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FA-WALCA-CF: A NOVEL METHOD TO MACHINE-PART GROUPING PROBLEMS

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Abstract:
Cellular manufacturing system is the formation of optimised machine cells, which forms part families with similar processing requirements and associates machines into machine cells in order to optimise the overall production process. To effectively solve this problem a hybrid novel approach is demonstrated in this paper, which is based on weighted average linkage clustering algorithm and fuzzy-ART neural network technique. The proposed technique is tested on published datasets of past literature and the experimental results presented in this study indicate that the method is very effective for small to medium size problems. Testing large size problems and inclusion of ratio level data could be the prospective scope of future for this research work. This work is a significant addition in the on-going research in cellular manufacturing and could be helpful to the future researchers and practitioners in the aforementioned domain of study.

Key Words: Cellular Manufacturing, Machine-Part Grouping, Neural Network, Clustering Analysis, Correlation Coefficient

1. INTRODUCTION

In recent era manufacturing businesses are facing extreme challenges due to the growing demands of global marketplace. Briefer product life-cycles, impulsive demands, and varied customer needs have compelled manufacturing firms to function more competently and realistically in order to meet the varying necessities. Traditional manufacturing systems, such as job shops and flow shops, cannot manage such situations. Cellular manufacturing (CM), which incorporates the tractability of job shops and the high production rate of flow shops, has been materialized as a viable replacement in such cases [1, 2, 3]. CM is the application of the concept of group technology (GT) in manufacturing systems. GT is a manufacturing philosophy that utilizes similarities in product design and production processes. A primitive concern in CM is the determination of part families and machine cells. This problem is known as the cell formation problem (CF/CFP). The CFP involves the breakdown of a manufacturing system into cells. Part families are recognized in such a way that these could be processed within a cell. The cells are formed to take the advantages of GT such as reduced setup times, reduced in-process inventories, improved product quality, shorter lead times, reduced tool requirements, improved productivity, and better overall control of operations [4]. The CFP has long been identified as the trickiest problem in grasping the concept of cellular manufacturing. It fits in the class of NP-hard problems, which means that intensification in the problem size will cause an exponential expansion in the computational time for all established optimisation techniques. Due to the NP-hard nature of the problem [5], many computational techniques are heavily practised for improved solutions to the CFP, a thorough discussion can be found in past literature [6].

Over the last few decades many clustering methods are proposed by researchers to solve CFPs, such as ZODIAC [7], GRAFICS [8], minimum spanning tree (MST) [9], K-Harmonic Mean algorithm [5], Fuzzy C-Means algorithm [10] etc.

In this article a new clustering approach is proposed to solve CFPs by clubbing fuzzy ART Neural Network technique and Pearson's correlation coefficient method, further hybridized with weighted average linkage clustering algorithm.

2. REVIEW OF LITERATURE

Various techniques are developed to solve manufacturing cell formation problems since last four decades, these include similarity coefficient methods, clustering analysis, array based techniques, graph partitioning methods etc. The similarity coefficient approach was first implemented by McAuley [11]. The foundation of similarity coefficient method is to measure the similarity between each pair of machines and subsequently group the machines into cells based on their similarity measurements. Most similarity based methods utilize machine–part mapping matrices. Some of the methods, which have practiced this approach, are Single linkage clustering algorithm [11], Average linkage clustering algorithm [12]. Clustering methods are categorized as hierarchical and non-hierarchical methods. Orthodox or particularly designed clustering techniques could be utilized to develop clusters of either components or machines. Machine–part grouping analysis is based on production flow analysis, in which the machine-part groups are formed by rearranging rows and columns of the machine-part mapping matrix in the form of a {0-1} incidence matrix. Some of the methods are Rank order clustering [13], Bond energy algorithm [14] etc. Dimopoulos and Mort stated a hierarchical algorithm combined with genetic programming for a simple cell formation problem [15]. Array based methods consider the rows and columns of the machine-part incidence matrix as binary patterns and reconfigure them to obtain a block diagonal cluster formation. The rank order clustering algorithm is the most familiar array-based technique for cell formation [13]. Substantial alterations and enhancements over rank order clustering algorithm have been described in other articles [16, 17]. The direct clustering analysis has been developed in this context [18] and further bond energy analysis is proposed to solve the said problems [14]. Graph theoretic approach depicts the machines as vertices and the similarity between machines as the weights on the arcs [19]. Chandrasekharan and Rajagopalan proposed an ideal seed non-hierarchical clustering algorithm for cellular manufacturing [17]. To improve the quality of solution graph searching algorithm is demonstrated which select a key machine or part according to a pre-fixed criterion [20]. A non-heuristic network approach was further stated to construct manufacturing cells with minimum inter-cellular moves [21]. Srinivasan implemented a method using minimum spanning tree for the machine-part cell formation problem [9]. A polynomial-time algorithm named as vertex-tree graphic matrices is also proposed for optimal cell formation in other article [22].

