Computers & Industrial Engineering 101 (2016) 35–52

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

A vibration damping optimization algorithm for solving a new multi-objective dynamic cell formation problem with workers training

Esmaeil Mehdizadeh *, Seyed Vahid Daei Niaki, Vahid Rahimi

Faculty of Industrial and Mechanical Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran

A R T I C L E I N F O

Article history:
Received 5 March 2016
Received in revised form 18 August 2016
Accepted 20 August 2016
Available online 23 August 2016

Keywords:
Dynamic cell formation problem
Cellular manufacturing system
Multi-Objective mathematical programming
Production planning
Vibration damping optimization algorithm

A B S T R A C T

This paper presents a comprehensive multi-objective mixed integer mathematical programming model which considers cell formation and production planning problems simultaneously. This comprehensive model includes dynamic system reconfiguration, multi period production planning, operation sequence, alternative process plans for part types, machine and worker flexibility, duplicate machines, machine capacity, available time of workers and worker assignment. The aim of the proposed model is to minimize inter and intra-cell movement costs, machine and reconfiguration costs, setup costs, production planning costs (holding, backorder and subcontracting costs) and workers hiring, firing, training and salary costs, as well as minimizing summation of machines idle times as a second objective. Due to NP-hardness of the problem, a recent and efficient meta-heuristic algorithm namely multi-objective vibration damping optimization (MOVDO) is designed for finding Pareto-optimal frontier. In order to check the efficiency of the developed algorithm, it is compared with two salient multi-objective genetic algorithms named NSGAII and NRGA. Finally, by generating some test problems in small and large scales and using some multi-objective comparison metrics, the algorithms are compared and analyzed statistically.

1. Introduction

Generally, in real world environment, many problems have the same solving method. Therefore, by grouping these similar problems a same method can be used to solve a set of problems. As result, time and cost of the systems are saved. Group Technology (GT) which works based on this grouping concept can be defined as a production philosophy for identifying similar parts and grouping them together in order to access their similarity benefits in design and manufacturing (Selim, Askin, & Vakharia, 1998). Cellular Manufacturing (CM) is one application of GT and has been appeared as a promising alternative manufacturing system. Cellular Manufacturing System (CMS) is one of the efficient systems for manufacturing process with high production volume and variety that predispose growth and progress in global markets.

CM includes creation and operation of manufacturing cells. Parts are grouping into part families and machines into cells. In this process, a number of machines that usually have different performance are grouping into a manufacturing cell which is called machine cell. This cell is responsible for completing operation related to similar parts which are in a group and are known as a part family. Machine assignment into groups consists processing of all existent part in a part family by a group of machines. Major advantages of CMS are simplifying and reducing material handling, reducing work in process inventory, decreasing setup time, increasing flexibility, better production control and lead time reduction. Identifying similar parts (part families) and machine cells in designing a cellular manufacturing system is generally noted as cell formation. Cell formation problem is the most significant step in implementing group technology. Hence, different methods are proposed by researchers to solve cell formation problem. Because of increasing the variety of consuming goods and reduction in product life cycles, manufacturing organizations often face with fluctuation in product demand and product mix which results in a dynamic or turbulent production environment (Rheault, Drolet, & Abdulnour, 1995). In dynamic environment a planning horizon can be divided into smaller periods where each period has different product mix and demand requirements. Consequently, the formed cells in a current period may not be optimal and efficient for the subsequent period. To overcome the disadvantages of traditional CMS, the concept of Dynamic Cellular Manufacturing System (DCMS) has been introduced (Rheault et al., 1995). DCMS refers to manufacturing cell reconfiguration which includes part family and machine group formation in each period. Reconfiguration includes exchange current machines among cells which is called machine relocation and consists adding new machines to cell including machines duplication and removing current machines from cells. In this case, the decision maker in order to make an appropriate decision to keep balance between production and

* Corresponding author.
E-mail address: emehdi@qiau.ac.ir (E. Mehdizadeh).

http://dx.doi.org/10.1016/j.cie.2016.08.012
0360-8352/

outsourcing costs should select through available choices like adding a new machine, machines relocation among current cells, subcontracting for some parts and workers hiring or firing strategy. Outsourcing requirement such as inventory, backorder and subcontracting can have an important effect on cell formation over the planning horizon by relocating, adding and removing machines continuously. A comprehensive review of the DCMS literature can be acquired in Safaei, Saidi-Mehrabad, and Jabal-Ameli (2008) and Balakrishnan and Cheng (2007).

Good and useful discussion of cellular manufacturing systems can be found in Suresh and Meredith (1985), Singh (1993), Joines, King, and Culbreth (1995), Reisman, Kumar, Motwani, and Cheng (1997), Selim et al. (1998), Kia et al. (2012) and Houshyar et al. (2014). Defersha and Chen (2008) proposed a comprehensive mathematical model for designing DCMS based on tools requirements for parts and tools availability on machine. This model minimizes machine operational cost, reconfiguration cost, inter-cell transportation cost, tool consumption cost, parts outsourcing cost and inter-cell workload balancing. They used a new parallel genetic algorithm method to solve the model. Rezaeian, Javadian, Tavakkoli-Moghaddam, and Jolai (2011) presented a nonlinear programming model in a dynamic environment. Furthermore, they proposed a novel hybrid approach based on the genetic algorithm and artificial neural network to solve the presented model. Majazi-Delfard (2013) presented a nonlinear integer programming model for a dynamic CF problem in CMS based on the number and average length of inter/intra cell movements. Because of the presented model is NP-hard, a simulated annealing embedded in branch and cut was performed to solve the problem.

Using a multi-objective programming models has been attracted a few attention among accomplished researches in this concept as yet in spite of very desirable efficiency in cell formation problem model especially in case of studying contradictory objectives simultaneously. Bajestani, Rabbani, Rahimi-Vahed, and Khoshkhou (2009) developed a bi-objective DCMS model with objectives like minimizing general cost (machine constant cost, inter-cell transportation cost and machine relocation cost) and total work variables. They applied MOSS algorithm to solve the proposed model and compared results with SPEA-II and NSGA-II algorithms. Ghotboddini, Rabbani, and Rahimian (2011) presented a new multi-objective mixed integer model for DCMS. Their model solved the part and machine grouping simultaneously with labor assignment to minimize the cost of various terms like reassignment cost of human resources, over time cost of equipments and labors and maximize utilization rate of human resources. Daei Niaki, Mehdizadeh, and Tavakkoli-Moghaddam (2011) developed a comprehensive multi-objective mixed integer mathematical programming model which considers cell formation problem, production planning and worker assignment, simultaneously. They considered dynamic system reconfiguration, multi period production planning, operation sequence, alternative process plans for part types, machine and worker flexibility, duplicate machines, machine capacity, available time of workers and worker assignment. However, they didn't present any approach to solve the model in large scale instance.

Because of the effect of production planning goals on reconfiguration and cell formation in dynamic condition, integrating these concepts is an important problem which has been studied in some limited researches. Chen and Cao (2004) proposed an integrated model for a production planning (PP) in a CMS that minimizes the inter-cell material handling cost, fixed charge cost of setting up manufacturing cells, cost of holding the finished items over the planning horizon, cost of setting up the system to process different parts in different time periods and machine operating cost. They developed a heuristic method to solve the presented problem. Solimanpur, Vrat, and Shankar (2004) proffered a fuzzy goal programming approach to solve a multi-objective mathematical model of cell formation problem and production planning in a virtual dynamic cellular manufacturing system with considering worker flexibility. Kioon, Bulgak, and Bektas (2009) proposed a production planning and dynamic cell formation integrated model with aims such as minimizing inter and intra cell material handling cost, inventory and production costs, reconfiguration costs and machine operation and overhead costs. Safaei and Tavakkoli-Moghaddam (2009) studied effect of parts subcontracting on reconfiguration with adding machine constant costs and backorder costs to objective function of model in Kioon et al. (2009). Sakhaii and et al. (2015) developed a new integrated mixed-integer linear programming model to solve a dynamic cellular manufacturing system with unreliable machines and a production planning problem simultaneously. There model incorporated with dynamic cell formation, intercell layout, machine reliability, operator assignment, alternative process routings and production planning concepts. They, to cope with the parts processing time uncertainty, a robust optimization approach immunized against even worst-case adopted.

On the other hand, considering worker requirements is such a critical parameter in implementation of cell formation phase which increases the designing efficiency of cellular manufacturing systems and make the proposed model more practical. Bidanda, Ariyawongrat, Needy, Norman, and Tharmmaphornphilas (2005) presented a generic review and evaluation on a wide range of worker related issues in cellular manufacturing system. The first paper which was allocated to operator related issues of dynamic cell formation is the one of Aryanezhad, Deljoo, and Mirzapour Al-e-Hashem (2009). They presented a new mathematical model to deal with the dynamic cell formation and worker assignment problems, simultaneously. Since the presented model was nonlinear integer, the authors linearized the presented model. The objective function of this model includes two components of which both related to system costs consisting of machine, operating, inter-cell material handling, machine relocation, worker hiring, firing, training, and salary costs. Mahdavi, Aalaei, Paydar, and Solimanpur (2010) presented a mixed integer mathematical model for designing dynamic cellular manufacturing systems with considering production planning and worker assignment. The advantages of their proposed model was considering multi-period production planning, dynamic system reconfiguration, machine duplication, machine capacity, available time of workers and worker assignment. Papaioannou and Wilson (2010) studied a literature review of cell formation problem concentrating formulation proposed in the last decades. They reviewed a number of solution approaches that have been employed for CF such as mathematical programming heuristic and meta-heuristic methodologies and artificial intelligence strategies. Rafiei and Ghodsi (2013) considered a dynamic cell formation problem with the consideration of human related issues and developed a bi-objective model. The first objective seeks to minimize related the costs of the problem such as machine procurement and relocation costs, machine variable cost, inter and intra cellular movement costs, overtime costs and operator shifting cost between cells, and the second objective seeks to maximize operator utilization. Because of NP-hardness of dynamic CF problem, a hybrid ACO-GA meta-heuristic developed. Bagheri and Bashiri (2014) considered a CF problem with intercell layout and operator assignment problems in a dynamic CMS, simultaneously. They proposed a new mathematical model based on three mentioned sub-problems. The objective of the model is to minimize inter and intra cell movements, machine relocation costs, and operator related issues. Due to commensurable statements in objective function, the preferred solution is obtained by the LP-metric approach. The generated example solved by branch and bound technique. A real case study is illustrated in an automobile producer company.

The goal of this paper is expanding the integrated model which presented by Daei Niaki et al. (2011) for production planning and cell formation in dynamic cellular manufacturing systems with multi-objective approach that concentrating on workers optimum assignment, selecting a production plan with least costs, reducing inventory and trade-off between parts outsourcing and reconfiguration for planning horizon. Moreover, proposing an appropriate solving method including multi-objective programming approaches and meta-heuristic algorithms with respect to NP-hard class of the problem is another goal of this study. In fact, in this new model, optimum production plan and worker assignment to manufacturing cells are determined simultaneously and a recent mataheuristic algorithm namely vibration damping optimization (VDO) algorithm is applied to solve the model specially for large scale problems.

Vibration damping optimization (VDO) algorithm is a new meta-heuristic algorithm and stochastic search method based on the concept of the vibration damping in mechanical vibration introduced by Mehdizadeh and Tavakkoli-Moghaddam (2009). Mehdizadeh, Tavakkoli-Moghaddam, and Yazdani (2015) developed this algorithm for optimizing the identical parallel machine scheduling problem with sequence-independent family setup times. They compared the results obtained by the proposed VDO with the results of the genetic algorithm (GA) and branch-and-bound method. Also, Hajipour, Mehdizadeh, and Tavakkoli-Moghaddam (2014) developed a Vibration Damping Optimization (VDO) algorithm to solve multi-objective optimization problems for the first time. The results compared with Multi-Objective Simulated Annealing (MOSA) and Non-dominated Sorting Genetic Algorithms (NSGA-II) presented as state-of the-art in evolutionary multi-objective optimization algorithms.

This paper is organized as follows. Section 2 describes problem formulation of the proposed model. In Section 3, first some required concepts of multi-objective algorithms are explained. Then, the mechanism of our proposed MODVO algorithm and its operators are presented in detail. Section 4 presents numerical outputs of the paper. In this section, after explanations of the model parameters and test problem generation information, algorithms are tuned via Taguchi method. Then, implemented multi-objective metrics are introduced and algorithms are compared according to these metrics on generated test problems statistically. Finally, Section 5 concludes the paper.

