International Journal of Sustainable Applied Science and Engineering (IJSASE)

Contents lists available at IJSASE

International Journal of Sustainable Applied Science and Engineering

journal homepage: IJSASE

Volume 2, No. 3, 2025

New Approach to Solving Cell Formation Design with an Improved Similarity Coefficient Method

Azadeh Rasouli [a]

[a] *Department of Industrial Engineering, Azad University of Karaj, Karaj, Alborz, Iran,*

ARTICLE INFO

Received: 2025/08/07

Revised: 2025/09/12

Accept: 2025/10/15

Keywords:

Cellular Manufacturing System, Cell Formation, Similarity Coefficient Method, Decomposed Mathematical Model.

ABSTRACT

Cellular manufacturing systems consider effective ways to increase the productivity of labor, materials, space, and time. In this way, the same machines are grouped into cells, which are then allocated to the family of similar parts. There are several ways to classify parts and cars in the cell. One of these methods is the use of a similarity coefficient. This new approach facilitates cell formation. This approach is divided into two stages. The first stage involves processing the sequence similarity coefficient presented in this article. In contrast, the second stage considers the number of repeat operations to identify parts with the maximum similarity, taking into account the family. In the second phase, a new mathematical model is presented, incorporating key operational aspects such as alternative routing, machine capacity, demand components, operational duration, and machine allocation to minimize costs across machine, operating, and transportation between cells. A performance test method, which had several issues identified in the literature, was tested and analyzed.

1- Introduction

Due to increasing global competition, a shortening product life cycle, changing market demand, and diverse customer needs, manufacturers are compelled to adopt technologies that enhance production system efficiency, optimize the use of existing facilities, and keep pace with market

[a] Corresponding author email address: rasoooliazadeh@gmail.com (Azadeh Rasouli).
Doi: https://doi.org/10.22034/ijsase.v2i3.181
Available online 10/16/2025

3060-6349 /BGSA Ltd.

changes. Therefore, they have shifted their production systems from mass production to hybrid production systems so that they might keep up with a quickly changing market.

To adapt to such a transition, their production systems must be more efficient and flexible.

Group technology is a manufacturing philosophy that enables the economic production of both small batch production and mass production. The technology encompasses the same elements in the same manner, including product design, process planning, manufacturing, and assembly.

Cellular Manufacturing System (CMS) is a type of GT application that divides machines into machine groups and parts into part families, assigning production cells to related groups and families to minimize inter- and intra-cell movements and unnecessary costs.

Cellular manufacturing is a lean manufacturing approach that integrates the high flexibility of individual production with the high efficiency of mass production, thereby reducing the cost of individual production and the rigidity of mass production.

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.

In general, CMS offers efficiency, flexibility, high order, and independence, which enhance quality, optimize the use of space, manpower, and machinery, and reduce labor costs, material transportation costs, and material inventory during construction.

Currently, an increasing number of researchers and enterprise managers are focusing on the importance of efficiency, flexibility, self-discipline, and independence in cellular manufacturing, leading to remarkable achievements. Cellular manufacturing is typically viewed as the problem of identifying a set of parts that a group of machines can process. This identification is called cell formation (CF).

The CF problem aims to assign machines into machine groups and parts into part families and determine manufacturing cells with the corresponding machine group and part family. The CF must consider various strategic-level operational issues, including machine capacity, machine cost, operation sequence and routing, material handling cost, and overall operation cost. Furthermore, a meaningful cellular manufacturing system is necessary to align with operational objectives, including high machine utilization, minimal work in process, and optimal workload balance. Therefore, CF can be used to shorten lead time, reduce work in process, improve productivity, simplify scheduling, and reduce logistics time and cost in the cellular manufacturing system.

Since CF was first asserted by Burbidge in 1971, minimizing intercellular movement times, distances, machine costs, operation costs, and the number of exceptional parts and machines (where parts or machines are assigned to more than one cell for processing) are common design objectives.

There are three strategies used to form manufacturing cells in existing CF design methods.

Cell formation (CF), the layout group (GL), and the Planning Group (PG) are three important steps in the production of cells [2]. Among them, CF is primarily [7] and is a key step in the per-cell production problem [8]. Cell formation involves the same processes that identify the required family of parts and assign them to cells associated with the processing machinery [1], [2], [7]. Ideally, each cell producing cells should act as an independent production unit. CF approach to eliminate/minimize the transcell costs between the parts. [5], [6], [9-12].