3. CELL FORMATION PROBLEM AND PERFOMANCE MEASURE

The cell formation problem in group technology begins with two fundamental tasks, namely, machine-cell formation and part-family identification. To form machine-cell similar machines are grouped and they are dedicated for the manufacture of one or more part-families. In part-family formation, parts with similar design features, attributes, shapes are grouped so that the group of parts can be manufactured within a cell. Generally, the cell formation problems are represented in a matrix namly 'machine-part incident matrix' in which all the elements are presented as either 0 or 1. Parts are arranged in cloumns and machines are in row in the incidence matrix. An example matrix is presented in Figure 1. It depicts that part 2 is processed through machine 1, part 1, 4 are processed through machine 2, part 3 is processed through machine 1, 3 and part 5 is processed through machine 1, 2, 3. In this matrix a 0 indicates no mapping or no processing and a 1 indicates mapping or processing. The Block diagonal structure is illustrated in resultant matrix which is known as solution matrix.

	P1	P2	P3	P4	P5
M1	0	1	1	0	1
M2	1	0	0	1	1
M3	0	0	1	0	1

	P3	P5	P2	P1	P4
M1	1	1	1	0	0
M3	1	1	0	0	0
M2	0	1	0	1	1

Figure 1: Machine-part incidence matrix (3×5).

In Figure 1 cells are shown block diagonally as square boxes. It can be interpreted that cell 1 contains machine 1 and 3 and the part family formed for cell 1 is part 2, 3, 5 and cell 2 contains machine 2 and the corresponding part family contains part 2, 4. A 1 outside the block means a part processed through some machine which does not belong to the corresponding machine cell, i.e. bottleneck machine, therefore the intercellular move cost will be added. This element is known as an exceptional element (EE) and a 0 inside a cell means an unutilized space in cell, therefore lesser utilization of space. It is known as 'void'. The objective of cell formation is to minimize the EEs and voids.

To formulate the cell formation problem the following are considered,

I = set of m machines, $i = 1,\dots,M$

J= set of n parts, $j = 1,\dots,P$

The incidence matrix is A = [a_{ij}] demonstrates the mapping between machines and parts,

$$a_{ik} = \begin{cases} 1 \; if\; part\; j\; goes\; through\; machine\; i \\ 0 \quad\quad otherwise \end{cases} \tag{1}$$

To measure the goodness of solutions, different performance measures have been proposed by researchers since past few decades. Various measures can be obtained from the critical survey of performance measures [23]. In this study grouping efficacy has been considered which is heavily utilized by other authors to measure the efficiency of obtained solutions [24] and it is given as:

$$\tau = \frac{E - E_e}{E + E_v} \tag{2}$$

Where

E = Total number of 1s in matrix A

E_e = Total number of exceptional elements (1s outside the cluster block)

E_v = Total number of voids (0s inside the cluster block)

The objective function which maximizes the efficiency is as follows:

$$Maximize F = \frac{E_v + E_e}{E + E_v} \tag{3}$$

subject to

$$\sum_{k=1}^{K} x_{ik} = 1 \qquad i = 1, \ldots, M \tag{4}$$

$$\sum_{k=1}^{K} y_{jk} = 1 \qquad j = 1, \ldots, P \tag{5}$$

$$\sum_{k=1}^{K} x_{ik} \geq 1 \qquad k = 1, \ldots, K \tag{6}$$

$$\sum_{k=1}^{K} y_{jk} \geq 1 \qquad k = 1, \ldots, K \tag{7}$$

$$x_{ik} = 0 \text{ } or \text{ } 1 \qquad i = 1, \ldots, M; \; k = 1, \ldots, K \tag{8}$$

$$y_{jk} = 0 \text{ } or \text{ } 1 \qquad j = 1, \ldots, M; \; k = 1, \ldots, K \tag{9}$$

