JIEMS

Journal of Industrial Engineering and Management Studies

journal homepage: WWW.JIEMS.ICMS.AC.IR

Flexible flow shop scheduling with forward and reverse flow under uncertainty using the red deer algorithm

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Received: Apr 2022-25/ Revised: Aug 2022-18/ Accepted: Feb 2023-07

Abstract

This paper discusses the modeling and solution of a flexible flow shop scheduling problem with forward and reverse flow (FFSP-FR). The purpose of presenting this mathematical model is to achieve a suitable solution to reduce the completion time (Cmax) in forward flow (such as assembling parts to deliver jobs to the customer) and reverse flow (such as disassembling parts to reproduce parts). Other important decisions taken in this model are the optimal assignment of jobs to each machine in the forward and reverse flow and the sequence of processing jobs by each machine. Due to the uncertainty of the important parameters of the problem, the Fuzzy Jiménez method has been used. The results of the analysis with CPLEX solver show that with the increase in the uncertainty rate, due to the increase in the processing time, the Cmax in the forward and reverse flow has increased. GA, ICA and RDA algorithms have been used in the analysis of numerical examples with a larger size due to the inability of the CPLEX solver. These algorithms are highly efficient in achieving near-optimal solutions in a shorter time. Therefore, a suitable initial solution has been designed to solve the problem and the findings show that the ICA with an average of 273.37 has the best performance in achieving the near-optimal solution and the RDA with an average of 31.098 has performed the best in solving the problem. Also, the results of the T-Test statistical test with a confidence level of 95% show that there is no significant difference between the averages of the objective function index and the calculation time. As a result, the algorithms were prioritized using the TOPSIS method and the results showed that the RDA is the most efficient solution algorithm with a utility weight of 0.9959, and the GA and ICA are in the next ranks. Based on the findings, it can be said that industrial managers who have assembly and disassembly departments at the same time in their units can use the results of this research to minimize the maximum delivery time due to the reduction of costs and energy consumption, even though there are conditions of uncertainty

Keywords: flexible flow shop scheduling problem; forward and reverse flow; red deer algorithm; fuzzy Jiménez.

Paper Type: Original Research.

1. Introduction

Planning is the decision for the future, and production planning means determining the production strategy for how to allocate production lines to meet orders. One of the most prominent factors in preparing a production schedule for production lines is determining the size of the accumulation, the sequence of orders, and how resources are allocated over time (Kian, 2021). Scheduling is generally defined as allocating resources to jobs over time to optimize performance (Parviznejad & Asgharizadeh, 2021). From the point of view of production planning, resources and jobs can be considered as machines and activities, respectively. In addition, the performance index is equal to the completion of activities time. The scientific approach to the problem of scheduling and sequencing operations is rooted in the Industrial Revolution and Gantt's enduring artistic endeavors (Azaiez et al., 2022). Today, one of the most important issues discussed in operations research science is the scheduling problem, which allocates resources over time to perform a set of jobs in different situations (Nahr et al., 2021). Generally, in such issues, the goals are based on efficient use of resources, rapid response to demand, and accurate compliance with delivery times and deadlines (Safari et al., 2022). An efficient and appropriate scheduling program leads to increased profitability, reduced costs, reduced time required to complete activities, and gaining customer trust. In most manufacturing plants and service companies, timely supply of customer orders or timely service is essential (Nozari et al., 2022). Delays in these issues hurt the customer and reduce service companies or manufacturing plants (Nozari et al., 2022). Therefore, scheduling issues have become crucial in many management and planning

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principles. The flow shop scheduling problem involves independent activities, each with its process and set of machines (Li et al., 2022).

Each activity also has a set of pre-defined scheduled operations. Scheduling issues are known as NP-Hard issues and are for the sequence of machine operations to minimize the time to complete all activities. The flow shop scheduling problem assumes that there is only one machine for each operation. Each activity has a feasible process schedule; In real-world scheduling issues. However, there are broader conditions and constraints; For example, considering the setup time is one of the conditions that can be regarded as in flow shop problems (Mohd Rose & Nik Mohamed, 2022).

Flexible flow shop scheduling problem (FFSP) includes scheduling n jobs on m machine. Each job has a number of operations; for each operation, it is possible to use a set of usable machines. Due to their special place in production centers, FFSP are highly regarded by managers of production units (Nahr et al., 2021). Also, the special mathematical features of this problem have made it possible for researchers in this field of mathematics to provide efficient solutions to solve this problem. The simple form of the FFSP is the classical flow shop production scheduling problem, which is in the form of n job scheduling $J_1, J_2, J_3,\ldots,J_n$ on the M set of machines, including m machines $M_1,M_2,M_3,\ldots,M_m$. Each job has h_j operations that must be performed in order. Index j represents job and index h represents operations. Also, one of the important issues in FFSP is the setup time of operations (Li et al., 2021). Setup time is usually considered as independent or dependent on the previous operation of the machine. If the setup time depends on the previous operation, the setup time of the machine for the new operation depends on the previous operation of that machine. A special case of dependent setup time is the setup schedule dependent on the family of operations. In this case, given that a set of similar operations can be considered in a family, the time to launch an operation on a machine can be considered the same for all previous operations of that family (Nouri et al., 2019). On the other hand, the growth of environmental concerns and other economic challenges has caused many companies to focus on the return and recycling of products nearing completion (Nozari and Sadeghi, 2021) Szmelter-Jarosz et al., 2021). This theorem is expressed using a new flow in the supply chain called reverse flow (Szmelter-Jarosz et al., 2021). In the classic supply chain, flows flow from suppliers to the factory, and eventually the final product is delivered to customers. In contrast, products approaching the final stages of production are returned from their final destination (in most customer materials) to the manufacturer to decide whether the products should be re-processed or discarded (Ghahremani Nahr, 2020; Nory & Ghahremani Nahr, 2019). Over the last 15 years, research activities on reverse logistics have been on the rise. Reverse flows can also be considered in single product lines. Examples are assembly or disassembly plants in which products are in reverse sequence in the operational process (Tosun et al., 2020). Despite the use of reverse currents in various industry sectors, such as the automation industry, electronic tools and weapon systems, the literature on this type of reverse current is limited. Most research focuses on the return of products in the supply chain (Dios et al., 2018; Engin & Yılmaz, 2022). Therefore, due to the competitive market conditions, organizations must seek to increase efficiency and optimize their production operations in order to survive. For this reason, in workshops and production and assembly plants, it is very important to pay attention to the scheduling of flexible flow shop processes and production lines and reverse flows. Many kinds of research have been done in the field of flow shop problem.

The importance of examining this issue and also presenting a mathematical model in this research is to pay attention to the needs of industrial and production units in which there is timing for both forward and reverse flow. In industries such as household appliances, electronic components, etc., where the assembly and disassembly of parts are done simultaneously, therefore, FFSP is of great importance. Because in addition to the main attention to the timing of assembly of parts and their distribution to customers, the timing of disassembly of parts and the use of recycled parts is also important.

