MANUFACTURING CELL FORMATION CONSIDERING VARIOUS PRODUCTION FACTORS USING MODIFIED ART1 NETWORKS

A. MANIMARAN[1], G.NAGARAJ[2], P. VENKUMAR[3], and R.GANESAMOORTHY[4]

ABSTRACT: Manufacturing cell formation is one of the initial and important steps in Group Technology (GT) / Cellular Manufacturing System (CMS). In this paper binary input Adaptive Resonance Theory (ART1) neural network is used for cell formation (CF). Numbers of research papers have been published in cell formation using ART1 neural networks. But those papers do not deal with production factors. They deal only part-machine incidence matrix (PMIM) optimization. This modified ART1 (MART1) deals with binary data, non-binary data, operation sequences and operation sequence with production volume. This MART1 is tested with the set of literature problems and compared. The MART1 results are best or equal when compared with all other algorithms. The comparison of results and consistency of the MART1 are presented in this paper.

KEY WORDS: Group Technology, Cell Formation and ART1 Neural Networks

1 INTRODUCTION

GT is a manufacturing philosophy in which similar parts are identified and its associated machines are grouped together to form a GT cell. The objective of the GT cell is that all the similar parts (called part family) are processed in its associated machine group (called machine cells). CMS is defined as an application of GT to production. There are significant benefits that can be achieved by implementing the CMS. They are setup time reduction, work-in-process inventory reduction, material handling cost reduction, equipment cost reduction, direct/indirect labor cost reduction, improvement of machine utilization, improvement in quality, improvement in space utilization and improvement in employee morale.

The process of identification of Part Families (PF) and Machine Cells (MC) are called CF. There are number of research work done in CF for the last three decades.

[1,4]Department of Mechanical Engineering, SBM College of Engineering and Technology, Dindigul, Tamil Nadu, India.
[2]Department of Mechanical Engineering, Sethu Institute Technology,Virudhunagar,Tamil Nadu, India.
[3]Department of Mechanical Engineering, SCAD College of Engineering, Tirunelveli, Tamil Nadu India.
Email:mullaimaran@rediffmail.com; nagarajsasi@gmail.com; pvenkumar@yahoo.com,; ganesamoorthy72@gmail.com

The researchers developed number of algorithms for CF using production flow analysis. In the production flow analysis CF, the PF and MC are formed by the PMIM, which is obtained from the route card. Some of the familiar production flow analyses are (i) Array-based methods (ii) Clustering methods (iii) Mathematical programming-based methods (iv) Graph theoretic approach (v) Search methods and (vi) Neural network-based methods. Comprehensive summaries and taxonomies of studies devoted to part-machine grouping problems were presented by (Manimaran et.al. 2010).

The ART network is an unsupervised vector classifier that accepts input vectors that are classified according to the stored pattern they most resemble. It also provides for a mechanism-adaptive-expansion of the output layer of neurons until an adequate size is reached based on the number of classes, inherent in the observation. The ART network can adaptively create a new neuron corresponding to an input pattern if it is determined to be “sufficiently” different from existing clusters. This determination called the vigilance test is incorporated into the adaptive backward network. Thus, the ART architecture allows the user to control the degree of similarity of patterns placed in the cluster.

Number of research have already been done in ART1 CF. The performance of ART1 network based CF has been investigated by (Kusiak and Chung, 1991), (Kaparthi and Suresh, 1992), (Liao and Chen, 1993), (Dagli and Huggahalli, 1995), (Chen and Cheng, 1995), (Chen, Chen and Park, 1996) and (Ming-Laing Chen et al. 2002). In the earlier ART1 based CF, the input of ART1 was only the PMIM. But in this MART1, the CF is done by using the binary data (i.e. PMIM), non-binary matrix data, operation sequence data and operation sequence with production volume data. For each data input, the output of the MART1 is compared with the set of literature problems and the conclusions are presented in this paper.

The section 2 will define PMIM CF, non-binary matrix CF, operation sequence CF and operation sequence with production volume CF. The section 3 will define the MART1. The section 4 gives vigilance parameter selection and the section 5 gives the experimentation on data from the literature and in section 6 the conclusion and future scope of this research is presented.