2. Problem formulation

In this section a multi-objective mixed integer mathematical programming model is presented which surveys cell formation problem in cellular manufacturing systems. A comprehensive multi-objective model is presented that studies cell formation problem and production planning in a dynamic cellular manufacturing system in an integrated manner. Also this model seeks to determine optimum production policy (like determining production, inventory and subcontracting level for parts) and worker optimum assignment to manufacturing cells. The noted model is able to dynamic optimum cell formation (part families, machine groups and worker assignment to each cell in each period), select the best processing route among available routes for processing each part (because of machine flexibility in processing one or multiple operation of each part and accessibility to alternative machine for performing each operation) and choose required worker among workers who all have capability of working on specified machine (worker flexibility for worker optimum assignment among alternative workers) over the planning horizon. Main constraints of the proposed model include machine capacity, investment on machines, workers available times and minimum cell size.

2.1. Notations

2.1.1. Indices

p	Index for part types ($p = 1,\dots,P$)
j	Index for operations belong to part p ($j = 1,\dots,O_p$)
m	Index for machine types ($m = 1,\dots, M$)
c	Index for manufacturing cells ($c = 1,\dots,C$)
h	Index for periods ($h = 1,\dots,H$)
w	Index for worker types ($w = 1,\dots,W$)

2.1.2. Input parameters

P	Number of part types
C	Maximum number of cells that can be formed
M	Number of machine types
H	Number of time periods
O_p	Number of operations required for part p
W	Number of worker types
D_{ph}	Demand for part type p in period h
λ_{ph}	Unit subcontracting cost of part type p in period h
γ_{ph}	Unit holding cost of part type p in period h
ρ_{ph}	Unit backorder cost of part type p in period h
α_m	Maintenance and overhead costs of machine type m
β_m	Variable cost of machine type m for each unit time
S_m	Installing cost of machine type m
R_m	Removing cost of machine type m
a_{jpm}	1 if operation j of part type p can be done on machine type m; 0 otherwise
t_{jpm}	Processing time required to perform operation j of part type p on machine type m
C_{jpm}	Setup cost for operation j of part type p on machine type m
B_p^{inter}	Batch size for inter-cell movements of part p
B_p^{intra}	Batch size for intra-cell movements of part p
γ^{inter}	Inter-cell movement cost per batch
γ^{intra}	Intra-cell movement cost per batch
Lc	Lower bound for cell size in terms of the number of machine types
Uc	Upper bound for cell size in terms of the number of machine types
Uw	Upper bound for cell size in terms of the number of workers
A_m	The number of available machines of type m
A_w	The number of available workers of type w
LB	Lower bound for subcontracting parts
UB	Upper bound for subcontracting parts
$UB_{LMachin}$	Maximum number of machines which a worker can serve
P_{mw}	1 if worker type w is ready to work on machine type m or be able to acquire capability of working on machine by training; 0 otherwise
ϕ_{mw}	Training cost per time unit of worker w for attaining performing skill on machine type m for a worker who can get necessary skill of working on machine by training
T_m	Required time for training a worker who serves machine type m in terms of time unit
H_{wh}	Hiring cost of worker type w within period h
F_{wh}	Firing cost of worker type w within period h

(continued on next page)

S_{wh}	Salary cost of worker type w within period h
T_{mh}	Available time for machine type m in period h
T_{wh}	Available time for worker type w in the period h
A	An arbitrary big positive number

2.1.3. Decision variables

N_{mch}	Number of machines type m allocated to cell c in period h
N^{+}_{mch}	Number of machines type m added in cell c in period h
N^{-}_{mch}	Number of machines type m removed from cell c in period h
L_{wch}	Number of workers of type w allocated to cell c during period h
L^{+}_{wch}	Number of workers of type w added to cell c during period h
L^{-}_{wch}	Number of workers of type w removed from cell c during period h
Q_{ph}	Number of demand of part type p to be produced in period h
S_{ph}	Number of demand of part type p to be subcontracted in period h
I_{ph}	Inventory level of part type p at the end of period h; $I_{p0} = I_{pH} = 0$
B_{ph}	Backorder level of part type p in period h; $B_{p0} = B_{pH} = 0$
Y_{ph}	1 if $Q_{ph} > 0$; 0 otherwise
Y'_{ph}	1 if $I_{ph} > 0$ and equals to 0 if $B_{ph} > 0$
p_{mw}	1 if worker type w is used to work on machine type m; 0 otherwise
X_{jpmwch}	1 if operation j of part type p is done on machine type m with worker w in cell c in period h; 0 otherwise

2.2. Mathematical model

$$Min\ Z1 = \sum_{h=1}^{H}\sum_{m=1}^{M}\sum_{c=1}^{C}(\alpha_m N_{mch}) + \sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{j=1}^{O_p}\sum_{m=1}^{M}\sum_{w=1}^{W}(\beta_m Q_{ph} t_{jpm} X_{jpmwch}) +$$
$$\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{m=1}^{M}(S_m N^{+}_{mch} + R_m N^{-}_{mch}) + \sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{w=1}^{W}(H_{wh} L^{+}_{wch} + F_{wh} L^{-}_{wch}) +$$
$$\frac{1}{2}\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{j=1}^{O_p}\sum_{w=1}^{W}[Q_{ph}/B_p^{inter}]\gamma^{inter}\left[\left|\sum_{m=1}^{M}X_{(j+1)pmwch} - \sum_{m=1}^{M}X_{jpmwch}\right|\right] +$$
$$\frac{1}{2}\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{j=1}^{O_p}\sum_{w=1}^{W}[Q_{ph}/B_p^{intra}]\gamma^{intra}\left[\sum_{m=1}^{M}|X_{(j+1)pmwch} - X_{jpmwch}| - \left|\sum_{m=1}^{M}X_{(j+1)pmwch} - \sum_{m=1}^{M}X_{jpmwch}\right|\right] + \quad (1\text{-}1)$$
$$\sum_{h=1}^{H}\sum_{p=1}^{P}[\gamma_{ph} I_{ph} + \rho_{ph} B_{ph} + \lambda_{ph} S_{ph}] + \sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{j=1}^{O_p}\sum_{m=1}^{M}\sum_{w=1}^{W}([Q_{ph}/B_p^{intra}]C_{jpm} X_{jpmwch}) +$$
$$\sum_{m=1}^{M}\sum_{w=1}^{W}(P_{mw}\phi_{mw} T_m) + \sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{w=1}^{W}(S_{wh} L_{wch})$$

$$Min\ Z_2 = \sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{m=1}^{M}\left[N_{mch} T_{mh} - \sum_{p=1}^{P}\sum_{j=1}^{O_p}\sum_{w=1}^{W} Q_{ph} t_{jpm} X_{jpmwch}\right] \quad (1\text{-}2)$$

St:

$$\sum_{p=1}^{P}\sum_{j=1}^{O_p}\sum_{w=1}^{W} X_{jpmwch} t_{jpm}\ Q_{ph} \leqslant N_{mch} T_{mh} \quad \forall m, c, h \quad (2)$$

$$\sum_{p=1}^{P}\sum_{j=1}^{O_p}\sum_{m=1}^{M} X_{jpmwch} t_{jpm}\ Q_{ph} \leqslant L_{wch} T_{wh} \quad \forall w, c, h \quad (3)$$

$$D_{ph} = Q_{ph} + I_{p(h-1)} - B_{p(h-1)} - I_{ph} + B_{ph} + S_{p(h-1)} \quad \forall p, h \quad (4)$$

$$\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{j=1}^{O_p}\sum_{w=1}^{W} X_{jpmwch} \leqslant A\ Q_{ph} \quad \forall p, h \quad (5)$$

$$N_{mch} = N_{mc(h-1)} + N^{+}_{mch} - N^{-}_{mch} \quad \forall m, c, h \quad (6)$$

$$L_{wch} = L_{wc(h-1)} + L^{+}_{wch} - L^{-}_{wch} \quad \forall w, c, h \quad (7)$$

$$\sum_{m=1}^{M} N_{mch} \geqslant Lc \quad \forall c, h \quad (8)$$

$$\sum_{m=1}^{M} N_{mch} \leqslant Uc \quad \forall c, h \quad (9)$$

$$\sum_{w=1}^{W} L_{wch} \leqslant Uw \quad \forall c, h \quad (10)$$

$$\sum_{c=1}^{C} N_{mch} \leqslant Am \quad \forall m, h \quad (11)$$

$$\sum_{c=1}^{C} L_{wch} \leqslant Aw \quad \forall w, h \quad (12)$$

$$p_{mw} \leqslant P_{mw} \quad \forall w, m \quad (13)$$

$$\sum_{w=1}^{W} p_{mw} = 1 \quad \forall m \quad (14)$$

$$\sum_{m=1}^{M} p_{mw} \leqslant UB_{LMachin} \quad \forall w \quad (15)$$

$$\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{w=1}^{W} a_{jpm} X_{jpmwch} = Y_{ph} \quad \forall j, p, h \quad (16)$$

$$LB \leqslant S_{ph} \leqslant UB \quad \forall p, h \quad (17)$$

$$I_{pH} - B_{pH} = 0 \quad \forall p \quad (18)$$

$$Q_{ph} \leqslant AY_{ph} \quad Q_{ph} \geqslant Y_{ph} \quad \forall p, h \quad (19)$$

$$I_{ph} \leqslant AY'_{ph} \quad B_{ph} \leqslant A(1 - Y'_{ph}) \quad \forall p, h \quad (20)$$

$$N_{mch},\ N^{+}_{mch},\ N^{-}_{mch},\ Lwch, L^{+}_{wch},\ L^{-}_{wch},\ Q_{ph},\ S_{ph},\ I_{ph},\ B_{ph} \geqslant 0 \text{ and are integer}$$
$$X_{jpmwch},\ p_{mw},\ Y_{ph},\ Y'_{ph} \in \{0, 1\} \quad (21)$$

The first objective function includes several cost terms as follows: The first term shows machine constant cost consisted of maintenance and overhead cost of machines. The second term shows machine operation cost consisted of operation (variable) cost is sum of total load allotted to each machine in each cell. The third term shows machine relocation cost consisted of the cost of installing added machines in a period and removing deleted machines from a period. The fourth term shows hiring and firing cost consisted of adding worker to a cell (because of worker shortage in this cell) from a period to the next one (hiring cost) and removing worker from a cell (because the cell not needed to this worker) from a period to the next one (firing cost). The fifth term shows inter-cell material handling cost which is incurred to the model whenever all required operations for manufacturing a part is not processed within a cell and it is needed to move to another cell for processing its next operation except the cell which it is assigned (Safaei & Tavakkoli-Moghaddam, 2009). The sixth term shows intra-cell material handling cost which is considered when two consecutive operations which are required for processing a part will be done within a cell but on different machines (Safaei & Tavakkoli-Moghaddam, 2009). The seventh term shows production planning cost which is consisted of inventory, backorder and subcontracting costs for all parts in all periods for the planning horizon. The eighth term shows set up cost which calculates set up cost of each production batch on different machines. The ninth term shows worker training cost which minimizes training cost according to labor present skills. As regards it is a time consuming procedure, considering time cost of workers training is a matter identical real world situation. The tenth term shows salary cost which refers to the salary paid for workers in the planning horizon.

The second objective function minimizes summation of machines idle time. Machine idle times for each cell includes difference between sum of available times and sum of machines busy times for that cell. This objective function computes summation of all these idle times in all cells and then minimizes them.

Constraint (2) ensures capacity of machines is not exceeded. Constraint (3) assures that available times for workers are not exceeded. Constraint (4) is material balance well known equation which creates equivalency for all parts quantity level between two consecutive periods. Constraint (5) shows that if a part has not been produced in a period or $Q_{ph} = 0$ none of its operation should have been dedicated to a machine, cell and worker. Constraint (6) balances number of each machine types in each cell and each period. Constraint (7) balances number of available workers between two consecutive periods. Constraints (8) and (9) indicate lower and upper bound for cell size respectively. Constraint (10) represents minimum number of workers that is assigned to each cell in each period. Constraint (11) guarantees number of machine types allotted to all cells in each period will not exceed number of available machines from that type in this period. Constraint (12) shows that in each period, total number of workers allotted to all cells from type *w* should not be more than number of available workers from type w in that period. Constraint (13) ensures that worker type *w* must have allocated to a machine which is able to work on it. Constraint (14) guarantees that each machine can be served only by one worker. Constraint (15) controls upper bound for number of machines which worker *w* serves them. Constraint (16) ensures that if a partial portion of part demands must be produced in a specific period, each required operation for processing that part on its related machine in each period just could have been assigned to one cell and be done only by one worker who is able to work on that machine. Constraint (17) indicates lower and upper bound for subcontracting quantity for each part in each period. Constraint (18) expresses that inventory and backorder level must be zero at the end of periods. Constraint (19) is supplementary for Constraint (16). If necessary operations for processing parts in Equation (16) can be done, then some portion of demand could be produced in that specific period. Constraint (20) ensures that inventory and backorder cannot happen simultaneously. Constraint (21) determines the type of decision variables.