Therefore, the main challenge in FFSP models is to pay attention to two forward and reverse flow at the same time. Because not paying attention to the timing of each of the departments will lead to the use of more manpower, more energy consumption and delays in the delivery time of the jobs. The delay in the delivery time will lead to a fine for the production unit, both in the distribution of products to customers and the reuse of disassembled and recycled parts in the reproduction of parts. Also, one of the upcoming challenges in such production units is the uncertainty in the processing time (assembly-disassembly of parts). It parameter control also has a significant impact on the delivery time. To solve the above issues, it is necessary to simultaneously pay attention to the forward and reverse flow in the scheduling of the FFSP.

This paper aims to present a more comprehensive mathematical model that includes flexible flow shop by considering forward and reverse flow. Since the literature proves the NP-Hardness of flow shop scheduling problems, in this paper we use meta-heuristics algorithms such as Genetic Algorithm (GA), Imperialist Competitive Algorithm (ICA), and Red Deer Algorithm (RDA) to solve the problem. Used. One of the side goals is to compare the results obtained from this type of flow shop and other models and list their advantages and disadvantages.

The main question in this research is expressed as follows: "How is the modeling of the FFSP-FR under uncertainty?" To answer the above question, some sub-questions are also raised:

- Which of the machines should be assigned to each job?

• What is the sequence of processing jobs in the forward and reverse flow by each machine?

• How to control the uncertainty parameter of the problem?

The structure of the article is as follows. In the second part, the published articles in the field of flow shop scheduling are reviewed and finally the resulting research gap is determined. In the third part, a comprehensive model of the FFSP-FR under uncertainty. In the fourth section, the initial solution of the problem is designed to solve the model with meta-heuristic algorithms. In the fifth section, computational results, sensitivity analysis as well as the performance of algorithms, are considered. Finally, the sixth section concludes and presents future research proposals.

2. Literature review

Many studies have been done on the timing of the FFSP. However, the problem of reverse currents has not been studied much in the literature. The first traces of the mathematical formulation of scheduling problems can be found in the 1960s. Shapiro (1993) presented mathematical planning models and methods for solving them used in various scheduling and planning problems. Naderi et al. (2011) have divided the flow shop production scheduling problem into two categories: partial flexible flow shop production scheduling problem and general flexible flow shop production scheduling problem. If the machine set available for operation is a subset of the problem machine set, it is called the partial flexible flow shop production schedule. Other categories of literature related to setup time in scheduling models, the setup time is considered to be dependent on the previous sequence. In this case, the time to launch an operation on a machine depends on the previous operation performed on that machine. In this case, the timing of launching a particular operation in different sequences may differ. In this regard, Kuo and Yang (2007), the sequence-dependent setuup time in single-machine machine models, Ruiz et al. (2005), the sequence-dependent setup time in the flow shop models, and Saidi-Mehrabad & Fattahi (2007) the sequence-dependent setup time Flexible in flow shop scheduling models. Tran and Ng (2011) investigated the flow shop problem by limiting the capacity of the middle warehouses and considering it with the objectives of minimizing the maximum completion time, the balanced sum of latency and reverse flow times, and presented the water flow algorithm. Naderi et al. (2009) proposed a hybrid algorithm based on refrigeration simulation and a simple search method for the multi-objective flow shop problem with sequence-dependent preparation times and transport time and considering inverse flows. Thomalla (2001) proposed a discrete-time integer scheduling model for the flow shop scheduling problem with the aim of reducing the sum of weighted activity delays and developed an algorithm for it. In this paper, the researcher also considers reverse currents. Zandieh et al. (2005) have considered the problem of mixed flow shop by considering the preparation time of works on machines and have proposed two mathematical models of complex integer programming. Ruiz et al. (2008) have modeled a real production environment and, in order to reduce the gap between theoretical and real problems, have analyzed the effect of several features and constraints that affect corporate planning operations. Luo et al. (2013) proposed an ant colony algorithm to solve a two-objective mixed flow shop problem. In addition to considering the objective function of minimizing the completion time to increase production efficiency, they have studied the cost of electricity consumption of machines according to the cost of electricity consumption time and the results of their proposed algorithm in terms of effectiveness and efficiency with two algorithms. Objectives have been compared. Naderi et al. (2014) have proposed four different complex integer linear programming mathematical models for this problem. They have also used the particle swarm optimization algorithm to solve this problem, in which they have presented an acceptance criterion and an innovative local search method. Lin and Chen (2015) modeled the flow shop scheduling problem for a semiconductor manufacturing company. For this purpose, they used Genetic algorithm to solve the problem and minimize the flow time. Wang et al. (2015) modeled the two-stage flows hop scheduling problem and used the branch method to solve the problem. Their main goal in this research was to allocate optimal jobs to machines and determine the optimal priority of jobs in each machine.

Alinaghian and Goli (2017) considered an uncertain integrated model for the simultaneous location of temporary health care centers in affected areas, allocation of affected areas to these centers and routing to transport the goods they need. Due to the NP-Hardness of the mathematical model, they proposed an improved harmony search algorithm. Dios et al. (2018) sought to minimize the completion time of all activities by providing a model for mixed flow shop scheduling problems. In this paper, comparing different metaheuristics algorithms, they show that the algorithm presented by them is highly efficient in terms of computational time as well as relative differences to the optimal value. Öztop et al. (2019) used different meta-heuristic algorithms to solve the mixed flow shop scheduling problem. The objective function of their problem was to minimize the completion time of all jobs. To do this, they designed 30 large sample problems and showed that the metaheuristics algorithm they developed was highly efficient in solving the problem.

Goli et al. (2019) addressed the optimization of the stock portfolio under uncertainty based on improved artificial intelligence. In this article, by applying an improved neural network with the root running algorithm (RRA), the

