Journal of Applied Research on Industrial Engineering
www.journal-aprie.com

A Hybrid Multi-Objective Algorithm to Solve a Cellular Manufacturing Scheduling Problem with Human Resource Allocation

Vahid Razmjoei; Iraj Mahdavi; Selma Gutmen

PAPER INFO	ABSTRACT
Chronicle: *Received: x Month xx* *Reviewed: x Month xx* *Revised: x Month xx* *Accepted: x Month xx* **Keywords:** *Cellular Manufacturing.* *Scheduling.* *Multi-Objective Optimization.* *Human Resource Allocation.*	A cellular manufacturing system (CMS) is a suitable system for the economic manufacture of part families. Scheduling the manufacturing cells plays an effective role in successful implementation of the manufacturing system. Due to the fact that in the CMS, bottleneck machine and human resources are two important factors, which so far have not been studied simultaneously in a mathematical model, there should be a model to consider them. Therefore, this research develops a bi-objective model for CMS in a three-dimensional space of machine-part and human resources. The main objective is to minimize the maximum completion time of all tasks in the system and reduce the number of intercellular translocation based on bottleneck machines' motion and human resources. Due to the NP-hardness of the studied problem, applying the conventional solution methods is very time-consuming, and is impossible in large dimensions. Therefore, the use of metaheuristic methods will be useful. The accuracy of the proposed model is investigated using LINGO by solving a small example. Then, to solve the problem in larger dimensions, a hybrid Multi-Objective Tabu Search-Genetic Algorithm (MO-TS-GA) is designed and numerical results are reported for several examples.

1. Introduction

Manufacturing industries are under great pressure from the global competitive market. Decreasing product life cycle, marketing required time, and different customer needs have encouraged manufacturers to improve the efficiency and productivity of their operations. Cellular manufacturing system (CMS) leads to a smooth flow due to arranging people and equipment layout in the efficient and process-oriented cells, which reduces setup times of customer orders.

Manufacturing systems must be able to produce the most economical and highest-quality products, in the shortest possible time, to deliver just-in-time products to customers. Moreover, manufacturing systems must be able to adapt or rapidly respond to changes in product demand without the need for major investment. Manufacturing systems such as job shop scheduling and flow shop scheduling systems are not able to meet these needs and requirements [1]. Therefore, the production system must be able to change and redesign to rapidly responding to the changes in product demand. As a result, cellular manufacturing has emerged as a promising and remedial manufacturing system. CMS is one of the group applications in manufacturing systems. Furthermore, it is one of the new production

DOI:10.22105/jarie.2021.279189.1282

methods, which are used today in most large manufacturing centers, with relatively high product diversity, and with multipurpose facilities. The design of a CMS consists of three phases.

The first phase is cell formation. The Cell Formation Problem (CFP) consists of two basic tasks: assigning a machine to a cell, or forming machine groups, and assigning a part to a cell, or forming ‘‘part families’’. The second phase is the facility layout, and the last one involves scheduling, which is responsible for scheduling tasks in each cell. Most of the research in the last two decades has been focused on the cell formation phase, while in today's competitive world, effective sequencing and scheduling are essential to survival in the market environment. Scheduling is a means to optimize using available resources. Resources and tasks in scheduling can be various. Time has always been a fundamental constraint. As the industrial world expands, resources become more critical. Scheduling these resources leads to increased efficiency and capacity utilization, reducing the time required to complete tasks, and ultimately, increasing the profitability of an organization. Effective scheduling of resources such as machines, human resources, etc., is a requirement in today's highly competitive environment. Therefore, this study deals with integrated cellular scheduling, with the allocation of human resources.

The research is structured as follows: Section 2 reviews the research literature. Problem definition and mathematical modeling are presented in Section 3. Section 4 describes the solution approach to the proposed model. Section V includes the validation of the proposed model and the research computational results, and finally, Section VI concludes the research and describes the future suggestions.

2. Literature Review

The problem of CMS scheduling, due to its wide range of applications, has become an important problem in the field of scheduling. In a cellular manufacturing environment, types of machines or parts (tasks) are grouped within part families, each of which is then assigned to a manufactured cell. Thus, the problem of CMS scheduling is mainly related to the sequence of part family operations, and parts within families, in which each manufactured cell is assigned to produce a certain number of part families. In a manufactured cell, parts (tasks) with similar implementing and instrumentalization conditions can be considered as part families. Many developed algorithms for group scheduling problems have two steps. The first step is determining the sequence of parts in the group, and the second step is determining the sequence of the groups. It is worth noting that group scheduling is an NP-Hard problem [2]. There are various studies on solving group scheduling problems using heuristic methods. Considering the number of cells, the existing research literature can be classified into two groups: those that consider a cell individually, and those that consider multiple cells.

Barzinpour and Zakari [2] proposed a new mathematical model for scheduling the parts family, and parts in each family, in a CMS with a “job shop flow” structure. In this model, there is an assumed part family sequence-dependent setup times and cell translocation. In this problem, there are several production processes to manufacture each part, and the model chooses one of them, which makes the production system flexible. They used a Simulated Annealing (SA) algorithm to solve the problem. Lajandaran et al. [3] suggested three Tabu Search (TS) based response methods for the two-machine group scheduling problem, consisting of sequence-dependent part families, with a total completion time criterion. Schaller [4] considered the scheduling problem of a single machine manufactured cell to minimize the total tardiness.

The available research literature on scheduling a manufactured cell with more than two machines can be divided into two groups. Gupta and Schaller [5] considered scheduling a set of tasks in a manufactured cell, with sequence-independent family setup times, to minimize total turnaround time. Hendizadeh et al. [6] proposed a metaheuristic method based on the TS for the problem of CMS scheduling the regular flow line, considering the sequence-dependent part family preparation times. This paper introduces TS-based metaheuristic methods for scheduling parts and tasks to minimize total manufacturing time, in which the setup time of each cell depends on the sequence of parts. The concepts of estimation and adaptation, the worst action of SA in the proposed metaheuristic method, have been tested to improve strength and variety; the efficiency and effectiveness of the proposed TS-based metaheuristic method are compared with the best heuristic and metaheuristic reported algorithms in this problem. The computational results show that the TS method is quite effective in minimizing the total manufacturing time of a reasonable processing time.

Zandiyeh et al. [7] used three Metaheuristic methods based on “TS”, “SA” and “Genetic Algorithm (GA)” for a group scheduling problem with sequence-dependent setup times, during hybrid flexible flow shop. Salmasi et al. [8] proposed a mathematical planning model with the aim of minimizing time in the total flow for the sequence-dependent flow shop group scheduling problem. They heuristically used the TS algorithm and hybrid Ant Colony Optimization (ACO) algorithm to solve the problem and to evaluate the algorithms used a Lower Bounds (LB) method based on the branch and price algorithm. They reported the superiority of the hybrid ACO over the TS.

