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Cell formation with ordinal-level data using ART1-based neural networks

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Abstract: In Cell Formation Problem (CFP), the zero-one Part-Machine Incidence Matrix (PMIM) is the common input to any clustering algorithm. The output is generated with two or more machine cells and corresponding part families. The major demerit with such models is that real-life production factors such as operation time, sequence of operations and lot size of the product are not accounted for. In this paper, the operation sequence of the parts is considered to enhance the quality of the solution. A neural network-based algorithm is proposed to solve the CFP. The performance of the proposed algorithm is tested with example problems and the results are compared with the existing methods found in the literature. The results presented clearly shows that the performance of the proposed ART1-based algorithm is comparable with the other methods.

Keywords: Cell Formation; CF; ART1; grouping efficiency.

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1 Introduction

The primary concern in cellular manufacturing is to adopt Group Technology (GT) so that the machine cells and part families can be identified in such a manner that the movement of parts from one GT cell to another cell can be minimised. Usually, a Part–Machine Incidence Matrix (PMIM) developed from route sheet information is presented as input to any clustering algorithm, and part families and machine cells are identified from the diagonal blocks of the output matrix. If any value exists in the off-diagonal blocks, it indicates the intercell movements of the respective parts (alternatively known as exceptional elements). There have been several methods to solve Cell Formation (CF) problem viz., array manipulation, hierarchical clustering, non-hierarchical clustering, mathematical programming, graph theory, heuristics, *etc*. These methods are found to produce good solutions for well-structured matrices where part families and machine cells exist naturally. However, they fail to do so if an ill-structured matrix is presented to the algorithm and results in many exceptional elements.

The neural network applications proposed by Carpenter and Grossberg (1987) and Dagli and Huggahalli (1995) have demonstrated the ability of a neural network in solving cell formation problem. The iterative activation and competition model proposed by Moon (1990) exhibited a significant advantage over earlier algorithms when PMIM was presented as the input. The major demerit with such approaches is that they do not take into account the other important real-time production factors such as sequence of operations, operation time, lot sizes, *etc*. When actual production factors are considered, the input matrix consists of non-binary and real valued elements and finds difficulties in representation while solving CF problems. However, two popular algorithms *viz.*, the clustering algorithm (Nair and Narendran, 1998) and fuzzy ART algorithm (Suresh *et al.*, 1999) found in the literature have been proved to produce satisfactory results for the CF problem with non-binary data.

In this work, an attempt has been made to use the operation sequence of the parts known as *ordinal-level data*, which is obtained through the route sheets, to group the parts into part families and machines into machine cells. The proposed algorithm employs the principle of ART1 network found in the literature (Carpenter and Grossberg, 1987). Basically, the ART1 network classifies a set of binary vectors into groups based on their similarities. The ART1 recognises patterns and clusters the binary vectors with the recognised pattern based on the comparison mechanism. The proposed algorithm first converts the given non-binary data into a zero-one binary matrix known as Part–Machine Precedence Matrix (PMPM) and feeds the ART1 network with PMPM as the input matrix.

2 Literature review

Literature review on cellular manufacturing reveals that basically, six approaches *viz.*, Similarity Coefficient Methods (SCM), graph theory, mathematical programming, metaheuristics, fuzzy set theory and neural networks are predominantly used to solve CF problems. McAuley (1972) and Seifoddini (1990) used similarity coefficient methods to form machine cells whereas Srinivasan *et al.* (1991) made use of similarity coefficient as input to an assignment model for producing part families. King and Nakornchai (1982) proposed a heuristic-based rank order clustering method for the concurrent formation of machine cells and part families. Chandrasekaran and Rajagopalan (1986) extended the basic rank order clustering method to propose MODROC for improving solution quality. Chu and Tsai (1999) have made a comparative study of the array-based clustering techniques. These techniques mainly deal with zero-one machine part incidence matrix and ignore important real-life production factors. In order to make the solution methodology more realistic, Srinivasan and Narendran (1991) have proposed an algorithm known as GRAFICS, which enables the decision maker to consider sequence of operations when a part passes through a number of machines.