future demand of each product is predicted, and the risk index of each product is calculated based on its predicted future demand. Li et al. (2019) proposed a two-objective mathematical model for modeling the flow shop scheduling problem mixed with normal activity time. Their objective functions were to minimize the waiting and total delay. They used the NSGA II bi-objective algorithm to solve the problem. Dridi (2019) minimized the completion time of all jobs in a three-step flow shop scheduling problem with dedicated machines. In this paper, they present a heuristics algorithm and show that in larger size problems, the standard deviation of the results with the optimal value is less than 0.8. Zheng et al. (2020) used the CCA algorithm to solve the multi-objective fuzzy distributed flow shop scheduling problem. In this paper, the effect of key parameters on the performance of the proposed algorithm is investigated using the Taguchi design experimental method. Also, the comparison and statistical analysis results show the effectiveness of the proposed algorithm in solving the problem.
Gully and Malmir (2020) presented an allocation and routing model for relief vehicles in disaster-affected areas under fuzzy demand and used a blanket tour approach to reduce response time. They proposed the GRASP algorithm to solve the problem, which showed that this algorithm has a high efficiency in solving the proposed model. Yu et al. (2020) used a multi-objective algorithm called NSGA II to solve a flexible two-objective flow shop scheduling model. The main objectives of this study were to minimize latency and minimize Cmax. Goli and Keshavarz (2021) studied a parallel machine sequence dependent group scheduling problem with the objective of minimizing the early weight and total tardiness. They used BBO and VNS algorithms to solve the problem and showed that the maximum gap of BBO algorithm is 1.04% and VNS algorithm is 1.35%.
Shao et al. (2021) modeled a no-wait flexible flow shop scheduling problem with the makespan criterion. They proposed 5 local search methods to solve the problem, which had the ability to search the entire solution space. Ozsoydan and Sağir (2021) presented an iterative learning greedy search meta-heuristic to minimize the maximum completion time in a hybrid flexible flow shop problem with sequence-dependent setup times encountered in a manufacturing plant. Gelli et al. (2021) presented an integrated framework based on statistical tests, time series neural networks and improved MLP, ANFIS and SVR with new meta-heuristic algorithms in order to achieve the best DPD prediction. Since the regression relationship is not able to correctly predict this demand, artificial intelligence tools including MLP, ANFIS and SVR with the help of new meta-heuristic algorithms such as gray wolf optimization (GWO), invasive weed optimization (IWO), cultural algorithm (CA) and Improved particle swarm optimization (PSO) were used. Gheisariha et al. (2021) proposed a multi-objective harmonic search (EMOHS) algorithm and a Gaussian jump to solve flexible flow shop scheduling problems with sequence-based setup time, transportation time, and probabilistic rework. They evaluated the efficiency of the proposed algorithm using computational experiments based on five diversity measurement criteria, simultaneous acquisition rate for two targets, average ideal distance, quality metric, and coverage.
Tirkolaee et al. (2022) developed a novel mathematical model to design a sustainable mask Closed-Loop Supply Chain Network (CLSCN) during the COVID-19. They designed a three-objective model by optimizing the aspects of sustainable and used the MOGWO algorithm to solve the problem. The results show that MOGWO algorithm is more efficient than NSGA II algorithm in terms of dispersion and quality of solutions.
Maciel et al. (2022) proposed a genetic algorithm to solve the hybrid flow shop scheduling problem with sequence dependent setup time. The model's objective function consists of the minimization of Cmax and the relative deviation is used as a performance measure. Goli and Mohammadi (2022) proposed a new method to determine supply chain performance based on sustainable strategies. In this method, a set of strategies is first determined through a balanced scorecard, then by applying the path analysis method, the best strategic paths are determined and then the Shapely value of the listed paths is calculated. Wang et al. (2022) modeled a dynamic flexible shop flow scheduling problem with sequence dependent lead time. The aim of this model was to minimize Cmax. They also proposed a heuristic algorithm to solve their model, which was capable of solving large-sized examples. Zhu et al. (2022) solved the no-wait flow shop scheduling problem. Their goal was to minimize the sum of early and late time based on the fruit fly algorithm (DKLFOA). The simulation results show that DKLFOA has advantages for solving the proposed model compared to the other algorithms. Castaneda et al. (2022) modeled a mutation flow shop problem under stochastic and fuzzy uncertainty. They used fuzzy programming method to control their uncertain parameter.
Table (1) compares the main features of articles in combined flow shop scheduling.

Table 1. Comparison of research features in FFSP

Author	Year	Hybrid Flow shop	Objective	Forward Flow	Reverse Flow	Solution	Model	Control Method	Uncertainty Parameter
Zheng et al.	2020	*	Min Cmax Min total tardiness	*		cooperative coevolution algorithm	Uncertainty	Fuzzy Programming	Processing Time and Due Date
Tirkolaee et al.	2020		Min Total Cost Min Total energy consumption	*		Artificial Fish Swarm Algorithm	Uncertainty	Fuzzy Programming	Processing Time
Villarinho et al.	2021		Min Cmax	*		Heuristic Method	Uncertainty	Stochastic	Processing Time
Ozsoydan & Sağir	2021	*	Min Cmax	*		learning iterated greedy search metaheuristic			
Branda et al.	2021		Min Cmax Min total tardiness and earliness penalty	*		Genetic Algorithm Harmony Search (HS)	Deterministic		
Shao et al.	2021		Min Cmax	*		Nawaz-Enscore-Ham Heuristic	Deterministic		
Yan & Wu	2022	*	Min Cmax Min Waiting Time			IMOEA/D	Deterministic		
Lu & Qiao	2022	*	Min Cmax Min Energy	*		Traditional Genetic Algorithm	Deterministic		
Fernandez-Viagas	2022	*	Min Cmax	*		Greedy Algorithm	Deterministic		
Wang et al.	2022	*	Min Cmax	*		Heuristic algorithm	Deterministic		
Maciel et al.	2022	*	Min Cmax	*		Genetic algorithm	Deterministic		
Zhu et al.	2022		Min total tardiness and earliness	*		discrete knowledge-guided learning fruit fly optimization algorithm	Deterministic		
Castaneda et al.	2022		Min Cmax	*		Cplex Solver	Uncertainty	Fuzzy Programming	Processing Time
This Paper	2022	*	Min Cmax	*	*	Red deer Algorithm Genetic Algorithm Imperialist Competitive Algorithm	Uncertainty	Jiménez Fuzzy	Processing Commissioning and Transfer Time

Based on the studies, it can be said that there are very few studies on forward and reverse flows in the flow shop schedule and no developed model can be found for it. Therefore, in this paper, considering the shortcomings of the developed models, a comprehensive model of the FFSP-FR is presented. Also, the subject literature study shows that methods for controlling uncertain parameters such as Fuzzy Jiménez (2007) lead to linear modeling. As a result, this method has been used in problem modeling. The use of the red deer algorithm by providing a suitable initial solution and comparing it with other meta-heuristics algorithms to solve the problem is one of the main features of the paper.

As a result, the innovations of the article can be expressed as follows:

- Provide a comprehensive model of the FFSP-FR
- Using the Fuzzy Jiménez method to control the fuzzy numbers of dependent preparation time
- Provide an efficient initial solution display to solve the problem by implementing it in the Red Deer algorithm
- Comparing meta-heuristic algorithms with each other in terms of achieving the objective function in a shorter time

The purpose of applying Jiménez Fuzzy method is its linear limitations in controlling the uncertainty parameters of the problem compared to other methods. In this method, by using alpha uncertainty rate, the parameters of the model are controlled under linear relationships and the nonlinearity of the mathematical model is prevented. If in methods such as robust, the mathematical model is controlled non-linearly.
On the other hand, in this research, different algorithms were used to solve the problem. According to the literature review, the advantage of using these algorithms is that they are population oriented. Therefore, in these algorithms,

the possibility of obtaining a solution close to the optimum is high due to the simultaneous search of several solutions. While each of the algorithms has its own specific operators and achieving the optimal solution is different in each of them. Based on the literature review, the ICA has the highest efficiency in achieving near-optimal solutions, and the GA has a high speed in searching for solutions and convergence. The RDA is also a population-based algorithm modeled on the behavior of deer. This algorithm has been used in various mathematical models and has proven its effectiveness, and the results have shown that the speed of problem solving in this algorithm is much higher than other meta-heuristic algorithms. Therefore, this article aims to examine the efficiency of these algorithms, each of which has different advantages over the other.