Solimanpur et al. [9] addressed setup time-based cellular scheduling with several cells and have allowed intercellular translocation. In this case, they considered a two-step policy to solve their model. In the first step, the work sequence is determined, and in the second step, the bottleneck machine is identified and arranged based on the binary comparison. Finally, they solved their model using the two-step SVS algorithm, and the response was compared with the results of the LN-PT method, and they concluded that the SVS algorithm is more efficient than the LN-PT; it should be noted that, according to this article, the LN-PT method is derived from Lajandaran et al [3]. They examined different methods of solving, combining three methods of PT, LN, CDS, and finally, concluded that the LN-PT method is better than CDS-PT, PT-CDS, PT-LN. In this method, LN and PT are used in the first and second stages, respectively. Zakari and Bohloli [10] investigated the effect of learning on group scheduling with a job shop flow structure with the aim of minimizing the maximum completion time and assuming sequence-dependent setup times of the parts family. They developed two GAs and a heuristic method to solve it. The learning effect in this paper means reducing the processing time of tasks, by repeating tasks and increasing the skill and ability of the worker. Zandieh and Karimi [11] examined a multi-objective group scheduling problem, in a flexible hybrid job shop flow with sequence-dependent setup times, or the goal of minimizing total weighted tardiness, and the maximum completion time, simultaneously. To solve this problem, they proposed a multi-population GA. Li et al. [12] presented the problem of parts dynamic scheduling in a multicellular manufacturing system, taking into account intercellular translocation and flexible paths.

Tavakoli Moghaddam et al. [13] proposed a new model for scheduling the CMS and used GA and Memetic algorithm to solve the problem. In the proposed model, like other group scheduling problems, scheduling includes cell scheduling and part family scheduling within the cell family. In it, intercellular translocation is allowed, and the processing path of parts is identified and is one of the attributes of the problem. The objective function of the model is minimizing intercellular translocation time and total manufacturing time. In fact, there is, in the model, the effect of intercellular translocation on schedule taking into account the time tardiness on each translocation and minimizing intercellular translocation time. Tavakoli Moghaddam et al. [13] developed a model and discussed a multi-criteria group scheduling problem considering intercellular translocation, and developed a scatter search method to solve the problem. The difference between this problem and the previous one, and in fact, the dimensions in which the model is developed are: In this model, one of the simplifying assumptions of the problem is removed. The setup time of the machines, in the previous article, was assumed to be zero, while here, it is considered non-zero and cell sequence-dependent. In this paper, the objective function, in addition to intercellular translocation time, and total construction time, includes two other criteria: tardiness time and cell setup cost, which depends on the cell sequence. To standardize the type of criteria, all of them are considered the cost. The goal was to minimize costs. Using parts in the multicellular system and intracellular translocation, Solimanpur and Elmi [14] employed the SVS, NTS algorithm, and minimized the time to complete all tasks.

Considering the literature, it can be found that most of the literature on CMS scheduling is presented as a group scheduling with a job shop flow structure, and in a small number, as a flow line scheduling. Whereas, despite intracellular translocation, determining the best sequence of intracellular parts and then sequencing cells may lead to the least completion time; thus determining the sequence of all parts should not lead to the shortest completion time, therefore, determining the sequence of all intracellular parts should be done in parallel. Li et al. [12] proposed a nonlinear programming model for this problem and used a scatter search metaheuristic method to solve the problem. Subsequently, Solimanpur and Elmi [14] presented an integer linear model for the JSCS problem, despite intercellular translocation and reverse parts, and used the SA algorithm to solve it. In this model, the part family and the production process of parts are determined.

According to the literature review, it can be said that development and research in this field have been done in different dimensions. Considering various objective functions, dynamic conditions, system flexibility, using the human resource in the problem, the attributes of production design in the cellular system, have been among these dimensions, which all these efforts have been to bringing the problem closer to real-world condition and applying their results. In some papers, due to the complexity of problems and time-consuming exact solution methods, various metaheuristic methods have been proposed to solve large-scale problems. There have been extensive studies in the field of scheduling, which results of which can be seen in the field of CMS scheduling. As it is obvious in the cellular scheduling literature, in most cases, group scheduling has been used in CMS scheduling problems, which first deal with the elements of the group and then, the scheduling of the groups. One of the constraints of group scheduling methods is that, in most cases, it is assumed that there are no intercellular machines, and this assumption is not taken into account, because the intercellular machines complicate the flow of materials and manufacturing scheduling system. There is limited research on intercellular machines so that the only research is the study of Solimanpur and Elmi [14] and Tavakoli Moghaddam et al. [15] on scheduling with job-shop structure.

Egilmez et al. [16] studied a stochastic skill-based manpower allocation problem. Three stochastic nonlinear mathematical models were developed to deal with manpower level determination, cell loading and individual worker assignment phases. Karthikeyan et al. [17] presented an optimization model for worker assignment in a dynamic cellular manufacturing system. They developed a GA to solve the model. Azadeh et al. [18] studied human factors on a multi-objective dynamic CMS to minimize the total cost and inconsistency in the decision-making style of operators. Two metaheuristic algorithms including non-dominated sorting genetic algorithm (NSGA) and multi-objective particle swarm optimization (MOPSO) are developed. Mendez-Vazquez [19] studied the impact of organizational factors on worker-cell assignment in cellular manufacturing systems. Chu et al. [20] studied a CMS considering workers' assignment with learning-forgetting effect. An adaptive memetic differential search algorithm is developed to solve the proposed model. The application of heuristic and metaheuristic algorithms was reviewed by Kesavan et al. [21] for solving CMS problems. Recently, a novel methodology was developed by Goli et al. [22] to address the fuzzy integrated cell formation and production scheduling including Automated Guided Vehicles (AGVs) and human factors. They employed a hybrid GA and a Whale Optimization Algorithm (WOA) to tackle the complexity of the problem.

Now, if we concentrate on CFP in the presented scheduling models so far, we find that in some of them, both machine groups and the part families are among the parameters of the model [2, 23] and in some others, the allocation of the part to the cell, except for decision variables, and in machine groups, is still a parameter [14, 13, 15]. Since the tasks scheduling is doing depends on the allocation of machines and parts to the cells and the manufacturing process related to the parts, changing each one will definitely affect the other, however, has not been addressed in the existing papers. On the other hand, the CFP is developed with the presence of the worker, and human resources are an effective factor in the execution of tasks, which has also been ignored in CMS scheduling.