3. Multi-objective evolutionary algorithms (MOEA)

MOEAs are a group of multi-objective meta-heuristic algorithms that can be classified into three major groups according to their selection strategy, including (1) aggregating methods, (2) Pareto-based methods, and (3) population-based methods (Coello, Van Veldhuizen, & Lamont, 2002).

In this section, a new Pareto-based algorithm called MOVDO is developed. To do so, first implemented principles and concepts of multi-objective algorithms are introduced. Then, two pioneer and popular algorithms called NAGAII and NRGA are explained. All required designing of the MOVDO, including solution representation, coding and decoding schemes, and neighborhood structures are also explained on these algorithms. Finally, by using explained principles and designed operators of the NSGAII and NRGA, MOVDO algorithm is developed.

3.1. Fundamental concept of multi-objective algorithms

Consider a minimization multi-objective algorithm with a set of conflict objective functions as follows:

$$F(\vec{x}) = [f_1(\vec{x}),\ldots,f_k(\vec{x})] \text{ subject to } g_i(\vec{x}) \leqslant 0,\ i = 1,2,\ldots,m, \quad \vec{x} \in \Re^n$$

In this model, objective functions and constraints can be the both linear or non-linear and $\vec{x}$ denotes an n-dimensional vector that can get real, integer, or even Boolean value. Now, according to mentioned notations, vector $\vec{x}$ can dominate vector $\vec{y}$ if only if $\vec{x}$ being partially less than $\vec{y}$. This concept which is denoted by $\vec{x} \prec \vec{y}$ is described mathematically as $\forall i \in \{1,\ldots,k\}$, $x_i \leqslant y_i \wedge \exists i \in \{1,\ldots,k\}: x_i < y_i$. In this definition, symbol '$\prec$' denotes domination concept. Accordingly, Pareto front is called to the set of those solutions of the search space that their objective vector components cannot be improved simultaneously. Each solution of this set is called Pareto solution. Finally, Pareto optimal front is called to the set of those Pareto solutions that for each solution (x) of that $\{x \in \Re | \nexists x' \Re F(x') \prec F(x)\}$.

Other main concept that need to be mentioned are the two main features of the Pareto-based multi-objective algorithms which are (i) convergence to a good Pareto optimal front and (ii) keeping good diversity within the Pareto front. These definitions will be more assessed within next subsections.

3.2. NSGAII and NRGA

NSGAII is a pioneer and popular Pareto-based MOEA proposed by Deb (Deb, Pratap, Agarwal, & Meyarivan, 2002). NRGA is a developed version of the NSGAII which has some differences in its selection strategies (Al Jadaan, Rao, & Rajamani, 2008). In following subsection, similar and dissimilar operators of these algorithms are presented.

3.2.1. Solution representation

In population based methods where the problem solution space is increased from multiple points simultaneously, the data set which include values of decision variables and often is shown by a single or multiple row string, is considered as a feasible solution (chromosome) in the related problem.

According to the proposed model, a feasible solution should represent followings:

1. Each operation of each related part should only assign to one machine, one worker and one cell. So a feasible solution must represent operation assignment to machine, worker and cell simultaneously. With respect to flow flexibility in processing of the parts, a specific can be done by alternative multiple machines or workers, but in a feasible solution this operation must be assigned to only one of these machines or workers.
2. In each period, the number of machine type m in cell c (N_{mch}) should be specified. Also, the number of machines which in each period added to cell c (N^{+}_{mch}) or removed from it (N^{-}_{mch}) must be determined.
3. In each period, the number of available workers type w in cell (L_{wch}) must be specified as well as the number of added workers in each period to cell c (L^{+}_{wch}) and removed workers from it (L^{-}_{wch}).

According to the mentioned explanations, the form of solution representation in this paper is a $1 * 11$ dimensional matrix where each of the matrix arrays is another multi-dimensional matrix. The dimension of each inner matrix is different with others. A scheme of the representation and its example are presented in Figs. 1 and 2 respectively.

3.2.2. Selection and elitism scheme

For creating this scheme two operators, called fast non-dominated sorting (*FNDS*) and crowing distance (*CD*), are implemented in NSGAII. *FNDS* is used for ranking individuals of the population according to concept of domination, while *CD* is used for controlling the diversity of the solutions. In fact, *CD* is calculated for the solutions with the same rank and estimates density of solutions which are laid surrounding a particular solution in the population.

Mechanism of selection and elitism of NSGA-II is illustrated in Fig. 3. In this figure, P_t denotes the main population at iteration t. In this step, to create population of the next iteration, a mating pool is created and filled, applying the binary tournament selection rule to the main population.

In this specific selection, after randomly selection of two solutions from the population, the one with lower rank is selected. But, incase both of the solutions are from same ranks the one with higher crowding distance is selected. Then, crossover and mutation operators are executed on the solutions in mating pool to create a new population Q_t. In this step, for inserting elitism concept in the evolution process, main and new populations are merged to create a larger population (R_t). Then, R_t is classified into several fronts. Finally, the main population of the next iteration P_{t+1}, should be created as the same size as P_t. To do so, the fronts are inserted to P_{t+1}, in increasing order of their ranks. By adding the first front that exceeds the capacity of P_{t+1}, front inserting is stopped and a partial selection is done by implementing *CD* operator.

The main differences of the NRGA and NSGAII are in this part (Al Jadaan et al., 2008). In other words, NRGA uses roulette wheel selection instead of binary tournament selection. In NRGA after *NFDS*s and *CD*s calculation, two tiers of rank based roulette wheel selection are used.

3.2.3. Crossover operator

In the designed crossover operator, after choosing of parent solutions via a binary tournament selection, some cells of these parents are selected and replaced with each other (tow point crossover strategy). In the next step, feasibility test is done on the offspring and then feasible solutions are inserted in the next iteration's population. A scheme of this operator is illustrated in Fig. 4.

3.2.4. Mutation operator

A parent solution is selected by means of binary tournament selection and by implementing swap, Reversion and insertion methodologies (selection is randomly and with equal probability)

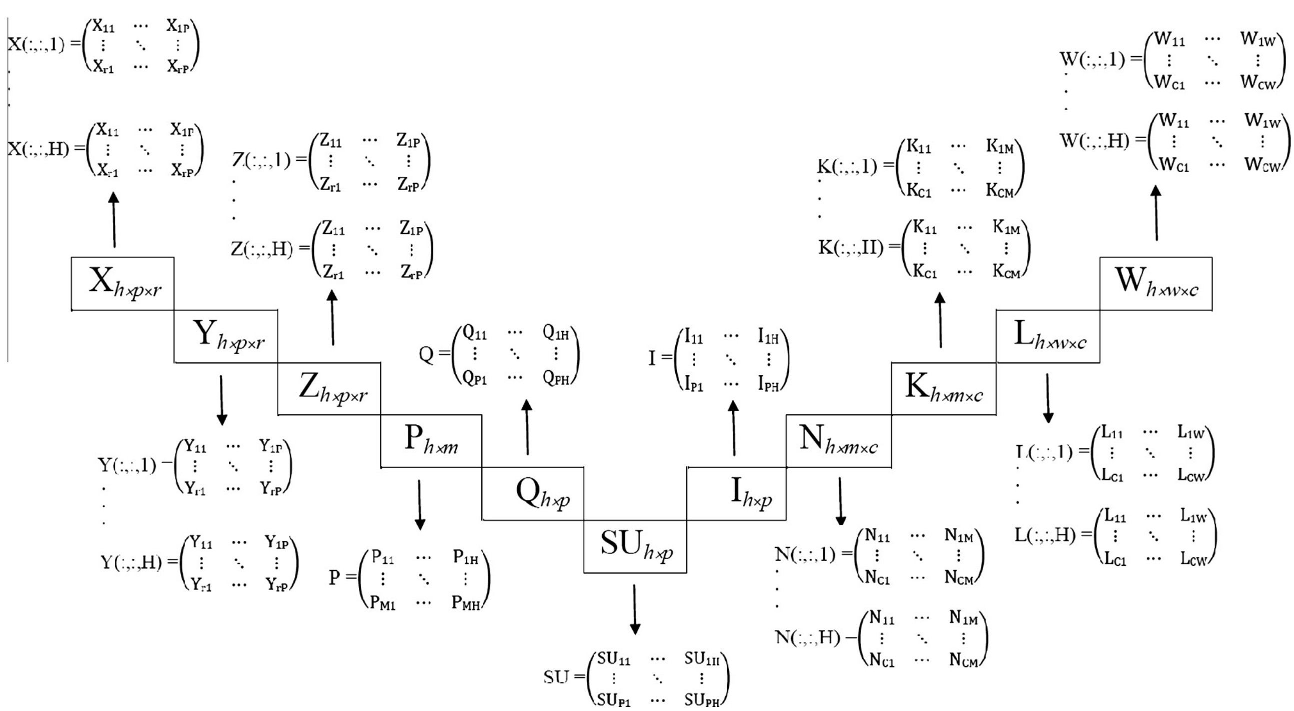


Fig. 1. Chromosome representation structure.

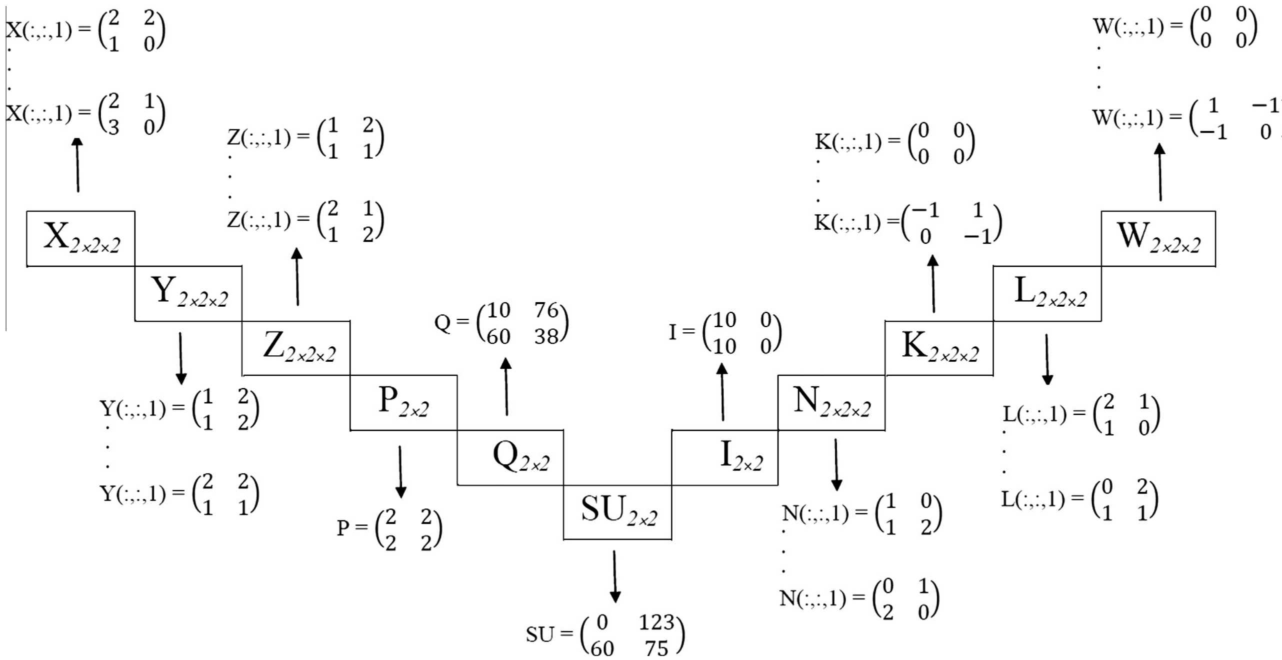


Fig. 2. Example of the chromosome representation structure.

