Available online at www.sciencedirect.com

ScienceDirect

Materials Today: Proceedings 5 (2018) 1766–1775

materialstoday: PROCEEDINGS

www.materialstoday.com/proceedings

Genetic Algorithm approach for Machine Cell Formation with Alternative Routings

Manash Hazarika*, Dipak Laha

Department of Mechanical Engineering, Jadavpur University, Kolkata-700032, India

Abstract

In cellular manufacturing systems, study and optimization of machine cell formation (CF) problems have long drawn attention of researchers. Optimum CF results in reduction of overall processing time, material handling cost, labor cost, in-process inventories and number of set-ups requirements. Also, it simplifies process plans and improves product quality. Since the modern manufacturing machines in a cell are generally multifunctional, the processing of parts are performed following alternative processing routes. The objective of study is to determine the optimal alternative processing route in order to minimize the total intercellular movements of parts in CF problems. Intercellular movements of parts depend on many factors such as parts volume including batch size and number of batches, sequence of processes and routes of production. In this paper, a genetic algorithm heuristic is presented for the CF problem with multiple process routes, sequence of processes and parts volume. Computational experimentation was performed with five benchmark problems. The results demonstrate that the performance of the proposed approach in terms of total intercellular movements of parts and best route selection are either better or competitive with the well-known existing methods.

Selection and Peer-review under responsibility of International Conference on Processing of Materials, Minerals and Energy (July 29th – 30th) 2016, Ongole, Andhra Pradesh, India.

Keywords: *Cellular manufacturing system; Genetic algorithm; Alternative process routings; Intercellular movement of parts; Best route selection*

1. Introduction

In cellular manufacturing systems (CMS), the application of group technology (GT) identifies part families and machine cells, which simplifies the layout design, product design and products flow processes. The application of GT reduces material time, cost, labor requirement, in-process inventories, processing times and number of set-ups [1]. It also, increases productivity, product quality, customers' satisfaction and better management [2-3].

* Corresponding author. Tel.: +91-943-540-3539
E-mail address: memhazarika12@rediffmail.com

Selection and Peer-review under responsibility of International Conference on Processing of Materials, Minerals and Energy (July 29th – 30th) 2016, Ongole, Andhra Pradesh, India.

GT in CMS helps to minimize number of intercellular movements of parts [4]. For grouping machines into machine cells, dissimilar machines are grouped into a machine cell such that processing operations can be accomplished with minimum number of intercellular movements, resulting in reduced overall cost.

In the literature survey, it is seen that most of the cell formation techniques have been applied for single process route, equal production volume and without any sequence of process [5-7]. But in advanced CMSs or in batch-type production systems, a part can be processed following multiple process routings, unequal production volume of parts [8].

In this paper, a genetic algorithm approach is proposed to solve the CF problem with alternative routings, operation sequence of the parts and uneven part volume. Section 2 deals a brief literature review on CF techniques. Section 3 presents the problem formulation of CF problems and problem formulation for alternative routing, operation sequence of the parts and uneven part volume. In Section 4, a genetic algorithm heuristic is presented to solve CF problems. The computational results are presented in Section 5 and finally, Section 6 concludes.

2. Literature review

In literature, most of the CF problems have been studied considering single process routing and unique volume parts. But now-a-days, manufacturing equipment are multifunctional and therefore, production process can be accomplished by more than one process routes. Alternative process routes provide better configuration of cell design and flexibility in cell design [9]. It also reduces intercellular material movements of parts [10] and capital investment in machines providing more independent cells and increase machine utilization [11].

Kusiak and Cho [12], Chow and Hawaleshka [13] recommended similarity coefficient methods for cell formation in alternative routing of parts problems. Chow and Hawaleshka [13] considered part volume also in their model. Gupta [14] extended Jaccard's similarity coefficient integration with alternative routes, operation sequences and uneven part volumes and used complete linkage clustering (CLINK) techniques.

Wafik and Kim [15] used Jaccard's similarity coefficient for cell formation, integrating with alternative routes only. Yin and Yasuda [16] extended the Wafik and Kim [15] used Jaccard's similarity coefficient by integration of process sequence, part volume and processing time. Farouq [17] proposed another modified the Jaccard's similarity coefficient integrated with process sequence and part volume. Hazarika and Laha [18] used Euclidean distances matrix to find correlations of machines for cell formation; integration of part volume, process sequence and process routes problems. They applied SLINK clustering for minimum Euclidean distance.