Heydari and Azami [24] developed a job shop scheduling problem with sequence-dependent setup times to minimize the maximum tardiness and make span. As they considered two objectives, the ε-constraint method is applied to solve the problem. Dehnavi Arvani et al. [25] developed an integrated scheduling problem and cell information in a cellular manufacturing system. They considered automated guided vehicles to make the flexibility in the handling system. Aghajani Delavar et al. [26] developed a multi-objective vibration-damping algorithm for solving a cellular manufacturing system considering human resource and tool allocation. They used three multi-objective algorithms including NSGA-II, MOPSO, and MOIWO to validate their proposed algorithm. Guo et al. [27] developed a new optimization model for a digital twin and flexible cellular manufacturing system. They considered the air conditioner production line as a case study.

Now, considering the gap in the literature, in the present study, we will pay attention to the CFP and cellular scheduling, simultaneously. A novel model presented where bottleneck machines and human resources are considered. Thus, cellular scheduling is done simultaneously along with cell formation, in the three-dimensional space of machine-part-human resource, with goals of minimizing the completion time of all tasks in the system and minimizing intercellular translocations related to bottlenecks machines and human resource. It should be noted that the scheduling is doing with a job-shop structure, there is a sequence in the operation of each part, the multi-skill of the workers and the ability to performing several different operations by each machine, has caused flexibility in the process of manufacturing parts.

3. Problem Statement

Due to the wide applications of cellular manufacturing, CMS scheduling has become important in the field of scheduling. Scheduling of parts and part families plays an effective role in the successful implementation of cellular manufacturing systems. According to the importance of flexibility in the manufacturing system, this feature has received less attention in most cellular manufacturing problems [28]. One of the flexibility levels is using machinery that can produce parts with different manufacturing processes, in which the manufacturing time of each operation is different in the process. In this case, depends on the type of flexibility in the cellular system, different manufacturing processes (by different machines) can be used to manufacture parts in each family, which is indicated as a “multiple process schedule”. The “process schedule” of each part includes the machinery required in the operation sequence of that part. In CMS problems, if there is a “multiple process schedule”, in most cases, the selection of the manufacturing process in the manufacturing cell formation stage is considered. In the next step, the parts’ scheduling affects each other, and an integrally consider the process scheduling can lead to better use of manufacturing resources and improving scheduling goals, which have received less attention in the field of cellular systems.

Considering the sequence operation in the CFP provides more information for the designer. Sequence operation determines the order of processing parts and tasks in the manufacturing process. Regardless of the sequence operation in cell formation, it is possible to miscalculate intercellular and intracellular movements based on the cells in which a part is moved for processing. Another key point in the CMS is human resources. In real life, grouping machines and parts not only can make the system more efficient, but the allocation of human resources also plays a key role in optimizing production resources. Since human resource plays an important role in doing tasks on machines, allocating them to machines is an important factor to full efficiency of the cellular system, and ignoring them significantly reduces the benefits of cellular manufacturing. Some previous research has addressed this issue [29]. In order to increase production flexibility, a unique manufacturing system requires multi-skilled workers. To this end, a multi-skilled workforce has been used, as it has a significant impact on the success of cellular manufacturing.

The CMS scheduling problem is NP-Hard [4], and one of the most difficult and important hybrid optimization problems. Due to the inherent complexity of hybrid optimization problems, and in particular the problem of CMS scheduling, the use of heuristic methods to solve such problems has led to effective improvements in produce acceptable solutions. By increasing the dimensions of the problem, the traditional methods of determining the optimal solution will be practically inefficient due to the time-consuming calculations.

This study introduces a mathematical model for scheduling tasks on machines in the three-dimensional space of machine-part-human resources. In the proposed model, there are machine flexibility and human resource. That is, each machine is capable of performing several different operations, and each worker has the skill of working with multiple machines. Moreover, the sequence operations for each part are considered in this model. It should be noted that in the proposed model, unlike most cellular scheduling models, instead of sequencing parts within each family, and sequencing cells in both steps, only the sequence of tasks on each machine is specified, which includes two mentioned sequences.

3.1. Assumptions

- The time of each operation of a part on different machines is specific and constant.
- The number of machines is specified and constant.
- The number of cells in the CMS is specified.
- All machines are available for processing at the moment of zero.
- The machine's efficiency is 100%.
- There will be no failure time for machines.

3.2. Notations

The main components of the proposed model are given by *Tables 1-3*.

Table 1. Definitions of indices.

Notations	Definitions
$\boldsymbol{c}$	Number of cells (c = 1, 2,…, C),
$\boldsymbol{p}$	Number of parts (p = 1, 2,…, P),
$\boldsymbol{k}$	Number of machines ($\boldsymbol{k}$ = 1, 2,…, $\boldsymbol{K}$),
$\boldsymbol{w}$	Number of workers (w =1, 2,…, W),
$\boldsymbol{f}$	Part families (f = 1, 2,…, F),
$\boldsymbol{I_i}$	The operation number of part i.

Table 2. Definitions of Parameters.

Notations	Definitions
$\boldsymbol{t_{ij}}$	The processing time of the operator *j* on part *I*,
$\boldsymbol{s_{fk}}$	Setup time of machine k for processing the part family *f*.
$\boldsymbol{M}$	A large positive real number.
$\boldsymbol{a_{ijk}}$	If operator *j* on part *i* requires machine *k*, it takes 1; otherwise it takes 0.
$\boldsymbol{b_{fi}}$	If part *i* belongs to part family *f*, it takes 1; otherwise it takes 0.
$\boldsymbol{d_{ikw}}$	If part *i* is processed on machine *k* with worker *w*, it takes 1; otherwise it takes 0.
$\boldsymbol{c_{fk}}$	If machine *k* belongs to the part family *f*, it takes 1; otherwise it takes 0.

Table 3. Definitions of variables.

Notations	Definitions
$\boldsymbol{B_{fk}}$	Start time of part family *f* on machine *k*.
$\boldsymbol{B_{fkw}}$	Start time to part family *f* on machine *k* by worker *w*.
$\boldsymbol{D_{fk}}$	End time of part family *f* on machine *k*.
$\boldsymbol{cp_{ij}}$	End time of operator *j* on part *i*.
$\boldsymbol{RM_W}$	Available time of worker *w*.
$\boldsymbol{Q_{ff'}}$	Binary variable to detect a partial sequence of part families *f* and *f'*.
$\boldsymbol{z_{ii'}}$	Binary variable to detect a partial sequence of parts *i* and *i'*.
$\boldsymbol{s_{cn}}$	Setup time of machine *n* in cell *c*.

