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Development of similarity coefficient for machine-component cell formation of cellular manufacturing system and its comparison

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ABSTRACT

The cell formation problem is a crucial component of a cellular manufacturing system. The purpose of this manufacturing system is to build manufacturing clusters by grouping component families and machine cells with the aim of minimizing the total cost of production. In this paper, the cell formation problem is scrutinized by two similarity index methods. In the first phase, a new similarity coefficient method is proposed to identify the closeness of components/machines and this closeness is in the form of a similarity distance matrix. In the second phase, principal component analysis (PCA) and agglomerative clustering algorithm (ACA) are applied to group components into component families and machines into machine cells. In the third phase, a performance comparison of PCA and ACA was carried out with two different measures, viz. grouping efficiency and grouping efficacy. At the end, a complete factorial experiment is used to compare the results of the two algorithms, in which "Problem" is used as Factor A, "Algorithm" is used as Factor B and "Similarity Coefficient Method" is used as Factor C and the results are reported.

Contribution/ Originality
In this article a new similarity coefficient index is proposed to identify the closeness between the machines and component in the shop floor. The proposed similarity index proves the result quality compared to other similarity coefficients.

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1. INTRODUCTION

The productivity of an organization is the combined effect of excellence of several subsystems of the organization. The production system is the core in the entire value chain of the organization, where major conversion/ value addition activities take place. There are many dimensions of improving productivity at shop floor level. Among all, the organization of layout forms an important basis, because it guides a flow of components and/ or subassemblies that are routed in the shop floor. Among the types of layout, viz. process layout, product layout, group technology layout and fixed position layout, the group technology layout gains lot of importance, because it combines the benefits of process and product layouts. Further, this type of layout is present in all modern manufacturing practices, viz. CIM, FMS, etc. The other name for this layout is cellular layout and the corresponding system is called as cellular manufacturing system.

The objective of the cellular layout is to group the given set of components and a set of machines into a meaningful number of machine groups and component groups based on the similarity of operation sequences of components and assign the machines in each machine group to the corresponding component groups such that preferably the operational requirements of all the components assigned to each machine group are fully met within that machine group itself. The grouping of machines and components into a distinct number of machine-component cells gives a scheme for implementing the layout, in which a given combination of a group of machines and a group of components is called as a machine-component cell. But, it may not be possible always to have such ideal machine-component cell formation. Under such situation, the objective is to form the machine-component cells such that the number of odd elements in the off-diagonal is minimized, which will minimize the number of inter-cell moves.

Initially, a machine-component incident matrix is formed using the operation sequences of components. The rows of the machine-component incident matrix represent the machines which are required to process the components. The columns of the matrix represent the component numbers. This matrix is treated as $[A_{ij}]$ as shown in Figure 1. The matrix is represented in the form of binary numbers. If the sequence of the component j has the machine number i, then the respective matrix element C_{ij} is assumed as 1; otherwise it is assumed as 0.

		Components j					
		1	2	3	4	5	6
	1	0	1	0	0	1	0
Machine i	2	1	0	0	0	1	1
	3	0	0	1	1	0	1
	4	1	0	1	0	0	0
	5	1	1	0	1	1	0

Figure 1: Machine-components incident matrix

Many researchers have contributed various algorithms to obtain machine-component cells with least exceptional elements and voids. Among these methods, the similarity index based clustering method is more flexible to deal with the cell formation problem. Though many researchers contributed to this field, very few of them used the similarity index matrix as an input in their proposed algorithms. In this paper, the authors made an attempt to compare the proposed similarity coefficient method with an existing similarity coefficient method (Panneerselvam *et al.*, 1990), in terms of grouping efficiency as well as grouping efficacy.

2. LITERATURE REVIEW

The similarity coefficient methods are classified into problem-oriented and general purpose similarity coefficient (Yin and Yasuda, 2006). The general purpose similarity coefficients are widely used in other disciplines, like biology, sociology, medical science, economics, etc. The problem-oriented similarity is designed to solve specific problem, such as cell formation problem. This problem-oriented similarity is either based on binary data or production information data. In this paper, the similarity coefficient based on binary data is considered. McAuley (1972) was the first to examine the Jaccard similarity coefficient (General purpose similarity coefficient) method to identify similar groups of machines and components.

