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A hybrid neural network approach to cell formation in cellular manufacturing

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Abstract: The design of Cellular Manufacturing Systems (CMS) has attained the significant interest of academicians, researchers and practitioners over the last three decades. CMS is regarded as an efficient production strategy for batch type of production. Literature suggests that since the last two decades neural network based methods have been intensively used in cell formation problems while production factor such as operation time is merely considered. This paper presents a new hybrid neural network approach, Fuzzy ART-Centroid Linkage Clustering Technique (FACLCT), to solve the part machine grouping problems in cellular manufacturing systems considering operation time. The performance of the proposed technique is tested with problems from open literature and the results are compared with the existing clustering models such as simple C-Linkage, K-Means, modified ART1 and genetic algorithm and achieved better performance. The novelty of this study lies in the simple and efficient methodology to produce quick solutions with least computational efforts.

Keywords: cell formation; group technology; cellular manufacturing; artificial neural network; fuzzy adaptive resonance theory; centroid linkage; agglomerative clustering.

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1 Introduction

Over the past three decades, in response to the competitive markets need for increased industrial automation, product diversification and the trend towards shorter product life cycles, new manufacturing philosophies have been adopted by many of the established manufacturing firms. Among those new manufacturing philosophies, group technology (GT) has been used to reduce throughput and material handling times, to decrease work-in-progress and finished goods inventories and to increase the ability to handle forecast errors (Won and Currie, 2007). Group technology can be defined as a manufacturing philosophy identifying similar parts and grouping them together to take advantage of their similarities in manufacturing and design (Selim et al., 1998). Cellular manufacturing (CM) is an application of GT and has emerged as a promising alternative manufacturing system. CM could be characterised as a hybrid system linking the advantages of both the jobbing (flexibility) and mass (efficient flow and high production rate) production approaches. CM entails the creation and operation of manufacturing cells. Parts are grouped into part families and machines into cells. As reported by Wemmerlöv and Hyer (1989), the aim of CM is to reduce set-up and flow times and therefore to reduce inventory and market response times. Set-up times are reduced by using part-family tooling and sequencing, whereas flow times are reduced by minimising set-up and move times, wait times for moves and by using small transfer batches. Group technology addresses issues such as average lot size decreasing, part variety increasing and increased variety of materials with diverse properties and requirements for closer tolerances. As described in a review (Venugopal, 1999), the basic idea behind GT/CM is to decompose a manufacturing system into sub-systems by identifying and exploiting the similarities amongst part and machines. The very first step in this process is to solve the complex Part Machine Grouping (PMG) problem and the problem being quite challenging under real-time scenario, various approaches have been developed, and among which soft computing approach has an eminent role in the GT/CM literature. Soft computing is the state-of-the-art approach to artificial intelligence which mostly comprises fuzzy logic, artificial neural network and evolutionary computing. This paper presents a new hybrid neural network approach, Fuzzy ART Centroid Linkage Clustering Technique (FACLCT), to solve the PMG problem in cellular manufacturing systems considering operation time. In light of the literature survey, it is well understood that very few studies focus on cell formation considering production factors such as operational time, operational sequence, batch size, production volume and other factors. In this work, it is attempted to form the cells considering operation time, a real-time production factor. To solve such problem the zero-one Machine Part Incidence Matrix (MPIM) is converted into real valued workload data. The workload represents the operational time required by the parts in the machines. The proposed hybrid model has been tested on wide variety of problems from literature and compared to the solutions obtained from simple C-Linkage, K-Means, modified ART1 and genetic algorithm in the recent literature.

2 Literature review

Burbidge (1977) viewed group technology as a change from an organisation of people mainly on process, to an organisation based on completed products, components and major completed tasks. Since 1960, various approaches were presented to solve the machine part grouping problem. Initially the methods like Similarity Coefficient Methods (SCM) (Seifoddini and Wolfe, 1986), graph theory (Rajagopalan and Batra, 1975) and Rank Order Clustering (ROC) (King, 1980) methods were developed only to group the similar machines into machine cells while the grouping of parts into part families was done in the supplementary step of the procedure. Later clustering methods such as the MODROC (Chandrasekharan and Rajagopalan, 1986), ZODIAC (Chandrasekharan and Rajagopalan, 1987) MACE (Waghodekar and Sahu, 1984) are reported for solving the cell formation problems. Since late 1980s soft-computing approaches began to gain popularity (Venugopal, 1999; Papaioannou and Wilson, 2009) which included artificial neural network, fuzzy logic and meta-heuristics like simulated annealing (SA) algorithm, genetic algorithm (GA), tabu search (TS).

