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Effective Artificial Neural Network Approach for Non-Binary Incidence Matrix-Based Part-Machine Grouping

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■ Abstract ■

This paper proposes an effective approach for the part-machine grouping(PMG) based on the non-binary part-machine incidence matrix in which real manufacturing factors such as the operation sequences with multiple visits to the same machine and production volumes of parts are incorporated and each entry represents actual moves due to different operation sequences. The proposed approach adopts Fuzzy ART neural network to quickly create the initial part families and their machine cells. A new performance measure to evaluate and compare the goodness of non-binary block diagonal solution is suggested. To enhance the poor solution due to category proliferation inherent to most artificial neural networks, a supplementary procedure reassigning parts and machines is added. To show effectiveness of the proposed approach to large-size PMG problems, a psuedo-replicated clustering procedure is designed. Experimental results with intermediate to large-size data sets show effectiveness of the proposed approach.

Keyword : Part-Machine Grouping, Artificial Neural Network

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1. Introduction

Under the present competitive market in the rapid development of technology and short life cycles of new products, cellular manufacturing (CM) which is an application of group technology (GT) has attracted many academic researchers and practitioners since CM has been proved a very effective approach for improving the productivity of small to medium-size batch-type manufacturing system [33].

The fundamental step toward designing CM is to create part families and associated machine cells or vice versa, which has been known as the part-machine grouping (clustering) (PMG) or cell formation(CF) problem in literature. Part family is a collection of parts that have similar operations and require a similar set of machines for the completion of these operations. A set of machines grouped to produce the parts in a specific part family is called the machine cell. The fundamental objective of PMG is to find independent machine cells with minimum interaction between cells so that a set of part family can be completely produced in a cell. During the last three decades, a lot of papers have addressed the PMG. For broad literature review of PMG, readers are referred to Joins *et al.*[8] and Selim *et al.*[31].

Given m part types and n machine types, the basic input to analysis of PMG is an $m \times n$ binary part-machine incidence matrix(PMIM) A where the element a_{ij} is 1 or 0 depending on whether or not part i requires processing on machine j. Most of the approaches for solving PMG problem have attempted to find part families and machine cells by transforming its initial PMIM into the block diagonal matrix.

However, the conventional binary PMIM-based approach to PMG is valid only when the production volumes of the parts are equal and the operation sequences of parts are not considered [43]. The conventional binary PMG approaches assume that each part-type makes identical demands on each machine type it uses. Obviously, this does not reflect shop floor reality. Since an intermediate operation of a part outside its cell involves two inter-cell moves while the first or last operation requires just one inter-cell moves, a "1" outside the main diagonal block can indicate more than one inter-cell moves depending on the sequence of operation and the volume of that particular part being processed [7, 21]. Therefore, the PMG ignoring the operation sequences and production volumes of parts tends to distort the real extent of material handling efforts within and outside the cells.

In recent years, a new research stream emphasizing the importance of real-world manufacturing factors such as the operation sequences and production volumes of parts has attracted researchers [4, 6, 7, 10, 20, 21, 28, 32, 33, 36, 37, 39, 42]. For good review of the recent literature on the PMG considering the operation sequences, readers are referred to Sarker and Xu [26, 27]. However, little researches considering the combined impact of multiple visits to the same machine and production volumes of parts have been performed. Existing methods for PMG reflecting the operation sequences with multiple visits to the same machine and production volumes of parts did not provide fundamental analytical tool replacing conventional binary PMIM as a basic input. To find the part family and then allocate machines to cells, separate time-consuming mathematical models and subsequent heuristic algorithms are often needed [4, 27].

Artificial neural network(ANN) model, a recent development in artificial intelligence, is a mathematical model that can be applied to discern patterns in data. Since the problem of transforming a matrix representing the association of parts and machines into a block diagonal form is similar to pattern recognition, it can be applied to PMG for the design of CM system. Detailed review of the application of ANNs to GT/CM can be found in Venugopal [38] and Park and Suresh [22].