Carrie (1973) suggested a numerical taxonomy for group technology and examined the cell formation problem by developing a new similarity coefficient. Rajagopalan and Batra (1975) developed a graph theoretic approach to solve the cell formation problem. They used a matrix of Jaccard similarity coefficient (McAuley, 1972) for grouping similar machines. Waghodekar and Sahu (1984) developed a heuristic based on similarity coefficient. Seifoddini and Wolfe (1986) developed a similarity coefficient which overcomes the short coming of the similarity coefficient developed by McAuley (1972) and Seifoddini and Hammid (1984). This method gives a flexibility to deal with duplication of bottleneck machines and overcome the chain problem of single linkage cluster algorithm (SLCA). Kusiak (1987) developed a similarity coefficient method, in which p-median method is implemented to identify similarities of machines and components.

Mosier (1989) proposed a similarity coefficient method and used an agglomerative clustering algorithm to identify similar groups of machine cells and component families. Wang and Roze (1995) presented an experimental study on machine cells and component families based on original and modified p-median models using similarity coefficient. They considered three similarities, viz. McAuley (1972), Kusiak (1987) and Wei and Kern (1989) to compare eleven machine-component incident matrixes. Srinivasan (1994) used minimum spanning tree (MST) for clustering the machines and components, in which distance based similarity coefficient is used. Nambirajan and Panneerselvam (1999) used a simulated annealing algorithm to solve the cell formation problem.

Hachicha *et al.* (2008) presented the multivariate approach PCA (Principal component analysis) to form a machine / component matrix. In this paper, a correlation matrix is used as the similarity coefficient matrix and this matrix is used as an input for PCA to obtain factor loadings to identify the similar groups. Kitaoka *et al.* (1999) constructed a double centering similarity coefficient matrix and applied quantification method to identify the eigenvalues and eigenvectors of the double centering matrix. Then, a clustering algorithm is applied to form machine cells and component families such that the distances of the eigenvectors are minimized.

Chattopadhyay *et al.* (2011) used PCA and self-organizing map (SOM) algorithm in which non-binary operation sequences are used for visual clustering of machine-component cell formation. In this paper, two types of similarity index (an existing and a proposed) are considered. Their effects on the solution accuracy are tested using two different algorithms, viz. principal component analysis (PCA) and agglomerative clustering algorithm (ACA).

3. FRAMEWORK OF THE PROPOSED APPROACH

The proposed approach consists of four phases as shown in Figure 2.

3.1. Phase 1: Similarity coefficient method

As stated earlier, this paper consists of two different similarity coefficients, the proposed similarity coefficient and an existing similarity coefficient (Panneerselvam *et al.* 1990).

The formula for the proposed similarity coefficient for components is as given below.

$$S_{ij} = \frac{\sum_{K=1}^{m} p_{ij}}{m}$$

where, $p_{ij} = 1$ if $a_{ki} = a_{kj}$, $k = 1,2,\ldots, m$.
m = is the number of machines

