

A comparative case study of e-learning tools for manufacturing cell formation

Oliver ILIĆ* and Biljana CVETIĆ*

*University of Belgrade, Faculty of Management Sciences

Jove Ilića 154, 11040 Belgrade, Serbia

E-mail: ioliver@fon.bg.ac.rs

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Abstract

Manufacturing cell formation is the first and foremost issue in designing cellular manufacturing system. The main objective in the cell formation problem is to cluster machines into machine cells and parts into part families so that the minimum of both intercell and intracell flows will be achieved. The purpose of this paper is to enhance solving the cell formation problem with the help of e-Learning tools in the educational environment. An efficient method and supporting tool for solving manufacturing cell formation problem are proposed. Therefore, the original similarity coefficient-based heuristic (SCBH) algorithm for solving the cell formation problem is presented. It incorporates the pure combinatorial optimization models for maximization the sum of similarity coefficients between machine/part pairs. Additionally, the LAYOUT tool is offered as a supporting tool for the SCBH. A comparative case study is conducted to validate the performance of the proposed SCBH algorithm and LAYOUT tool, and the results showed that their implementation is significant for reducing both intercell and intracell flows. The results of this work can be helpful for future or existing practitioners to become the real-world cell formation problem solvers.

Key words: Cell formation problem, Similarity coefficient, Heuristic algorithm, Cluster analysis, E-Learning tool, Comparative case study

1. Introduction

Cellular manufacturing is one of the major applications of *group technology* (GT) in manufacturing (Jayakumar and Raju, 2011; Paydar, et al., 2011) in which all or a portion of a firm's manufacturing system has been converted into cells. The design of a *cellular manufacturing system* (CMS) includes the following four stages: (1) *cell formation problem* (CFP); (2) group layout; (3) group scheduling; and (4) resource allocation; among them the CFP is the most important for prosperity of the whole system (Chattopadhyay, et al., 2013). CFP can be defined as grouping the parts into part families and the machines into machine cells and then assigns the part families into corresponding machine cells (Liu, et al., 2010; Paydar, et al., 2011). The parts are similar either because of geometric design features or because similar processing requirements, such as operations, tolerances, and machine tool capacities (John, et al., 2011; Chattopadhyay, et al., 2013). Generally, research suggests that is the best to use the processing routes for collection of parts (John, et al., 2011). On the other side, formation of machine cell supposes grouping machines into a manufacturing unit capable of processing a part family for its entire set of operations (Seifoddini and Djassemi, 1995). Solving the CFP is complex for real life problems because of their nature. CFP is known as an NP-hard problem, due to its computational complexity. Extended classifications and reviews of the various approaches adopted/developed for solving the CFP are available in the literature (Singh, 1993; Selim, et al., 1998; Papaioannou and Wilson, 2010; Chattopadhyay, et al., 2013).

Four connected challenges can be recognized in relation with the CFP: (1) solving the CFP in real-life manufacturing environment; (2) developing new successful methods for solving the CFP; (3) developing new methods for integrating the CFP, group layout, group scheduling and resource allocation; and (4) enhancing teaching methods and tools in the field of CFP. The imbalance between theoretical and applied research, highlighted back in 1997 by

Reisman, et al. and continued until nowadays, should be mitigated, and the teaching and training in this field should be improved in that way that the future practitioners became the real-world CFP solvers. This paper is just an attempt to contribute to solving the CFP in the educational environment.

The main contributions of this paper are: (1) the establishment of the *similarity coefficient-based heuristic* (SCBH) algorithm for solving the CFP; and (2) the comparison of results obtained by proposed SCBH algorithm and LAYOUT tool with Irani, et al. (2000) version of PFAST (Production Flow Analysis and Simplification Toolkit), Irani and Huang (2005) version of PFAST and Irani (2012) version of PFAST through a case study.

The originality of SCBH comes from the use of pure combinatorial optimization models, first for maximization the sum of similarity coefficients between machine pairs, and then for maximization the sum of similarity coefficients between part pairs. These models are involved in evaluation of goodness of heuristic solutions. It leads to the minimization of both intercell and intracell flows. In the previous years, more attention has been given to models that tend to maximize only one criterion of these two. For example, for maximization of the sum of similarity coefficients between part pairs Kusiak (1987) suggested the use of a linear integer-programming model, while Won and Kim (1994) proposed a simple linear programming model.

The remainder of the paper is organized as follows. In the next section, a brief presentation of similarity coefficient-based approaches is given. In Section 3, the SCBH algorithm for solving the CFP is presented. Also, the LAYOUT tool is suggested as a supporting tool of SCBH algorithm for generation near-optimal permutations of machines and parts. In Section 4, the advantages of using the SCBH algorithm and LAYOUT tool are demonstrated through a comparative case study. Conclusion and directions for future research are presented in the last section.

2. Similarity coefficient methods

Similarity coefficient-based approaches are distinguished from the other approaches by their flexibility in incorporating various types of manufacturing data into the CFP (Yin and Yasuda, 2006; Garbie, et al., 2008; Yin, et al., 2011) and suitability for development software tools. Similarity coefficient represents a measure of similarity between machines/parts which is used to group them together. The value of similarity coefficient usually ranges from 0 to 1. If this value is equal to 0, there is no similarity between two machines/parts. Conversely, as this value is nearly to 1, the two machines/parts are more similar. A number of similarity coefficients have been analyzed and proposed in literature (Yin and Yasuda, 2005; Yin and Yasuda, 2006). Among various similarity coefficients, Jaccard similarity coefficient was the most used in the literature and the most stable similarity coefficient (Yin and Yasuda, 2005).

