can be defined as follows:

$$\upsilon_t = \mathrm{D^o} - \mathrm{D^m}$$
$$\upsilon'_t = \mathrm{D^m} - \mathrm{D^p}$$
$$\mathrm{h^m} = \frac{\mathrm{D^o} + \mathrm{D^p}}{2} \tag{22}$$

It is worth noting that the ε parameters represent the minimum degree of satisfaction of the flexible constraints, whose value should be determined by the opinion and experience of field experts ($0 \leq \varepsilon \leq 1$). Finding the optimal value of satisfaction levels is a difficult problem for decision-makers, and increasing the number of uncertain parameters and soft constraints can make it more complicated and time-consuming. Also, there is no assurance that the final value determined is the optimal satisfaction level and can lead to the optimal value of the objective function. On the other hand, since the objective function is formulated based on the expected value of the fuzzy numbers, any deviation from the uncertain parameters can lead to the unreliability of the model's results and bring great losses to companies. In this regard, the above-controlled model is described as follows:

$$\min \mathrm{Z} = \mathrm{Fy} + \left(\frac{\mathrm{C^o} + 2\mathrm{C^m} + \mathrm{C^p}}{4}\right)\mathrm{x} + \eta[\mathrm{D^p} - (1-\alpha)\mathrm{D^m} - \alpha\mathrm{D^p}] + \varrho\left[\left(\mathrm{h^m} + \frac{\upsilon_t + \upsilon'_t}{4}\right)(1-\varepsilon)\right]$$
$$\text{s.t.:}$$
$$\mathrm{Ax} \geq [(1-\alpha)\mathrm{D^m} + \alpha \mathrm{D^p}] + \left[\left(\mathrm{h^m} + \frac{\upsilon_t + \upsilon'_t}{4}\right)(1-\varepsilon)\right] \tag{23}$$
$$\mathrm{Ex} \leq \mathrm{Sy}$$
$$\mathrm{y} \in \{0,1\}, \qquad \mathrm{x} \geq 0$$

In the above model, η is the penalty coefficient for not fully satisfying the demand and ϱ is the stability coefficient of the model. Based on this, the final model of the MTOSC problem in controlled conditions will be as follows.

$$\begin{aligned}\text{Min OBF} = {} & \sum_{j=1}^{J} \mathrm{f_j Z_j} + \sum_{r=1}^{R}\sum_{s=1}^{S} \mathrm{cp_{rs} V_{rs}} \\ & + \sum_{i=1}^{I}\sum_{r=1}^{R}\sum_{s=1}^{S}\sum_{j=1}^{J}\sum_{k=1}^{K}\left[\frac{\mathrm{ci^o_{rsi}} + 2\mathrm{ci^m_{rsi}} + \mathrm{ci^p_{rsi}}}{4}\right]\mathrm{U_{rsi} b_r}(\mathrm{de_{ijk} S_{ijk}}) \\ & + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(\left[\frac{\mathrm{cpd^o_{ij}} + 2\mathrm{cpd^m_{ij}} + \mathrm{cpd^p_{ij}}}{4}\right] + \left[\frac{\mathrm{cdr^o_{jk}} + 2\mathrm{cdr^m_{jk}} + \mathrm{cdr^p_{jk}}}{4}\right]\right)\mathrm{de_{ijk} S_{ijk}}\end{aligned} \tag{24}$$

$$+\eta\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(\left(d_k^p-(1-\alpha)d_k^m-\alpha d_k^p\right)-de_{ijk}S_{ijk}\right)$$
$$+\varrho\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left[\left(\left(\frac{3d_k^o-d_k^p}{4}\right)-de_{ijk}S_{ijk}\right)(1-\varepsilon)\right]$$

s.t.:

$$\sum_{j=1}^{J}X_{jk}=1,\quad \forall k\in K \tag{25}$$
$$\sum_{i=1}^{I}W_{ij}=Z_j,\quad \forall j\in J \tag{26}$$
$$\sum_{s=1}^{S}U_{irs}=1,\quad \forall i\in I, r\in R \tag{27}$$
$$S_{ijk}\le X_{jk}\le Z_j,\quad \forall j\in J, k\in K \tag{28}$$
$$S_{ijk}\le W_{ij}\le Z_j,\quad \forall i\in I, j\in J \tag{29}$$
$$S_{ijk}\ge X_{jk}+W_{ij}-1,\quad \forall i\in I, j\in J, k\in K \tag{30}$$
$$U_{irs}\le V_{rs},\quad \forall i\in I, r\in R, s\in S \tag{31}$$
$$\lambda_j=\sum_{k=1}^{K}\left(\left[(1-\alpha)d_k^m+\alpha d_k^p\right]+\left[\left(\frac{3d_k^o-d_k^p}{4}\right)(1-\varepsilon)\right]\right)X_{jk},\quad \forall j\in J \tag{32}$$
$$\sigma_i=\sum_{k=1}^{K}\sum_{j=1}^{J}\left(\left[(1-\alpha)d_k^m+\alpha d_k^p\right]+\left[\left(\frac{3d_k^o-d_k^p}{4}\right)(1-\varepsilon)\right]\right)S_{ijk},\quad \forall i\in I \tag{32}$$
$$\pi_{0i}=\left[\sum_{i'=0}^{\tau_i-1}\frac{1}{i'!}\left(\frac{\sigma_i}{\delta_i}\right)^{i'}+\frac{1}{\tau_i!}\left(\frac{\sigma_i}{\delta_i}\right)^{\tau_i}\left(\frac{\tau_i\delta_i}{\tau_i\delta_i-\sigma_i}\right)\right]^{-1},\quad \forall i\in I \tag{33}$$
$$\left(\sum_{i'=0}^{\tau_i}\frac{\sigma_i^{i'}}{i'!\,\delta_i^{i'}}+\sum_{i'=\tau_i+1}^{\tau_i+C_i}\frac{\sigma_i^{i'}\tau_i^{\,i'-\tau_i}}{i'!\,\delta_i^{i'}}\right)\pi_{0i}\ge(1-\gamma_i),\quad \forall i\in I \tag{34}$$
$$\pi_{0j}=\left[\sum_{j'=0}^{\vartheta_j-1}\frac{1}{j'!}\left(\frac{\lambda_j}{\mu_j}\right)^{j'}+\frac{1}{\vartheta_j!}\left(\frac{\lambda_j}{\mu_j}\right)^{\vartheta_j}\left(\frac{\vartheta_j\mu_j}{\vartheta_j\mu_j-\lambda_j}\right)\right]^{-1},\quad \forall j\in J \tag{35}$$
$$\left(\sum_{j'=0}^{\vartheta_j}\frac{\lambda_j^{j'}}{j'!\,\mu_j^{j'}}+\sum_{j'=\vartheta_j+1}^{\vartheta_j+B_j}\frac{\lambda_j^{j'}\vartheta_j^{\,j'-\vartheta_j}}{j'!\,\mu_j^{j'}}\right)\pi_{0j}\ge(1-\theta_j),\quad \forall j\in J \tag{36}$$
$$Tw_i=\left[\frac{\pi_{0i}}{\tau_i!}\left(\frac{\sigma_i}{\delta_i}\right)^{\tau_i!}\frac{\tau_i\delta_i}{(\tau_i\delta_i-\sigma_i)^2}+\frac{1}{\delta_i}\right],\quad \forall i\in I \tag{37}$$
$$Tv_j=\left[\frac{\pi_{0j}}{\vartheta_j!}\left(\frac{\lambda_j}{\mu_j}\right)^{\vartheta_j!}\frac{\vartheta_j\mu_j}{(\vartheta_j\mu_j-\lambda_j)^2}+\frac{1}{\mu_j}\right],\quad \forall j\in J \tag{38}$$
$$de_{ijk}=\left(\left[(1-\alpha)d_k^m+\alpha d_k^p\right]+\left[\left(\frac{3d_k^o-d_k^p}{4}\right)(1-\varepsilon)\right]\right)e^{-\omega T_{ijk}},\quad \forall i\in I, j\in J, k\in K \tag{39}$$
$$T_{ijk}=\left(\max_{\forall r\in R,s\in S}[(ts_{rs}+ti_{si})U_{irs}]+(tp_i+tw_i)+tpd_{ij}+td_{jk}+\left(tv_j+td_j\right)\right),\quad \forall i\in I, j\in J, k\in K \tag{40}$$
$$S_{ijk},Z_j,U_{irs},X_{jk},W_{ij},V_{rs}\in\{0,1\} \tag{41}$$
$$de_{ijk},T_{ijk},\lambda_j,\sigma_i,Tw_i,Tv_j,\pi_{0j},\pi_{0i},\omega\ge 0 \tag{42}$$

Some studies have proved that MTOSC problems are NP-hard, which can be referred to [22]. In this article, due to the use of queuing system equations in MTOSC, it can be concluded that the degree of difficulty of the model presented in this article is at least equal to the degree of difficulty of MTO problems. Therefore, various algorithms have been used to solve the problem described below.

4. Solution Method

Due to the NP-hardness of the mathematical model, four algorithms LCA, SSA, and PSO are proposed to solve the problem. The proposed algorithms are population-based algorithms and simultaneously search for a set of generated solutions in each iteration. These algorithms have been investigated separately in the literature on MTO problems, and the purpose of using these algorithms is to check their efficiency on the proposed model. Therefore, in figures (2) to (4), the flowchart of each algorithm is presented.