A notable feature of ANNs is their ability to handle large-size PMG problem with low execution times compared conventional hierarchical PMG methods [13, 14, 34]. The low execution times with ANNs are because they can be operated as leader algorithms which do not require the entire PMIM to be sorted and manipulated.

Various types of ANNs have been applied to PMG. Some examples are the backpropagation network [11, 12, 18], self-organizing network [16, 17, 24], Adaptive Reasonance Theory (ART) [3, 5, 14, 15, 25], and Fuzzy ART [2, 9, 22, 23, 34, 35]. Among them, Fuzzy ART provides the best results for large-scale PMG problems [34]. It can handle both binary-valued and analogue inputs. However, the conventional ART/Fuzzy ART algorithms tend to produce too many clusters due to category proliferation resulting from the exemplar contraction [3, 5, 34]. Furthermore, the solution quality based on ART/Fuzzy ART algorithms highly depends on the ordering of input vector.

The recent development of Fuzzy ART ANN includes the incorporation of the part operation sequence data into the network [22, 35]. But existing methods did not incorporate the operation sequences with multiple visits to the same machine and production volumes of part into the network simultaneously by relying on separate binary-valued precedence matrices which represent the routing sequence for a part.

In this paper, an effective methodology adopting Fuzzy ART neural network is presented to solve the PMG problem considering the operation sequences with multiple visits to the same machine and production volumes of parts. The proposed methodology adopts the non-binary PMIM develpoed by Won and Lee [41] so that it can simultaneously capture the real manufacturing factors such as the operation sequences with multiple visits to the same machine and production volumes of parts. The non-binary entries normalized with production volume of each part are fed into network. To enhance the block diagonal solution after the initial grouping of part families and machine cells, supplementary procedure is added to avoid category proliferation. The proposed approach will be justified on large-size data sets generated with a psuedo-replicated clustering procedure which is a modification over conventional replicated clustering procedure [19, 22].

The paper is organized as follows. Section 2 illustrates the failure of Fuzzy ART algorithm applied to a small-size binary PMG problem. Section 3 describes the representation scheme for our Fuzzy ART network and proposes a new measure for evaluating the goodness of non-binary block diagonal solution. Section 4 describes the algorithm. Section 5 of applies our approach to intermediate-size data sets available in literature and compares the solution quality. Section 6 reports the experimental results with large-size data sets. The last section gives the summary and conclusion of the paper.

2. Failure of Fuzzy ART Algorithm

The objective of this section is to show that the conventional Fuzzy ART algorithm can produce poor bock diagonal solution due to the category proliferation even on small-size PMG problem.

[Figure 1] shows the initial binary PMIM for a manufacturing system which consists of 5 parts and 5 machines.

		Machines				
		1	2	3	4	5
	1		1		1	1
	2	1		1		
Parts	3	1		1		1
	4		1		1	
	5	1	1			1

[Figure 1] Initial binary PMIM

For this data set, the Fuzzy ART algorithm in Suresh and Kaparthi [34] is applied with the choice parameter $\alpha=0.5$ and learning rate $\beta=0.1$. The vigilance threshold indicating the degree of maximum difference between two input patterns (part vectors) in the same category (cluster or part family) varies between 1 and 0. On this problem the Fuzzy ART algorithm is implemented with the vigilance threshold decreased by 0.01 from 0.95 to 0.1. This can lead to a variety of alternative configuration of part families and machine cells since lowering the vigilance threshold contributes fewer clusters.

[Figure 2] shows the solution matrix that consists of three part families, PF-1 = {1, 4}, PF-2 = {2, 3} and PF-3 = {5}, and their associated three machine cells, MC-1 = {1, 3}, MC-2 = {1, 3} and MC-3 = {5}. Machine assignment to cells corresponding to their part families follows the maximum density rule[34].