Oliveira, et al. (2008) reviewed 8 different similarity coefficients. Four of them are Jaccardian and the rest are non-Jaccardian coefficients. They concluded that the one similarity coefficient can be chosen over others according to the preference of the cell formation. For example, if the fewest intercell flows is the main focus, McAuley's Jaccardian coefficient should be used. Also, McAuley's Jaccardian coefficient is preferred when the strength of clustering is the key factor of judging the quality of a solution. Because of these reasons, in this paper we employ the most popular and the most stable (Yin and Yasuda, 2005) similarity coefficient – Jaccardian coefficient.

Similarity coefficient-based methods 'rely on similarity measures in conjunction with clustering algorithms' (Yin, et al., 2011, p. 331). They usually follow the following procedure. First, construct the initial machine-part matrix in a form of a binary matrix whose rows are machines and columns stand for parts. The entry "1" in the matrix means that machine is needed to process part and otherwise, entry "0" means that machine is not needed to process that part. Second, construct the machine and/or part similarity matrices based on previously selected similarity coefficients. Third, use a clustering algorithm to process the values from machine and/or part similarity matrices and by help of dendrograms identify the machine cells and part families. Finally, select the performance measures and evaluate the goodness of solution.

Similarity coefficient-based approaches have been widely used since McAuley (1972) for the first time combined the Jaccard similarity coefficient with the *single linkage cluster analysis* (SLCA), which resulted in construction of a tree called a dendrogram. This was followed by development of other similarity coefficient-based approaches. Recently, the *cluster analysis* (CA) was discussed and attention was drawn to the main decisional step of CA based on similarity coefficient methods (Manzini, et al., 2010). One group of researchers used similarity coefficient-based method for generation good initial solution for CFP (Wu, et al., 2009; Chung, et al., 2011). An e-Learning tool considering similarity measures is presented by Ilić (2014).

3. Similarity coefficient-based heuristic algorithm

The SCBH algorithm is a result of a logical extension of Ilić's (2014) research. This algorithm is proposed by considering a working sample of parts. The flow chart of the proposed algorithm is given in Fig. 1. The 11 steps of the SCBH algorithm are:

Step 1: Construction of an initial machine-part matrix. The initial machine-part matrix is a representation of the original operation sequences of parts in the form of a matrix. The three types of the initial machine-part matrix are considered: binary (zero-one) matrix, production volume matrix, and operation time matrix.

Binary matrix indicates which machines are used to produce each part. An entry u_{ki} is defined as follows

$$u_{ki} = \begin{cases} 1, & \text{if part } k \text{ visits machine } i \\ 0, & \text{otherwise} \end{cases}$$

where i is the machine index ($i=1, \dots, m$), k the part index ($k=1, \dots, n$), m the number of machines, and n the number of parts.

Production volume matrix indicates production volume of part k processed by machine i . An entry q_{ki} is defined as follows

$$q_{ki} = v_k u_{ki}$$

if parts have no backtracking operations. Otherwise, q_{ki} is found by adding v_k to the backtracking operations. Where v_k is the production volume for part k .

Operation time matrix indicates operation time of part k processed by machine i . An entry r_{ki} is defined as follows

$$r_{ki} = t_{ki} v_k u_{ki}$$

if parts have no backtracking operations. Otherwise, r_{ki} is found by adding $t_{ki} v_k$ to the backtracking operations. Where t_{ki} is the operation time on part k performed on machine i .

Step 2: Creation of machine similarity coefficient matrix. The elements of this matrix, i.e. similarity coefficients for all possible pairs of machines can be calculated using Eq. (1) or (2) based on Jaccard similarity coefficient, depending on the type of the initial machine-part matrix.

$$s_{ij}^M = a_{ij}^P / (a_{ij}^P + b_{ij}^P + c_{ij}^P), \quad 0 \leq s_{ij}^M \leq 1 \quad (1)$$

where

s_{ij}^M Similarity coefficient between machines i and j

a_{ij}^P Number of parts visit both machines i and j

b_{ij}^P Number of parts visit machine i but not j

c_{ij}^P Number of parts visit machine j but not i

$$\tilde{s}_{ij}^M = \tilde{d}_{ij}^P / (\tilde{d}_{ij}^P + \tilde{e}_{ij}^P + \tilde{f}_{ij}^P), \quad 0 \leq \tilde{s}_{ij}^M \leq 1 \quad (2)$$

where

\tilde{s}_{ij}^M Similarity coefficient between machines i and j considering production volume/operation time

\tilde{d}_{ij}^P Production volume/operation time of parts visit both machines i and j

\tilde{e}_{ij}^P Production volume/operation time of parts visit machine i but not j

\tilde{f}_{ij}^P Production volume/operation time of parts visit machine j but not i

Step 3: Drawing of a dendrogram for machines. The SLCA algorithm (McAuley, 1972), an initial solution or any random generation of ordering of machines can be used for constructing dendrograms.