In the late 1990s, metaheuristics were introduced for solving many hard problems such as vehicle routing, travelling salesman, multicellular flexible manufacturing problems (Ganesh and Narendran, 2007; Manzini *et al*., 2006; Ganesh and Narendran, 2005). However, Boctor (1991) and Chen *et al*. (1995) have proposed a solution methodology using a simulated annealing algorithm approach for the CF problem. Venugopal and Narendran (1992) adopted the genetic algorithm model for multiobjective cell formation problems. Wu *et al*. (2004) proposed two methods based on tabu search for small-size problems. Kao and Moon (1991) introduced the back propagation neural network model for group technology, whereas Kaparthi and Suresh (1992) and Venkumar and Haq (2005) made an attempt to introduce the adaptive resonance theory (ART1). Kumar and Chandrasekaran (1990) proposed grouping efficacy as a performance measure for the solution obtained in block diagonal forms from binary input matrices.

3 The overview of ART1

The ART network is an unsupervised vector classifier that accepts input vectors classified according to the stored pattern they most resemble. It also provides for a mechanism-adaptive expansion of the output layer of neurons until an adequate size is reached based on the number of classes inherent in the observation. The ART network can adaptively create a new class corresponding to an input pattern if it is determined to be sufficiently different from existing clusters. This determination, called the vigilance test, is incorporated into the network. Thus, the ART architecture allows the user to control the degree of similarity of patterns placed in the cluster. In this work, the ART1 network is adopted to group the binary matrix, which is given in the form of PMPM for the considered CF problem. The functioning of ART1 consists of two phases. The first phase has two layers. One is the input layer (also called the comparison layer) and the other one is the output layer (also called the recognition layer). Every input (bottom) neuron is connected to every output (top) layer neurons. There are bottom-up weights (b_{ij}) associated with the input neurons to the output neurons and top-down weights (t_{ji}) associated with the output neurons to the input neurons. The bottom-up weights are used for cluster competition while top-down weights are used for cluster verification.

In this work, an ART1-based algorithm is being proposed to handle the CF problem with the operation sequence of the parts. In Section 3, the algorithm based on ART1 is proposed for solving the CF problem with the operation sequence information as input data.

4 The ART1-based algorithm for cell formation with operation sequence

The input to the algorithm is the sequence-based Part–Machine Incidence Matrix (PMIM) of size '$N \times M$' for the M machines and N jobs cell formation problem.

Phase 1 Formulation of PMPM

Step 1 Using the given PMIM with the sequence data, for every part, a Machine–Machine Precedence Matrix (MMPM) of size $M \times M$ is constructed. Each row of a MMPM represents a machine and the '1's in the row indicate the machines that are required for the part j subsequently. The row corresponding to the first machine visited by the part, '1's are assigned to all the columns (machines) required by the part; thus it holds the maximum number of ones in the MMPM of the particular part. The number of '1's is decreased by '1' to the subsequent machines required by the part. For the rows corresponding to the machine which are not required by the part, all the elements are assigned with zero.

Step 2 Using the 'N' number of MMPMs, a single Part–Machine Precedence Matrix (PMPM) of size '$N \times (M \times M)$' is constructed. Each row of the PMPM corresponds to a part and the element of the row is obtained by placing all the rows of the MMPM in a linear sequence.

Phase 2 Grouping of parts into part families using ART1

The PMPM obtained from Phase 1 is given as input to the ART1 network:

Step 1 Before starting the network training process, the bottom-up weights b_{ij} and top-down weights t_{ji} are set to initial values by using Equations (1) and (2), respectively.

$$b_{ij} = \frac{1}{(1+N)} \qquad \text{for all i and j} \tag{1}$$

$$t_{ji} = 1 \qquad \text{for all i and j.} \tag{2}$$

The vigilance threshold ρ is suitably selected such that $0 < \rho < 1$.

Step 2 Apply new input vector X_i.