2 CF CONSIDERING VARIOUS PRODUCTION FACTORS

The objective of this paper is to formulate a new ART1 paradigm that incorporates process routings; operation sequences, non-binary incidence matrix values (i.e. part demands, machine capacities, processing times) and operation sequence with production volume are considered.

2.1 PMIM CF

The PMIM (a_{ij}) consists of 0, 1 entries only; a 1 entry in row i, column j indicates that part corresponding to the i^{th} row is processed by the machine corresponding to the j^{th} column. A 0 entry means that the part is not required by the corresponding machine. The rearrangement of the rows and columns of the matrix will provide a block diagonal form. If there is any 1 entry is in the off diagonal block then the corresponding part to be processed in more than one cell is called exceptional element. The CF is often recognized as an NP (Non-polynomial) complete problem in the literature.

(Chandrasekharan and Rajagopalan, 1986) have developed a very first performance measure in CF. The performance measure was grouping efficiency. One other performance measure which has been introduced by (Sureshkumar and Chandrasekharan, 1990) is grouping efficacy which is a new performance measure. The higher grouping efficiency and efficacy will result in better grouping. The effectiveness of the MART1 CF is measured by the total number of exceptional element (E), the grouping efficiency (η) and grouping efficacy (τ).

2.2 Non-binary incidence matrix CF

A PMIM also consists of analogue data (called non binary incidence matrix NBIM) that will include part demands, machine capacities, processing times, etc. NBIM is used to represent the relationships between machines and parts. Block diagonalization is considered as the best approach to form machine cells and part families (Sarker 2001). In the best solution of a CF problem, all the non-zero elements will remain in the diagonal blocks and all other zeros in the off diagonal blocks.

In the MART1 CF of the NBIM, the primary measure is to maximize the density of cells by rearranging the large non-zero elements in cells. The exceptional element (E) and sum of exceptional element values or objective function value (OFV) are considered as the performance measure to measure the MART1 CF.

2.3 Operation sequences CF

Another important factor in the design of CMS is the operation sequence of parts. The sequence of machines visited by a part is recorded in the matrix (s_{ij}), called Operation Sequence Incidence Matrix (OSIM).

$$s_{ij} = \begin{cases} k & \text{if part 'i' visits machine 'j' for the } k\text{th operation} \\ 0 & \text{otherwise} \end{cases}$$

k is an integer representing the operation for which part 'i' visits machine 'j'.

$$\left[q_{ijr}\right] = \begin{cases} 1 & \text{if r is 1 or } n_i \\ 2 & \text{if r is neither 1 nor } n_i \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

$A = \left[q_{ijr}\right]$ is the inter-cell move matrix

The above representation enables us to capture routing sequence information, which is useful in determining material flow between machine pairs. In this case, if the first or last operation is an inter-cell movement, then the particular part has only one inter-cell move. Otherwise there will be two inter-cell moves. For the operation sequences CF using MART1, minimization of inter-cell movement (exceptional movement) is considered.

2.4 Operation sequences with production volume

In addition to the PMIM, the data on the operation sequences and production volume of each part are given. Since an intermediate operation on a part performed outside its cell involves two inter-cell flows while the first or last operation requires one such flow, the actual flows to or from machine '*j*' by part '*i*' accompanied by the production volumes of each part are calculated using (Youk Yung Won and Kun Chang Lee, 2001).

$$u_{ij} = \sum_{r \in R_{ij}} f_{ijr} d_i \tag{2}$$

$$\text{where} \quad f_{ijr} = \begin{cases} 1 & \text{if r is 1 or } n_i \\ 2 & \text{if r is neither 1 nor } n_i \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

r is the index of operation sequence number, $r = 1, \ldots, n_i$ and

R_{ijr} is the set of the operation sequence number along which part 'i' visits machine '*j' and*

d_i is the production volume of part i

$IM = \lfloor u_{ij} \rfloor$ is the inter-cell move matrix

From the equation (2), note that part processing, which consists of a single operation in a single machine, is assigned the flows equal to the demand for the specific part even though such processing requires no inter-machine moves by part.

