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Formation of Machine Cells/ Part Families in Cellular Manufacturing Systems Using an ART-Modified Single Linkage Clustering Approach – A Comparative Study

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Abstract

This paper proposes an Art Modified Single Linkage Clustering approach (ART-MOD-SLC) to solve cell formation problems in Cellular Manufacturing. In this study, an ART1 network is integrated with Modified Single Linkage Clustering (MOD-SLC) to solve cell formation problems. The Percentage of Exceptional Elements (PE), Machine Utilization (MU), Grouping Efficiency (GE) and Grouping Efficacy (GC) are considered as performance measures. This proposed heuristic ART1 Modified Single Linkage Clustering (ART-MOD-SLC) first constructs a cell formation using an ART1 and then refines the solution using Modified Single Linkage Clustering (MOD-SLC) heuristic. ART1 Modified Single Linkage Clustering has been applied to most popular examples in the literature including a real time manufacturing data. The computational results showed that the proposed heuristic generates the best solutions in most of the examples. The proposed method is compared with the well-known clustering approaches selected from the literature namely ROC2, DCA, SLC and MOD-SLC. Comparison and evaluations are performed using four performance measures. Finally analysis of results is carried out to test and validate the proposed ART-MOD-SLC approach. The MCF methods considered in this comparative and evaluative study belong to the cluster formation approaches and have been coded by using C++ with an Intel P-IV compatible system.

Keywords: Cellular Manufacturing; Group Technology; Cell Formation; Modified Single Linkage Clustering (MOD-SLC); ART-MOD-SLC; Performance Measures

1. Introduction

In the competitive business environment today, many businesses focus attention especially on the rapidity for responding to their customers' needs. For this reason, continuous improvements are needed to increase response times to customer changes. One of the strategies is called Group Technology which focuses on Cellular Manufacturing. Group technology (GT) is a manufacturing philosophy that has attracted a lot of attention because of its positive impacts in the batch-type production. The problems in batch manufacturing are high level of product variety and small manufacturing lot sizes (Singh and Rajamani 1996). In the design of a CM system, similar parts are grouped into families and associated machines into groups so that one or more part families can be processed within a single machine group. The process of determining the part families and machine groups are referred to as the cell formation (CF) problem. Group technology is a tool for organizing and using information about component similarities to improve the production efficiency of manufacturing firm. Successful application of group technology, promises improvement of productivity through the reduction of material handling cost, throughput time etc.

The two major tasks that the company must undertake are (a) Identification of part families: if the plant makes 10,000 different parts, reviewing all the part drawing and grouping the parts into families is a substantial task that consumes a significant amount of time. (b) Rearranging production machines into machine cells: It is time consuming and costly to plan and accomplish this rearrangements and machines are not producing during change over. GT offers a substantial benefit to companies that have the perseverance to implement it. Formation of machine cells is one of first important steps in the development and implementation of GT. New achievement in computer technology and artificial intelligence have provided the opportunity to apply more advanced clustering technique to group technology problem.

The ART1 neural network is a novel method for the cell formation problem in-group technology. ART1 is an unsupervised network where the desired output (desired number of clusters) is not known. Cluster formation is dependent on the vigilance parameter value as well as the number of machines and parts present in an input incidence matrix. Iteration taken by ART1 for cluster

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formation also depends on size of input of the incidence matrix and group efficiency. After forming a cell or a cluster of machines or parts, Modified Single Linkage Clustering (MOD-SLC) is used to obtain the optimized part family or machine cell according to its maximum use in a cluster.

2. Literature Survay

Detailed survey of literature has been carried out to identify the findings and directions given by the researchers. The contributions and directions of selective research works reported in the literature have been presented below. The literature yields seven array-based clustering heuristics, namely: 1. Bond Energy Analysis (McCormick et al [1]); 2. Rank Order Clustering (King, [2]; King et al. [3]); 3. Modified rank order clustering (Chandrasekharan et al. [4]); 4. Direct clustering analysis (Chan et al. [5]); 5. Occupancy Value Method (Khator et al. [6]); 6. Cluster Identification Method (Kusiak et al. [7]); and 7. Hamiltonian Path Heuristic (Askin et al., [8]). The SLC method (McAuley, [9]; Carrie, [10]; Waghodekar et al., [11]) merges clusters based on the maximum similarity of their members. Chandrasekharan et al. [12] analyzed the performance of the grouping efficiency in evaluating the solution qualities of a set of well-structured and ill-structured problems. The deficiency of the grouping efficiency has been investigated by Kumar et al. [13]. Chu et al. [14] compared three array-based machine-part grouping methods: ROC, DCA and BEA. Murugan and Selladurai (15) compared three array-based cell formation methods on a real time manufacturing data. Miltenburg and Zhang [16] compared nine cell formation methods including similarity measure method, non-hierarchical clustering and rank order methods. Cheng C.H. et al. [17] carried out comparative examination of selected cellular manufacturing clustering algorithms. Dimopoulos et al. [18] used the grouping efficacy performance measure in evaluating and comparing a genetic programming based SLC method to five other procedures. The following neural network models have been used to solve the machine and/or part grouping problems: back propagation network (Kaparthi et al. [19]), self-organizing network (Lee et al. [20]). Adaptive Resonance Theory (ART) (Dagli et al. [21], Kusiak et al. [22]. There are several variations of an ART network, namely, ART1 (Carpenter et al. [23, 24]), ART2 (Carpenter et al. [25]). The ART1 can handle binary input patterns, while others can process both binary and analogue. Kusiak. A, et al. [26] addressed on neural networks to form machine cells to map the concept of machine cell formation onto the network.

Akturk et al. [27] proposed an integrated algorithm that solves the machine/product-grouping problem by simultaneously considering the within-cell layout problem. Charles C. Willow [28] proposed a feed forward multi-layer neural network for machine cell formation in computer integrated manufacturing. Hark Hwang et al. [29] proposed another measure to enhance the performance of the model using p-median model. [30] Baroni et al. proposed on Similarity on binary data. Yong Yin et al. [31] compared the performance of 20 well-known similarity coefficients. Yong Yin et al. [32] developed a comprehensive overview and discussion for similarity coefficients. Prabahakaran et al. [33] addressed on an application of the maximal Spanning Tree approach for machine cell formation. Chang-Chun Tsai et al. [34] proposed a multi-functional MP model. Alhourani Farouq et al. [35] proposed a new ordinal production data similarity coefficient based on the sequence of operations and the batch size of the parts. Logendran et al. [36] proposed a nonlinear programming model, comprised of binary and general integer variables. Mingyuan, et al. [37] proposed an integrated model for production planning in cellular manufacturing (CM) systems. Zahir Albadawi et al. [38] proposed a new mathematical approach for forming manufacturing cells.