Step 4: Generation of the best ordering of machines based on the similarity coefficient for machines and a dendrogram for machines, i.e. finding of an assignment $X = \{x_1, \dots, x_m\}$ which maximizes Eq. (3) or (4), depending on the type of the machine similarity coefficient matrix.

$$Z^M(X) = \sum_{h=1}^{m-1} s_{x_h x_{h+1}}^M \quad (3)$$

$$\check{Z}^M(X) = \sum_{h=1}^{m-1} \check{s}_{x_h x_{h+1}}^M \quad (4)$$

Here the solution is represented by the permutation $\{x_1, \dots, x_m\}$ of the numbers $\{1, \dots, m\}$, where x_h is the number of machine for column h of the final machine-part matrix. The problem of finding optimal solution to such problem is *combinatorial problem* (CP).

Step 5: Drawing of a CA dendrogram for machines based on the best ordering of machines generated in the previous step.

Step 6: Creation of part similarity coefficient matrix. The elements of this matrix, i.e. the similarity coefficients for parts can be calculated using the Eq. (5) or (6) based on Jaccard similarity coefficient, depending on the type of the initial machine-part matrix.

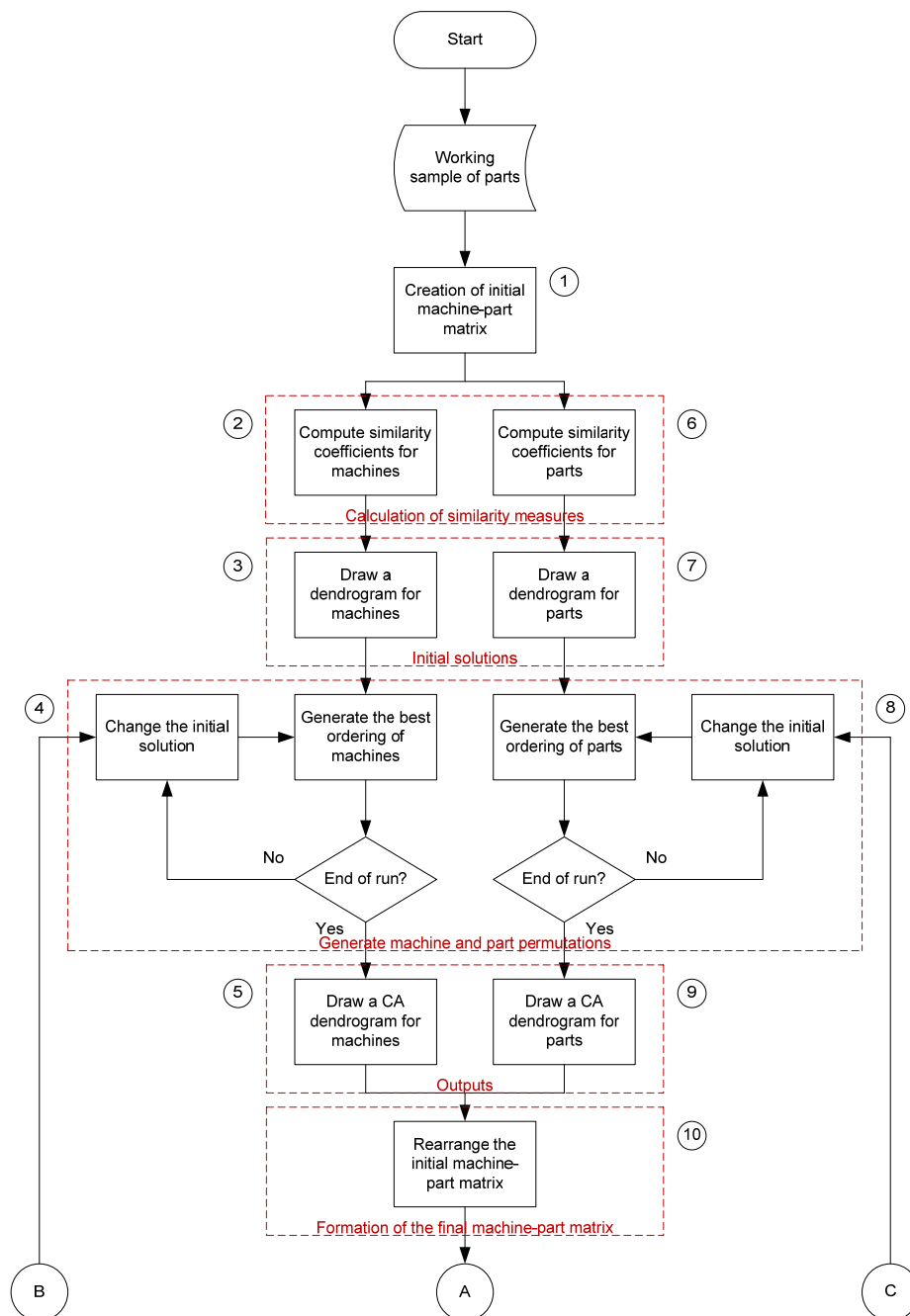


Fig. 1 Flow chart of the proposed SCBH algorithm (Part 1)

