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A Comparative Study of Integrating Feasibility Assessment and Cell Formation Problem Using Modified Similarity Coefficient Method

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ABSTRACT

The focus of this research is on cellular manufacturing systems based on group technology concepts. The primary goal of CM is to organize machines and parts into cells and families. The cell creation problem is the focus of the majority of suggested models, algorithms, and approaches. Only a few people have thought about the feasibility study and the cell formation issue. A new similarity coefficient strategy for handling cell formation challenges in cellular manufacturing is proposed along with operation sequence in this research. Three strategies are used to integrate a feasibility assessment with the cell formation challenge in this study. This study takes into account performance indicators such as the percentage of Exceptional Elements (PE), Machine Utilization (MU), Bond Efficiency (BE), Grouping Technology Efficiency (GTE), and Efficiency of Intra-cell Movements (EIM). The proposed similarity coefficient approach is used to identify the optimal number of cells before generating a cell formation. The proposed method has been tested on some of the most well-known cases in the literature, such as real-occasion industrialized data. The computational findings show that in the majority of the situations, the proposed similarity coefficient approach produces the best outcomes. The suggested technique is evaluated to two familiar clustering approaches, Rusell & Rao and the ROC algorithm, which were chosen from the literature. Five performance measures are used for comparison and evaluation. Finally, the data are analyzed to see if the proposed similarity coefficient approach can be tested and validated. The results show that using the novel similarity coefficient approach produces results that are on par with or better than those obtained using other clustering methods.

KEY WORDS: *Cellular manufacturing, Group technology, Feasibility assessment, Similarity coefficient measure, Cell Formation, Operation sequence.*

INTRODUCTION

Today's competitive business environment, many companies place a premium on the speed with which they respond to their consumers' requests. As a result, ongoing enhancements are required to enhance response times in response to consumer changes. Group Technology, which concentrates on Cellular Manufacturing, is one of the strategies. Group technology (GT) is a production concept that has received a lot of concentration due to its benefits in batch production. Similar components are categorized into families and related machines are divided into groups in the architecture of a CM system so that one or even more part families can be processed inside a single machine cluster. The cell formation (CF) issue refers to the process of generating part families and machines groupings. Cluster technology is a method for organizing and utilizing information regarding part similarities in order to increase a manufacturing firm's production efficiency. The successful implementation of group technology offers increased productivity by reducing throughput time, material handling costs, and other factors. The quantity of machines and components in an key incidence matrix, as well as the vigilance parameter value, influence cluster formation. Following the formation of a cell or a group of

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machines or components, the customized similarity coefficient approach is used to choose the best component family or machine group based on its highest exploit in a cluster.

LITERATURE SURVEY

A thorough review of the literature was conducted in order to discover the findings and recommendations made by the researchers. The following sections outline the achievements and directions of selected research studies that have been published in the literature. The effectiveness of the grouping efficiency in assessing the solution qualities of a collection of very well structured and ill-structured problems was investigated by Chandrasekharan et al. [1]. In computer integrated manufacturing, Charles C. Willow [2] presented a feeding forward multi - layer neural network for machine cell creation. A new mathematical technique for creating manufacturing cells was proposed by Zahir Albadawi et al. [3]. Steudel et al. [4] established the Cell Bond Strength (CBS), a similarity metric that is dependent on component routing and production needs. The performance of 20 familiar resemblance coefficients was compared by Yong Yin et al. [5]. In cellular manufacturing (CM) systems, Mingyuan et al. [6] suggested an integrated paradigm for production planning. A heuristic strategy for creating part families and machine groups was given by Heragu et al. [7]. Cheng C.H. et al. [8] compared a number of cellular manufacturing clustering techniques. Okogba et al [9] devised a method for resolving the problem of part-machine cell formation. Logendran et al. [10] suggested a binary and generic integer variable nonlinear programming paradigm. On the basis of the series of operations and the lot size of the components, Alhourani Farouq et al. [11] suggested a new ordinal operational data similarity coefficient.