Mahdavi et al. [39] proposed a heuristic method based on iterative set partitioning for incremental cell formation where part of the operations can be processed on alternative machines. Mahdavi et al. [40] proposed on minimizing of the Exceptional Elements (EE) and number of voids in cells to achieve the higher performance of cell utilization. Bin Hu et al. [41] developed an integrated method to solve a multi objective cell formation problem that consists of an integer programming model and a heuristic algorithm for generating alternative cell formations. Steudel et al. [42] developed a similarity measure known as the Cell Bond Strength (CBS) which depends on part routing and production requirements. Harhialakis et al [43] proposed a two-stage heuristic algorithm to solve the cell formation problem. Sule [44] developed a procedure to determine the number of machines. Okogba et al [45] developed an algorithm to solve the part-machine cell formation problem. Heragu et al. [46] presented a heuristic method for forming part families and machine groups. Lin et al [47] proposed a two stage integer-programming model for forming part-machine cells.

Hassan M. Selim et al. [48] compared a modified single linkage clustering heuristic (MOD-SLC) against the three well-established machine cell formation methods. Adenso-Díaz, et al. [49] proceeded on part-machine grouping using weighted similarity coefficients. Foulds et al [50] proposed an approach to solve manufacturing cell creation with machine modification costs and the objective is to minimize the sum of the machine modification cost. Peker et al. [51] proceeded on parameter setting of the Fuzzy ART neural network to part-machine cell formation problem. Gajendra K. Adil et al. [52] proposed an enhanced diversity/similarity model to form part families. Venkumar et al. [53] addressed on Fractional cell formation in group technology using modified ART1 neural networks. Venkumar et al. [54] proposed the cell formation and fractional cell formation using Kohonen Self-Organizing Map (KSOM) neural networks.

While conducting the detailed literature survey, it has been found at many cell formation methods have been used to reduce the percentage of exceptional elements (PE) and to increase the grouping efficiency (GE). The results of the literature survey indicated the absence of an analysis on cell formation methods using the real time data to predict the performance. The findings of the literature survey highlighted that there is a wide scope for solving the cell formation problem towards achieving the optimal performance. A suitable new integrated approach is proposed and applied for analysing the performance measures by incorporating the ART1 neural network with modified single clustering algorithm (ART-MOD-SLC).

The remainder of this paper is organized as follows. Section 3 discusses the statement of the problem and Section 4 discusses about the existing clustering algorithms with examples and section 5 introduces a new integrated ART- MOD-SLC approach with numerical examples are presented to compare with other approaches in the literature. Finally, the conclusions are given in Section 6.

3. Problem Definition

Batch manufacturing is a dominant manufacturing activity in the world, generating great deal of industrial output. It accounts for 60 to 80 percent of all manufacturing activities. The major difficulties in batch manufacturing are due to high level of product variety and small manufacturing lot sizes. The product variations present design engineers with the problem of designing many different parts. The impact of these product variations in manufacturing is high investment in equipment, high tooling costs, complex scheduling and loading, lengthy setup time and costs, excessive scrap, and high quality control costs. For this purpose, some innovative methods are needed to reduce product cost and lead time and profitability. It needs a higher level of integration of the design and manufacturing activities in a company. Group technology (GT) provides such a link between design and manufacturing.

4. Methodology

4.1. Rank order clustering 2 (ROC2):

ROC is a well-known clustering technique that attempts to create a block diagonal form by repeatedly reallocating the columns and rows of a machine/part matrix according to binary values. ROC-2 was developed by King and Nakornchai (1982) to overcome the limitations of ROC. This algorithm is a faster and more efficient method compared with ROC. The main feature of ROC-2 is that it can identify block diagonal structure (of a machine part incident matrix) very quickly that makes it practicable to use in an interactive manner even for large matrices. The step-by-step procedure is shown in the Figure 1.

4.1.1. Algorithm:

Step 1: Start from the last column, move the rows with positive entries to the top of the matrix.
Step 2: Repeat step1 for all the columns.
Step 3: Start from the last row, move the columns with positive entries to the left of the matrix.
Step 4: Repeat step 3 for all rows.
Step 5: Compare the matrix with the previous result. If the matrices are different go to step otherwise go to step 6.
Step 6: Print the final machine-component incidence matrix.

Flow Chart.

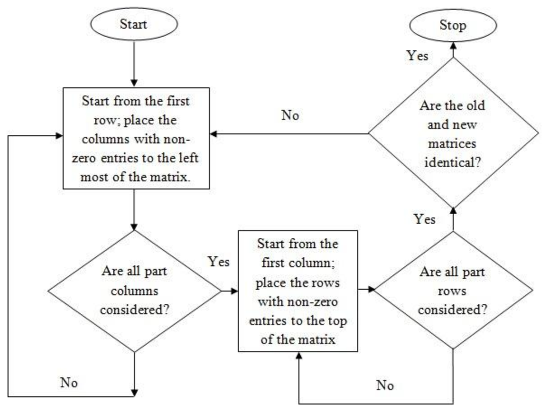

Figure 1: Flow Chart of Rank Order Clustering -2 (ROC-2).

4.1.2. Rank order clustering-2 (ROC-2) example:

Table 1: Initial Machine-Part Matrix of ROC-2.

a. Initial Metrix.

M/C	**Parts**							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1	1		1					
2	1	1			1	1	1	1
3			1		1		1	1
4				1		1		
5	1		1		1	1		1
6			1			1		
7	1	1			1	1	1	1

b. Row Ordering.

Columns	**Row order**						
8	**1**	**2**	**3**	**4**	**5**	**6**	**7**
7	2	3	5	7	1	4	6
6	2	7	1	4	6	3	5
5	2	7	3	5	1	4	6
4	5	2	7	3	1	4	6
3	1	4	6	5	2	7	3
2	5	3	1	4	6	2	7
1	1	2	7	5	3	4	6
Final	2	5	7	1	3	4	6

c. Column Ordering

Rows	Column order							
6	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
4	4	7	1	2	3	5	6	8
3	4	7	1	2	3	5	6	8
1	3	6	8	4	7	1	2	5
7	4	7	2	3	6	8	1	5
5	7	6	8	1	4	2	3	5
2	6	8	1	3	5	7	4	2
Final	6	8	1	2	3	5	7	4

Table 2: Final Matrix of ROC-2.

M/C	Parts							
	6	**8**	**1**	**7**	**2**	**3**	**5**	**4**
2	1	1	1	1	1			
7	1	1	1	1	1			
5	1	1	1			1	1	
3	1	1				1		
1				1	1			1
4				1				1
6				1				1

4.2. Direct clustering analysis (DCA):

In the DCA algorithm, the initial matrix is rearranged according to the row and column assignments. After the rearrangement the rows and columns are rearranged to form the clustered machine component incidence matrix.