3.3. Proposed Mathematical Model

In this model, the following two objectives have been examined. The first objective (F_1) (*Eq. (1)*) is to minimize the completion time of all tasks in the system. The second objective (F_2) (*Eq. (2)*) is to minimize the number of intercellular translocation related to machine bottlenecks and human resources. In fact, this model deals with integrated cellular scheduling to achieve both effective objectives simultaneously.

$$\text{minimize} \quad (F_1) = C_{max} \tag{1}$$

$$\text{minimize } (F_2) = \sum_{i=1}^{w} interw_i + \sum_{j=1}^{k} interk_j \tag{2}$$

The following are the constraints of the problem:

$$\sum_{w=1}^{W} d_{ikw} = 1 \qquad (k \in \{1,2,\dots,K\}, i \in \{1,2,\dots,p\}). \tag{3}$$

Constraint (3) indicates that any work can be processed on one machine and by one worker.

$$B_{fk} + M \times (1 - c_{fk}) \geq s_{fk} \qquad (f \in \{1,2,\dots,F\}, k \in \{1,2,\dots,K\}), \tag{4}$$

$$B_{f'k} + M \times (1 - (c_{fk} \times c_{f'k}) + Q_{ff'}) \geq s_{f'k} + D_{fk} \qquad (f, f' \in \{1,2,\dots,F\} \,|\, f = f', k \in \{1,2,\dots,K\}), \tag{5}$$

$$B_{fk} + M \times (2 - (c_{fk} \times c_{f'k}) - Q_{ff'}) \geq s_{fk} + D_{f'k} \qquad (f, f' \in \{1,2,\dots,F\} \,|\, f = f', k \in \{1,2,\dots,K\}). \tag{6}$$

Constraints (4), (5) and (6) ensure that the processing time on each machine is equal or greater than the completion time of the previous part family on that machine.

$$B_{fkW} + M \times (1 - c_{fk}) \geq RM_W \qquad (f \in \{1,2,\dots,F\}, k \in \{1,2,\dots,K\}, w \in \{1,2,\dots,W\}). \tag{7}$$

According to *Constraint (7)* at the time of processing of the part, the worker related to that machine is available.

$$p_{ij} - t_{ij} + M \times (1 - (b_{fi} \times a_{ijk})) \geq B_{fk} \qquad (f \in \{1,2,\dots,F\}, k \in \{1,2,\dots,K\}, i \in \{1,2,\dots,p\}, j \in \{1,2,\dots,I_i\}). \tag{8}$$

Constraint (8) indicates that the processing of each part on each machine is scheduled after the start time of the related part family.

$$cp_{ij} - t_{ij} + M \times (1 - (a_{ijk} \times a_{i\,j-1\,k'})) \geq cp_{i.j-1} \qquad \left(k, k' \in \{1,2.\dots,K\} \middle| \begin{matrix} k \neq k', i \in \{1,2,\dots,p\}, \\ j \in \{1,2.\dots,I_i\} \end{matrix}\right). \tag{9}$$

Constraint (9) indicates that each operation on each part will start after ending processing time on the previous part.

$$cp_{ij} - t_{ij} + M \times (1 - (a_{ijk} \times a_{i'j'k'} \times b_{fi} \times b_{fi'}) + z_{ii'})) \geq cp_{i'j'}, \\ (i, i' \in \{1,2,\dots,p\} | i \neq i', f \in \{1,2,\dots,F\}, j \in \{1,2,\dots,I_i\}, j' \in \{1,2,\dots,I_{i'}\}, k \in \{1,2,\dots,K\}). \tag{10}$$

$$cp_{i'j'} - t_{i'j'} + M \times (2 - (a_{ijk} \times a_{i'j'k'} \times b_{fi} \times b_{fi'}) - z_{ii'})) \geq cp_{ij}, \\ (i, i' \in \{1,2,\dots,p\} | i \neq i', f \in \{1,2,\dots,F\}, j \in \{1,2,\dots,I_i\}, j' \in \{1,2,\dots,I_{i'}\}, k \in \{1,2,\dots,K\}). \tag{11}$$

Constraints (10) and (11) indicate the sequence operating of parts are processed on a machine. These constraints ensure that no two operations are processed on a machine simultaneously.

$$D_{fk} + M \times (1 - (b_{fi} \times a_{ijk})) \geq cp_{ij} \qquad (f \in \{1,2,\dots,F\},\ k \in \{1,2,\dots,K\}, i \in \{1,2,\dots,p\}, j \in \{1,2.\dots,I_i\}). \qquad (12)$$

Constraint (12) ensures that the processing of each part family on each machine is completed, if all operations of that part family are completed on that machine.

$$c_{max} \geq D_{fk} \qquad (f \in \{1,2,\dots,F\}, \quad k \in \{1,2,\dots,K\}) \qquad (13)$$

Constraint (13) defines makespan as the end time of all part families.

$$c_{max} \geq 0, \qquad (14)$$

$$b_{fi}, a_{ijk}, d_{ikw}, c_{fk} \in \{0,1\} \qquad \forall\, i,j,f,k. \qquad (15)$$

Constraints (14) and (15) are introduced as negative and binary variables, respectively.

4. Proposed Solution Approach

As mentioned, this study addresses the CFP and cellular scheduling. Reviewing previous studies shows that for each of these two problems, various algorithms have been proposed and implemented, and acceptable results have been obtained. These algorithms include GA, TS, and SA algorithms. Selecting GA and TS algorithm among them is due to some reasons, which are briefly mentioned: The presentation model is bi-objective, and applying the GA to multi-objective problems is simple and useful. Therefore, the GA was used. However, the nature of the problem did not allow us to use this algorithm alone, because the proposed algorithm had to focus on each solution to the CFP and also search the various solutions to the scheduling problem. The GA, on the other hand, was only responsive to a large-scale search and did not provide the necessary focus. To solve this problem, algorithms such as TS and SA had to be used. Therefore, a combination of GA and TS algorithm was used to solve the problem, in which its expected scatter is provided using the GA and the expected intensity, is provided by the TS algorithm. The performance of the multi-objective hybrid algorithm (MO-TS-GA) is expressed in the following execution steps:

Step 1. Initialization of machine to cell (CM) and worker to cell (CW) chromosomes.

Step 2. Definition of Tabu list to assign the machine and the worker to the cell.

Step 3. Repetition of the following steps until the stop condition is met:

Sub-step 3.1. Addition of selected solutions to the tabu list.

Sub-step 3.2. Formation of a population of solutions related to assigning parts operations, and scheduling them to machines and workers (Ind) according to the solutions of assigning machine to cell and worker to cell (CM, CW).

Sub-sub-step 3.2.1. Repetition of the following steps until the stop condition is met:

Sub-sub-step 3.2.2. Ranking the population members.

Sub-sub-step 3.2.3. Formation based on intersection space rankings.