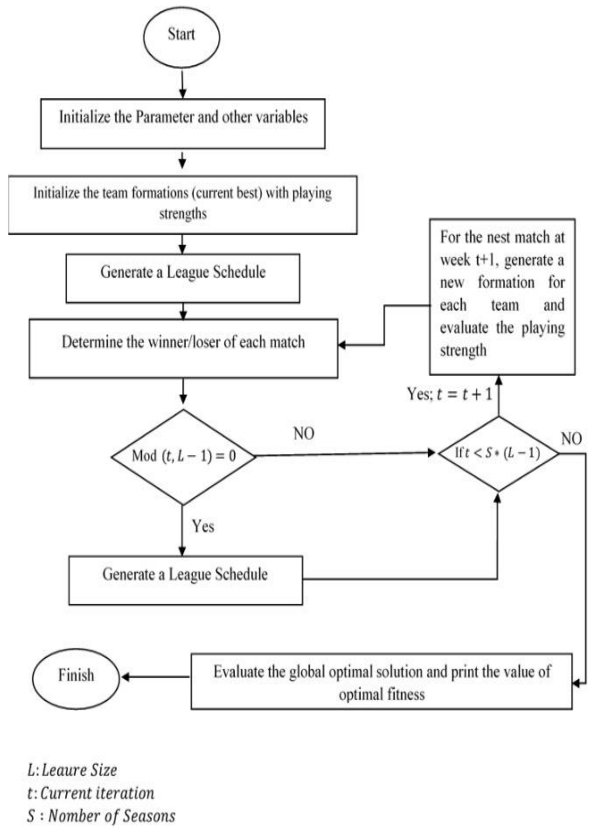


Fig. 2. Flowchart of LCA algorithm

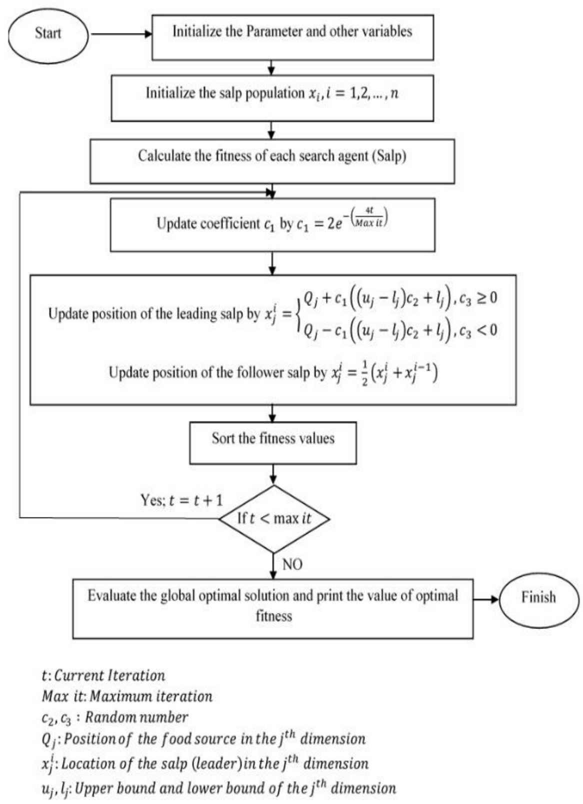


Fig. 3. SSA algorithm flowchart

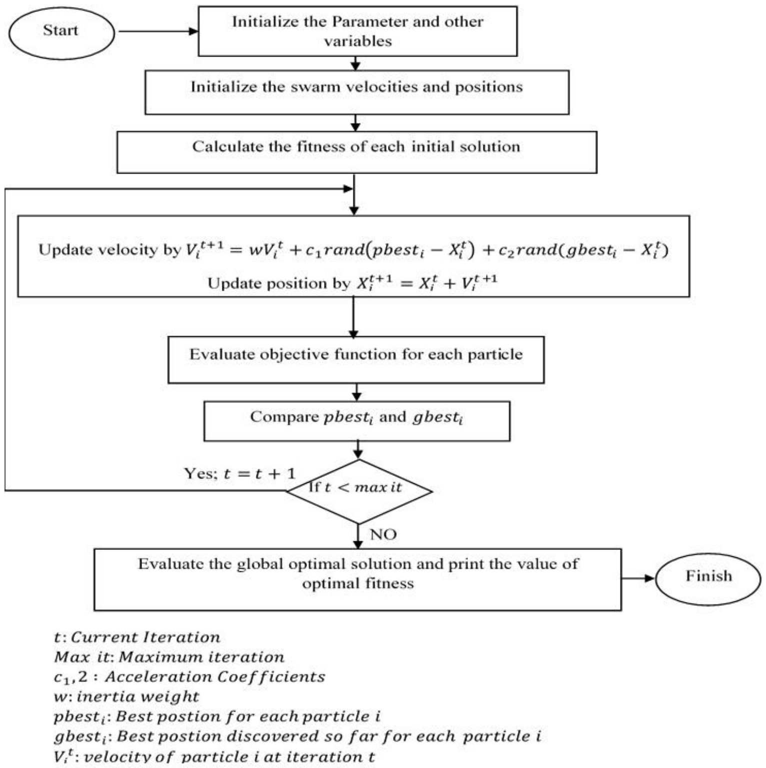


Fig. 4. PSO algorithm flowchart

Each meta-heuristic algorithm proposed in this article needs an initial solution to search the problem space. The initial solution is the most important step in defining and using meta-heuristic algorithms to solve optimization problems. The initial solution in the MTOSC problem proposed in this paper is defined as Figure (5). In this figure, for a hypothetical example with 3 suppliers, 4 production centers, 4 distribution centers and 5 customers including 2 raw materials, the initial solution is a matrix $2 * (|K| + |S|)$.

	Customer				
Node	1	2	3	4	5
Allocate to Distribution Center	1	2	2	1	2
Allocate to Production Center	2	2	3	1	2

	Supplier		
Node	1	2	3
Raw material	1	2	1
Allocate to Production Center	2	1	3

Fig. 5. Initial solution of the problem

According to figure (5), it can be seen that the initial solution was arranged based on the number of distribution and production centers as well as raw materials. In order to allocate customers to distribution and production centers, the number of each center is randomly generated. For example, customer number (1) has been assigned to production center number (2) through distribution center number (1). Also, supplier number (2) has been assigned to production center number (1), which is responsible for supplying raw material number (2). Based on this, it is possible to estimate the structure of the form and the hard limits of the problem, and then determine the real demand according to the equations of the queue system and the delivery time of the products to the customers. Figure (6) shows the decoding of the initial solution to achieve the near-optimal objective function value by meta-heuristic algorithms.

$Step\ 1: Calculate\ X_{jk}, W_{ij}\ and\ U_{irs}\ based\ on\ Fig. 5$
$Step\ 2: Calculate\ S_{ijk}\ based\ X_{jk}, W_{ij}\ from\ step\ 1$

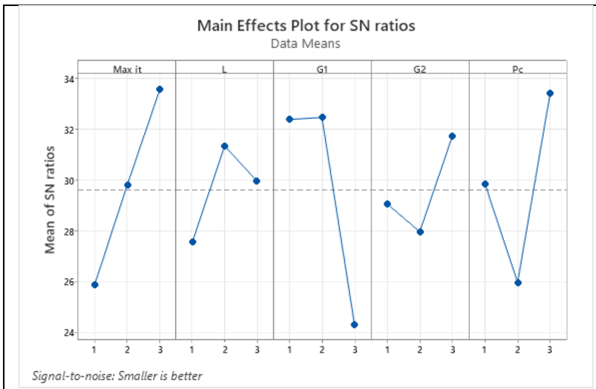
$Step\ 3: Calculate\ Z_j\ based\ W_{ij}\ from\ step\ 1$
$Step\ 4: Calculate\ V_{rs}\ based\ U_{irs}\ from\ step\ 1$
$Step\ 5: Calculate\ \lambda_j\ and\ \sigma_i\ based\ \ X_{jk}\ and\ S_{ijk}\ from\ step\ 2$
$Step\ 6: Calculate\ \pi_{0i}\ and\ \pi_{0j}\ based\ \ \lambda_j\ and\ \sigma_i\ from\ step\ 5$
$Step\ 7: Calculate\ Tw_i\ and\ Tv_j\ based\ on\ \pi_{0i}\ and\ \pi_{0j}\ from\ step\ 6$
$Step\ 8: Calculate\ T_{ijk}$
$Step\ 9: Calculate\ de_{ijk}\ based\ on\ T_{ijk}\ from\ step\ 8$
$Step\ 10: Calculate\ objective\ function$

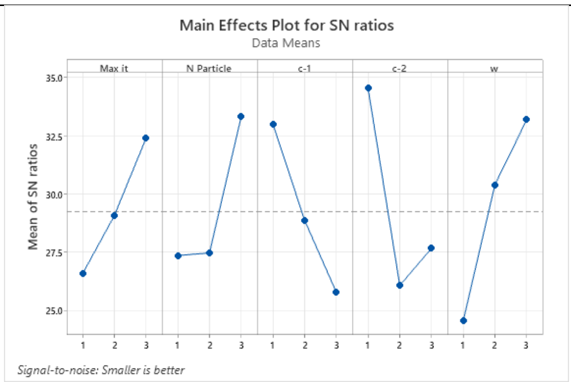
Fig. 6. Decoding the initial solution to obtain the OBF value