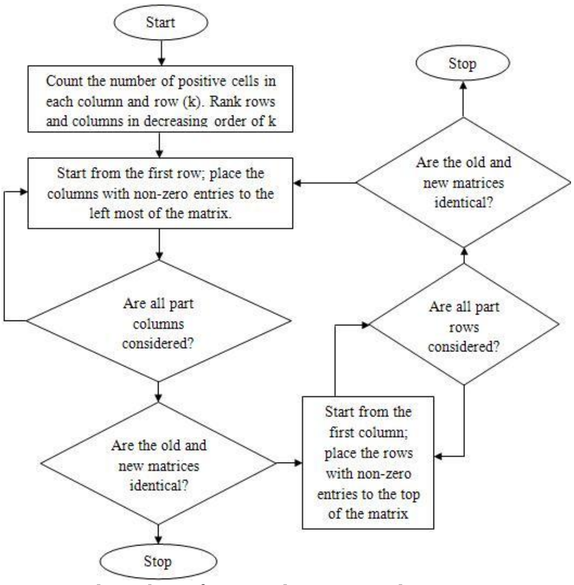

Figure 2: Flow Chart of Direct Clustering Analysis.

4.2.1. Algorithm

Step 0: Input Machine component incidence matrix (MCIM) formed from the operation sequence of each part.
Step 1: The row and column ranks are found by adding their corresponding positive entries.
Step 2: The matrix is rearranged according to the ranks.
Step 3: Start from the first row, move the columns with positive entries to the left of the matrix
Step 4: Repeat the step 3 for all the rows.
Step 5: Start from the first column, move the rows with positive entries to the top.
Step 6: Repeat the step 5 for all the columns.
Step 7: Compare the matrix with the previous result. If the matrices are different go to step 3 otherwise go to step 8.
Step 8: Print the final machine component incidence matrix.

4.2.2. Direct clustering analysis (DCA) example:

M/C	Parts							
	1	**2**	**3**	**4**	**5**	**6**	**7**	
1		1		1			1	3
2			1		1			2
3	1	1		1			1	4
4	1		1			1		3
5			1	1	1	1		4
	2	2	3	3	2	2	2	

Counting the positive cells.

M/C	Parts						
	6	**5**	**4**	**3**	**7**	**2**	**1**
5	1	1	1	1			
3			1		1	1	1
4	1			1			1
1			1		1	1	
2		1		1			

Conducting column interchanges based on First row.

M/C	Parts							
	7	**6**	**5**	**2**	**1**	**4**	**3**	
5		1	1			1	1	4
3	1			1	1	1		4
4		1			1		1	3
1	1			1		1		3
2			1				1	2
	2	2	2	2	2	3	3	

Ranking rows in descending order and columns in ascending order.

Freeze previous changes; continue the column interchanges based on the remaining until no further changes.

M/C	Parts						
	6	**5**	**4**	**3**	**7**	**2**	**1**
5	1	1	1	1			
4			1		1	1	1
3	1			1			1
1			1		1	1	
2		1		1			

Conducting row interchanges based on First column.

4.3. Single linkage clustering:

It is a hierarchical machine grouping method known as Single-Linkage Clustering using similarity coefficients between machines. The similarity coefficient between two machines is defined as the ratio of the number of parts visiting both machines and the number of parts visiting one of the two machines:

$$s_{ij} = \frac{\sum_{k=1}^{N} X_{ijk}}{\sum_{k=1}^{N} (Y_{ik} + Z_{jk} - X_{ijk})} \quad (1)$$

Where

Xijk = operation on part k performed both on machine i and j,
Yik = operation on part k performed on machine i,
Zjk = operation on part k performed on machine j.

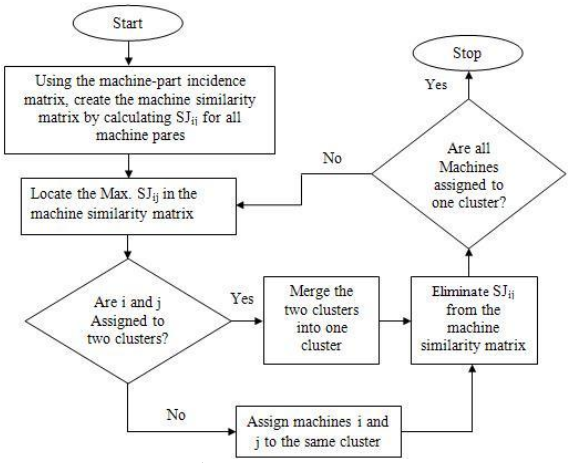

Figure 3: Flow Chart of Single Linkage clustering.

4.3.1. Single linkage clustering (SLC) Example:

Table 3: Initial Matrix of SLC.

M/C	Parts							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1		1		1				
2	1	1				1	1	1
3			1			1		1
4				1			1	
5	1		1		1	1		1
6				1			1	
7	1	1				1	1	1

Table 4: Similarity Matrix of SLC.

Machine	Machine						
	1	**2**	**3**	**4**	**5**	**6**	**7**
1		0.33		0.67		0.67	0.33
2			0.33	0.17	0.43	0.17	1.00
3					0.60		0.33
4						1.00	0.17
5							0.43
6							0.17
7							

Table 5: Final Matrix of SLC.

M/C	**Parts**							
	4	**7**	**1**	**2**	**3**	**5**	**6**	**8**
4	1	1						
6	1	1						
1	1	1		1				
2		1	1	1			1	1
7		1	1	1			1	1
3					1		1	1
5			1		1	1	1	1

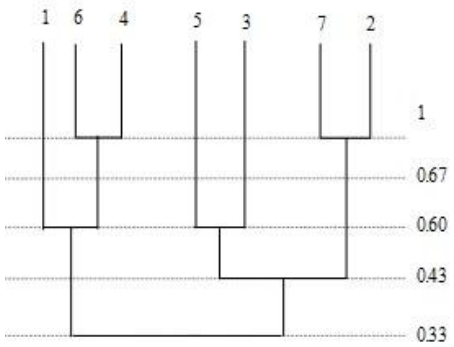

Figure 4: SLC Dendogram.