Waghodekar et al., [12] combines clusters based on their members' highest similarity. A multi-functional MP model was proposed by Chang-Chun Tsai et al. [13]. Baroni et al. [14] proposed the concept of binary data similarity. Bin Hu et al. [15] devised an integrated method for solving a multi-goal cell formation issue, which combines an integer programming model with a heuristic algorithm for creating alternative cell formations. Sule [16] devised a method for calculating the total number of machines. Raja and Anbumalar [17] proposed a new heuristic technique based on a modified flow matrix to tackle the situation of cell formation and machine layout design. The operation sequence and quantity of component visits among the data were employed as inputs by these researchers in their analysis. Prabahakaran et al. [18] looked at how the maximum Spanning Tree technique may be used to construct machine cells.To map the notion of machine cell production onto the network, Kusiak, A, et al. [19] utilized neural networks to build machine cells. Mahdavi et al. [20] recommended reducing the amount of Exceptional Elements (EE) and voids in cells to improve cell usage performance. To overcome the cell production problem, Harhialakis et al [21] suggested a two-stage heuristic technique. The grouping efficacy evaluation metric was utilised by Dimopoulos et al. [22] to evaluate and compare a genetic programming-based SLC approach to five other processes. Akturk et al. [23] offered a comprehensive approach that considers the within-cell layout issue while solving the machine/product grouping problem. For constructing part machine cells, Lin et al [24] devised a two-stage integer-programming technique.

Miltenburg and Zhang [25] examined nine cell creation techniques, as well as the similarity measure approach, nonhierarchical bunching, and rank order techniques. Kumar et al.

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[26] looked at the issue of grouping efficiency inadequacy. For resemblance coefficients, Yong Yin et al. [27] presented a complete analysis and conversation. Murugan and Selladurai (28) used real-time manufacturing data to examine three array-based cell generation strategies. Erry Yulian and Sanaa Ali Hamza T.Adesta [29] used three basic methods to combine CF and FA: Rank order clustering, Baroni-urbani, and Buser and Sorenson similarity coefficient.Bashir H.A and S.Karaa [30] provided a easy empirical method based on eigen values for analysing group propensity in the construction of cellular manufacturing systems. Using a 0 – 1 product – machine occurrence matrix, they investigated the efficacy of the Jaccard resemblance coefficient in the feasibility analysis of cellular manufacturing. Chu et al. [31] compared ROC, DCA, and BEA, three array-based machine-component grouping algorithms. Hark Hwang and colleagues using the p-median model, [32] provided additional measure to improve the model's performance. Mahdavi et al. [33] developed a heuristic method for incremental cell generation relying on iterative set partitioning, where part of the operations might be done on other machines. To our knowledge, only a few studies have included a feasibility evaluation and cell formation problem, as well as operation sequence requirements, to determine whether transition to cellular manufacturing is viable or possible. A new similarity measure coefficient technique is given in this study for dealing with cell formation issues in cellular manufacturing, as well as operation sequence. This study compares three strategies for integrating a feasibility assessment with a cell formation challenge. These three methods are put into practise using well-known key benchmark examples, and a comparison has been made between them. The remainder of this work is structured in the following manner. Section 3 explains how to define the problem, including how to generate cells based on the operation sequence. The proposed approach is explained in Section 4. All three approaches will be explained using numerical examples in section 5. The numerical solutions of test issues for all three techniques are presented in Section 6. Finally, section 7 brings the research to a conclusion.

PROBLEM DEFINITION

Table-1 shows an example of an initial component-machine occurrence matrix based on process sequencing. This contribution matrix was created using a flow production with six machines, eight parts, and 24 activities. The reorganization of rows and columns of a component-machine incidence matrix to construct machine clusters and component families is referred to as a cell formation problem. Table-2 shows the output form of two cells from the original part-machine incidence matrix. Two cells aren't totally self-contained. Each part family (p8, p1, p3, p2, p4, p5, p6, p7) must be processed in a specific machine group (m1,m3,m5 and m6,m4,m2). To limit the sum of 0s inside slanting blocks (voids) and the amount of process sequence values outside the diagonal block, an ideal number of cells is employed (exceptional elements). We infer from the existing literature that the majority of cell formation researches do not cover finding the ideal number of cells, and only a few studies describe detecting the best number of cells

Table-1 Machine-Component incidence matrix based on Operation series example#1

Machines	Parts							
	P1	P2	P3	P4	P5	P6	P7	P8
M1	2	2	1	3				1

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M2					3	2	1	
M3	3	3	2		1			2
M4		1		1		1		
M5	1			2	2		2	3
M6			3				3	4