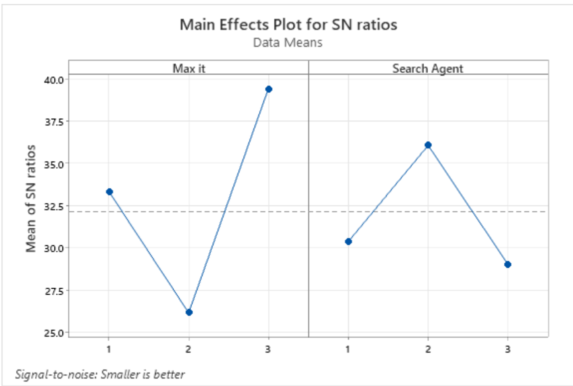
Before analyzing different numerical examples with LCA, SSA and PSO methods, Taguchi method should be used to adjust the initial parameters of each algorithm. Setting the parameter increases the algorithms' efficiency in searching the solution space. If the parameters of each algorithm are set correctly, it will reach the near-optimal solution in a shorter time. For this purpose, three levels are proposed for each of the parameters, and achieving the right combination of these three levels is done by Taguchi tests. Equation (43) shows the RPD value of each Taguchi test in each of the combined levels.

$$\mathrm{Response_i} = \frac{\mathrm{OBF_i} - \min\limits_{\mathrm{i}} \mathrm{OBF_i}}{\min\limits_{\mathrm{i}} \mathrm{OBF_i}} \tag{43}$$

In the above equation, OBF_i is the value of the objective function obtained in each of Taguchi's tests and $\min\limits_{i} OBF_i$ is the lowest value of the objective function among all the tests. Based on $Response_i$ obtained from each experiment, the average S/N graph is analyzed. Figure (7) shows the average S/N graph for each of the algorithms. The numerical value corresponding to the highest level of the graph is considered as the optimal value of the parameter for that algorithm.







Method	Parameter	Best Level	Best Value
LCA	Max it	3	200
	L	2	100
	ψ_1	2	4
	ψ_2	3	1.1
	p_c	3	0.07
SSA	Max it	3	200
	Search agent	2	150
PSO	Max it	3	200
	N particle	3	150
	c_1	1	1
	c_2	1	1.5
	w	3	0.8

Fig. 7. Parameter setting of meta-heuristic algorithms

5. Analysis of Sample Problems

5.1. Solving various example problems with meta-heuristic algorithms

After setting the parameters of the meta-heuristic algorithms, different sample problems have been solved in different sizes. Considering that the problem is NP-hard, the article's main focus is on the efficiency of meta-heuristic algorithms. Therefore, to validate the obtained results, Baron has been used to solve small size problems. Tables (1) and (2) show the values of the main parameters of the problem and the size of different sample problems, respectively.

Tab. 1. Interval limits of problem parameters according to uniform distribution function

Parameter	Optimistic	Likely	Pessimistic
$\tilde{d}_k$	$\sim U(100,150)$	$\sim U(150,200)$	$\sim U(200,250)$
$\widetilde{ci}_{rsi}$	$\sim U(5,10)\$$	$\sim U(10,15)\$$	$\sim U(15,20)\$$
$\widetilde{cpd}_{ij}$	$\sim U(6,12)\$$	$\sim U(12,18)\$$	$\sim U(18,25)\$$
$\widetilde{cdr}_{jk}$	$\sim U(8,15)\$$	$\sim U(15,22)\$$	$\sim U(22,25)\$$
Parameter	Value	Parameter	Value
tp_i	$\sim(0.5,1)h$	$\vartheta_j \leq B_j$	3
td_j	$\sim(0.5,0.75)h$	$\tau_i \leq C_i$	4
ts_{rs}	$\sim(1,1.5)h$	μ_j	$\sim(50,120)$
ti_{si}	$\sim(1,2)h$	δ_i	$\sim(80,150)$
tpd_{ij}	$\sim(0.5,2)h$	θ_j	0.3
tpr_{jk}	$\sim(0.5,1)h$	γ_i	0.2
cp_{rs}	$\sim(1000,2500)\$$	η	3
f_j	$\sim(18000,25000)h$	α	0.5
b_r	$\sim(0.2,1.3)$	ϱ	10
B_j	6	ε	0.3
C_i	5		

Tab. 2. Size of sample problems in different sizes

Sample Problem	$\lvert S\rvert \times \lvert I\rvert \times \lvert J\rvert \times \lvert K\rvert \times \lvert R\rvert$	Sample Problem	$\lvert S\rvert \times \lvert I\rvert \times \lvert J\rvert \times \lvert K\rvert \times \lvert R\rvert$
1	$3 \times 4 \times 4 \times 4 \times 2$	6	$22 \times 10 \times 18 \times 22 \times 3$
2	$5 \times 4 \times 6 \times 6 \times 2$	7	$28 \times 12 \times 20 \times 28 \times 4$
3	$8 \times 6 \times 8 \times 8 \times 2$	8	$32 \times 15 \times 25 \times 34 \times 4$
4	$12 \times 6 \times 10 \times 12 \times 3$	9	$38 \times 18 \times 28 \times 40 \times 5$
5	$18 \times 8 \times 15 \times 16 \times 3$	10	$45 \times 25 \times 30 \times 50 \times 5$

In order to reduce the calculation error, each algorithm is used 3 times to solve each sample problem and the lowest value of the objective function is shown in table (3). In this table, the value of GAP and RPD of each algorithm is also specified.