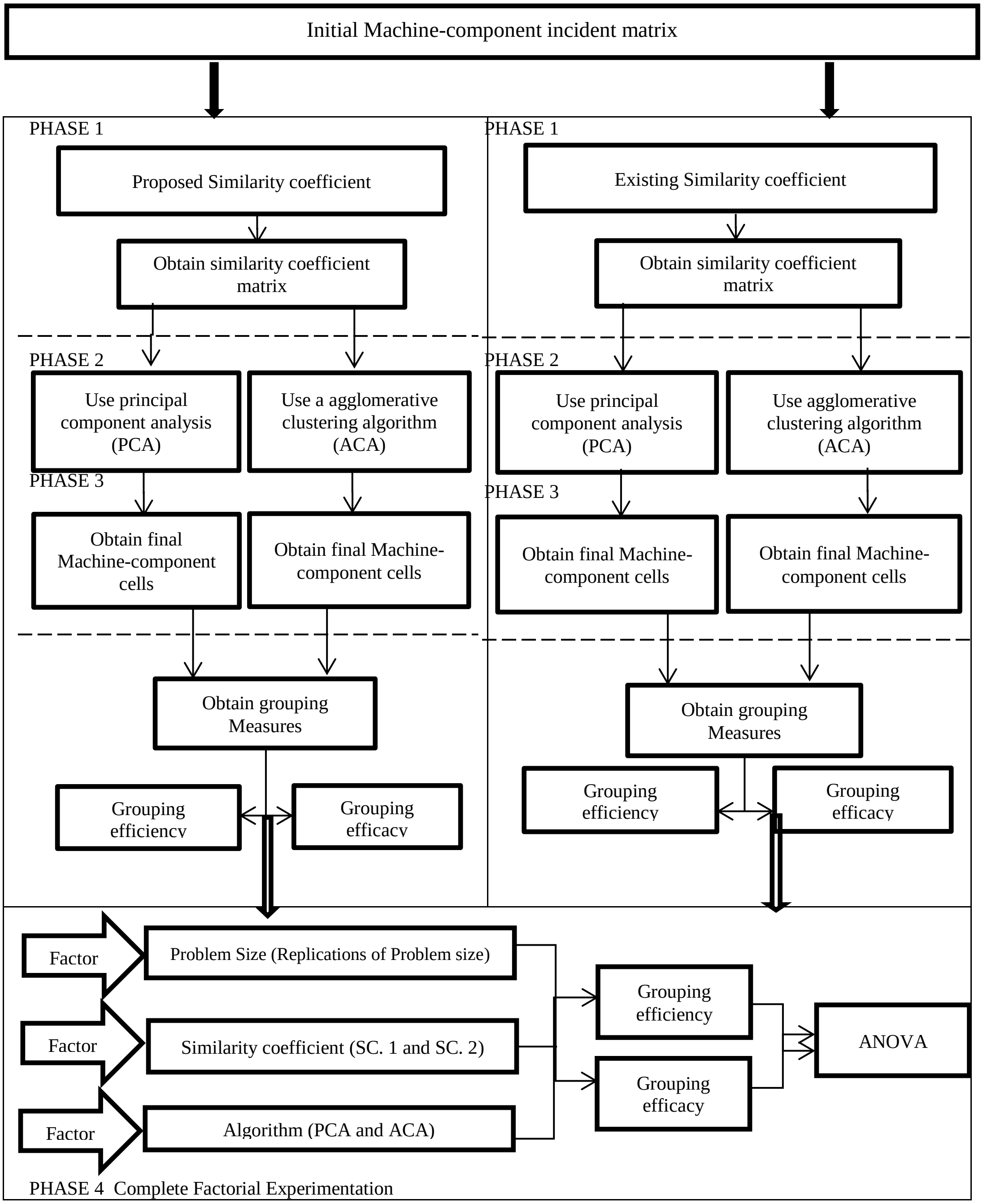

Figure 2: Framework of the proposed approach

The formula for the proposed similarity coefficient for machines is as given below.

$$S_{ij} = \frac{\sum_{K=1}^{n} p_{ij}}{n}$$

where, $p_{ij} = 1$ if $a_{ki} = a_{kj}$, k = 1,2,…..,n.
n = is the number of machines

Next, the existing similarity coefficient proposed by Panneerselvam *et al.* (1990) is used to the similarity coefficient between component *i* (machine *i*) and component *j* (machine *j*) (S_{ij}) is given below:

$$S_{ij} = \frac{\text{Number of common machining operations between component } i \text{ and component } j}{\text{Number of machining operations in component } i}$$

$$S_{ij} = \frac{\sum_{k=1}^{m} q_{ij}}{\sum_{p=1}^{m} a_{ki}}$$

where, $q_{ij} = 1$ if $a_{ki} = a_{kj}$, k = 1,2,…..,m.

m = is the number of machines

In the same way, the similarity coefficient matrix w.r.t different pairs of machines can be computed using the following formula.

$$S_{ij} = \frac{\sum_{k=1}^{n} q_{ij}}{\sum_{p=1}^{n} a_{ki}}$$

where, $q_{ij} = 1$ if $a_{ki} = a_{kj}$, k = 1,2,…..,n.

n = is the number of machines

After obtaining the similarity coefficient matrix, the PCA and ACA are employed to identify similar groups of component families and machine cells. The quality of the solution of these groups is measured by grouping efficiency as well a grouping efficacy.

3.2. Phase 2: Clustering methods

This section presents two different clustering methods, viz. Principle Component Analysis (PCA) and Agglomerative Clustering Algorithm (ACA) for the machine-component cell formation.