3 MODIFIED ART1

3.1 Procedure for PMIM CF

The MART1 consists of two phases. The first phase is almost similar to the standard ART1 except the cluster learning process. In the second phase, the weights are fixed and there is no change in the weights.

3.1.1 First phase

The architecture of the first phase of MART1 has two main layers. One is the input layer, also called comparison layer and the other one is the output layer, also called recognition layer. Every input (bottom) neuron is connected to every output (top) layer neurons. There are bottom-up weights (b_{ij}) associated with the arcs from the input neurons to the output neurons and top-down weights (t_{ji}) associated with the arcs from theoutput neurons to the input neurons. The bottom-up weights are used for cluster competition and top-down weights are used for cluster verification. The first phase of the MART1 architecture is shown in Figure 1.

The first phase of ART1 procedure consists of three processes. The first one is cluster search process, in which the network computes a matching score to reflect the degree of similarity of the present row-wise input vector (X_i) to the existing stored neurons.

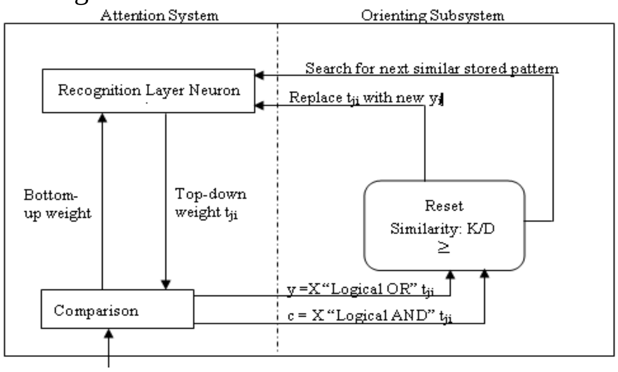

Fig.1. First phase of MART1

The initial t_{ji} and b_{ij} weights are initialized by using the following equations:

$$b_{ij} = \frac{L}{(L - 1 + N)} \qquad \textit{for all i and j} \tag{4}$$

$$t_{ji} = 1 \qquad \textit{for all i and j} \tag{5}$$

The matching score for neuron j, denoted by net_j, is defined by

$$net_j = \sum_{i=1}^{N} b_{ij} c_i \tag{6}$$

where c_i is output of the "logical AND" operator applied between X_i and t_{ji}.

L is a constant > 1 and

N is the number of input neurons (i.e total number of parts).

The largest net_j, say net_J, implies that the most like group and the associated group J is the candidate of the group.

The next process in the first phase is cluster verification process. Even though J is the "most like" group, it does not guarantee that the (X_i) will pass the vigilance test. The vigilance parameter (ρ), $0 \leq \rho \leq 1$, determines the degree of the required similarity between the current input and a neuron already stored. The vigilance test passed means S > ρ, where S is the similarity ratio. The S is the ratio of number of 1s in the c_i to the number of 1s in the X_i . If the input X_i passes the test, it is included as a member of group J. Otherwise, the process returns to the cluster search process and tries the next largest net_j.

The above two processes are similar to the standard ART1 except the last cluster learning process. If the similarity between the X_i and the group J is good enough, then the vector X_i is accepted as a member of group J. The learning process updates b_{ij} and t_{ji}. For the new group the t_{ji} is identical to the X_i. But for the already stored neuron the "logical OR" is applied between X_i and the t_{ji}. The learning bottom-up weights are

$$b_{ij} = \frac{Ly_i}{(L-1+\sum y_i)} \tag{7}$$

where y_i is the "logical OR" operator applied between X_i and t_{ji}. The weights will be updated only for the weights associated with group J.

In the standard ART1, the learning of top-down weights vector t_{Ji} is the "logical AND" and is applied between X_i and top-down weights. The major disadvantage of the standard ART1 is that for CF, the group is degraded during this operation. That is eleminated by using the "logical OR" operation.