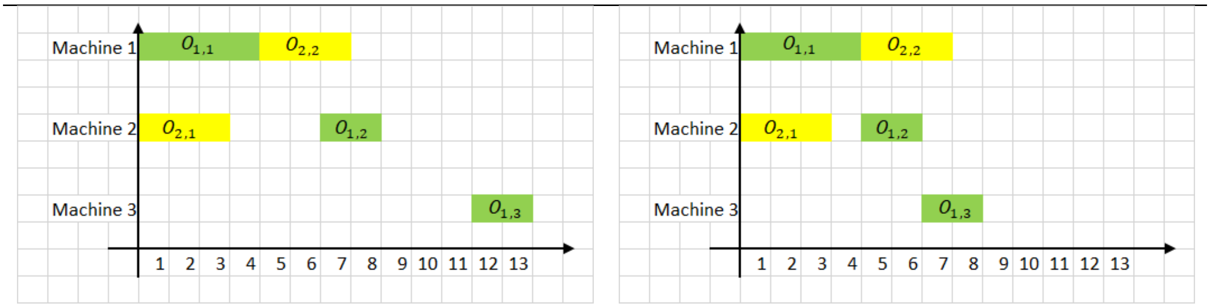
3. Problem definition and modeling

This section defines the problem using a numerical example. This example considers a FFSP with 2 jobs, 3 machines, and 3 activities. Assume that the processing time is definite as well as the total setup and transfer time as shown in Table (2).

Table 2. Processing time of each operation on each machine

Time	job	Activity / Machine	Machine		
			Machine 1	**Machine 2**	**Machine 3**
Processing time of each operation on each machine	job 1	$O_{1,1}$	4	-	-
		$O_{1,2}$	4	2	-
		$O_{1,3}$	5	7	2
	job 2	$O_{2,1}$	-	3	5
		$O_{2,2}$	3	2	4
Setup time and transfer of any job between machines	job 1	Machine 1	3	2	1
		Machine 2	4	1	3
		Machine 3	1	8	5
	job 2	Machine 1	5	1	3
		Machine 2	1	3	2
		Machine 3	3	4	4

The best solution to the problem is taking into account the transfer time and without considering the transfer and setup time, as shown in Figure (1). As shown in Figure (1), there is a difference between the completion time of all activities and the output of the problem.



A) Considering the transfer time and setup B) Regardless of transfer time and setup

Figure 1. Gantt chart for hypothetical problem

According to Figure (1-a), the time of job transfer from machine 1 to machine 2, has led to an increase in finishing time. According to Figure (1-a), the job transfer time from machine 1 to machine 2, leads to an increase in completion time. As a result, in this research, a mathematical model has been designed based on this, in addition to the setup time, the transfer time of the job from one machine to another, and identifying the priorities for doing the job in the forward and reverse flow. According to the following assumptions, the problem of FFSP-FR can be modeled and solved by considering the setup time under the uncertainty of processing time and setup and transmission time:

- There is an unlimited number of transmissions between machines.
- The processing time, commissioning and transfer are considered as indefinite and fuzzy triangular.
- There is no delay in transferring job from one machine to another.

- Each operation must be assigned to one device.
- The jobs are considered in two categories, forward and reverse.
- The start time of all activities is from moment 0.
- If an activity starts, all machines must complete it without any interruption

According to the above assumptions, the set, parameters and decision variables for indefinite and definite mathematical modeling are expressed as follows:

Sets:

	Set of jobs $j, h = \{1, \dots, J\}$
J	Jobs in forward flow $f_o = \{1, \dots, F_o\}$
	Jobs in reverse flow $re = \{F_o + 1, \dots, J\}$
M	Set of machines $i, k = \{1, \dots, M\}$
L	Set of job operations j $l, z = \{1, \dots, N_j\}$
F	Set of machine i positions $f = \{1, \dots, R_i\}$

Parameters:

N_j	Number of job operations j
R_i	Number of activities eligible for machine processing i
$O_{j,l}$	lth job activity j
$\tilde{P}_{j,l,i}$	Uncertain processing time $O_{j,l}$ on machine i
$\tilde{T}_{j,k,i}$	Setup time and transfer of job j from machine k to machine i
$E_{j,l,i}$	Parameter 0 or 1, if the activity $O_{(j,l)}$ qualifies for the machine method i.
BM	A large non-negative number

Decision Variables:

$X_{j,l,i,f,k}$	If $O_{j,l}$ in position f of machine i is processed on machine k after processing job j, the value is 1 and otherwise it is 0.
$C_{j,l}$	Activity completion time $O_{j,l}$

$$Min\, Z = C_{max} \tag{1}$$

$s.t.$:

$$\sum_{i=1}^{I}\sum_{f=1}^{R_i}\sum_{k=1}^{I} X_{j,l,i,f,k} = 1, \quad \forall j \in Fo, l > 1 \tag{2}$$

$$\sum_{i=1}^{I}\sum_{f=1}^{R_i} X_{j,1,i,f,0} = 1, \quad \forall j \in Fo \tag{3}$$

$$\sum_{j=1}^{J}\sum_{l=2}^{N_j}\sum_{k=1}^{I} X_{j,l,i,f,k} + \sum_{j=1}^{Fo} X_{j,2,i,f,0} \le 1, \quad \forall i, f \in R_i \tag{4}$$

$$\sum_{i=1}^{I}\sum_{f=1}^{R_i}\sum_{k=1}^{I} X_{j,l,i,f,k} = 1, \quad \forall j \in Re, l > 1 \tag{5}$$

$$\sum_{i=1}^{I}\sum_{f=1}^{R_i} X_{j,1,i,f,0} = 1, \quad \forall j \in Re \tag{6}$$

$$\sum_{j=1}^{J}\sum_{l=2}^{N_j}\sum_{k=1}^{I} X_{j,l,i,f,k} + \sum_{j=1}^{Re} X_{j,2,i,f,0} \le 1, \quad \forall i, f \in R_i \tag{7}$$

$$\sum_{f=1}^{R_i}\sum_{k=1}^{I} X_{j,l,i,f,k} \le E_{j,l,i}, \quad \forall j, l > 1, i \tag{8}$$