		Machines				
		2	4	1	3	5
	1	1	1			1
	4	1	1			
Parts	2			1	1	
	3			1	1	1
	5	1		1		1

[Figure 2] Solution matrix

On this data set, lowering the level of vigilance threshold does not lead to smaller number of clusters and the problem of category proliferation is not resolved if two part families and machine cells are sought on this small system. [Figure 3] shows the progress of weight vector adaptation as the input part vectors are presented to the network. The maximum number of clusters is assumed to be 4 on this problem. After part 5 is presented to the network, cluster 3 is the winning node. Since the similarity with the best-matching node 3 is 1.0, node 3 always passes the resonance test for all the values of vigilance threshold and part 5 remains in the third cluster.

Parts	After presenting part 1			
	1*	2	3	4
1	0.9	1	1	1
2	1	1	1	1
3	0.9	1	1	1
4	1	1	1	1
5	1	1	1	1

Parts	After presenting part 2			
	1	2*	3	4
1	0.9	1	1	1
2	1	0.9	1	1
3	0.9	1	1	1
4	1	0.9	1	1
5	1	1	1	1

Parts	After presenting part 3			
	1	2*	3	4
1	0.9	1	1	1
2	1	0.81	1	1
3	0.9	1	1	1
4	1	0.81	1	1
5	1	0.90	1	1

Parts	After presenting part 4			
	1*	2	3	4
1	0.81	1	1	1
2	1	0.81	1	1
3	0.81	1	1	1
4	1	0.81	1	1
5	0.9	0.9	1	1

Parts	After presenting part 5			
	1	2	3*	4
1	0.81	1	1	1
2	1	0.81	1	1
3	0.81	1	0.9	1
4	1	0.81	0.9	1
5	0.9	0.9	1	1

* indicates the best matching node selected for each part

[Figure 3] Weight vector adaptation in Fuzzy ART

The expository example above shows that ancillary procedure is needed to improve poor CM solution which causes many inter-cell moves due to the existence of exceptional parts requiring operations in more than one parent block. In the solution shown in [Figure 2], parts 1, 4, and 5 are exceptional parts and machines 1, 2, and 5 are exceptional machines processing parts belonging to more than one part family. Exceptional part often causes improper assignment of part where it undergoes more portions of operations on machines in other cell rather than its parent cell corresponding to its parent family. Similarly, exceptional machine can cause improper assignment of machine where it has more part processing outside rather than its parent family corresponding to its parent cell. This is known as the chaining problem [29] in literature and reassigning those improperly assigned parts and machines to their most appropriate family and cell is an effective remedy to overcome the chaining problem [3, 29, 40].

3. Methodology for Non-Binary PMG

3.1 Input representation scheme

In order to present the non-binary inputs to ANN, appropriate input presentation scheme capturing the manufacturing characteristics like the operation sequences with multiple visits to the same machine and production volumes of parts needs to be prepared. Since the most fundamental objective of PMG is the creation of compact machine cells with minimum inter-cell part moves and maximum within-cell machine utilization, the use of non-binary PMIM reflecting such manufacturing characteristics effectively can lead to good block diagonal solution.

In this paper, the type I production data-based PMIM in Won and Lee [41] is employed for input presentation since it reflects the manufacturing characteristics such as the operation sequences with multiple visits to the same machine and production volumes of parts simultaneously, unlike Park and Suresh's [22] binary precedence matrix just representing the routing sequences for parts.

Each non-binary element b_{ij} of the type I production data-based PMIM B, is given by

$$b_{ij} = \sum_{r \in R_{ij}} f_{ijr} d_i \tag{1}$$

where

d_i = production volume of part i,

R_{ij} = set of operation sequence number along which part i visits machine j,

n_i = total number of operations by part i,

$$f_{ijr} = \begin{cases} 1 & \text{if } r = 1 \text{ or } n_i \\ 2 & \text{if } 1 < r < n_i \\ 0 & \text{otherwise.} \end{cases}$$

Each element b_{ij} in the type I production data-based PMIM reflects the total amounts of moves incurred by part i with production volume of d_i by assigning one inter-cell move to the first or last operation and two inter-cell moves to an intermediate operation.