To achieve the objectives, various CF techniques have been proposed in existing literature. The main techniques include classification and coding systems, mathematical and heuristic approaches, similarity coefficient-based clustering methods, graph theoretic methods, fuzzy clustering methods, evolutionary approaches, and neural network approaches, among others.

While more realistic and effective methods can be developed considering the flexibility of the manufacturing data and the different products involved, among the CF-based methods, the similarity coefficient technique is more flexible and easier to implement [8]. McAuley is the first researcher to use SCM for machine cell grouping [13-17].

McAuley [8] introduced the Jaccard similarity coefficient to measure the similarity between each pair of machines and then to group the machines within a cell based on their similarity measure.

Although many factors of similarity of parts or machines have been considered in previous research, few of them address both the factors of operation sequence and the number of repetitions of operations simultaneously. In many practical manufacturing systems, it is natural for parts to meet machines more than once [18-19]. The sequence of operations, including repeated ones, considers both the machine's requirements and the material flow. These factors are influential in evaluating the similarity coefficient of parts/machines. Also, the combination of important properties such as production volume, operation sequence, cost/time of movements between cells, alternative process plans (routing flexibility), identical machines, and sequence of operations of parts (operation flexibility), which are used to apply direct and indirect relationships between machines, is not considered in the previous similarity coefficients. In this paper, a mathematical programming model is employed to assign a family of similar parts to machines in a cell. This model considers both the similarity coefficient and the sequence of operations, as well as the number of repetitions of operations, to identify the family of parts with the maximum degree of similarity. It also discusses past research that is deeply related to this research.

The machine components in the cell are identified using two different similarity coefficients to determine the similarity between parts and used machines. The framework of the remainder of the content is organized as follows: Section 2 describes the two-phase procedure of the proposed new approach. In Section 3, one example is presented to illustrate that the new approach is efficient and feasible. Conclusions and future research are provided in Section 4.

2-Problem description and model

This section is devoted to explaining the two-phase methodology mentioned above. Phase I involves identifying part families using the improved similarity coefficient method. Phase II presents a decomposed model for assigning machines to part families under multi-objective design. Before the description of the two-phase methodology, the notations used throughout this research are listed in Table 1.

2.1 Notations and Symbols

Table 1: Notation of the two-phase method

Index	**Description**
$i', i = \{1, \ldots\ldots.., I\}$	Index of parts
j={1,…….,J}	Index of machines
c={1……., C}	Index of cells
op={1……, OP}	Index of operations
k={1….,K_i}	Operation sequence number of parts i
t={1….,n_i^{op}}	Index of operations op for part i
t'={1….,$n_{i'}^{op}$ }	Frequency of operation op process part i'

Parameters	**Description**
$\mathrm{r_{opi}^{t}}$	Sequence number of part i, is processed by operation op in the (t) time
$\mathrm{r_{opi'}^{t}}$	Sequence number of part j, is processed by operation op in the (t) time
$\mathrm{a_{ii'}^{op}}$	1, if operation op processes both part i and i

Parameters	**Description**
	0, otherwise
$b_{ii'}^{op}$	1, if operation op process part i, but does not process part i′
	0, otherwise
$c_{ii'}^{op}$	1, if operation op process part i' but does not process part i
	0, otherwise
$d_{ii'}^{op}$	1, if operation op processes neither part i nor i′
	0, otherwise
ν_i	Demand of part i
h_i	Material inter-cell movement cost for per unit part i
c_j	Cost of machine j
C_j	Available capacity of machine j
s_j	Operation cost of machine j for unit time
t_{ijk}	Operation time of kth operation of part i on machine j
Y_{ic}	1, if part i is assigned into cell c
	0, otherwise
b_{ijk}	1, if operation k of part i is performed on machine j 0, otherwise
Variables	**Description**
$S_{ii'}$	Improved similarity coefficient between part i and i′
u_{ijk}	1, if operation k of part i is performed on machine j in cell c, otherwise; 0
N_{ic}	Number of machine j will be assigned into cell c
r_{ic}	Surplus capacity of exceptional machine j in cell c
w_{jc}	Wjc Minimum inter-cell movement cost induced by removing exceptional machine j, which is utilized incompletely
V_{ikc}	Quantity of part i processed by operation k for the W_{jc}
a_{jc}	1, if the incompletely utilized exceptional machine j is assigned to cell c
	0, otherwise
Q_{jc}	Minimum utilization of exceptional machine j in cell c