Sub-sub-step 3.2.4. Formation of the offspring population using mutation and intersection functions.

Sub-sub-step 3.2.4. Calculation of the rank of the offspring population.

Sub-sub-step 3.2.5. Formation of the next generation.

Sub-step 3.3. Updating the front solutions.

Sub-step 3.4. Calculate the probability of updating the best solutions for assigning the machine to the cell and worker to the cell by comparing the best-obtained front and the resulting front of the current repetition.

Sub-step 3.5. Updating the solutions based on the above possibility.

Step 4. Report of the best-obtained front.

According to the above pseudo-code, in the proposed algorithm, there is a multi-objective GA embedded in a TS algorithm, which changes the assignment of the machine and worker to the cell by the TS algorithm, and changes in the scheduling processing work through the GA. Finally, by calculating a simple probability, the solutions are related. The flowchart of the algorithm is shown in *Fig. 1*.

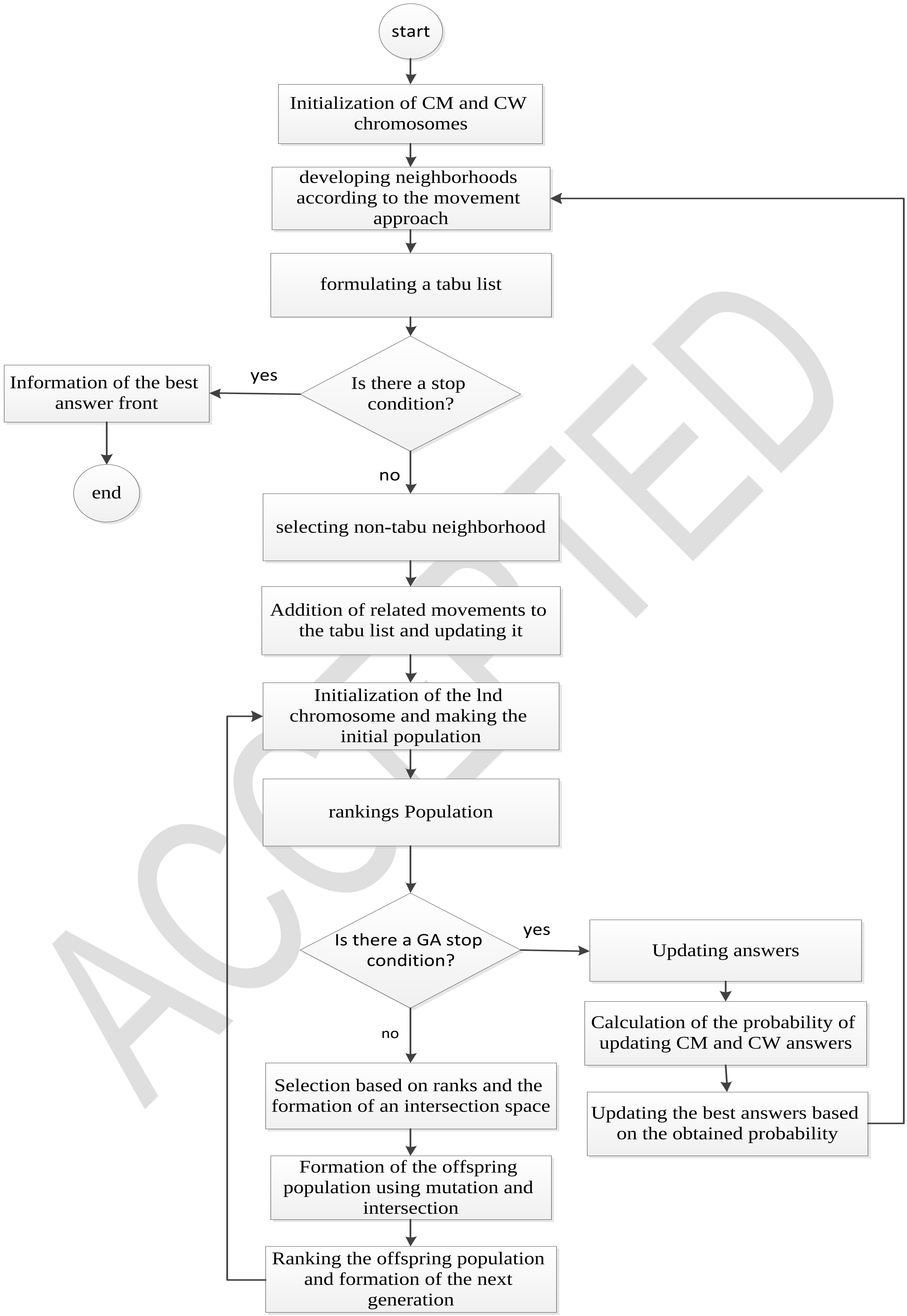

Fig. 1. *Flowchart of MO-TS-GA hybrid algorithm.*

5. Computational Results

The studied problem in this research is computationally complex since the CFP belongs to the NP-Hard problems. The problem of CMS scheduling, considering computational complexity, is classified as an NP-Hard problem [4]. As mentioned before, this study addresses the CFP and CMS scheduling in the three-dimensional space of machine-part-human resources. Therefore, the complexity of the studied problem is obvious, and only the small-scale problems can be solved in a reasonable time using software such as LINGO.

It is impossible to solve large-scale problems because of the lots of time required to solve them, and also the required large memory by the computer. Therefore, in this chapter, a multi-objective hybrid algorithm based on GA and TS algorithms is suggested according to the proposed model, and the computational results are presented at the end.

5.1. Developing a Sample Problem

In this part, to examine the validity of the proposed model, a sample problem is provided, and then, will be solved using the Global solution approach in LINGO software. This example includes 2 cells, 2 workers, 2 machines, and 2 parts with a maximum of 2 operations. *Table 4* shows the ability of each worker to work with machines. For example, worker 1 can work on machines 1 and 2. *Table 5* shows the processing time of operations on the machines. The least number of machines and workers assigned to each cell is 1.

Table 4. *Input information of machine-worker.*

	w_1	w_2
m_1	*1*	*0*
m_2	*1*	*1*

Table 5. *Processing times of parts operations (seconds).*

	m_1	m_2
p_1	*7*	*5*
p_2	*4*	*3*

5.2. Exact Solution of the Sample Problem

Since LINGO cannot solve bi-objective models, the Min-Max method was used to solve the example. In other words, the model was solved for each of the objectives and using the optimal solutions and the Max-Min method the optimal solution was obtained simultaneously for two objectives. The resulting values are given in *Table 6*. The resulting allocations are also shown in *Table 7*. The network graph of the problem is shown in *Fig. 2* to show the system scheduling. In *Fig. 2*, for each machine, the worker who performs the operation of the part related to that machine, and the time to complete the processing of that operation, are listed. Machine 2, for example, has completed the first operation on part 1, by worker 1, in 5 seconds.