Due to the "logical OR" operation in the learning process, if the number of 1s increases in t_{Ji} when compared to the previous t_{Ji} vector then the new t_{Ji} is removed from t_{Ji} and y_i is given as input to the network. If any other stored neuron wins then the entire group is merged with the winner group and the weights are updated. But if the new neuron wins then the same stored patterns are maintained. The final output of the first phase of the MART1 is machine groups.

3.1.2 Second phase

In this phase there will be three processes called cluster search process, cluster tuning process and constraint verification process. In the cluster search process, the top-down weights are fixed called fixed top-down weights (Tji) based on the previous grouped rows and fixed bottom-up weights (Bij)is initialized by using equation (8).

$$B_{ij} = \frac{LT_{ji}}{\left(L-1+m\right)} \tag{8}$$

where m is number of input neurons

The column-wise inputs are applied to the network, which computes a matching score to reflect the degree of similarity of the present column-wise input vector (X_i) to the existing cluster. The matching score for node j, denoted by $fnet_j$ is defined as

$$fnet_j = \sum_{i=1}^{m} B_{ij} X_i \tag{9}$$

The maximum $fnet_j$, say $fnet_J$, implies that the most like group, and the associated cluster J is the candidate cluster. This step will ensure minimization of exceptional element. For each and every row or column input, e is calculated by using the equation (10)

$$e = \sum_{j=1}^{G}\left(fnet_j\right) - \max . fnet_J \tag{10}$$

where G is the total number of cells (i.e. total number of neurons in the recognitio layer).

If there is more than one largest $fnet_J$, then for the largest equal values the $ffnet_j$ is computed

$$ffnet_j = \sum_{i=1}^{l} h_i \tag{11}$$

where l is the total number of equal largest value vectors.

h_i is the "logical OR'' is applied between the T_{ji} and X_i.

The smallest $ffnet_j$, say $ffnet_J$ that the most like group and associated cluster J is the candidate cluster. If it is more than one then the first one is choosen as the associated cluster J. This step will ensure minimization of voids.

After all the column-wise inputs are made, the column groups are identified. The output of this process is the part families. In the second cluster tuning process the weights T_{ji} *is* fixed based on the previous part groups and row-wise inputs are applied to the second phase of the network. The output is grouped rows. If the previous row groups are identical to this current row groups then the tuning process ends. Otherwise once again the weights are fixed based on the current row groups and column-wise inputs are applied to the second phase of the network. The current row and column groups are the best groups.

In the last, constraint verification process, the maximum number of cells permitted constraint is verified; if the constraint is satisfied then the MART1 gives final machine and part groups. If it is not satisfied then each individual cell block-diagonal density is verified, lowest cell block-diagonal density is identified then that cell diagonal machine-part alone is given as input to the network and the new cells are found which are added to the original result. The weights are fixed based on the final grouped rows and column-wise inputs applied to the same second phase. The second stage continues and the output is final grouped columns. Similarly the weights are fixed based on the grouped columns and row-wise inputs are applied and the final row groups are identified.

3.2 Procedure for CF with Production Factors

Few more modifications are made in the MART1. The first phase is similar to the MART1 CF. The given matrix is converted into machine part incidence matrix (MPIM) and then it is given as input to the first phase of the MART1 CF networks. After the completion of the first and second phase of the MART1 CF, there is one more process in the second phase called objective identification process.

In this process once again row-wise inputs are applied to the network. The top-down weight is fixed based on the final part groups and there is no bottom-up weight for this process. In this process row-wise non-binary incidence matrix inputs are applied to the network and the row which gives minimum $inet_j$, say $inet_J$, and implies that the most like group and the associated cluster J is the candidate cluster. After the all row-wise input, finally the row groups (i.e. part family) are identified.

$$inet_j = \sum_{i=1}^{m} T_{ji} X_i \tag{12}$$

where X_i is the input from NBIM

For Process sequence the X_i is from the matrix A

For sequence with production volume the X_i is from the matrix IM

The total objective function value is calculated by using the following equation.

$$OFV = \sum \sum_{j=1}^{G} inet_j - \max(inet_j) \tag{13}$$

Similarly the top-down weight only fixed based on the previous tuning process output machine cells and the column-wise inputs are applied to the network. The column which gives minimum $inet_j$, say $inet_J$, implies that the most like group and the associated cluster J is the candidate cluster. After the all row-wise input, finally the row groups are identified (i.e. machine cells) and the total objective function value is also calculated.