Where,

$$x_{ik} = \begin{cases} 1 \; if \; machine \; i \; is \; in \; cell \; k \; (\mathrm{i} = 1, \ldots, \mathrm{M} \text{ and } \mathrm{k} = 1, \ldots, \mathrm{K}) \\ 0 \qquad otherwise \end{cases} \tag{10}$$

and

$$y_{ik} = \begin{cases} 1 \; if \; part \; j \; is \; in \; cell \; k \; (\mathrm{j} = 1, \ldots, \mathrm{P} \text{ and } \mathrm{k} = 1, \ldots, \mathrm{K}) \\ 0 \qquad otherwise \end{cases} \tag{11}$$

To evaluate the objective function *F*, it can be demonstrated:

$$E_e = E - \sum_{k=1}^{K} \sum_{i=1}^{M} \sum_{j=1}^{P} a_{ij} x_{ik} y_{jk} \tag{12}$$

$$E_v = \sum_{k=1}^{K} \sum_{i=1}^{M} \sum_{j=1}^{P} (1 - a_{ij}) x_{ik} y_{jk} \tag{13}$$

This objective function *F* is a fractional function in *x* and *y*.The constraints (4) and (5) depict that each machine and each part is assigned to exactly one cell, respectively. Further constraints (6) and (7) demonstrate that each cell contains at least one machine and one part respectively. Binary variables are expressed in (8) and (9). Constraints (6) and (7) ensure the elimination of empty cells, if any.

4. THE PROPOSED TECHNIQUE

In this article the similarity measure method is utilized based on Pearson's corellation coefficient [25]. In general, sample X_k has *n* measurements or features, therefore it can be written as $X_k = \{x_{1k}, x_{2k}, \ldots, x_{nk}\}$.The formula that can be used to calculate *r* is given as:

$$r = \frac{n\sum_{i=1}^{n} x_{ik}x_{im} - (\sum_{i=1}^{n} x_{ik})(\sum_{i=1}^{n} x_{im})}{\sqrt{[n\sum_{i=1}^{n} x_{ik}{}^{2} - (\sum_{i=1}^{n} x_{ik})^{2}][n\sum_{i=1}^{n} x_{im}{}^{2} - (\sum_{i=1}^{n} x_{im})^{2}]}} \quad (14)$$

Pearson's correlation coefficient can be used to calculate the similarity between two samples by using the formula:

$$S = \frac{(r+1)}{2} \quad (15)$$

In addition, this correlation coefficient can be used to calculate a distance between the samples using the formula:

$$D = (1-r) \quad (16)$$

This abovementioned Pearson’s correlation technique is utilized in this study to calculate the similarity coefficient value between two machine rows in incidence matrix and to generate the similarity matrix. Figure 2 shows the similarity matrix obtained from the example problem given in Figure 1.

	M1	M2	M3
M1	1		
M2	-0.667	1	
M3	0.667	-0.167	1

Figure 2: Similarity matrix of example problem (3×5).

Hierarchical linkage clustering techniques have an affinity to group machines which are basically dissimilar in nature due to the chaining problem they suffer from [11, 15]. That is the reason why researchers are interested in improving the linkage technique. To overcome this flaw McAulay proposed average linkage clustering algorithm for CF problem. In this research an Weighted Average Linkage Clustering model is introduced in the next stage of the algorithm as a cure to this problem.Weighted Average Linkage Clustering Algorithm (WALCA) is conceptually and mathematically simple algorithm practiced in hierarchical clustering analysis of data [26]. It delivers informative descriptions and visualization of potential data clustering structures. When there exists hierarchical relationship in data this approach can be more competent. In this article a fuzzy art based hybrid WALCA approach, namely FA-WALCA-CF is proposed which is combined with Pearson’s correlation coefficient to facilitate efficient cell formation. Weighted average linkage method uses a recursive definition for the distance between two clusters. If cluster *r* is to be created by combining clusters *p* and *q*, the distance between *r* and another cluster *s* is defined as the average of the distance between *p* and *s* and the distance between *q* and *s* as given as:

$$d(r,s) = \frac{(d(p,s) + d(q,s))}{2} \quad (17)$$

A matrix is generated using (17),which is a *(m-1)×3* matrix, where *m* is the number of machines in the original dataset. Columns of the matrix contain cluster indices linked in pairs to form a binary tree. The leaf nodes are numbered from *1 to m*. Leaf nodes are the singleton clusters from which all higher clusters are built. Further the dendrogram can be obtained from the matrix which indicates a tree of potential solutions. Therefore it’s the decision maker’s job to decide how to obtain a particular group of machines based on pre-selected similarity threshold. Dendrogram structure obtained for the machines is shown in Figure 3, which clearly states that two clusters are formed, cluster 1 contains machine 1 and 3 and cluster 2 contains machine 2.