Table 6. *Output information of objective functions.*

Total intercellular translocations = f_2	*2*
Maximum time to complete all tasks = f_1	*12*
Run time (seconds)	*656*

Table 7. *Output information of assigning part, machine, and worker to cells.*

Part assigned to		Machines in		Workers assigned to	
Cell 1	**Cell 2**	**Cell 1**	**Cell 2**	**Cell 1**	**Cell 2**
1	*2*	*2*	*1*	*2*	*1*

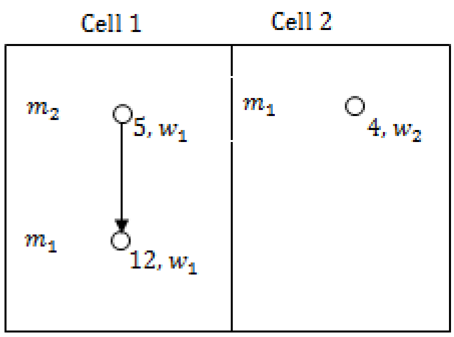

Fig. 2. *Network graph problem.*

According to the sample, as expected, the cell formation method and the selection of the parts manufacturing process, and the completion time of all system tasks influenced each other, and by presenting and solving the proposed model, we were able to minimize both objectives to some extent. Another noteworthy point is the time to solve the model by LINGO. By adding just one part with two operations to the sample, after a few hours, LINGO was still unable to solve the problem, which indicates the high complexity of the problem and proves the need to use a metaheuristic algorithm.

5.3. Computational Results of MO-TS-GA Hybrid Algorithm

Since metaheuristic algorithms are stochastic in nature, using a set of parameters in different problems generally leads to different solutions. Accordingly, setting the parameters of the algorithm to solve a specific problem is of particular importance. Extensive experiments were performed to select the appropriate values for the parameters of GA and TS algorithm. To judge the selection of proper parameters from a set of values, two criteria were considered: Pareto optimal solutions and computer processing time. These two criteria are in conflict. For example, increasing the number of populations in the GA or increasing the iterations in the TS algorithm leads to a better solution, which increases the execution time of the algorithm, especially for large-scale problems.

Based on the stochastic nature of these algorithms, the setting parameter is, in fact, a stochastic multi-objective problem. The following method was used considering the complexity of the stochastic multi-objective parameter setting problem of this research. In order to limit the search space, some candidate values were selected for each parameter. A list of parameters and their levels is summarized in *Table 8*.

Table 8. *List of MO-TS-GA parameters and their values.*

Parameters	Values
Psize	*15,23,35*
OffsSize	*40,50,70*
P_c	*0.85,0.9,0.95*
P_m	*0.01,0.05,0.09*
GAItr	*10,30,50*
TSItr	*10,15,30*

According to *Table 8*, several combinations of parametric values were selected for the proposed algorithm. Based on the stochastic behavior of metaheuristic algorithms, each problem needed to be solved several times.

Therefore, two examples of test problems were considered: (The largest-scale problem with 15 machines, 7 workers, 30 parts with 3 operations and 3 cells; the smallest - scale problem, with 2 machines, 2 workers, 2 parts and 2 operations for each part and 2 cells). The algorithm was run 10 times for each set of parameters. According to these results, the best parameters were selected. For example, the results of 10 combinations of the compounds on the smallest-scale problem are given in *Table 9*.

After selecting the best algorithm, several other tests were performed, including the selection of two superior parameter sets, and considering another test problem involving 5 machines, 2 workers, and 18 parts and 2 operations for each part and 2 cells. Finally, more effective parameters than the others were selected and used to perform the examples.

After setting the parameters, we implemented the proposed algorithm for large-scale problems. Since the proposed MO-TS-GA approach is stochastic in nature, each sample problem is solved 30 times for small-scale problems with small and medium dimensions, 10 times for large-scale problems, and then the minimum, maximum and mean values are reported for objective function and runtime.

Table 9. *The effect of parameter values on algorithm efficiency measures.*

Row	**Time (seconds)**	**Pareto optimal solutions**	**Psize**	**OffsSize**	P_c	P_m	**GA.Itr**	**TS.Itr**
1	*3.097*	*5*	*15*	*40*	*0.85*	*0.01*	*10*	*10*
2	*4.14*	*8*	*15*	*50*	*0.85*	*0.05*	*10*	*15*
3	*6.50*	*12*	*25*	*50*	*0.9*	*0.09*	*30*	*30*
4	*12.77*	*15*	*25*	*70*	*0.95*	*0.09*	*50*	*15*
5	*5.94*	*6*	*35*	*40*	*0.85*	*0.09*	*30*	*10*
6	*7.61*	*10*	*25*	*50*	*0.95*	*0.05*	*30*	*15*
7	*7.23*	*9*	*35*	*70*	*0.95*	*0.01*	*50*	*10*
8	*4.57*	*7*	*15*	*40*	*0.95*	*0.01*	*10*	*10*
9	*15.10*	*13*	*35*	*70*	*0.95*	*0.09*	*50*	*30*
10	*5.15*	*7*	*25*	*50*	*0.9*	*0.05*	*30*	*15*

The attribution of the GA part, according to the parameter setting, is as follows.

The population size (popsize) is considered 25 for the large-scale problem, and 15 for the rest.

- Initialization of machine. The offspring size (offsSize) is considered 50 for the large-scale problem, and 40 for the rest.
- The number of genetics is considered 30 for the large-scale problem, and 10 for the rest.
- The mutation and the intersection operator rates are considered 0.05 and 0.95, respectively.

Moreover, the attribution of the TS algorithm part is as follows:

- The number of iteration in the TS is considered 15 for the large-scale problem, and 10 for the rest.

General attribution also includes:

- The processing time of the operation of each part is correct in small-scale problem and is randomly generated from [1-10].
- In medium and large-scale problems, stochastic number processing times are selected from [0-1].

According to the explanations, the numerical results obtained from the algorithm are described in *Table 10*.

