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A Heuristic Method for Manufacturing Cell Formation Problem using Correlation Analysis Approach

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Abstract - **In cellular manufacturing system parts are grouped in part families and machines are grouped in machine cells, based on their resemblance in manufacturing, to reduce intercellular movement of parts and machine. The aim of this article is to formulate a method to form cell using correlation analysis approach. The proposed method is carried out in following steps: first data (machine-part matrix) is obtained from literature. To make the initial matrix more sufficiently meaningful and significant, its standardization is needed. Several methods of standardization are found in the literature. In this article, the general standardization of primary data set is used. In the next step a correlation matrix (similarity matrix) is calculated using standardized matrix. Principal component analysis (PCA) is applied to find the eigenvalues and eigenvectors on the correlation similarity matrix. A cluster analysis based on scatter plot is performed to make simultaneously machine groups and part families while maximizing correlation between elements. In the next stage a hybrid algorithm is developed to assign exceptional machines. Assignment of exceptional part is simply based on Euclidian distance while for assignment of exceptional machine a hybrid algorithm is developed. One numerical example is solved to illustrate the proposed method. The result obtained from this method shows that the present approach is very efficient and practical.**

The outline of the paper is as follows: section 1 describes the Introduction and some literature review. Section 2 describes Preliminaries of proposed method. In section 3 description of proposed method is mentioned along with a numerical example. In Section 4 comparison of performance criteria obtained from proposed methods and existing methods and lastly a conclusion is made in section 5.

Keywords Cell Formation Problem, Cellular Manufacturing System, Correlation Analysis, Group Technology, Principal Component Analysis.

1. INTRODUCTION

Cellular manufacturing has been recognised as one of the most recent technological innovations in job shop or batch type production to gain economic advantage similar to those of mass production [12]. Many firms have adopted cellular manufacturing system recently in order to survive in today's competitive market. The firms that have adopted cellular manufacturing system have reported a reduction in material handling cost, production lead time and enhanced productivity [20].

Cell formation is the major step in designing of cellular manufacturing system. Machine part cell formation is the technique of grouping of similar machines to manufacture one or more part families by rearranging the initial machine part incidence matrix with an objective of minimizing the no of parts travelling between cells. A large no of methods have been developed in the last three decades. A number of review paper based on group technology have been published. The main techniques are principal component analysis, mathematical and heuristic approaches, similarity coefficient based clustering methods, knowledge-based method, graph theoretic methods and pattern recognition methods, fuzzy clustering methods, evolutionary approaches and neural network approaches [17].

The proposed method is based on similarity coefficient. This approach consists of identifying the machine group and part families simultaneously. A hybrid algorithm is suggested to assign the exceptional machines. Most of the existing cell formation methods have one or more drawbacks. Their major drawbacks are limited industrial application due to the unavailability of software programs supporting them and inflexibility in determining the number of cells. The proposed method overcomes the before said drawbacks. This method performs very well in a number of well-known criteria, have flexibility to decide the number of cell in advance. In addition to this it also supports available commercial software programmes in order to facilitate industrial application.

The problem has been extensively studied in the literature. McCormick et al. [29] defined the clustering technique as an attempt to display similar group from a given input object-object or object-attribute data matrix. Heragu [18] modified the classification of cell formation as (1) techniques that identify machine group only (2) techniques that identify part families' only (3) techniques that identify machine groups and part families simultaneously. Srinivasan et al. [39] proposed an assignment based algorithm that identifies machine groups first and then part families.

In addition to this various array based clustering algorithms, such as, rank order clustering (ROC), direct clustering analysis (DCA) and bond energy analysis (BEA) for cell formation have been proposed by researchers (Chu & Tsai [12]; Murugan & selladurai [31]). Prabhaharan et al. [34] and Kao and Fu [25] developed ant colony based clustering algorithm for manufacturing cell design. Various metaheuristic algorithms are introduced by Muruganandam et al [32], Adil and Ghosh [1] and Yin et al. [52] to solve the machine cell formation problem in group technology.

