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Unique NSGA-II and MOPSO algorithms for improved dynamic cellular manufacturing systems considering human factors

A. Azadeh[a,*], M. Ravanbakhsh[a], M. Rezaei-Malek[a,b], M. Sheikhalishahi[a], A. Taheri-Moghaddam[a]

[a] School of Industrial Engineering, Center of Excellence for Intelligent Based Experimental Mechanic and Department of Engineering Optimization Research, College of Engineering, University of Tehran, North Kargar st., Tehran, Iran
[b] LCFC, Arts et Métiers ParisTech, 57078 Metz, France

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ABSTRACT

In this study, we present a new mathematical model of a multi-objective dynamic cellular manufacturing system (MDCMS) that considers human factors. Human factors are incorporated into the proposed model in terms of human reliability and decision-making processes. Three objective functions are considered simultaneously. The first objective minimizes the total cost of the MDCMS. The second objective function minimizes inconsistency in the decision-making style of operators in the common manufacturing cells. The third objective function balances the workload of cells with respect to the efficiency of operators, which is calculated based on human reliability analysis. Various studies have been conducted in the field of MDCMS, but human factors have not received sufficient attention as important elements. Due to the NP-hardness of the MDCMS problem, two innovative meta-heuristic algorithms are developed, i.e., a non-dominated sorting genetic algorithm (NSGA-II) and a multi-objective particle swarm optimization method. The results obtained by the algorithms were compared and analyzed using different criteria. Several test problems were considered to verify and validate the proposed model and solution methods. To the best of our knowledge, this is the first study to consider human reliability and decision-making styles in a large MDCMS in an actual production setting.

1. Introduction

The cellular manufacturing system (CMS) is a significant application of group technology (GT) principles [1,2]. The philosophy of GT divides parts into groups and machines into cells by considering the similarities of parts in terms of their construction and design processes. CMS involves the analysis of a set of similar parts within a group of machinery or production processes [3]. The poor efficiency of job shops and flow lines at responding quickly to major fluctuations, such as high demand changes, has forced production companies to employ a more efficient system, i.e., CMS. CMS has the advantages of both job shops and flow lines. However, compared with these traditional methods for workplace design, the advantages of CMS include reducing the setup time, cost, tools required, lead times, and work-in-process inventories. Moreover, CMS increases flexibility, improves the promised delivery time with more reliability, as well as simplifying programing and the flow of parts and tools [4,5]. The CMS design includes four main steps where the cell formation problem (CFP) is the most impor-

* Corresponding author.
E-mail addresses: aazadeh@ut.ac.ir, ali@azadeh.com (A. Azadeh).

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Table 1
Consistency degree of decision-making styles (Azadeh et al.[48]).

DMS	Decisive	Flexible	Hierarchic	Integrative	Systemic
Decisive	CO	NCNI	NCNI	NCNI	SI
Flexible	NCNI	SCO	IN	CO	IN
Hierarchic	NCNI	IN	CO	CO	CO
Integrative	IN	CO	NCNI	SCO	CO
Systemic	SI	SI	IN	NCNI	CO

DMS: decision-making style, SCO: strongly consistent, CO: sonsistent, NCNI: neither consistent nor inconsistent, IN: inconsistent, SI: strongly inconsistent.

Table 2
Literature review of the human resources allocation in CMS.

Author(s)	Movement cost		Dynamic	Operator workload balance	Operators			APR	Solution method
	Intra-cell	Inter-cell			Skill	Reliability	DMS		
Aryanezhad et al. [30]	√	–	√	–	√	–	–	√	Hierarchical method
Satoglu and Suresh [22]	√	–	–	–	√	–	–	–	Goal programing
Mahdavi et al. [23]	√	√	√	–	√	–	–	–	Lingo 8.0
Ghotboddinia et al. [31]	√	√	√	√	–	–	–	√	Benders' decomposition
Rafiei and Ghodsi [24]	√	√	√	√	–	–	–	√	Ant colony algorithm
Bagheri and Bashiri [25]	√	√	√	–	√	–	–	–	LP-metric approach
Aghajani et al. [50]	√	–	√	–	–	–	–	–	NSGA-II and ε-constraint
Azadeh et al. [48]	√	–	–	–	√	–	√	–	ε-constraint
Rezaei-Malek et al. [13]	√	–	–	–	√	–	√	–	MOFA* and NSGA-II
This paper	√	√	√	√	–	√	√	√	NSGA-II and MOPSO

* Multiobjective firework algorithm.

tant. CFP categorizes machines and parts in terms of the similarity among parts in order to achieve full efficiency and flexibility via standardization and common processing [35,48]. In general, various techniques can be used to solve CFP, such as descriptive procedures, clustering analysis procedures, graph approaches, artificial intelligence-based approaches, and mathematical programing [6–14,48]. Previous studies of CMS have assumed that the performance of machines is 100% during the programing period. Only a few studies have considered the reliability of machinery, which is a key element in the production system and its failure incurs high costs. In particular, Jabal-Ameli et al. [15] used the ε-constraint method to minimize the different costs of CMS based on considerations of production line stoppage, maintenance costs, and machinery replacement.

In this study, we incorporate the reliability of machinery and lost time due to the machine failure into the CMS model. Furthermore, an important aspect of CMS is the assignment of operators to cells. Operators play important roles in the operation of machines, so their appropriate allocation to cells can increase the efficiency of CMS, but manpower issues have received insufficient attention in previous studies of CMS. In summary, the main contributions of this study can be summarized as follows.

- We propose a new multi-objective dynamic mixed integer mathematical model for CMS design that considers machine failure and alternative process routes (APRs).
- The optimal assignment of manpower among cells is based on two factors: (1) the consistency of the decision-making style (DMS) of operators, and (2) workload balance among cells by considering efficiency measures as a human reliability concept (see Table 1).
- We propose two multi-objective evolutionary algorithms comprising a non-dominated sorting genetic algorithm (NSGA-II) and a multi-objective particle swarm optimization (MOPSO) method.
- We demonstrate the applicability of the proposed model using an actual data set.

Table 2 compares the proposed approach with previous studies of the cell formation and worker assignment problem (CFWAP).

2. Literature review

Many studies have addressed the CFP but most tackled the problem in only one period or multiple independent periods (e.g., see Heragu and Chen [16] and Zhao and Wu [17]). Therefore, they assumed that the product demand is determined and fixed in all periods. However, due to increasing industrial competition in recent years, the formation and demand levels of products can change in different periods of time [18]. Thus, the configuration of cells obtained for each time period is not necessarily optimized and cell reconfiguration is required at the end of each period [18]. This type of CFP according to dynamic considerations is known as dynamic CFP (DCFP). The concept of a dynamic manufacturing system in its current form with cellular reconfiguration and synchronized changes in the parts family and machinery group was first proposed by Rheult et al. [19].

One of the extensions to the CFP is including the operator assignment problem (i.e., CFWAP) by incorporating related issues such as the required skill [11]. Ignoring these issues may reduce profits and/or increase the failure of manufacturing systems. In the last decade, numerous studies have considered the optimal manpower assignment for manufacturing cells in CMS. Bidanda et al. [20] presented a large-scale analysis of manpower issues in CMS based on a comprehensive review of related research. Cesani and Steudel [21] proposed a simulation model that considers worker flexibility in CMSs where operators can have mobility. Satoglu and Suresh [22] developed a three-phase hybrid CMS model to decrease the overall costs, including the hiring and firing costs of labor assignment, and operator training costs. Mahdavi et al. [23] proposed an integer mathematical programing model for the dynamic CFWAP (DCFWAP) that considers constraints on the machine capacity, duplicate machines, and the time available for workers in CMS, where the objective function of this model aims to minimize the backorder costs, holding costs, intra- and inter-cell material handling costs, hiring and firing costs, salary costs for operators, and machinery reconfiguration costs. Rafiei and Ghodsi [24] developed a bi-objective mathematical model for DCFP that considers labor utilization, where their model includes the conventional assumptions of the DCFWAP. The first objective function in this model minimizes the purchase costs for machines, relocation costs for machines, processing costs, inter- and intra-cell movement costs for parts, overtime costs for personnel, and the costs of labor shifting among cells. The second objective function maximizes the utilization of labor. The DCFWAP problem is categorized as an NP-hard problem, so a hybrid algorithm comprising a genetic algorithm (GA) and ant colony optimization was employed. Bagheri and Bashiri [25] developed a multi-objective mathematical model for DCFWAP and inter-cell layout problem. The objective functions of the proposed model aim to minimize the inter- and intra-cell trips of parts, machine relocation costs, and costs related to issues involving operators, including hiring, firing, and salaries, which are all transformed into one objective using the LP-metric approach.