Other heuristic techniques for alternative routing, uneven part volumes and sequential CF problems include simulated annealing [4, 19], fuzzy approach [20], tabu search [21] and branch and bond [22].

3. Problem formulation

The machine-part cell formation problem is generally formulated as '$m \times p$' incidence matrix (where m is the number of machines and p is the number of parts) as shown in Table 1. Here, columns and rows stand for machines and parts respectively. Elements of the matrix represent operation indices of parts (no operation is performed in empty place). For example, in Table 1, $a_{2,1_1} = empty\ (or\ 0)$, i.e., no operation is performed in the machine M2 for the part P1 considering the first route; $a_{4,5_1} = 2$, second operation is performed for the part P5 considering the first route on machine M4 and so on.

Table 1. The cell formation problem with 5 Machines and 7 parts

Parts	Part route	Machines				
		M1	M2	M3	M4	M5
P1	1	2			1	
	2	1		2	3	
P2	1	1			2	
P3	1		2			1
	2		1	3		2
P4	1	2	1			3
	2		1	3		2
P5	1	1			2	
	2	1		2	3	
P6	1		1			2
P7	1		2			1

Indices and parameters:

i Index for machines
j Index for parts
r Index for routes
R_j Total number of routes of part j
k Index for cells
C Total number of cells
M Total number of machines
P Total number of parts
D_j Demand rate of part j
L_k Minimum number of machines in cell k
U_k Maximum number of machines in cell k

Decision variables:

x_{ik}=1 if machine i is assigned to cell k; otherwise 0
$\sigma_{j(kk')}$=1 if successive operations of part j is done on cells $k$and k'; otherwise 0

Objectives of problems

The objective of the proposed method is to minimize the intercellular movements of each part j (I_j). As a result, total number of intercellular movements (Z) for the entire production system will be minimized. I_j and Z can be formulated as

$$I_j = \sum_{r=1}^{R_j} \sum_{i=1}^{M} \sum_{k=1}^{C} D_j \sigma_{j(kk')}(1 - x_{ik}) \quad (1)$$

$$Z = \sum_{j=1}^{P} I_j \quad (2)$$

Constraints:

1. Assignment of one machine to only one cell

$$\sum_{k=1}^{C} x_{ik} = 1 \ \forall i \quad (3)$$

2. Lower bound and upper bound of a cell size

$$L_k \leq \sum_{i=1}^{M} x_{ik} \leq U_k \ \forall k \quad (4)$$

4. Genetic Algorithm approach

Genetic algorithm proposed by Holland (1975) is a stochastic search and optimization technique, based on mechanism of natural selection and natural genetics. GA [23] starts with an initial set of random solutions called population and each individual in the population is called a chromosome, representing a solution of the objective function. Then, members of the population are selected by an evaluation function called as fitness function according to its objective function or best neighborhood solution. For the next iteration, a new set population is generated from the selected best neighborhood solutions using crossover and mutation operators. Next, the process is repeated for a certain number of iterations known as stopping criterion. The steps of GA are as follows:

Step 1. Generation of initial random populations
Step 2. Evaluation of fitness of each individual population
Step 3. Selection or sorting populations
Step 4. Generation of new set of population from best individual by crossover
Step 5. Mutation
Step 6. Obtaining the best solution (put the number of iteration to stop the process).

4.1. Generation of initial population

Generation of a set of initial random population is the starting point of the evolutionary process. In this study, each individual of the initial population is formed using integers from 1 to the number of maximum possible groups (depending upon the maximum machine numbers in a machine cell). In the chromosome, integers indicate that which machine is assigned to which machine cell. For a problem having 5 machines and 7 parts as shown in Table 1, maximum cell size is, say, three machines. Therefore, total cell numbers will be $5/3 = 2$ (rounded next integer).

Fig. 1 shows a candidate solution or a randomly generated chromosome for two groups or cells. Machine M2, M4 and M5 are grouped in cell 1 and machines M1 and M3 are grouped in cell 2.

M1	M2	M3	M4	M5
2	1	2	1	1

Fig. 1. Randomly generated chromosome for 5 machines and 7 parts problem

Evaluation of fitness of each individual in the population is a criterion of the selection process for measuring the goodness of the candidate solutions with respect to objective functions. The larger the fitness is higher the probability of survival in the next generation. The fitness value of each individual in the population in the proposed algorithm is intercellular movements of parts (function for minimization).