3.2.1. Principle component analysis

The principle component analysis (PCA) aims to derive a reduced set of factors from a given set of variables. The application of PCA for the machine-component cell formation is carried out in two stages. The first stage is to derive factors (machine groups) by treating all the machines (rows) as the given set of variables and the second stage is to derive factors (component groups) by treating all the components (columns) as the given set of variables. The machine-component incident matrix is constructed by keeping the machines of machine clusters on rows one after another and keeping the components of component clusters on columns one after another. Then the presence of machine-component blocks is to be checked in this matrix. In this approach, the factor loadings for machines as well as for components are obtained usng Varimax factor rotation. Then the grouping of machines and components are carried out based on two dimensional scatter plot analysis (Hachicha *et al.*, 2008). The criteria for grouping the machines and components by scatter plot analysis are given below.

Criteria 1: If two machines (components) have low angle distance, they consequently belong to the same cell.
Criteria 2: If two machines (components) angle distance are almost 90^o then they are independent and they do not belong to the same cell.
Criteria 3: If the two machines (components) angle distance is almost 180^o then they are negatively correlated and they do not belong to the same cell.
Criteria 4: If the machines (components) do not come under these three criteria, then the machines (components) are considered as exceptional elements.

3.2.2. Agglomerative clustering algorithm

An agglomerative clustering algorithm (Panneerselvam, 2004) is a bottom-up approach in which each object is assumed as a separate cluster and then they will be clustered in succession until a single cluster which consists of all the objects is formed. It is a hierarchical clustering method. The steps of this method are presented below.

Step-0: Initialize i to the total number of objects, i = m.
Step-1: Imagine the points in n dimensional plane , where n is the number of variables.
Step-2: Find the distance between each pair of points.
Step-3: Identify the two points (p,q) which are having the least distance between them.
Step-4: Find the centroid of the two points (p,q). Let it be *ci* and the distance between them be *di*.
Step-5: Identify the next two nearest clusters of point(s) and group them together. Then, find the centroid of the newly formed cluster.
Step-6: Set $i = i - 1$
Step-7: If $i > 1$, then go to Step-5; otherwise go to step- 8.
Step-8: Draw dendrogram of the sequence of cluster formation.

As per the clustering criterion, determine the number of clusters and the objects of the clusters. An example of clustering criterion may be the sudden jump in the distance between clusters while adding a cluster to another cluster. Draw a line in the dendrogram where there is a sudden jump in the distance between any two clusters and identify the final set of clusters accordingly.

3.3. Phase 3: Grouping measures

The goodness of block-diagonal matrix, obtained by clustering algorithms for cellular production system are measured by two measures namely grouping efficiency and grouping efficacy are used. The grouping efficiency (Chandrasekharan and Rajagopalan, 1986 a, 1986 b) to define the quality of the solution, namely as grouping efficiency (η) , which is the weighted sum of two functions as given below.

$$\eta = q\,\eta_1 + (1-q)\,\eta_2$$

where, η_1: is the ratio of number of 1^s in the diagonal blocks to the total number of elements in the diagonal blocks.

η2: is the ratio of number of 0s in the off-diagonal blocks to the total elements in the off-diagonal blocks.
q: Weighting factor (0≤q≤1) and it is usually assumed as 0.5

Kumar and Chandrasekaran (1990) proposed another measure named grouping efficacy (E), which overcomes the weaker discriminating power of grouping efficiency measure by assigning equal weight for the number of voids and the number of exceptional elements. This measure is defined as follows.

$$E = \frac{(e - e_0)}{(e + e_v)}$$

Where, e: Total number of 1s in the matrix
e_0: The number of exceptional elements
e_v :The number of voids in the diagonal box

In this paper these two measures are considered to measure the grouping accuracy of the machine-component cell formation.

3.4. Phase 4: Comparison of similarity coefficient (Factorial Experimentation)

The objective of this paper is to select the similarity coefficient out the two such methods listed earlier, which gives the best result in terms of grouping measures.