Now the row-wise input total OFV and the column-wise input OFV are compared and the group which gives minimum total OFV is the best part family or machine cell. Based on that group the top-down weights are fixed and the other part family or machine cell is identified. They are the final machine cells and part families.

4 VIGILANCE PARAMETER SELECTION

In the standard ART1 the selection of vigilance parameter (ρ) is problematic. For PMIM problem is too high a vigilance value will result in groups that are more similar, at the expense of creating too many groups. Too low a vigilance value will result in everything being placed into just a few groups, essentially performing no true classification.

For the selection of vigilance parameter in the MART1 network, (Chandrasekharan and Rajagopalan, 1989) seven datasets were tested with different ρ values. The first four (Chandrasekharan and Rajagopalan, 1989) datasets are well structured datasets and all other three data sets are not well structured datasets. For all the seven datasets are tested with the vigilance parameter value between 0.1 and 1.0. (Chandrasekharan and Rajagopalan, 1989) used ZODIAC algorithm for CF with a constraint of total number of cells (G) of 7. The MART1 is tested with the same constraint of G =7. The results obtained from MART1 for various ρ values are shown in the Table 1.

Table 1: Different ρ results for Chandrasekharan and Rajagopalan (1989) problems

Dataset No.	Vigilance Parameter (ρ)											
	0.1			0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
	η	τ	E									
1	1.0000	1.0000	0	√	√	√	√	√	√	√	√	√
2	0.9520	0.8511	10	√	√	√	√	√	I	I	I	I
3	0.9116	0.7351	20	√	√	I	I	-	-	-	-	-
4	0.9078	0.7285	20	√	I	I	I	-	-	-	-	-
5	0.7775	0.4624	45	√	I	I	I	-	-	-	-	-
6	0.7277	0.3971	48	√	I	I	I	I	I	I	I	I
7	0.7257	0.3812	53	√	I	I	I	I	I	I	I	I

It is observed that for the well structured and ill-structured datasets the ρ =0.1 gives best results. The same best result obtained from the different ρ values is shown in the Table 1 with a '√' mark. In the table, the letter 'I' indicates the MART1 solution which is inferior for the corresponding ρ value. That the solution is inferior means the η and τ are low and E is high when compared to the best result. The Table 1 also shows '-', which indicates that for the particular ρ value the MART1, does not give any output (i.e. all the machines and parts are grouped into a single cell).

5 EXPERIMENTATION ON DATA FROM THE LITERATURE

5.1 For PMIM CF

For CF using MART1 was tested with different benchmark datasets which are collected from the literature. In all the tested problems the ρ value is taken as 0.1. The results are compared with the different CF approaches with various performance measures.

The datasets (Chandrasekharan and Rajagopalan, 1989) are already tested for the vigilance parameter selection. The comparative results are shown in the Table 2. For the first two datasets the MART1 results are equal to the (Chandrasekharan and Rajagopalan, 1989) solutions.. For the dataset 3 and 4 E are equal, the MART1 grouping efficiency is high when compared to the (Chandrasekharan and Rajagopalan, 1989) grouping efficiency. For all other datasets the E is low and η is high when compared to the (Chandrasekharan and Rajagopalan, 1989) E and η.

Table. 2: Comparison of results with Chandrasekharan and Rajagopalan (1989)

	Chandrasekharan and Rajagopalan (1989)		MART1	
Data set No.	**E**	**η (%)**	**E**	**η (%)**
1	0	100.00	0	100.00
2	10	95.20	10	95.20
3	20	91.14	20	**91.16**
4	20	85.04	20	**90.78**
5	51	77.31	**45**	**77.75**
6	56	72.43	**48**	**72.77**
7	57	69.33	**53**	**72.57**