4.2. Selection or sorting population

Selection is the procedure through which a new population (called offspring) is formed by choosing individual population with greater fitness values (called parent chromosome) and ignoring the individuals with smaller fattiness values. The commonly used techniques are roulette-wheel-selection, tournament and 50 % truncation.

4.3. Generation of new set of population from best individual by crossover

Crossover is analogous to biological reproduction. It is a process of taking more than one parent chromosome and producing offspring from them. The most useful crossover techniques are uniform crossover, one-point crossover, two-point crossover and single point preservation. In this GA approach, we use one point crossover.

For the above mentioned problem, two selected chromosomes, say, parent 1 and parent 2 use crossover operator at a randomly selected location and they generate another two new chromosomes, say, offspring 1 and offspring 2. Fig. 2 shows two parent chromosomes and their crossover points and Fig. 3 shows two offspring (offspring 1 and offspring 2), generated after the crossover of parent 1 and parent 2.

Parent 1	2	1	2	1	1
Parent 2	2	2	1	1	2

Crossover point

Fig. 2. Two parent chromosomes and their crossover points

Offspring 1	2	1	2	1	2
Offspring 2	2	2	1	1	1

Fig. 3. Two offspring generated after the crossover of parent 1 and parent 2 of Fig. 2

4.4. Mutation

Mutation is an operator used to maintain genetic diversity from one generation of a population to the next. It is also analogous to biological mutation. It alters one or more gene values (or bit value) by a random change with a probability equal to the mutation rate in a chromosome from its initial state. It does not guarantee that mutation always gives a positive direction towards the optimal solution.

For mutation, consider a chromosome as shown in Fig. 4. Fig. 5 shows the chromosome after mutation. Here mutation point is 4^{th} gene.

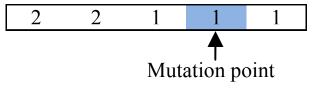

Fig.4. A chromosome with mutation point (before mutation)

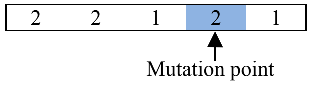

Fig.5. Changed form of the previous chromosome (after mutation)

4.5. Obtaining the best solution

To obtain the best and feasible solution, repeat the above process for a certain number of iterations. The number of iterations depends upon the size of problem.

4.6. Algorithm parameters

The proposed algorithm starts with generation of initial population. After the generation of initial population, loop starts and during execution of the loop, the algorithm first selects the feasible solutions from initial population at selection rate. The crossover and mutation processes are also executed within the loop sequentially. Offspring are generated by single point crossover operator from the selected population. For mutation, we use single point mutation operator.

The proposed algorithm searches better solutions (minimizing intercellular movement) and ignore inferior solutions (or chromosome) while running each iteration. So, in each iteration, a new solution is created and better solution is selected. To run the algorithm, following parameters are considered and these have a crucial role on optimal solutions. The parameters are

a) *Maximum number of cells*
b) *Population size*: 20
c) *Number of generations*: $2 \times P \times M$
d) *Crossover operator*: single-point crossover
e) *Selection*: Rank-based roulette wheel selection
f) *Probability of mutation*: 0.01 to 0.015
g) *Number of selected chromosomes*: 2
h) *Number of trials*: 10

5. Computational results

Five numbers of problems (collected from literature) are solved to evaluate the performance of the proposed algorithm. The sources of benchmark problems and their sizes are shown in Table 2. The proposed algorithms were developed in MATLAB R2010a and run on a PC of Core i5, 3.30 GHz speed with 8.00 GB of RAM.

Table 2. Sources of tested problems and their sizes

Problem No.	Problem source	Size
1.	Raja and Anbumalar [24]	5×7
2.	Yin and Yasuda [16]	5×7
3.	Yin and Yasuda [16]	6×8
4.	Nair and Narendran [25]	8×20
5.	Yin and Yasuda [16]	12×12

Problem 1. 5 Machines and 7 parts

This is single route, unit volume part (and single batch) and sequential CF problem. The problem is represented by Table 3.

Table 3. 5 Machines and 7 parts, problem 1

Parts	Machines				
	M1	M2	M3	M4	M5
P1	1		2	3	
P2	2		1	3	
P3	1	2			3
P4	1	2	3		
P5		1			2
P6	3		1	2	
P7		1			2

Table 4 shows the solutions of cell formation by CLASSPAVI and the proposed approach.