DMS is a personality characteristic in psychology [26] that describes how individuals make decisions. Therefore, it can be considered as a human psychological factor. DMS plays an important role in manufacturing systems that rely heavily on human resources. Thus, in the manufacturing systems where personnel interact with each other to perform their jobs, it has already been shown that the consistency of DMSs will affect job satisfaction and productivity [13,48]. For example, in CMSs, operators who work in common manufacturing cells have large numbers of interactions.

Various classifications are available for DMSs but one of the most acceptable is that proposed by Driver et al., which classifies DMSs into five categories [26]: decisive, hierarchic, flexible, integrative, and systemic. People with a decisive style use information as much as necessary and they only consider one option during decision making. Speed and efficiency are crucial for these individuals. Individuals with a hierarchic style fully investigate a subject from every aspect, which leads to the best single solution. People with a flexible style use information to the extent that it is necessary and if one method does not lead to a decision they will look for another option. People with an integrative style comprehensively investigate an issue, before presenting several options for decision making, but they are not decisive. Finally, people with a systemic style use the integrative and hierarchic styles alternatively to assess the options by considering one or several criteria. This style is very ordered and rigorous [26]. Workers cooperate with each other for long periods of time (about 40 h per week) in the same production cells, so considering the consistency of their personal characteristics (i.e., DMSs) could improve job satisfaction and the productivity of the manufacturing system [13]. Azadeh et al. [48] determined a compatibility degree for DMSs, specifically in the manufacturing areas based on Driver et al. [26] (see Table 1). In the present study, we employ these values to assign operators with more compatible DMSs to common cells.

Azadeh et al. [48]developed a novel bi-objective mathematical model for CFWAP that considers the DMSs of workers, where the objectives of this model are; (1) minimizing inter-cell material movements and the cell establishment costs, and (2) minimizing the inconsistency of the DMSs among operators assigned to the same cells. Rezaei-Malek et al. [13] extended the method of Azadeh et al.[48], where they considered the consistency of the DMSs of skilled operators and the machines assigned among all the manufacturing cells. Furthermore, Rezaei-Malek et al. [13] proposed a hybrid algorithm for multi-objective fireworks and NSGA-II for large test problems. The proposed hybrid algorithm outperformed NSGA-II and the multi-objective algorithm. However, their model failed to consider operators and the reliability of machines in a dynamic environment.

At present, due to the increased flexibility and multi-functioning of machines, APRs need to be processed for each part [27]. Increasing the flexibility of the production routes can also enhance flexibility of the CMS design [28,29]. Adil et al. [28] considered the APR assumption and proposed a nonlinear integer programing model for identifying groups of parts and machine cells. Aryanezhad et al. [30] considered the APR feature and the capacity of promoting workers from one skill level to another. Ghotboddinia et al. [31] proposed a dynamic model for CFWAP that simultaneously considers two objective functions, where the first minimizes the total costs, including the fixed and variable expenses of machinery operations, inter- and intra-cell replacements, purchases, and sales during different time periods; and the second objective function maximizes the manpower productivity ratio in different cells.

In CFWAPs, the most significant feature of the optimal assignment of operators is the proportion of the workload on each cell relative to the number of individuals assigned to the cell. However, it should be noted that the abilities of individuals are not equal, so the reliability and efficiency of operators should be considered. The roles of individuals must be considered in the design, manufacture, and utilization of industrial processes. For example, statistics indicate that more than 90% of industrial accidents are caused directly or indirectly by worker errors [32].

Human reliability is a component of human factors and ergonomics, and it is considered in diverse fields such as production, transportation, and medicine. Indeed, individual performance may be influenced by factors including health, age, intellectual aptitude, sentiments, inclination to common mistakes, and cognitive prejudices. Williams [33] first noted that human reliability should be considered to increase the reliability of systems. Human reliability analysis (HRA) is rooted in human performance studies. Early HRA studies by empirical psychologists and behavioral scientists developed structural blocks for contemporary analysis and qualification techniques, include classifications of behaviors, work analysis techniques, and psychometric techniques. Common methods for estimating human reliability are: confusion matrices, expert estimation, task analysis linked evaluation techniques, human error rate prediction, and simulations of personnel performance. The efficiency can be assessed based on the reliability of individuals. Givi et al. [34] proposed a new mathematical model for estimating the human error rate in an assembly station under the impacts of learning–forgetting and fatigue–recovery. This HRA model can dynamically measure the error rate and reliability of humans. Khakestani [32] obtained influential factors based on HRA questionnaire containing questions about risk rates, physical and intellectual health, communication, inherent psychological traits, stress causes, skill level, anthropometry, and human error. Using the data obtained, they determined the input and output variables for a neural-fuzzy inference system. After network training, they calculated each operator's efficiency using ANFIS. In the present study, we employ the approach proposed by Khakestani [32] to calculate the efficiency score for each operator based on his/her reliability. Thus, the efficiency of the operators is calculated as an index of their reliability.

3. Problem description and formulation

In this section, a multi-objective mathematical model for DCFWAP is presented that considers some real-world assumptions. The proposed model allocates human resources with respect to the mutual consistency of the DMS of individuals as well as groupings of parts and machines. In addition, the workload of different cells is balanced by considering individual efficiency. Objective function (1) minimizes various costs in the DCFWAP, including the fixed and variable costs of machinery operations, inter- and intra-cell movements of parts, machinery purchases and sales within the planning horizon, and manpower movements among cells. Objective function (2) maximizes the mutual DMS compatibility of individuals assigned to each cell. Finally, objective function (3) balances the utilization of employees in different cells by considering their efficiency. The problem is formulated according to the following assumptions.

3.1. Assumptions

- Each part requires several operations to be processed and each operation must be performed in its respective order.
- Each part can be processed by several routes, but only one of them should be selected.
- The fixed costs for each machine and the cost of manpower during regular time and overtime are known.
- Machines are multi-functional.
- The times required for machinery operations, manpower, and setup are known.
- The capacity of each machine is fixed for each period in regular time.
- Purchasing costs and marginal revenues of selling each machine are fixed.
- The size of each batch is fixed for every intra- and inter-cell movement, and it is assumed that the costs of intra- and inter-cell movement are the same and equal.
- The demand for each part is predetermined and it may change in each period.
- Backorder is not allowed.
- The costs of inter- and intra-cell manpower transfers are fixed and determined.
- In each period, the maximum number of cells that can be formed and their respective capacities are known.
- The number of operators is fixed for all periods and hiring or firing is not allowed.
- Machinery breakdowns follow a Poisson distribution, where the amount of λ for each machine is known.

$$f(x) = \frac{e^{-\lambda}\lambda^{x}}{x!}$$

- The mean time to repair each machine is specified.
- The DMS of each operator is determined using the approach proposed by Driver et al. [26].
- Each operator has sufficient skill to work with every type of machine.

3.2. Indices

c	index of manufacturing cells ($c = 1, \ldots, C$)
m	index of machine types ($m = 1, \ldots, M$)
p	index of part types ($p = 1, \ldots, P$)
h	index of time periods ($h = 1, \ldots, H$)
j	index of operations required for processing part p ($j = 1,\ldots,$ OP)
l	index of operators ($l = 1, \ldots, L$)

3.3. Parameters

H	number of periods

P	number of part types
OP	number of operations required for part p
M	number of machine types
C	number of cells
L	total amount of labor
D_{ph}	demand for part p in period h
ϑ_{ph}	1 if part p is planned for production in period h; otherwise, 0
UB	allowable quantity of machines in each cell
γ_p^{inter}	inter-cell movement cost per batch p (USD)
γ_P^{intra}	intra-cell movement cost per batch p (USD)
φ_m	cost of purchasing machine type m (USD)
ω_m	revenue from selling machine type m (USD)
α_m	fixed cost of machine type m in each period (USD)
ρ_h	fixed cost of inter-cell labor movement in period h (USD)
δ_m	relocation cost of machine type m (USD)
T_{mh}	time capacity of machine type m in period h in regular time (h)
t_{ipm}	processing time required to perform operation j for part type p on machine type m (h)
t'_{jpm}	time required for operator to perform operation j for part type p on machine type m (h)
a_{jpm}	1 if operation j for part p can be performed on machine type m; otherwise, 0
BR_m	cost of the breakdown of machine type m (USD)
$MTBF_m$	mean time between failures on machine type m (h)
$MTTR_m$	mean time to repair for machine type m (h)
WT	available time per worker (h)
E_{fl}	efficiency of operator l
β_m	variable cost of machine type m for each unit time in regular time (h)
B_p	batch size for movement of part type p
$\pi_{l\xi}$	DMS inconsistency of two operators l and ξ