Variables	Description
f_{ijkc}	Additional quantity of part i, whose operation k will be performed by exceptional machine j, transferred to cell c from another cell

2.2-Phase I—an improved similarity coefficient method

For part family identification, SCM has been widely applied to the CF problem, as shown in Section 2. The similarity coefficient is a value that ranges from 0 to 1, representing the relationship between two-part types/machine types. The two-part types/machine types will be more similar if the value of the similarity coefficient is larger, and vice versa.

Based on similarity measurement, parts and machines can be grouped using a cluster algorithm. The improved SCM innovatively considers the operation sequence and the number of repeat operations simultaneously for part family identification in this phase. The operation sequence of parts is an ordering of operations in the manufacturing system, just as the serial number for each part column in Table 2. A similar operation sequence between two parts can lead to a high similarity coefficient between them. Meanwhile, it is generally known that repeated operations widely exist in the real-world manufacturing environment. Repeated operation means a part needs the same operation more than once, as indicated by multiple figures in the elements of Table 2.

We believe that the number of repeated operations will significantly influence the similarity of parts. Before applying the similarity coefficient measure, an optimized design will be implemented to group parts preliminarily according to the inclusion relationships of operation sequences, thereby reducing the problem size. The detailed steps of phase I are as follows:

Step 1: Attain the part-operation incidence matrix from production.

A simple example is used to demonstrate the part operation incidence matrix in Table 2. In the example, the production system consists of four parts and four operations.

Table 2: Part operation incidence matrix

Operation	Part			
	Part 1	Part 2	Part 3	Part 4
1	1.3	1.3	0	0
2	2	2	1	0
3	0	4	2	1
4	0	0	3	2

Numbers in the matrix represent the operation sequences of each part. Notably, elements with multiple numbers represent repeated operations of parts; specifically, part P1 and part P2 are performed by operation op1 twice, at the first and third processes. And the element "0" means a part does not need the corresponding operation.

Step 2: Group parts to reduce the problem size.

Step 2.1 Check all the elements of the part-operation incidence matrix.

Step 2.2 Find out all inclusion relations of operation sequences between any pair of parts. In the example of step 1, parts P1 and P2 can be merged into one group because the operation sequence of P1 is contained in P2. In some cases, if the operation sequence of a part is contained in two or more parts, the one with the shortest operation sequence should be chosen to form a group. If ties are happening, random selection is a general approach.

Step 2.3 Treat group members as a single entity to obtain the new part-operation incidence matrix. The resulting composite operation sequence is always the longer sequence of the group members. Therefore, the operation sequence of the group of P1 and P2 conforms to P2 in the example.

Step 2.4 Back to step 2.1 until no inclusion relations can be found.

Step 3: Calculate the similarity coefficient based on the grouped part-operation incidence matrix. We deem that parts will have higher similarity if they are performed at more similar operation sequences. If not, the correlation would be lower relatively. In this sense, the operation sequence ratio $OSR_{ii'}$ between parts i and i′ is defined as follows:

$$OSR_{ii'} = \frac{\sum_{op=1}^{OP}(\propto_{ii'}{}^{op}.W_{ii'}{}^{op}).}{2.\sum_{op=1}^{OP}[\propto_{ii'}{}^{op}.\max(n_{\mathrm{i}}{}^{op}, n_{i'}{}^{op})]} \tag{2}$$