2.1 Artificial neural network

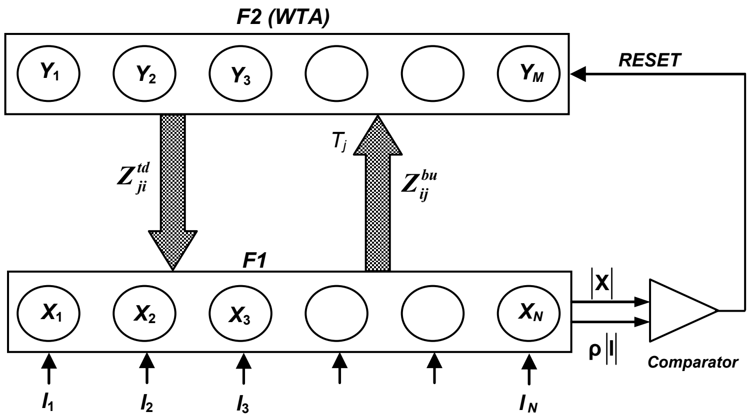
Neural networks are massively parallel computer algorithms (Wasserman, 1989) with an ability to learn from experience. They have the capability to generalise, adapt, approximate given new information, and provide reliable classifications of data. These algorithms involve numerous computational nodes that have a high connectivity. Each of the nodes operates in a similar manner which makes them ideal for a parallel implementation. During the execution, each node receives an input, processes this information, and produces an output which is provided as an input to other nodes in the network. The connections between the nodes, and in particular the learning rules that modify the strength between the connections, give neural networks their power and flexibility (Enke et al., 2000). The neural network approach has been the subject of intensive study by interdisciplinary researchers for a long time. Though neural networks have been successfully applied in a variety of fields, their use in cellular manufacturing problems started in the late 1980s and early 1990s. Recognising ANN's pattern recognition ability, several researchers began to investigate neural network methods for the part-machine grouping problem. Neural network is of major interest because when it is connected to computer, it mimics the brain and bombard people with much more information.

2.2 Fuzzy adaptive resonance theory

Fuzzy ART proposed by Grossberg (Carpenter et al., 1991) belongs to the class of unsupervised, adaptive neural networks. Adaptive neural networks always had an important role in cellular manufacturing beginning in the early 1990s in the works of Kao and Moon (1991), Malave and Ramachandran (1991), Dagli and Huggahalli (1991) and

Moon and Chi (1992). Dagli and Huggahalli used ART1 in such problems while Malave and Ramachandran used competitive learning. Fuzzy ART was another common adaptive resonance framework as presented in the works of Suresh and Kaparthi (1994), Burke and Kamal (1995), Kamal and Burke (1996), Suresh et al. (1999), Peker and Kara (2004), Won and Currie (2007) and Ozdemir et al. (2007) which provided a unified architecture for both binary and continuous valued inputs. Although fuzzy ART does not require a completely binary representation of the parts to be grouped, it possesses the same desirable stability properties as ART1 and a simpler architecture than that of ART2. Figure 1 shows the architecture of the fuzzy ART network (Chang et al., 2005). It consists two layers of computing cells or neurons, and a vigilance sub-system controlled by an adjustable vigilance parameter. The input vectors are applied to the fuzzy ART network one by one. The network seeks for the ‘nearest’ cluster that ‘resonates’ with the input pattern according to a ‘winner-take-all’ strategy and updates the cluster to become ‘closer’ to the input vector. In the process, the vigilance parameter determines the similarity of the inputs belonging to the same cluster. For the same set of inputs, the similarity of elements in one cluster grows as the vigilance parameter increases, leading to a larger number of trained clusters. The choice parameter and the learning rate are two other factors that influence the quality of the clustering results. In this paper, fuzzy ART is used to form the part families while agglomerative centroid linkage-hierarchical clustering algorithm is used to form the machine groups. The detailed description of the hybrid algorithm is discussed in the next section.

Figure 1 Topological structure of the fuzzy ART architecture



3 The proposed hybrid approach

This study presents a hybrid FACLCT, a new pattern recognition neural network approach, for clustering problems, and illustrates its use for machine cell design in group technology. FACLCT is a bimodal clustering model. While mode1 is concerned with the identification of part families using the fuzzy ART architecture, mode2 is concerned with the formation of machine groups using the centroid linkage-agglomerative hierarchical clustering algorithm. The fuzzy ART neural network was introduced by Carpenter et al.

(1991) and Suresh and Kaparthi (1994) implemented it to the CF problem. The latter found that in terms of bond energy recovery, fuzzy ART outperformed ART1 and ART1/KS. The execution time of fuzzy ART was higher than ART1 and ART1/KS, but for larger datasets, execution times were significantly lower than DCA and ROC2. The fuzzy ART neural network involves several changes to ART 1: (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 step-by-step illustration of fuzzy ART network is as follows (Suresh and Kaparthi, 1994):

Step 1: Initialisation

Connection weights: $w_{ij}(0) = 1$.