Table-2 Output structure of matrix after reform example#1

Machines	Parts							
	P8	P1	P3	P2	P4	P5	P7	P6
M1	1	2	1	2	3			
M3	2	3	2	3	0	1		
M5	3	1	0	0	2	2	2	
M6	4	0	3	0	0		3	
M4				1	1	0	0	1
M2						3	1	2

METHODOLOGY

The number of manufacturing cells was estimated in numerous cell formation methods, including mathematical model approaches, graph-theory methods, Rank order clustering and other heuristic-based approaches. If the amount of manufacturing units is estimated, it may have an impact on the cluster structure, resulting in a bad cell design. Both new similarity co-efficients and operation sequences are permitted here, and they are compared to existing similarity co-efficient. In this work, the feasibility evaluation and cell formation problem in a cellular manufacturing system are investigated using the parts operation sequence. We offer a new similarity coefficient approach to simultaneously handle feasibility evaluation and cell creation problem depending on operation series to provide a solution for such a challenge. This research begins with a CMS evaluation in the form of a machine-component incidence matrix, followed by determining the optimal number of manufacturing cells using Eigen value, which is calculated from a similarity coefficient matrix tabulated with a new similarity co-efficient.

In all three proposed techniques, our study utilized the identical processes as Basher and Karaa in [30] for predicting the number of machine cells in FA. In FA, Basher and Karaa used Jaccard, whereas this study used Rusell and Rao. In the first and second methods of cell creation, the current study followed the protocols of Garbie et al.[34], whereas the third method used Rank order clustering. The current study's technique is separated into three methods depending on the use of the Similarity coefficient in both phases of CMS design. The suggested novel similarity coefficient approach is compared to existing methods using percentages of exceptional elements, machine utilization, intra-cell movement efficiency, bond efficiency, and group technology efficiency. The current study's technique is separated into three methods depending on the use of the similarity coefficient in both phases of CMS design. The three strategies are described in greater detail in Table 3.

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Table 3 Details of three methods

Methods	Types of similarity coefficient	
	Feasibility Assessment(FA)	Cell Formation(CF)
First method	New proposed SC	New proposed SC
Second method	Rusell and Rao	Rusell and Rao
Third method	Rusell and Rao	Rank Order Clustering

The Steps of the algorithm are outlined below:
Step 1: The initial machine component matrix problem was adapted from prior research.
Step 2: Using the new Similarity Coefficient approach, find the values of the similarity coefficients between the machines.
Step 3: Creating a Matrix with the values of the similarity coefficients.
Step 4: Using the similarity coefficient matrix, calculate the eigen values.
Step 5: Determine the optimal number of cells based on eigen values.
Step 6: Using the similarity values acquired from all three approaches, group the machines into cells.
Step 7: Assigning parts to cells one by one using all methods.
Step 8: Putting Forward Flow First on Cell Arrangements.
Step 9: Evaluate the effectiveness of all three ways.
Step 10: Comparing the outcomes of three different methods

NEW PROPOSED SIMILARITY COEFFICIENT METHOD

$$S_{ij} = \left[\frac{\left[2a + (ad)^{1/2}\right]}{\left[2a + b + c + (ad)^{1/2}\right]} \right]$$

Where,
a= Sum of the parts visited both machine i and j.
b= Sum of the parts visited machine i only.
c= Sum of the parts visited machine j only.
d= Sum of the parts visited neither i nor j.

SECOND METHOD OF RUSELL AND RAO'S
Non-Jarccardian measures were proposed by Russel and Rao's and Ochiai's in Romesburg [35]

$$S_{ij} = \left[\frac{a}{(a + b + c + d)} \right]$$

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RANK ORDER CLUSTERING:

ROC is such a best bunching approach that tries to generate a block slanting shape by rearranging the rows and columns of machine/part matrices according to binary values continuously.

To overcome the limitations of ROC, King and Nakornchai [36] created ROC-2. When compared to ROC, this approach is faster and more efficient. The key characteristic of ROC-2 is that it can quickly determine block diagonal arrangement (of a machine component incidence matrix), allowing it to be used interactively even for huge matrices.