However, each element of part vectors needs to be converted into the analogue value ranging between 0 and 1 before it is presented into the Fuzzy ART neural network and hence the input vector normalization scheme suitable to feed Fuzzy ART neural network is needed. A typical approach for normalizing input vectors is to find the minimum and maximum values for each attribute of all the input vectors and linearly scale the data [9]. To use this scheme, the whole information on the operation sequences and production volumes of all the parts must be stored *in advance* before they are presented to the network and this means that such a scaling scheme uses the entire PMIM at the beginning stage of applying the neural network. However, a major advantage from the application of ANN is that the entire PMIM needs not to be stored in memory from the beginning stage of algorithm since only one row is processed at a time [13, 34]. To avoid exploiting the whole PMIM from the beginning stage of algorithm and process only one row at a time, this paper adopts a simple scheme for normalizing input patterns. The proposed scheme normalizes each element b_{ij} of input pattern (part vector) i with its maximum value in pattern i as follows :

$$\frac{b_{ij}}{\max\{b_{ij} \mid j = 1, \cdots, n\}} \tag{2}$$

To show the application of the proposed input normalization scheme with type I PMIM, the routing information for part 1 shown in [Figure 1] is reconsidered and modified so that it represents the multiple visits to the same machine and production volume. Let us assume that the routing sequence for part 1 is denoted as 2-4-2-4-5 and its production volume is 20 units. Then, the input vector for part 1 before normalization is given by [0, 60, 0, 80, 20] from equation (1) and then we have the normalized input vector [0, 0.75, 0, 1.0, 0.25] from equation (2).

3.2 Performance measure

In order to evaluate the goodness of the bock diagonal solution to binary PMG, a lot of popular measures have been proposed and used to compare the effectiveness of different solution methods [26]. But the conventional measures of effectiveness of binary PMG can not be used to evaluate the goodness of the non-binary bock diagonal solution.

To evaluate the performance of PMG considering the operation sequences of part, Kiang *et al.* [16] proposed the cohesion measure which requires the calculation of the similarity (dissimilarity) coefficients between every pair of parts within the resulting clusters (part families). But their measure did not reflect inter-cell part moves directly.

In this paper, a simple measure of the goodness of non-binary bock diagonal solution, called weighted grouping capability index (WGCI), is proposed. WGCI which is a straightforward extension of grouping capability index(GCI) [30] does not require the calculation of the similarity coefficients between every pair of parts within part families. WGCI is defined as

$$\mathrm{WGCI} = 1 - \frac{\text{the sum of exceptional } b_{ij}\text{s}}{\text{the sum of all } b_{ij}\text{s}} \qquad (3)$$

The sum of exceptional b_{ij} s in a type I production data-based PMIM represents the actual flows incurred by the operations performed outside the main diagonal blocks and hence WGCI measures the proportion of the actual flows incurred by the operations performed within the main diagonal blocks. Since the sum of exceptional b_{ij} s includes all the actual flows incurred by the parts which have non-consecutive multiple operations on a machine, WGCI reflects both the operation sequences and production volumes of parts and is not affected by subjective weighting factor which is arbitrarily assigned by cell designer, unlike conventional performance measure such as grouping efficiency [26]. The WGCI measure reduces to the conventional GCI measure if the binary PMIM is considered.

The WGCI measure can be used to evaluate the goodness of two different block diagonal solutions. If two different block diagonal solutions have equal number of blocks, the solution with higher WGCI is preferred since it has less inter-cell moves under the same number of cell configuration. If two different block diagonal solutions have different number of blocks and equal WGCI, the solution with more blocks is preferred since it has more compact cells due to higher within-cell machine utilization under the cell configuration of equal inter-cell moves. The solution with higher WGCI under more blocks is absolutely preferred since it means both less inter-cell part moves and higher within-cell machine utilization.

