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METHODOLOGIES AND APPLICATION

Enhancing performance of cell formation problem using hybrid efficient swarm optimization

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Abstract

Cellular manufacturing design is apprehensive about the conception and activity of cells to take the benefits of adaptability, effective flow, and high creation rate. The way toward forming manufacturing cells with the greatest efficiency is the most critical strides in cellular manufacturing. In this paper, a new monarch butterfly optimization (MBO) and firefly (FF)-based meta-heuristic is proposed to solve a multi-objective cell formation problem (CFP). This hybridized MBO–FF acquires optimal arrangements in a worthy measure of time, particularly for big size problems also focused to enhance the working of CFP. This algorithm is competent to investigate the search space viably and recognize the global optimal within a short measure of time. Here, percentage of exceptional elements, machine utilization, grouping efficacy and cell efficiency are measured for the performance enhancement. Computational outcome of the presented MBO–FF herein demonstrates superior or equivalent to the benchmark instance collected from the literature.

Keywords Cell formation problem · Exceptional elements · Grouping efficacy · Hybrid optimization · Monarch butterfly · Firefly algorithm

1 Introduction

Cell formation problem is the division of group technology (GT) which was presented by Mitranov (1959) and later disseminated by Burbidge (1971) for the application of many manufacturing industries. Grouping of machines and parts in a cellular manufacturing framework in view of resemblance is known as the cell formation problem (Mehdizadeh et al. 2016). Cell formation (CF) forms group of parts that work in a predetermined group of specific machines (Kong et al. 2018). Sometimes cell configurations are streamlined in diverse planning periods for the variety of product mix and demand volumes (Zohrevand et al. 2016). Based on this formation, there is a fundamental relation among machines and parts (Li et al. 2010). Parts would then be able to be doled out to families to such an extent that all parts in the family are handled on a similar gathering of machines, and comparatively, machines can be assembled into cells on the off chance that they procedure a similar arrangement of parts (Pailla et al. 2010). The cell formation problem demonstrated that it is an NP-difficult problem (Elbenani et al. 2012).

There are a few targets to measure the viability of cellular manufacturing system, for example minimized inter/intracell movements, the part procedure carried out inside a particular cell, higher machine utilization, reduced expenses by decreasing setup times, work-in-process (WIP), negligible capital speculation and minimum number of voids in the cells (Mahdavi et al. 2013). Cellular manufacturing system (CMS) design includes interconnected divided problems, specifically grouping of machines, formation of family of parts and cell design (Mohammadi and Forghani 2017). The total system of production is divided into fabrication cells on CM for the maximization of the part flows practiced inside cells (Wu et al. 2010).

CFP has been considered as an optimized problem in manufacturing for over 90 years (Car and Mikac 2006).

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Because of the NP-hard nature of the CFP, heuristic, meta-heuristics and hybrid meta-heuristics approaches have been effectively proposed to produce satisfactory arrangements with in a nominal time (Arkat et al. 2011).

Chung et al. (2011) analyzed the CFP to solve the NP-hard like difficult problem, structure by utilizing combined algorithms. Dalfard (2013) suggested that the implementation of cell manufacturing system which attracts lesser preparation time, material transportation cost, work in process also improved production, quality of product and work flexibility. Paydar and Saidi-Mehrabad (2013) proposed a hybrid meta-heuristic algorithm to maximize the grouping efficacy with unknown number of cells on real-sized problems. Yurtkuran and Emel (2016) adapted the artificial bee colony combinatorial optimization procedure to solve the scheduling of solitary machine by employing random selection from an operator pool.

An efficient model for CFP was presented a changeable quantity of production cells Bychkov and Batsyn (2018). To develop this model, a mixed-integer linear programming technique and Dinkelbach approach were used. They found that the computational time was decreased by analyzing two sets of databases. Buruk Sahin and Alpay (2016) formulated a genetic algorithm for solving CFP. They had a great attention to the problem of part/machine/worker cell formation for large-size datasets. The authors found an optimal solution in small-size problems, but the large-size problems got a nearly optimal solution within reasonable time. Modified adaptive reverberation hypothesis neural network was considered to form cell that dealt with binary, nonbinary data, sequence of operation and production volume (Manimaran et al. 2014).

Mehdizadeh and Rahimi (2016) worked out the vibrant CFP using mathematical modeling for inter/intracellular layout problems and operator assignment with reduced cost. They also presented four numerical examples and validated by using meta-heuristics approaches: multi-goal simulated annealing and vibration damping optimization.

A complete cell formation is clustering the parallel component family and relevant machinery into cells also with the issues of human. Strategies to assign suitable workers are used for making decision to the particular tasks between the cells (Feng et al. 2017).

Arkat et al. developed a novel heuristics for the solution of CFP in (Arkat et al. 2012). They compared their proposed branch and bound algorithm and hybrid combination of genetic algorithm with numerical modeling. The results illustrated that the maximum effect achieved in that hybrid model for large-sized CF problems.

Feng et al. (2018) demonstrated a hybrid approach for concurrent cell formation and layout plan. They compared two hybrid algorithms as the combination of genetic algorithm and simulated annealing with linear programming. These algorithms produce low production cost and maximum machine utilization rate.

1.1 Related work

To solve the CFP, an extensive range of heuristic and meta-heuristic algorithms has been presented in the past three decade.

Laha and Hazarika (2017) represented the Euclidean distance matrix to produce best machine cells and families of parts based on their similarities in process and to cluster machines. Hazarika and Laha (2017) presented a genetic algorithm-based approach for CFP for the minimization of intercellular moves of an element, maximization of utilization of machines, execution of the optimal route and balanced machine cells. As the modern manufacturing machines are mostly multi-dimensional, the operation executed through another routes to satisfy the aim of the proposed approach. Hazarika (2018) presented a genetic algorithm method to resolve the optimal cells of machines, parts volume, optimal route, balanced cells, multi-process routes and process sequence.

Mukattash et al. (2018) recommended a new grouping measure named comprehensive grouping efficacy to overwhelm the shortcoming of the commonly known grouping effectiveness procedures. CGE is used to find the efficiency of block-diagonal form and its subsystem, sparsity index and efficacy index. Nalluri et al. (2019) recommended a novel clonal selection algorithm to solve the multi-goal CFP also combined with genetic algorithm to generate possible sequences of cell. Two novel functions developed to solve the multi-aim CFP. Niakan et al. (2016) proposed a new twin goal arithmetical model by considering the assignment of worker, environment and societal measures with the minimization of costs for production as well as labor and entire wastes of production.