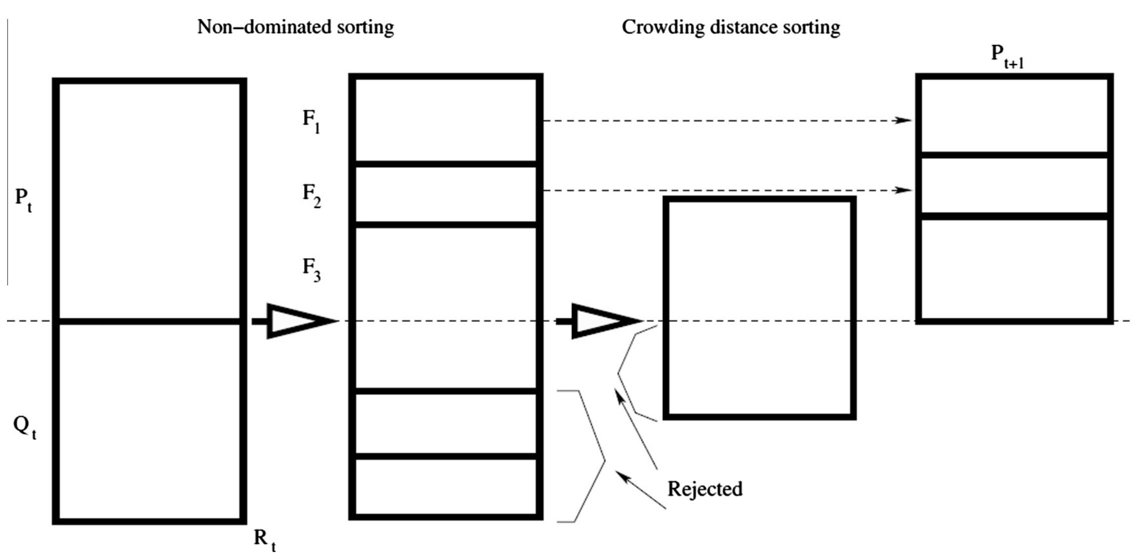


Fig. 3. Selection and elitism scheme in NSGA-II.

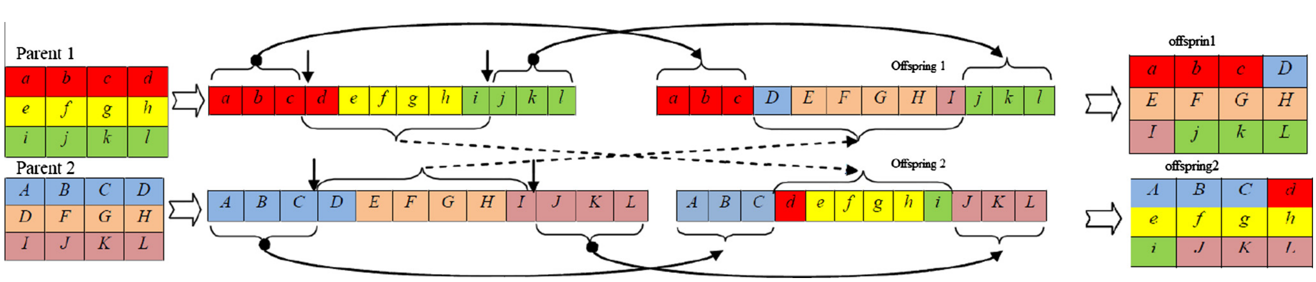
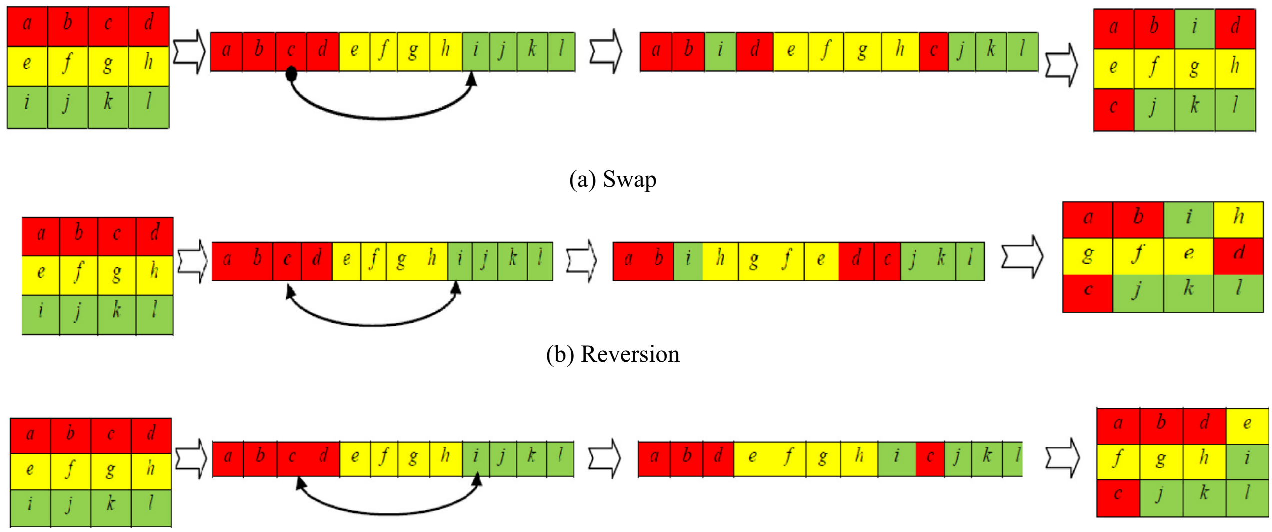


Fig. 4. Scheme of crossover operator.



(a) Swap

(b) Reversion

(c) Insertion

Fig. 5. Scheme of the mutation operator.

some of its cells are changed. And feasibility test is done on the offspring and then feasible solutions are inserted in the next iteration's population. A scheme of this operator is illustrated in Fig. 5.

3.2.5. NSGAII flow chart

Fig. 6 illustrates the flow chart of NSGAII and NRGA algorithm simultaneously.

3.3. Multi-objective vibration-damping optimization (MOVDO)

Vibration-damping optimization (VDO) is an optimization algorithm which works based on the damping process (Mehdizadeh & Tavakkoli Moghaddam, 2008). This algorithm, which was proposed for solving parallel machine scheduling problem, works based on the concept of the vibration damping process from mechanical vibration. This algorithm has also been used in different researches (Aliabadi, Jolai, Mehdizade, & Jenabi, 2011; Fattahi, Hajipour, & Nobari, 2015; Hajipour, Kheirkhah, Tavana, & Absi, 2015; Mehdizadeh & Fatehi Kivi, 2014; Mehdizadeh & Rahimi, 2016; Mehdizadeh, Tavarroth, & Hajipour, 2011; Mehdizadeh, Tavarroth, & Mousavi, 2011; Mousavi, Akhavan Niaki, & Mehdizade, 2012; Yazdani, Zandieh, Tavakkoli-Moghaddam, & Jolai, 2015). In damping process, variation amplitude is neutralized during the time. In this process, since for wider variation amplitude wider area of responses is under control, more new responses are expected to be obtained. As the time passes, this amplitude is diminished. In this situation, the probability of finding new responses is also decreased. A scheme of this process is illustrated in Fig. 7. In this figure, t represents time of the damping process and $+A$ and $-A$ denotes positive and negative variations according to horizontal axis, respectively.

MOVDO is an algorithm that works based on the single objective version of the VDO algorithm (Mehdizadeh et al., 2015) and multi-objective operators of Pareto-based algorithms such as NSGA-II (Deb et al., 2002). In the rest of this section, different operators of the MOVDO are explained.

3.4. Solution representation

Solution representation of the MOVDO is just similar to chromosome structure of the NSGAII.

3.5. Neighborhood structure

Mutation operator of the NSGAII is used for making neighborhood solutions. This operator helps MOVDO for escaping from local optimality.

3.6. MOVDO process

In the beginning of the MOVDO algorithm initial parameters including, population size (*nPop*), amplitude (A), iteration number (*Maxit*), number of the implementation if the neighborhood structure on each solution of the population (*nMove*) are determined. Then, a population of the solutions is generated. In this algorithm, amplitude (A) controls the possibility of the acceptance of deteriorating solutions. At high amplitude (generally in beginning of the search process), the algorithm is flexible to move to worse solutions. However, at lower amplitude (generally in final steps of the search process) this flexibility diminishes.

After generating initial population, each solution is evaluated and objective functions are calculated for the solutions. Then, *FNDS* and *CD* operators are implemented on the population and sort it according to the obtained ranks and crowding metrics. This part is just like the same sorting in NSGA-II (Deb et al., 2002). In this step, by using the sorted population (P_t), a new population (S_t) is developed via repetitive implementations of neighborhood structure on each solution of the population.

The obtained population (S_t) is evaluated again and after implementing *FNDS* and *CD*, the population is sorted. Now, if each member of the S_t ($S_t(i)$) dominates the related same ranked solution of P_t ($P_t(i)$), it is replaced with that. Otherwise, it is replaced with if a randomly generated number between 0 and 1 becomes less than p which is calculated as $p = 1 - e^{-A^2/2\sigma^2}$. After this step a population called Q_t is generated.

Then, to keep the elitism of the algorithm, a new process, mimicked from NSGA-II evolution process, is developed. In this process, the new generated population (Q_t) is combined with the population before implementation of the neighborhood structure denoted by P_t. This combination create a new population named R_t ($R_t = P_t \cup Q_t$). Now, *FNDS* and *CD* are implemented and sort R_t. Then, the next iteration population as size as *popsize* is chosen (P_t). Finally, this population is added to the archive (A_t) and archive

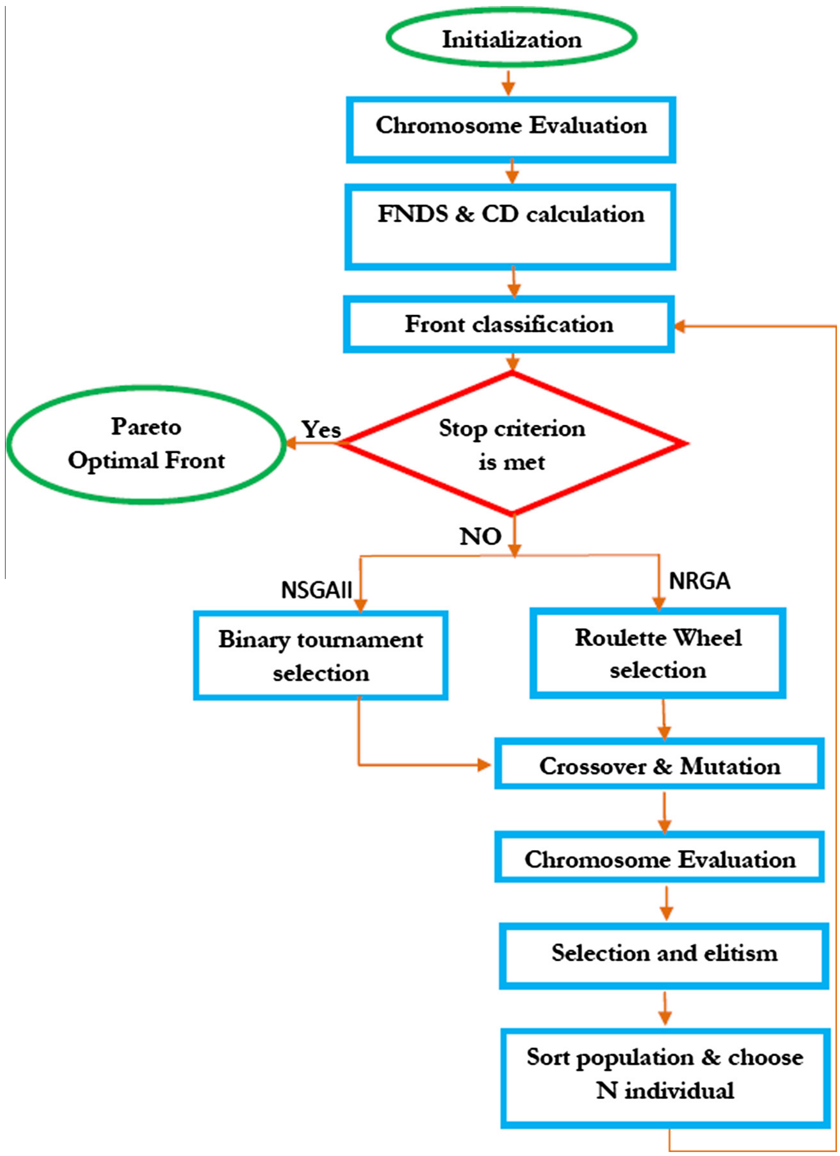


Fig. 6. Flow chart of the NSGA-II and NRGA (Hajipour et al., 2014).