4.4. Modified single linkage clustering:

Similarity coefficients are either Jaccardian or non-Jaccardian, with respect to the similarity coefficient. The Jaccardian similarity coefficients are expressed as a measure of level of matches, in which the number of matches (Xij) is divided by a normalized quantity usually represented by the expected number of matches. Non-Jaccardian similarity coefficients have an additional term, the number of misses (Yij), appears in the numerator and then divided by the normalizing term. The status of the number of misses (Yij) in similarity coefficients applied to the CM problem is ambiguous. It refers to the number of parts not processed by either machine or the number of machines not needed by either part type. The researchers who adopted Jaccardian similarity coefficients assume that the similarity coefficients measure the degree of commonality between the two machines in terms of parts processed. Therefore, the number of misses does not contribute to the machine pair similarity coefficient. On the other hand, a significant part of the literature shows that Jaccardian similarity coefficients are unable to reflect the true values of similarity, as the Jaccardian measures do not consider the number of misses (Yij).

Baroni-Urban and Buser (1976) defined a set of properties of similarity coefficients and applied these properties to the several similarity coefficients. There does not exist any similarity coefficient which follows all the properties defined by Baroni-Urban and Buser (1976). Islam and Sarker (2000) modified the properties proposed by Baroni- Urban and Buser (1976) and stated them as follows (Sij is the machine i and machine j similarity coefficient):

- No mismatch, Sij→ 1 for Xi = Xj = 0.
- Minimum matches, Sij→ 0 for Xij, Yij→ 0.
- No match, Sij→ 0 for Xij, = 0.
- Complete match, Sij = 1 for Xij = number of parts.
- Maximum matches, Sij→ 1 for Xij + Yij→ number of parts.

The similarity measure developed by Baroni- Urban and Buser (1976) - BUB measure has conformed to the five properties. This similarity coefficient has superior properties of distribution compared to other coefficients because the distribution of its values is more normal and continuous and the BUB similarity coefficient is defined as follows:

$$SB_{ij} = \frac{X_{ij} + \sqrt{X_{ij} Y_{ij}}}{X_i + X_j + X_{ij} + \sqrt{X_{ij} Y_{ij}}} \quad (2)$$

Where SBij = BUB similarity between machine i and machine j, $0 \leq SBij \leq 1$. In order to justify the application of non- Jaccardian similarity coefficients to the MCF problem, Islam and Sarker (2000) used properties 2 and 5 to conclude that both matches (Xij) and misses (Yij) must be included in the numerator of the defining similarity coefficient. To satisfy properties 2, 3, 4, and 5, the product Xij Yij is considered in addition to Xij in the numerator. The square root is used to maintain the order consistency (Baroni-Urban and Buser, 1976). When there are no misses (Yij = 0), BUB measure is reduced to Jaccard's measure which is the ratio of the number of parts processed by both machines to the total number of parts processed by both or one of the machines.

If (Yij) the BUB coefficient value increases to reflect the real similarity of machine/part pairs. Islam and Sarker (2000) modified BUB measure by adding the number of misses (Yij) to the denominator and called it 'relative matching measure'. The Jaccard measure has conformed to only three out of the same five properties namely, properties 1, 3 and 4.

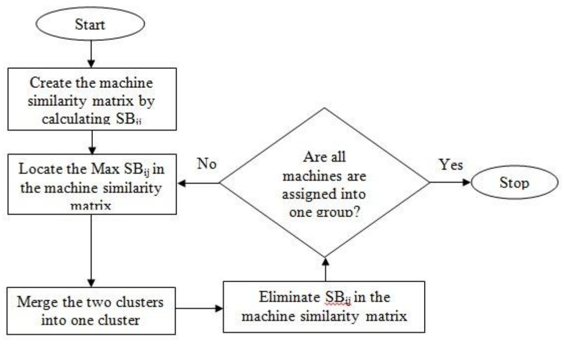

Figure 5: Flow chart of MOD-SLC.

4.4.1. MOD-SLC Example:

Table 6: Initial machine component incidence matrix.

M/C	Parts							
	1	2	3	4	5	6	7	8
1	0	1	0	1	0	0	0	0
2	1	1	0	0	0	1	1	1
3	0	0	1	0	0	1	0	1
4	0	0	0	1	0	0	1	0
5	1	0	1	0	1	1	0	1
6	0	0	0	1	0	0	1	0
7	1	1	0	0	0	1	1	1

Table 7: Similarity Co-efficient Matrix of MOD-SLC.

M/C	1	2	3	4	5	6	7
1	0	0.33	0	0.62	0	0.62	0.33
2			0.5	0.5	0.54	0.5	1
3				0	0.75	0	0.5
4					0	1	0.33
5						0	0.54
6							0.33
7							0

$$SB_{12} = \frac{X_{ij} + \sqrt{X_{ij} Y_{ij}}}{X_i + X_j + X_{ij} + \sqrt{X_{ij} Y_{ij}}} = 0.33$$

$X_{ij} = 1$; $Y_{ij} = 2$; $X_i = 1$; $X_j = 4$

Table 8: Final Matrix of MOD-SLC.

M/C	7	4	5	6	3	8	2	1
4	1	1	0	0	0	0	0	0
6	1	1	0	0	0	0	0	0
1	0	1	0	0	0	0	1	0
3	0	0	0	1	1	1	0	0
5	0	0	1	1	1	1	0	1
2	1	0	0	1	0	1	1	1
7	1	0	0	1	0	1	1	1

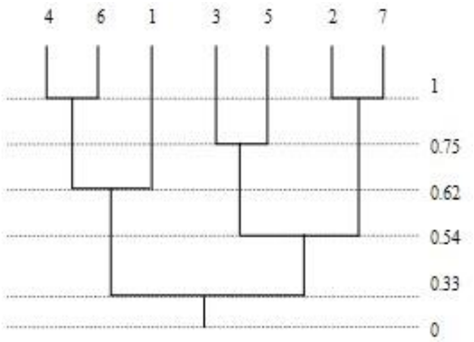

Figure 6: MOD-SLC Dendogram.

5. Proposed ART-MOD-SLC Approach

A cell formation problem can be viewed as a clustering problem that parts with similar machine operation can be grouped into same cluster. There are several neural networks that can be used to solve the clustering problem. In this research work, the application of ART for the machine cell/ part family clustering has been demonstrated. The ART1 network accepts an input vector X = {xi, i = 1, 2,…….N} directly from a binary machine part incidence matrix and assigns it to a cluster whose classified parts match with the input vector. Then, a vigilance test is carried out to determine whether the input vector meets the expectation or not. If input vector passes the test it is accepted as a member of cluster and the set of weights associated with the cluster are changed.

The problem of cluster formation methods uses a different strategy for cluster formation; their relative performance has often been compared in terms of the number of inter-cell moves they generate. The MCF problem cluster analysis-based solution approaches consist of two phases. The first step is to develop an ART network for clustering the raw data (Machine Part Incident Matrix) and the second phase is to apply a solution methodology to solve the MCF problem.