Danilovic and Ilic (2019) suggested a modern method to utilize the specifications of the input to reduce the set of feasible solutions, and to enhance the efficiency of optimization practice. Imran et al. (2017) bring attention to get minimization of value-added activities in practice for the auto part deliver industry of CF in CMS by formulating a mathematical model and solved by the incorporation of simulation with the combination of genetically proved algorithm to attain the objective.

Hazarika and Laha (2018) presented a heuristic algorithm for the CFP with multi-faceted routes of practice, ordered procedure and volume of parts to satisfy the objective of different processing routes for the minimization of complete intercellular travels of parts.

Thanh et al. (2016) introduced multi-diverse search techniques to solve the CFP; they are first local search method used the diversification and intensification strategies for an execution of simulated annealing (SA), the second search method named adaptive simulated annealing is updated at every iteration and then elected the neighborhood and the combination of people orientation-based technique and a limited explore process. Lee and Ahn (2013) developed a novel goal measure named GT efficacy for the new statistics that replicate on intercellular moves and firmness restricted by the cells.

Karoum et al. (2016) presented an immunity structure algorithm artificially to the CFP to the maximization of efficiency through the distinguished tabu search methodology for the best solutions with shorter span of time. Solimanpur et al. (2010) proposed an optimized ant technique to solve the CFP. They used a pheromone matrix in their mathematical model. The usefulness of the recommended method is tested, and the solution attained indicates around 6% enhancement on intercellular travels and emptiness.

Regarding higher-dimensional works, the MBO method has the absolute advantage but for the lower-dimensional works, the performance of MBO is equal to or inferior the remaining techniques which is the disadvantage of the algorithm. The attraction between fireflies fixes the search behavior, and attractions between fireflies should be less than 1. Even though chaotic appeal reduces the difficulty of calculation and speed up the exploration, early convergence may occur. The mutated Cauchy and chaotic appealing is applied for the solution of the early convergence problem. Cauchy mutation enhances the overall exploration and also prevents confined to local minima.

Many authors experienced to solve mathematical programming model, this model may give an optimal solution, but it reaches a much more computational time when it receives large-size problems. In years growing, authors worked on meta-heuristics methods like genetic algorithms, linear programming, simulated annealing, clustering, ant colony, fuzzy logic, and neural network optimization algorithms. These algorithms give a better solution but not guaranteed for multi-goal problems. CFP's objective is to attain most advantageous solution for all problems with minimum computational time. To achieve these objectives and consider the shortcomings of those reviews, this methodology creates a MBO–FF hybrid model to solve CFP and achieve an optimal solution in large-sized problems.

2 Formulation of problem

Here, an arithmetical modeling is formulated for the solution of CFP. Here, a few presumptions are considered to evaluate CFP as only one machine of each kind is accessible,

- The count of formation of cells is known ahead of time,
- all equipment also be doled out and
- every machinery is relegate to just a single cell; each part has just a single procedure plan for production.

Nomenclature

i Index for parts; $i = 1, 2, \ldots .P$

j Index for machines; $j = 1, 2. \ldots M$

k Index for cells; $k = 1, 2, \ldots .C$

b_{ij} $\begin{cases} 1 & \text{if part } i \text{ is assigned to machine } j \\ 0 & \text{otherwise} \end{cases}$

p_{ik} $\begin{cases} 1 & \text{if part } i \text{ is assigned to cell } k \\ 0 & \text{otherwise} \end{cases}$

q_{jk} $\begin{cases} 1 & \text{if machine } j \text{ is assigned to cell } k \\ 0 & \text{otherwise} \end{cases}$

C_k $\begin{cases} 1 & \text{if cell } k \text{ is formed;} \\ 0 & \text{otherwise} \end{cases}$

2.1 Modeling of CFP

To explain the modelling of CFP, 7 machines and 11 parts incidence matrix is considered which is given in Table 1(a) taken from the source Boctor (1991). The aim of 3-cell division minimizes the number of parts working on another cell as shown in Table 1(b). In this separation: Cell-1 includes 2nd and 3rd machineries and 1st, 2nd, 6th, 9th parts. Cell-2 consists 1st, 5th, 6th equipments and 3rd, 7th, 11th parts, and Cell-3 comprises 4th, 7th equipments and parts 4th, 5th, 8th, 10th parts.

Mathematical programming strategies are broadly used to manage CFP with various optimization objectives. The proposed model is validated by utilizing simulation modeling. Here, the proposed MBO–FF amplifies the performance measures. Viability of the proposed model is examined on existing known problems.

2.2 Objective function

The mathematical model has an objective to maximize the grouping efficacy, cell efficiency and machine utilization and also to minimize exceptional elements.

Grouping efficacy (GE): GE controls the exceptional elements and voids which are present in the diagonal matrix (DM) of CFP. In this examination, grouping efficacy measure (Eq. 1) is used as the solution evaluation and is expressed as:

$$GE = \left(\frac{\sum_{i=1}^{m} \sum_{j=1}^{p} \sum_{k=1}^{C} b_{ij} p_{ik} q_{jk}}{\sum_{i=1}^{m} \sum_{j=1}^{p} b_{ij} + \sum_{i=1}^{m} \sum_{j=1}^{p} \sum_{k=1}^{c} (1 - b_{ij}) p_{ik} q_{ik}} \right) \quad (1)$$

Constraints

Table 1 Example of CFP

Parts												
(a) Initial matrix												
M		1	2	3	4	5	6	7	8	9	10	11
A	1	1	1	0	0	0	1	0	0	0	0	0
C	2	0	1	0	0	0	1	0	0	1	0	0
H	3	1	0	1	0	0	0	1	0	0	0	1
I	4	0	0	1	0	0	0	1	0	0	0	0
N	5	0	0	1	1	0	0	0	0	0	0	1
E	6	0	0	0	1	1	0	0	0	0	1	0
S	7	0	0	0	0	1	0	0	1	0	1	0

	Parts											
(b) Final matrix												
M		4	5	8	10	1	2	6	9	3	7	11
A	4	*1*	*1*	*0*	*1*	0	0	0	0	0	0	0
C	7	*0*	*1*	*1*	*1*	0	0	0	0	0	0	0
H	2	0	0	0	0	*1*	*1*	*1*	*0*	0	0	0
I	3	0	0	0	0	*0*	*1*	*1*	*1*	0	0	0
N	1	0	0	0	0	1	0	0	0	*1*	*1*	*1*
E	5	0	0	0	0	0	0	0	0	*1*	*0*	*0*
S	6	1	0	0	0	0	0	0	0	*1*	*1*	*1*

1. $\sum_{k=1}^{C} p_{ik} = 1 \quad \forall i$

2. $\sum_{k=1}^{C} q_{jk} = 1 \quad \forall j$

3. $q_{jk} \le c_k \quad \forall j, k$

4. $p_{ik} \le c_k \quad \forall i, k$

5. $p_{ik,}\ q_{jk,}\ c_k\ \in 0,\ 1 \quad \forall i, j, k$

Constraint (1) assures all equipment should be dispersing to a solitary group. Constraint (2) promises every element ought to be allotted to a single cell. Constraints (3) and (4) ensure that every equipment and part can be doled out to one cell, if and just if the cell is encircled. Constraint (5) connotes that decision variables are paired.