3.4. Decision variables

x_{jpmch}	1 if operation j for part type p is performed on machine type m in cell c in period h; otherwise, 0
ψ_{chl}	1 if operator l is assigned to cell c in period h; otherwise, 0
N_{mch}	number of machine types m allocated to cell c in period h
k^+_{mch}	number of machine types m added to cell c in period h
k^-_{mch}	number of machine types m removed from cell c in period h
I^-_{mh}	number of machine types m sold in period h
I^+_{mh}	number of machine types m purchased in period h
OP_h	utilization percentage of operators in period h
CP_{ch}	utilization percentage of operators in cell c in period h

3.5. Mathematical model

Based on the definitions given above, the following multi-objective nonlinear mathematical model is presented.

$$\begin{aligned}
\text{Min } Z_1 = & \sum_{m=1}^{M}\sum_{c=1}^{C}\sum_{h=1}^{H} N_{mch}\,\alpha_m + \sum_{m=1}^{M}\sum_{h=1}^{H} I^+_{mh}\,\varphi_m - \sum_{m=1}^{M}\sum_{h=1}^{H} I^-_{mh}\,\omega_m \\
& + \sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{j=1}^{OP}\sum_{m=1}^{M} \beta_m\, D_{ph}\, t_{jpm}\, x_{jpmch} \\
& + \frac{1}{2}\sum_{h=1}^{H}\sum_{p=1}^{P} \gamma_p^{inter}\left\lceil \frac{D_{ph}}{B_p}\right\rceil \sum_{j=1}^{OP-1}\sum_{c=1}^{C}\left|\sum_{m=1}^{M} x_{(j+1)pmch} - \sum_{m=1}^{M} x_{jpmch}\right| \\
& + \frac{1}{2}\sum_{h=1}^{H}\sum_{p=1}^{P} \gamma_p^{intra}\left\lceil \frac{D_{ph}}{B_p}\right\rceil \sum_{j=1}^{OP-1}\sum_{c=1}^{C}\left(\sum_{m=1}^{M}\left|x_{(j+1)pmch} - x_{jpmch}\right| - \left|\sum_{m=1}^{M} x_{(j+1)pmch} - \sum_{m=1}^{M} x_{jpmch}\right|\right) \\
& + \frac{1}{2}\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{l=1}^{L} \rho_h\left(\left|\psi_{c(h+1)l} - \psi_{chl}\right|\right)
\end{aligned}$$

$$+\frac{1}{2}\sum_{h=1}^{H}\sum_{m=1}^{M}\sum_{c=1}^{C}\delta_m\left(k^+_{mch}+k^-_{mch}\right)+\sum_{m=1}^{M}\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{j=1}^{OP}\frac{D_{ph}\,t_{jpm}\quad x_{jpmch}BR_m}{MTBF_m} \tag{1}$$

$$\text{Min } Z_2 = \sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{\xi=l+1}^{L}\psi_{chl}\psi_{ch\xi}\pi_{l\xi} \tag{2}$$

$$\text{Min } Z_3 = \sum_{h=1}^{H}\sum_{c=1}^{C}\left| CP_{ch}-OP_h\right| \tag{3}$$

s.t.

$$\sum_{c=1}^{C}\sum_{m=1}^{M}a_{jpm}\ x_{jpmch}=\vartheta_{ph}\quad\forall\ j,p,h \tag{4}$$

$$x_{jpmch}\le a_{jpm}\quad\forall\ j,p,h,c,m \tag{5}$$

$$\sum_{p=1}^{P}\sum_{j=1}^{OP}D_{ph}\,t_{jpm}\,x_{jpmch}\le N_{mch}\,T_{mh}-\sum_{p=1}^{P}\sum_{j=1}^{OP}\frac{D_{ph}\,t_{jpm}\,x_{jpmch}MTTR_m}{MTBF_m}\qquad\forall\ h,c,m$$

$$\text{or}:\sum_{p=1}^{P}\sum_{j=1}^{OP}D_{ph}\,t_{jpm}\,x_{jPmch}\left(1+\frac{MTTR_m}{MTBF_m}\right)\le N_{mch}\,T_{mh}\quad\forall\ h,c,m \tag{6}$$

$$\sum_{c=1}^{C}N_{mch}-\sum_{c=1}^{C}N_{mc(h-1)}=I^+{}_{mh}-I^-{}_{mh}\quad\forall\ h,m \tag{7}$$

$$N_{mc(h-1)}+k^+{}_{mch}-k^-{}_{mch}=N_{mch}\quad\forall\ h,c,m \tag{8}$$

$$\sum_{n=1}^{M}N_{mch}\le UB\quad\forall\ h,c \tag{9}$$

$$\sum_{c=1}^{C}\sum_{l=1}^{L}\psi_{chl}=L\quad\forall\ h \tag{10}$$

$$\sum_{c=1}^{C}\psi_{chl}=1\quad\forall\ h,l \tag{11}$$

$$CP_{ch}=\frac{\left(\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{j=1}^{OP}D_{ph}\,t'_{jpm}\,x_{jPmch}\right)}{\left(WT\ \sum_{l=1}^{L}\frac{\psi_{chl}}{Ef_l}\right)}\quad\forall c,h \tag{12}$$

$$OP_h=\frac{\left(\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{p=1}^{p}\sum_{j=1}^{OP}D_{ph}\,t'_{jpm}\quad x_{jPmch}\right)}{\left(WT\sum_{c=1}^{C}\sum_{l=1}^{L}\frac{\psi_{chl}}{Ef_l}\right)}\quad\forall h \tag{13}$$

$$x_{jPmch},\ \psi_{chl}\in\{0,1\},\ k^-_{mch},\ k^+_{mch},\ I^+_{mh},\ I^-_{mh},\ N_{mch}\in N^+$$
$$T_{mCh},\ OP_h,\ CP_{ch}\ge 0 \tag{14}$$

Objective function (1) minimizes the total cost of the DCFWAP in all the time periods, which comprise the fixed cost of allocating machines to cells (term 1), purchasing cost of the machines required (term 2), revenue from selling second-hand machines (term 3), variable cost of machines required for processing the parts (term 4), costs of inter- and intra-cell movements of parts (terms 5 and 6, respectively), cost of inter-cell movement of manpower including the training cost for improving the skills of workers (term 7), reconfiguration cost of machines (term 8), and finally the cost of machine failure, which is calculated based on the workload of each machine, failure cost, and the average time span between each two failures (term 9). Objective function (2) minimizes the total DMS inconsistency among operators in common cells. Objective function (3) minimizes the total difference between the utilization percentage of all operators in CMS and the utilization percentage of operators in each cell. In fact, this objective function maximizes the workload homogeneity of operators in different cells.

Eq. (4) guarantees that each operation on a part is processed by only one machine in a manufacturing cell. Constraint (5) does not allow variable x to be equal to one if its related parameter a is zero. Constraint (6) guarantees that the total operating time of each machine does not exceed the time available. Eq. (7) shows the quantity of machines in different periods in terms of the purchased and sold machines. Eq. (8) balances the quantity of machines in each cell in terms of the replacement of machines in different periods. Constraint (9) specifies the capacity limitation of each cell in terms of the number of machines. Eq. (10) shows the total number of operators. Eq. (11) ensures that every operator in each period is allocated only to one cell. Eq. (12) computes the percentage of operator utilization during each period in each cell. Eq. (13) calculates the utilization of operators in each period. Eq. (14) identifies the types of variables.

Table 3
Part information of the test problem.

Route	P1			P2			P3			P4		
	1	2	3	1	2	3	1	2	3	1	2	3
M1	.08			.64	.11		.48	.65	.46		.82	
M2	.09	.90	.61			.17		.45		.48	.98	.40
M3			.66	.57			.54		.36			
M4		.97			.07	.27				.56		.61
D_{ph}												
Period1	200			0			0			650		
Period2	500			450			0			500		
B_p	8			12			10			16		

Table 4
General information of the test problem.

Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value
H	2	M	4	ρ_h	500	$\sum_{m=1}^{M} a_{jpm}$	2
OP	3	p	4	t'_{jpm}	$\sim t_{jpm}/10$	γ_P^{intra}	$\sim \gamma_P^{inter}/10$
C	3	*WT*	100	UB	3	γ_P^{inter}	100

3.6. Linearization of the proposed model

The proposed model is nonlinear and thus we aim to make it as linear as possible in the following. Eq. (1) is a nonlinear integer equation because of the absolute terms. To transform this function into a linear function, six positive variables (z^1_{jpch}, $z^2_{jpch}, y^1_{jpmch}, y^2_{jpmch}, w^1_{chl}, w^2_{chl}$) are defined and the objective function is rewritten as follows.

$$\begin{aligned}\text{Min } Z_1 = &\sum_{h=1}^{H}\sum_{m=1}^{M}\sum_{c=1}^{C} N_{mch}\,\alpha_m + \sum_{h=1}^{H}\sum_{m=1}^{M} I^+_{mh}\,\varphi_m - \sum_{h=1}^{H}\sum_{m=1}^{M} I^-_{mh}\,\omega_m\\ &+\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{j=1}^{OP}\sum_{m=1}^{M} D_{ph}\,t_{jpm}\,x_{jpmch}\left(\beta_m + \frac{BR_m}{MTBF_m}\right)\\ &+\frac{1}{2}\sum_{h=1}^{H}\sum_{p=1}^{P}\gamma_p^{inter}\left\lceil\frac{D_{ph}}{B_P}\right\rceil\sum_{j=1}^{OP-1}\sum_{c=1}^{C}\left(z^1_{jpch} + z^2_{jpch}\right)\\ &+\frac{1}{2}\sum_{h=1}^{H}\sum_{p=1}^{P}\gamma_p^{intra}\left\lceil\frac{D_{ph}}{B_P}\right\rceil\sum_{j=1}^{OP-1}\sum_{c=1}^{C}\left(\sum_{m=1}^{M}\left(y^1_{jpmch} + y^2_{jpmch}\right) - \left(z^1_{jpch} + z^2_{jpch}\right)\right)\\ &+\frac{1}{2}\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{l=1}^{L}\rho_h\left(w^1_{ch} + w^2_{ch}\right)\\ &+\frac{1}{2}\sum_{h=1}^{H}\sum_{m=1}^{M}\sum_{c=1}^{C}\delta_m\left(k^+_{mch} + k^-_{mch}\right)\end{aligned} \tag{15}$$

s.t.

$$z^1_{jpch} - z^2_{jpch} = \sum_{m=1}^{M} x_{(j+1)pmch} - \sum_{m=1}^{M} x_{jpmch} \quad \forall\ j, p, m, c, h \tag{16}$$

$$y^1_{jpmch} - y^2_{jpmch} = x_{(j+1)pmch} - x_{jpmch} \quad \forall\ j, p, m, c, h \tag{17}$$

$$w^1_{chl} - w^2_{chl} = \psi_{\ c(h+1)l} - \psi_{\ chl} \quad \forall\ c, h, l \tag{18}$$

$$z^1_{jpch},\ z^2_{jpch},\ y^1_{jpmch},\ y^2_{jpmch}, w^1_{ch},\ w^2_{ch} \geq 0 \quad \forall\ j, p, m, c, h \tag{19}$$

3.7. Validation and verification

We consider a small test problem to validate the proposed model. Table 3 shows the parts routes and demands for each part during each period and batch size. Tables 4 and 5 show the parameter values and machine information for the model, respectively. Table 6 shows the labor information and inconsistency between them.

Table 5
Machine information of the test problem.

	$T_{mh}(\$)\forall h$	$\varphi_m(\$)$	$\omega_m(\$)$	$\alpha_m(\$)$	$BR_m(\$)$	$\delta_m(\$)$	$\beta_m(\$)$	$MTBF_m$	$MTTR_m$
M1	700	12,000	10,000	120	300	60	3	850	70
M2	700	14,000	11,500	140	150	70	1.5	510	50
M3	700	15,000	10,500	150	350	75	3.5	400	85
M4	700	14,000	12,300	140	200	70	2	370	90

Table 6
Labor information of the test problem.

	L1	L2	L3	L4	L5	L6
DMS	Flexible	Hierarchic	Flexible	Decisive	Hierarchic	Integrative
Ef_l	0.38	0.65	0.85	0.62	0.82	0.73
Inconsistency						
L1	_	7	1	5	7	3
L2	7	_	7	5	3	3
L3	1	7	_	5	7	3
L4	5	5	5	_	5	5
L5	7	3	7	5	_	3
L6	3	5	3	7	5	_

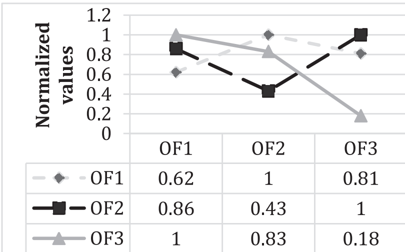

Fig. 1. Behavior of the objective functions.

Table 7
Quantified consistency of DMS (adopted from Azadeh et al. [48]).

DMS	Decisive	Flexible	Hierarchic	Integrative
Decisive	3	5	5	5
Flexible	5	1	7	3
Hierarchic	5	7	3	3
Integrative	7	3	5	1

The normalized optimal value of each objective function was obtained by GAMS 22.1 on a PC ASUS Core i7, 2.2 GHz system with 4GB RAM. Fig. 1 depicts the behavior of the objective functions. According to the results, the objective functions do not exhibit consistent behavior and they must be considered separately.

4. Methodology

The questionnaire developed by Driver et al. [26] is used to assess the DMSs of operators. Each style has a different consistency and compatibility with respect to other styles, so the quantification method proposed by Azadeh et al. [48]was applied (see Table 7). Due to the rarity of the systemic style, only four basic styles are considered.

To determine the human efficiency values, the questionnaire proposed by Khakestani [32] is used. Due to the NP-hardness of large problems, two meta-heuristic algorithms are used to solve the proposed model, i.e., MOPSO and NSGA-II. The non-dominated solution (NDS) concept is explained as follows.

4.1. NDS

It is possible to simply determine the best solution for a single-objective problem, where a solution with the lowest value (in a minimization form) is an optimal solution. However, in real-world applications, decision-makers often deal with multi-objective problems where there is no single optimum solution for all the objectives (e.g., see Azadeh et al. [35], Salehi Sadghiani et al. [36], Azadeh et al. [37], Azadeh et al. [38], Rezaei-Malek et al. [39], Zahiri et al. [40,41], Firoozi et al. [42], and

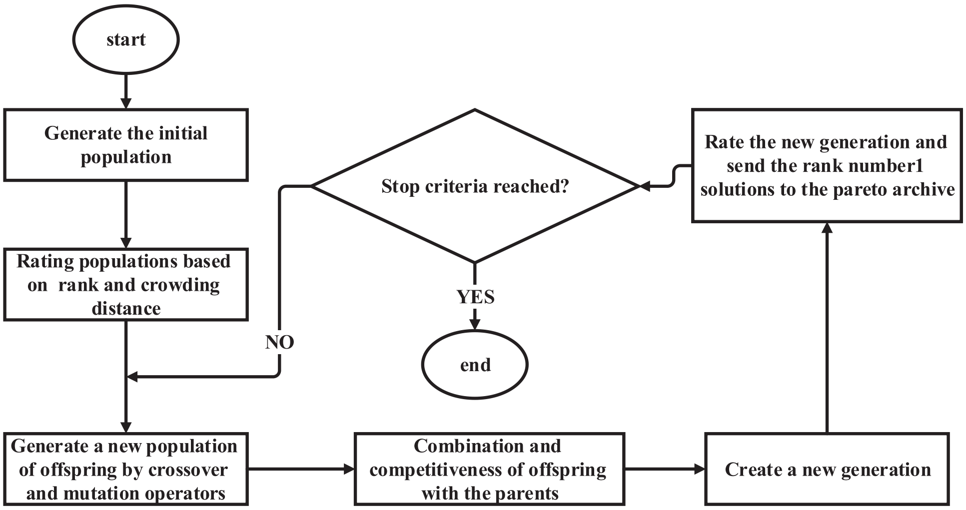

Fig. 2. Flow chart of NSGA-II.

Salehi et al. [43], Zhalechian et al. [49]). For these problems, it is possible to obtain a set of NDSs where each solution is not better than the others. Thus, a feasible solution $\widehat{x}$ is considered to be non-dominated if no other feasible solution is better than $\widehat{x}$ among one or more objective functions without degrading the others [44]. The ranking of solutions in evolutionary multi-objective algorithms is based on the non-dominated pareto fronts. When the ranking of a NDS set is 1, it is called Front #1. After the solutions to Front #1 have been eliminated, the remaining NDSs are called Front #2 (their ranking is equal to 2). Similarly, after the solutions to Front #2 have been eliminated (as well as those to Front #1), the remaining NDSs are called Front #3 (their ranks are equal to 3). This process is repeated until the rankings of all the solutions are determined.