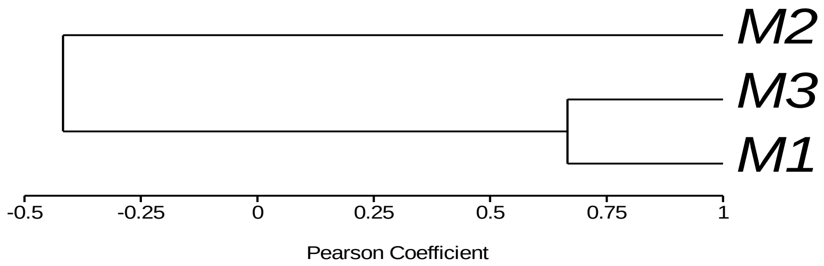

Figure 3: Dendrogram of machine grouping of example problem (3×5).

4.1 Fuzzy ART Approach

Fuzzy Adaptive Resonance Theory (ART) was first proposed by Grossberg [27], which belongs to the class of unsupervised, adaptive neural networks. Adaptive neural networks always had an important role in cellular manufacturing since early 90's [28, 29, 30, 31]. Fuzzy ART was another common adaptive resonance framework [32, 33, 34] that provides a unified architecture for both binary and continuous valued inputs. The Fuzzy ART neural network involves several changes to previous ART model: (a) non-binary input vectors can be processed; (b) there is a single weight vector connection (w_{ij}); and (c) in addition to vigilance threshold (ρ), two other parameters have to be specified: a choice parameter (α) and a learning rate (β).The proposed FA-WALCA-CF algorithm is depicted in sub-section 4.2 and the final block diagonal formation is of the example problem is shown in Figure 1. The grouping efficacy value obtained is 77.78.

4.2 Proposed Hybrid Algorithm

Proposed FA-WALCA-CF

Input: *Machine-part incidence matrix A*
Procedure *correlation_matrix_formation ()*
1.1. Compute similarity values between pair of machines using (14), (15), (16)
1.2. Compute the similarity matrix of the machines
Procedure *machine_grouping ()*
2.1. loop
2.2. Compute the weighted average distance of clusters using (17) by taking the similarity input from previous procedure which replaces the distance calculation
2.3. Construct matrix of size (m-1)×3 to from the hierarchical relationship
2.4. construct dendrogram from the binary matrix computed using weighted average linkage rule
2.5. loop
2.6. Create machine cells for the highest level of similarity coefficient
Procedure *Fuzzy_art_part_grouping ()*
3.1. Create and initialize the Fuzzy ART network
3.1.1. Create and initialize the weight matrix.
weight = ones(total_Number_of_Machines, 0);
3.1.2. Create the structure and return
Fuzzy_Art=struct (' total_Number_of_Machines ', { total_Number_of_Machines }, 'Total_Number_of_Categories', {0}, 'Maximum_Number_of_Categories', {100}, 'weight', {weight}, 'vigilance', {0.75}, 'bias', {0.000001}, 'total_Number_Of_Epochs', {200}, 'learning_Rate', {1.0});
3.2. Training the Fuzzy ART network
3.2.1. Set the return variables
Fuzzy_Art = {};
Classification = ones(1, Total_Number_of_Parts);
3.2.2. For each epoch go through the incidence matrix A
3.2.3. Classify and learn on each part

3.2.3.1. Activate the classifications
3.2.3.2. Rank the activations
3.2.3.3. In the sorted list go through each classification and find the best match.
3.2.3.4. Must create a new classification if no classifications yet found
3.2.3.5. Calculate the match
3.2.3.6. If the match is greater than the vigilance then update the weights and induce resonance
3.2.3.7. Else choose the next classification in the sorted classification list
3.2.4. Stop training if the network does not change at all
3.3.Final Part machine clustering
3.3.1. Set up the return variables.
Classification = ones(1, Total_Number_of_Parts);
3.3.2. Classify and learn on each part
3.3.2.1. Activate the classifications
3.3.2.2. Rank the activations
3.3.2.3. look for the best match
3.3.If the match is greater than the vigilance then induce resonance
3.4. Else choose the next classification in the sorted classification list
If it is the last classification in the list, set the classification for the return value as -1 and induce resonance.
3.5.From the return variable part group is identified
Output: *Optimized machine cell configuration and part family structure*