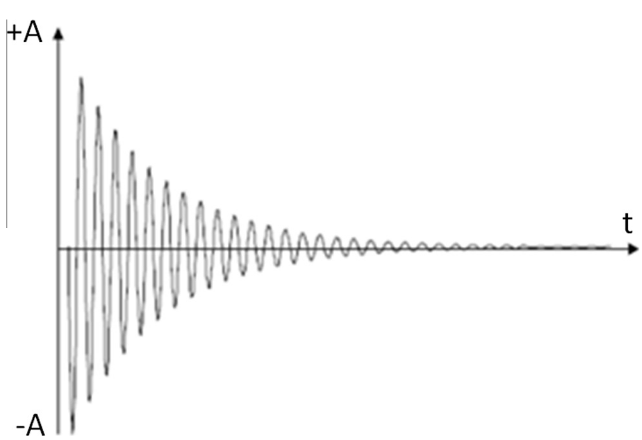


Fig. 7. Damping process during the time (Al Jadaan et al., 2008).

is ranked and sorted again. Meanwhile, if the number of members of the archive exceeds the determined amount (A), some of the worst members are eliminated. The next iteration is started according to the final obtained P_t and a similar process continued up to the final iteration. A summary of this multi-objective modification is illustrated in Fig. 8. The total pseudo code of the MOVDO is shown in Fig. 9.

4. Computational results

In order to verify and validate the proposed model, a numerical example is presented. This example is solved by branch and bound (B&B) approach using Lingo 9.0 software which has run on a PC including Core i5 and 6 GB RAM.

This example includes two machines, three parts, two cells, three machines, two workers and two production periods. It is assumed that each part has 2 operations which must be processed on its required machines according to operation-part-machine incident matrix. Also each operation can be done by two alternative workers which cause more flexibility in assignment process. Also, other required information of example is provided in the following.

Necessary information for machines and parts are shown in Tables 1 and 2 respectively.

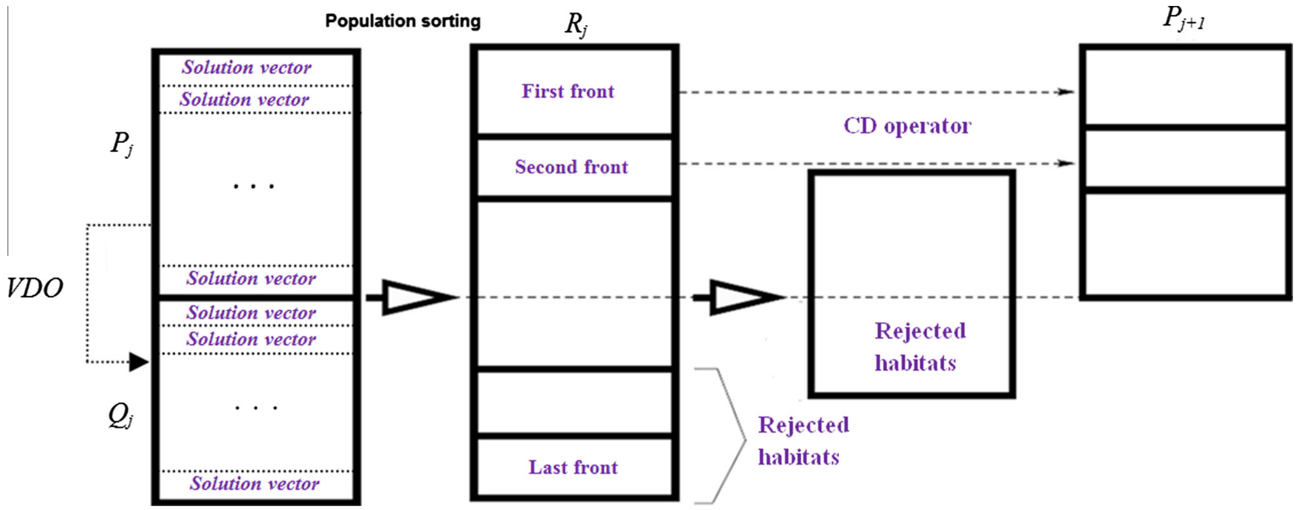


Fig. 8. Selection and elitism scheme in MOVDO (Hajipour et al., 2014).

$\boldsymbol{parametersetting}: \boldsymbol{nPop}, \boldsymbol{nMove}, \boldsymbol{MaxIt}, \boldsymbol{A_0}, \boldsymbol{\sigma}, \boldsymbol{\gamma}, L$
$\boldsymbol{Initialization}: \boldsymbol{Generateinitialsolutions}$
$\boldsymbol{Evaluatin}: \boldsymbol{Evaluateinitialsolutions}$

$Performnon-dominatedsortingandcalculateranks$
$Calculatecrowdingdistance(CD)$
$SortpopulationaccordingtorankandCDs$
$Pop = population$
$Forit = 1{:}\,MaxIt$
$forl = 1{:}\,l$
$fori = 1{:}\,nPop$
$forj = 1{:}\,nMove$
$pop1(i,j) = Performneighbourhoodstructureonthesolutioniofthepopulation$
end
end
$Performnon-dominatedsortingandcalculateranks(pop1)$
$Calculatecrowdingdistance(CD)(pop1)$
$SortpopulationaccordingtorankandCDs(pop1)$

$fori = 1{:}\,nPop$
$ifDominates\big(pop1(i), Pop(i)\big)$
$Pop(i) = pop1(i)$
$else$
$p = 1 - e^{-A^2/2\sigma^2}$
$ifrand < p$
$Pop(i) = pop1(i)$
end
end
end

$Performnon-dominatedsortingandcalculateranks(Pop)$
$Calculatecrowdingdistance(CD)(Pop)$
$SortpopulationaccordingtorankandCDs(Pop)$
end
$UpdateA\left(A = A_0 e^{-\frac{\gamma t}{2}}\right)$
end

Fig. 9. Pseudo code of MOVDO algorithm.

Table 1
Information required for machine in example.

Machine type	Machines information						
	α_m	β_m	S_m	R_m	T_m	A_m	T_{m1}	T_{m2}
1	1200	8	400	300	30	2	500	500
2	1500	4	600	375	45	2	500	500
3	1800	6	500	450	25	2	500	500

Table 2
Information required for parts in example.

Part type	Parts information														
	D_{p1}	D_{p2}	LB_{p1}	LB_{p2}	UB_{p1}	UB_{p2}	λ_{p1}	λ_{p2}	γ_{p1}	γ_{p2}	ρ_{p1}	ρ_{p2}	B_p^{inter}	B_p^{intra}	γ^{inter}	γ^{intra}
1	0	150	0	75	0	300	3	3	1	1	14	14	50	5	25	5
2	60	80	30	40	120	160	6	6	2	2	12	12	50	5	30	6
3	120	100	60	50	240	200	9	9	3	3	10	10	50	5	15	3

The machine related input data, including fixed, operating, installing and removing costs, number of available machines, time capacity of machines and training cost on each machine type, for example, are reported in Table 1.

The part related input data, including demand, lower and upper bound of outsourcing, batch size and intra-cell and inter cell movement costs and holding cost and outsourcing cost of each part type, for example are presented in Table 2.

Table 3 indicates information that is required for workers that is including hired, fired and training costs, number of available workers and time capacity of available workers in each period.

The data set related to operation-part-machine incidence matrix is shown in Table 4. This matrix delineates processing time and set up cost respectively for each part operations on different machine types.

Minimum and maximum cell size (lower and upper bound for number of machines allowed in each cell) for example are considered 1 and 3 respectively. Maximum cell size in terms of number of workers and maximum number of machines which a worker can serve them are determined 2.

Whereas the proposed model is a two objective mathematical model, we transformed it to a single objective model by weighted method before solving it. Weight value for each objective function depends on decision maker viewpoint. So we considered 0.8 for the first and 0.2 for the second objective function. In this section, the results of solving the proposed model with information about the data example are given. The values of objective functions and its components are shown in Table 5 and the production plan, for presented example, are shown in Table 6. Likewise part families, machine groups and assigned workers to each cell are presented in Table 7 for presented example.

After the proposed model was linearized for numerical example, it contains 870 variables and 1676 constraints and the computational time is 4.2 min.

Table 3
Machine-worker incidence matrix and the workers information.

Worker type	Machine			(φ_{mw}) Machine								
	1	2	3	1	2	3	H_{w1}	H_{w2}	F_{w2}	A_w	T_{w1}	T_{w2}
1	1	0	1	0	1000	5	200	200	150	2	500	500
2	0	1	1	1000	5	0	200	200	150	2	500	500

Table 4
Operation-part-machine incidence matrix includes processing time and setup cost for example.

Machine type	Part 3		Part 2		Part 1	
	O_1	O_2	O_1	O_2	O_1	O_2
1	[a]6,0.4	0,0	5,0.3	0,0	0,0	7,0.1
2	8,0.2	0,0	0,0	6,0.4	7,0.3	0,0
3	0,0	7,0.3	8,0.2	0,0	5,0.1	0,0

[a] The first number is setup cost and the second number is processing time.

Table 5
Objective functions and components for the proposed example.

Idle times	Worker relocation	Salary	Training	Setup	Variable cost	Constant Cost	Intra-cell movement	Inter-cell movement	Sub-contracting	Holding	Total
1916	300	1000	225	570	408	5400	150	500	1380	150	**8449.6**

Table 6
Production plan for presented example.

	Period 1			*Period 2*		
	Part 1	*Part 2*	*Part 3*	*Part 1*	*Part 2*	*Part 3*
Sub-contracting		*80*	*100*			
Backorder						
Holding	*150*					
Production	*150*	*60*	*120*			
Demand		*60*	*120*	*150*	*80*	*100*

Table 7
Parts, machines and worker assignment to cells for presented example.

	Parts		Machines		Workers	
	Cell 1	Cell 2	Cell 1	Cell 2	Cell 1	Cell 2
Period 1	1, 2, 3	2	1, 2, 3	1	1, 2	1
Period 2	–––––	–––––	–––––	–––––	–––––	–––––

4.1. Analysis of computational efficiency of algorithms

In this section, performance of the algorithms is evaluated via different experiments. In the beginning, some popular multi-objective metrics are introduced. Then, to extract better performance of the meta-heuristic algorithms their parameters are tuned. In the next step, the introduced metrics are calculated for each algorithm. Finally, according to the obtained values for the metrics, performances of the algorithms are analyzed by means of different tables, graphs, and statistical tests.

4.1.1. Test problem developing

In order to generate numerical examples to solve the proposed model, 10 problems were produced with different sizes. The size of each problem depends on these factors: (1) the number of required operation for each part [O_p], (2) the number of part types [P], (3) the number of machine types [M], (4) the number of workers [W], (5) the number of manufacturing cells [C] and (6) the number of periods [H]. The characteristics of designed test problems in this paper are shown in Table 8.

Also, the information which are related to the model input parameters like product mix and demand, operation order and times, machines capacity and capabilities, number of available machines and workers and other required information for test problems are shown in Table 9.

4.1.2. Multi-objective metrics

As mentioned in previous section, Pareto-based multi-objective algorithms seek two main goals during their iterations, including (1) convergence to the Pareto optimal front and (2) maintenance of diversity within the set of solutions of Pareto front. Thus, different types of metrics are used in the literature to assess the performance of these algorithms in an absolute sense. Obviously, some of these measures are implemented for evaluating the diversity of the

Table 8
The required information of the test problems.

Problem no.	O_p	P	M	W	C	H
1	2	3	3	2	2	2
2	2	4	4	2	2	2
3	2	4	3	3	2	3
4	3	5	4	3	2	2
5	3	5	4	3	2	3
6	3	6	5	3	2	2
7	3	6	5	3	2	3
8	3	7	5	3	2	3
9	3	9	6	4	2	3
10	4	11	7	6	3	3

Table 9
The required random information for test problem generating.