Machine utilization (MU): MU demonstrates the % of quantity the machineries inside the cells are utilized in manufacturing. The MU is processed like:

$$\mathrm{MU} = \left[\frac{N(1)}{\sum_{k=1}^{K} m_k p_k}\right] \times 100 \tag{2}$$

where MU signifies the machine utilization; $N(1)$ represents the total quantity of one's inside the DM; m_k represents the quantity of machineries in kth group; p_k depicts the quantity of components in the kth group;

Cell efficiency (CE): CE shows the proportion of emptiness into an entire quantity of voids in the problem ought to be less and the proportion of a number of ones in DM to the entire work ought to be high. CE is figured like:

$$\mathrm{CE} = \left({}^{\delta}/_{1+\phi}\right) \times 100 \tag{3}$$

where δ denotes the entire quantity of work;ψ identifies the quantity of voids inside the DM.

Percentage of exceptional elements (EE): EE is acquired from the quantity of exceptional elements to the entire quantity of elements as 'one.'

2.3 Validation of CFP on a hybrid algorithm

Arithmetical approach of CFP process probably forces the challenges in computing perhaps resolvable by utilizing newly developed programs for extensive measured works. In this manner, proficient heuristic strategies are required to take care of the bigger size works. A hybrid algorithm, i.e., the combination of monarch butterfly optimization with firefly to solve the proposed model, was presented.

2.3.1 Fitness function

The objective function can be calculated through the fitness function. The fitness task $F(z)$ is evaluated as maximizing the GE, CE, MU and minimizing percentage of EE. It is shown in Eq. (4).

$$F(z) = \left\{ \begin{array}{l} \max(\mu, \tau, \psi) \\ \min(\text{Percentage of EE}) \end{array} \right\} \quad (4)$$

2.4 Monarch butterfly optimization (MBO)

MBO works on the basis of naturally inspired monarch butterflies. It is motivated by the ruler butterfly while relocation.

2.4.1 Steps for MBO algorithm

Nature inspired monarch method is presented by Wang et al. (2015); the whole populace of monarch butterfly (MB) is separated by secondary residents 1 and secondary residents 2, respectively.

Step 1 Initial phase. Fix creation count t as one; fix primary populace P arbitrarily; fix NP1 in territory 1 and NP2 in territory 2; butterfly amend rate BAR, relocation period peri, and the relocation proportion p.

Step 2 Suitability estimation. (Estimate every fly based on the place).

Step 3 If $t <$ Max Gen goto arrange all the fly individuals based on the fitness.

Made partition into two secondary residents (territory 1 and territory 2);

for i = 1 to NP1 goto create new secondary residents one.

conclude for i;

for j = 1 to NP2 (for secondary residents 2) goto create new secondary residents two.

conclude for j.

The measure of the whole population, secondary residents 1 and secondary residents 2 are individually MB_T,$\mathrm{MB}_1(l \times \mathrm{MB}_T)$ and $\mathrm{MB}_2(\mathrm{MB}_T - \mathrm{MB}_1)$ where MB_T denotes the entire population of monarch butterflies, MB_1 refers to the secondary residents 1 and MB_2 secondary residents 2; l signifies the proportion of secondary residents 1 in the entire population.

Parameters initialization: At first, fix the population NP1 in territory 1 and NP2 in territory 2, which referred to as secondary residents 1 and secondary residents 2. Here, each monarch butterflies position represents combination of components and machineries on cells. Evaluation is based on the fitness by the position of each MB. Based on the relocation operator and the butterfly adjusting operator, the locations of the monarch butterflies are updated.

Migration operator: So as to keep the population unaltered, the migration operator supplanting its parent with recently produced one in the event that it has better fitness when contrasted with its parent. The location of individual i from creation t to additional one can be defined in Eq. (5).

$$o_{i,t}^{h+1} = \begin{cases} o_{r1,t}^{h} & \text{if } r \le l \\ o_{r2,t} & \text{else} \end{cases} \quad (5)$$

where $o_{i,t}^{h+1}$ represents the tth constituent of o_i at creation $h+1$ that given the location of the monarch butterfly i, $o_{r1,t}^{h}$ shows the tth constituent of o_{r1} is the just now created location of the MB i, h is the recent creation count. The value of h is fix as 5th of 12 based on relocation time, where $r1$ and $r2$ are arbitrarily elected through subpopulation1 and subpopulation 2 and r is calculated from,

$$r = rand \times peri \quad (6)$$

Here $rand$ is an arbitrary digit in [0, 1] and $peri$ designates the relocation time.

Butterfly adjusting operator: For creature i in subpopulation 2, its place on exploration space mostly relies upon the accompanying 3 perspectives: the universal top individual on the whole populace, outsider individual on subpopulation 2 and journey rate. The development of individual i from creation t to additional one is communicated as

$$o_{i,t}^{h+1} = \begin{cases} o_{\mathrm{best},t}^{h} & \text{if } rand \le h \\ o_{r3,t}^{h} & \text{if } rand > h \wedge rand \le BAR \\ o_{i,t}^{h} + \beta(do_h - 0.5) & \text{if } rand > h \wedge rand > BAR \end{cases} \quad (7)$$

where $o_{\mathrm{best},t}^{h}$ designates the tth constituent of the present universal top individual on the total populace in creation h. Butterfly adjusting rate is a managing factor which chooses a MB changing rate, and do is acquired by utilizing a journey rate. The factor β (load factor) is resolved

$$do = Levy\left(o_j^h\right) \quad (8)$$

$$\beta = W_{\max} / h^2 \quad (9)$$

where $W_{\max}$ means the most extreme march pace that a MB individual made movement in a single phase at the current creation h. MBO is supplant the nearly inferior result to a novel conceivably superior result and maintain it to the future production. To create a best result, machineries and components are elected and are appointed to the machinery group in light of control parameter and irregular walk. The arrangement of MBO enhances the fitness work and gets an optimal arrangement.