Hachicha et al. [17] used correlation analysis to get an original similarity coefficient matrix in the first phase of the procedure, and in the second phase, the PCA was applied to find the eigenvalues and eigenvectors on the correlation similarity matrix. They also used a 'scatter plot' as a cluster analysis which was applied to form machine groups. Their comparative results on multiple performance criteria duly establish the effectiveness, efficiency and practical suitability of their approach. Seifoddini [37]; Gupta [15] developed software packages to verify the suitability of the usage of similarity coefficient Obtained using production data for machine-component grouping decisions in the design of a cellular manufacturing system. Some researchers, in the recent past, developed similarity coefficient algorithms for solution and presented them with illustrated numerical problems and computational results (Waghodekar & Sahu, [47]; Kusiak& Cho, [26]).

Hierarchical clustering (McAuley,[28]), Non-hierarchical clustering (Chandrasekharan & Rajagopalan,[10]), graph based clustering (Rajagopalan & Batra, [35]), Neural network (Kao & Moon, [24]) fuzzy logic (Xu & Wang, [51]; Ravichandran & Rao, [36]) and metaheuristics like Simulated Annealing (Boctor, [7]; Venugopal, & Narendran, [46]; Akturk & Yayla, [2]; Arkat et al., [4]), tabu search (Wu et al., [50]; Lei & Wu, [27]) and Genetic Algorithm (Joines, [22]; Jawahar et al., [21] ; Khoo et al., [40]; Mak et al., [42]; Asokan et al., [6]; Pai et al., [43]) based procedures have been applied in finding CF solution.

II. PRELIMINARIES

A. *similarity coefficient methods*

A similarity coefficient represents the degree of commonality between two parts or two machines. Different types of similarity coefficient have been proposed by different researcher in the different field. A similarity coefficient between two parts measures he degree of commonality between two parts in terms of the number of machine visited. Similarly a similarity coefficient between two machines measures the degree of commonality between two machines in terms of parts processed [48].

Based on the definition of Jaccard similarity coefficient, McAuley (1972) first defined a similarity coefficient between any two machines as the ratio of the number of parts that visit both machines to the number of parts that visit either or both machines.

Kusiak sought to maximize the sum of similarity coefficient defined between pairs of parts using a linear integer programming model.

Wei and Kern [28] introduced a different similarity coefficient to overcome the shortcoming of the Jaccard similarity coefficient. There are different types of similarity coefficient have been developed by many researchers for example in Gupta & Seifoddini [14], Seifoddini & Djassemi [38] & Genwook et al. [13]

Kitaoka et al. [41] proposed a double centring machine matrix for similarity of machines and parts as a similarity coefficient matrix.

Very few research studies have used multivariate analysis tool in cell formation problem. Albadawi et al. [3] used Jaccard's similarity coefficient and proposed a multivariate analysis based on principal component analysis for machine cells only.

B. *Principal component analysis*

PCA perhaps is the best known and oldest techniques in multivariate analysis [23], Pearson [33] was first to introduced it to recast linear regression analysis into a new form. After that it is developed by Hotelling [19] in the field of psychometry. PCA is applied as a cluster analysis tool to form machine groups and part families simultaneously [16]. PCA is used to represent the data in a smaller number of variables (Wall et al., 2002).

Hotelling [19] developed the principal component method to maximize the sum of squared of each factor extracted. The principal component factor can explain more variance than any other loading obtained from any other methods of factoring. The objective of PCA is the construction out of a given set of variables X's (j=1, 2, 3. . .) of new variables (p_i), called principal components which are linear combinations of X.

$$P_1=a_{11}X_1+a_{12}X_2+\ldots\ldots\ldots a_{1k}X_k \quad (1)$$

$P_i = a_{11}X_1 + a_{12}X_2 + \ldots\ldots\ldots a_{1k}X_k$ (2)

$P_k = a_{k1}X_1 + a_{k2}X_2 + \ldots\ldots\ldots A_{kk}X_k$ (3)

The a_{ij} are called loading and are solved in such a way that the extracted principal component satisfy two conditions: (1) PC are uncorrelated (orthogonal) and (2) the first PC has the maximum variance, the second PC has the next maximum variance and so on.