Tab. 3. OBF value and calculation error of each solution method

Sample Problem	OBF				Min Gap *vs* Baron %	RPD %		
	Baron	SSA	LCA	PSO		SSA	LCA	PSO
1	26814.67	27347.07	27164.38	27495.45	1.304	1.219	0.000	0.673
2	32115.93	32589.90	33156.42	32661.11	1.476	0.218	1.738	0.000
3	-	35362.19	35041.72	35075.48	-	0.096	0.000	0.915
4	-	42598.34	42837.92	42242.80	-	0.000	1.409	0.842
5	-	50542.75	50550.13	50804.86	-	0.519	0.015	0.000
6	-	53498.00	54223.98	53687.62	-	0.354	1.357	0.000
7	-	58284.20	57182.01	57991.75	-	1.416	0.000	1.928
8	-	63510.11	63787.41	64087.16	-	0.909	0.437	0.000
9	-	72388.31	72813.24	71738.02	-	0.000	1.499	0.906
10	-	78497.15	77997.32	78521.85	-	0.673	0.000	0.641
Mean		51430.61	51475.45	51461.80		0.540	0.645	0.590

According to the results of table (3), it can be seen that Baron could only solve two sample problems and the gap between Baron and meta-heuristic algorithms was 1.5%. Also, RPD comparison between different solution methods shows that meta-heuristic algorithms have very close results in achieving OBF. On average, SSA has obtained the lowest OBF value compared to PSO and LCA. Figure (8) shows the computational time obtained from solving sample problems of different sizes for the MTOSC problem.

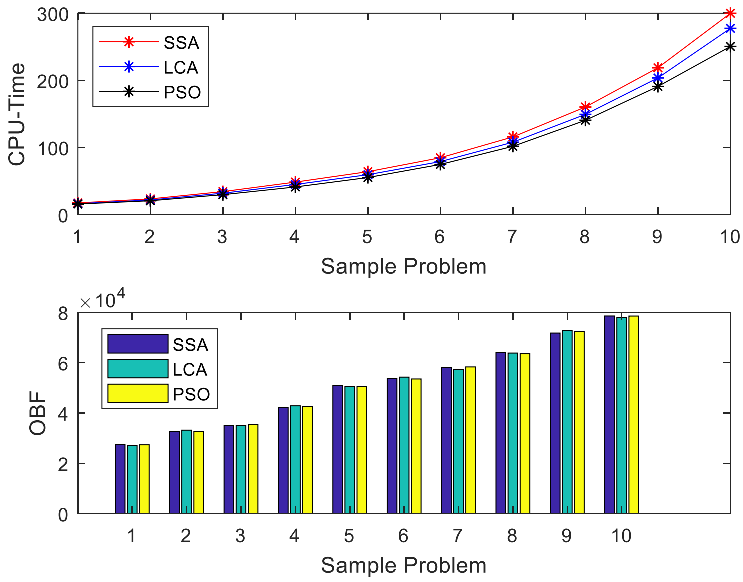


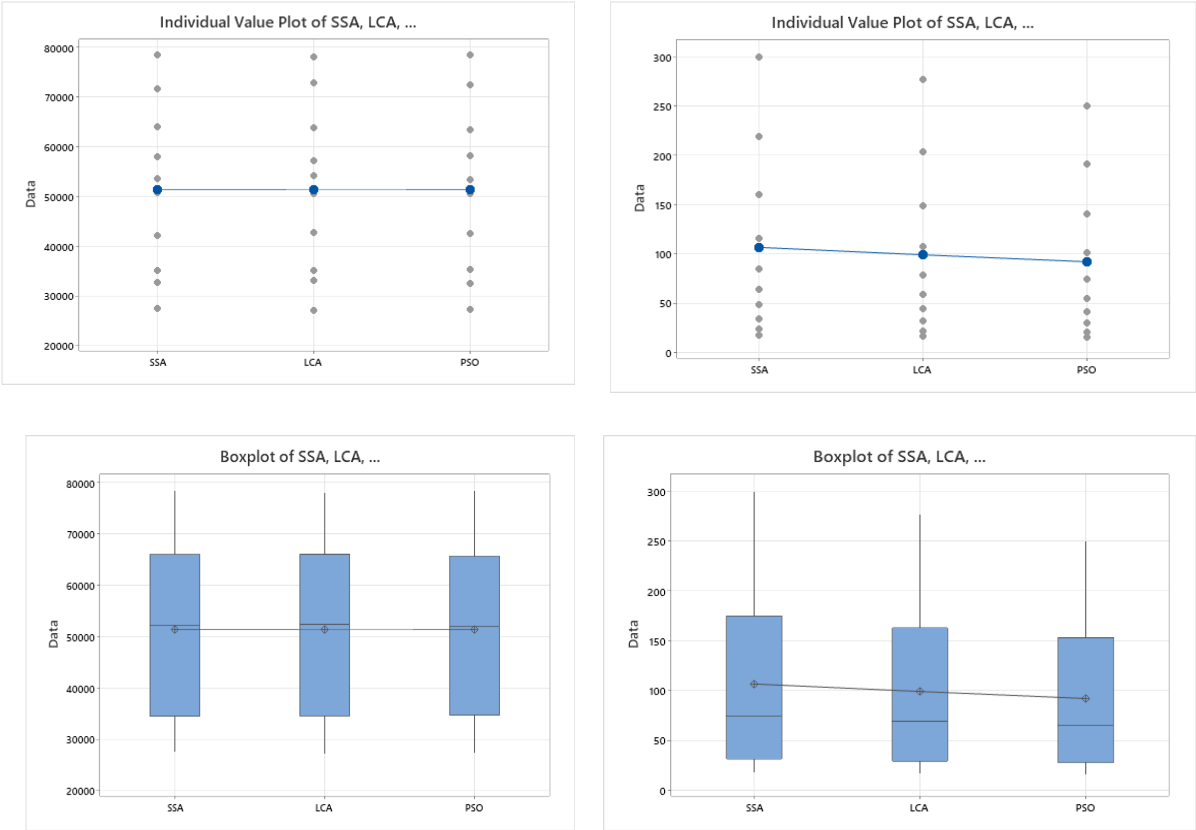
Fig. 8. Comparison of OBF value and computational time between solution methods

Based on the results obtained from Figure (8), it can be seen that with the increase in the size of the problem, the solution time has increased exponentially. This shows that the MTOSC problem is an NP-hard problem. Also, on average, PSO has obtained the lowest solution time among different solution methods.