5.1. Architecture of ART-MOD-SLC:

The figure below shows the architecture of ART-MOD-SLC:

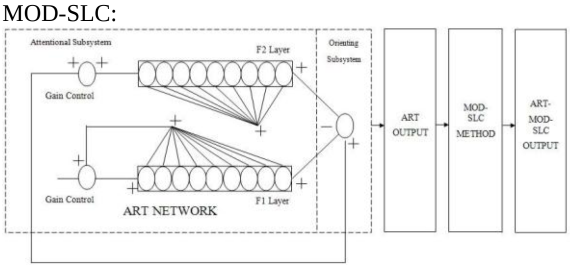

Figure 7: Architecture of ART-MOD-SLC.

5.2. ART-MOD-SLC algorithm:

The ART-MOD-SLC algorithm is explained in detail as below and also shown in the flow chart -Figure 8

Step 0: Define the number of neurons in input layer Nin and the number of neurons in the output layer Nout and select the value of vigilance parameter ρ between 0 and 1.

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Nin = the number of columns of machine part incidence matrix.
Nout = the maximum expected number of machine cells.

Step 1: Enable all output units and initialize top down weights Wt and bottom up weights Wb.

$$W^t = 1 \tag{3}$$

$$W^b = \frac{1}{(1+N_{in})} \tag{4}$$

Wt = Top down weights from neuron j in output layer to neuron i in input layer.
Wb = Bottom up weight from neuron 'i' in the input layer to neuron 'j' in output layer.
Where, Netj is the output of neuron j in output layer.
Step 2: Present a machine vector X to input layer, X consists of zero/one elements.
Step 3: Compute-matching scores for all the enabled output nodes.

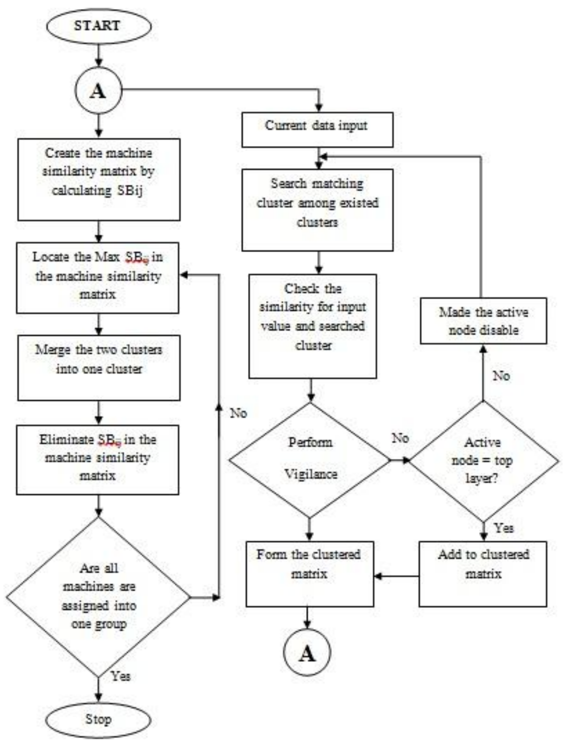


Figure 8: Flow chart of ART – MOD – SLC.

Step 4: Select the node with the largest value of matching scores as best matching exemplar, let this node be j. in the event of tie, the unit on left side is selected.

$$Net = \Sigma Wbji+xi \tag{5}$$

Step 5: Perform vigilance test to verify that input pattern X belongs to cluster (cell).

$$Netj = \max \{Netj\} \tag{6}$$

Step 6: Disable the best matching exemplar. Since the vector x does not belong to cluster j the output of node j selected in step 3 is temporarily disabled and removed from future competitions; Go to step 2.

Step 7: Adapt the best matching exemplar.

$$Wtij = Wtij * xi \tag{7}$$

$$W^t_{ij} = \frac{W^t_{ij} * X_i}{0.5 + \sum W^t_{ij} * X} \tag{8}$$

Step 8: Using the best matching exemplar obtained from the step 7, create the machine similarity matrix by calculating SBij for all machine pair.
Step 9: Locate the Max SBij in machine similarity matrix, are i and j are assigned to two clusters.
Step 10: By eliminating SBij in machine similarity matrix, merge the two clusters into one cluster.
Step 11: Check all the machines are assigned to one cluster then print the final machine component incidence matrix if not go to step 9.

5.2.1. ART-MOD-SLC Examples:

Example 1:

Table 9: Initial Matrix of ART-MOD-SLC (Final Matrix of ART1).

M/C	**Parts**								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**class**
1	0	1	0	1	0	0	0	0	0
2	1	1	0	0	0	1	1	1	1
3	1	1	0	0	0	1	1	1	1
4	0	0	1	0	0	1	0	1	2
5	0	0	0	1	0	0	1	0	3
6	0	0	0	1	0	0	1	0	3
7	1	0	1	0	1	1	0	1	4

Table 10: Similarity Co-efficient Matrix of ART-MOD-SLC.

M/C	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1		0.33	0.33	0	0.62	0.62	0
2			1	0.5	0.33	0.33	0.54
3				0.5	0.33	0.33	0.54
4					0.75	0	0.75
5						1	0
6							0
7							

Example Calculation:

$$SB_{12} = \frac{X_{ij} + \sqrt{X_{ij}Y_{ij}}}{X_i + X_j + X_{ij} + \sqrt{X_{ij}Y_{ij}}} = 0.33$$

Xij = 1; Yij = 2; Xi = 1; Xj = 4

Table 11: Final Matrix of ART-MOD-SLC.

M/C	Parts							
	6	**3**	**8**	**5**	**1**	**7**	**4**	**2**
2	1	0	1	0	1	1	0	1
3	1	1	1	0	0	0	0	0
4	0	0	0	0	0	1	1	0
7	1	0	1	1	1	1	0	1
5	1	1	1	0	1	0	0	0
6	0	0	0	0	0	1	1	0
1	0	0	0	0	0	0	1	1

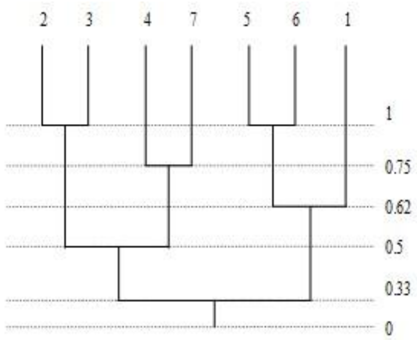


Figure 9: ART-MOD-SLC Dendogram.