In PCA, first find the set of orthogonal eigenvectors or covariance matrix of the variables. The matrix of principal components is the product of the eigenvector matrix with the matrix of independent variables. The first principal component accounts for the largest percent of the total data variance. The second principal component accounts the second largest percent of the total data variance, and so on. The ultimate goal of principal components is to explain the maximum amount of variance with the fewest number of components.

C. Performance criteria

The purpose of this section is to evaluate the quality of clustering method. The first is called grouping efficiency (GE) and is defined by Chandrasekharan and Rajagopalan [10] as follows:

$$GE = \alpha.\frac{UE-EE}{\sum_{K=1}^{Q} mkpk} + (1-\alpha)\left(1-\frac{EE}{m.p-\sum_{k=1}^{Q} mkpk}\right) \quad (4)$$

Where $\alpha \in [0,1]$ is a weighting parameter. (A value of α=0.5 is commonly used for m_k and P_k). The number of machines in cell k and number of parts in family k, Q is no of cells, m is the total number of machines and p is the total number of parts.

The second criterion is machine utilization which is defined by Chandrasekharan and Rajagopalan [10] as the frequency of visits to machines within cells.

$$MU = \frac{UE-EE}{\sum_{K=1}^{Q} mkpk} \quad (5)$$

Where m_k and P_k denote the number of machines in cell k and number of parts in family k respectively

III. DESCRIPTION OF METHODOLOGY

A. standardization and similarity coefficient matrix

The first step is to standardize the initial machine part incidence matrix. Several standardization methods are found in literature [scaffer and green (1996) and others].in this paper the used standardised method is as follows:

$$A = \begin{bmatrix} a_{11}a_{12} & \ldots & a_{1m} \\ a_{21}a_{22} & \ldots & a_{2m} \\ . & & \\ . & & \\ . & & \\ a_{p1}a_{p2} & \ldots & a_{pm} \end{bmatrix} \quad (6)$$

Where a_{ij}=1 if machine j is required to process part I and a_{ij}=0 otherwise.

M_j is a binary row vector from the matrix A: $M_j^A[a_{1j}$ $a_{2j}\ldots\ldots.,a_{pj}]$.

$$M_j^B = \frac{M_j^A - Ej}{\sigma j} \quad (7)$$

Where E_j is the average of the row vector M_j

$$E_j = \frac{\sum_{k=1}^{p} akj}{p} \quad (8)$$

According to Huyghens-Koning theorem

$$\sigma_j^2 = E_j - E_j^2 \quad (9)$$

Similarity coefficient is derived from the incidence matrix. The correlation matrix S is defined as follows

$$S = \frac{1}{p}B' \quad (10)$$

S_{ij} is m x m matrix which elements are given by:

$$S_{ij}=1 \text{ and } S_{ij} = \frac{1}{p}\sum_{k=1}^{p} b_{ik}b_{jk} \quad (11)$$

In order to explain the methodology of the approach, a manufacturing system is considered with five machines (labelled M1–M5) and 7 parts (labelled P1–P7). This example is provided by Wang J [48].

Table 1: The machine-part matrix [A] Prob.1

	M1	M2	M3	M4	M5
P1	0	0	1	1	0
P2	1	0	1	0	0
P3	0	1	0	1	1
P4	1	0	1	0	1
P5	0	1	0	0	1
P6	0	0	0	1	1
P7	1	0	1	0	0

Now applying Eqs (7), (8) and (9) to the initial machine part incidence matrix given in Table (1) yields the standardized matrix B given in Table (2).