$$\sum_{f=1}^{R_i} X_{j,1,i,f,0} \le E_{j,1,i}, \quad \forall j, i \tag{9}$$

$$\sum_{f=1}^{R_i} X_{j,l,i,f,k} \le \sum_{f=1}^{R_k}\sum_{t=1}^{I} X_{j,l-1,k,f,t}, \quad \forall j, l > 2, i, k \tag{10}$$

$$\sum_{f=1}^{R_i} X_{j,2,i,f,k} \le \sum_{f=1}^{R_k} X_{j,1,k,f,0}, \quad \forall j, i, k \tag{11}$$

$$C_{j,l} \ge C_{j,l-1} + \sum_{i=1}^{I}\sum_{f=1}^{R_i}\sum_{k=1}^{I} X_{j,l,i,f,k}. \left\{ \begin{array}{c} \left(\begin{array}{c} (1-\alpha).\left[\dfrac{P_{j,l,i}^{2} + P_{j,l,i}^{1}}{2}\right] \\ +\alpha.\left[\dfrac{P_{j,l,i}^{2} + P_{j,l,i}^{3}}{2}\right] \end{array} \right) \\ + \left(\begin{array}{c} (1-\alpha).\left[\dfrac{T_{j,k,i}^{2} + T_{j,k,i}^{1}}{2}\right] \\ +\alpha.\left[\dfrac{T_{j,k,i}^{2} + T_{j,k,i}^{3}}{2}\right] \end{array} \right) \end{array} \right\}, \forall j, l > 1 \tag{12}$$

$$C_{j,1} \ge \sum_{i=1}^{I}\sum_{f=1}^{R_i} X_{j,1,i,f,0} . \left(\begin{array}{c} (1-\alpha).\left[\dfrac{P_{j,1,i}^{2} + P_{j,1,i}^{1}}{2}\right] \\ +\alpha.\left[\dfrac{P_{j,1,i}^{2} + P_{j,1,i}^{3}}{2}\right] \end{array} \right), \quad \forall j \tag{13}$$

$$C_{j,l} \ge C_{h,z} + \left(\begin{array}{c} (1-\alpha).\left[\dfrac{P_{j,l,i}^{2} + P_{j,l,i}^{1}}{2}\right] \\ +\alpha.\left[\dfrac{P_{j,l,i}^{2} + P_{j,l,i}^{3}}{2}\right] \end{array} \right) - BM.\left(1 - \sum_{k=1}^{I} X_{j,l,i,f,k}\right) -$$
$$BM.\left(1 - \sum_{t=1}^{f-1}\sum_{k=1}^{I} X_{h,z,i,t,k}\right), \quad \forall j, l > 1, h, z > 1, j \ne h, i, f \in R_i > 1 \tag{14}$$

$$C_{j,l} \ge C_{h,z} + \left(\begin{array}{c} (1-\alpha).\left[\dfrac{P_{j,1,i}^{2} + P_{j,1,i}^{1}}{2}\right] \\ +\alpha.\left[\dfrac{P_{j,1,i}^{2} + P_{j,1,i}^{3}}{2}\right] \end{array} \right) - BM.\left(1 - X_{j,1,i,f,0}\right) - \tag{15}$$

$$BM.\left(1-\sum_{t=1}^{f-1}\sum_{k=1}^{I}X_{h,z,i,t,k}\right),\quad \forall j,h,z>1,j\neq h,i,f\in R_i>1$$

$$C_{j,l}\geq C_{h,1}+\left(\begin{array}{c}(1-\alpha).\left[\dfrac{P_{j,l,i}^{2}+P_{j,l,i}^{1}}{2}\right]\\ +\alpha.\left[\dfrac{P_{j,l,i}^{2}+P_{j,l,i}^{3}}{2}\right]\end{array}\right)-BM.\left(1-\sum_{k=1}^{I}X_{j,l,i,f,k}\right)- \tag{16}$$

$$BM.\left(1-\sum_{t=1}^{f-1}X_{h,1,i,t,0}\right),\quad \forall j,l>1,h,j\neq h,i,f\in R_i>1$$

$$C_{j,1}\geq C_{h,1}+\left(\begin{array}{c}(1-\alpha).\left[\dfrac{P_{j,1,i}^{2}+P_{j,1,i}^{1}}{2}\right]\\ +\alpha.\left[\dfrac{P_{j,1,i}^{2}+P_{j,1,i}^{3}}{2}\right]\end{array}\right)-BM.\left(1-X_{j,1,i,f,0}\right)- \tag{17}$$

$$BM.\left(1-\sum_{t=1}^{f-1}X_{h,1,i,t,0}\right),\quad \forall j,h,j\neq h,i,f\in R_i>1$$

$$C_{max}\geq C_{j,N_j},\quad \forall j \tag{18}$$

$$C_{j,l}\geq 0\quad and\quad X_{j,l,i,f,k}\{0,1\} \tag{19}$$

Equation (1) minimizes the total value of makespan. Equation (2) ensures that each operation, except for the first forward-running operation, is assigned to one of the positions between the machines. Equation (3) ensures that the first operation of each job is assigned to a position of each machine in the forward flow. Equation (4) ensures that the position of each device in the forward flow is occupied only once. Equation (5) ensures that each operation, except for the first reverse flow operation, is assigned to one of the positions between the machines. Equation (6) ensures that the first operation of each job is assigned to a position of each machine in reverse flow. Equation (7) ensures that the position of each device in reverse current is occupied only once. Equations (8) and (9) ensure that the operation assigned to each machine can be performed when the machine is qualified to perform that operation on the job. Equations (10) and (11) ensure that the next operation of each job is performed when the previous operation is completed. Equations (12) to (17) show each activity's completion time according to the activity's position on each machine. Equation (18) calculates the final value of makespan. Equation (19) shows the type and sex of decision variables.

In the next section, after presenting the initial chromosome of the problem, the sample problems in different sizes are solved. Therefore, a small sample design problem is first solved using Cplex Solver GAMS software. In the following, due to the Np-Hard nature of the problem, larger sample size problems are solved using GA, ICA, and RDA. Based on the studies conducted in the literature review, the ICA has been the most effective in solving the forward FFSP. Also, the GA has the ability to quickly search for solutions to the problem. Therefore, the results obtained from these two algorithms have been compared with a new algorithm (RDA). This paper's purpose was to evaluate these algorithms' efficiency in solving the proposed problem.

4. Designing the initial solution and decoding

This section presents the initial solution used in problem solving for meta-heuristic algorithms. To design the primary chromosome, consider an example with two jobs and 3 machines: the operation time and the setup and transfer time as shown in Table (2). Given the time of the operation as well as the setup and transfer time mentioned, the primary chromosome of the problem is as shown in Figure (2).