Step 3 Compute matching scores using Equation (3).

The output u_j of every output node j equals:

$$\mu_j = \sum_i b_{ij}(t)x_i \quad \text{for } j = 0,1,\ldots(M-1). \tag{3}$$

Step 4 Select the best matching exemplar, *i.e.*, node (θ) with maximum output $\mu_\theta = \max(\mu_j)$. Outputs of other neurons are suppressed. In case of tie, choose the neuron with the lower j.

Step 5 Vigilance test, *i.e.*, test of similarity with best matching exemplars

Compute $\|X\| = \sum_i x_i$ number of 1s in the input vector

Compute $\|T \cdot X\| = \sum_i t_{i\theta} \cdot x_i$ number of perfectly matching 1s between the input vector and the best matching exemplar.

Step 6 Similarity check. If their similarity $\frac{\|T \cdot X\|}{\|X\|} > \rho$ then go to Step 7.

Step 7 Disable the best exemplar temporarily; output of the best matching node selected in Step 4 is temporarily set to zero; other outputs have already been suppressed. Then go to Step 3. In Step 3, a new neuron in the output layer gets selected to represent the new class.

Step 8 Update best matching exemplar using Equations (4) and (5).

$$t_{i\theta}(t+1) = t_{i\theta}(t).x_i \tag{4}$$

$$b_{i\theta}(t+1) = \frac{t_{i\theta}(t).x_i}{0.5 + \sum_i t_{i\theta}(t)x_i}. \tag{5}$$

Step 9 Repeat Step 2 after enabling any nodes disabled in Step 6.

The output of this phase will be the optimal number of part families and the list of parts within each part family.

Phase 3 Grouping of machines into machine cells

Step 1 Each machine is allocated to a cell corresponding to a particular part family where the total number of operations required by all the parts in the family put together is maximum.

Step 2 The columns of the output are rearranged into block diagonal form such that the number of intercell movements are kept to a minimum.

5 Measure of performance

There are some popular measures such as grouping efficiency and group efficacy (Kumar and Chandrasekaran, 1990) for measuring the goodness of the block diagonal structure of the output matrix in CF problems. However, all these measures treat all the operations equally and are suitable only for the binary matrix (Mahapatra and SudhakaraPandian, 2007). These measures cannot be adopted for generalised CF problems where operational sequence of the parts is considered.

Therefore, Group Technology Efficiency (GTE) given by Harhalakis *et al.* (1990) can be conveniently used to measure the performance considering sequence of parts of the operations, respectively. Group technology efficiency is defined as the ratio of the difference between the maximum number of intercell travels possible and the number of intercell travels actually required by the system to the maximum number of intercell travels possible as given in Equations (6 and 7).

The maximum number of intercell travels possible in the system is:

$$I_p = \sum_{j=1}^{N} (n-1). \tag{6}$$

The number of intercell travels required by the system is:

$$I_r = \sum_{j=1}^{N} \sum_{w=1}^{n-1} t_{njw}. \tag{7}$$

The group technology efficiency is calculated using Equation (8):

$$\mathrm{GTE} = \frac{\mathrm{I_p} - \mathrm{I_r}}{\mathrm{I_p}}. \tag{8}$$

$\mathrm{I_p}$ = maximum number of intercell travel possible in the system
$\mathrm{I_r}$ = number of intercell travel actually required by the system
n = number of operations (w = 1,2,3,…,n)

t_{njw} = 0 if the operations w, w + 1 are performed in the same cell

= 1 otherwise.

Table 1 shows the sequence-based PMIM of an example problem wherein seven parts are to be processed using five machines. For every part, a MMPM is constructed. Table 2 shows the MMPM for parts P1 and P2. Table 3 shows the PMPM constructed as per Step 2 of Phase I of the algorithm.