For example, for machine M1

$$E_1=\frac{3}{7} = 0.4285$$

$$\sigma_1 = \sqrt{0.4285 - 0.4285^2} = 0.4948$$

The member coefficient between part 1 and machine, b_{11} is calculated as follows

$$b_{11}= \frac{0-0.4285}{0.4948} = -0.8660$$

$$b_{21}= \frac{1-0.4285}{0.4948} = 1.1547$$

The same procedure be applied for the others elements of matrix B.

Table 2: Standardized matrix [B]

-0.8660	-0.6325	0.8660	1.1547	-1.1547
1.1547	-0.6325	0.8660	-0.8660	-1.1547
-0.8660	1.5811	-1.1547	1.1547	0.8660
1.1547	-0.6325	0.8660	-0.8660	0.8660
-0.8660	1.5811	-1.1547	-0.8660	0.8660
-0.8660	-0.6325	-1.1547	1.1547	0.8660
1.1547	-0.6325	0.8660	-0.8660	-1.1547

The similarity matrix S is shown in table (3), which can be obtained by applying equation (10)

Table 3 Similarity matrix [S]

1.0000	-0.5477	0.7500	-0.7500	-0.4167
-0.5477	1.0000	-0.7303	0.0913	0.5477
0.7500	-0.7303	1.0000	-0.4167	-0.7500
-0.7500	0.0913	-0.4167	1.0000	0.1667
-0.4167	0.5477	-0.7500	0.1667	1.0000

B. *Clustering analysis*

The second phase of applied approach is to identify machine group and part families by principal component analysis method.

In the PCA method, the initial cells are extracted out by the eigenvalues–eigenvector analysis of the similarity coefficient matrix as presented in equation (12)

$$(S-\lambda_i I)V_i = 0, \quad i= 1, 2 \ldots P \qquad (12)$$

Where S is a P×P similarity coefficient matrix, I is the identity matrix, λ_i are the characteristic roots (eigenvalues).

Here eigen values and eigen matrix is calculated using Matlab which is shown in table 4 and table 5 respectively.

Table 4 The eigenvalues matrix [E]

0.0969	0	0	0	0
0	0.1374	0	0	0
0	0	0.4842	0	0
0	0	0	1.1458	0
0	0	0	0	3.1357

Table 5 The eigenvector matrix [V]

-0.7067	0.2741	-0.2275	-0.3583	-0.4953
-0.1164	0.4797	0.6380	-0.4043	0.4311
0.5290	0.6414	0.0649	0.1428	-0.5330
-0.3779	0.4393	-0.1602	0.7282	0.3291
0.2536	0.3006	-0.7151	-0.3969	0.4200

The computed eigenvalues for the matrix given in Table (3) are listed and ranked in a descending order in Table (6). According to Kaiser's criterion, only the first two components are needed to group the machines.

Table 6 illustrates the initial statistics for each component. The total variance explained by each component is listed in the column labelled eigenvalues. The next column contains the percentage of the total variance attributable to each component. The percentage of the total variance explained by each factor is used to decide on the number of cells. The last column indicates the cumulative percentage, which is the percentage of variance attributable to each component.

Table 6 shows that approx 85% of the total variance is attributable to the first two cells. The remaining three components together, account for only 15% of the variance. One of the best advantages of this method is the possibility of obtaining the optimum number of cells by considering the cells with the greater percentages of the total variance.

Table 6 Eigenvalues and associated percentage of variance

Components	Eigenvalues	% of total variance	Cumulative %
1	3.1357	62.7145	62.7145
2	1.1458	22.9160	85.6305
3	0.4842	9.6837	95.3142
4	0.1374	2.7485	98.0627
5	0.0969	1.9373	100.0000
Sum total	5(must be equal to m)	100	

Here eigenvalue (Table 4) corresponding to machine 5 is highest and corresponding to machine 4 is second highest. Hence column 5 and column 4 of similarity matrix (Table 3) is chosen as the x-coordinate and y-coordinate respectively in the scatter plot. The scatter plot indicates the relationship between machine and another machine, between machine and part and between part and another part. There should be high correlation among machines strongly associated with the same cell and low correlation among machines that are associated with different cells.