2.5 Fire fly optimization (FF)

Yang (2010) was presented the fire fly initially, which impersonate the societal activities of fireflies on sultry atmosphere (Yelghi and Kose 2018; Wang et al. 2017; Shakya 2020). Fireflies convey, search in favor of prey and discover mates using shifted blinking samples. Fundamentally, FF uses the associated 3 glorified principles: Fireflies are present as solitary gender with the goal that each fly is attracted another flies by putting slight respect toward his or her gender. The desirability is related to the blinking and is reduced if their interval increases. Consider 2 numbers of blinking fireflies, higher the luminous will attract the lesser blinking fire fly. The dazzling of a fire fly is considered as goal task.

2.5.1 Steps for FF optimization

Step 1 Each part of machine operation is randomly chosen and sequenced to the point that all operations are attracted request to make a firefly, which speaks to a matrix validation. This random selection is rehashed to construct a swarm of fireflies with the necessary range. The distance of spaces within the fireflies is equivalent to the total number of operations to be performed. The measure of the firefly population decides the cell formation or the measure of search in the solution space.

Step 2 The following step is to compute the luminous concentration of the fire fly relies upon the problem considered, and the assessment of the dependability of schedules is estimated through fitness function.

Step 3 Every fire fly is assessed to decide the target task rate. The goal task rate of every fire fly is related to the luminous concentration of the comparing fire fly. FF with less blinking is moved to a firefly with more brightness. Light intensity is resolved from Eq. 10:

$$L_i = L_{i0} e^{-\lambda r^2} \tag{10}$$

where L_{i0} is the pleasant appearance $r = 0$ and λ is an assimilation coefficient, which limit the reduction of luminous concentration.

Step 4 The pleasant appearance is ascertained for each fire fly, and the progress of the fire fly is regulated.

$$\xi = \xi_0 e^{-\lambda r^2} \tag{11}$$

where ξ_0 is the brightness pleasant appearance at $attr = 0$, the space among any 2 fire flies p and q at locations P_p and P_q, and the Cartesian space is explained as:

$$r_{pq} = \sqrt{\sum_{f=1}^{d} \left(P_p^f - P_q^f\right)^2} \tag{12}$$

where P_p^f is the fth element of spatial direct of pth firefly and d is the dimensional numeral. Finally, progress of the firefly p, when fascinated with the added luminous fire fly q, is find by:

$$P_p^{f+1} = P_p^f + \zeta\left(P_q^f - P_p^f\right) + \sigma\left(rand - \frac{1}{2}\right) \tag{13}$$

where P_p^{f+1} is the future production firefly position. P_p is the second term of a firefly's pleasant appearance, and the last term is utilized for the chance development when no further brilliant fire fly. The arbitrariness constraint σ and a rand are a chance figure created consistently circulated in the range of 0 and 1.

Step 5 Follow all previous works repetitively done till the end prompt.

2.6 Proposed hybrid model (MBO–FF)

All the meta-heuristic algorithms can be classified into two types: local search heuristic methods and global search techniques.

Global search techniques work with a set of solutions, whereas the local search heuristic technique functioned by the solitary result.

The proposed hybrid MBO–FF approach is the population-based meta-heuristic algorithm to maximize the GE, CE and MU to minimize percentage of EE in cell formation environment.

The CF problem can rectify and the performance will improve to the best by execution of the proposed hybrid MBO–FF approach. Computational results of CFP showed that the hybrid algorithm gives an optimal solution when compared with the existing results.

Step 1 Initial Phase. Fix creation count t as one; fix primary populace P arbitrarily; each part of machine operation is randomly chosen. This chance taken is revised to produce a group of fireflies with the requisite range.

Step 2 Suitability estimation. Estimate every fire fly based on the place. To measure the blinking luminous concentration of the firefly is estimated by the fitness function.

Step 3 If $t <$ Max Gen does sort all the monarch butterfly individuals based on the fitness. Made partition into two secondary residents (territory 1 and territory 2); for i = 1 to NP1. Every firefly is evaluated to conclude the objective task rate. FF lesser luminous is moved to a firefly with higher luminous.

Step 4 To keep the population unaltered, the migration operator supplanting its parent with recently produced one in the event that it has better fitness when contrasted with its parent.

The attractiveness is ascertained for every firefly and rank.

Step 5 Update the position by butterfly adjusting operator. Update the position of firefly.

Create new secondary residents 1 and 2 based on steps 1 and 2.

All previous works repetitively carried out till the end prompt.

end for i

end for j.

2.6.1 Optimal solution

The hybridization procedure provides the new solutions sets also the robustness rate is originate for the latest updated solutions. The result which offers the minimized/maximized fitness function is the best possible solution (Eq. 14). Repetitively followed the above steps until the fresh solution sets obtain. To compare both the individual algorithms (MBO–FF), the best solution is considered as an optimal solution.

$$F(z)_{\text{optimal}} = \left\{ \begin{array}{l} \max\,(\mu, \tau, \psi) \\ \min(\text{Percentage of EE}) \end{array} \right\}_{\text{optimal}} \tag{14}$$

where $F(z)_{\text{optimal}}$ represents the optimal fitness function which has been achieved by the above processes. Figure 1 depicts the flowchart of presented methodology—hybrid MBO–FF techniques.