$0 \leq \mathbf{I} \leq N - 1, 0 \leq j \leq (M - 1)$

Select values for: $\alpha > 0$, $\beta\ \varepsilon\ (0, 1)$, $\rho\varepsilon\ (0, 1)$

Step 2: Read a new input vector **I** consisting of binary or analogue elements

Step 3: Compute choice function (T_j) for every input node

$T_j = ||\mathbf{I} \wedge wj|| / [\alpha + ||wj||], 0 \leq j \leq (M - 1)$,

where ^ is the fuzzy AND operator, defined as: $(x \wedge y) = \min (x_i, y_i)$

Step 4: Select the best matching exemplar.

$\mathrm{T}_\Theta = \max \{T_j\}$

Step 5: Resonance test:

If $||\mathbf{I} \wedge w_\Theta|| / ||\mathbf{I}|| \geq \rho$ then go to step 7 otherwise go to step 6

Step 6: Mismatch reset: set $\mathrm{T}_\Theta = -1$ and go to step 4

Step 7: update best matching exemplar (learning law)

$\mathrm{w}_\Theta^{new} = [\beta \times (\mathbf{I} \wedge \mathrm{w}_\Theta^{old})] + [(1 - \beta) \times \mathrm{w}_\Theta^{old}]$

Step 8: Repeat: go to step 2.

The above algorithm although could produce efficient clustering solutions, the literature suggests that hybrid approaches often produced better clusters. To establish the fact, centroid linkage-hierarchical clustering algorithm is integrated to the fuzzy ART neural network to form the machine group based on the part families formed by the neural model.

Hierarchical Agglomerative Clustering (HAC) is conceptually and mathematically simple algorithm practised in clustering analysis of data (Anderberg, 1973).[AQ1] It delivers informative descriptions and visualisation of potential data clustering structures. When there exists hierarchical relationship in data this approach can be more competent. The algorithm in contrast to machine grouping is presented below.

AQ1: The references flagged with [AQ1] are not included in the reference list. Please provide the complete reference details to include in the reference list.

3.1 Step 1: formation of input dataset

An input dataset for HAC is a machine–part incidence matrix. Machines are the items that should be grouped based on their similarities. Parts are the components that contain routing information. The type of input dataset can be classified into binary data (contains only 0 or 1, i.e. the routing information) and ratio data (contains information about production volume, operation time). Figure 2 shows a 5 × 7 binary dataset.

Figure 2 5 × 7 input matrix

	p1	p2	p3	p4	p5	p6	p7
m1	0	1	0	1	1	1	0
m2	1	0	1	0	0	0	0
m3	1	0	1	0	0	1	1
m4	0	1	0	1	0	1	0
m5	1	0	0	0	1	0	1

3.2 Step 2: computing pair-wise distance between pairs of machines

This function computes the distance between each pairs of machines of the given input of data matrix. It produces an output vector of length $m(m-1)/2$ where m is the number of rows of the input matrix. This output is commonly used as dissimilarity matrix in clustering or in multidimensional scaling. Instead of a matrix the output is considered as a vector in order to minimise the time and space complexities. The distance is computed using Minkowski distance metric. The computation is performed using following formula:

$$\sqrt[p]{\sum_{k=1}^{n}\left|m_{ik}-m_{jk}\right|^{p}} \tag{1}$$

This matrix is a generalised form of Euclidian, Chebychev and City block distance matrices. M is denoted as machines of the incidence matrix. The computational result obtained by applying this method on above-mentioned 5 × 7 input matrix is a vector

$$\mathbf{D}=\begin{bmatrix}1.0000 & 2.4495 & 2.4495 & 2.2361 & 2.2361 & 2.2361 & 2.4495 & 1.4142 & 1.7321 & 1.7321\end{bmatrix}$$

3.3 Step 3: HAC tree formation

This function is developed on the basis of hierarchical cluster formation. If cell r is formed from cell p and q, and n_r is the number of machines in cell r, x_{ri} is the i-th machine of cell r, then centroid linkage is computed using the formula