4.2. NSGA-II

The NSGA-II algorithm is an evolutionary algorithm that operates in a similar manner to the selection of genes. In this algorithm, previous data are extracted and used in the search process [45,46]. A chromosome is a string of numbers called genes. In each iteration, new chromosomes (offspring) are generated by the algorithm's operators, including crossover and mutation. The offspring are then evaluated and better qualified chromosomes are chosen by a selection procedure such that the selected chromosomes have a population size that is the same as the initial population and they are transferred to the next generation. In this process, the algorithm converges to the best chromosome that represents an optimal or sub-optimal solution. In this study, we use another criterion (i.e., the crowding distance (CD)) to sort solutions with the same rank. In addition to the convergence of the solutions to a real Pareto front, they should be uniformly distributed across the front. CD indicates the absolute distance among the normalized objective functions of the adjacent elements, where the solution is more desirable when its value is higher.

The structure of the NSGA-II is depicted in Fig. 2. Single-cut crossover is applied and each set of variables is crossed with the same type of variable as the parent's genes. It should be noted that one of the parents in the crossover operator is chosen from the NDSs set and the other parent is chosen from the last population. The probability of selection for each NDS is based on its *CD* value, where a greater *CD* leads to a higher chance of selection. Eq. (20) calculates *CD*, where $x_{i\text{-}1}$, x_i and x_{i+1} are consecutive members of the NDS. $f_1(x_i)$, $f_2(x_i)$, and $f_3(x_i)$ are the values of the first, second,,and third objective functions of the *i*th point of the NDS, respectively. $f_1{}^{max}$, $f_2{}^{max}$, and $f_3{}^{max}$ are the maximum values of the first, second, and third objective functions on the Pareto front, respectively. $f_1{}^{min}$, $f_2{}^{min}$, and $f_3{}^{min}$ are the minimum values of the first, second, and third objective functions on the Pareto front, respectively. The probability of selection for the other parent (which is chosen from the population) is equal to the crossover rate (input parameter in the NSGA-II) for all the members of the population.

$$CD_i = \frac{|\, f_1(x_{i+1}) - f_1(x_{i-1}) \,|}{f_1^{max} - f_1^{min}} + \frac{|\, f_2(x_{i+1}) - f_2(x_{i-1}) \,|}{f_2^{max} - f_2^{min}} + \frac{|\, f_3(x_{i+1}) - f_3(x_{i-1}) \,|}{f_3^{max} - f_3^{min}} \tag{20}$$

Exploitation (i.e., mutation) is only considered for the NDS set. Experiments showed that if neighborhood search is only established for the NDS set, then the computational time will decrease without any change in the quality of the solutions. Therefore, we only mutate members of the NDS set and a high-quality solution has the chance of being considered in the next population, or even in the next NDS set. The probability of mutation for each chromosome (from the NDS set) is equal to the mutation rate, which is an input parameter in the NSGA-II algorithm. The next generation is selected from the previous generation and the new offspring, which are generated by the crossover and mutation operators. The probability of selection is based on *CD*, which can be calculated using Eq. (20). Thus, a chromosome with a greater *CD* has a higher

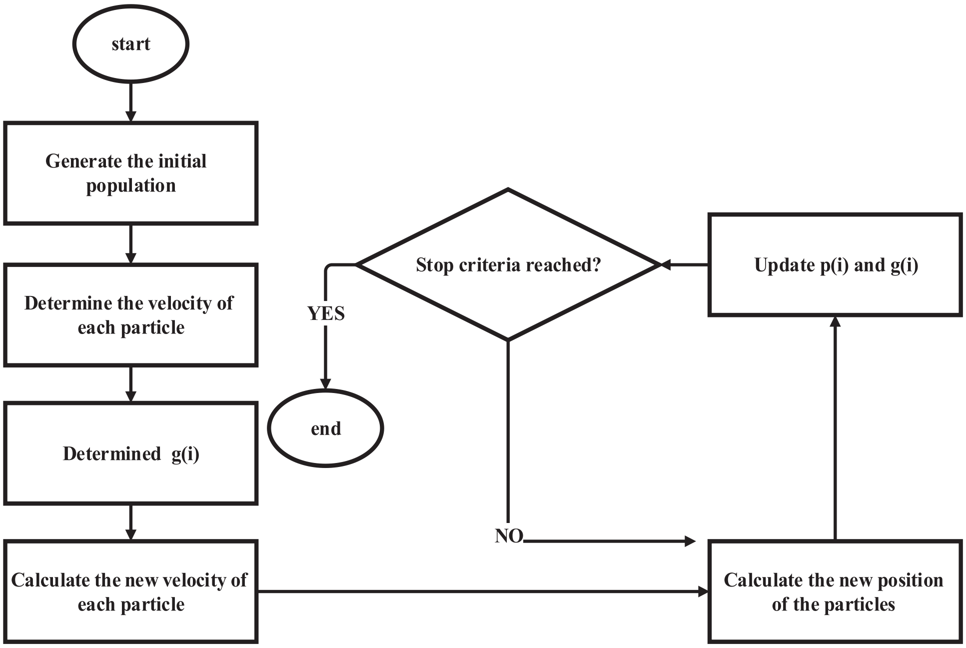

Fig. 3. Flow chart of MOPSO.

chance of being selected for the next generation. This approach provides greater variability in the production of generations. In addition, if the number of NDSs is more than the archive size, then NDSs with lower CD values are eliminated by the algorithm. The optimum values of the algorithm's parameters are calculated using the TAGUCHI method, which is a common approach for designing experiments. Table 9 presents the input parameters of the proposed NSGA-II.

4.3. MOPSO

Particle swarm optimization (PSO) is a well-known meta-heuristic algorithm, which is based on models of social behavior by birds. In this algorithm, the initial birds (i.e., solutions) are generated randomly and an initial velocity is then assigned to each of them. According to the bird's current velocity as well as its distance from the best position in the personal memory and its distance from the best position found by the leader birds (best global solutions found), a new velocity and position are calculated for the bird using Eqs. (21) and (22), respectively. If the new position dominates the best personal memory, it will replace the old personal memory (see Eqs. (23) and (24)); otherwise, one of them will be selected randomly. The notations used in the algorithm are as follows: x_i indicates the current position of the particle, v_i denotes the velocity of the particle, p_i represents the best personal memory, g_i indicates the best position found by the leader particles, r_1 and r_2 are random numbers between 0 and 1, ω is the weight of inertia and, c_1 and c_2 are acceleration values.ω, c_1, and c_2 represent the weighted-impact of the current velocity, the best position in the personal memory, and the best global position at the new velocity, respectively.

The proposed MOPSO algorithm assumes that the NDS set comprises the leader particles. As can be inferred from Eq. (21), only one leader should be selected for each particle (g_i) whereas the NDS set has several members. Leaders are selected from the NDS set according to their CD index, which is calculated by Eq. (20) in a similar manner to the NSGA-II algorithm. Thus, the probability of selection for each NDS as the leader of each particle is calculated based on the CD index (an NDS with a greater CD has a higher chance of being selected as the leader). The algorithm eliminates the NDSs with the lowest CD values from the NDS set if the number of NDSs exceeds the size of the archive. The structure of the proposed MOPSO algorithm is shown in Fig. 3.

$$V_i(t) = \omega\ (t-1)\ V_i(t) + c_1 r_1 (p_i(t-1) - x_i(t-1)) + c_2 r_2 (g_i(t-1) - x_i(t-1)) \tag{21}$$

$$x_i(t) = x_i(t-1) + V_i(t) \tag{22}$$

$$p_i(t) = p_i(t-1) \text{ if } f(x_i(t)) \geq f(p_i(t-1)) \tag{23}$$

$$p_i(t) = x_i(t) \text{ if } f(x_i(t)) \leq f(p_i(t-1)) \tag{24}$$

Experimental design by TAGUCHI in MINITAB is used to find the optimum values of the input parameters for the MOPSO and NSGA-II algorithms (see Table 8).

Table 8
NSGA-II and MOPSO input parameters.