Example 2:

Table 12 : Initial machine component incidence matrix

M/C	Parts									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	1	0	0	1	0	1	0	0	0	0
2	0	0	0	0	0	0	0	0	1	1
3	0	1	0	0	0	0	1	0	1	1
4	0	0	0	0	0	0	0	0	1	1
5	0	0	1	0	0	0	0	0	0	0
6	0	0	1	0	0	0	0	1	0	0
7	0	0	0	0	1	1	0	0	0	0
8	0	1	0	0	0	0	1	0	1	0
9	0	0	0	0	0	0	0	1	0	0
10	1	0	0	0	1	1	0	0	0	0

Table 13: Final Matrix of ART MOD-SLC.

M/C	Parts									
	2	**7**	**9**	**10**	**1**	**5**	**6**	**3**	**8**	**4**
4	1	1	1	1	0	0	0	0	0	0
3	1	0	1	1	0	0	0	0	0	0
9	1	1	1	0	0	0	0	0	0	0
10	0	0	0	0	1	1	1	0	0	0
8	0	0	0	0	0	1	1	0	0	0
1	0	0	0	0	1	0	1	0	0	1
6	0	0	0	0	0	0	0	1	1	0
5	0	0	0	0	0	0	0	1	0	0
7	0	0	0	0	0	0	0	0	1	0
2	0	0	1	1	0	0	0	0	0	0

5.3. Performance measures:

The performance of cluster formation methods can be evaluated either according to computational efficiency or according to clustering effectiveness (Chu and Tsai 1989). Clustering efficiency is normally measured in terms of program execution time, the amount of memory needed, and the complexity of the algorithm. In this research work, four measures have been selected because of their wide usage in the literature.

5.3.1. Number of exceptional elements (PE):

The number of off-diagonal positive entries (exceptional elements) in the final machine part incidence matrix can measure the quality of the cluster formation method. PE can be computed as

$$PE = e_0 \tag{9}$$

Where e_0, is the number of exceptional elements or the off-diagonal positive entries.

5.3.2. Machine utilization (MU):

MU indicates the percentage of times the machines within clusters (cells) are used in production. MU can be computed as (Chandrasekharan and Rajagopalan, 1986a)

$$MU = \frac{e_d}{\sum_{i=1}^{C} m_k n_k} \tag{10}$$

Where ed is the number of positive entries in the diagonal blocks,
mk is the number of machines in the kth cell,
nk is the number of parts in the kth cell, and
C is the number of cells.
The higher the value of MU, the better the machines is being utilized.

5.3.3. Grouping Efficiency (GE):

GE is an aggregate measure that takes both the number of exceptional elements and the machine utilization into consideration. A convex combination of both terms is considered to reveal the relative importance of each term. GE can be defined as

$$GE = \alpha MU + (1-\alpha)\frac{e_0}{M.N - \sum_{k=1}^{c} m_k n_k} \tag{11}$$

Where α is a weight; 0 ≤α ≤1, M is the total number of machines, N is the total number of parts, as a general rule, the higher the grouping efficiency, the better the clustering results.

5.3.4. Grouping Efficacy (GC):

GC overcomes the problems of selecting and the limiting range of GE. GC has the requisite properties like non-negativity, zero to one range and is not affected by the size of the machine-part matrix. GC, defined by Kumar and Chandrasekharan (1990) and Sandbothe (1998) is given as in equation

$$GC = \frac{e - e_0}{e_\gamma} \tag{12}$$

Where e_γ is the number of zeros in the diagonal blocks.

5.4. Problem data source:

The 36 data sets have been classified into three groups based on the number of machines (M), three groups based on the number of parts (N), and three groups based on the density level (D). Table 14 shows the value ranges of M, N and D for each group. The selected density range values are based on the selected data sets and specific implementation in the literature. Densities between 0.10 and 0.30 represent the different scenarios adequately.

Table 14: Value Ranges of Machines and Parts.

No.	**Problem Source**	M	N	D
1	Kumar *et al.* (1986)	30	41	0.104
2	Chandrasekharan and Rajagopalan	24	40	0.136
3	Chandrasekharan and Rajagopalan	24	40	0.135
4	Chandrasekharan and Rajagopalan	24	40	0.136
5	Chandrasekharan and Rajagopalan	24	40	0.136
6	Chandrasekharan and Rajagopalan	20	35	0.193
7	Randomly generated	20	35	0.200
8	Randomly generated	20	35	0.204
9	Randomly generated	20	35	0.215
10	Randomly generated	20	35	0.211
11	Harhalakis *et al.* (1990)	20	20	0.197
12	Shafer and Rogers (1993b)	20	20	0.147
13	Randomly generated	20	20	0.210
14	**Murugan and Selladurai (2007)**	**16**	**15**	**0.217**
15	Chan and Milner (1982)	15	10	0.306
16	Chan and Milner (1982)	15	10	0.330
17	Balasubramanian and Panneerselvam	15	10	0.280
18	Randomly generated	15	10	0.193
19	Askin *et al.* (1991)	14	24	0.181
20	McAuley (1972)	12	10	0.316
21	Srinivasan *et al.* (1990)	10	20	0.245
22	Randomly generated	10	20	0.195
23	Askin *et al.* (1991)	10	15	0.326
24	Mukhopadhyay and Golpalakrishnan	10	10	0.240
25	Randomly generated	10	10	0.190
26	Arvindh and Irani (1994)	10	8	0.325
27	Srinivasan and Narendran (1991)	8	20	0.381
28	Kusiak *et al.* (1993)	8	9	0.236
29	Randomly generated	8	9	0.194
30	Mukhopadhyay *et al.* (1994)	7	11	0.270
31	Randomly generated	7	11	0.194
32	Mukhopadhyay *et al.* (1994)	7	9	0.412
33	Kusiak and Cho (1984)	6	8	0.458
34	Seifoddini (1989c)	5	18	0.470
35	Mukhopadhyay *et al.* (1994)	5	18	0.511
36	King and Nakornchai (1982)	5	7	0.400

Table 15 shows the data set groups and factor ranges for the above problem sets and grouped into nine groups with three factors based on the number of machines.

Table 15: Data set groups and factor ranges.

Factor	Group label	Value Range	Data Problems
M	M1	M≤8	3
	M2	8<M≤16	5
	M3	M>16	28
N	N1	N≤10	11
	N2	10<N≤25	18
	N3	N>25	7
D	D1	D≤0.2	15
	D2	0.2<D≤0.3	9
	D3	D>0.3	12

5.5. Comparative studies with other approaches:

The proposed ART-MOD-SLC cluster formation method has been designed and tested against MCF solution methods using the well-known cluster formation approaches on the selected data sets along with the real time manufacturing data. The ART-MOD-SLC is compared with four well-known cluster formation methods selected from the literature, namely ROC2, DCA, SLC and MOD-SLC. The comparison and evaluation are based on four different performance measures selected from the literature, namely Percentage of Exceptional Parts (PE), Machine Utilization (MU), Grouping Efficiency (GE) and Grouping Efficacy (GC).