The examined sample problems showed that LCA, PSO and SSA methods each efficiently achieve near-optimal solutions. So that SSA has the best average OBF and PSO has the best average computing time. The two-sided paired T-test statistical test was used to check the significance of the averages of these two indicators between the solution methods. Table (4) shows the results of the two-sided paired T-test in examining the significant difference between the two investigated indicators. Figure (8) also shows the graphs obtained from the one-way ANOVA test in examining the significant difference of the indicators.

Tab. 4. Results of two-sided paired T-test

Method	Index	Mean	StDev	SE Mean	95% CI for µ_difference	T-Value	P-Value
SSA-LCA		45	598	189	(-383 473)	0.24	0.818
SSA-PSO	OBF	31	361	114	(-227 289)	0.27	0.791
LCA-PSO		14	554	175	(-383 410)	0.08	0.940
SSA-LCA		7.52	6.85	2.17	(2.62 12.420	3.47	0.007
SSA-PSO	CPU-Time	14.59	14.65	4.63	(4.11 25.07)	3.15	0.012
LCA-PSO		7.07	7.89	2.50	(1.42 12.72)	2.83	0.020



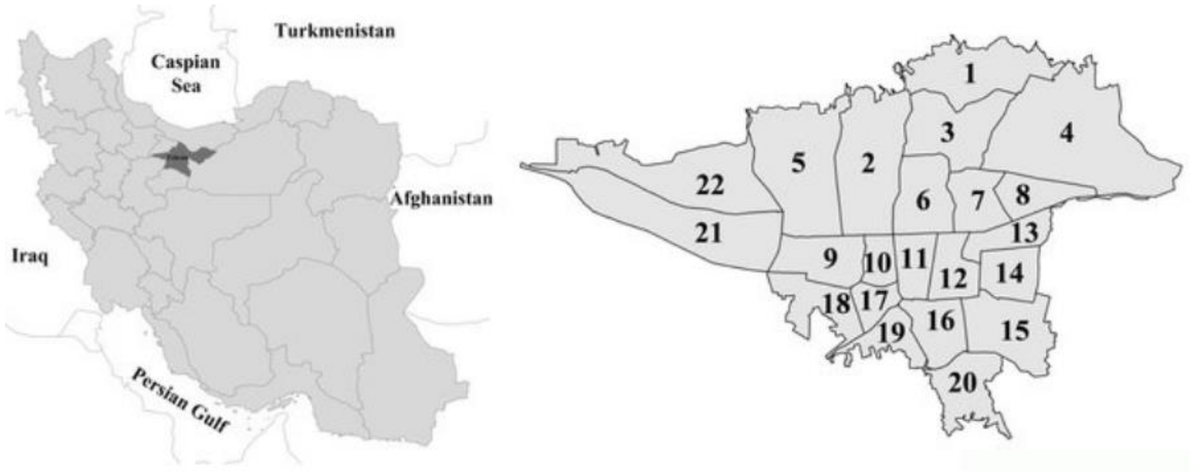
OBF *CPU-Time*

Fig. 9. Box diagram of comparisons of significant differences of indicators with one-way ANOVA

The results obtained from the statistical tests show that the value of P-Value among all meta-heuristic algorithms in the calculation time index is less than 0.05 and hence there is a significant difference between the averages of this index. While there is no significant difference between the OBF averages between any of the used algorithms.

5.2. Case study analysis

The high efficiency of LCA, SSA and PSO methods in solving the MTOSC problem has led to the analysis of a case study in Tehran metropolis in Iran. A case study has been conducted for electronic components used in computer production in this province. This province has 22 regions according to figure (10), all regions of this province are considered as demand points. Also, areas 8, 16, 10, 6, 5 and 22 are considered distribution centers, and areas 8, 6, 22, 18, 16 and 14 are considered production centers. The suppliers of electronic parts are also regions 20, 19, 22 and 4. According to the information of www.irica.ir and the estimation of export and import, the ideal demand of electronic components based on experts' opinions in this field is shown in table (5). The time of transferring products between centers considering the vehicle's average speed in the city (60 km/h) is also shown in table (6).



Supplier: Regions 4-19-20-22
Customers: All Regions
Production Centers: Regions 6-8-14-16-18-22
Distribution Centers: Regions 5-6-8-10-16-22

Fig. 10. Case study in iran

Tab. 5. Amount of demand for electronic components in 22 regions

Region	$\tilde{d}_k \sim (d_k^o, d_k^m, d_k^p) \times 1000$	Region	$\tilde{d}_k$
1	$\sim U[(100,120);(120,150);(150,180)]$	12	$\sim U[(80,90);(90,100);(100,130)]$
2	$\sim U[(80,100);(100,135);(135,150)]$	13	$\sim U[(85,105);(105,115);(115,130)]$
3	$\sim U[(85,95);(95,100);(100,120)]$	14	$\sim U[(110,120);(120,140);(140,180)]$
4	$\sim U[(100,120);(120,140);(140,160)]$	15	$\sim U[(125,145);(145,150);(150,160)]$
5	$\sim U[(95,105);(105,130);(130,135)]$	16	$\sim U[(85,95);(95,100);(100,120)]$
6	$\sim U[(100,110);(110,125);(125,135)]$	17	$\sim U[(100,120);(120,130);(130,150)]$
7	$\sim U[(100,120);(120,130);(130,140)]$	18	$\sim U[(75,100);(100,125);(125,140)]$
8	$\sim U[(80,100);(100,110);(110,130)]$	19	$\sim U[(100,115);(115,130);(130,140)]$
9	$\sim U[(100,120);(120,130);(130,165)]$	20	$\sim U[(100,120);(120,150);(150,180)]$
10	$\sim U[(75,100);(100,125);(125,150)]$	21	$\sim U[(90,105);(105,110);(110,135)]$
11	$\sim U[(100,115);(115,130);(130,140)]$	22	$\sim U[(100,130);(130,150);(150,160)]$

Tab. 6. Time of transporting products between different regions of Tehran province