Table 4. Solutions using different approaches for problem 1

Approach	Reference	Machine cells		Number of intercellular moves
		I	II	
CLASSPAVI	Raja and Anbumalar [24]	M1,M3,M4	M2,M5	3
GA		M1,M3,M4	M2,M5	3

The solution of the proposed approach is given as 2 machine cells and 3 intercellular moves. This solution is same as reported by Raja and Anbumalar [24].

Problem 2. 5 Machines and 7 parts

The problem is represented by Table 5. This is the multiple routes, part volume and sequential CF problem.

Table 5. 5 Machines and 7 parts, problem 2

Parts	Part volume	Part route	Machines				
			M1	M2	M3	M4	M5
P1	50	1	2			1	
		2	1		2	3	
P2	5	1	1			2	
P3	20	1		2			1
		2		1	3		2
P4	30	1	2	1			3
		2		1	3		2
P5	40	1	1			2	
		2	1		2	3	
P6	10	1		1			2
P7	35	1		2			1

Table 6. Solutions using different approaches for problem 2

Approach	Reference	Machine cells		Number of intercellular moves
		I	II	
Similarity coefficient method	Yin and Yasuda [16]	M2,M3,M5	M1,M4	0
Similarity coefficient method (CLINK)	Gupta [14]	M1,M4,M3	M2,M5	30
GA		M2,M3,M5	M1,M4	0

The proposed procedure produced 2 machine cells and zero intercellular moves. This is the same number of intercellular moves reported by Yin and Yasuda [16]. A total of 30 intercellular moves are resulted by Gupta [14]. The best routes of proposed approach is P1(1), P2(1), P3(2), P4(2), P5(1), P6(1) and P7(1). Table 6 shows the solutions of problem 2.

Problem 3. 6 Machines and 8 parts

The problem is represented by Table 7. This is the multiple routes, part volume (and single batch) and sequential CF problem.

Table 7. 6 Machines and 8 parts, problem 3

Parts	Part volume	Part route	Machines					
			M1	M2	M3	M4	M5	M6
P1	50	1	1	3		2		
		2		1	2		3	4
		3		2	1		3	4
P2	30	1			1		3	2
P3	20	1			1		2	3
P4	30	1	1			2		
		2	2	1		3		
P5	20	1		3	2		4	1
		2			1			2
P6	10	1	1	2	3			
		2	1	2				3
P7	15	1		3			1	2
		2			3		1	2
		3		1				2
P8	40	1		2		1		

Table 8. Solutions using different approaches for problem 3

Approach	Reference	Machine cells		Number of intercellular moves
		I	II	
Similarity coefficient method (CLINK)	Gupta [14]	M2,M3,M5,M6	M1,M4	50
Similarity coefficient method	Yin and Yasuda [16]	M1,M2,M4	M3,M5,M6	10
Similarity coefficient method	Alhourani [17]	M1,M2,M4	M3,M5,M6	10
GA		M1,M2,M4	M3,M5,M6	10

A total of 10 intercellular moves are produced by the proposed procedure. This is the same number of intercellular moves as reported by Yin and Yasuda [16] and Alhourani [17]. A total of 50 intercellular moves are generated by Gupta [14]. Best routes produced by proposed approach are P1(1), P2(1), P3(1), P4(2), P5(2), P6(1), P7(2) and P8(1). Table 8 shows the solutions of problem 3 by different approach.

Problem 4. 8 Machines and 20 parts

Table 9. 8 Machines and 20 parts for problem 4

Part	Machines							
	M1	M2	M3	M4	M5	M6	M7	M8
P1					2	1		
P2	1		2					
P3	2	1		5			3	4
P4		1		2			3	4
P5					2	1		
P6		1		2	5		3	4
P7		4		2			3	1
P8	1		2					
P9	1		3			2		
P10				2	3	1		
P11	3		2				1	
P12					1	3	2	
P13	1		2					
P14	1	2	3					
P15				1	2			
P16	1		2					
P17	3		1		2			
P18		2		1			4	3
P19	1		2					
P20		2		1		3	4	5

The problem is represented by Table 9. This is the single route, unit volume part (and single batch) and sequential CF problem. Here, maximum permissible number of machines in a cell is given as five.

The proposed procedure produced solutions 2 machine cells and 13 intercellular moves. This is the same number of intercellular moves reported by Alhourani and Seifoddini [26]. Table 10 shows the solutions of problem 4 by different approach.