Table 1 PMIM with sequence data of size 7 × 5

Parts/Machines	*m1*	*m2*	*m3*	*m4*	*m5*
p1	1	2	0	3	0
p2	0	1	2	0	3
p3	2	0	0	1	3
p4	0	1	2	0	3
p5	1	2	0	3	0
p6	3	0	1	0	2
p7	0	3	0	2	1

Table 2 MMPM for parts

	For part-1						*For part-2*				
Machines	*m1*	*m2*	*m3*	*m4*	*m5*	*Machines*	*m1*	*m2*	*m3*	*m4*	*m5*
m1	1	1	0	1	0	m1	0	0	0	0	0
m2	0	1	0	1	0	m2	0	1	1	0	1
m3	0	0	0	0	0	m3	0	0	1	0	1
m4	0	0	0	1	0	m4	0	0	0	0	0
m5	0	0	0	0	0	m5	0	0	0	0	1

Table 3 Precedence similarity matrix for the problem size 7 × 5

Row index (M × M)	*p1*	*p2*	*p3*	*p4*	*p5*	*p6*	*p7*
1	1	0	1	0	1	1	0
2	1	0	0	0	1	0	0
3	0	0	0	0	0	0	0
4	1	0	0	0	1	0	0
5	0	0	1	0	0	0	0
6	0	0	0	0	0	0	0
7	1	1	0	1	1	0	1
8	0	1	0	1	0	0	0
9	1	0	0	0	1	0	0
10	0	1	0	1	0	0	0
11	0	0	0	0	0	1	0
12	0	0	0	0	0	0	0
13	0	1	0	1	0	1	0
14	0	0	0	0	0	0	0
15	0	1	0	1	0	1	0
16	0	0	1	0	0	0	0
17	0	0	0	0	0	0	1
18	0	0	0	0	0	0	0
19	1	0	1	0	1	0	1
20	0	0	1	0	0	0	0
21	0	0	0	0	0	1	0
22	0	0	0	0	0	0	1
23	0	0	0	0	0	0	0
24	0	0	0	0	0	0	1
25	0	1	1	1	0	1	1

Table 4 shows the output of the algorithm. There are two part families and machine cells. Parts p2, p3, p4 and p6 are associated with the machines m1, m2 and m4 in one family; parts p1, p5 and p7 are in another family associated with the machines m3, m4 and m5, which is shown in the output matrix in Table 4.

Table 4 Output matrix of size (7 × 5)

Parts/Machines	*m3*	*m5*	*m1*	*m2*	*m4*
p2	2	3	0	1	0
p3	0	3	2	0	1
p4	2	3	0	1	0
p6	1	2	3	0	0
p1	0	0	1	2	3
p5	0	0	1	2	3
p7	0	1	0	3	2

It is observed from the output matrix that parts p2, p4, p6 and p7 have one exceptional element each and one intercell move. Part p3 has two exceptional elements and one intercell move. Hence there are six exceptional elements and five intercell moves. The group technology efficiency (Nair and Narendran, 1998) is calculated using Equation (8). The value of GTE is 64.3%.

6 Results and discussion

The proposed algorithm has been coded in C++ and executed in a Pentium III, 700 MHz system. Table 5 shows the block diagonal matrix produced by the proposed algorithm for the 40 × 25 example problem found in the literature (Nair and Narendran, 1998). Table 6 shows the problems of different sizes selected from open literature (Nair and Narendran, 1998) for testing the proposed algorithm. For all the 15 trial data sets shown in Table 7, the input matrix is generated with uniformly distributed random numbers in the range of 1 to 9 for operational sequence. The problem sizes considered in this work range from 5 × 4 to 90 × 35.