The four performance measures, PE, MU, GE, and GC are computed for each data set in each group of the nine groups. Table 16 summarizes the computational results of average PE values for each data group. Table 17 summarizes the computational results of MU average values for each data group. Table 18 summarizes the computational results of average GE values and is an aggregate measure that takes both the number of exceptional elements and the machine utilization into consideration. Table 19 summarizes the computational results of average GC values for each data group.

From the results, the proposed ART-MOD-SLC approach has achieved the highest value of PE, MU, GE and GC and yields the best result towards the optimal performance for the entire GT problem and the results are highlighted and also presented graphically in figures 10 to 15.

Table 16: PE values for CF problems.

Group	ROC2	DCA	SLC	MOD-SLC	ART-MOD-SLC
M1	8.8197	7.0179	9.8054	7.6404	6.0652
M2	5.7583	4.9013	2.6786	3.6402	2.3461
M3	15.5804	14.348	6.0133	6.0508	5.9895
N1	6.0653	6.7029	3.3804	4.1899	3.1348
N2	11.0154	6.9867	8.3567	7.2227	6.5823
N3	14.8807	14.4546	5.5058	5.5103	5.2631
D1	8.2717	6.5401	3.6776	3.5758	3.3257
D2	12.1430	12.1979	4.3256	4.9919	4.1263
D3	11.1461	9.2712	10.0365	9.4346	8.9842
OVER	10.2812	9.0150	5.8155	5.6444	**5.0908**

Table 17: MU values for CF problems.

Group	ROC	DCA	SLC	MOD-SLC	ART-MOD-SLC
M1	0.7154	0.6625	0.7310	0.7439	0.7623
M2	0.7545	0.7173	0.6876	0.7281	0.5824
M3	0.4551	0.4514	0.6269	0.5824	0.6589
N1	0.7208	0.6927	0.6591	0.6910	0.7381
N2	0.6895	0.6427	0.7208	0.7390	0.7452
N3	0.4480	0.4384	0.6142	0.5877	0.6245
D1	0.5428	0.5176	0.6124	0.5847	0.6317
D2	0.5635	0.5566	0.6274	0.6537	0.6675
D3	0.8085	0.7536	0.8047	0.8332	0.8456
OVER	0.6321	0.6029	0.6759	0.6748	**0.6952**

Table 18: GE values for CF problems.

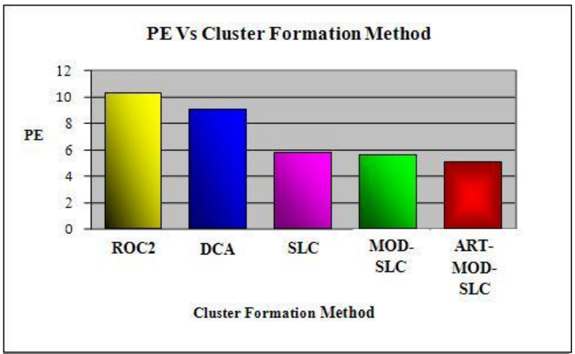
Group	ROC2	DCA	SLC	MOD-SLC	ART-MOD-SLC
M1	0.8250	0.8000	0.8387	0.8420	0.8526
M2	0.8642	0.8467	0.8373	0.8554	0.8732
M3	0.7033	0.7022	0.7927	0.7887	0.8127
N1	0.8432	0.8257	0.8212	0.8322	0.8543
N2	0.8160	0.7471	0.8396	0.8482	0.8512
N3	0.7011	0.6952	0.7983	0.7875	0.8010
D1	0.7614	0.7498	0.7904	0.7887	0.7998
D2	0.7580	0.7546	0.8110	0.8180	0.8243
D3	0.8658	0.8405	0.8707	0.8227	0.8957
OVER	0.7933	0.7797	0.8207	0.8265	***0.8405***

Table 19: GC values for CF problems.

Group	ROC2	DCA	SLC	MOD-SLC	ART-MOD-SLC
M1	0.6580	0.5541	0.6517	0.6869	0.6954
M2	0.7210	0.6916	0.6695	0.7036	0.7316
M3	0.4279	0.4250	0.6011	0.5710	0.6571
N1	0.6864	0.6576	0.6606	0.6643	0.6946
N2	0.6361	0.6164	0.6592	0.6910	0.7132
N3	0.4239	0.4135	0.6165	0.5736	0.6256
D1	0.5273	0.5083	0.5958	0.5723	0.6028
D2	0.5357	0.5257	0.6101	0.6332	0.6498
D3	0.7323	0.7010	0.7225	0.7628	0.7721
OVER	0.5941	0.5738	0.6388	0.6489	***0.6825***

5.6. Results and discussion:

The Figures below show the number of exceptional elements (PE).



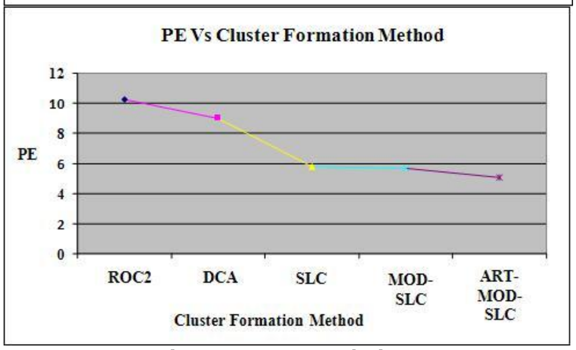
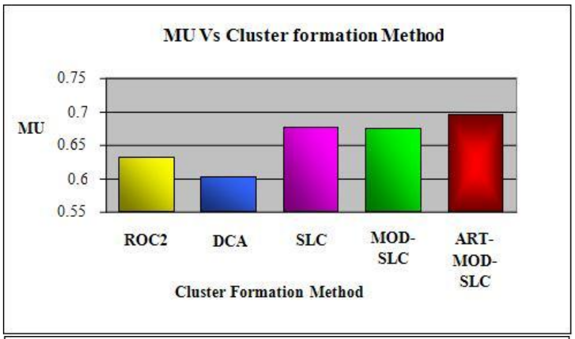


Figure 10: PE Vs Cluster Formation Method.