Parameter	Value	Parameter	Value	Parameter	Value
D_{ph}	U (1,100)	F_{wh}	U (110,160) $	A_w	U (2,3)
a_{jpm}	U (0,1)	S_{wh}	U (400,500) $	α_m	U (1000,2000) $
t_{jpm}	U (0,1) h	λ_{ph}	U (1,5) $	B_m	U (1,10) $
C_{jpm}	U (5,10) $	γ_{ph}	U (1,5) $	S_m	$\alpha_m/4\alpha$
P_{mw}	U (0,1)	ρ_{ph}	U (20,30) $	R_m	$\alpha_m/3\alpha$
ϕ_{mw}	U (0,5) $	B_p^{inter}	U (10,50)	LB	0.5 * D_{ph}
T_m	U (400,500) h	B_p^{intra}	$B_p^{inter}/5$	UB	2 * D_{ph}
T_{mh}	500 h	γ^{inter}	50	Lc	1
T_{wh}	500 h	γ^{intra}	5	Uc	M
H_{wh}	U (200,300) $	A_m	U (2,3)	Uw	W

Table 10
Utilized performance measures of the paper.

	Metric	Mathematical Formulation	Performance Summary
1	Diversity (D) Aliabadi et al. (2011)	$D = \sqrt{\sum_{j=1}^{m}(\max_i f_i^m - \min_i f_i^m)^2}$	It is used to evaluate the spread of the curve
2	Spacing (S) Fattahi et al. (2015)	$S = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(d_i - \bar{d})^2}$ $d_i = \min_{k\in n,\ k\neq i}\sum_{m=1}^{2}\lvert f_m^i - f_m^k\rvert$ $\bar{d} = \frac{1}{n}\sum_{i=1}^{n} d_i$	It is used to measure uniformity of the distribution of solutions within a front
3	Mean ideal distance (MID) Hajipour et al. (2015)	$MID = \frac{1}{NOS}\sum_{i=1}^{NOS} c_i$ $c_i = \sqrt{\sum_{j=1}^{m} f_{ji}^2}$	It is used to measures the closeness of solutions of a Pareto front with an ideal point which is usually considered as (0, 0)
4	Number of the non-dominated solutions in final Pareto (NOS)		Measures number of the Pareto solutions

solutions while as other ones are used for assessing the convergence. The popular metrics of the literature that are used in this paper are presented in Table 10.

4.1.3. Parameter tuning

In the literature of the meta-heuristic algorithms, different types of design of experiment techniques have been implemented in the literature. Among these methods, Taguchi method is a fractional factorial experiment (FFE) that is proposed by Taguchi as an efficient alternative for full factorial experiments (Yazdani et al., 2015). It means that this method reduces the experiments in a large scale. In this paper, Taguchi method is used for parameter tuning. However, since performance this method highly depends on the defined response and our problem is a multi-objective model, a novel response is developed according to the multi-objective goals. This new response, called multi-objective response (MORE), considers the both Pareto-based goals, including good (1) convergence and (2) diversity. In this metric, which is formulated as Eq. (22), MID is a representation of the first goal (good convergence) and NOS is the representation for the second goal (good diversity).

$$MORE = \frac{MID}{NOS} \tag{22}$$

Table 4 presents factor level of the parameters of the algorithms.

In the beginning of the MOVDO algorithm, initial parameters such as population size (*nPop*), amplitude (A_0), and iteration number (*MaxIt*), number of the implementation of the neighborhood structure on each solution of the population (*nMove*) are determined.

Related S/N ratio figures of the Taguchi method obtained from Minitab software are also illustrated in Fig. 10 for all algorithms. According to these figures tuned parameter of the algorithms can be determined. These values are highlighted in Table 11.

4.1.4. Outputs of the algorithms on the metrics

Tables 12 and 13 summarize outputs of the introduced metrics. For each of these metrics a statistical test called one-way analyze

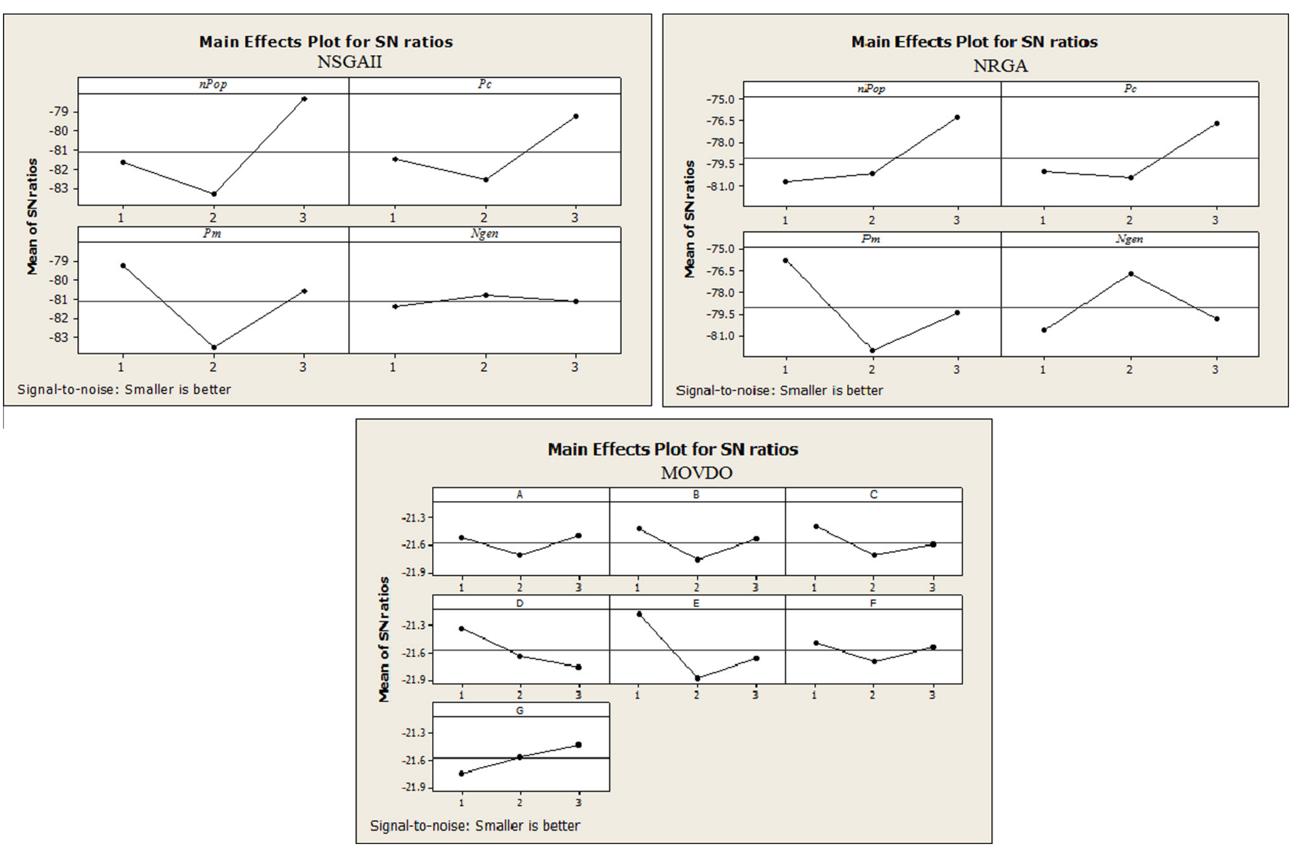


Fig. 10. S/N ratio figure of the Taguchi method of all algorithms.

Table 11
Factor levels of the parameters of the algorithms.

Multi-objective algorithms	Algorithm parameters	Parameters range	Low (1)	Medium (2)	High (3)
NSGA-II	nPop (A)	25–200	25	100	**200**
	P_c (B)	0.6–0.99	0.6	**0.8**	**0.99**
	P_m (C)	0.1–0.4	**0.1**	**0.2**	0.4
	Ngen (D)	50–500	50	**100**	150
NRGA	nPop (A)	25–200	25	100	**200**
	P_c (B)	0.6–0.99	0.6	0.8	**0.99**
	P_m (C)	0.1–0.4	**0.1**	0.2	0.4
	Ngen (D)	50–500	50	**100**	150
MOVDO	A0 (A)	50–200	50	100	**200**
	L (B)	50–100	**50**	70	100
	σ (C)	15–50	**15**	30	50
	γ (D)	0.005–0.5	**0.005**	0.05	0.5
	nPop (*E*)	50–150	**50**	100	150
	MaxIt (F)	100–200	**100**	150	200
	nMove (G)	5–10	5	8	**10**

Table 12
The output of the algorithms on the first group of metrics.

#	NSGAII			NRGA			MOVDO		
	NOS	MID	MORE	NOS	MID	MORE	NOS	MID	MORE
1	2	6966.68	3483.34	1	4900.96	4900.96	5	7566.414	1513.283
2	6	15220.9	2536.817	2	14704.03	7352.015	1	12842.09	12842.09
3	3	23031.56	7677.187	2	10843.36	5421.68	2	10505.87	5252.937
4	1	22892.91	22892.91	1	27330.55	27330.55	2	23379.66	11689.83
5	8	64211.22	8026.403	2	48188.11	24094.06	2	50613.24	25306.62
6	3	46205.89	15401.96	1	47205.83	47205.83	1	40570.56	40570.56
7	3	74399.51	24799.84	2	75743.01	37871.51	1	57639.87	57639.87
8	3	97574.03	32524.68	2	98846.23	49423.12	2	94121.87	47060.94
9	2	140993.1	70496.53	3	146804.7	48934.91	1	135020.5	135020.5
10	5	230393.5	46078.7	4	245611.3	61402.82	6	234592.6	39098.77
Average	**3.6**	72188.93	**20052.48**	2	72017.81	36008.9	2.3	**66685.27**	28993.6

Table 13
The output of the algorithms on the second group of metrics.

#	NSGAII		NRGA		MOVDO	
	S	D	S	D	S	D
1	0	2161.84	–	0	140.5573	3580.007
2	746.5	3728.18	0	2554.03	–	0
3	453.91	2062.31	0	3539.14	0	1010.701
4	–	0	–	0	0	1277.868
5	2343.45	20476.43	0	13034.23	0	941.7096
6	336.54	2423.19	–	0	–	0
7	354.95	9086.85	0	12920.32	–	0
8	885.62	4663.83	0	8567.96	0	15533.08
9	0	11367.91	6186.85	15775.52	–	0
10	2056.3	20864.45	3829.89	21537.73	2176.338	24702.47
Average	797.4744	7683.499	1430.963	**7792.893**	**386.1492**	4704.583

variance (ANOVA) test is done. The outputs of this test on different metrics are presented in Table 14. Some supplementary illustrations are also shown to illustrate the quality of the outputs more explicitly. It should be mentioned that to run the algorithms, MATLAB programming language is used on a PC with 4-GB RAM and 2.4-GHz CPU.

As mentioned, Tables 12 and 13 present the outputs of the algorithms on the metrics. The reason of the separation of these tables is only for more traceability and explicitly. In the last row of these tables, an average summery of the performance of each algorithm on each metric is shown. Then, according to the concept of the each metric, best algorithm on that metric is determined. Accordingly, NSGAII has the best performance on NOS, bigger values are desired, and MORE, smaller values are better. NRGA has the best

Table 14
The computational time for three algorithms for each test problems.