Table 5 Output matrix by the proposed ART1-based algorithm for example problem of size (40 × 25) PMIM

Parts/ Machines	*4*	*5*	*7*	*12*	*16*	*18*	*19*	*23*	*1*	*2*	*17*	*24*	*3*	*11*	*20*	*25*	*8*	*9*	*10*	*6*	*13*	*14*	*15*	*21*	*22*
1	5		3		4	2													**1**						**6**
4				1				2																	
5	3			2		1																			
6				3	2			1																	
7	3		2		4	1													**5**						
8		1			3		2																		
15		3			1		2			**4**									**5**						
16	1		3		2	4																			
17			1			2													**3**						
20								1																	
23		2			3		1																		
24		1			2																				
26	2			3				1															**4**		
29		3																		**2**				**1**	
30	4		2		3	1																			
34				2				1				**3**													
37			3	2				1																	
39				1																					
40					1				**2**										**3**						
2									2	3	4					**1**									
12									1		3	2	**4**			**5**									
31		**2**					**3**				1														
36									2	3	1			**4**											
3													2	3	1										
9													3	4	1	2									
13													3	2	1										
14		**1**											4	2	3										
22											**1**		3				**4**	**2**							
33														1	3	2									
10																3	2	1							
11																	2				**3**			**1**	
19																	1	3	2						
21																	1	3	2						
28																	2	1	3						
38																	2	3							**1**
18																						3	2		1
25																				1			3	2	
27				**1**																				3	2
32																					2	1	3		4
35																				2			4	1	3

Table 6 Comparison of results of the proposed algorithm with CASE

			CASE (1998)			*Proposed algorithm*		
S.No	*Problem size*	*No. of cells*	*Exceptional elements*	*Intercell moves*	*Group technology efficiency*	*Exceptional elements*	*Intercell moves*	*Group technology efficiency*
1	7 × 7	2	2	4	69.25	2	4	69.25
		3	3	6	53.85	3	6	53.85
2	20 × 8	3	10	17	58.54	10	17	58.54
3	20 × 20	4	–	–	–	12	15	74.58
		5	15	19	67.8	16	18	69.49
4	40 × 25	5	–	–	–	26	22	72.04
		8	35	31	66.67	35	31	66.67

Table 7 Performance of the proposed algorithm on test data sets

S.No	*Problem size*	*Exceptional elements*	*Intercell moves*	*Group technology efficiency*
1	5 × 4	0	0	100.00
2	5 × 5	1	1	85.71
3	7 × 5	6	5	64.30
4	8 × 6	2	2	84.61
5	19 × 12	8	9	83.93
6	20 × 12	11	10	78.00
7	20 × 20	3	3	94.00
8	30 × 15	21	17	76.71
9	37 × 20	25	25	71.59
10	50 × 25	49	46	69.13
11	55 × 20	15	19	81.20
12	60 × 28	39	38	70.50
13	65 × 30	58	52	76.68
14	80 × 32	53	59	74.57
15	90 × 35	54	56	77.69

The results are compared with the results produced by CASE algorithm (Nair and Narendran, 1998) as shown in Table 6. The results are found to be consistent for all the data sets tested, which are shown in Table 7. The output sequence matrix (PMIM) for the proposed algorithm of problem size 12 × 10 considered from literature is shown in Table 8. The result of the example problem of size 12 × 10 obtained by the proposed algorithm outperforms the other two methods namely, ACCORD (Nair and Narendran, 1999) and the analytical iterative approach (George *et al.*, 2003) as shown in Table 9. In addition to the group technology efficiency and the number of exceptional elements used as performance measures in the literature, the number of intercell movements is also used for evaluating and comparing the performance of the algorithms. As far as sequence matrix is concerned, the intercell moves are calculated using Equations (6 and 7). If the operation of a part is allotted in the same cell where the previous operation of the part has taken place, then the intercell move is considered as zero. The total possible intercell moves are calculated just by taking a summation of the difference between one and maximum operation of each part as given in Equation (6). In modified ART1, the vigilance threshold (ρ) value greatly influences the number of cells obtained. The vigilance threshold value for each problem varies from 1 to 9. It is found that the number of cells is equal to the total number of parts if the vigilance threshold value is set at zero. Figure 1 shows the effect of the vigilance threshold with the number of cells and it is inferred from Figure 1 that the number of cells is inversely proportional to the value of the vigilance threshold. As the vigilance threshold value increases, the number of cells is reduced. If the vigilance threshold value is further relaxed, the algorithm produces only one cell. Therefore, the vigilance threshold value plays a vital role in obtaining quality solution. For each sample problem, the vigilance threshold has been varied to tune the algorithm and it is incremented in steps of 0.5 starting from zero till the desired solution is obtained.