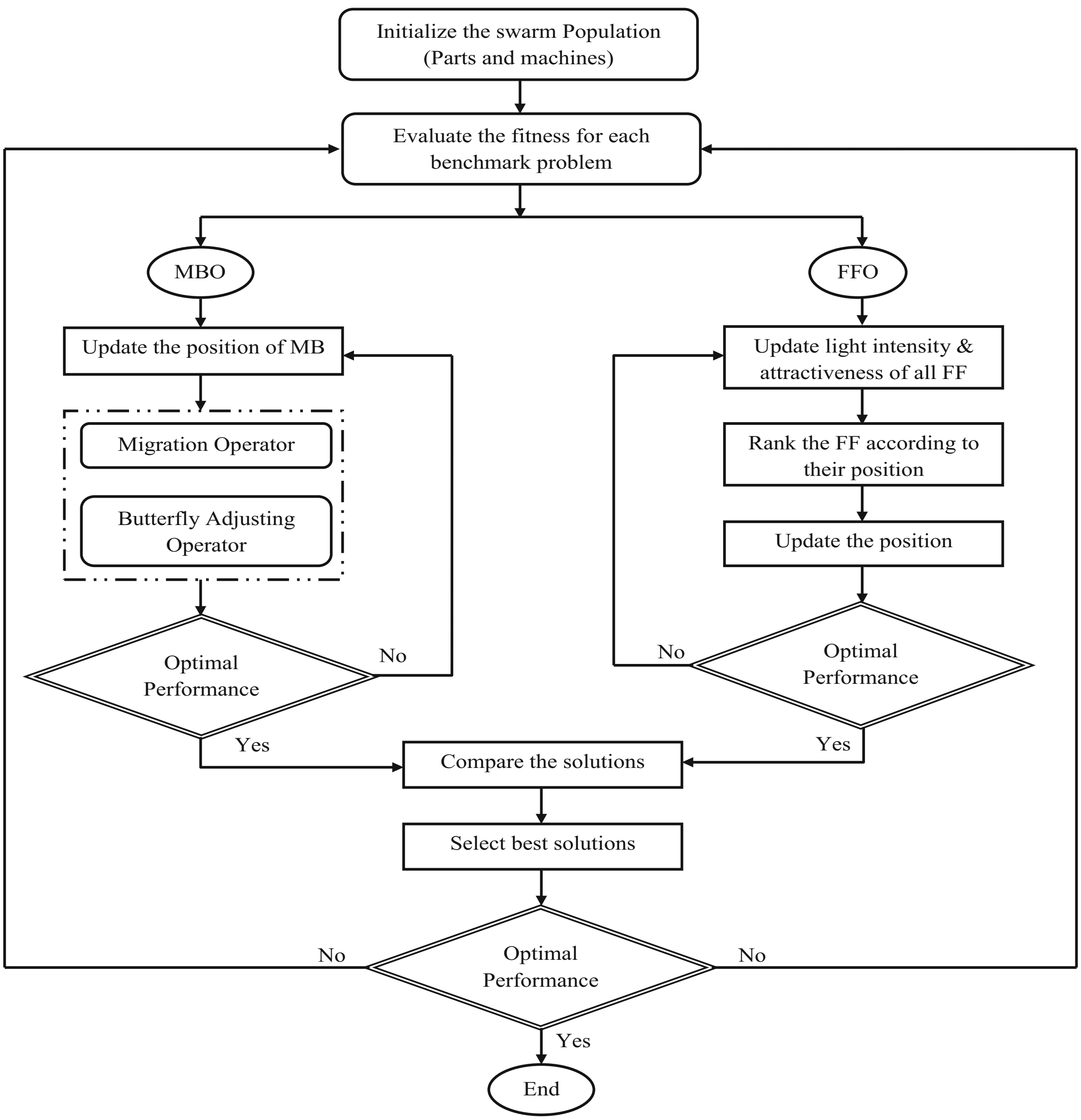

Fig. 1 Flowchart for the proposed model

Table 2 Relationship between performance measures of the presented method with few methodologies

Problem source	M	P	C	Grouping efficacy			Cell efficiency			Machine utilization			Percentage of EE		
				Actual	DF-FFA	MBO–FF	Actual	DF-FFA	MBO–FF	Actual	DF-FFA	MBO–FF	Actual	DF-FFA	MBO–FF
King (A1)	5	7	2	82.3	85	85.96	69.35	70.6	74.58	82.35	80.57	83.3	0	0	0
Waghodekar and Sahu (A2)	5	7	2	69.5	74.5	77.45	74.12	73.2	75.36	82.35	81.47	82.9	12.5	18.8	12.5
Seifoddini (A3)	5	18	2	80.85	81.11	83.95	85.64	85.32	86.35	82.35	82.96	82.56	12.5	12.5	12.5
Kusiak and Cho (A4)	6	8	2	79.17	84.29	89.45	96.32	96.54	89.89	92.59	90.56	92.85	25	18.8	24.6
Kusiak and Chow (A5)	7	11	3	60.87	63.75	64.12	46.99	50.36	58.63	85.29	83.14	88.57	23.7	18.4	23
Boctor (A6)	7	11	3	70.83	83.33	89.77	85.63	89.97	85.99	92	91.22	92.65	0	0	0
Seifoddini and Wolfe (A7)	8	12	3	69.44	70	75.19	74.35	74.82	75.36	99	95.86	98.56	14.8	8.2	14.6
Chandrasekharan and Rajagopalan (A8)	8	20	3	85.25	86.75	87.32	78.52	78.75	79.46	68.6	70	70.65	3.3	3.3	3.3
Chandrasekharan and Rajagopalan (A9)	8	20	2	58.72	61.8	62.54	81.97	81.35	80.98	79.43	80.05	80.14	1.4	2.4	1.3
Mosier and Taube (A10)	10	10	3	75	76.76	76.68	85.79	89.74	86.33	61.81	65.74	68.6	2.4	2.3	2.4
Chan and Milner (A11)	10	15	3	92	92.69	93.66	86.37	86.48	86.99	50.59	65.32	76.54	0.8	0.7	0.8
Askin and Subramanian Stanfel (A12)	14	24	5	71.62	72.27	77.48	56.33	56	56.35	36.67	36.24	36.43	0.7	0.6	0.7
Stanfel (A13)	14	24	5	72.86	74.59	76.58	57.98	57.99	57.84	75.58	75	76.32	18.8	18.8	18.8
McCormick and Schweitze (A14)	16	24	6	52.33	58.97	60.24	69	70.36	71.58	76	76.06	76.74	12.5	12.5	12.3
Srinivasan et al. (A15)	16	30	4	67.83	68.2	69.87	67.44	67.53	68.36	59.9	60.05	60.35	6.6	6.5	6
King (A16)	16	43	5	57.33	58.87	59.63	62.69	62.74	63.55	37.58	38.74	38.41	4.3	4.2	1.2
Carrie (A17)	18	24	6	57.73	61	62.39	68.57	68.81	69.99	47.17	47.96	48.12	2.2	2	2.2
Mosier and Taube (A18)	20	20	5	40.97	41.14	43.74	67.36	67.39	68.31	61.81	62.31	62.33	2.4	2.3	2.4
Kumar et al. (A19)	20	23	5	50.81	51.12	52.47	58.74	58.97	59.36	76.56	76.98	77.12	14.6	14.6	14.6
Carrie (A20)	20	35	4	76.22	77.13	77	91.44	91.5	91.54	89.66	89	89.9	21.3	20	21.3