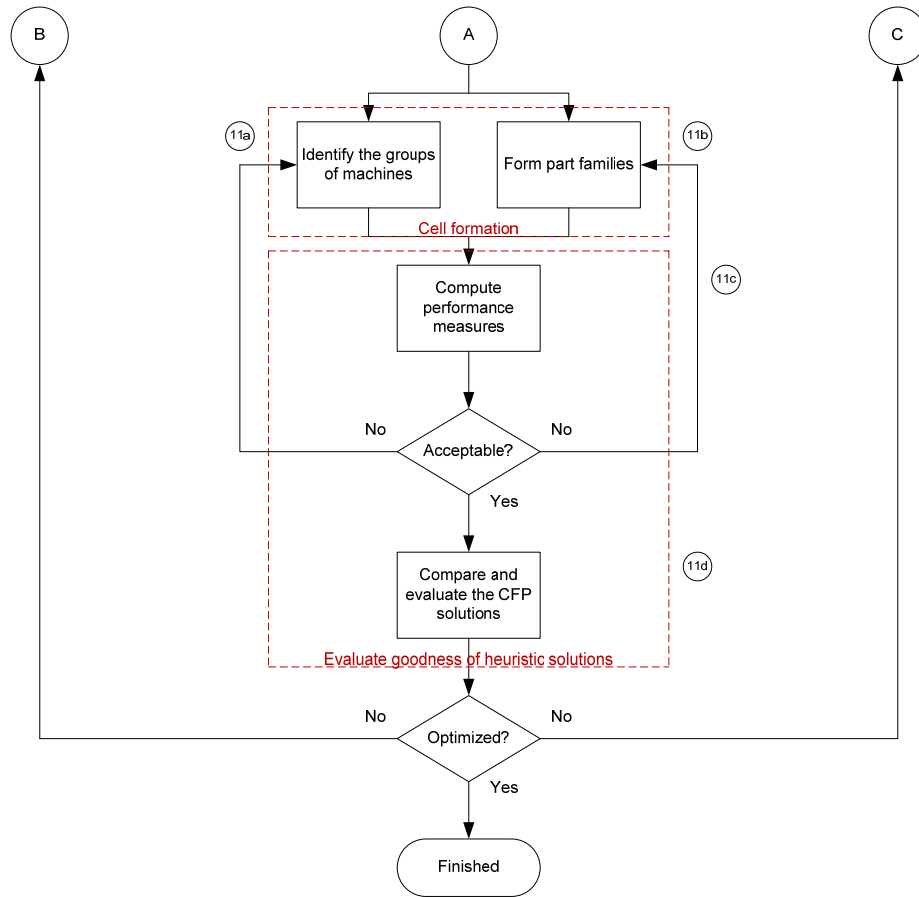


Fig. 1 Flow chart of the proposed SCBH algorithm (Part 2)

$$s_{kl}^P = a_{kl}^M / (a_{kl}^M + b_{kl}^M + c_{kl}^M), \quad 0 \leq s_{kl}^P \leq 1 \quad (5)$$

where

s_{kl}^P Similarity coefficient between parts k and l

a_{kl}^M Number of machines used by both parts k and l

b_{kl}^M Number of machines used by part k but not l

c_{kl}^M Number of machines used by part l but not k

$$\tilde{s}_{kl}^P = \tilde{d}_{kl}^M / (\tilde{d}_{kl}^M + \tilde{e}_{kl}^M + \tilde{f}_{kl}^M), \quad 0 \leq \tilde{s}_{kl}^P \leq 1 \quad (6)$$

where

\tilde{s}_{kl}^P Similarity coefficient between parts k and l considering production volume/operation time

\tilde{d}_{kl}^M Production volume/operation time of machines used by both parts k and l

\tilde{e}_{kl}^M Production volume/operation time of machines used by part k but not l

\tilde{f}_{kl}^M Production volume/operation time of machines used by part l but not k

Step 7: Drawing of a dendrogram for parts by using the similarity coefficient for parts computed in the previous step. The SLCA algorithm, an initial solution or any random generation of ordering of parts can be used for constructing dendrograms.

Step 8: Generation of the best ordering of parts based on the similarity coefficient for parts and a dendrogram for parts, i.e. finding of an assignment $Y = \{y_1, \dots, y_n\}$ which maximizes Eq. (7) or (8), depending on the type of the part similarity coefficient matrix.

$$Z^P(Y) = \sum_{w=1}^{n-1} s_{y_w y_{w+1}}^P \quad (7)$$

$$\tilde{Z}^P(Y) = \sum_{w=1}^{n-1} \tilde{z}_{y_w y_{w+1}}^P \quad (8)$$

Here the solution is represented by the permutation $\{y_1, \dots, y_n\}$ of the numbers $\{1, \dots, n\}$, where y_w is the number of part for row w of the final machine-part matrix. The problem of finding optimal solution to such problem is CP.

Step 9: Drawing of a CA dendrogram for parts based on the best ordering of parts generated in the previous step.

Step 10: Rearrangement of the initial machine-part matrix according to the best orderings of machines and parts to form the final machine-part matrix. In the final machine-part matrix parts that use similar or identical sets of machines will be grouped together into “blocks of 1’s” that appear along the diagonal of the matrix. Also, in the final machine-part matrix machines that produce similar or identical sets of parts will be grouped together into “blocks of 1’s” that appear along the diagonal of the matrix.

Step 11: Identification of the machine cells and part families, and evaluation of goodness of heuristic solutions based on the selected performance measures (for example, the number of intercellular/intracellular part movements and the total number of duplicated machines).

3.1 Support tool for the SCBH

The problems of generating the best ordering of machines and parts (steps 4 and 8 of SCBH) are formulated as pure CP. Manual generation of permutations is possible only for the problems of small dimension. However, the problems with a large number of machines and parts should be solved by using some software tool. The using of LAYOUT tool (Ilić, 2003) is proposed.