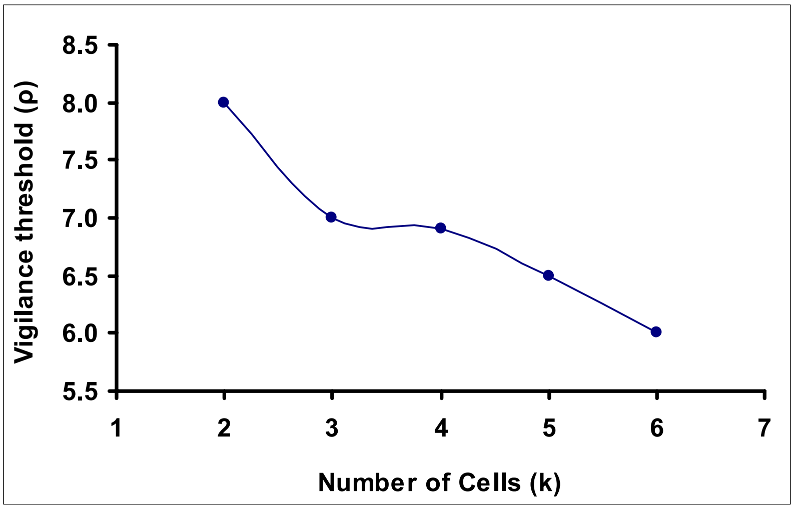
Table 8 Output sequence matrix for the problem of size (12 × 10)

Parts/ Machines	*1*	*3*	*6*	*2*	*5*	*8*	*10*	*4*	*7*	*9*
1		1	3					2		
5	3	5	1			2		4		
9	4	1	2			3				
10	3	1	2							
2				1	3	4	2			
3				2	4	1	3			
8				1			2			
12				3	2	1				
7				1	3		2			
4								1	3	2
6								1	3	2
11									1	

Table 9 Comparison of the results of the proposed method over existing methods for the problem of size 12 × 10

Factors considered	*ACCORD*	*Analytical iterative approach*	*Proposed method*
Exceptional elements	5	5	4
Grouping efficiency	0.881	0.881	0.897
Grouping efficacy	1.026	1.026	1.026
Group Technology Efficiency (GTE) %	80.00	80.00	84.00

Figure 1 Effect of vigilance threshold



The proposed algorithm provides solution in a single iteration only. The advantage of the proposed algorithm lies in its ability to generate quality solution for large-size problems. The algorithm is flexible in such a way that the maximum number of parts to be accommodated in a family can be limited. From Table 9, it is observed that the grouping efficiency and group technology efficiency are better in the case of the proposed algorithm, whereas grouping efficacy produces the same values for all the three methods compared.

It is found that the proposed algorithm for machine cell formation with sequence data gives satisfactory results, which are either superior or the same as the existing methods found in literature.

7 Conclusion

In this work an ART1-based algorithm has been developed to solve the CF problem taking into account the production sequence data of the parts. In the proposed algorithm the non-binary sequence data is converted into a binary data and fed into a ART1 network. The performance of the proposed algorithm is compared with that of the popular algorithms found in the literature namely, CASE, ACCORD (Nair and Narendran, 1999) and the analytical iterative approach (George *et al.*, 2003) for all the example problems cited in the literature. It is found that the proposed ART1-based algorithm outperforms the existing algorithms for larger-size problems both in terms of the group technology efficiency and the number of intercell movements, the performance measures commonly used in literature.

The methodology of converting the non-binary sequence data into a suitable binary data and subsequently by feeding into the ART1 networks to solve the CF problem for the specific objective of minimum intercell movements can be suitably modified or extended to solve the CF problem with other production data such as workload, batch sizes, *etc.*, for different objective criteria.

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