#	NSGA-II	NRGA	MOVDO
1	1247.54	1190.55	1657.9
2	1490.69	1433.58	2586
3	1764.42	1722.92	2898.34
4	2350.7	2377.64	7741
5	3431	3064.96	6352.7
6	4138.65	3074.67	12,076
7	5698.41	5825.42	16,588
8	4602.03	6822.02	19,349
9	8582.12	11732.46	32,543
10	52,251	34092.78	84203.23
Average	8555.656	**7133.7**	18599.52

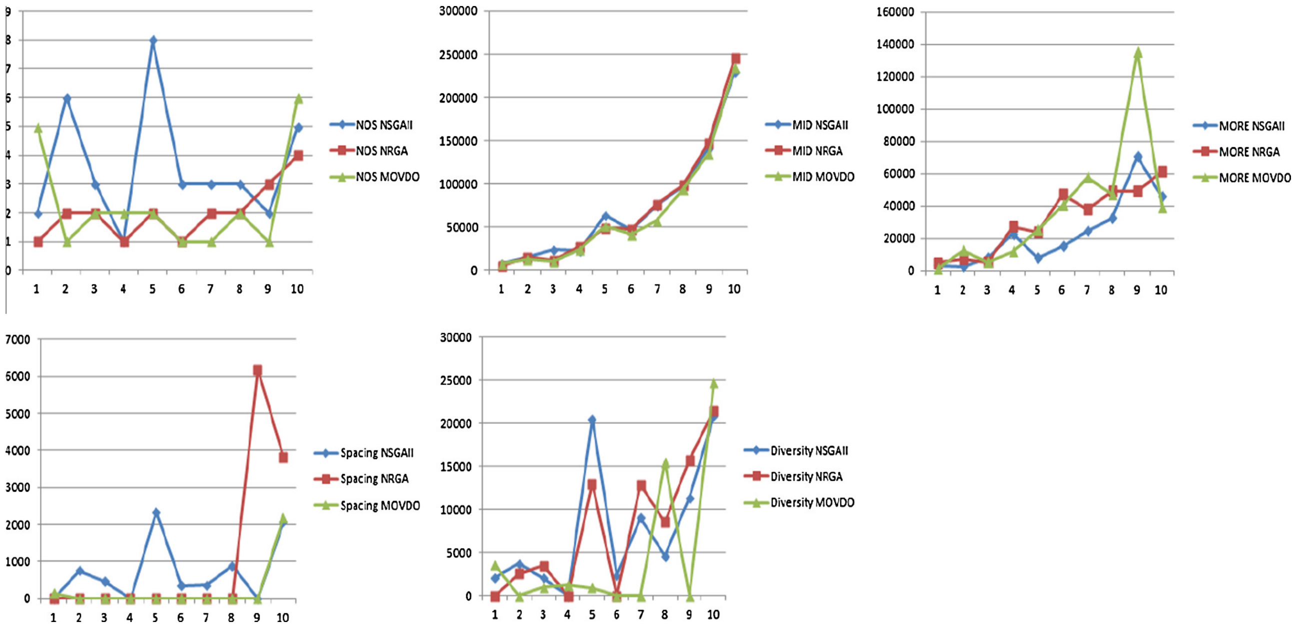


Fig. 11. Graphical summery of the performance of the algorithms on the metrics.

Table 15
Statistical comparison of developed MOVDO with NSGAII and NRGA.

	ANOVA	
	P-value	Result
NOS	**0.096**	Null hypothesis is not rejected
MID	**0.981**	Null hypothesis is not rejected
MORE	**0.541**	Null hypothesis is not rejected
Spacing	**0.5**	Null hypothesis is not rejected
Diversity	**0.621**	Null hypothesis is not rejected

performance on Diversity (D), bigger values are desired, and MOVDO has the best performance on the two remain metrics which are MID and Spacing, smaller values are better. A graphical view of the performance of the algorithms on the metrics is also shown in Fig. 11. In fact, this figure is a visual summary of Tables 12 and 13.

According to Fig. 11, there is not a significant difference among MOVDO and the selected pioneer and famous algorithms of the literature. This claim can also be proved through our statistical tests. In Table 14, the computational times for three algorithms for each test problems are shown.

In order to compare three algorithms for any multi-objective criteria, we defined two hypothesis (the null hypothesis H0 (i.e., no difference between three algorithms for this criteria) and the alternative hypotheses H1 (i.e., significant difference between three algorithms for this criteria)). Usually in statistical analysis, the confidence level is set to 95% and we used the same setting here. Utilizing the criteria values of three algorithms in Tables 5 and 6, p-values can be computed. For each criteria, if p-value is less than significant level (0.05), we can conclude that the test results

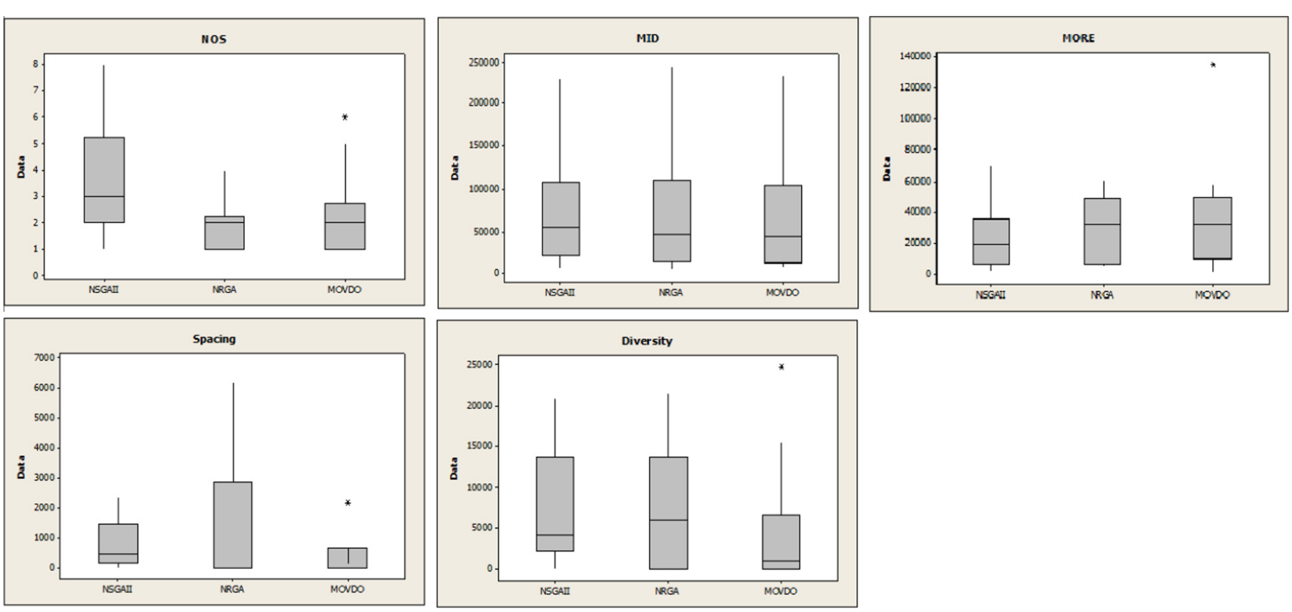


Fig. 12. Box Plot of the statistical test on all metrics.

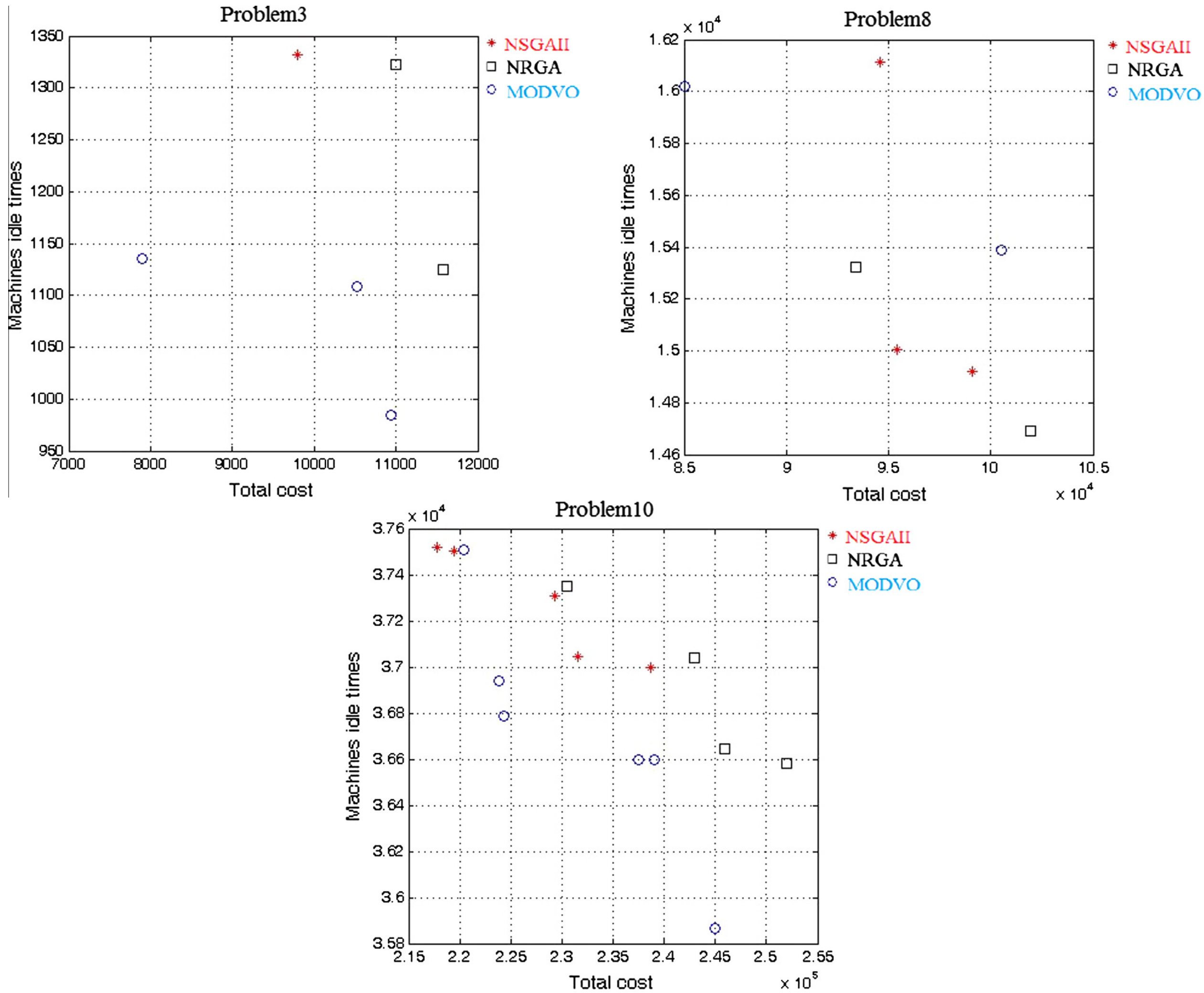


Fig. 13. Pareto optimal front of the algorithms on three test problems.

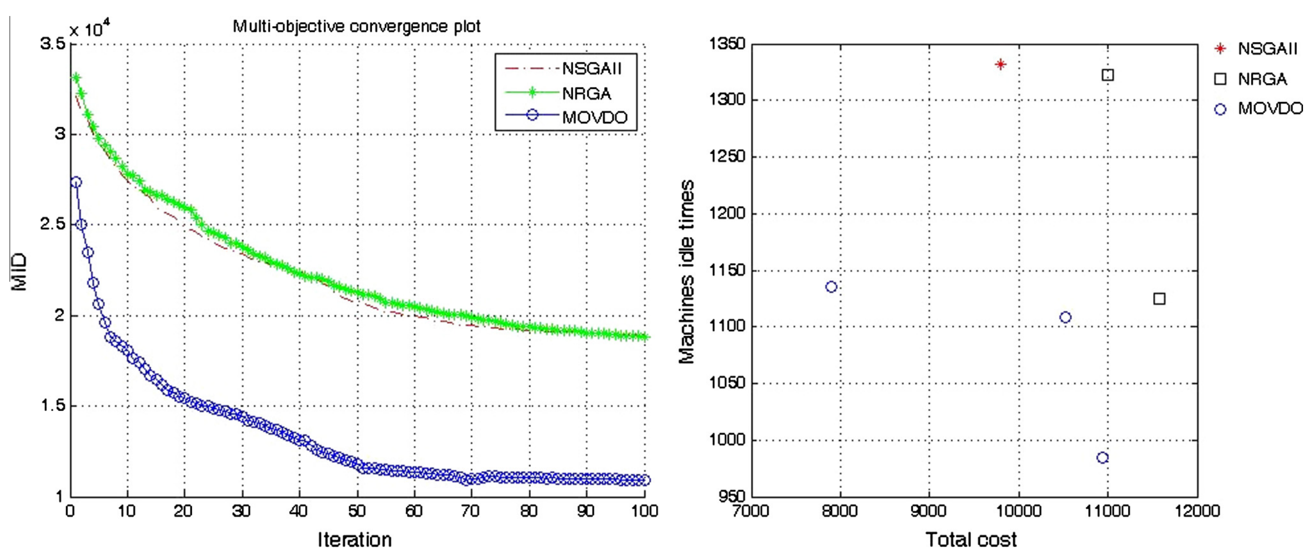


Fig. 14. Multi-objective convergence plots of the algorithms related to Pareto fronts of the Problem3.

attain statistical significance, thereby rejecting the null hypothesis H0. The statistical analysis is done on criteria using Minitab software. Table 15 shows the obtained values of the ANOVA test of the three algorithms on different metrics. According to this table, the algorithms do not have significant difference on any metrics. Fig. 12, which illustrates Box plot of the statistical tests on the metrics, can also be used as a statistical figure for checking the null hypothesis of the ANOVA tests (equality of the average values of metrics).