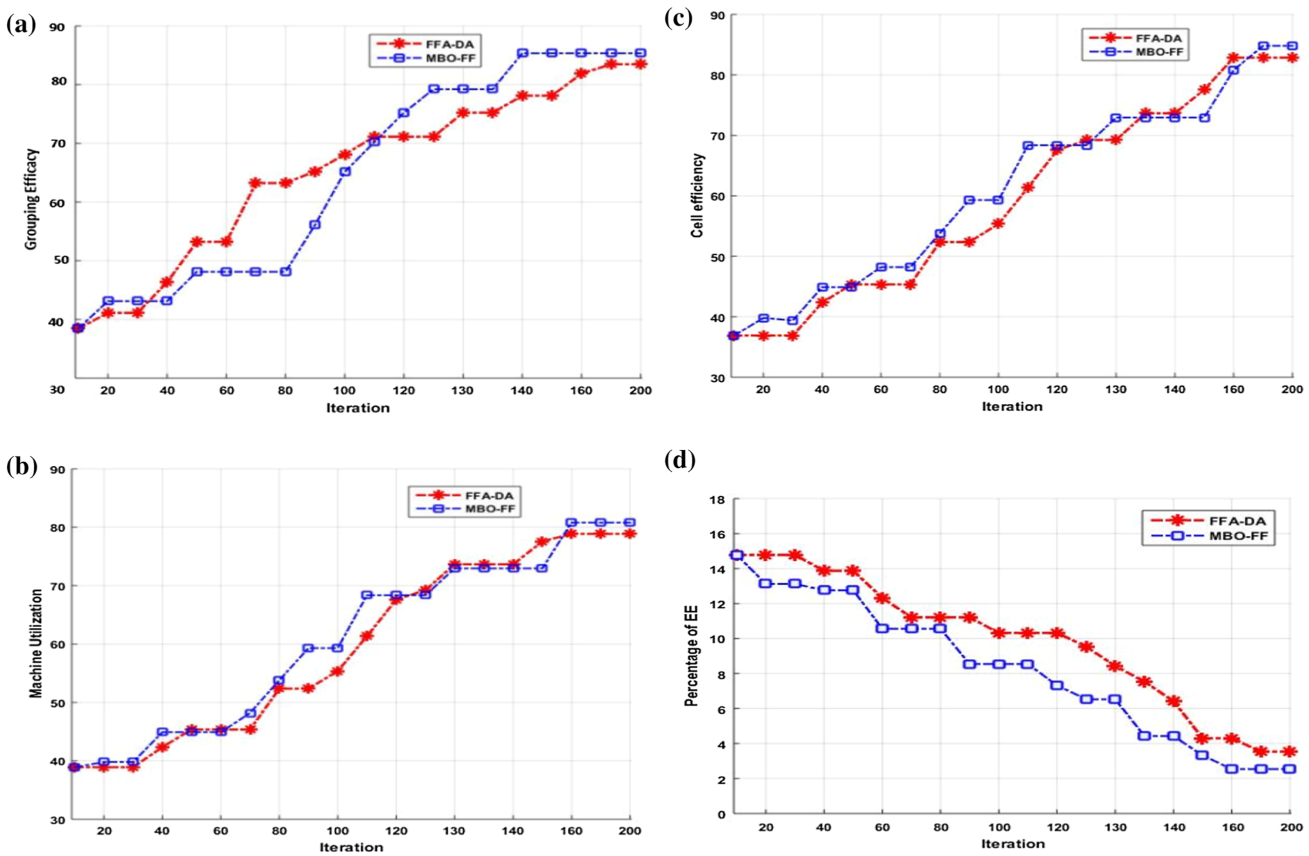

Fig. 2 Performance evaluation of MBO–FF

3 Results and discussion

The presented CFP method for accomplishing the optimal solution is finished by utilizing MATLAB of variant 2016a most recent form and having 8 GB RAM with a 64-bit i5 processor. The performance of the hybrid algorithm MBO–FF is methodically assessed by comparing with some premiere testing techniques. The data are available on http://opt-hub.com/problems/cfphub.

3.1 Performance evaluation

Table 2 depicts the relationship between performance measures of the presented method with few methodologies with computational results. Here, the performances of CFP for twenty benchmark problems are analyzed and are named as A1, A2 … up to A20. In this table, M signifies the machines; P identifies parts and C indicates cell.

The GE, CE, MU and percentage of EE are compared with every problem. The evaluation of the proposed MBO–FF is compared with the existing techniques such as dragonfly-fruit fly algorithm (DF-FFA). The MBO–FF attains optimal value, and it reaches the global optimum solution based on increasing the efficiency, efficacy and machine utilization and reducing the exceptional elements. The potential of the presented method MBO–FF is evaluated on twenty different benchmark test problems that taken from the studies.

For every problem source number of machines, parts, cells, grouping efficacy, cell efficiency, machine utilization and percentage of exceptional elements are showed. In addition, this table reported the computational period and the good response to all problems of the presented method.

The result of grouping efficacy acquired through the MBO–FF shows superior as the top result that presented in the literature. The acquired result is superior to that of the entire 20 methods. Thus the presented technique achieves best to the entire methods. Cell efficiency of the solutions obtained by the MBO–FF is superior to the 17 methods out of 20 methods. Therefore, the proposed method performs well. The performance on machine utilization attained by the MBO–FF is shown improvement in 18 methods out of 20 techniques. The percentage of exceptional elements by the proposed MBO–FF model is outperforms on 7 methods and equivalent to the remaining 13 problems that are taken from the 20 techniques.