So, a complete factorial experiment has been designed to carry out this comparison. The complete factorial experiment has three factors, viz, Problem Size (Factor A), Algorithm (Factor B) and Similarity Coefficient (Factor C). The number of levels of the problem size is 10 (5X7, 7X7, 8X20, 9X10, 10X12, 12X19, 14X24, 15X10, 24X40 and 30X50) and the number of levels for the Algorithm is two, viz. Principle Component Analysis and Agglomerative Clustering Method, and the number of levels for the Similarity Coefficient is 2 (New and Existing). The number of replications carried out under each of the experimental combinations is 2. So, the total number of observations of this experiment is 80 for each of the grouping measures, viz. grouping efficiency and grouping efficacy. The model of ANOVA is as given below.

$$Y_{ijkl} = \mu + A_i + B_j + AB_{ij} + C_k + AC_{ik} + BC_{jk} + ABC_{ijk} + e_{ijkl}$$

where,

Y_{ijkl} is the l^{th} replication under the i^{th} treatment of the Factor A, the j^{th} treatment of the Factor B and the k^{th} treatment of the Factor C.
μ is the overall mean of the response.
A_i is the effect of the i^{th} treatment of the Factor A on the response.
B_j is the effect of the j^{th} treatment of the Factor B on the response.
AB_{ij} is the interaction effect of the i^{th} treatment of the Factor A and the j^{th} treatment of the Factor B on the response.
C_k is the effect of k^{th} treatment of the Factor C on the response.
AC_{ik} is the interaction effect of the i^{th} treatment of the Factor A and the k^{th} treatment of the Factor C on the response.
BC_{jk} is the interaction effect of the j^{th} treatment of the Factor B and the k^{th} treatment of the Factor C on the response.
ABC_{ijk} is the interaction effect of the i^{th} treatment of the Factor A, the j^{th} treatment of the Factor B and the k^{th} treatment of the Factor C on the response.
e_{ijkl} is the random error associated with the l^{th} replication under the i^{th} treatment of the Factor A, the j^{th} treatment of the Factor B and the k^{th} treatment of the Factor C.

A factorial experiment as per the proposed design has been carried out for each grouping measure and the results are as given in Table 1 for grouping efficiency and in Table 2 for grouping efficacy.

Table 1: Results of grouping efficiency

Problem Size	Replication	SC1(Book) PCA Efficiency	SC1(Book) ACM Efficiency	SC2 (New) PCA Efficiency	SC2 (New) ACM Efficiency
5x7	1	83.00	83.00	85.62	85.62
	2	77.09	77.09	79.09	77.09
7x7	1	68.18	68.18	68.18	70.83
	2	75.08	75.83	75.08	75.08
8x20	1	95.83	94.40	94.40	94.40
	2	65.19	71.02	63.93	71.02
9x10	1	65.83	76.66	73.76	75.98
	2	69.61	68.88	64.67	66.81
10x12	1	64.73	65.83	65.83	65.83
	2	78.96	64.47	79.91	77.50
12x19	1	72.06	62.05	70.74	74.43
	2	72.45	62.56	75.68	70.74
14x24	1	84.67	75.89	75.89	82.17
	2	76.29	74.56	83.33	76.11
15x10	1	74.96	88.31	88.31	88.31
	2	96.00	96.00	96.00	96.00
24x40	1	100	100	100	100
	2	93.79	92.51	95.86	92.19
30x50	1	68.33	68.33	71.76	72.06
	2	62.98	5.43	61.76	54.02

Table 2: Results of grouping efficacy

Problem Size	Replication	SC1(Book) PCA Efficacy	SC1(Book) ACM Efficacy	SC2 (New) PCA Efficacy	SC2 (New) ACM Efficacy
5x7	1	70.00	70.00	73.68	73.68
	2	68.00	68.00	68.00	68.00
7x7	1	40.00	40.00	40.00	46.15
	2	53.33	55.55	53,33	53.33
8x20	1	85.24	83.60	83.60	83.60
	2	52.58	56.07	49.10	56.07
9x10	1	39.68	55.31	51.02	44.82
	2	46.00	45.09	40.00	42.59
10x12	1	30.76	32.78	32.78	32.78
	2	56.09	34.42	57.50	54.54
12x19	1	49.18	37.57	47.18	52.80
	2	50.00	38.19	54.70	47.18
14x24	1	67.90	51.78	51.78	61.90
	2	52.58	49.56	65.90	52.21
15x10	1	51.28	75.00	75.00	75.00
	2	92.00	92.00	92.00	92.00
24x40	1	100	100	100	100
	2	82.63	75.86	80.57	79.86
30x50	1	36.66	36.66	43.27	43.67
	2	26.94	10.86	25.05	13.77

3.4.1. Hypotheses

Factor A (Problem Size)

H_o: There is no significant difference in terms of solution between different pairs of treatments of the Factor A (Problem size).