5.1 For CF with Production Factors

The first dataset of NBIM is adapted from the (Peker and Kara, 2004). They tested their Fuzzy ART network approach by using 7 X 7 NBIM. The same problem is considered for the evaluation of the MART1. First of all the NBIM is converted into a PMIM and it is given as input to the MART1 CF network to get the final output of grouped parts and machines. Then the NBIM CF procedure is followed and the final output is obtained. The OFV (i.e. the sum of exceptional value) is 2.4. The result is identical to the (Peker and Kara, 2004) result. The next NBIM data is taken from (Vohra et al. 1990). They used machining time NBIM of size 7 X 7. (Vohra et al. 1990) tested the dataset with a constraint of two and three cells and their objective function is to minimize the total machining times of the inter-cellular movement.For two cells the MART1 result is shown in the Table 3.

The MART1 is considered for minimization of exceptional elements and minimization of total inter-cellular machining time. In the MART1 the number of exceptional element is 1 and the total inter-cellular movement is 8. But (Vohra et al. 1990) used network approach and their number of exceptional element is 3 and their total inter-cellular machining time is only 4. (Vohra et al. 1990) is not considering the minimization of exceptional elements.

Table 3: Result for Vohra et al. (1990) NBIM problem

		PARTS						
		1	**2**	**3**	**4**	**7**	**5**	**6**
MACHINES	**1**	5	3	1	0	7	0	0
	2	1	0	9	0	2	0	0
	4	0	7	0	6	2	0	0
	6	9	0	0	0	0	0	0
	7	0	0	0	5	0	0	0
	3	0	0	8	0	0	3	10
	5	0	0	0	0	0	7	11

For three cells the MART1 number of exceptional element is 2 and the total inter-cellular machining time is 14. But (Vohra et al. 1990) gives only 9 total inter-cellular machining time and the number of exceptional element is 4.

The next dataset is OSIM. The dataset is taken from the (Suresh et al. 1999). They used 15 X 15 OSIM. The OSIM is converted into a PMIM and it is given as input to the MART1 and the final output is grouped machines and parts. Based on the output the inter-cell move matrix is obtained by using the equation (1) and the MART1 with production factors procedures are followed. The result is identical to the Suresh et al. (1999) result.

The next two OSIM data is adapted from (Nair and Narendran, 1998). The size of the first dataset is 7 X 7. The result is identical to the (Nair and Narendran, 1998) result. They used CASE algorithm. The second (Nair and Narendran, 1998) dataset is 20 X 20 and the number of groups is 3. The MART1 result is identical to (Nair and Narendran, 1998). The next dataset is operational sequence with production volume dataset which is adapted from (Youk Yung Won and Kun Chang Lee, 2002). The operation sequences and production volumes for the parts are shown in Table 4. The table is converted into PMIM and it is given as input to the MART1 network and the final output is grouped machines and parts. The inter-cell flows are calculated by using equation (2). The MART1 with production factor steps are followed and the final output is identical to the (Youk Yung Won and Kun Chang Lee, 2001) solution

Table 4: Operation sequences with production volume problem

Part No	Operation Sequence	Production Volume
1	2 – 4 – 2 – 4 – 5	20
2	1 – 3	10
3	1 – 3 – 1 – 5	50
4	4 – 2 – 4	40
5	2 – 1 – 5 – 1 – 2 – 1 – 5 – 1	30

6 CONCLUSION

The MART1 neural network has been successfully implemented for cell formation problems. The MART1 gives PF and MC and the number of exceptional elements with the constant vigilance parameter. The MART1 algorithm itself straightaway gives the number of exceptional elements. The computational effort is very low in the MART1 when compared to all other algorithms. The MART1 network is suitable for any size of PMIM. This MART1 deals with non-binary data, operation sequences and operation sequence with production volume. The modified approach is tested with the set of literature problems and compared. The MART1 results are best or equal when compared with all other algorithms. The modified ANN approaches are coded with the Mat Lab 6.5. The test datasets were tested with the Pentium IV 900 MHz, Systems. Several improvements to the MART1 network is also possible for CF. The scope of this MART1 are restricted for the CF with an objective of minimization of exceptional elements and maximization of the grouping efficiency. Some of the issues like more number of constraints, multi-objectives etc. can be implemented in this MART networks.

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