	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	0.257	0.115	0.242	0.328	0.235	0.252	0.243	0.457	0.405	0.337	0.353	0.330	0.395	0.402	0.440	0.412	0.537	0.470	0.520	0.562	0.475
2		0.212	0.327	0.075	0.177	0.238	0.302	0.212	0.155	0.217	0.303	0.368	0.433	0.455	0.358	0.223	0.290	0.277	0.452	0.305	0.288
3			0.227	0.232	0.125	0.132	0.225	0.377	0.325	0.272	0.223	0.322	0.387	0.392	0.312	0.310	0.402	0.367	0.510	0.458	0.392
4				0.368	0.285	0.208	0.112	0.475	0.452	0.395	0.313	0.115	0.180	0.285	0.387	0.467	0.578	0.465	0.393	0.598	0.570
5					0.225	0.288	0.352	0.247	0.217	0.275	0.382	0.418	0.465	0.502	0.407	0.338	0.327	0.337	0.500	0.280	0.228
6						0.093	0.173	0.250	0.150	0.115	0.170	0.202	0.237	0.255	0.213	0.210	0.328	0.268	0.372	0.333	0.427
7							0.102	0.368	0.343	0.182	0.142	0.130	0.212	0.217	0.228	0.348	0.525	0.412	0.335	0.453	0.457
8								0.425	0.247	0.262	0.257	0.047	0.128	0.235	0.340	0.415	0.548	0.435	0.358	0.510	0.550
9									0.150	0.218	0.342	0.560	0.517	0.472	0.363	0.165	0.118	0.203	0.365	0.095	0.427
10										0.070	0.165	0.252	0.278	0.285	0.188	0.070	0.177	0.178	0.282	0.243	0.408
11											0.088	0.350	0.222	0.227	0.130	0.087	0.153	0.157	0.260	0.295	0.483
12												0.258	0.152	0.165	0.125	0.132	0.277	0.190	0.142	0.353	0.668
13													0.080	0.213	0.315	0.395	0.507	0.393	0.322	0.770	0.542
14														0.138	0.212	0.287	0.432	0.320	0.248	0.697	0.823

15	0.130	0.205	0.357	0.243	0.172	0.622	0.748
16		0.160	0.278	0.167	0.082	0.543	0.670
17			0.103	0.090	0.255	0.277	0.442
18				0.128	0.303	0.208	0.472
19					0.188	0.335	0.553
20						0.552	0.680
21							0.317

The product preparation time in the production center is equal to 2h and in the distribution center is equal to 1h, and the transportation costs are also equal to $\sim U(0.05,0.1,0.15)$$ per kilometer. The cost of selecting distribution centers in region 5 is estimated at $20,000, region 6 at $22,000, region 8 at $21,000, region 10 at $25,000, region 16 at $19,500, and region 22 at $21,000. The number of service providers in each production and distribution center is equal to 4. According to the provided information, the convergence of the algorithms in achieving the near-optimal solution has been obtained in Figure (11). In this figure, the total cost obtained from LCA is $152,365.56, SSA is $151,397.95, and PSO is $152,423.67.

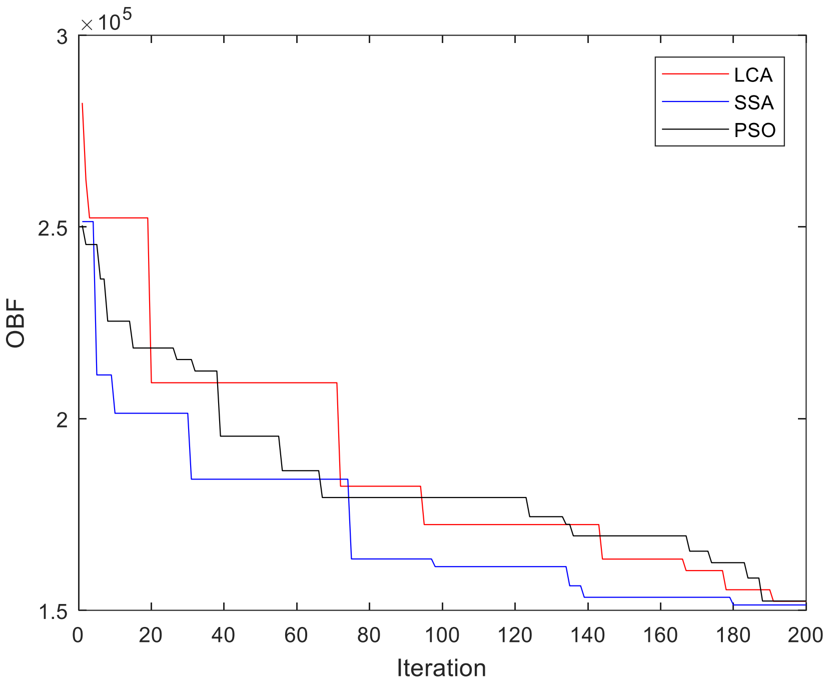


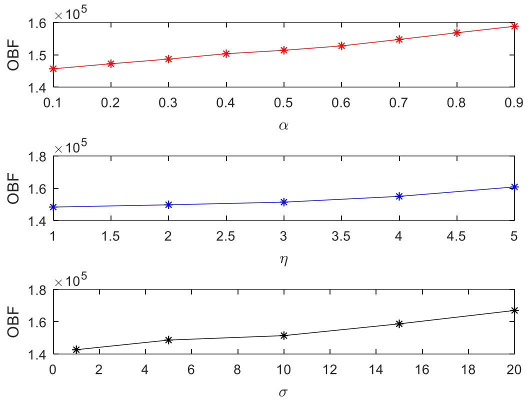
Fig. 11. Convergence of algorithms in achieving a solution close to optimal

The best value of the objective function obtained by SSA has been obtained, and the most important decisions made in this optimization include the selection of distribution centers and the allocation of supply chain levels to each other in Table (7).

Tab. 7. Selected distribution centers and allocation of levels to each other with SSA

Supplier		Production Center		Distribution Center		Customer
4	→	8	→	8	→	1-3-4-6-7-8-13
19	→	18	→	10	→	10-11
20	→	16	→	16	→	16-15-20-19-17-12-14
22	→	22	→	5	→	2-5-21-22-9-18

According to the obtained results, 4 distribution centers number (8-18-16-22) have been selected from among 6 potential distribution centers. Based on the allocation and also the obtained results, only 2.68% shortage occurred in the network. Figure (12) shows the changes in the value of the objective function of the problem for changes in the uncertainty rate as well as the stability coefficient of the model.