H_1: There is significant difference in terms of solution between different pairs of treatments of the Factor A (Problem size).

Factor B (Similarity coefficient)

H_o: There is no significant difference in terms of solution between different pairs of treatments of the Factor B (Similarity coefficient method).

H_1: There is significant difference in terms of solution between different pairs of treatments of the Factor B (Similarity coefficient method).

Factor C (Algorithm)

H_o: There is no significant difference in terms of solution between the two treatments of the Factor C (Algorithm).

H_1: There is significant difference in terms of solution between the two treatments of the Factor C (Algorithm).

3.4.1.1. Interaction components

Factor A X Factor B: (AB_{ij})

H_o: There is no significant difference in terms of solution between different pairs of interaction between Factor A and Factor B.

H_1: There is significant difference in terms of solution between different pairs of interaction between Factor A and Factor B.

Factor A X Factor C: (AC_{ik})

H_o: There is no significant difference in terms of solution between different pairs of interaction between Factor A and Factor C.

H_1: There is significant difference in terms of solution between different pairs of interaction between Factor A and Factor C.

Factor B X Factor C: (BC_{jk})

H_o: There is no significant difference in terms of solution between different pairs of interaction between Factor B and Factor C.

H_1: There is significant difference in terms of solution between different pairs of interaction between Factor B and Factor C.

Factor A X Factor B X Factor C: (ABC_{ijk})

H_o: There is no significant difference in terms of solution between different pairs of interaction between Factor A, Factor B and Factor C.

H_1: There is significant difference in terms of solution between different pairs of interaction between Factor A, Factor B and Factor C.

$\alpha = 0.05$ – level of significance for testing the above hypotheses.

3.4.2. Comparison Based on grouping Efficiency:

The data on grouping efficiency which are shown in Table 1 are analyzed using a three factor complete factorial ANOVA, whose model is already shown. The results of ANOVA based on the grouping efficiency are shown in Table 3.

Table 3: ANOVA based on grouping efficiency

	Sum of Square	Degree of freedom	Mean sum of square	F-ratio	Significance ($\alpha = 0.5$)
A	9033.031	9	1003.67	8.4488	2.12
B	180.1875	1	180.1875	1.51680	4.08
AB	75.6875	1	75.6875	0.63713	4.08
C	318.2188	9	35.3576	0.29763	2.12
AC	625.7188	9	69.5243	0.58525	2.12
BC	61.5	1	61.5	0.51770	4.08
ABC	351.4063	9	39.0451	0.32867	2.12
Error	4751.75	40	118.7938		
Total	15397.5	79			

From this table, it is clear that the calculated F values are lesser than the respective table F values for all the components at a significant level of 5%, except for the Factor A. The calculated F value for the Factor A is 8.44884161 as against the table F value of 2.12. Hence, the corresponding null hypotheses is to be rejected and its alternative hypotheses is to be accepted. This means that there is a significant difference between the problems.

The calculated F value for the Factor B, Factor C, and interaction between AB, AC, BC and ABC are lesser than the respective table F values. Hence, the corresponding null hypotheses are to be accepted and their alternative hypotheses are to be rejected. As a researcher, we are very much keen in whether there is significant difference between the similarity coefficients in terms of the grouping efficiency. As per the ANOVA result, there is no significant difference between the similarity coefficient methods in terms of grouping efficiency. So, any one of the similarity coefficient methods can be used to solve the machine-component cell formation problem.

However the mean, standard deviation and coefficient of variation of the grouping efficiencies of the similarity coefficient methods are presented in Table 4.