$$d(r,s)=\left\|\bar{x}_r-\bar{x}_s\right\|_2 \tag{2}$$

which is the Euclidean distance between the centroids of two cells where

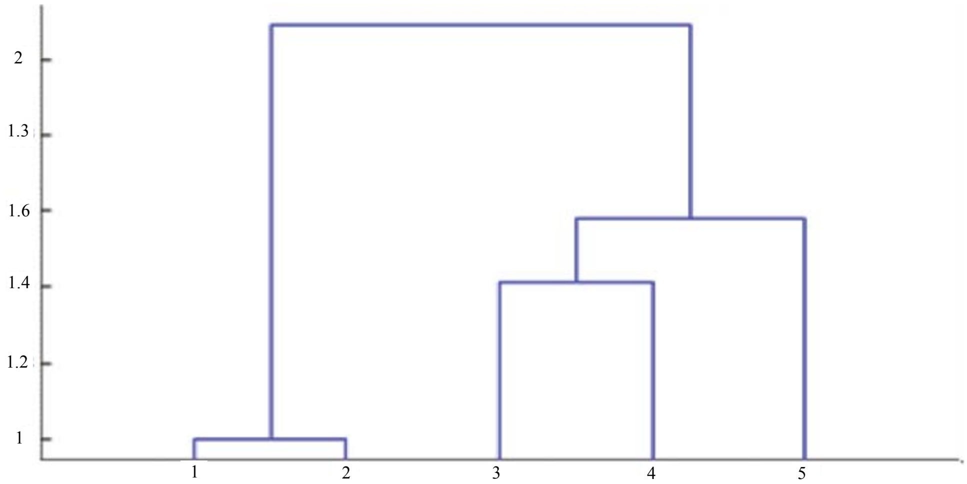
$$\bar{x}_r=\frac{1}{n_r}\sum_{i=1}^{n_r}x_{ri} \tag{3}$$

This linkage function is applied on the vector obtained from 5 × 7 input matrix in the step 2. It generates the matrix Z defining a tree of hierarchical clusters of the rows of the vector **D**. Z is a $(m-1)\times 3$ matrix, where m is the number of machines in the original dataset. Columns 1 and 2 of Z 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. The dendrogram obtained from Z is shown in Figure 2. It clearly indicates the hierarchical structure and relationship between clusters.

$$Z = \begin{bmatrix} 1.0000 & 2.0000 & 1.0000 \\ 3.0000 & 4.0000 & 1.4142 \\ 5.0000 & 7.0000 & 1.5812 \\ 6.0000 & 8.0000 & 2.0883 \end{bmatrix}$$

Figure 3 Dendrogram obtained from centroid linkage algorithm (see online version for colours)



3.4 *Step 4: constructing agglomerative clustering from centroid linkage*

This routine constructs clusters from the agglomerative hierarchical cluster tree, as generated by the linkage function. Z is a matrix of size $(m - 1) \times 3$, where *m* is the number of machines in the original data. A threshold value is used for cutting Z into clusters. Clusters are formed when a node and all of its sub-nodes have inconsistent value less than the threshold value. All leaves at or below the node are grouped into a cluster. Output is a vector of size *m* containing the cluster assignments of each machine row.

In the hybrid model the centroid linkage-hierarchical clustering algorithm is integrated into the fuzzy ART architecture and on execution both the part and machine group clusters are produced. This integrated approach helps reduce computational time and often produce better or comparable results when tested on the problems found in the literature. Another important aspect of the model proposed in this work is the ability to handle workload data. The model is equally capable of handling workload matrix as compared to Part Machine Incidence Matrix (MPIM) and the machine cells are formed based on the operation time, a real-time production factor. The detailed step-by-step approach of the integrated model is presented below.

Step 1: Input the workload matrix
Machines in rows and parts in columns
Step 2: Normalise input matrix by complement coding
Step 2.1: Determine the size of the data.
[totalNumofMachines, TotalNumofParts] = size(workloadMatrix);
Step 2.2: Create the return variable.
C = ones(2* totalNumofMachines, TotalNumofParts);
Step 2.3: For each part do the complement coding
for j = 1: TotalNumofParts
count = 1;
for i = 1:2:(2* totalNumofMachines)
C(i, j) = data(count, j);
complementCodedData(i + 1, j) = 1 - data(count, j);
count = count + 1;
Step 3: Create and initialise the fuzzy ART network
Step 3.1: Create and initialize the weight matrix.
weight = ones(totalNumofMachines, 0);
Step 3.2: Create the structure and return
FuzzyArt = struct('totalNumofMachines', { totalNumofMachines },
'TotalNumofCategories', {0}, 'MaximumNumofCategories', {100}, 'weight', {weight},
'vigilance', {0.75}, 'bias', {0.000001}, 'totalNumOfEpochs', {200},
'learningRate', {1.0});
Step 4: Training the fuzzy ART network
Step 4.1: Set the return variables
FuzzyArt = {};
Classification = ones(1, TotalNumofParts);
Step 4.2: for each epoch go through the complement coded workload matrix
Step 4.3: Classify and learn on each part
Step 4.3.1: Activate the classifications
Step 4.3.2: Rank the activations
Step 4.3.3: In the sorted list go through each classification and find the best match.
Step 4.3.4: must create a new classification if no classifications yet found
Step 4.3.5: Calculate the match
Step 4.3.6: if the match is greater than the vigilance then update the weights and induce resonance
Step 4.3.7: else choose the next classification in the sorted classification list
Step 4.4: if at the last epoch the network does not change at all, equilibrium is reached and stop training
Step 5: Final Part machine clustering
Step 5.1: Set up the return variables.
Classification = ones(1, TotalNumofParts);
Step 5.2: Classify and learn on each part
Step 5.3.1: Activate the classifications
Step 5.3.2: Rank the activations
Step 5.3.3: look for the best match
Step 5.4: if the match is greater than the vigilance then induce resonance

Step 5.5: 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.