4. Algorithm

The algorithm for PMG based on type I production data-based PMIM has two major stage: clustering stage and enhancement stage. Clustering stage uses Fuzzy ART neural network to quickly cluster parts into families and then assigns machines to cells. The proposed algorithm attempts to create the block diagonal solution accomplishing minimum inter-cell part moves and maximum within-cell machine utilization.

Clustering stage yields the configuration of part families. To present the results in traditional block diagonal form, a separate routine is needed to form machine cells by assigning machines to different clusters. As the row vectors are scanned, the amount of part processing of each machine by each cluster represented by the sum of b_{ij}s is calculated and each machine is assigned to the cluster which has the most part processing. If a machine is not an exceptional machine, its assignment to cell is straightforward.

However, the result with clustering stage may not be able to bring the most similar parts together due to the decay of exemplar template. Category proliferation due to the exemplar contraction tends to produce too many clusters(part families). As a result, the solution matrix may show improper block diagonal structure including the following undesirable features :

- Empty part families where no machines to process the parts of a part family are assigned or empty machine cells where no parts to process on the machines of a machine cell are assigned are found.
- Singleton part families which consist of a part are found.
- Improperly assigned parts and/or machines are found.

Since empty part families(machine cells), singleton part families, and improper assignment of parts and machines are the sources of degrading the effectiveness of CM system, supplementary procedure reassigning parts and machines should be added after the clustering stage is complete. Reassignment of parts and machines can lead to lower inter-cell part moves and higher within-cell machine utilization.

The reassignment procedure adopted in enhancement stage is a modification of reassignment procedure in Chen and Cheng [3] and Won [40] applied on the binary PMIM. The proposed reassignment procedure applied on the non-binary PMIM seeks to minimize inter-cell part moves and maximize within-cell machine utilization based on the following weighted maximum density rule which is an extension over the conventional maximum density rule :

Weighted maximum density rule

- For an exceptional part i, find its most appropriate part family in which it undergoes the most portions of operations represented by the sum of b_{ij}s than any other part family and reassign it to that part family. If ties occur, select the part family in which that part undergoes the most operations. If ties occur again, select the smallest part family.
- For an exceptional machine j, find its most appropriate machine cell in which it processes the most portions of operations represented by the sum of b_{ij}s than any other machine cell and reassign it to that machine cell. If ties occur, select the machine cell in which that machine processes the most parts. If ties occur again, select the smallest machine cell.

Stopping condition of the algorithm is stated as follows :

Stopping condition :

i) No empty part families exist,

ii) no singleton part families exist, and

iii) no parts(machines) are improperly assigned.

Note that if all the parts belonging to empty part families are reassigned to their most appropriate part families, empty machine cells are removed automatically because all the parts are assigned to non-empty machine cells, and the stopping condition for non-empty machine cells needs not to be considered.

The whole algorithm is then described as follows :

Clustering stage :

[Step 0] Use equation (2) to prepare for the input vectors.

[Step 1] For the specfied vigilance threshold ρ, choice parameter α and learning parameter β, apply Fuzzy ART algorithm to cluster parts into families.

[Step 2] Assign machines to their most appropriate cells.

Enhancement stage :

[Step 3] Apply the weighted maximum density rule to reassign improperly assigned parts and machines to their most appropriate part families and machine cells.

[Step 4] If stopping condition is satisfied, stop. Otherwise, go to [Step 3] and repeat.

5. Illustrative Examples

Many data sets based on the binary PMIM have been provided in literature and applied to justify the effectiveness of new PMG methods. However, few data sets with non-binary PMIM containing both the operation sequences with multiple visits to the same machine and production volumes of parts are available in literature. To show and compare the application and effectiveness of the proposed algorithm to the PMG problem based on non-binary PMIM, two ill-structured intermediate- size data sets available in open literature have been selected and illustrated. The algorithm has been written in C++objected-oriented language and implemented on a Pentium III PC with 1 GHz.