5. EXPERIMENTAL RESULTS

The FA-WALCA-CF is tested with a set of 12 problems that have been published in the literature. All the data sets were transcribed from the original articles to avoid the inconsistency in data. The sources of the datasets are shown in Table I. The FA-WALCA-CF is simulated with Multivariate Statistical Analysis Toolbox and Matlab 7.1 and tested on a laptop with a 2.1GHz processor and 2GB of RAM. Comparisons of the FA-WALCA-CF against the best results obtained from the literature are given in Table II. Results are obtained from published article [5, 35]. For the problems solved with FA-WALCA-CF to obtain optimal solution, the grouping efficacy value is better or equal in all instances. All the outputs are obtained with negligible computational time (<15 sec.) This observation indicates that this hybrid technique is very efficient and less complex because of its simplicity in simulation. Therefore this technique is highly comparable with other complex soft computing techniques such as genetic algorithms, evolutionary techniques, genetic programming etc. The FA-WALCA-CF is shown to outperform the standard techniques in 6 instances, and equal in 6 instances, which further depicts 50% improved result than published results which is significant in terms of solution quality and time and space complexities.

Table I: Source of datasets.

#	dataset	size
1	Waghodekar and Sahu (1984) [36]	5×7
2	King and Nakornchai (1982) [16]	5×7
3	Seifoddini (1989) [37]	5×18
4	Kusiak and Cho (1992) [38]	6 x 8
5	Boctor (1991) [39]	7×11
6	Kusiak and Chow (1987) [40]	7×11
7	car and Mikac (2006) [41]	8×10
8	Chandrasekharan and Rajagopalan (1986) [17]	8×20
9	Chu and Hayya (1991) [42]	9×9
10	Goncalves and Resend (2004) [43]	15×12
11	Jayakrishnan and Narendran (1998) [44]	20×8
12	Masnata and settineri (1997) [45]	25×10

6. CONCLUSIONS

This paper proposes a fuzzy ART based hybrid clustering technique namely FA-WALCA-CF that combines Pearson's correlation coefficient method with weighted average linkage clustering technique. A mathematical programming model is also considered for the cell formation problem objective which utilizes the grouping efficacy measure in terms of E_e and E_v. Experimental results presented in Section 5 demonstrate that the FA-WALCA-CF outperforms the other techniques, and delivers improved results in comparison with the published results. This article states that, by enjoining the Pearson correlation coefficient into a traditional hierarchical clustering technique can improve the solution quality substantially, and inclusion of fuzzy ART method would not only enhance clustering but it also reduces the variability of the solutions obtained. The FA-WALCA-CF obtains better quality solutions by consuming lesser computational time and resources than that of the traditional complex soft computing based methodologies. It is also shown that the FA-WALCA-CF performs at least as well as, and often better than the available algorithms for the cell formation on all problems tested. Hence it is verified as a promising method in aforestated area. Further work can be done by utilizing this technique in large-scale and complex cell formation problem which deals with ratio data of production volume, operational time, worker assignment by considering multi-objective factors. Future work can also be done by combining soft computing techniques with FA-WALCA-CF, such as fuzzy mathematics, Particle Swarm Optimization or Artificial Bees Colony techniques, which would be the extension of present research.

Table II: Comparison of the results obtained from CLCA-CF technique with published results.

#	Best result found in literature	FA-WALCA-CF	cell	EE	void	improvement
1	62.5	**69.56****	2	6	2	**12.10%**
2	73.68	73.68	2	2	3	0.00%
3	79.59	79.59	2	7	3	0.00%
4	76.92	76.92	2	2	4	0.00%
5	70.37	70.37	3	2	6	0.00%
6	53.13	**59.26**	4	7	4	**11.54%**
7	66.67	**68.96**	4	7	2	**3.43%**
8	85.24	**86.67**	3	8	0	**1.68%**
9	73.53	**74.28**	3	6	3	**1.02%**
10	86.67	86.67	4	0	6	0.00%
11	83.87*	82.25	3	9	1	0.00%
12	63.93	**70.27**	4	9	13	**9.91%**

** Inconsistent result obtained in [5], actual calculated result would be 82.25*
*** Boldfaces are better or improved results obtained in present article*

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