In the facility layout module of LAYOUT, from-to charts showing number of deliveries required between different stations can be treated as the similarity coefficient matrices for machines and parts. Also, in this module, from-to charts showing the distances of deliveries between different locations in a layout can be treated as Eq. (9) or (10), depending on the type of the similarity coefficient matrix for machines or parts.

$$d_{i_1 i_2}^M = |i_1 - i_2|, (i_1=1, \dots, m; i_2=1, \dots, m) \quad (9)$$

$$d_{k_1 k_2}^P = |k_1 - k_2|, (k_1=1, \dots, n; k_2=1, \dots, n) \quad (10)$$

where

$$0 \leq d_{i_1 i_2}^M \quad \text{Distance from location } i_1 \rightarrow \text{location } i_2 \text{ for machines}$$

$$0 \leq d_{k_1 k_2}^P \quad \text{Distance from location } k_1 \rightarrow \text{location } k_2 \text{ for parts}$$

Using the LAYOUT tool, the matrices of similarity coefficients and the matrices of distances are used as input and the near-optimal permutations of machines and parts are generated. This is because the facility layout module of LAYOUT uses the steepest descent pairwise and/or three way exchange heuristic. The effectiveness of the steepest descent method implemented in the LAYOUT tool is given in Ilić (2003). Generally, the steepest descent pairwise and/or three way exchange heuristic yields desirable permutations. The best way to avoid local minimum is to repeatedly change the initial solution for multiple runs. This can be done easily in the LAYOUT tool.

3.2 Potential users of SCBH and LAYOUT

The SCBH algorithm and LAYOUT tool can be used for educational purposes and also in industry (machining, pipe fabrication, forging, woodworking, cable manufacturing, electronic assembly, welding job shops, aerospace and defense). At the Faculty of Management Sciences, the undergraduate students of course Computer Integrated Manufacturing are introduced with the basis of the field GT. Instructors teach the Production Flow Analysis (PFA) with the use of software PFAST (Irani and Huang, 2005; Irani, 2012) as an e-Learning support tool, among other things. The proposed SCBH algorithm and LAYOUT tool are offered to graduate students of Computer Integrated Manufacturing Systems (CIMS) course who are interesting in solving a CFP. The next case study is used as a supplement to the CIMS course.

4. Comparative case study and results

This comparative case study presents the advantages of using the SCBH algorithm and LAYOUT tool in the educational environment. The SCBH algorithm and LAYOUT tool have been used for resolving a CFP of 19 parts and 12 machines that was previously solved by Vakharia and Wemmerlov (1990), Sarker and Xu (2000), Irani, et al. (2000), and Irani and Huang (2005). The objective of this problem is to evaluate different alternatives for cell formation and compare and evaluate them to select the system configuration which minimizes intercell flows. In addition, the result is compared with the results obtained with the help of PFAST of Irani, et al. (2000), Irani and Huang (2005), and Irani (2012).

The SCBH algorithm steps-to-solution for problem:

Step 1: Construction of initial machine-part matrix. The operation sequences of parts (Table 1) are converted into an initial machine-part matrix (Table 2). The created initial machine-part matrix is a type of binary matrix.

Table 1 Operation sequences of parts (Adapted from Irani, et al. (2000); Irani and Huang (2005))

Part #	Sequence of machines
1	1 → 4 → 8 → 9
2	1 → 4 → 7 → 4 → 8 → 7
3	1 → 2 → 4 → 7 → 8 → 9
4	1 → 4 → 7 → 9
5	1 → 6 → 10 → 7 → 9
6	6 → 10 → 7 → 8 → 9
7	6 → 4 → 8 → 9
8	3 → 5 → 2 → 6 → 4 → 8 → 9
9	3 → 5 → 6 → 4 → 8 → 9
10	4 → 7 → 4 → 8
11	6
12	11 → 7 → 12
13	11 → 12
14	11 → 7 → 10
15	1 → 7 → 11 → 10 → 11 → 12
16	1 → 7 → 11 → 10 → 11 → 12
17	11 → 7 → 12
18	6 → 7 → 10
19	12

Step 2: Creation of machine similarity coefficient matrix. The similarity coefficients for all possible pairs of machines are calculated using Eq. (1) and the results are presented in form of a machine similarity coefficient matrix (Ilić, 2014).

Step 3: Drawing of dendrogram for machines. This dendrogram is presented on Fig. 2.

Step 4: Generation of the best ordering of machines. LAYOUT tool is used for generating the best ordering of machines. LAYOUT output for machine permutations is given on Fig. 3.

Step 5: Drawing of CA dendrogram for machines. This dendrogram is presented on Fig. 4.

Step 6: Creation of part similarity coefficient matrix. The similarity coefficients for parts are calculated using Eq. (5) and the results are presented in form of a part similarity coefficient matrix (Ilić, 2014).

Step 7: Drawing of dendrogram for parts. This dendrogram is presented on Fig. 5.

Step 8: Generation of the best ordering of parts. LAYOUT tool is used for generating the best ordering of parts. LAYOUT output for part permutations is given on Fig. 6.

Step 9: Drawing of CA dendrogram for parts. This dendrogram is presented on Fig. 7.

Step 10: Rearrangement of the initial machine-part matrix according to the best orderings of machines and parts to form the final machine-part matrix. The final machine-part matrix (Table 3) is created by inserting the machine and part permutations obtained using LAYOUT.