Step 5.6: from the return variable part group is identified

Step 5.7: Compute the pair-wise distance between pairs of machines in the workload matrix

Step 5.8: HAC tree formation

Step 5.9: Construct agglomerative clustering from centroid linkage

Step 5.10: based on the return variable machine groups are identified.

Step 6: Show Results

4 Results and discussion

In this study, an efficient artificial neural network based hybrid model FACLCT has been proposed for cell formation considering operational time of the parts to be processed in the machines instead of conventional zero-one incidence matrix based on part visit to respective machines with the objective of minimising exceptional elements and voids while improving the grouping efficiency. In order to measure the grouping efficiency of an algorithm for machine-part cell formation, a performance measure is needed. Many performance measures for evaluating the goodness of PMG have been proposed over the years. Some popular performance measures that have been widely adopted in literature (Won and Currie, 2007) are grouping efficiency proposed by Chandrasekharan and Rajagopalan in 1986, grouping efficacy, proposed by Kumar and Chandrasekharan in 1990 [AQ1] and Grouping Capability Index (GCI), proposed by Seifoddini and Hsu in 1994. [AQ1] However, the above-mentioned measures are not applicable to the proposed FACLCT model for part machine grouping since they are based on the block diagonal configuration of binary part machine PMIM and they do not incorporate the real-field data such as the operation time. To measure the clustering efficiency considering operation time, in this work Modified Grouping Efficiency (MGE) (Mahapatra and Sudhakarapandian, 2008) is used. The MGE is calculated using the following formulation in equation (4).

$$\mathrm{MGE} = \frac{T_{pti}}{T_{pto} + \sum_{k=1}^{c} T_{ptk} + \sum_{k=1}^{c} T_{ptk} \frac{N_{vk}}{N_{ek}}} \tag{4}$$

where T_{pti}: Total processing time inside the cells

T_{pto}: Total processing time outside the cells

T_{ptk}: Total processing time of cell k

N_{vk}: No. of voids in cell k

N_{ek}: Total number of elements in cell k

Unlike grouping efficiency, modified grouping efficiency does not treat all the operations equally. Moreover, a weighting factor for voids is considered to reflect the packing density of the cells. It produces 100% efficiency when the cells are perfectly packed without any voids and exceptional elements. The FACLCT algorithm is coded in MATLAB 7.1 and tested on the Intel Celeron M processor. The real valued workload matrix is presented to the algorithm as input. The proposed approach is tested on

18 datasets available in the GT/CM literature which were converted to workload matrix. The results obtained are compared to simple C-Linkage, K-Means, modified ART1 and genetic algorithm as present in the literature (e.g. Mahapatra and Sudhakarapandian, 2005; Mahapatra and Sudhakarapandian, 2006; Ponnambalam et al., 2007). In order to compare the performance with the mentioned work in the literature, instead of generating the workload matrix from the PMIM in the literature in a random manner, the same workload matrix is taken as referred in the above-mentioned published works (Sudhakarapandian, 2007). Around 27.77% of the solutions indicated clear improvement compared to the four other techniques as measured in terms of minimum exceptional elements and maximum MGE. Apart from the above mentioned 27.77%, most of the other solutions obtained from the proposed hybrid neural approach often outperformed at least three of the compared techniques while the rest demonstrated similar results with minor exceptions. The learning rate is initialised to 1 and the vigilance parameter is considered as 0.75. Table 1 presents the source of the datasets used from the literature to demonstrate the proposed model and Table 2 presents the comparison between the results obtained from FACLCT and the C-Linkage, K-Means, modified ART1 and genetic algorithm available literature.

Table 1 Source of the datasets used from the literature

DS No.	*Source*	*Problem size*	*DS No.*	*Source*	*Problem size*
1	King and Nakornchai (1982) [AQ1]	5 × 7	10	Askin et al. (1987) [AQ1]	14 × 23
2	Seifoddini (1989) [AQ1]	5 × 18	11	Srinivasan et al. (1990) [AQ1]	16 × 30
3	Kusiak (1992) [AQ1]	6 × 8	12	Carrie (1973) [AQ1]	20 × 35
4	Kusiak (1987) [AQ1]	7 × 11	13	Kumar et al. (1986) [AQ1]	23 × 20
5	Seifoddini and Wolfe (1986)	8 × 12	14	Chandrasekharan et al. (1989a) [AQ1]	24 × 40
6	Chandrasekharan et al. (1986a) [AQ1]	8 × 20	15	Stanfel (1985a) [AQ1]	30 × 50
7	Chandrasekharan et al. (1986b) [AQ1]	8 × 20	16	Boe et al. (1991) [AQ1]	20 × 35
8	Mosier et al. (1985) [AQ1]	10 × 10	17	Mccornick et al. (1972) [AQ1]	24 × 16
9	Chan et al. (1982) [AQ1]	10 × 15	18	Kumar et al. (1987) [AQ1]	30 × 41