5.1 Example 1

The proposed algorithm has been applied to the data set in Wu [42]. On this problem, the Fuzzy ART neural network with $\alpha = 0.5$, $\beta = 0.1$, and the vigilance threshold of 0.95 has been applied.

[Figure 4] shows the type I PMIM at the end of clustering stage, which yields the six part families and their associated machine cells. It can be noticed from the solution matrix that clustering stage generates two empty part families that consists of parts 2 and 5, respectively, and a singleton part family consisting of part 8.

The parts belonging to these part families should be reassigned and algorithm goes to enhancement stage. After three iterations of enhancement stage, the solution with WGCI equal to 94.62% as shown in [Figure 5] is obtained. The configuration of part families and machine cells shown in [Figure 5] is slightly different from the one of Wu's solution but two solutions give equal WGCI.

		Machines												
		5	8	9	12	13	2	6	7	3	10	11	1	4
	1	1200	800	800	800	400								
	3	1250	500	3750	2500	2500								
	7	600	400							200				
	11	1560		1040	1040	520								
	2						620		310				310	
	4						350	700	350					
Parts	10						560	560	280				280	560
	13						180		270				90	
	5	360	360								360	180	180	
	6									120	120			240
	9									860	860	430	430	860
	12									150	300	150		
	8												2200	2200

[Figure 4] Type I solution matrix at the end of clustering stage

		Machines												
		5	8	9	12	13	2	6	7	3	10	11	4	1
	1	1200	800	800	800	400								
	3	1250	500	3750	2500	2500								
	7	600	400							200				
	11	1560	1040		1040	520								
	5	360	360								360	180		180
	4						350	700	350					
Parts	10						560	560	280				560	280
	13						180		270					90
	2						620		310					310
	6									120	120		240	
	9									860	860	430	860	430
	12									150	300	150		
	8												2200	2200

[Figure 5] Type I solution matrix at the end of enhancement stage

5.2 Example 2

The second data set has been adopted from Nair and Narednran [21]. Although it does not include the operation sequences with multiple visits to the same machine and different production volumes for parts, it has been selected to compare the solution qualities based on the reference algorithm and the proposed method. In this data set, production volumes for each part is assumed to be one unit. On this problem the Fuzzy ART neural network with $\alpha = 0.5$, $\beta = 0.1$ has also been applied. To ensure proper comparison of the solutions under equal number of clusters, the Fuzzy ART neural network has been implemented for various vigilance thresholds decreasing by 0.01 from the starting value of 0.95.

[Figure 6] shows the solution matrix implemented at the vigilance threshold of 0.93 and [Figure 7] shows the solution matrix provided in Nair and Narendran. Their method

Machines

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

[Figure 6] Type I solution matrix at the end of enhancement stage

Machines

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

[Figure 7] Type I solution matrix by Nair and Narendran has yielded the solution with WGCI equal to 76.58%, whereas the proposed algorithm yields better solution with WGCI equal to 78.19.

The solution by the proposed algorithm is compared with the one in Park and Suresh [22]. Since they only showed the configuration of part families and did not provide the configuration of machine cells, however, the unified comparison using WGCI is impossible among the solutions. <Table 1> shows the configuration of part families in Park and Suresh. From the table, it can be notice that there are minor differences in the solutions. But Park and Suresh's method which also includes supplementary merging procedure for countering the category proliferation problem has produced singleton part family. whereas the proposed method does not yield any singleton part family and this results in the block diagonal solution with higher WGCI.

〈Table 1〉 Solution by Park and Suresh

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

6. Experiments with Large-Size Data

The effectiveness of the proposed algorithm needs to be tested on ill-structured large-size PMG problems. In order to show the robustness and recoverability of PMG algorithms to randomly generated large-size data sets, replicated clustering has often been used [19, 22]. In replicated clustering. a known solution is generated first and randomly reordered, and these scrambled data are presented to an algorithm. The clusters resulting from the algorithm are then compared and evaluated with the known starting solution [22].