Table 2 Initial machine-part matrix

Part	Machine											
	1	2	3	4	5	6	7	8	9	10	11	12
1	1			1				1	1			
2	1			1			1	1				
3	1	1		1			1	1	1			
4	1			1			1		1			
5	1					1	1		1	1		
6						1	1	1	1	1		
7				1		1		1	1			
8		1	1	1	1	1		1	1			
9			1	1	1	1		1	1			
10				1			1	1				
11						1						
12							1				1	1
13											1	1
14							1			1	1	
15	1						1			1	1	1
16	1						1			1	1	1
17							1				1	1
18						1	1			1		
19												1

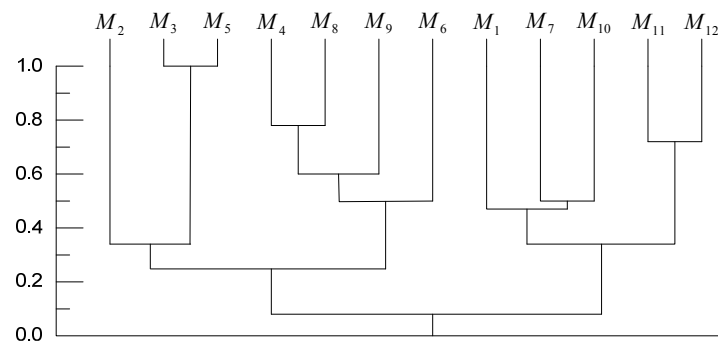


Fig. 2 Initial dendrogram for machines

$$M_2 - M_5 - M_3 - M_6 - M_9 - M_8 - M_4 - M_1 - M_7 - M_{10} - M_{11} - M_{12}$$

$$Z^M(X) = s_{25}^M + s_{53}^M + s_{36}^M + s_{69}^M + s_{98}^M + s_{84}^M + s_{41}^M + s_{17}^M + s_{710}^M + s_{1011}^M + s_{1112}^M = 5.870$$

Fig. 3 LAYOUT output for machine permutation

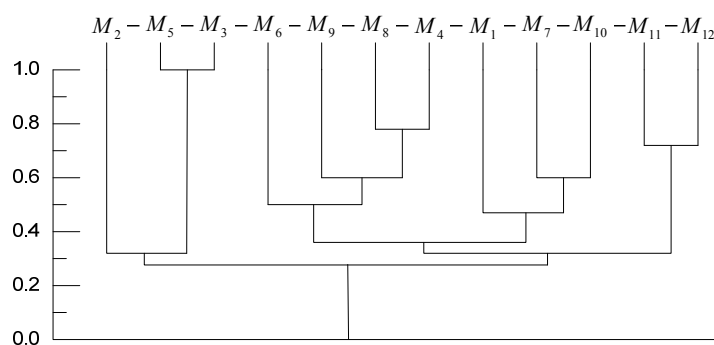


Fig. 4 CA dendrogram for machines

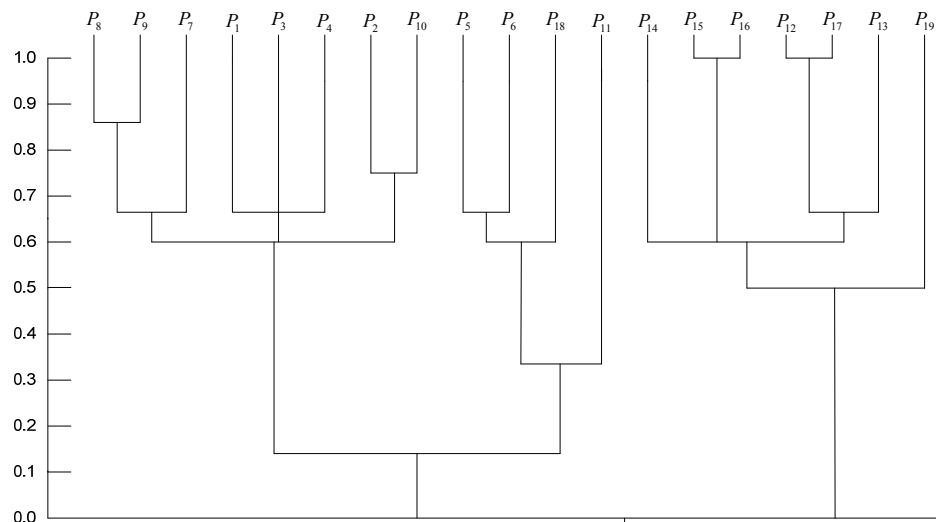


Fig. 5 Initial dendrogram for parts

$$Z^P(Y) = s_{118}^P + s_{89}^P + s_{97}^P + s_{71}^P + s_{13}^P + s_{310}^P + s_{102}^P + s_{24}^P + s_{45}^P + s_{56}^P + s_{618}^P + s_{1814}^P + s_{1415}^P + s_{1516}^P + s_{1617}^P + s_{1712}^P + s_{1213}^P + s_{1319}^P = 11.418$$