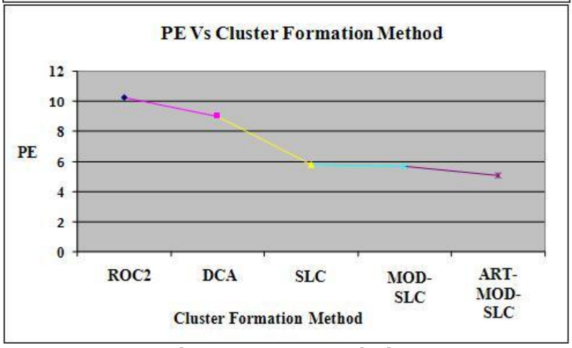
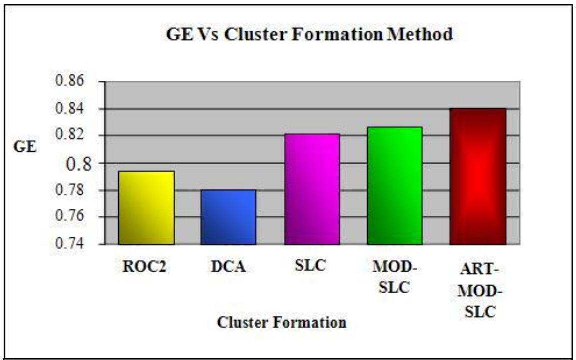


Figure 11: MU Vs Cluster Formation Method.



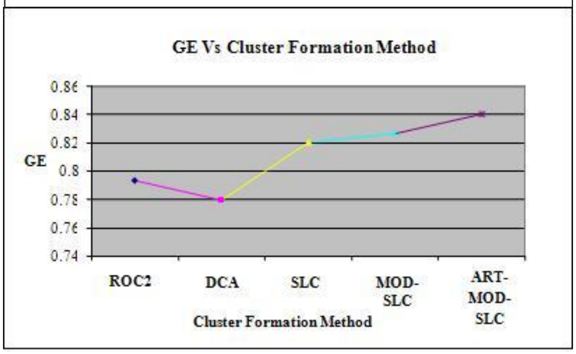
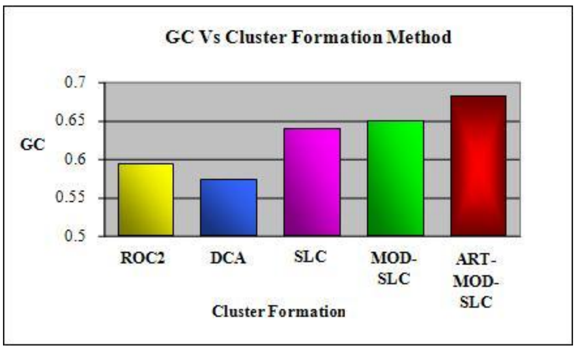


Figure 12: GE Vs Cluster Formation Method.



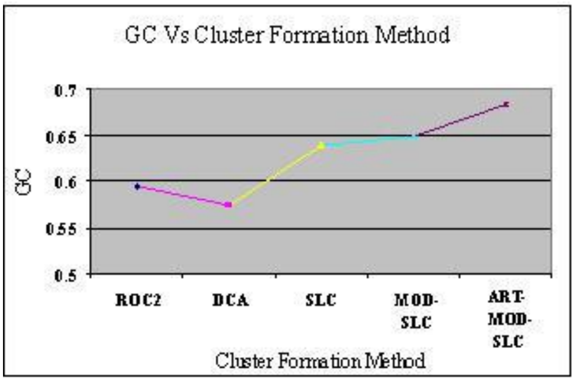


Figure 13: GC Vs Cluster Formation Method.

The following figures show the comparison of cluster formation methods.

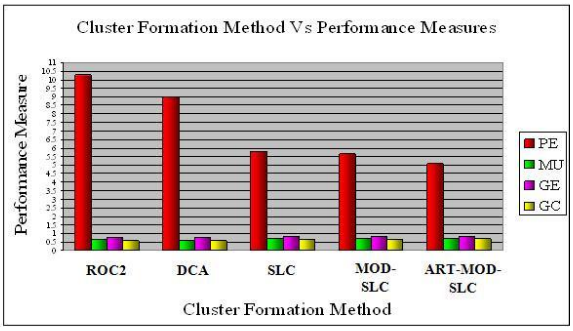


Figure 14: Cluster Formation Method Vs Performance Measures.

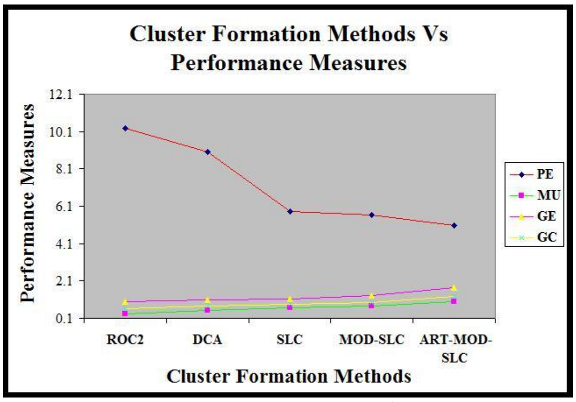


Figure 15: Cluster Formation Method Vs Performance Measures.

6. Conclusion

In this research work, an ART1 neural network has been integrated with MOD-SLC approach and successfully implemented for the cell formation problems collected from the literature, including the real time manufacturing data.

- Application of ART1 to machine-part matrix has been successfully demonstrated to form the clusters of a machine cell and part families. Thereafter machine and parts are arranged by Modified Single Linkage Clustering method (MOD-SLC).
- It is observed that the quality of grouping solution is influenced by the sequence of machines or parts in initial machine part incidence matrix. The numbers of clusters are used to calculate the group efficiency.

- Cluster validation is made after calculation of GE, PE, MU, and GC. Processing time does not increased significantly for large problems or complex conditions. ART-MOD-SLC achieved the higher value of grouping efficiency that yields better clustering results.
- The results are compared with popular existing algorithms and found that the modified ART-MOD-SLC solution is superior to others. The ART-MOD-SLC gives parts and machine clusters and the number of exceptional elements.
- The computational effort is very low in the ART-MOD-SLC compared with all other algorithms and is suitable for large size of machine-part incidence matrix.
- ART-MOD-SLC method has been tested against four MCF solution methods using the cluster formation approaches, namely ROC2, DCA, SLC, and MOD-SLC and also demonstrated an evaluative and comparative analysis using four different performance measures namely percentage of exceptional elements, within cell machine utilization, grouping efficiency, and grouping efficacy.
- The ART- MOD-SLC approach improves the average values of the four performance measures, PE, MU, GE and GC and the results are presented graphically.
- The performance of the four cluster formation methods considered (ROC2, DCA, SLC, and MOD-SLC) are poorer than the proposed ART-MOD-SLC approach.
- From the graphical results, the Percentage of Exceptional Elements (PE) reduced by 10%, Machine Utilization (MU) has been increased by 3%, Grouping Efficiency (GE) has been increased by 2% and Grouping Efficacy (GC) increased by 5% than the earlier approaches considered.

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