Table 7 Co-ordinates of each machine in the scatter plot

Machine	X_i	Y_i
M1/Data1	-0.4167	-0.7500
M2/Data2	0. 5477	0.0913
M3 /Data3	-0.7500	-0.4167
M4 /Data4	0.1667	1.0000
M5/ Data5	1.0000	0.1667

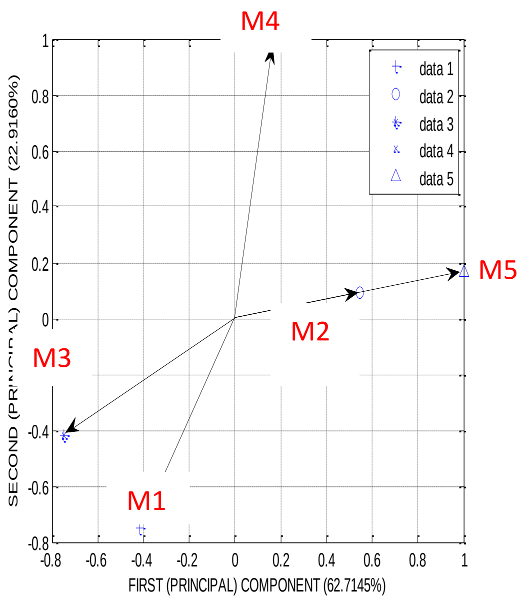

Fig.1. Graphical illustration of the scatter plot for machine

Four major situations for the classification of machines can be obtained:

- Two machines which have a low angle distance measure. Consequently they belong to the same cell. Examples can be illustrated in the Fig. 1 by (M2 and M5).
- If the angle distance between two machines is almost 180. This means that they are negatively correlated and may not belong to the same cell. Examples can be illustrated in the Fig.1 by (M1 and M4), (M2 and M3) and (M5 and M3)
- Two machines for which the angle distance measurement between them is almost 90°. This means that they are independent and do not belong to the same cell. Examples can be illustrated in Fig.1 by (M3 and M4), (M1 and M2) and (M1 and M5)
- If none of the three cases above are verified, the machine is not affected to any cell. This means that it is an exceptional machine.

Hence cell1 can be formed with M2 and M5 (minimum angular distance), while cell2 can be formed with M1 and M3. Till now we have exceptional machine is M4.

C. Assign algorithm for exceptional elements.

In the third phase of this approach a separate algorithm is used to assign the exceptional machines and exceptional parts.

1) Assignment of exceptional machines

This iteration will continue until all exceptional machines are assigned to a particular machine groups. Let e_m is the number of exceptional machines.

For k=1: e_m do (k is a loop variable)

Step1: Machines which have minimum angular distances cluster them as a cell and will ultimately behave like a single machine.

Step 2: Since the objective is to group machines with minimum angle distance, machine M_i, which has the smallest angle distance with M_k, is assigned to the machine group Mi.

Here M2 and M5 are merged in such a way that if P_i is either used by M2 or M5 or both then it is assigned 1 otherwise 0. Similar concept is applied while merging M1 and M3.

Table 8 Machine parts incidence matrix after 1st iteration.

	Group1(M2-M5)/ data1	Group2(M1-M3)/ data2	M4/data3
P1	0	1	1
P2	0	1	0
P3	1	0	1
P4	1	1	0
P5	1	0	0
P6	1	0	1
P7	0	1	0

Thus 5 machines problem is reduced to 3 machines Problem after 1st iteration. Again it reached to the first phase of the problem. It is repeated till machine groups are formed.