Fig. 6 LAYOUT output for part permutation

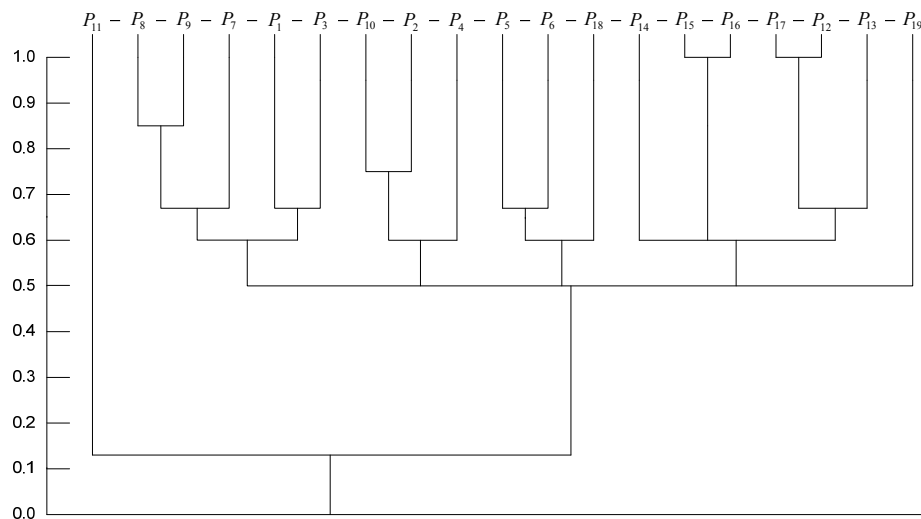


Fig. 7 CA dendrogram for parts

Step 11: Identification of machine cells and part families, and evaluation of goodness of heuristic solutions based on the selected performance measures. The final machine-part matrix (Table 3) is used to suggest groups of parts that should be placed together into part families and groups of machines that can be placed together into machine cells.

In that sense, first the two part families are formed by splitting the hierarchical CA dendrogram between parts 18 and 14. There are:

Part Family 1 which consists of parts 11, 8, 9, 7, 1, 3, 10, 2, 4, 5, 6 and 18; and

Part Family 2 which consists of parts 14, 15, 16, 17, 12, 13 and 19.

Second, by outlining blocks of 1's, the groups of machines are identified that will constitute the different machine cells that correspond to the part families previously formed. It can be concluded that there are two machine cells:

Machine Cell 1 which consists of machines 2, 5, 3, 6, 9, 8, 4, 1 and 7; and

Machine Cell 2 which consists of machines 10, 11 and 12.

Third, the 1's outside the blocks are marked as "external operations". The external operations indicate sharing the machines among cells. For example, in the final machine-part matrix (Table 3), it can be seen that, in the case of implementation of two cells, the machine 10 needs to be located in Machine Cell #1, and machines 1 and 7 need to be

located in Machine Cell #2. Unless these machines are duplicated and assigned to both cells, intercell flows will occur that are not easy to coordinate and will be disruptive to operations in both cells.

Table 3 Final machine-part matrix obtained by the proposed SCBH algorithm and LAYOUT tool

Part	Machine											
	2	5	3	6	9	8	4	1	7	10	11	12
11				1								
8	1	1	1	1	1	1	1					
9		1	1	1	1	1	1					
7				1	1	1	1					
1					1	1	1	1				
3	1				1	1	1	1	1			
10						1	1		1			
2						1	1	1	1			
4					1		1	1	1			
5				1	1			1	1	1		
6				1	1	1			1	1		
18				1					1	1		
14									1	1	1	
15								1	1	1	1	1
16								1	1	1	1	1
17									1		1	1
12									1		1	1
13											1	1
19												1

Finally, two decisions are considered: (1) duplication of each machine in every cell where it is required and (2) “starving” of certain cells with insufficient allocation of machines to them. These two decisions lead to the following two solutions of the problem:

Cellular layout without intercell flows: To form two independent cells, i.e. they will have no intercell flows of parts that must use capacity outside their host cell, machines 1, 7 and 10 must be duplicated.

Cellular layout with intercell flows: In this situation, there are intercell flows, caused by sharing of machines 1, 7 and 10 between the two part families.

To see the effect of use the proposed SCBH algorithm and LAYOUT tool, the solution obtained by the proposed SCBH algorithm and LAYOUT tool (Table 3) is compared with the results obtained by Irani, et al. (2000) version of PFAST using TSP (Travelling Salesman Problem) tours and QAP (Quadratic Assignment Problem) – generated machine and part permutations (Tables 4 and 5), Irani and Huang (2005) version of PFAST (Table 6), and Irani (2012) version of PFAST (Table 7).

The number of external/internal operations, the number of parts/machines with external operations, and the total objective function value for machine/part permutation are selected as the performance measures for evaluating goodness of solutions (Table 8). (High) and (low) labels refer to the expected values for best performing the CFP and CMS.

The number of external operations is the number of “1’s” operations outside the sub-matrices that determined cells in the final machine-part matrix. This can be viewed as a direct measure of the quality of a solution in terms of cost (Wang and Roze, 1995) since the number of external operations affects duplication of machines or “starving” of certain cells caused by sharing of machines. The number of internal operations is the number of “1’s” operations inside the sub-matrices that determined cells. Obviously, the sum of the numbers of external and internal operations represents the total number of operations. The number of parts with external operations is the number of parts that have “1’s” operations outside the sub-matrices that determined cells. The number of machines with external operations is the number of machines that have “1’s” outside the sub-matrices that determined cells. This measure indicates the machines that need to be used in more than one cell. The total objective function value for machine permutation (Eq. 3)

is the sum of similarity coefficients of machine pairs determined by permutation. The total objective function value for part permutation (Eq. 7) is the sum of similarity coefficients of part pairs determined by permutation.