Based on the performance measures such as grouping efficacy, cell efficiency, machine utilization and percentage

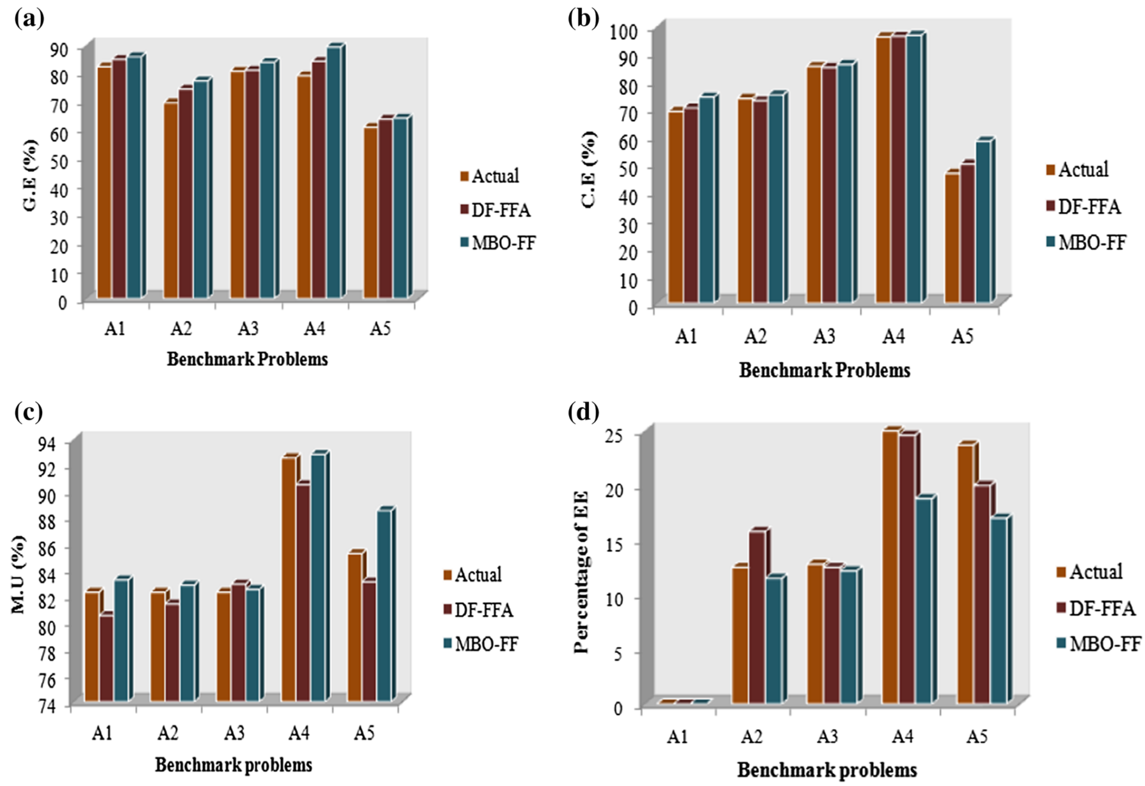

Fig. 3 Comparison of **a** GE, **b** CE, **c** MU and **d** percentage of EE analysis

of exceptional elements, the MBO–FF shows best performances.

Figure 2 shows the convergence graph representation of all the performance parameters compared with different techniques. The GE, MU, CE and percentage of EE are attained for varying iterations. It clearly denotes that the increasing iterations will improve the optimal solution. That means for large-sized problems the result can be confirmed optimal. Comparing the results of different techniques is a difficult task, but the convergence graph illustrates that the optimal solution achieved in MBO–FF than DF-FFA.

3.2 Comparison evaluation

The comparative analysis of performance parameters based on the five sample benchmark problems is given in Fig. 3 such as King (A1), Waghodekar and Sahu (A2), Seifoddini (A3), Kusiak and Cho (A4) and Kusiak and Chow (A5), DF-FFA and the proposed MBO–FF. Here, actual value refers to the experimental values of the above-mentioned existing techniques.

The grouping efficacy for MBO–FF values of A1-85.96, A2-77.45, A3-83.95, A4-89.45 and A5-64.12 is greater than the actual values of A1-82.3, A2-69.5, A3-80.85, A4-79.17 and A5-60.87. The benchmark problem works under the basis of cell forming of particular parts working in machines. On cell efficiency and machine utilization, the proposed algorithm MBO–FF scores maximum performance as given in Fig. 3.

Percentage of exceptional elements for MBO–FF values of A1-0, A2-12.5, A3-12.5, A4-24.6 and A5-23 are the minimum of the actual values of A1-0, A2-12.5, A3-12.5, A4-25 and A5-23.7.

This study concludes that MU, GE, CE achieve maximum value in proposed model, i.e., maximum GE reaches 93.66%, CE as 91.54%, MU as 92.85%, and minimum in the percentage of EE as 0 and 0.7. The proposed model achieves an optimal result in CFP.

4 Conclusion

In this investigation, a hybridization model MBO–FF method for solving CFP is presented and has maximization of GE, CE, and MU also minimizing the percentage of exceptional elements as aim. The MBO–FF algorithm is proficient to tackle the CFP and got the optimal solution on entire benchmark problems based on the comparison and assessment that done on performance measures. The performance of the presented methodology is compared with 20 problems taken from the continually living techniques. The superiority of the MBO–FF technique with other methods indicates that the methodology provides best outcome on CFP. Computational outcomes played out that optimal fitness function accomplished in the proposed model when contrasted with experimental algorithms and dragon fly-fruit fly algorithm. The improvement and newness of this work in association with the current endeavor are:

- Preparing a mathematical representation for the CFP and evaluating the attained result with the continually living techniques.
- Computational results of the proposed model produce superior quality outcomes.
- Providing a monarch butterfly optimization with firefly for the solutions of large-sized CFP.
- Comparing the functions of presented methodology with the 20 existing methods.
- Validating such meta-heuristic technique by providing solution to the real-sized problems using cellular manufacturing models is the future research.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Haman and animal rights Animals and humans are not involved in this research work.