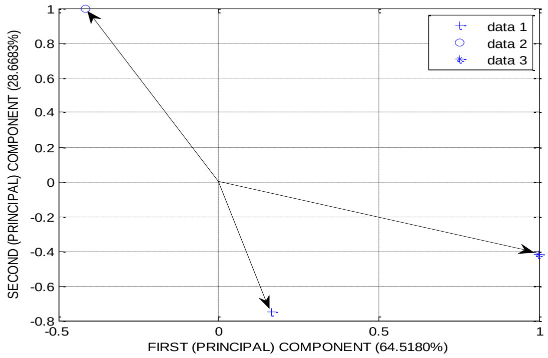

Fig.2. Scatter plot for machine after 1st iteration

Since the angular distance between data1 and data3 is minimum, hence data1 (M2-M5) and data 3 (M4) is grouped as a single cell (M2-M5-M4)

Machine group 1- (M2-M5-M4)

Machine group 2- (M1-M3)

Table 9 Formation of machine groups

	M2	M5	M4	M1	M3
P1	0	0	1	0	1
P2	0	0	0	1	1
P3	1	1	1	0	0
P4	0	1	0	1	1
P5	1	1	0	0	0
P6	0	1	1	0	0
P7	0	0	0	1	1

Similarly for parts, we can plot scatter plot shown in Fig .3.

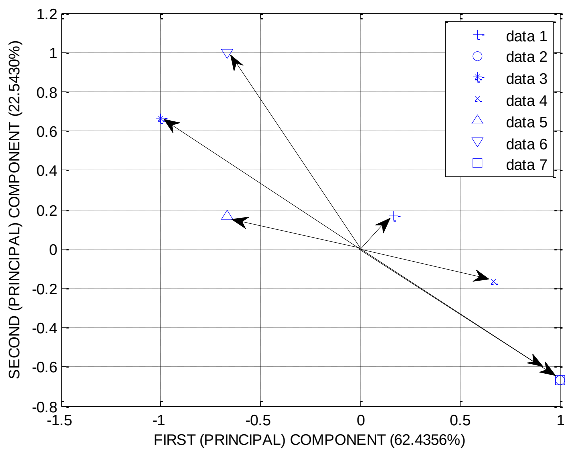

Fig.3. Scatter plot for part

From the above figure 3 parts P3-P5-P6 can be grouped in a cell and parts P2-P4-P7 can be grouped in another cell. So we have exceptional part is P1. (data1).

2) Assignment of exceptional parts

Let e_p is the number of exceptional part. The clustering algorithm for exceptional part is as follows:

This iteration will continue until all exceptional parts are assigned to particular part families.

For k=1: e_p do

Step 1: calculate Euclidean distance for each part (different to P_k and not an exceptional part), with the exceptional part P_k

$$d(P_k, P_i) = \sqrt{(x_k - x_i)^2 + (y_k - y_i)^2} \qquad (13)$$

Where (x_i, y_i) are the coordinates of P_i in the scatter plot.

Step 2: Part P_i which have the smallest distance, is assigned to the part families Pi.

To complete the cell formation process, we need to allot P1 in any cell. To do so we calculate Euclidian distance between Exceptional parts and remaining parts.

Minimum distance $(P1, P_k)$; k=1, 2, 3….11; k≠1

P_{12} = 1.1785
P_{13} = 1.2693
P_{14}= 0.600
P_{15} =0.8334
$_{16}$= 1.1785
P_{17}=1.1785

Minimum distance is P_{14}. Hence P1 is assigned with P4.

Hence Part families 1 - P1-P2-P4-P7

And Part families 2 - P3-P5-P6

Table10 final cell formation of example problem 1

	M2	M5	M4	M1	M3
P1	0	0	1	0	1
P2	0	0	0	1	1
P4	0	1	0	1	1
P7	0	0	0	1	1
P3	1	1	1	0	0
P5	1	1	0	0	0
P6	0	1	1	0	0

EE (Exceptional Element) = 2

VOID=3

UE (overall unity element) = 16

IV. COMPUTATIONAL RESULTS AND DISCUSSION

In order to evaluate the proposed approach and to compare its performance with other cell formation methods, ten sets of data (problems) have been chosen from the literature. Table 11 summarizes the special features and the sources of these data sets used in this paper. This table is partly adopted from Hachicha et al. [17].