Table 4: Means, standard deviations and coefficient of variations of grouping efficiencies of algorithms

Measure	Existing Similarity Coefficient		New Similarity Coefficient	
	PCA	ACA	PCA	ACA
Mean	78.4900	78.3095	77.2515	73.5500
Standard deviation	11.6994	11.5271	11.4622	19.8130
Coefficient of variation	14.9056	14.7200	14.8375	26.9381

From Table 4, it is clear that the mean grouping efficiency of PCA of the existing similarity coefficient is the highest, but its coefficient of variation is next to that of ACA of the existing similarity coefficient in the increasing order. So, one has to see the trade-off between PCA and ACA of existing similarity coefficient. The difference between the mean grouping efficiencies of PCA and ACA for existing similarity coefficient is 0.18%. Similarly, the difference between the coefficient of variations of the existing similarity coefficient for PCA and ACA is 0.19% and since this difference is very minimal, the existing similarity coefficient with the maximum mean grouping efficiency, which is PCA (Principal component analysis), is suggested for implementation to maximize the grouping efficiency of the machine-component cell formation problem.

3.4.3. Comparison based on grouping efficacy

The data on grouping efficacy as shown in Table 2 are analyzed using a three factor complete factorial ANOVA, whose model is already shown. The results of ANOVA based on the grouping efficacy are shown in Table 5.

Table 5: ANOVA based on grouping efficacy

	Sum of Square	Degree of freedom	Mean sum of square	F-ratio	Significance ($\alpha = 0.5$)
A	25923.25	9	2880.361	17.332	2.12
B	123.3125	1	123.3125	0.7420	4.08
AB	35.3437	1	35.3437	0.2126	4.08
C	165.9063	9	18.4340	0.1109	2.12
AC	375.25	9	41.6944	0.2508	2.12
BC	12.6562	1	12.6562	0.0761	4.08
ABC	235.8438	9	26.2048	0.1576	2.12
Error	6647.344	40	166.1836		
Total	33518.91	79			

From this table, it is clear that the calculated F values are lesser than the respective table F values for all the components at the significant level of 5%, except for the Factor A. The calculated F value for the Factor A is 17.3324022 as against the table F value of 2.12. Hence, the corresponding null hypotheses is to be rejected and its alternative hypotheses is to be accepted. This means that there is a significant difference between the problems. The calculated F values for the Factor B, Factor C, and interaction between AB, AC, BC and ABC are lesser than the respective table F values. Hence, the corresponding null hypotheses are to be accepted and their alternative hypotheses are to be rejected. As per the ANOVA result, there is no significant difference between the similarity coefficients in terms of grouping efficacy. So, any one of the similarity coefficient can be used to solve the machine-component cell formation problem.

However, the mean grouping efficacy, standard deviation and coefficient of variation of the grouping efficacy of the similarity coefficients methods are presented in Table 6.

Table 6: Means, standard deviations and coefficient of variations of grouping efficacy of algorithms

Measure	Existing Similarity Coefficient		New Similarity Coefficient	
	PCA	ACA	PCA	ACA
Mean	59.2230	58.6975	57.5425	55.4150
Standard deviation	20.0728	20.8478	20.3177	22.4671
Coefficient of variation	33.8937	35.5173	35.3091	40.5435

From Table 5, it is clear that the mean grouping efficacy of PCA of the existing similarity coefficient is the highest, and for coefficient of variation the same PCA of the existing similarity coefficient is the highest. So, the existing similarity coefficient with the maximum mean grouping efficacy, which is PCA (Principal component analysis), is suggested for implementation to maximize the grouping efficacy of the machine-component cell formation problem.

4. CONCLUSION

In this paper, the author stated the importance of similarity coefficient matrix as a better input for superior algorithms to solve a cell formation problem. In this paper, an attempt has been made to select the best similarity index out the proposed similarity index and an existing similarity index through comparison of results using a complete factorial experiment. Through the ANOVA result, it is found that there is no significant difference between these similarity coefficients in terms of each grouping measures (grouping efficiency, grouping efficacy). By taking the means and coefficient of variations of the grouping efficiencies of the two similarity coefficients, it is suggested to use the Principal Component Analysis (PCA) of the existing similarity coefficient to maximize the grouping efficiency of the machine-component cell formation problem. By doing a similar comparison with respect to grouping efficacy, it is suggested to use the same Principle Component Analysis (PCA) of the existing similarity coefficient to maximize the grouping efficacy. Hence, it is recommended to use the relevant algorithm depending on the objective (maximizing grouping efficiency/ grouping efficacy) as the seed generation algorithm if meta-heuristic is used to solve the machine component cell formation problem. Further, if the hybrid algorithm is designed for this problem, depending on the objective (maximizing grouping efficiency/ grouping efficacy), relevant algorithm may be used at some stage of the algorithm or as a local optimization procedure in such algorithm.