Operation Sequence (Activities)					**Machin selection**				
1	1	2	2	1	2	1	3	1	2

Figure 2. Initial solution of the problem

According to Figure (2), the initial chromosome consists of machine selection and sequence of operations (activity). For example, the number 2 in the first aunt of the "machine Selection" section means that Machine 2 has been selected to perform the first operation, $O_{1,1}$. Figure (3) shows the mechanism of this part of the chromosome.

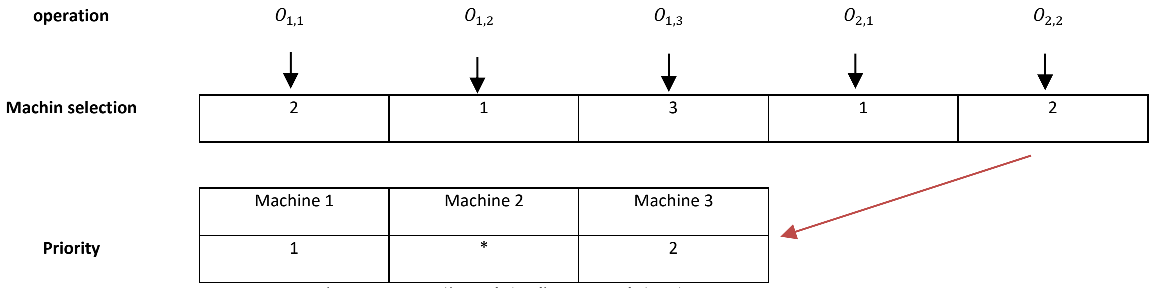


Figure 3. Decoding of the first part of the chromosome

According to Figure (3), since machine number 2 cannot operate 1 for job 1, only two priorities remain, ie priority number 2 is assigned to machine number 3. The second part of the chromosome is related to the sequence of operations. In this part of the chromosome, each job's corresponding number of operations and the numbers corresponding to that job are generated. For example, according to the example, it is observed that to perform job 1, three operations are required, so in this part of chromosome 3, the number 1 should be observed. Take Figure (4) for example.

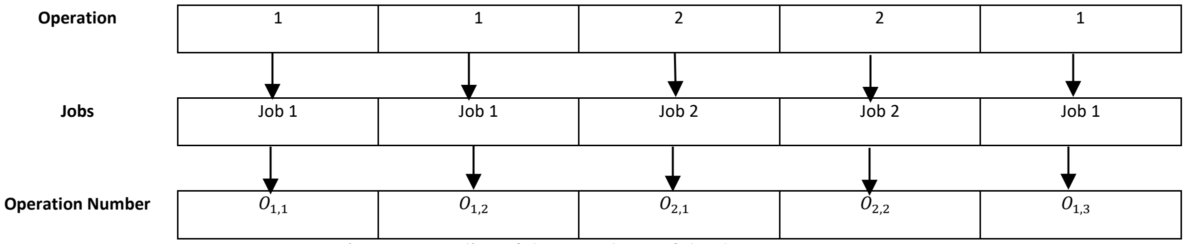


Figure 4. Decoding of the second part of the chromosome

After random production of numbers, it is observed that the first job is number 1, which activity number 1 should be done. Then activity 2 job 1, activity 1 job 2, activity 2 job 2 and activity 3 job 1 should be done.

5. Sample problem analysis

5.1. Solve the sample problem in small size

In this part of the research, a small sample problem is considered. The sample problem considered includes 5 jobs, for each job 2 to 4 activities should be performed according to Table 4-1. Also, 3 machines are provided for this operation. Table (3) shows the values of the initial parameters of the problem. In this analysis, the uncertainty rate value is considered equal to 0.5. Also, Experiments were implemented in MATLAB and GAMS software using a laptop with Intel(R) Core (TM) i7-4710HQ CPU @ 2.50GHz, and 8GB RAM.

Table 3. Values of the initial parameters of the problem

Parameter	Optimistic	possible	Pessimistic
$\tilde{P}_{j,l,i}$	~U(5,10)	~U(10,20)	~U(02,40)
$\tilde{T}_{j,k,i}$	~U(1,5)	~U(5,10)	~U(10,20)

The processing time shows the activities of each job along with the processing time, taking into account an uncertainty rate of 0.5. According to the given data, the value of the objective function is equal to 70 in the time model of 1203 seconds. Figure (5) is drawn to examine other decision variables as well as the timing of jobs. This figure shows how machines do things and the priority of each machine.

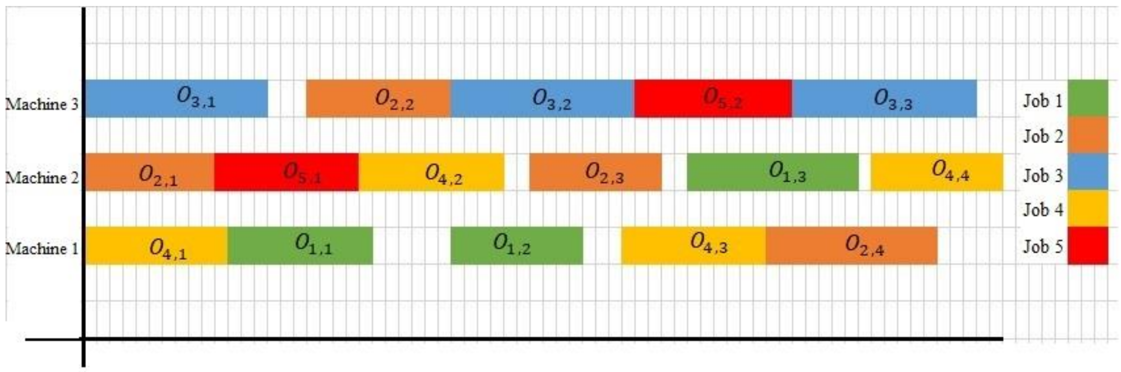


Figure 5. Scheduling of jobs in the small sample size problem

In Table (4) the value of the objective function of the problem is investigated under an uncertainty rate of 0.2 to 0.9.

Table 4. The effect of uncertainty rate on the value of the objective function

Uncertainty rate	Total Cmax	Computational time
0.9	84	1201.34
0.8	82	1200.36
0.7	80	1198.67
0.6	75	1220.46
0.5	70	1207.64
0.4	67	1223.34
0.3	63	1209.47
0.2	62	1247.64

According to Table (4), it is observed that with increasing uncertainty rate, due to increasing processing time as well as increasing startup and transport time, the value of the objective function has increased. To make it easier to investigate the problem, the trend of changes in the objective function to increase the uncertainty rate is shown in Figure (6).