References

Arkat J, Abdollahzadeh H, Ghahve H (2012) A new branch and bound algorithm for cell formation problem. Appl Math Model 36(10):5091–5100

Arkat J, Hosseini L, Farahani MH (2011) Minimization of exceptional elements and voids in the cell formation problem using a multi-objective genetic algorithm. Expert Syst Appl 38(8):9597–9602

Boctor FF (1991) A linear formulation of the machine part cell formation problem. Int J Prod Res 29(2):343–356

Burbidge JL (1971) Production flow analysis. Prod Eng 50(4.5):139–152

Buruk Sahin Y, Alpay S (2016) A metaheuristic approach for a cubic cell formation problem. Expert Syst Appl 65:40–51

Bychkov I, Batsyn M (2018) An efficient exact model for the cell formation problem with a variable number of production cells. Comput Oper Res 91:112–120

Car Z, Mikac T (2006) Evolutionary approach for solving cell-formation problem in cell manufacturing. Adv Eng Info 20(3):227–232

Chung SH, Wu TH, Chang CC (2011) An efficient tabu search algorithm to the cell formation problem with alternative routings and machine reliability considerations. Comput Ind Eng 60(1):7–15

Dalfard VM (2013) New mathematical model for problem of dynamic cell formation based on number and average length of intra and intercellular movements. Appl Math Model 37(4):1884–1896

Danilovic M, Ilic O (2019) A novel hybrid algorithm for manufacturing cell formation problem. Expert Syst Appl 135:327–350

Elbenani B, Ferland JA, Bellemare J (2012) Genetic algorithm and large neighborhood search to solve the cell formation problem. Expert Syst Appl 39(3):2408–2414

Feng H, Da W, Xi L, Pan E, Xia T (2017) Solving the integrated cell formation and worker assignment problem using particle swarm optimization and linear programming. Comput Ind Eng 110:126–137

Feng H, Xi L, Xia T, Pan E (2018) Concurrent cell formation and layout design based on hybrid approaches. Appl Soft Comput 66:346–359

Hazarika M (2018) Machine cell formation with alternative routings based on genetic algorithm. Proced Comput Sci 133:357–367

Hazarika M, Laha D (2017) Application of genetic algorithm in generalized machine cell formation problem. In: International conference on energy, communication, data analytics and soft computing (ICECDS-2017), pp 1855–1860

Hazarika M, Laha D (2018) Genetic algorithm approach for machine cell formation with alternative routings. Mater Today Proc 5:1766–1775

Imran M, Kang C, Lee YH, Jahanzaib M, Aziz H (2017) Cell formation in a cellular manufacturing system using simulation integrated hybrid genetic algorithm. Comput Ind Eng 105:123–135

Karoum B, Noussaima El Khattabi N, Elbenani B, El Imrani AA (2016) An efficient artificial immune system algorithm for the cell formation problem. Comput Methods Sci Eng 16(4):733–744. https://doi.org/10.3233/jcm-160687

Kong T, Seong K, Song K, Lee K (2018) Two-mode modularity clustering of parts and activities for cell formation problems. Comput Oper Res 100:77–88

Laha D, Hazarika M (2017) A heuristic approach based on euclidean distance matrix for the machine-part cell formation problem. Mater Today Proc 4(2):1442–1451

Lee K, Ahn Kwang-Il (2013) GT efficacy: a performance measure for cell formation with sequence data. Int J Prod Res 51(20):6070–6081

Li X, Baki MF, Aneja YP (2010) An ant colony optimization metaheuristic for machine-part cell formation problems. Comput Oper Res 37(12):2071–2081

Mahdavi I, Teymourian E, Baher NT, Kayvanfar V (2013) An integrated model for solving cell formation and cell layout problem simultaneously considering new situations. J Manuf Syst 32(4):655–663

Manimaran A, Nagaraj G, Venkumar P, Ganesamoorthy R (2014) Manufacturing cell formation considering various production factors using modified ART1 network. Acad J Manuf Eng 12:54–61

Mehdizadeh E, Daei Niaki SV, Rahimi V (2016) A vibration damping optimization algorithm for solving a new multi-objective dynamic cell formation problem with workers training. Comput Ind Eng 101:35–52

Mehdizadeh E, Rahimi V (2016) An integrated mathematical model for solving dynamic cell formation problem considering operator assignment and inter/intracell layouts. Appl Soft Comput 42:325–341

Mitranov SP (1959) The scientific principles of group technology. National Lending Library, London

Mohammadi M, Forghani K (2017) A hybrid method based on genetic algorithm and dynamic programming for solving a bi-objective cell formation problem considering alternative process routings and machine duplication. Appl Soft Comput 53:97–110

Mukattash A, Dahmani N, Al-Bashir Adnan, Qamar Ahmad (2018) Comprehensive grouping efficacy: a new measure for evaluating block-diagonal forms in group technology. Int J Ind Eng Comput 9:155–172

Nalluri MSR, Kannan K, Gao XZ, Roy DS (2019) An efficient hybrid meta-heuristic approach for cell formation problem. Soft Comput. https://doi.org/10.1007/s00500019037987

Niakan F, Baboli A, Moyaux T, Genoulaz VB (2016) A bi-objective model in sustainable dynamic cell formation problem with skill-based worker assignment. J Manuf Syst 38:46–62

Pailla A, Trindade AR, Parada V, Ochi LS (2010) A numerical comparison between simulated annealing and evolutionary approaches to the cell formation problem. Expert Syst Appl 37(7):5476–5483

Paydar MM, Saidi-Mehrabad M (2013) A hybrid genetic-variable neighborhood search algorithm for the cell formation problem based on grouping efficacy. Comput Oper Res 40(4):980–990

Solimanpur M, Saeedi S, Mahdavi I (2010) Solving cell formation problem in cellular manufacturing using ant-colony-based optimization. Int J Adv Manuf Technol 50:9–12

Shakya Subarna (2020) Intelligent and adaptive multi-objective optimization in WANET using bio inspired algorithms. J Soft Comput Parad 02(1):13–23

Thanh LT, Ferland JA, Elbenani B, Thuc ND, Nguyen VH (2016) A computational study of hybrid approaches of meta-heuristic algorithms for the cell formation problem. J Oper Res Soc 67(1):20–36. https://doi.org/10.1057/jors.2015.46

Wang GG, Deb S, Cui Z (2015) Monarch butterfly optimization. Neural Comput Appl 31:1–20

Wang H, Wang W, Zhou X, Sun H, Zhao J, Yu X, Cui Z (2017) Firefly algorithm with neighborhood attraction. J Inf Sci 382–383:374–387

Wu TH, Chung SH, Chang CC (2010) A water flow-like algorithm for manufacturing cell formation problems. Eur J Oper Res 205(2):346–360

Yang XS (2010) Nature-inspired metaheuristic algorithms, 2nd edn. Luniver Press, pp 81–96

Yelghi A, Kose C (2018) A modified firefly algorithm for global minimum optimization. Appl Soft Comput 62:29–44

Yurtkuran A, Emel E (2016) A discrete artificial bee colony algorithm for single machine scheduling problems. Int J Prod Res 54(22):6860–6878. https://doi.org/10.1080/00207543.2016.1185550

Zohrevand AM, Rafiei H, Zohrevand AH (2016) Multi-objective dynamic cell formation problem: a stochastic programming approach. Comput Ind Eng 98:323–332