Table 2 Comparison between C-Linkage, K-Means, modified ART1, GA and FACLCT

		C-Linkage		*K-Means*		*Modified ART1*		*Genetic algorithm*		*FACLCT*	
DS	*NC*	*EE*	*MGE*	*EE*	*MGE*	*EE*	*MGE*	*EE*	*MGE*	*EE*	*MGE*
1	2	2	77.25	2	77.25	2	77.25	2	77.25	2	77.26
2	2	7	81.87	7	81.87	7	81.87	7	81.87	7	81.88
3	2	2	79.85	2	79.85	2	79.85	2	79.85	2	79.85
4	2	3	61.77	3	61.77	3	61.77	3	61.77	3	62.06*
5	2	6	57	6	57	4	69.7	6	69.7	4	64.15
6	2	28	60	28	60	25	61.3	28	61.3	22	60.75
7	3	9	83.4	9	83.4	9	83.4	9	83.4	9	83.45
8	3	0	77.14	0	77.14	0	77.14	0	77.14	0	77.17

Table 2 Comparison between C-Linkage, K-Means, modified ART1, GA and FACLCT (continued)

		C-Linkage		*K-Means*		*Modified ART1*		*Genetic algorithm*		*FACLCT*	
DS	*NC*	*EE*	*MGE*	*EE*	*MGE*	*EE*	*MGE*	*EE*	*MGE*	*EE*	*MGE*
9	3	0	93.28	0	93.28	0	93.28	0	93.28	0	93.06
10	2	2	59.43	2	59.43	2	60.59	0	62.42	0	59.81
11	3	15	64.81	15	64.81	15	64.81	20	64.81	16	67.2*
12	3	1	71	1	71	1	71.15	1	71.15	1	70.96
13	3	38	51.7	38	51.7	42	50.5	42	51.92	40	48.17
14	6	0	90.28	0	90.28	0	90.28	0	94.58	0	90.28
15	6	20	61.84	20	61.84	26	55.51	22	62.23	17	59.3
16	4	31	61.5	31	61.5	28	61.71	32	61.7	27	61.63*
17	4	30	51.39	34	46.7	30	51.39	29	52.02	27	54.03*
18	3	17	53.98	12	56.65	17	53.98	15	56.14	7	57.62*

Notes: *improvement; DS: dataset number; NC: number of cells; EE: exceptional elements; MGE: modified grouping efficiency.

From Tables 1 and 2, it could be seen that a wide variety of datasets have been chosen from the literature with part machine workload matrices ranging from 5 × 7 to 30 × 50. From the results the efficiency of the hybrid model in handling workload data and capability of clustering machine part workload matrix with minimum exceptional elements and maximum possible MGE is justified and hence could be established as a simple and efficient methodology to produce quick solutions for shop floor managers with least computational efforts and time. Figure 4 shows an input workload matrix while Figures 5–7 demonstrate the solution sets obtained from FACLCT.

Figure 4 Input workload matrix for example problem of size 5 × 7, dataset 1

	p1	p2	p3	p4	p5	p6	p7
m1	0	0.53	0	0.99	0.83	0.91	0
m2	0.82	0	0.83	0	0	0	0
m3	0.91	0	0.92	0	0	0.86	0.97
m4	0	0.79	0	0.56	0	0.88	0
m5	0.53	0	0	0	0.51	0	0.98

Figure 5 Output matrix by the proposed FACLCT-based algorithm for example problem of size 5 × 7, dataset 1

	p6	p2	p5	p4	p1	p3	p7
m1	0.91	0.53	0.83	0.99	0	0	0
m4	0.88	0.79	0	0.56	0	0	0
m2	0	0	0	0	0.82	0.83	0
m3	0.86	0	0	0	0.91	0.92	0.97
m5	0	0	0.51	0	0.53	0	0.98

Figure 6 Output matrix by the proposed FACLCT-based algorithm for example problem of size 20 × 35, dataset 16