PERFORMANCE MEASURES:

The success of group formation approaches can be measured either in terms of computing efficiency or clustering performance (Chu and Tsai [37]).

Clustering efficiency is typically quantified in terms of programme execution time, memory requirements, and algorithm complexity. Because of their widespread use in the literature, five metrics were chosen for this study.

Percentage of exceptional elements:

The number of exceptional items in the incidence matrix divided by the number of operations in the incidence matrix is the ratio (King [36].

$$PE = \frac{EE}{UE} X \ 100$$

where,

PE-- Percentage of exceptional elements.

UE-- Number of operation in the incidence matrix.

EE—Number of exceptional elements in the incidence matrix.

Machine utilization:

The percentage of time that the machines within the cells are employed to operate parts is referred to as machine utilization. Rajagopalan and Chandrasekharan [38]

$$MU = \left[\frac{UE - EE}{\sum_{K=1}^{N_{CELL}} AV} \text{ X } 100 \right]$$

Where,

A-- number of machines in cell k

V-- number of parts in family k

N_{cell} -- number of cells.

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Group Technology Efficiency

It's the ratio of the difference between the system's highest number of inter-cell travels and the actual number of inter-cell travels to the system's maximum number of possible inter-cell travels.

$$\eta_{GT} = \frac{I_P - I_a}{I_P}$$

Where,

η_{GT} = Group technology efficiency

I_p = Maximum number of inter cell travels possible in the system

I_a = Actual number of inter cell travels in the system

Bond Efficiency

Nair and Narendran proposed a new measure named bond efficiency.

$$\eta_B = q\left(\frac{Ip - Ia}{Ip}\right) + (1-q)\left[\frac{No}{No + Nv}\right]$$

Where,

η_B -- Bond efficiency

q-- Weighting factor

No-- Number of operation within the cells

Nv-- Number of voids within the cells

Efficiency Of Intra-Cell Movements

It's the ratio of the total number of product flows in the incidence matrix divided by the sum of the number of continuous forward flows in each cell. The following is our newly proposed formula for calculating intra-cell movement efficiency.

$$\eta_{im} = \frac{\sum_{K=1}^{N_{CELL}} C_{ff}}{T_{pf}}$$

Where,

C_{ff} -- Number of continuous forward flow in the each cell

T_{pf} --Total number of product flow in the in the each cell

NUMERICAL EXAMPLE

First Method (based on same SC):

From George, Rajendran, and Ghose [39], one data set with the size (10*12) has been chosen from the literature, which contains the operation sequence machine-part matrix. Where any number refers to a specific part that must be used on a certain machine, and zero otherwise.

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Table 4 George, Rajendran&Ghose [39]—10x 12 machine–part matrix

Machine	Parts											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
M1					3				4	3		
M2		1	2				1	1				3
M3	1				5				1	1		
M4	2			1	4	1						
M5		3	4				3	3				2
M6	3				1				2	2		
M7				3		3					1	
M8		4	1		2				3			1
M9				2		2						
M10		2	3				2	2				

STEP 1- Problem Taken From Previous Literature
The following 10×12 machine-part incidence matrix was taken from George, Rajendran&Ghose.
STEP-2 Finding Similarity Coefficient Values Using New Similarity Coefficient Formula
NEWLY PROPOSED SIMILARITY COEFFICIENT FORMULA:

$$S_{ij} = \left[\frac{\left[2a + (ad)^{1/2}\right]}{\left[2a + b + c + (ad)^{1/2}\right]} \right]$$

STEP-3 Using Sc Values Formulating Sc Matrix

Table 5 Similarity Coefficient matrix

Machines	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
M1	1	0	0.918	0.5	0	0.918	0	0.673	0	0
M2		1	0	0	0.930	0	0	0.601	0	0.930
M3			1	0.666	0	1	0	0.685	0	0
M4				1	0	0.666	0.727	0.408	0.8	0
M5					1	0	0	0.784	0	0.844
M6						1	0	0.614	0	0
M7							1	0	0.891	0
M8								1	0	0.720
M9									1	0
M10										1

STEP-4 Finding Eigen Values from Sc Matrix

Table 6 Eigen values and Optimum number of cells

Data size	Eigen values of similarity matrix	Optimum number of cells	Whether it is feasible or not