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Reference

Carrie, A. S. (1973). Numerical taxonomy applied to group technology and plant layout. *International Journal of Production Research, 11*(4), 399-416. *view at Google scholar* / view at publisher

Chandrasekharan, M. P., & Rajagopalan, R. (1986a). An ideal seed non-hierarchical clustering algorithm for cellular manufacturing. *International Journal of Production Research, 24*, 451–464. *view at Google scholar* / view at publisher

Chandrasekharan, M. P., & Rajagopalan, R. (1986b). MODROC: An extension of rank order clustering for group technology. *International Journal of Production Research, 24*, 1221–1233. *view at Google scholar* / view at publisher

Chattopadhyay, M., Dan, P. K., & Majumdar, S. (2011). Principal component analysis and self organizing map for visual clustering of machine-part cell formation in cellular manufacturing system. *Systems Research Forum, 5*(1), 25-51. *view at Google scholar* / view at publisher

Hachicha, W., Masmoudi, F., & Haddar, M. (2008). Formation of machine groups and part families in cellular manufacturing systems using a correlation analysis approach. *International Journal of Advance Manufacturing Technology, 36*, 1157–1169. *view at Google scholar* / view at publisher

Kitaoka, K., Nakamura, R., Serizawa, S., & Usuki, J. (1999). Multivariate analysis model for machine-part cell formation problem in group technology. *International Journal of Production Economics, 60-61*, 433-438. *view at Google scholar* / view at publisher

Kumar, C. S., & Chandrasekharan, M. P. (1990). Grouping efficacy: A quantitative criterion for goodness of block diagonal forms of binary matrices in group technology. *International Journal of Production Research, 28*, 233–243. *view at Google scholar* / view at publisher

Kusiak, A. (1987). The generalized group technology concept. *Journal of Production Research, 25*(4), 561-569. *view at Google scholar* / view at publisher

McAuley, J. (1972). Machine grouping for efficient production. *The Production Engineer, 51*, 53–57. *view at Google scholar* / view at publisher

Mosier, C. T. (1989). An experiment investigating the application of clustering procedures and similarity coefficients to the GT machine cell formation problem. *International Journal of Production Research, 27*(10), 1811-1835. *view at Google scholar* / view at publisher

Nambirajan, T., & Panneerselvam, R. (1999). Machine- component cell design using simulated annealing. *International Journal of Management and Systems, 15*(2), 185-208.

Panneerselvam, R. (2004). *Research methodology.* First Ed, Prentice Hall of India, New Delhi.

Panneerselvam, R., Balasubramanain, K. N., & Nambirajan, T. (1990). Group technology machine-component cell formation. *Industrial Engineering Journal, 9*, 22-32. (Also a corrigendum, *Industrail Engineering Journal, 19*, p.21). *view at Google scholar*

Panneerselvam, R., Balasuramanian, K. N., & Nambirajan, T. (1990). Grouping technology machine-component cell formation. *Industrial Engineering Journal*, 9, 22-32. view at publisher

Rajagopalan, R., & Batra, J. L. (1975). Design of cellular production systems a graph-theoretic approach. *International Journal of Production Research*, 13(6), 567-579. *view at Google scholar* / view at publisher

Seifoddini, H., & Wolfe, P. M. (1986). Application of the similarity coefficient method in group technology. *IIE Transaction, 18*(3), 271-277. *view at Google scholar* / view at publisher

Waghodekar, P. H., & Sahu, S. (1984). Machine-component cell formation in group technology: MACE. *International Journal of Production Research, 22*(6), 937-948. *view at Google scholar* / view at publisher

Wang, J., & Roze, C. (1995). Formation of machine cells and part families in cellular manufacturing: An experimental study. *Computers ind. Engng, 29*(1-4), 567-571. *view at Google scholar* / view at publisher

Wei, J. C., & Kern, G. M. (1989). Commonality analysis: a linear cell clustering algorithm for group technology. *International Journal of Production Research*, *27*(12), 2053-2062. *view at Google scholar* / view at publisher

Yin, Y., & Yasuda, K. (2006). Similarity coefficient methods applied to the cell formation problem: A taxonomy and review. *International Journal of Production economics, 101*, 329-352. *view at Google scholar* / view at publisher