	p1	p5	p15	p17	p20	p8	p14	p16	p22	p25	p19	p23	p26	p32	p35	p30	p34	p29	p3	p4	p6	p9	p11	p21	p28	p33	p2	p7	p12	p13	p2	p7	p24	p31	p27	p18	p10
m17	0.9	0.82	0.89	0.65	0.57					0.97					0.88				0.5																		
m5		0.84		0.99			0.79					0.94	0.84																								
m6						0.7	0.93		0.98	0.92	0.73					0.92																					
m7	0.7	0.5	0.77	0.76	0.6				0.61		0.96	0.54	0.7	0.67		0.99		0.85	0.8									0.5	0.54			0.5	0.67	0.87			
m8	0.6	0.7	0.78	0.55	0.81							0.63			0.97							0.85															
m9						0.54	0.52				0.85	0.55		0.99	0.93																						
m10						0.94	0.8	0.68	0.63		0.6		0.7																								
m20						0.55	0.62				0.8	0.81	0.98																								
m1	0.5		0.82		0.91		0.91			0.97		0.92		0.56	0.53	0.79	0.88				0.9		0.83										0.86			0.83	
m3	0.6	0.5	0.69															0.63	0.6															0.68			
m11																				0.9	0.71	0.98	0.53	0.68		0.91											
m12																				0.5	0.76	0.88	0.79	0.52													
m15																0.81				0.66	0.87	0.74	0.7	0.77	0.85												
m16													0.92	0.78		0.83				0.63	0.6	0.96							0.53							0.9	
m19														0.61		0.52				0.55		0.84	0.67	0.92	0.85												
m4																											0.5	0.6	0.94	0.68	0.5	0.6	0.67		0.7		
m13																											0.9		0.78	0.52	0.9		0.72				
m14																											0.9	0.92	0.8	0.67	0.9	0.92	0.69	0.54	0.59	0.53	0.86
m18					0.53																						0.8	0.72	0.7	0.78	0.8	0.72	0.95	0.95			
m2											0.54																0.5		0.83	0.71	0.5		0.54	0.74		0.58	0.98

Figure 7 Output matrix by the proposed FACLCT-based algorithm for example problem of size 30 × 41, dataset 18

	p12	p23	p24	p40	p10	p31	p32	p33	p39	p19	p20	p41	p2	p11	p6	p7	p8	p15	p26	p28	p29	p35	p14	p16	p17	p25	p18	p27	p34	p5	p37	p36	p38	p1	p3	p9	p13	p21	p22	p30	p4
m1					0.5	1	0.8	0.9	0.8			0.8																													
m3	0.5	0.5		0.7		1	0.8																																		
m10	0.9	0.7							0.9		0.9		1																												
m12	1	0.5	0.7	0.9					0.7	0.6				0.8													0.6														
m21	0.8			0.8	0.5	0.9	0.8	0.5	0.9																																
m22	0.7	0.9		0.7	0.5	0.9	0.9		0.8																																
m23	0.7	0.6				0.5			0.7				0.5																												
m11					0.5			0.5	0.5			0.8																													
m2	0.9						1	0.8	0.6			0.9		0.9													0.9														
m4			0.5													0.6		0.5		0.6		0.6				0.7															
m5																									0.7				0.6	0.5		0.7									
m6															0.5				0.6																						
m7																								0.9				0.7	0.7			0.7									
m8																	0.8				0.8		0.9											0.8		1					
m13																										0.9	1						0.7								
m14																			0.8								0.9			0.7	0.6										0.6
m15																									0.8						0.6										
m16															1					0.5																					
m17																0.5								0.9				0.6				1									
m18																							0.9	0.9				0.8	0.7												
m26																								0.7				0.8	0.9			0.8									
m28																	1				0.5	0.9																			
m27																	0.6	0.6																							
m9																																			0.8		0.9	0.7			
n19																																		0.6	0.6			0.7	0.9	0.7	
m20																																		1	0.5			0.7	0.9		
m24																																	0.9								
m25																																									0.7
m29																																		0.9	0.8	0.8	1	0.5		0.8	
m30																																		0.9	0.7			0.6	1		

In cellular manufacturing systems the number of cells formed often has an effective role in maximising MGE and minimising exceptional elements. More number of cells increases exceptional elements thus affecting the MGE while in other cases it may increase MGE by reducing voids. Again under some circumstances it increases MGE without affecting the exceptional elements and could be referred as ideal number of cells. The optimal number of cells is thus required to find the best solution. The analysis is demonstrated in Figures 8–10 and finally concluded in Figure 11.

Figure 8 Dataset 5 with 2 cells

	p1	p2	p11	p12	p3	p4	p5	p6	p7	p10	p8	p9
m1	0.53	0.99	0	0	0.83	0.91	0	0	0	0	0	0
m7	0	0	0.68	0.67	0	0	0	0	0	0	0	0
m8	0	0	0.7	0.84	0	0	0	0	0	0	0	0
m5	0	0	0	0	0	0	0	0	0.63	0.63	0.53	0.69
m6	0	0	0.94	0	0	0	0	0	0.68	0	0.51	0.61
m2	0.82	0	0	0	0.83	0.91	0.92	0.86	0.97	0.79	0	0
m3	0	0	0	0	0.56	0.88	0.53	0.51	0.98	0	0.83	0.71
m4	0	0	0	0	0	0	0	0.58	0.54	0.63	0.54	0.74