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10X12	λ= **4.134, 3.109, 2.305,** 0.216, 0.162, 0.128, -0.108, 0.104, -0.544, -4.187	3	Feasible

Table 7 Higher Eigen Values in each row of SC matrix

S.No	Pair of Machines	The highest value of SC
1	M3-M6	1
2	M2-M5	0.930
3	M1-M3	0.918
4	M7-M9	0.891
5	M5-M10	0.845
6	M4-M9	0.8
7	M8-M10	0.720
8	M6-M8	0.615
9	M9-M10	0

STEP-5 Based On Eigen Values Predicting Optimum Number of Cells

Table 8 Allocation of machines into cells

S.NO	CELL	Machine in cell
1	Cell-1	1,3,6
2	Cell-2	2,5,10,8
3	Cell-3	4,9,7

STEP-6 Assign the machine in to the cells

Table 9 Final assigned machine-part incidence matrix

	P1	P5	P9	P10	P2	P3	P7	P8	P12	P4	P6	P11
M1	0	3	4	3								
M3	1	5	1	1								
M6	3	1	2	2								
M2					1	2	1	1	3			
M5					3	4	3	0	2			
M10					2	3	2	2	0			
M8		2	3		4	1	0	0	1			
M4	2	4								1	1	0
M7										3	3	1
M9										2	2	0

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STEP-7 **PERFORMANCE MEASURES FOR FIRST METHOD:**

Percentage of Exceptional Elements**:**

$$PE = \frac{EE}{UE} X\ 100 = 4/38 \times 100 = 10.52\%$$ 7.1.1.2

Machine Utilization:

$$MU = \left[\frac{UE - EE}{\sum_{K=1}^{N_{CELL}} AV} \text{ X } 100 \right] = (38\text{-}4) / [(3 \times 4)+(4 \times 5) + (3 \times 3)] \times 100 = 82.92\%$$

Group Technology Efficiency

$$\eta_{GT} = \frac{I_P - I_a}{I_P} \times 100 \quad = (26\text{-}3) / 26 \times 100 = 88.46\%$$

Bond Efficiency

$$\eta_B = q\left(\frac{Ip - Ia}{Ip}\right) + (1-q) \left[\frac{No}{No + Nv}\right] x100$$

$$= 0.5 \times (0.8846) + (1\text{- } 0.5) [38/(38+7)] \times 100 = 86.45\%$$

Efficiency of Intra-Cell Movements

$$\eta_{im} = \frac{\sum_{K=1}^{N_{CELL}} C_{ff}}{T_{pf}} x\ 100 = 15/26 \times 100 = 57.69\%$$

PERFORMANCE MEASURES FOR RUSSEL AND RAO'S METHOD

Percentage of exceptional elements:

$$PE = \frac{EE}{UE} X\ 100 = 4/38 \times 100 = 10.52\%$$

Machine utilization:

$$MU = \left[\frac{UE - EE}{\sum_{K=1}^{N_{CELL}} AV} \text{ X } 100 \right] = (38\text{-}4) / [(3 \times 4)+(4 \times 5) + (3 \times 3)] \times 100 = 82.92\%$$

Group Technology Efficiency

$$\eta_{GT} = \frac{I_P - I_a}{I_P} \times 100 \quad = (26\text{-}9) / 26 \times 100 = 88.46\%$$

Bond Efficiency

$$\eta_B = q\left(\frac{Ip - Ia}{Ip}\right) + (1-q) \left[\frac{No}{No + Nv}\right] x\ 100$$

$$= 0.5 \times (0.8846) + (1\text{- } 0.5) [38/(38+7)] \times 100 = 86.45\%$$

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Efficiency of Intra-Cell Movements

$$\eta_{im} = \frac{\sum_{K=1}^{N_{CELL}} C_{ff}}{T_{pf}} \times 100 = 2/26 \times 100 = 7.69\%$$

PERFORMANCE MEASURES FOR ROC METHOD

Percentage of exceptional elements:

$$PE = \frac{EE}{UE} X\ 100 = 13/38 \times 100 = 34.21\%$$

Machine utilization:

$$MU = \left[\frac{UE - EE}{\sum_{K=1}^{N_{CELL}} AV} \text{ X } 100\right] = (38\text{-}13) / [(4 \times 6)+(3 \times 3) + (3 \times 3)] \times 100 = 59.52\%$$