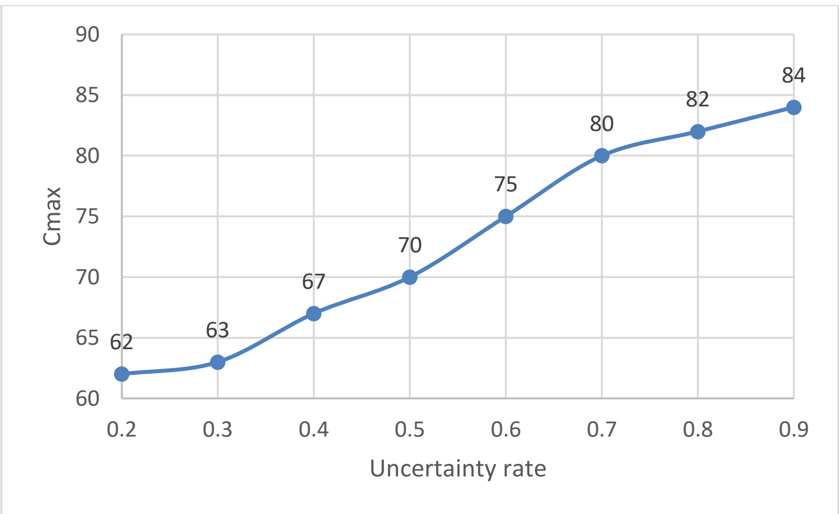


Figure 6. Trend of changes in the value of the objective function versus changes in the rate of uncertainty

Due to the inability of GAMS software to solve the problems of larger sample sizes, the following problems are solved in larger sizes using GA, ICA, and RDA. Therefore, first the parameters of meta-heuristic algorithms are regulated by Taguchi method.

5.2. Parameter setting

In the Taguchi method, first the appropriate factors must be identified and then the levels of each factor must be selected, and then the appropriate test design for these control factors must be determined. Once the test design is determined, the experiments are performed and analyzed to find the best combination of parameters. In this paper, 3 levels are considered for each factor. For each algorithm, the experiment's design and execution are determined according to the number of factors and the number of their levels. It should be noted that each of the experiments was repeated an average of 5 times and the average of the obtained values was finalized. Table (5) shows the parameters of the proposed algorithms and the levels of this parameter for the mentioned algorithms.

Table 5. Proposed and optimal levels of meta-heuristic algorithm parameters

Algorithm	Parameter	Lower bound	Middle bound	upper bound	The optimal amount
GA	Npop	50	75	100	100
	Pa	0.7	0.8	0.9	0.9
	Pb	0.6	0.7	0.8	0.7
	Pm	0.03	0.05	0.1	0.03
ICA	Ncoun	50	75	100	100
	Nimp	20	30	40	30
	RevRate	0.1	0.3	0.5	0.3
	DefRate	0.1	0.3	0.5	0.5
RDA	Ndear	50	75	100	100
	Gama	0.1	0.3	0.5	0.5
	b1	0.1	0.3	0.5	0.1
	b2	0.1	0.3	0.5	0.3

5.3. Solving sample problems in larger sizes with metaheuristic algorithm

After setting the parameter of meta-heuristic algorithms, the sample problems are solved in larger sizes. Therefore, 15 sample problems are solved according to Table (6) and based on the limits of the parameters produced based on the uniform distribution in Table (3), and the problem is solved using the 5 mentioned algorithms.

Table 6. Size of sample problems designed in larger size

Sample problem	Number of jobs	Number of machines	Number of priorities
1	10	5	4
2	15	5	4
3	20	5	6
4	25	8	6
5	30	8	8
6	35	8	8
7	40	10	10
8	45	10	10
9	50	10	12

Sample problem	Number of jobs	Number of machines	Number of priorities
10	55	15	12
11	60	15	14
12	70	15	14
13	80	20	16
14	90	20	18
15	100	20	20

According to the designed sample problems, from each problem 5 sub-problems of production, the average value of the objective function, and the computational time obtained from each algorithm are obtained as Table (7).

Table 7. Average value of objective function and computational time in large size sample problems

Sample problem	Cmax			Computational time		
	ICA	GA	RDA	ICA	GA	RDA
1	94.00	93.33	94.13	4.67	3.16	2.33
2	95.81	93.97	95.72	4.91	4.27	2.89
3	146.90	146.61	146.45	10.44	8.01	5.58
4	147.66	146.93	148.44	11.62	9.95	6.70
5	199.17	200.46	199.77	18.51	15.84	10.47
6	201.14	201.40	201.10	19.50	18.94	12.19
7	254.35	250.99	253.11	29.41	26.53	17.29
8	252.66	253.79	252.80	34.95	30.07	19.44
9	304.30	304.19	305.65	41.84	40.29	26.16
10	305.33	306.16	304.97	52.98	45.36	29.72
11	358.95	357.06	357.46	60.20	59.01	38.56
12	359.93	357.20	358.93	75.47	69.90	45.55
13	407.28	409.52	410.90	113.98	96.19	63.00
14	461.97	463.53	465.79	160.1	126.82	81.30
15	512.17	515.83	513.44	197.77	166.30	105.29

Figure (7) also shows the trend of changes in computational time and objective function in sample problems 1 to 15 for ICA, GA, and RDA.