Table 10. *Results of MO-TS-GA algorithm.*

Problem number	**Problem size**					**Number of performances**	**Run time (seconds)**			**The first objective function (Completion time)**			**Second Objective Function (Total Displacement)**		
	Number of cells	Number of workers	Number of machines	number of part	Maximum number of operations		Minimum	Mean	Maximum	Minimum	Mean	Maximum	Minimum	Mean	Maximum
1	*2*	*2*	*2*	*2*	*2*	*30*	*3.11*	*3.8*	*5.53*	*8*	*13.36*	*20*	*0*	*0.74*	*3*
2	*2*	*2*	*5*	*7*	*2*	*30*	*44.84*	*106.7*	*258.71*	*160*	*283.2*	*355*	*0*	*0.53*	*4*
3	*2*	*2*	*5*	*18*	*2*	*10*	*185.8*	*227.5*	*546.9*	*325.1*	*407.58*	*772*	*0*	*3.77*	*12*
4	*5*	*9*	*20*	*20*	*3*	*10*	*740.59*	*834.3*	*1296.32*	*492.9*	*638.12*	*740.6*	*0*	*17.72*	*44*
5	*3*	*7*	*15*	*30*	*3*	*10*	*885.88*	*974.9*	*2182.96*	*463.55*	*683.74*	*885.9*	*0*	*21.83*	*52*
6	*4*	*9*	*20*	*35*	*3*	*10*	*722.48*	*1021.4*	*3328.6*	*738.51*	*859.97*	*961.4*	*0*	*33.26*	*76*
7	*7*	*11*	*24*	*40*	*4*	*10*	*1317*	*1485.12*	*5127.81*	*793.8*	*963.41*	*1317*	*0*	*54.98*	*97*
8	*3*	*14*	*30*	*41*	*4*	*10*	*3595*	*5247.1*	*7292.11*	*1317.6*	*16.33*	*2354*	*0*	*58.17*	*124*

According to the results obtained from the proposed algorithm, it is demonstrated that our algorithm can yield high-quality solutions within reasonable run times. In fact, the best-found solutions were provided by the algorithm for each problem instance in terms of completion time, total displacement and run time. To this end, it is suggested to managers as a useful tool to tackle the complexity of the problem in manufacturing systems. Moreover, the proposed algorithm has sufficient flexibility in order to incorporate further assumptions related to the problem.

6. Conclusion

The present research has proposed a comprehensive model to design a CMS. The proposed model, considering two of the most important objectives of each cellular manufacturing unit, that is, intercellular translocation, and the maximum completion time of all tasks, and considering limitations such as the ability of workers to perform operations related to each part on each machine, and the time required to perform it, determines which operation of which part, should be performed on which machine, and by which worker, it also schedules tasks in a way that minimizes the maximum time of completing all task. In other words, this research integrally addresses the problem of CMS scheduling, and the fundamental and determining time limitations, in addition to other limitations, are considered in the cellular manufacturing system. The bottleneck machine, human resources, the sequence operation manufacture parts, and the flexibility in the manufacturing process of parts, have distinguished this research from previous research works and bring its situations closer to the real world.

This is clearly a very complex problem and it is not possible to solve it using traditional and precise methods particularly in medium and large sizes. Therefore, the present study designed a new hybrid multi-objective metaheuristic method based on GA and TS algorithm (MO-TS-GA) to solve this problem. The result of its implementation, both in terms of the quality of the solutions and in terms of the time of solving, was optimal in comparison with the solutions obtained from LINGO software.

After reviewing the research limitations, the following suggestions are made for future work. Extending the design model, and scheduling manufactured cells in a dynamic multi-criteria environment; developing a model to design and schedule manufactured cells in a multi-criteria environment by depending on the intercellular translocation of bottlenecks machines and workers, on the interval between them; and also, the developing a model to design and schedule manufactured cells employing more than one machine from each type of machine, as well as more than one worker from each type of worker having several human resources with the same skill. Moreover, other solution approaches like other metaheuristic algorithms can be applied [30-32]. Other multi-objective approaches such as goal programming can be used to solve the problem [33-34]. Finally, the effects of uncertainty can be studied in the problem through robust optimization [33, 35, 37], fuzzy programming [36, 38], stochastic optimal control [39], or grey systems [40].

References

[1] Tirkolaee, E. B., Goli, A., & Weber, G. W. (2020). Fuzzy mathematical programming and self-adaptive artificial fish swarm algorithm for just-in-time energy-aware flow shop scheduling problem with outsourcing option. *IEEE transactions on fuzzy systems*, 28(11), 2772-2783.

[2] Barzinpour, F., and Zakari, H. (2000). Presenting an SA method to scheduling in cellular manufacturing system considering multi-product process, 4th International Industrial engineering conference.

[3] Lajandaran, R., Salmasi, N., & Sriskandarajah, C. (2006). Two-machine group scheduling problems in discrete parts manufacturing with sequence-dependent setups. *Computers & Operations Research*, 33(1), 158-180.

[4] Schaller, J. (2000). A comparison of heuristics for family and job scheduling in a flow-line manufacturing cell. *International Journal of Production Research*, 38(2), 287-308.