Figure 9 Dataset 5 with 3 cells

	p1	p2	p11	p12	p3	p4	p5	p6	p7	p10	p8	p9
m1	0.53	0.99	0	0	0.83	0.91	0	0	0	0	0	0
m7	0	0	0.68	0.67	0	0	0	0	0	0	0	0
m8	0	0	0.7	0.84	0	0	0	0	0	0	0	0
m5	0	0	0	0	0	0	0	0	0.63	0.63	0.53	0.69
m6	0	0	0.94	0	0	0	0	0	0.68	0	0.51	0.61
m2	0.82	0	0	0	0.83	0.91	0.92	0.86	0.97	0.79	0	0
m3	0	0	0	0	0.56	0.88	0.53	0.51	0.98	0	0.83	0.71
m4	0	0	0	0	0	0	0	0.58	0.54	0.63	0.54	0.74

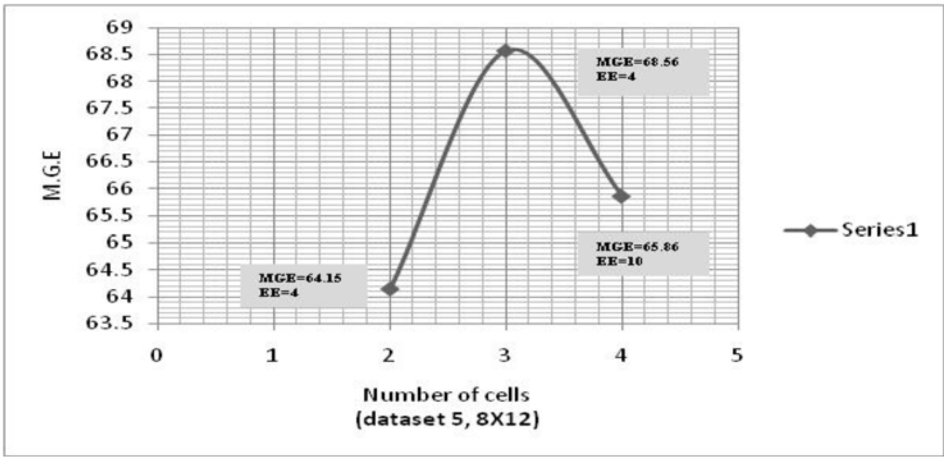
Figure 10 Dataset 5 with 4 cells

	p1	p2	p11	p12	p3	p4	p5	p6	p7	p10	p8	p9
m1	0.53	0.99	0	0	0.83	0.91	0	0	0	0	0	0
m7	0	0	0.68	0.67	0	0	0	0	0	0	0	0
m8	0	0	0.7	0.84	0	0	0	0	0	0	0	0
m2	0.82	0	0	0	0.83	0.91	0.92	0.86	0.97	0.79	0	0
m3	0	0	0	0	0.56	0.88	0.53	0.51	0.98	0	0.83	0.71
m5	0	0	0	0	0	0	0	0	0.63	0.63	0.53	0.69
m6	0	0	0.94	0	0	0	0	0	0.68	0	0.51	0.61
m4	0	0	0	0	0	0	0	0.58	0.54	0.63	0.54	0.74

Figure 8 shows a clustered result of a workload matrix of size 8 × 12 (dataset 5). In this case, 2 cells are formed with 4 exceptional elements and 64.15% MGE. Figure 9 shows the clustered result of the same workload matrix of size 8 × 12(dataset 5) as in Figure 8. In this case, 3 cells are formed. Number of exceptional elements is still 4 while MGE changes to 68.56%. Figure 10 also shows the clustered result of the same workload matrix of size 8 × 12 (dataset 5) as in Figures 8 and 9. In this case, 4 cells are formed. Number of exceptional elements increases to 10 while MGE reduces to 65.86%.

From the above experiment it could be seen that for the referred workload matrix of size 8 × 12, the optimal number of cells needed is 3 which gives the best solution as shown in Figure 11.

Figure 11 Optimal number of cells, dataset 5(8 × 12)



5 Conclusion

In this work an artificial neural network based hybrid clustering model (FACLCT) is proposed to solve the cell formation problem using the non-binary real valued workload data as an input matrix. The proposed algorithm is tested with benchmark problems found in the literature and the results are compared to the results achieved from C-Linkage, K-Means, modified ART1 and genetic algorithm. To measure the performance of the proposed model considering the workload data modified grouping efficiency (MGE) is used. The results obtained which often outperformed the results in the literature justified the efficiency of the model in cell formation and sets a new milestone for the hybrid neural network approaches in GT/CM literature. The work can be further extended in future incorporating production data like operation sequence, machine capacity, production volume, layout considerations and material handling systems enhancing it to a more generalised manufacturing environment.

AQ2: The references Cheung (2003), MacQueen (1967), Venugopal and Narendran (1992) are not cited in the text. Please provide citation in the text or delete the publication details from the reference list if not required.

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