α	OBF	η	OBF	ϱ	OBF
0.1	145671.01	1	148362.33	1	142674.66
0.2	147238.66	2	149756.47	5	148641.06
0.3	148675.68	3	151397.95	10	151397.95
0.4	150345.26	4	154986.66	15	158674.98
0.5	151397.95	5	160824.27	20	166972.60
0.6	152758.64				
0.7	154756.20				
0.8	156824.62				
0.9	158824.76				

Fig. 12. Total cost changes in different uncertainty rates and model stability

According to the results of Figure (12), it can be seen that with the increase in the uncertainty rate, the amount of ideal demand in the network has increased, and this problem has led to an increase in transportation costs as well as the costs of not fully estimating the demand. As a result, the total cost has increased with the increase in the uncertainty rate. The lowest and highest costs incurred on the case study in this analysis are $145,671.01 and $158,824.76, respectively. On the other hand, with the increase in the stability coefficients of the model, the number of distribution and production centers in the network has increased in order to reduce the shortage. This has led to increased costs for the entire MTOSC issue. So that by increasing the coefficient η from 3 to 5, the total cost has increased to $160,827.27 and the shortage has decreased to 1.22%. Also, changing the coefficient of ϱ from 10 to 20 has led to an increase in costs by 10.28% and a decrease in shortage by 53.33%.

In another analysis, the number of service providers in the order queue of production and distribution centers was included as 4. By changing the number of servers, the percentage of changes in the waiting time in the order queue as well as the total costs are shown in Table (8).

Tab. 8. Average changes of waiting time and total cost in different number of service providers

$\vartheta_j = \tau_i$	OBF	Total Wait Time Changes %	Total Shortage Cost %	Total Ideal Demand Changes %
3	150899.27	6.55 %	10.69%	-8.24%
4	151397.95	0	0	0
5	151927.54	-7.66 %	-12.68%	10.34%
6	152376.66	-13.52%	-29.64%	21.51%

According to the results of table (8), it can be said that with the increase in the number of servers in the production and distribution centers, the average waiting time for customers' order queue has decreased. This reduction in waiting time results in a 13.52% reduction when the number of servers is increased to 6 units. On the other hand, with the reduced waiting time, the total delivery time of customers' demand decreases and the actual demand increases. The increase in real demand in the network increases the total idleness costs of the MTOSC problem, while the total shortage costs of the MTOSC problem are reduced.

Finally, the lack of decision on the choice of algorithms in solving the case study has led to ranking algorithms using the TOPSIS method. TOPSIS results show that SSA's desirability weight equals 0.523, LCA's desirability weight equals 0.215, and PSO's desirability weight equals 0.411. Therefore, the SSA algorithm was chosen as an efficient algorithm to solve the case study.

6. Conclusion

This paper presents the modeling and solution of an MTOSC problem considering the order queuing system under uncertainty. The model presented in this article aimed to reduce the total costs of choosing distribution centers, purchasing from suppliers, transportation, and shortage penalty. For this purpose, customer demand is obtained according to the time of delivery of products to customers. Due to the indeterminacy of ideal customer demand as well as transportation costs, the RFP method was used to control the indeterminacy parameters. The MTOSC problem examined in this article is one of the MINLP models and is included in the category of NP_Hard problems. Therefore, the model was validated by Baron and LCA, SSA, and PSO methods. The analysis results of 10 sample problems in different sizes show that SSA has obtained the best average OBF compared to LCA and PSO. While the problem solving time by PSO was less than other methods. In these analyses, the maximum percentage of relative difference between meta-heuristic and Baron methods is reported to be less than 1.5%.

On the other hand, by comparing the RPD among 10 sample problems, it was also observed that the maximum RPD was less than 2%, indicating the algorithms' convergence in achieving the near-optimal solution. By comparing P-Value in the T-Test analysis between OBF averages and computing time, it was also observed that there was no significant difference between OBF averages among the solution methods, while there was a difference between computing time averages. According to this and using the TOPSIS method, the weight of SSA is equal to 0.523, the weight of LCA is equal to 0.215, and the weight of PSO is equal to 0.411. This shows that SSA is more efficient than other methods in terms of two average OBF and computing time.

Implementing the model in a real case study in Iran and Tehran metropolis showed that 4 regions (22-18-16-8) were selected as actual distribution centers. In the medium mode, the total cost of the MTOSC problem is equal to $151,397.95, in the pessimistic mode, it is equal to $158,824.76, and in the optimistic mode, it is equal to $145,671.01. The reason for this difference was the cost of increasing the amount of ideal demand in the network in line with increasing the uncertainty rate. On the other hand, with the increase in the stability coefficients of the model, the number of distribution and production centers in the network has increased in order to reduce the shortage. This has led to increased costs for the entire MTOSC issue. So that by increasing the coefficient η from 3 to 5, the total cost has increased to $160,827.27 and the shortage has decreased to 1.22%. Also, changing the coefficient of ϱ from 10 to 20 has led to an increase in costs by 10.28% and a decrease in shortage by 53.33%. Also, the analysis showed that with the increase in the number of servers in the production and distribution centers, the average waiting time for customers' order queues has decreased. This reduction in waiting time leads to a 13.52% reduction by increasing the number of servers to 6 units.On the other hand, with the reduced waiting time, the total delivery time of customers' demand decreases, and the actual demand increases. The increase in real demand in the network increases the total idleness costs of the MTOSC problem, while the total shortage costs of the MTOSC problem are reduced.

Analyzing the results obtained from the case study can help managers in better implementation of the model in order to reduce costs. Also, according to the obtained cost, managers can determine the number of service providers according to social and environmental aspects. This practice helps the managers to reduce the costs, the emission of greenhouse gases due to the transfer of products and increase the social responsibilities due to the maximum provision of the real demand. Lack of access to accurate data of stability coefficients, penalty cost leads to the use of data parameter adjustment with Taguchi method in future research. Also, these data can be considered as non-deterministic parameters in the problem. In order to reduce costs, vehicle routing should be used instead of single allocation. As a result, it is suggested to consider this issue in future research to reduce costs. Finally, future research can consider using precise methods instead of innovative methods and their development.

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