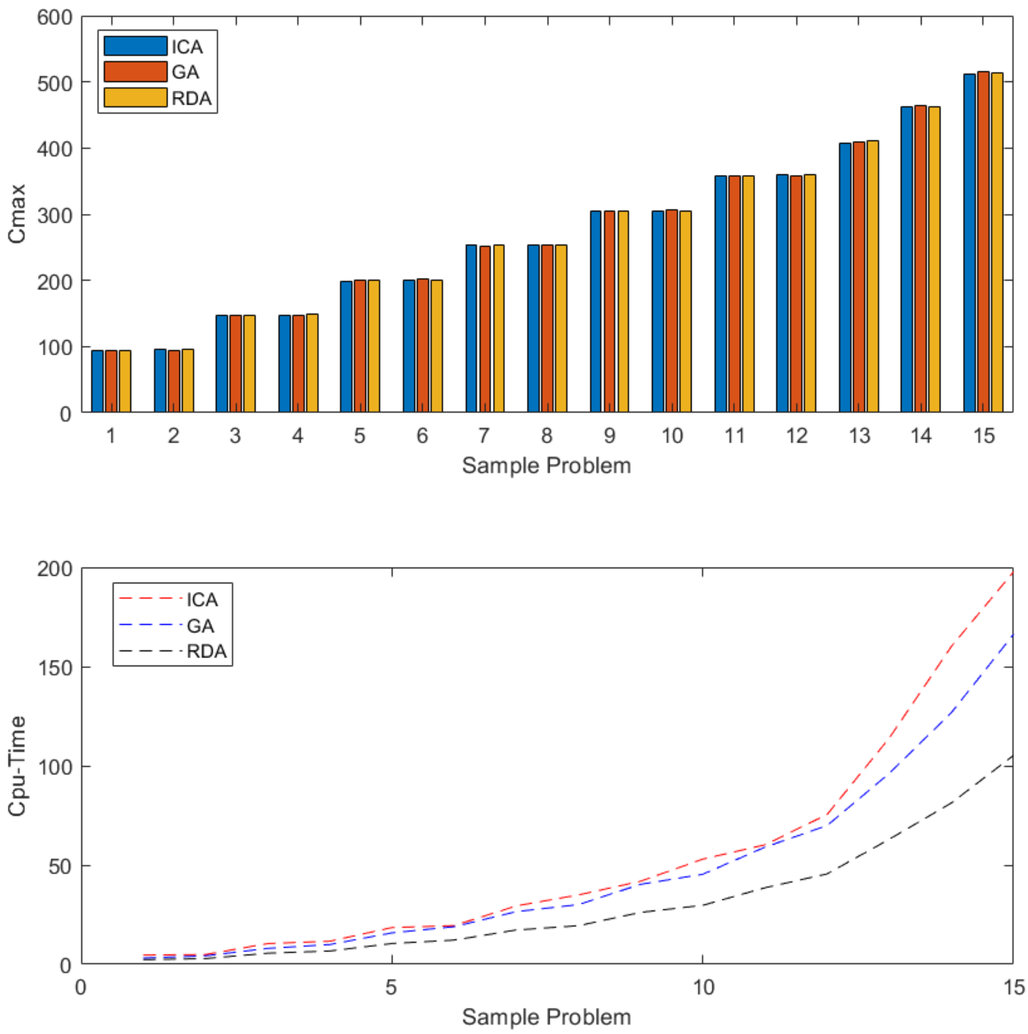


Figure 7. The process of changing the value of the objective function and computational time in large size sample problems

According to the trend of changes made in Figure (7), the computational time has increased exponentially with the size of the problem. This indicates that the problem under consideration is NP-Hard. Then, T-test at 95% confidence level was used to evaluate the significance of the means of the objective function and the computational time. If the P-value is less than 0.05, there is a significant difference between the means of that computational index. Table (8) summarizes the T-test results in the significant study of the means of the objective function and the computational time.

Table 8. Summary of T-test results in the significant study of computational time means

Indicator	Algorithms	Mean difference	The lower limit of the confidence interval	The upper limit of the confidence interval	T-Value	P-Value
Computational time	ICA-GA	7.7	-23.6	48	0.39	0.697
	ICA-RDA	24.7	-10.9	60.2	1.44	0.164
	GA-RDA	16.9	13.7-	47.6	1.14	0.265
The objective function	ICA-GA	0.0	-97.3	97.2	0.00	1.000
	ICA-RDA	0.3	-96.7	97.4	0.01	0.994
	GA-RDA	0.3	-97.1	97.7	0.01	0.995

According to Table (8), it is observed that there is no standard difference between the means of computational time and the means of the objective function between the algorithms. Therefore, the TOPSIS method has been used to rank the algorithms and select the most efficient algorithm to solve the proposed model.

5.4. Selecting the most efficient metaheuristic algorithm

Due to the lack of decision-making regarding selecting the most efficient algorithm, this section uses the TOPSIS multi-criteria decision-making method to rank the algorithms and select the most efficient ones. Table (9) shows the average of the two indicators of the value of the objective function and the computational time for the mentioned algorithms.

Table 9. Final averages of indicators used in meta-heuristic algorithms

Algorithm	Average of Cmax	Average computational time	The utility weight of the TOPSIS method	Rank by TOPSIS method
ICA	273.37	55.76	0.854	3
GA	273.39	48.04	0.8999	2
RDA	273.71	31.09	0.9959	1

Considering the weight of the obtained utility, it is observed that the RDA is known as the most efficient algorithm for solving the problem.

6. Conclusions

Today, scheduling job to complete job quickly and on time is one of the main goals of every company and production unit. Today, in addition to paying attention to this principle, product flow management, including product collection and recycling, is one of the main activities of companies. Therefore, only attention to the main production is considered in scheduling the production flow, and return flows from the stage of reproduction, recycling, etc. should also be considered. The importance of forwarding and reverse flow management in flow shop scheduling led to a comprehensive model of the problem in this paper. This paper presents a flexible model of flexible flow shop scheduling by considering forward and reverse currents under uncertainty. Due to considering the uncertain parameters of the problem as fuzzy triangular numbers (optimistic, probable and pessimistic), fuzzy Jiménez method was used to control the model. By examining the effect of uncertainty rate on the value of the objective function, it was observed that with increasing the uncertainty rate, the value of startup and transport parameters as well as processing time increase and in return the value of the objective function of the problem increases. Therefore, the results show that in the most pessimistic case, the value of Cmax is equal to 84, which has increased by 20% compared to the probable case. Also, in the most optimistic case and at an uncertainty rate of 0.2, the value of Cmax is equal to 62, which is 17.14% less than the probable case. Also, by examining GA, ICA, and RDA in solving large size numerical examples, it was observed that the ICA has the best results in obtaining the value of the objective function. However, this algorithm had the worst value in terms of time. So that the maximum of relative percentage difference (RPD%) between the results of the algorithms is equal to 0.123%. Also, the RDA has obtained the fastest time in solving numerical examples with an average calculation time of 31.098 seconds. Since the results of the two indexes of objective function value and computing time obtained by meta-heuristic algorithms were very close to each other, T-Test was used at 95% confidence level to check the significant difference between the average indexes. The results showed that the value of the P-Value statistic in all indicators was higher than 0.05. This shows no significant difference between the results obtained from the comparison of the averages of the indicators.

Due to the lack of decision-making regarding selecting the most efficient algorithm, this section used the TOPSIS multi-criteria decision-making method to rank the algorithms and select the most efficient ones. Based on the analysis, the RDA with a utility weight of 0.9959 was selected as the most efficient solution algorithm among the proposed algorithms. GA and ICA were placed in the next priorities with a utility weight of 0.8999 and 0.8540, respectively.

6.1. Managerial insights

Since a FFSP-FR is designed and solved in this paper, the developed model and proposed solutions can be used in industries such as automobiles, home appliances, and electronics. Especially in factories where assembly/disassembly of parts is done simultaneously. The importance of the mentioned issue in industries has led managers to use mathematical models to reduce total costs, energy consumption, fines for late delivery of works and customer loss. The results of this research help the managers to complete the job and deliver it to the customers in the shortest possible time, and on the other hand, to take steps towards the disassembly of the parts and the use of recycled parts to reproduce the materials in the shortest possible time. As a result, based on the results of the model, managers can know the maximum time to complete their job in the most optimistic and pessimistic scenario and act accordingly to deliver the job. Also, because the number of jobs and machines in the real world is large, as a result, an action should be taken to achieve a suitable decision to reduce the maximum time to complete the work. Therefore, the research results show that to speed up their decisions in the respective industries, managers should use meta-heuristic algorithms that are faster than exact solution methods.

6.2. Future Suggestions

Finally, to improve the article's content, it is suggested to use the robust planning method to control uncertain parameters and other meta-heuristic algorithms to solve the problem.

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