However, few authors have proposed systematic replicated clustering procedure for the generation of data sets including both the operation sequences with multiple visits to the same machine and the production volumes of parts. In this paper, a psuedo-replicated clustering procedure which is applicable as an alternative for conventional replicated clustering is proposed to generate large-size data sets including both the operation sequences with multiple visits to the same machine and the production volumes of parts. The psuedo-replicated clustering procedure proceeds as follows :

Psuedo-replicated clustering :

i) An appropriately intermediate-size problem is solved with PMG algorithm and identify the number of clusters and the value of WGCI.
ii) Assume that the incumbent solution to that problem is the best one and apply Adil *et al.*'s data expansion scheme [1] to replicate row and columns of the original problem. Scramble the order of input presentation at random.
iii) Apply PMG algorithm to expanded problem.

Adil *et al.*'s data expansion scheme that has been applied to binary PMIM can be applied to non-binary PMIM in a similar way so as to replicate row and columns of the original problem. Unlike the conventional replicated clustering to generate large-size data sets at one time, the psuedo-replicated clustering procedure generates large-size data sets by replicating row and columns many times. Furthemore, the proposed psuedo-replicated clustering can start with near-best solution to the original problem which is accepted by cell designer.

To apply psuedo-replicated clustering procedure, the original problem needs to be appropriately ill-structured and provide the manufacturing data of the operation sequences with multiple visits to the same machine and production volumes of parts. In our experiment, the data set shown in example 1 of the previous section has been selected to apply psuedo-replicated clustering since it is a good example of ill-structured problem providing the

〈Table 2〉 Experimental results with expanded data sets

Expansion level	2 (26 × 26)*			5 (65 × 65)*		10 (130 × 130)*	
Problem No.	ρ**	No. of clusters	WGCI	No. of clusters	WGCI	No. of clusters	WGCI
1	0.92	6	93.05	17	92.33	33	93.02
2	0.95	6	92.94	16	93.86	33	93.34
3	0.94	6	93.96	16	93.09	34	92.71
4	0.95	6	93.05	17	93.09	33	92.78
5	0.94	6	93.90	15	93.95	33	92.75
6	0.95	6	94.62	17	93.09	33	93.16
7	0.95	6	94.62	16	92.95	35	92.09
8	0.95	6	94.62	15	93.86	34	92.33
9	0.94	6	94.62	17	92.33	34	92.05
10	0.93	6	93.60	15	93.86	32	93.07
11	0.94	6	94.26	15	92.95	36	91.81
12	0.93	6	92.71	16	93.09	35	92.33
13	0.95	6	92.69	15	93.08	32	93.40
14	0.95	6	92.94	15	93.86	30	93.33
15	0.95	6	94.62	16	92.95	33	93.02
16	0.90	6	94.26	15	93.86	31	93.86
17	0.95	6	94.62	16	93.09	34	92.69
18	0.95	6	92.71	16	92.83	32	92.96
19	0.94	6	93.90	16	93.86	34	92.39
20	0.95	6	94.62	15	93.09	33	92.64
21	0.94	6	92.35	18	92.33	34	92.71
22	0.95	6	94.62	15	93.08	32	92.40
23	0.94	6	94.62	15	94.62	32	92.78
24	0.95	6	94.62	16	93.18	34	92.64
25	0.95	6	94.62	17	93.09	33	93.09
average			93.89		93.25		92.77

Note) * denotes the resulting problem size(no. of parts × no. of machines).
** denotes the vigilance threshold.

operation sequences with multiple visits to the same machine and production volumes of parts.

The proposed psuedo-replicated clustering procedure has been applied to the data set in Wu [42] with various expansion levels. In our experiments, the expansion levels equal to 2, 5, and 10 have been applied. The target value of WGCI revealing the recoverability of the proposed algorithm to expanded problems is set at 94.62% under the configuration of clusters not less than 6, 15, and 30, respectively, for each expansion level, For each expansion level, 25 problems have been generated and randomly scrambled. The data sets are available on request.