NSGA-II	Population	Number of generation	Crossover rate			Mutation rate	Size of archive
	100	50	0.7			0.5	100
MOPSO	Population	Number of generation	C1	C2	ω	Mutation rate	Size of archive
	120	50	2.5	2.5	0.8	0.3	100

4.4. Evaluation of the meta-heuristic algorithms

In this section, we present evaluations of the performance of the proposed algorithms, i.e., NSGA-II, MOPSO, and weighted-sum method (WSM). Five different common indexes were used to compare the performance of the proposed algorithms. (1) The number of Pareto optimal solutions, which indicates the Pareto optimal variability, where a larger value for this index results in better performance and more options for decision-makers. (2) The CPU time represents the calculation time required to solve a problem, where a lower value for this index indicates better performance. (3) The diversity of the solutions (D) denotes the diversity of the Pareto solutions on the Pareto front, where larger values for this index are preferable. (4) The spacing metric of the Pareto optimal solutions (S) is defined to measure the uniformity of the distributions of the Pareto solutions. Decision-makers always prefer solutions that are uniformly distributed because they then have more options. At lower values of this index, the Pareto solutions are distributed more uniformly compared with larger values. Thus, lower values are preferable. (5) The quality of the Pareto solutions ($Q(A,B)$) is the most important index for comparing the performance of multi-objective algorithms. The quality of the solutions obtained by an algorithm cannot be calculated individually. Thus, the quality of both algorithms is defined relative to each other.

The D index is calculated by Eq. (25), where i and j are solution indexes, and k is an objective function index.

$$D = \sum_{k=1}^{3} \max_{i,j} \left\{ \left| f_k(x_i) - f_k(x_j) \right| \right\} \tag{25}$$

The spacing metric (S) denotes the closeness of the Pareto optimal solutions. Eq. (26) is used to calculate this metric, where n is the number of Pareto optimal solutions and d_i (calculated by Eq. (27)) denotes the distance to the ith closest optimal solution.

$$S = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (\bar{d} - d_i)^2} \tag{26}$$

$$d_i = \min_{j \text{ and } j \neq i} \left\{ \left| f_1(x_i) - f_1(x_j) \right| + \left| f_2(x_i) - f_2(x_j) \right| + \left| f_3(x_i) - f_3(x_j) \right| \right\} \tag{27}$$

Some explanations must be provided before calculating the quality of the solutions. We assume that A and B are two sets of solutions that we want to compare. First, $C(A,B)$ and $C(B, A)$ should be calculated (see Eq. (28)). The Q (A, B) ratio is defined by Eq. (29), where $0 \le Q(A, B) \le 1$ and $Q(A, B) + Q(B, A) = 1$. If $Q(A, B) > Q(B, A)$, then this implies that solution A is better than solution B.

$$C(A, B) = \frac{\text{Number of solutions } B \text{ dominated by solutions } A}{\text{Number of solutions } B} \tag{28}$$

$$Q(A, B) = \frac{C(A, B)}{C(A, B) + C(B, A)} \tag{29}$$

We evaluated the algorithms based on 10 different randomly generated numerical test problems with different sizes. Replication was required to eliminate the stochastic nature of the meta-heuristic algorithms. Thus, each test problem was solved several times by each algorithm to increase the accuracy of the evaluations. Table 9 shows the size of each test problem and the replicate solutions.

To demonstrate the applicability of the proposed methods, WSM was coded in GAMS to solve the test problems. GAMS was unable to solve the medium and large test problems, so only the results of the small test problems were compared among the proposed algorithms. The test problems were solved using the proposed meta-heuristics and compared with the solutions obtained by WSM according to the metrics explained above. The means and standard deviations of the metrics for solving each test problem are shown in Tables 10–14.

Statistical tests were conducted to ensure that there was statistical evidence that the meta-heuristic algorithms could achieve good Pareto solutions within a reasonable time. We considered 100 hypothesis tests [47] for the metrics and different problem sizes. We assumed a 99% confidence level (i.e., type II error $\alpha = 1\%$) for all the tests. The null hypotheses and P-values are presented in Table 15. As shown in Table 15, the proposed NSGA-II algorithm performed better than MOPSO and WSM in some cases, such as the number of Pareto solutions, diversity of the solutions, and quality of the solutions. The proposed MOPSO algorithm performed better in terms of the CPU time. WSM performed better in terms of the uniform distributions of the Pareto solutions and the quality of the Pareto solutions. In some cases, all the algorithms

Table 9
Considered sizes for test problems.

Test problem number	$\lvert J\rvert \times \lvert P\rvert \times \lvert M\rvert \times \lvert C\rvert \times \lvert H\rvert \times \lvert L\rvert$	Number of replications (solving the same problem)
1	$2 \times 3 \times 4 \times 2 \times 2 \times 4$	30
2	$3 \times 4 \times 4 \times 3 \times 2 \times 6$	30
3	$3 \times 5 \times 5 \times 3 \times 2 \times 8$	20
4	$3 \times 6 \times 6 \times 3 \times 2 \times 10$	20
5	$3 \times 8 \times 6 \times 3 \times 3 \times 10$	10
6	$3 \times 12 \times 8 \times 3 \times 3 \times 14$	10
7	$3 \times 16 \times 10 \times 3 \times 3 \times 16$	5
8	$3 \times 20 \times 12 \times 4 \times 3 \times 16$	5
9	$4 \times 22 \times 16 \times 4 \times 4 \times 18$	5
10	$4 \times 24 \times 18 \times 4 \times 4 \times 20$	5

Table 10
Number of Pareto solutions.

Test problem	Sample size (replication of solving the same problem)	Mean			Standard deviation		
		NSGA-II	MOPSO	Weighted-sum	NSGA-II	MOPSO	Weighted-sum
1	30	**67.80**	44.27	7	2.75	0.10	0.00
2	30	**38.83**	29.07	11	0.27	1.65	0.00
3	20	39.55	**43.85**	13	0.27	4.08	0.00
4	20	**66.75**	51.40	8	2.78	4.41	0.00
5	10	**76.30**	62.20	12	0.82	1.29	0.00
6	10	**93.60**	74.80	Out-of memory	4.00	4.29	Out-of memory
7	5	**100**	88.20		0.02	2.05	
8	5	100	100		0.00	0.04	
9	5	100	100		0.00	0.00	
10	5	100	100		0.00	0.00	

Table 11
CPU time (s).

Test problem	Sample size (replication of solving the same problem)	Mean			Standard deviation		
		NSGA-II	MOPSO	Weighted-sum	NSGA-II	MOPSO	Weighted-sum
1	30	33.33	21.06	**12.37**	0.06	0.99	1.19
2	30	170.43	**104.47**	252.38	2.57	9.02	1.69
3	20	184.22	**115.14**	723.38	12.85	5.99	5.73
4	20	398.39	**246.23**	2529.03	28.53	2.50	4.40
5	10	856.73	**521.97**	8079.15	36.50	4.22	7.84
6	10	1104.32	**693.52**	Out-of memory	108.99	26.33	Out-of memory
7	5	**1381.85**	5994.75		83.73	306.44	
8	5	1943.86	**1199.84**		42.50	81.78	
9	5	2200.08	**1345.31**		70.22	396.70	
10	5	3759.37	**2906.90**		145.52	218.34	

performed well, so checking their weaknesses may be useful. WSM performed best in terms of the S and Q metrics, but it was unable to solve medium and large test problems because they required excessive amounts of CPU time, while the number of Pareto solutions and their diversity were also not acceptable. MOPSO performed best in terms of the CPU time metric, but it was worse than the other algorithms in terms of the other metrics. NSGA-II was the only algorithm capable of solving the test problems with different sizes in a reasonable amount of time with high-quality solutions. The statistical tests supported this claim, as summarized in Table 15.

The results of the comparisons imply the following.

- NSGA-II provided a larger archive of NDSs.
- The time required to obtain the optimum solutions was less using MOPSO than NSGA-II.
- NSGA-II had a greater average value of D compared with MOPSO, which indicates the greater uniformity of the Pareto solutions obtained by MOPSO compared with NSGA-II.
- The value of S obtained for the Pareto solutions was better using WSM than the MOPSO and NSGA-II algorithms.
- The quality of NDSs was better with NSGA-II than MOPSO and WSM (for large problems).

According to the results obtained, we strongly recommend using NSGA-II for large problems because although it takes slightly more time compared with MOPSO, the quality of the solutions is better. The proposed approach was also applied to a real CMS in Tehran, Iran, i.e., the company IMEN Compressed Air Industries, which assembles reciprocating compressors (type PC250). IMEN stated that the job satisfaction level of operators increased after considering the efficiency and DMS of operators. The company said that the number of reported complaints usually received per month decreased substantially

Table 12
Diversity of the solutions (D).