Table 10. Solutions of problem 4 using different approaches

Approach	Reference	Machine cells			Number of intercellular moves
		I	II	III	
Similarity coefficient method (CLINK)	Nair and Narendran [25]	M1,M3	M5,M6	M2,M4,M7,M8	17
Considering machines as 'points' in multi-dimensional space	George, Rajendran and Ghosh [27]	M1,M3	M5,M6	M2,M4,M7,M8	16
CLASSPAVI	Raja and Anbumalar [24]	M1,M3	M5,M6	M2,M4,M7,M8	16
Similarity coefficient method	Alhourani and Seifoddini [26]	M1,M3,M5	M2,M4,M6,M7,M8		13
GA		M1,M3,M6	M2,M4,M5,M7,M8		13

Problem 5. 12 Machines and 12 parts

The problem is represented by Table 11. This is the multiple routes, unit volume part (and single batch) and sequential CF problem. Here, maximum permissible number of machines in a cell is five.

Total of 12 numbers of intercellular moves are produced by the proposed procedure. This is best result than any other existing algorithms. This is a substantial improvement in the CF problem. Best routes produced by proposed approach are P1(2), P2(3), P3(2), P4(1), P5(1), P6(2), P7(1), P8(1), P9(1), P10(1), P11(1) and P12(1). Table 12 shows solutions of problem 5 by different approach.

Table 11. 12 Machines and 12 parts, problem 5

Part	Routes	Machines											
		M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
P1	1			3		2	1		5			6	4
	2					4	3	5			1	2	
P2	1	4	2		3	5					1		
	2	2		4	1		5				3		
	3		2				3						1
P3	1		3			2			1				4
	2								2				1
P4	1		2		3					1			
	2		1	3				2		4			
P5	1	1	4		3		2		5				
P6	1		3	2		6			5			4	1
	2					3			4		2	1	
P7	1					4		2			1	3	
	2			1	2			4			3		
P8	1		2		3	1							
P9	1		5	4			1	2				3	
	2		1	2			4					3	
P10	1				1	3			2				
P11	1		2	1						4	3		5
P12	1		3				1	2					

Table 12. Solutions using different approaches for problem 5

Approach	Reference	Machine cells			Number of intercellular moves
		I	II	III	
Simul. Annealing	Sofianopoulou [4]	M2,M4,M7,M9,M10	M3,M5,M8,M11,M12	M1,M6	15
Branch and Boud	Spiliopoulos and Sofianopoulou [22]	M1,M2,M4,M7,M10	M3,M5,M6,M8,M11	M9,M12	15
Simul. Annealing	Chen, Cotruvo, and Baek [19]	M4,M5,M7,M8,M10	M2,M3,M6,M11,M12	M1,M 9	17
Tabu Search	Sun, Lin, and Batta [21]	M4,M5,M7,M10,M11	M2,M3,M6,M8,M12	M1,M9	19
Fussy Approach	Chu and Hayya [20]	M1,M2,M4,M7,M9	M3,M6, M10,M11,M12	M5,M8	16
Simul. Annealing	Sofianopoulou [28]	M1,M6,M7,M10,M11	M2,M3,M4,M9,M12	M5,M8	13
Similarity coefficient method	Alhourani [17]	M2,M3,M4,M9,M12	M5,M6,M7,M8,M11	M1,M10	15
Similarity coefficient method	Yin and Yasudas [16]	M2,M3,M4,M12	M5,M6,M7,M8,M11	M1,M9,M10	15
GA		M5,M6,M7,M10,M11	M2,M4,M8,M9,M12	M1,M3	12

6. Conclusions

The objective of the proposed model is to find best route of parts as well as to minimize total number of intercellular movements in the entire system. In this study, an application of genetic algorithm (GA) is presented in machine CF problems. Computational results of proposed algorithm and comparisons with well-known existing methods for 5 benchmark problems are presented in Section 5 and the results reveal that proposed algorithm gives solutions either better than or competitive with the existing algorithms.

References

[1] Ham I., Hitomi K. and Yoshida T. Group Technology Application to Production Management (Boston: Kluwer-Nijhoff) 1985.

[2] Spiliopoulos K and Sofianopoulou S. Manufacturing cell design with alternative routings in generalized group technology: Reducing complexity of solution space. International Journal of Production Research; 2007, 45: 1355-1367.

[3] Hazarika M. and Laha D. Machine-part cell formation for maximum grouping efficacy based on genetic algorithm. 2015 IEEE Workshop on Computational Intelligence: Theories, Applications and Future Directions (WCI); 2015, 1 - 6, DOI: 10.1109/WCI.2015.7495521.