Besides, to have a better sense of the Pareto fronts, Fig. 13 is plotted to illustrate Pareto optimal front of the algorithms on the three selected test problems 3, 8, 10.

Another figure is also plotted to show convergence performance of the algorithms as Fig. 14. The left part of this figure illustrates improvement of MID during iterations. The right part is Problem3 which was illustrated in Fig. 13. Simultaneously watching of these two parts explains us how MOVDO converge to a good Pareto front on this problem in comparison with other algorithms.

All of these facts are evidence on the good performance of the developed MOVDO.

5. Conclusion

In this paper a new multi-objective mixed integer mathematical programming model was presented which comprehensively considered solving the integrated multi-period cell formation problem, production planning (optimum production policy like production, inventory and subcontracting quantity level) and workers optimum assignment to manufacturing cells simultaneously, in a dynamic cellular manufacturing system. Some advantages of the proposed model are: considering multi-period production planning, dynamic system reconfiguration, operation sequence, alternative process plans, machine and worker flexibility, duplicate machines, machine capacity, available time of workers and workers assignment. The first objective function included minimizing sum of miscellaneous costs like inter and intra-cell material handling cost, machine and reconfiguration cost, set up cost, inventory, backorder and subcontracting cost and workers hiring, firing, training and salary cost, as well as minimizing summation of machines idle times as a second objective. With increasing problem scales, required computational time for solving the problem is increased significantly. So because of NP-hard nature of cell formation problem we couldn't use exact optimization methods for large scale problems in a reasonable time. Hence, applying different types of heuristic and meta-heuristic algorithms for solving the proposed model in the real world large sized problems seems an important issue. Because of this reason and with regard to that the proposed model was multi-objective, a new and efficient meta-heuristic algorithm, which is called VDO was developed in a multi-objective manner and was applied to solve it. Furthermore, in terms of verifying performance and efficiency of proposed algorithm in producing Pareto solution with desirable quality and diversity, results were compared with two well-known and high usage multi-objective meta-heuristic algorithm named NSGA-II and NRGA. As we could found from analyzing computational results, the proposed MOVDO had good and acceptable performance in compare with other algorithms in terms of the closeness of results. Also according to statistical analysis and depicted plots for dispersion modality of comparison metrics, any meaningful difference between proposed MOVDO and two other algorithms was not demonstrated. Considering other critical issues in cell formation phase, like tools assignment and layout for machines and cells sounds an appropriate choice for future researches.

References

Al Jadaan, O., Rao, C. R., & Rajamani, L. (2008). Non-dominated ranked genetic algorithm for solving multi-objective optimization problems: NRGA. *Journal of Theoretical and Applied Information Technology*, 60–67.

Aliabadi, M., Jolai, F., Mehdizade, E., & Jenabi, M. (2011). A flow shop production planning problem with basic period policy and sequence dependent set up times. *Journal of Industrial and Systems Engineering, 5*(1), 286–304.

Aryanezhad, M. B., Deljoo, V., & Mirzapour Al-e-Hashem, S. M. J. (2009). Dynamic cell formation and the worker assignment problem: A new model. *International Journal of Advanced Manufacturing Technology, 41*, 329–342.

Bagheri, M., & Bashiri, M. (2014). A new mathematical model towards the integration of cell formation with operator assignment and inter-cell layout problems in a dynamic environment. *Applied Mathematical Modelling, 38*(4), 1237–1254.

Bajestani, A. M., Rabbani, M., Rahimi-Vahed, A. R., & Khoshkhou, G. B. (2009). A multi objective scatter search for a dynamic cell formation problem. *Computers and Operations Research, 36*, 777–794.

Balakrishnan, J., & Cheng, C. H. (2007). Multi-period planning and uncertainty issues in cellular manufacturing: A review and future directions. *European Journal of Operational Research, 117*, 281–309.

Bidanda, B., Ariyawongrat, P., Needy, K. L., Norman, B., & Tharmmaphornphilas, W. (2005). Human related issues in manufacturing cell design, implementation, and operation: A review and survey. *Computers & Industrial Engineering, 48*, 507–523.

Chen, M., & Cao, D. (2004). Coordinating production planning in cellular manufacturing environment using tabu search. *Computers & Industrial Engineering, 46*, 571–588.

Coello, Coello A., Van Veldhuizen, D. A., & Lamont, G. B. (2002). *Evolutionary algorithms for solving multi objective problems*. Kluwer Academic Publishers.

Daei Niaki, S. V., Mehdizadeh, E., & Tavakkoli-Moghaddam, R. (2011). A mathematical model for dynamic cellular manufacturing systems with production planning and labor assignment. In *POMS 23rd annual conference, Chicago, Illinois, U.S.A., April 20 to April 23.* .

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multi-objective genetic algorithm: NSGA-II. *IEEE Transaction Evolutionary Computing, 6* (4), 182–197.

Defersha, F., & Chen, M. (2008). A parallel genetic algorithm for dynamic cell formation in cellular manufacturing systems. *International Journal of Production Research, 46*(22), 6389–6413.

Fattahi, P., Hajipour, V., & Nobari, A. (2015). A bi-objective continuous review inventory control model: Pareto-based meta-heuristic algorithms. *Applied Soft Computing, 32*, 211–223.

Ghotboddini, M. M., Rabbani, M., & Rahimian, H. (2011). A comprehensive dynamic cell design: Bender's decomposition approach. *Expert Systems with Applications, 38*, 2478–2488.

Hajipour, V., Kheirkhah, A. S., Tavana, M., & Absi, N. (2015). Novel Pareto-based meta-heuristics for solving multi-objective multi-item capacitated lot-sizing problems. *International Journal of Advanced Manufacturing Technology, 80*, 31–45.

Hajipour, V., Mehdizadeh, E., & Tavakkoli-Moghaddam, R. (2014). A novel Pareto-based multi-objective vibration damping optimization algorithm to solve multi-objective optimization problems. *Scientia Iranica. Transaction E, Industrial Engineering, 21*(6), 2368.

Houshyar, A. N., Leman, Z., Moghadam, H. P., Ariffin, M. K. A. M., Ismail, N., & Iranmanesh, H. (2014). Literature review on dynamic cellular manufacturing system. *IOP conference series: Materials science and engineering* (Vol. 58(1), pp. 012016). IOP Publishing.

Joines, J. A., King, R. E., & Culbreth, C. T. (1995). A comprehensive review of production oriented manufacturing cell formation techniques. *International Journal of Flexible Automation and Intelligent Manufacturing, 3*, 254–264.

Kia, R., Baboli, A., Javadian, N., Tavakkoli-Moghaddam, R., Kazemi, M., & Khorrami, J. (2012). Solving a group layout design model of a dynamic cellular manufacturing system with alternative process routings, lot splitting and flexible reconfiguration by simulated annealing. *Computers & Operations Research, 39*, 2642–2658.

Kioon, S. A., Bulgak, A. A., & Bektas, T. (2009). Integrated cellular manufacturing systems design with production planning and dynamic system reconfiguration. *European Journal of Operational Research, 192*(2), 414–428.

Mahdavi, I., Aalaei, A., Paydar, M. M., & Solimanpur, M. (2010). Designing a mathematical model for dynamic cellular manufacturing systems considering production planning and worker assignment. *Computers and Mathematics with Applications, 60*, 1014–1025.

Majazi-Delfard, V. (2013). New mathematical model for problem of dynamic cell formation based on number and average length of intra and intercellular movements. *Applied Mathematical Modelling, 37*, 1884–1896.

Mehdizadeh, E., & Fatehi Kivi, A. (2014). Three meta-heuristic algorithms for the single-item capacitated lot-sizing problem. *IJE Transactions B: Application, 27*(8), 1223–1232.

Mehdizadeh, E., & Rahimi, V. (2016). An integrated mathematical model for solving dynamic cell formation problem considering operator assignment and inter/intra cell layouts. *Applied Soft Computing, 42*, 325–341.

Mehdizadeh, E., & Tavakkoli Moghaddam, R. (2008). Vibration damping optimization. In *Proceeding of the international conference operations research and global business, Germany, September 3–5.* .

Mehdizadeh, E., & Tavakkoli-Moghaddam, R. (2009). Vibration damping optimization algorithm for a parallel machines scheduling problem. In *The 2nd international conference of Iranian operations research society, May 20–22, 2009 – Babolsar, Iran.* .

Mehdizadeh, E., Tavakkoli-Moghaddam, R., & Yazdani, M. (2015). A vibration damping optimization algorithm for a parallel machines scheduling problem with sequence-independent family setup times. *Applied Mathematical Modelling, 39*(22), 6845–6859.

Mehdizadeh, E., Tavarroth, M. R., & Hajipour, V. (2011). A new hybrid algorithm to optimize stochastic-fuzzy capacitated multi-facility location-allocation problem. *Journal of Industrial Engineering, 7*(2011), 77–86.

Mehdizadeh, E., Tavarroth, M. R., & Mousavi, S. M. (2011). Solving the stochastic capacitated location-allocation problem by using a new hybrid algorithm. *Applied Mathematics*. ISBN: 978-960-474-263-9.

Mousavi, S. M., Akhavan Niaki, S. T., & Mehdizade, E. (2012). The capacitated multi-facility location–allocation problem with probabilistic customer location and demand: Two hybrid meta-heuristic algorithms. *International Journal of Systems Science*, 1–16.

Papaioannou, G., & Wilson, J. M. (2010). The evolution of cell formation problem methodologies based on recent studies (1997–2008): Review and directions for future research. *European Journal of Operational Research, 206*, 509–521.

Rafiei, H., & Ghodsi, R. (2013). A bi-objective mathematical model toward dynamic cell formation considering labor utilization. *Applied Mathematical Modelling, 37*, 2308–2316.

Reisman, A., Kumar, A., Motwani, J., & Cheng, C. H. (1997). Cellular manufacturing: a statistical review of the literature (1965–1995). *Operations Research, 45*(4), 508–520.

Rezaeian, J., Javadian, N., Tavakkoli-Moghaddam, R., & Jolai, F. (2011). A hybrid approach based on the genetic algorithm and neural network to design an incremental cellular manufacturing system. *Applied Soft Computing, 11*, 4195–4202.

Rheault, M., Drolet, J., & Abdulnour, G. (1995). Physically reconfigurable virtual cells: A dynamic model for a highly dynamic environment. *Computers & Industrial Engineering, 29*(1–4), 221–225.

Safaei, N., Saidi-Mehrabad, M., & Jabal-Ameli, M. S. (2008). A hybrid simulated annealing for solving an extended model of dynamic cellular manufacturing system. *European Journal of Operational Research, 185*(563), 592.

Safaei, N., & Tavakkoli-Moghaddam, R. (2009). Integrated multi-period cell formation and subcontracting production planning in dynamic cellular manufacturing systems. *International Journal of Production Economics, 120*(2), 301–314.

Sakhaii, M. et al. (2015). A robust optimization approach for an integrated dynamic cellular manufacturing system and production planning with unreliable machines. *Applied Mathematical Modelling*. http://dx.doi.org/10.1016/j.apm.2015.05.005.

Selim, M. S., Askin, R. G., & Vakharia, A. J. (1998). Cell formation in group technology: Review evaluation and directions for future research. *Computers and Industrial Engineering, 34*(1), 3–20.

Singh, N. (1993). Design of cellular manufacturing systems: An invited review. *European Journal of Operational Research, 69*, 284–291.

Solimanpur, M., Vrat, P., & Shankar, R. (2004). A multi-objective genetic algorithm approach to the design of cellular manufacturing systems. *International Journal of Production Research, 42*(7), 1419–1441.

Suresh, N. C., & Meredith, J. R. (1985). Achieving factory automation principles through group technology principles. *Journal of Operations Management, 5*(2), 151–167.

Yazdani, M., Zandieh, M., Tavakkoli-Moghaddam, R., & Jolai, F. (2015). Two meta-heuristic algorithms for the dual-resource constrained exible job-shop scheduling problem. *Scientia Iranica E, 22*(3), 1242–1257.