Test problems	Sample size (replication of solving the same problem)	Mean			Standard deviation		
		NSGA-II	MOPSO	Weighted-sum	NSGA-II	MOPSO	Weighted-sum
1	30	**2660.24**	866.69	639.61	11.49	7.41	0.00
2	30	**4899.27**	839.10	1101.60	46.88	4.43	0.00
3	20	**95739.09**	26968.13	2391.17	606.78	127.46	0.00
4	20	**3.91E + 05**	2.29E + 05	1.05E + 04	1643.02	1849.55	0.00
5	10	6.87E + 05	**8.70E + 05**	6.01E + 04	58.75	5829.72	0.00
6	10	2.76E + 06	**3.45E + 06**	Out-of memory	7111.49	7676.86	Out-of memory
7	5	**1.18E + 07**	1.09E + 07		7351.67	84220.95	
8	5	**4.19E + 07**	3.57E + 07		257549.44	327163.16	
9	5	**2.79E + 08**	2.07E + 08		1345477.83	236310.33	
10	5	5.30E + 08	**5.73E + 08**		1912703.76	5408625.18	

Table 13
Uniformly distribution of the Pareto solutions (S).

Test problem	Sample size (replication of solving the same problem)	Mean			Standard deviation		
		NSGA-II	MOPSO	Weighted-sum	NSGA-II	MOPSO	Weighted-sum
1	30	37.53	25.04	**10.72**	0.22	0.15	0.00
2	30	98.29	53.75	**27.67**	0.79	0.40	0.00
3	20	777.37	355.64	**92.72**	6.70	0.50	0.00
4	20	2964.26	2275.81	**275.14**	3.98	12.94	0.00
5	10	9333.08	8305.95	**1524.14**	62.53	35.21	0.00
6	10	**2.34E + 04**	2.52E + 04	Out-of memory	204.95	121.71	Out-of memory
7	5	8.71E + 04	**7.62E + 04**		436.66	480.32	
8	5	3.52E + 05	**2.77E + 05**		2405.77	1437.80	
9	5	**1.77E + 06**	1.89E + 06		16,932.34	18,712.21	
10	5	6.89E + 06	**4.33E + 06**		52,885.73	29,913.20	

Table 14
Quality of pareto optimal solutions.

Test problem	Sample size (replication of solving the same problem)	Mean			Standard deviation		
		Q(NSGA-II, MOPSO)	Q(NSGA-II, Weighted-sum)	Q(MOPSO, Weighted-sum)	Q(NSGA-II, MOPSO)	Q(NSGA-II, Weighted-sum)	Q(MOPSO, Weighted-sum)
1	30	0.4884	0	0	0.02	0.06	0.11
2	30	**0.5555**	0.4828	0.449	0.02	0.10	0.18
3	20	**0.609**	0.4869	0.4754	0.05	0.12	0.12
4	20	0.494	**0.5109**	0.4907	0.13	0.10	0.04
5	10	**0.7015**	**0.5572**	**0.5014**	0.10	0.04	0.17
6	10	**0.6623**	Out-of memory	Out-of memory	0.18	Out-of memory	Out-of memory
7	5	**0.5866**			0.04		
8	5	**0.864**			0.16		
9	5	**0.827**			0.04		
10	5	**0.7799**			0.20		

because the operators were more satisfied with their coworkers in the common cells and the workload was fairly divided between different cells.

5. Sensitivity analysis

We also performed a sensitivity analysis for the fifth test problem. First, the optimum value of the first objective function (i.e., total cost) was determined using GA, PSO, and GAMS regardless of the other objective functions. Next, the third objective function was calculated using the solution obtained. The optimum value of the third objective function (i.e., workload homogeneity) was specified using GA, PSO, and GAMS, and the first objective function was calculated using the solution obtained. The results are shown in Table 16.

Regardless of the other objective functions, the optimum value of the second objective function (i.e., inconsistency of operators) was determined using GA, PSO, and GAMS. Next, using the optimal solution for the second objective function, the eighth term of the cost objective function was calculated. The second objective function depends only on the allocation of manpower, so it only affects the eighth term of the cost objective function; thus it has no influence on the other cost components. Moreover, the optimum value of the eighth term of the first objective function was found and the second objective function was then determined using the optimal solution obtained, and the results are shown in Table 17.

Table 15
P-Values of the hypothesis tests.

Null hypothesis (H0)	Test problem index	1	2	3	4	5	6	7	8	9	10	Percentage of *P*-values which are less than 1% (The null hypothesis is rejected at 99% confidence level)
MOPSO performs better than NSGA-II	Number of pareto solutions	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**90%**
	CPU Time	1.000	1.000	1.000	1.000	1.000	1.000	0.000	1.000	0.995	1.000	10%
	Diversity (D)	0.000	0.000	0.000	0.000	1.000	1.000	0.000	0.000	0.000	1.000	**70%**
	Standard deviation (S)	1.000	1.000	1.000	1.000	1.000	0.000	1.000	1.000	0.000	1.000	20%
	Quality of solutions	1.000	0.000	0.000	0.685	0.000	0.000	0.000	0.000	0.000	0.000	**80%**
Weighted sum performs better than NSGA-II	Number of pareto solutions	0.000	0.000	0.000	0.000	0.000	Out-of memory					**100%**
	CPU Time	1.000	0.000	0.000	0.000	0.000						**80%**
	Diversity (D)	0.000	0.000	0.000	0.000	0.000						**100%**
	Standard deviation (S)	1.000	1.000	1.000	1.000	1.000						0%
	Quality of solutions	1.000	0.906	0.753	0.247	0.000						20%
Weighted sum performs better than MOPSO	Number of pareto solutions	0.000	0.000	0.000	0.000	0.000	Out-of memory					**100%**
	CPU Time	1.000	0.000	0.000	0.000	0.000						**80%**
	Diversity (D)	0.000	1.000	0.000	0.000	0.000						**80%**
	Standard deviation (S)	1.000	1.000	1.000	1.000	1.000						0%
	Quality of solutions	1.000	0.984	0.899	0.925	0.486						0%

Table 16
Optimum solution when one of the objectives (OF1 or OF3) is considered.

		Solution method	Value of OF3	Value of OF1	Machine constant	Machine variable	Purchasing and sale	Inter-cell movement	Intra-cell movement	Over time working	Labor transfer	Reconfiguration	Machine failure
Minimized objective function	OF1	GA	1.34	277,005	3600	22,089	124,600	57,900	5080	9437	40,000	757	13,542
		PSO	.93	282,032	6220	24,048	157,100	20,300	8760	5454	45,000	827	14,323
		GAMS	.98	260,186	3473	21,845	141,300	34,700	6480	7465	30,000	567	14,356
	OF3	GA	.003	394,256	5430	37,165	185,300	64,600	3975	7561	70,000	489	19,736
		PSO	.006	437,093	7394	34,805	238,400	74,600	8360	8649	45,000	948	18,937
		GAMS	.001	380,362	6548	31,450	195,200	54,720	5482	8654	60,000	654	17,654

Table 17
Optimum solution when one of the objectives (OF1; 8th term or OF2) is considered.

		Solution method	Value of Labor transfer (OF1)	Value of OF2
Minimized objective function	OF1; the 8th term	GA	0	453
		PSO	0	436
		GAMS	0	462
	OF2	GA	85,000	246
		PSO	50,000	251
		GAMS	75,000	242

The optimal value of the total cost and the optimal value of the balancing objective function were calculated, as shown in Table 16. In addition, Table 17 shows the minimum inconsistency and minimum costs due to labor transfer during the time periods. We then analyzed the relationship between the first and third objective functions, and the relationship between the second objective function and the cost of labor transfer during the planning horizon. Thus, we analyzed the impacts of minimizing the inconsistency and balancing the manpower workload on the costs of cellular manufacturing by

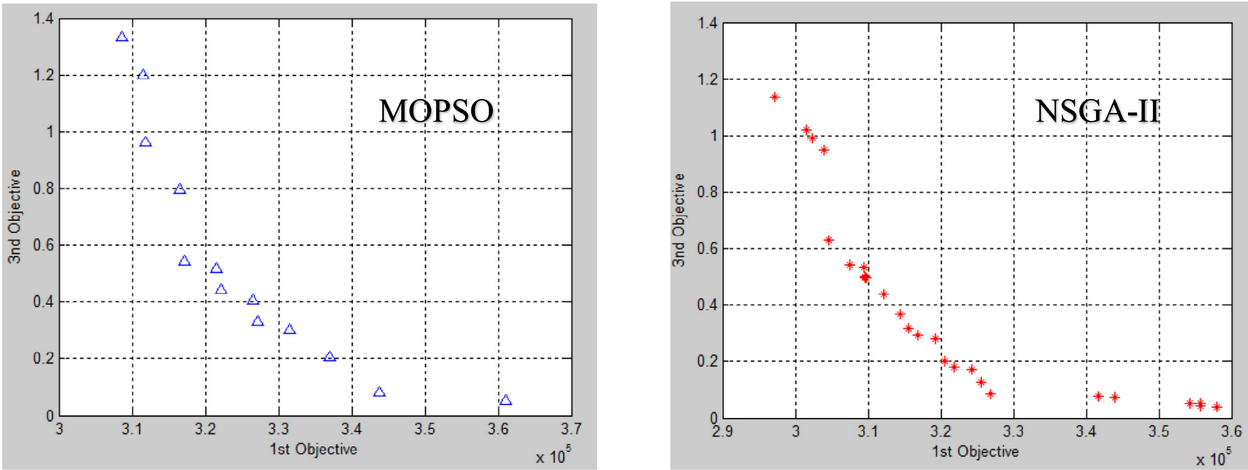

Fig. 4. MOPSO and NSGA-II Pareto front (OF3-OF1).