[4] Sofianopoulou S. Application of simulated annealing to a linear model for the formulation of machine cells in group technology. International Journal of Production Research; 1997, 35: 501-512.

[5] James T.L., Brown, E.C. and Keeling, K.B. A hybrid grouping genetic algorithm for the cell formation problem. Computers and Operations Research; 2007, 34: 2059–2079.

[6] Kashan A.H, Karimi, B. and Noktehdan, A. A novel discrete particle swarm optimization algorithm for the manufacturing cell formation problem. Int J Adv Manuf Technol; 2014, 73: 1543–1556.

[7] Laha D. and Hazarika M. A heuristic approach based on Euclidean distance matrix for the machine-part cell formation problem. Material Today: Proceedings; 2016 (in press).

[8] Kusiak A. The generalized group technology concept. International Journal of Production Research; 1987, 25: 561-569.

[9] Saeed J., Ameli M., and Arkat J. Cell Formation with Alternative Process Routings and Machine Reliability Consideration. Int J AdvManufTechnol; 2008, 35: 761–768.

[10] Cao D., Defersha F.M. and Chen M. Grouping Operations in Cellular Manufacturing Considering Alternative Routings and the Impact of Run Length on Product Quality. Computer & Industrial Engineering; 2009, 30: 423-431.

[11] Hwang H. and Ree P. Routes selection for the cell formation problem with alternative part process plans. Computer & Industrial Engineering; 1996, 30: 423-431.

[12] Kusiak A. and Cho M. Similarity coefficient algorithm for solving the group technology problem. International Journal of Production Research; 1992, 30: 2633–2646.

[13] Chow W. S. and Hawaleshka O. An effective algorithm for solving the machine chaining problem in cellular manufacturing. Computers & Industrial Engineering; 1992, 22: 95-100.

[14] Gupta T. Design of manufacturing cells for flexible environment considering alternative routing. International Journal of Production Research; 1993, 31: 1259-1273.

[15] Wafik Y. and Kim S. Multiple criteria clustering algorithm for solving the group technology problem with multiple process routings. Computers & Industrial Engineering; 1997, 32: 207-220.

[16] Yin Y. and Yasuda K. Manufacturing cells design of various production factors. International Journal of Production Research; 2002, 40: 885-906.

[17] Alhourani F. Clustering algorithm for solving group technology problem with multiple process routings. Computer & Industrial Engineering; 2013, 66: 781-790.
[18] Hazarika M. and Laha D. A Heuristic approach for Machine Cell Formation problems with Alternative Routings. Procedia-Computer Science; 2016 (in press).
[19] Chen C.L., Cotruvo N.A. and Baek W. A simulated annealing solution to the cell formation problem. International Journal of Production Research; 1995, 33: 2601–2614.
[20] Chu C. and Hayya J.C. A fuzzy clustering approach to manufacturing cell formation. International Journal of Production Research; 1991, 29: 1475–1487.
[21] Sun D., Lin L. and Batta R. Cell formation using tabu search. Computers & Industrial Engineering; 1995, 28: 485–494.
[22] Spiliopoulos K. and Sofianopoulou S. An optimal tree search method for the manufacturing systems cell formation problem. European Journal of Operations Research; 1998, 105: 537–551.
[23] Laha D. and Mandal P. Improved heuristically guided genetic algorithm for the flow shop scheduling problem. Int. J. Services and Operations Management; 2007, 3: 316-331.
[24] Raja S. and Anbumalar V. An effective methodology for cell formation and intra‑cell machine layout design in cellular manufacturing system using parts visit data and operation sequence data. The Brazilian Society of Mechanical Sciences and Engineering; 2016, 38: 869–882.
[25] Nair G.J. and Narendran T.T. CASE: A clustering algorithm for cell formation with sequence data. International Journal of Production Research; 1998, 36: 157-179.
[26] Alhourani F. and Seifoddini H. Machine cell formation for production management in cellular manufacturing systems. International Journal of Production Research; 2007, 45: 913-934.
[27] George A.P., Rajendran C. and Ghosh S. An analytical-iterative clustering algorithm for cell formation in cellular manufacturing systems with ordinal-level and ratio-level data. Int J AdvManufTechnol; 2003, 22: 125–133.
[28] Sofianopoulou S. Manufacturing cells design with alternative process plans and/or replicate machines. International Journal of Production Research; 1999, 37: 707- 720.