Table 4 Final machine-part matrix obtained by Irani, et al. (2000) version of PFAST using TSP tours

Part	Machine											
	5	2	3	6	9	8	4	1	7	10	11	12
11				1								
8	1	1	1	1	1	1	1					
9	1		1	1	1	1	1					
7				1	1	1	1					
1					1	1	1	1				
3		1			1	1	1	1	1			
10						1	1		1			
2						1	1	1	1			
4					1		1	1	1			
5				1	1			1	1	1		
6				1	1	1			1	1		
18				1					1	1		
14									1	1	1	
16								1	1	1	1	1
15								1	1	1	1	1
12									1		1	1
17									1		1	1
13											1	1
19												1

Table 5 Final machine-part matrix obtained by Irani, et al. (2000) version of PFAST using QAP-generated machine and part permutations

Part	Machine											
	5	3	2	4	8	9	6	1	7	10	11	12
11							1					
8	1	1	1	1	1	1	1					
9	1	1		1	1	1	1					
7				1	1	1	1					
1				1	1	1		1				
3			1	1	1	1		1	1			
10				1	1				1			
2				1	1			1	1			
4				1		1		1	1			
6					1	1	1		1	1		
5						1	1	1	1	1		
18							1		1	1		
14									1	1	1	
16								1	1	1	1	1
15								1	1	1	1	1
12									1		1	1
17									1		1	1
13											1	1
19												1

Table 6 Final machine-part matrix obtained by Irani and Huang (2005) version of PFAST

Part	Machine											
	2	3	5	4	8	9	6	1	7	10	11	12
8	1	1	1	1	1	1	1					
9		1	1	1	1	1	1					
7				1	1	1	1					
1				1	1	1		1				
3	1			1	1	1		1	1			
4				1		1		1	1			
2				1	1			1	1			
10				1	1				1			
5						1	1	1	1	1		
6					1	1	1		1	1		
18							1		1	1		
11							1					
14									1	1	1	
15								1	1	1	1	1
16								1	1	1	1	1
12									1		1	1
17									1		1	1
13											1	1
19												1

Table 7 Final machine-part matrix obtained by Irani (2012) version of PFAST

Part	Machine											
	2	3	5	6	9	8	4	1	7	10	11	12
11				1								
18				1					1	1		
5				1	1			1	1	1		
6				1	1	1			1	1		
8	1	1	1	1	1	1	1					
9		1	1	1	1	1	1					
7				1	1	1	1					
10						1	1		1			
2						1	1	1	1			
1					1	1	1	1				
3	1				1	1	1	1	1			
4					1		1	1	1			
14									1	1	1	
15								1	1	1	1	1
16								1	1	1	1	1
12									1		1	1
17									1		1	1
13											1	1
19												1

Table 8 Comparison of five approaches

Performance measure	Irani, et al. (2000) version of PFAST		Irani and Huang (2005) version of PFAST	Irani (2012) version of PFAST	The proposed SCBH algorithm and LAYOUT tool
	TSP (Algorithm 6)	QAP (Algorithm 7)			
Number of external operations (low)	10	10	12	10	10
Number of internal operations (high)	64	64	62	64	64
Number of parts with external operations (low)	8	8	10	8	8
Number of machines with external operations (low)	3	3	4	3	3
Total objective function value for machine permutation (high)	5.203	5.547	5.547	5.870	5.870
Total objective function value for part permutation (high)	11.418	11.204	10.918	11.075	11.418

According to the first-fourth selected measures, the results obtained by Irani, et al. (2000) version of PFAST using TSP and QAP, Irani (2012) and the SCBH algorithm and LAYOUT tool can be assessed as equally good. However, these results are significantly differ in terms of the last two selected measures, i.e. maximization of both sums of similarity coefficients between machine and part pairs. It can be seen that results obtained by Irani, et al. (2000) version of PFAST using TSP show maximization in total objective value for part permutation (11.418), while Irani (2012) results show maximization in total objective value for machine permutation (5.870). Only the results obtained via the proposed SCBH algorithm and LAYOUT tool show maximization in both of these measures, i.e. total objective value for machine permutation (5.870) and total objective value for part permutation (11.418). Therefore, it can be concluded that the proposed SCBH algorithm and LAYOUT tool is more suitable solution for solving the CFP.

5. Conclusion

Cellular manufacturing is one of the most important applications of GT that has gained popularity in both academic research and industrial applications. Among the problems of designing a cellular manufacturing, cell formation is the first and foremost problem. This paper proposes the SCBH algorithm and LAYOUT tool for solving the CFP. The pure combinatorial optimization models to evaluating goodness of heuristic solutions are incorporated that lead to the minimization of both intercell and intracell flows.

The advantages of using the SCBH algorithm and LAYOUT tool are demonstrated through a comparative case study. Comparison of five approaches in this case study showed that the solutions obtained via SCBH algorithm and LAYOUT tool are better than solutions in current versions of PFAST. The case study showed that the maximization of the total objective function value for machine/part permutation can make desirable changes in the block diagonal machine-part matrix and it can reduce the number of external operations and the number of parts/machines with external operations (the total number of duplicated machines).

Finally, the following scopes can be interesting for future research: (1) An experimental analysis should be made to test the proposed SCBH algorithm on different industrial and literature instances; (2) The SCBH algorithm can be modified in direction to include various: working samples of parts, initial machine-part matrices, similarity measures, modern heuristic techniques, clustering algorithms, and performance measures; (3) The SCBH algorithm can be fully automated.

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