Group Technology Efficiency

$$\eta_{GT} = \frac{I_P - I_a}{I_P} \times 100 \quad = (26\text{-}7) / 26 \times 100 = 73.07\%$$

Bond Efficiency

$$\eta_B = q\left(\frac{Ip - Ia}{Ip}\right) + (1-q)\left[\frac{No}{No + Nv}\right] \text{x}100 = 0.5 \times (0.7307) + (1\text{- }0.5)\ [38/(38+17)] \times 100 = 71.08\%$$

Efficiency of Intra-Cell Movements

$$\eta_{im} = \frac{\sum_{K=1}^{N_{CELL}} C_{ff}}{T_{pf}} \times 100 = 7/26 \times 100 = 26.92\%$$

RESULTS AND DISCUSSION

On selected data sets as well as real-time manufacturing data, the suggested new similarity coefficient method was developed and tested against Rusell Roa and ROC methodologies utilizing well-known cluster creation approaches. The suggested technique is compared to two well-known cluster creation methods, Rusell Roa's and ROC, which were chosen from the literature. Five different performance indicators taken from the literature are used for comparison and evaluation: PE stands for Percentage of Exceptional Parts, MU stands for Machine Utilization, GE stands for Grouping Efficiency, and GE stands for Grouping Efficacy (GC) and Efficiency of Intra-Cell Movements (ECM). PE, MU, GE, GC, and EIM are the five performance metrics generated for every data set in each group. For each data group, Table 9 presents the computational findings of all three approaches. The results of the computations reveal that the recommended similarity coefficient strategy delivers the best results in the vast majority of cases. The proposed method is compared to two well-known clustering methods, Rusell and Rao and the ROC algorithm, all of which were selected from the literature. For comparison and evaluation, five performance metrics are used. Finally, the data is examined to

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determine whether the proposed similarity coefficient method can be tested and validated. The findings reveal that employing the innovative similarity coefficient approach yields results that are comparable to or better than those achieved using other clustering approaches.

Table 10 Computational findings of all three approaches

Size	Proposed Method					Rusell Roa's					ROC Method				
	PE	MU	η_{GT}	η_B	η_{im}	PE	MU	η_{GT}	η_B	η_{im}	PE	MU	η_{GT}	η_B	η_{im}
10x12 George ghose	**10.5**	**82.9**	**88.4**	**86.4**	**57.6**	**10.5**	**82.9**	**88.4**	**86.4**	**7.69**	**34.2**	**59.5**	**73**	**71**	**26.9**
8x20 Nair narenran	**14.7**	**100**	**77.5**	**88.7**	**37.5**	**14.7**	**100**	**77.5**	**88.7**	**30.5**	**26**	**88.2**	**70**	**77**	**7.5**
20x20 Harhalakis &Nagi	**9.73**	**85.4**	**74.7**	**81.3**	**42.5**	**9.73**	**85.4**	**74.7**	**81.3**	**37.4**	**27.4**	**81.4**	**71.5**	**77.2**	**35.2**
7x11 Tsai Lee	**8.34**	**81.4**	**75.7**	**83.4**	**49.7**	**8.34**	**81.4**	**75.7**	**83.4**	**45.3**	**23.4**	**79.2**	**71.4**	**81.5**	**42.2**
7x14 X.wu et.al	**12.45**	**85.2**	**89.2**	**82.4**	**57.2**	**12.45**	**85.2**	**89.2**	**82.4**	**49.2**	**29.4**	**81.1**	**79.4**	**65.2**	**44.1**

CONCLUSION

We have incorporated Feasibility Assessment and Cell generation utilizing SC in CMS based on the results. Only a few researches have taken into account the feasibility evaluation and cell creation. However, in our research, we used a feasibility assessment to see if cell development was viable. The newly developed similarity coefficient outperformed the previous approaches in a comparison of three methods. When comparing the first and second methods, the proportion of exceptional elements, machine utilization, group technology efficiency, and bond efficiency are all the same in both, but the first method's intra-cell movement efficiency is superior to the second methods. As a result, we recommend that you utilize our newly proposed SC approach in the future because it produces better outcomes than existing methods for merging FA and CF.

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