<Table 2> shows the experimental results. The second leftmost whole columns show the values of vigilance threshold, number of clusters, and WGCI found when the original problem is replicated with the expansion level of 2. To compare the solution quality under equal number of clusters, the algorithm has been implemented with the values of vigilance threshold decreasing by 0.01 from the starting value of 0.95 until the six-cluster solution has been found. The experimental result with psuedo-replicated clustering shows minor gap within 1% from the target WGCI value of 94.62% on the average. In 11 problem instances of 25 problem, the proposed algorithm recovers the original problem. But their orders of input presentation are different. <Table 3> shows different input orders for those 11 problems and this indicates that the algorithm is not sensitive to the input order.

<Table 3> Different orderings of part input vector presentation

Problem No. / order	6	7	8	9	15	17	20	22	23	24	25
1	23	16	3	8	16	16	23	10	16	2	14
2	7	22	1	5	24	7	19	12	12	26	26
3	5	19	25	9	13	23	5	13	20	14	17
4	11	20	6	14	12	19	22	9	26	5	22
5	20	11	5	18	10	3	6	6	19	22	10
6	1	12	17	13	9	5	24	16	3	1	18
7	4	23	20	11	11	26	1	23	7	18	24
8	9	5	13	10	22	10	14	24	22	6	21
9	14	13	23	15	26	20	4	1	13	20	6
10	26	3	4	1	19	13	3	25	1	16	25
11	6	18	22	26	18	4	12	5	18	12	16
12	25	1	26	21	21	14	7	19	10	3	1
13	22	17	14	3	7	9	8	2	2	9	13
14	13	2	8	16	5	8	2	21	14	7	15
15	10	14	24	22	2	6	9	8	15	17	2
16	8	4	11	7	14	11	25	3	8	4	20
17	19	6	15	25	15	1	13	18	23	13	19
18	18	26	19	4	20	12	21	15	6	24	8
19	3	24	7	19	4	24	18	17	17	23	7
20	2	9	9	24	1	15	16	11	24	8	12
21	15	25	16	6	6	21	26	7	9	25	11
22	21	15	12	12	25	22	17	22	5	19	9
23	16	8	18	2	8	2	20	20	4	15	3
24	24	10	10	20	23	25	15	4	11	21	23
25	17	21	21	17	3	17	10	26	25	11	4
26	12	7	2	23	17	18	11	14	21	10	5

<Table 2> also reports the experimental results with the large-size problems replicated with the expansion levels of 5 and 10. To these large-size problems, the Fuzzy ART network with a vigilance threshold of 0.95 has been implemented to produce the solutions with the clusters not less than 15 and 30, respectively, for each expansion level. The table shows that the proposed algorithm has produced the solutions that have gap within 2% on the average from the target WGCI under the clusters more than the reference numbers on the data sets replicated with the expansion level of 10.

7. Concluding Remarks

In this paper, effective approach adopting Fuzzy ART neural network has been proposed to solve the non-binary PMG problem which considers real manufacturing factors such as the operation sequences with multiple visits the same machine and production volumes of the parts.

The proposed algorithm seeks to overcome the category proliferation problem that is inherent to most ANN algorithms by implementing supplementary procedure which reassigns improperly assigned parts and machines and finds good-quality solutions. New performance measure for evaluating and comparing the goodness of different non-binary bock diagonal solutions has been proposed. On ill-structured intermediate size problems, the proposed algorithm produces good-quality bock diagonal solutions.

To show the robustness and recoverability of the proposed algorithm on large-size data sets, psuedo-replicated clustering procedure that is a variant of the conventional replicated clustering has been suggested. The experimental results with psuedo-replicated clustering shows the robustness and recoverability of the proposed algorithm on large-size data sets within minor gap from the target value of the proposed new performance measure.

This paper does not consider the manufacturing factors such as minimization of the cell load variation based on the machine capacity, multiple copies of identical machines, and alternative process plans. Development of effective ANN models including such more comprehensive manufacturing factors is the future research to be done.

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