Table 11 Features and sources of cell formation problems

No	Size	No. of cells	references
Problem 1(example)	5×7 (example)	2	Wang J [48]
Datasheet 1	5×18	3	Seifoddini [37]
Datasheet 2	8×20	3	Chandrasekharan and Rajagopalan [10]
Datasheet 3	10×10	5	Mosier and Taube [30]
Datasheet 4	10×15	3	Chan and milner [9]
Datasheet 5	11×22	4	Cheng and Lee [11]
Datasheet 6	14×23	6	Askin and Subramanian [5]
Datasheet 7	14×24	7	Stanfel L.E. [45]
Datasheet 8	16×24	8	McCormick et al [28]
Datasheet 9	18×24	9	Carrie A.S. [8]

The performance evaluation results of these solutions are summarized in Table 12. It can be seen that the percentage of machine utilization ranges from 80.95 to 100%, and the percentage of grouping efficiency ranges from 74.21 to 96%. The proposed method achieved the highest grouping efficiency for the problem 1and datasheet 1, 2,5,6,7 also this method achieved highest machine utilization for datasheet 1,2,5,6,7. The best clustering performance results that are obtained

from the literature are also included for comparison purposes. The value of GE and MU is not found in literature for datasheet 8, 9.

Table 12 Summary of proposed approach results

No.	Size of the problem	Proposed approach results		Best known results	
		MU	GE	MU	GE
Problem 1 (example)	5×7	82.35	**85.62**	82.35	85.61
Data sheet 1	5×18	**100.00**	**90.00**	92.00	89.13
Datasheet 2	8×20	**85.93**	**74.21**	78.04	71.71
Datasheet 3	10×10	84.00	90.00	84.00	90.00
Datasheet 4	10×15	92.00	96.00	92.00	96.00
Datasheet 5	11×22	**87.14**	**88.62**	80.72	86.90
Datasheet 6	14×23	**80.95**	**89.12**	72.37	85.57
Datasheet 7	14×24	**85**	**90.688**	68.60	83.90
Datasheet 8	16×24	92.45	90.63	NA	NA
Datasheet 9	18×24	94.83	93	NA	NA

V. FINAL CONCLUSION

During the last three decades of research, numerous algorithms have been developed to solve cell formation problems and this research still remains of interest to this day. Designing appropriate cells is the first step towards configuring a cellular manufacturing system.

Here a new approach is presented to solve cell formation problem. First machine part incidence matrix is collected from literature and then it is converted into similarity coefficient matrix. PCA method is applied to find the optimal machine groups and part families. Scatter plot is used to group machine and parts into families.

The proposed method is a valid and complete approach to form cellular manufacturing systems. It is easily convenient to practice. More over it used PCA, which is easily accessible in many commercial packages. From computational experience, one can say that the proposed method is not too much time taking and gives better result than found in literature.

A total ten problem from different literatures is tested by this method. This approach is found better in 60% of the problem through the measure of grouping efficiency (Bold digit denoted better result) and in 40% problem the proposed method is as good as the best one found in cellular manufacturing system.

This approach can further applied to accommodate other manufacturing information like production volume, production time, sequence and alternative routings. Extending to this direction is our future research direction.

Appendix

Datasheet 1

	1	4	2	3	5
1	1	1	1		
3	1	1	1		
6	1	1	1		
8	1	1	1		
11	1	1	1		
12	1	1	1		
13	1	1	1		
2	1	1			
5	1	1			
16	1	1			
17	1	1			
14	1	1			
18			1	1	1
10			1	1	1
15			1	1	1
4			1	1	1
7			1	1	
9					1

Datasheet 2

	1	4	6	8	3	7	2	5
1	1		1	1				1
2			1	1			1	1
3	1	1		1			1	1
4	1	1		1			1	
5			1	1	1	1		
8		1	1	1	1	1		
9	1	1		1			1	
10	1	1	1	1				1
14	1	1	1	1				
15	1	1	1					1
16	1		1	1	1	1		1
18	1	1	1				1	
6					1		1	1
7		1	1		1	1	1	
11			1		1	1	1	
12			1		1	1		1
13		1		1	1	1		1
17		1		1	1	1		1
19	1	1	1		1	1		1
20		1			1	1		1