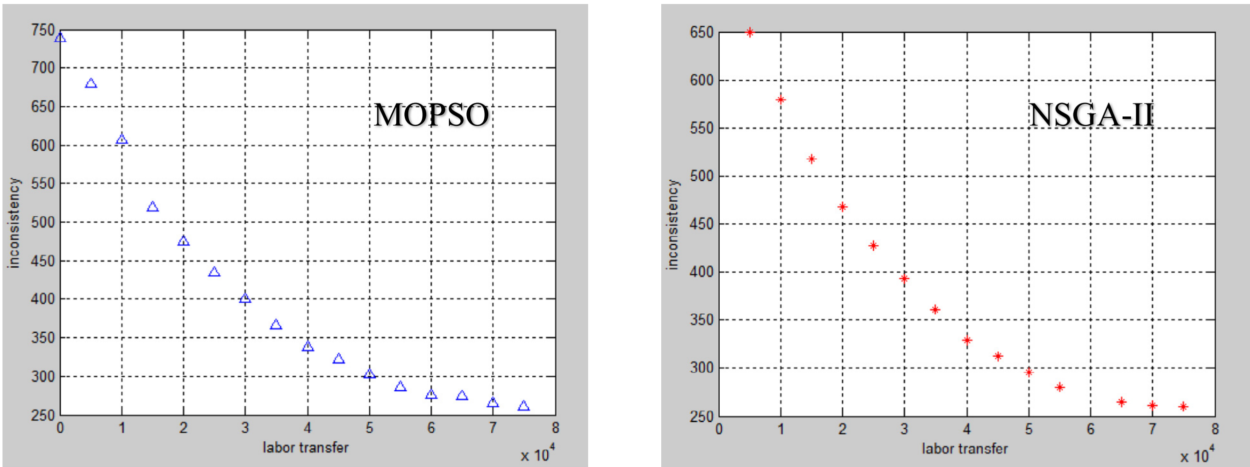

Fig. 5. MOPSO and NSGA-II Pareto front (OF2-OF1 (8th term)).

using the Pareto frontier obtained by NSGA-II and MOPSO (see Figs. 4 and 5). The results indicate reducing inconsistency and workload deviations would increase the total cost.

Different scenarios were generated by changing the input parameters. These scenarios were used to investigate the contributions of the proposed method, including the introduction of DMS, labor reliability, $MTBF_m$, $MTTR_m$, and BR_m into the DCFWAP problem. One of the parameters was changed in each scenario. Table 18 shows the different scenarios. In the first three scenarios, the DMSs of individuals were changed. In the next three scenarios, the failure parameters were changed. Finally, the reliability of the operators was changed in the last three scenarios. The results are shown on the Pareto frontier and they are compared with each other in Fig. 6.

The results show that employing labor with integrative DMS could reduce the inconsistency between workers because of their high consistency with the styles of others. Increasing the cost of damage or the frequency of system downtime increased the system costs (almost 25%). Furthermore, the workload balance between different cells was decreased by employing operators with various reliabilities.

6. Conclusion

In this study, we proposed a new mathematical model for dynamic CFP with worker assignment. Compared with previous CMS studies, the proposed model has several novel aspects including considerations of: (1) the reliability of human resource, (2) the DMSs of operators assigned to common cells, and (3) the reliability of machines. The problem is multi-objective and we developed two meta-heuristic algorithms (i.e., MOPSO and NSGA-II) to solve this problem. To evaluate the validity of the new added parameters, various test problems were generated and analyzed. We compared the performance of the proposed algorithms using several criteria (e.g., covered solution, spacing metric, CPU time, number

Table 18
Different scenarios.

Scenarios	Characteristic	labors										$MTBF_m$	$MTTR_m$	BR_m
		1	2	3	4	5	6	7	8	9	10			
1	DMS	D	H	D	F	H	I	F	I	H	D	U(300,900)	U(50,90)	U(100,400)
	Reliability	.38	.65	.85	.62	.73	.56	.82	.73	.52	.85			
2	DMS	I	I	I	I	I	I	I	I	H	H	U(300,900)	U(50,90)	U(100,400)
	Reliability	.38	.65	.85	.62	.73	.56	.82	.73	.52	.85			
3	DMS	F	F	F	F	I	I	I	I	D	D	U(300,900)	U(50,90)	U(100,400)
	Reliability	.38	.65	.85	.62	.73	.56	.82	.73	.52	.85			
4	DMS	F	H	F	D	F	D	H	I	D	D	U(200,800)	U(40,100)	U(100,500)
	Reliability	.38	.65	.85	.62	.73	.56	.82	.73	.52	.85			
5	DMS	F	H	F	D	F	D	H	I	D	D	U(100,300)	U(20,40)	U(200,800)
	Reliability	.38	.65	.85	.62	.73	.56	.82	.73	.52	.85			
6	DMS	F	H	F	D	F	D	H	I	D	I	U(200,1000)	U(20,3 0)	U(100,400)
	Reliability	.38	.65	.85	.62	.73	.56	.82	.73	.52	.85			
7	DMS	F	H	F	D	F	D	H	I	D	I	U(300,900)	U(50,90)	U(100,400)
	Reliability	.2	.2	.8	.5	.7	.56	.7	1	6	1			
8	DMS	F	H	F	D	F	D	H	I	D	I	U(300,900)	U(50,90)	U(100,400)
	Reliability	.3	.9	1	.4	.6	.8	.5	.4	.7	.3			
9	DMS	F	H	F	D	F	D	H	I	D	I	U(300,900)	U(50,90)	U(100,400)
	Reliability	1	1	1	1	1	1	1	1	1	1			

D: decisive, F: flexible, H: hierarchic, I: integrative.

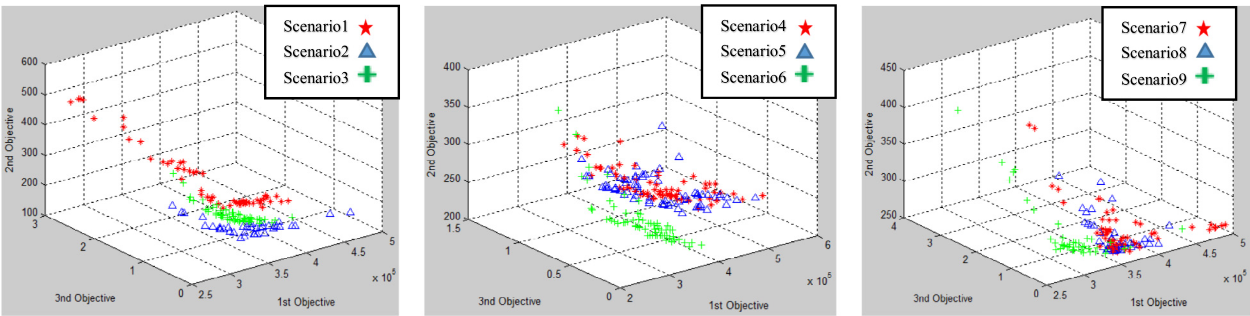

Fig. 6. Pareto front for the different scenarios (NSGA-II).

of Pareto solutions, and covered space). The results showed that it is better to use NSGA-II for large problems because although it takes slightly more time compared with MOPSO, the quality of its solution is better.

The proposed approach was applied to a real CMS in Tehran, Iran. According to the results, the job satisfaction levels of operators increased after considering the efficiency and DMS of operators. This claim was based on decreases in the number of complaints per month. In future research, different reliability values can be considered for operators due to the ability of individuals to work with different machines. Moreover, the DMS of an operator may change according to their assigned workload.

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