[5] Gupta, J. N., & Schaller, J. E. (2006). Minimizing flow time in a flow-line manufacturing cell with family setup times. *Journal of the Operational Research Society*, 57(2), 163-176.
[6] Hendizadeh, S. H., Faramarzi, H., Mansouri, S. A., Gupta, J. N., & ElMekkawy, T. Y. (2008). Meta-heuristics for scheduling a flowline manufacturing cell with sequence dependent family setup times. *International journal of production economics*, 111(2), 593-605.
[7] Zandieh, M., Dorri, B., & Khamseh, A. R. (2009). Robust metaheuristics for group scheduling with sequence-dependent setup times in hybrid flexible flow shops. *The International Journal of Advanced Manufacturing Technology*, 43(7-8), 767.
[8] Salmasi, N., Logendran, R., & Skandari, M. R. (2010). Total flow time minimization in a flowshop sequence-dependent group scheduling problem. *Computers & Operations Research*, 37(1), 199-212.
[9] Solimanpur, M., Vrat, P., & Shankar, R. (2004). A heuristic to minimize makespan of cell scheduling problem. *International journal of production economics*, 88(3), 231-241.
[10] Zakari, H., and Bohloli, E. (2008). Group scheduling considering the learning effect on cellular manufacturing system. *International Journal of Industrial Engineering*, 2(20).
[11] Zandieh, M., & Karimi, N. (2011). An adaptive multi-population genetic algorithm to solve the multi-objective group scheduling problem in hybrid flexible flowshop with sequence-dependent setup times. *Journal of Intelligent Manufacturing*, 22(6), 979-989.
[12] Li, D., Wang, Y., Xiao, G., & Tang, J. (2013). Dynamic parts scheduling in multiple job shop cells considering intercell moves and flexible routes. *Computers & Operations Research*, 40(5), 1207-1223.
[13] Tavakkoli-Moghaddam, R., Javadian, N., Khorrami, A., & Gholipour-Kanani, Y. (2010). Design of a scatter search method for a novel multi-criteria group scheduling problem in a cellular manufacturing system. *Expert Systems with Applications*, 37(3), 2661-2669.
[14] Solimanpur, M., & Elmi, A. (2013). A tabu search approach for cell scheduling problem with makespan criterion. *International Journal of Production Economics*, 141(2), 639-645.
[15] Tavakkoli-Moghaddam, R., Gholipour-Kanani, Y., & Cheraghalizadeh, R. (2008). A genetic algorithm and memetic algorithm to sequencing and scheduling of cellular manufacturing systems. *International Journal of Management Science and Engineering Management*, 3(2), 119-130.
[16] Egilmez, G., Erenay, B., & Süer, G. A. (2014). Stochastic skill-based manpower allocation in a cellular manufacturing system. *Journal of Manufacturing Systems*, 33(4), 578-588.
[17] Karthikeyan, S., Saravanan, M., & Rajkumar, M. (2016). Optimization of worker assignment in dynamic cellular manufacturing system using genetic algorithm. *Journal of Advanced Manufacturing Systems*, 15(01), 35-42.
[18] Azadeh, A., Ravanbakhsh, M., Rezaei-Malek, M., Sheikhalishahi, M., & Taheri-Moghaddam, A. (2017). Unique NSGA-II and MOPSO algorithms for improved dynamic cellular manufacturing systems considering human factors. *Applied Mathematical Modelling*, 48, 655-672.
[19] Méndez-Vázquez, Y. M., & Nembhard, D. A. (2019). Worker-cell assignment: The impact of organizational factors on performance in cellular manufacturing systems. *Computers & Industrial Engineering*, 127, 1101-1114.
[20] Chu, X., Gao, D., Cheng, S., Wu, L., Chen, J., Shi, Y., & Qin, Q. (2019). Worker assignment with learning-forgetting effect in cellular manufacturing system using adaptive memetic differential search algorithm. *Computers & Industrial Engineering*, 136, 381-396.
[21] Kesavan, V., Kamalakannan, R., Sudhakarapandian, R., & Sivakumar, P. (2020). Heuristic and meta-heuristic algorithms for solving medium and large scale sized cellular manufacturing system NP-hard problems: A comprehensive review. *Materials Today: Proceedings*, 21, 66-72.
[22] Goli, A., Tirkolaee, E. B., & Aydin, N. S. (2021). Fuzzy integrated cell formation and production scheduling considering automated guided vehicles and human factors. *IEEE Transactions on Fuzzy Systems*. doi: https://doi.org/10.1109/TFUZZ.2021.3053838.
[23] Elmi, A and M Solimanpur. A simulated annealing algorithm for the job shop cell scheduling problem with intercellular moves. *Computer and Industrial Engineering* (2011): 171-178.

[24] Heydari, M., & Azami, A. (2018). Minimizing the maximum tardiness and makespan criteria in a job shop scheduling problem with sequence dependent setup times. *Journal of Industrial and Systems Engineering*, *11*(2), 134-150.

[25] Dehnavi-Arani, S., Saidi-Mehrabad, M., & Ghezavati, V. (2019). An integrated model of cell formation and scheduling problem in a cellular manufacturing system considering automated guided vehicles' movements. *International Journal of Operational Research*, *34*(4), 542-561.

[26] Aghajani-Delavar, N., Mehdizadeh, E., Tavakkoli-Moghaddam, R., & Haleh, H. (2020). A multi-objective vibration damping optimization algorithm for solving a cellular manufacturing system with manpower and tool allocation. *Scientia Iranica*.

[27] Guo, H., Chen, M., Mohamed, K., Qu, T., Wang, S., & Li, J. (2021). A digital twin-based flexible cellular manufacturing for optimization of air conditioner line. *Journal of Manufacturing Systems*, *58*, 65-78.

[28] Allahverdi, A., Gupta, J. N., & Aldowaisan, T. (1999). A review of scheduling research involving setup considerations. *Omega*, 27(2), 219-239.

[29] Nembhard, D. A. (2001). Heuristic approach for assigning workers to tasks based on individual learning rates. *International Journal of Production Research*, 39(9), 1955-1968.

[30] Goli, A., Zare, H. K., Tavakkoli-Moghaddam, R., & Sadegheih, A. (2020). Multiobjective fuzzy mathematical model for a financially constrained closed-loop supply chain with labor employment. *Computational Intelligence*, 36(1), 4-34.

[31] Goli, A., & Davoodi, S. M. R. (2018). Coordination policy for production and delivery scheduling in the closed loop supply chain. *Production Engineering*, *12*(5), 621-631.

[32] Alinaghian, M., Tirkolaee, E. B., Dezaki, Z. K., Hejazi, S. R., & Ding, W. (2021). An augmented Tabu search algorithm for the green inventory-routing problem with time windows. *Swarm and Evolutionary Computation*, 60, 100802.

[33] Tirkolaee, E. B., Goli, A., Pahlevan, M., & Malekalipour Kordestanizadeh, R. (2019a). A robust bi-objective multi-trip periodic capacitated arc routing problem for urban waste collection using a multi-objective invasive weed optimization. *Waste Management & Research*, *37*(11), 1089-1101.

[34] Tirkolaee, E. B., Hadian, S., & Golpira, H. (2019b). A novel multi-objective model for two-echelon green routing problem of perishable products with intermediate depots. *Journal of Industrial Engineering and Management Studies*, 6(2), 196-213.

[35] Alimoradi, S., Hematian, M., & Moslehi, G. (2016). Robust scheduling of parallel machines considering total flow time. *Computers & Industrial Engineering*, 93, 152-161.

[36] Hematian, M., Seyyed Esfahani, M. M., Mahdavi, I., Mahdavi-Amiri, N., & Rezaeian, J. (2020). A multiobjective integrated multiproject scheduling and multiskilled workforce assignment model considering learning effect under uncertainty. *Computational Intelligence*, 36(1), 276-296.

[37] Tirkolaee, E. B., Mahmoodkhani, J., Bourani, M. R., & Tavakkoli-Moghaddam, R. (2019c). A self-learning particle swarm optimization for robust multi-echelon capacitated location–allocation–inventory problem. *Journal of Advanced Manufacturing Systems*, 18(04), 677-694.

[38] Tirkolaee, E. B., Abbasian, P., & Weber, G. W. (2021). Sustainable fuzzy multi-trip location-routing problem for medical waste management during the COVID-19 outbreak. *Science of the Total Environment*, 756, 143607.

[39] Savku, E., & Weber, G. W. (2018). A stochastic maximum principle for a markov regime-switching jump-diffusion model with delay and an application to finance. *Journal of Optimization Theory and Applications*, 179(2), 696-721.

[40] Roy, S. K., Maity, G., & Weber, G. W. (2017). Multi-objective two-stage grey transportation problem using utility function with goals. *Central European Journal of Operations Research*, 25(2), 417-439.