Datasheet 3

	2	7	9	10	8	3	1	4	5	6
2			1	1						
3	1	1	1	1						
4	1		1	1						
8	1	1	1							
6					1	1				
9					1					
5						1				
1							1	1		1
7									1	1
10							1		1	1

Datasheet 4

	3	4	6	9	1	7	10	2	5	8
1	1	1	1							
4		1	1	1						
6	1		1	1						
9	1	1	1	1						
14	1	1	1	1						
2					1	1	1			
7						1	1			
10					1	1	1			
11					1	1	1			
12					1	1	1			
3								1	1	1
5								1	1	1
8								1	1	1
13								1	1	1
15								1	1	1

Datasheet 5

	1	4	5	10	2	6	7	11	9	8	3
1	1	1	1	1							
2	1	1	1	1							
3	1	1	1	1							
15	1	1	1	1							
16	1	1	1	1							
20	1	1	1							1	
21	1	1	1								
22	1	1	1								
7			1	1							
11	1	1		1	1						
5				1	1	1				1	1
8				1	1	1					
12				1	1	1				1	1
19					1	1				1	1
4							1	1	1		
9							1	1	1	1	
10								1		1	
14							1			1	
17							1	1	1		
18				1			1	1	1	1	
6							1			1	1
13										1	1

Datasheet 6

	6	8	9	4	5	7	1	12	13	2	3	11	14	10
1	1	1												
6		1	1											
10	1	1	1										1	
12	1	1	1											
14	1	1												
15	1	1	1										1	
16	1	1												
2				1	1	1								
3				1	1	1								
17				1	1	1								
19				1										
20				1	1	1								
22				1	1				1					
7							1		1					
8						1	1	1	1					
9								1	1					
18									1					
4										1	1	1		1
5										1	1	1		
21											1	1		
11	1												1	
13			1										1	
23														1

Datasheet 7

	4	5	7	10	2	3	11	6	8	9	14	12	13	1
1	1	1	1											
2	1	1	1											
17	1	1	1											
19	1													
20	1	1	1											
23	1	1											1	
24				1			1							
3				1	1	1	1							
4					1	1	1							
21						1	1							
5									1	1				
9								1	1	1	1			
10								1	1					
12								1	1	1				
14								1	1					
15								1	1	1	1			
16								1	1					
22								1	1					
11								1			1			
13										1	1			
7			1									1	1	1
8												1	1	
18													1	
6													1	1

Datasheet 8

	10	11	12	16	1	2	8	3	14	9	13	4	7	6	5	15
9	1	1	1	1												1
11			1	1	1						1					
14	1	1	1	1					1							
20	1	1	1	1												1
24	1	1	1	1					1	1			1			
3			1		1		1							1		
10	1				1	1	1									
22	1				1	1	1									
23	1				1	1	1									
1					1		1	1	1				1			
4					1			1	1							
6					1			1	1							1
12									1							
16								1				1				
7		1			1		1			1	1					
8					1						1					
19					1			1				1	1			
2	1		1								1			1		
13							1							1		
15					1									1		
17	1			1		1		1						1		
18					1									1		
21														1	1	
5																1

Datasheet 9

	3	4	5	6	11	12	15	1	2	8	10	13	16	17	9	18	7	14
2	1	1	1								1						1	
5	1	1	1	1													1	
8	1	1	1	1								1						
9	1	1	1	1								1						
12	1	1	1								1						1	
15	1	1	1	1			1											
17	1	1	1	1			1											
7					1	1	1											
13						1	1	1										
14					1	1						1						
18					1	1	1											1
21					1	1												1
10			1	1				1		1								
23			1	1				1	1	1								
19						1					1	1						
22		1				1						1						
4			1							1			1	1				
1							1								1			
3				1						1					1			
24			1	1						1					1			
11			1													1		
16			1													1		
6		1				1											1	
20										1								1

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