$$\begin{cases} \propto_{ii'}{}^{op} = 0,\ W_{ii'}{}^{op} = 0 \\ \propto_{ii'}{}^{op} = 1, n_{\mathrm{i}}{}^{op} \geq n_{i'}{}^{op} \Rightarrow\ W_{ii'}{}^{op} = \sum_{t=1}^{n_{\mathrm{i}}{}^{op}} r_{opi}{}^{t}\ r_{opi'}{}^{t'} \\ r_{opi}{}^{t}\ r_{opi'}{}^{t'} = \begin{cases} 2 & if\ \ r_{opi}{}^{t} = \forall\ r_{opi'}{}^{t'},\ \ t' = 1,2,\dots,n_{i'}{}^{op} \\ 1 & otherwise \end{cases} \\ \propto_{ii'}{}^{op} = 1, n_{\mathrm{i}}{}^{op} < n_{i'}{}^{op} \Rightarrow\ W_{ii'}{}^{op} = \sum_{t'=1}^{n_{i'}{}^{op}} r_{opi}{}^{t}\ r_{opi'}{}^{t'} \\ r_{opi}{}^{t}\ r_{opi'}{}^{t'} = \begin{cases} 2 & if\ \ r_{opi'}{}^{t'} = \forall\ r_{op\mathrm{i}}{}^{\mathrm{t}},\ \ t' = 1,2,\dots,n_{\mathrm{i}}{}^{op} \\ 1 & otherwise \end{cases} \end{cases}$$

The number of repeated operations is another crucial factor for improving the similarity coefficient method. RMC is a commonly used similarity coefficient for the CF problem and was presented by Islam and Sarkar [3]. Currently, few researchers focus on how the number of repeated operations affects parts similarity, as illustrated below.

$$S_{ii'} = \frac{a_{ii'} + \sqrt{a_{ii'}.d_{ii'}}}{a_{ii'} + b_{ii'} + c_{ii'} + d_{ii'} + \sqrt{a_{ii'}.d_{ii'}}} \quad (3)$$

$$a_{ii'} = \sum_{op=1}^{OP} a_{ii'}{}^{op}.n_{\mathrm{i}}{}^{op}.n_{i'}{}^{op}$$

$$b_{ii'} = \sum_{op=1}^{OP} b_{ii'}{}^{op}.n_{\mathrm{i}}{}^{op}$$

$$c_{ii'} = \sum_{op=1}^{OP} c_{ii'}{}^{op}.n_{i'}{}^{op}$$

$$d_{ii'} = \sum_{op=1}^{OP} d_{ii'}{}^{op}$$

Finally, the improved similarity coefficient, which considers both the operation sequence and the number of repeated operations simultaneously, can be attained by combining formulas (1) and (2).

$$S_{ii'} = OSR_{ii'}.s_{ii'} \quad (4)$$

Step 4: Form part families using the cluster algorithm.

This step utilizes the P-median model, which was proposed by Kusiak [6], to form part families based on the result of the similarity coefficient. The objective of this model is to optimally identify part families by maximizing the similarity coefficient between parts in each family.

3.2 Phase II—a mathematical model for machine assignment

Phase II presents a new mathematical model to assign machines to part families identified in phase I. This model decomposes the complicated multi-objective CF problem into several simple subproblems, making it easier to explain and compute.

The first step involves identifying operation routing and the required machines, considering part demand and machine capacity constraints, to form machine groups that minimize both machine and operation costs. Exceptional machines can be judged in this step.

They are the machines required by multiple part families, whereas only one part family needs non-exceptional machines. To meet part of the demand, assignment of non-exceptional machines is supposedly fixed, even if their utilization will be low. However, the surplus capacity of exceptional machines in different cells can be merged by material inter-cell movement. Therefore, the second and third sub-problems are to decide how to merge the surplus capacity of exceptional machines that cannot be utilized fully. The decision is based on the minimum investment required for material inter-cell movement and exceptional machines. In the third step, we assign a weight q to determine the relative importance of intercell movement versus exceptional machine duplication for CF. q=0means inter-cell movement is not needed in the manufacturing system, and we refer to it as an "independent cell system." q=1 means exceptional machines should be required as few as possible in the manufacturing system; some parts can be transferred among cells for related operations, and we refer to them as a " dependent cell system. Furthermore, the last step is to determine the production planning of parts among cells under optimum machine utilization and workload balance. The problem is formulated according to the following assumptions: Each part has several operations that must be processed in a specific sequence.

- The processing time of the operation for each part is known.
- The part demand is known.
- The operation routing of some parts is an alternative.
- The cost, capacity, and operational cost of each machine are known.
- The inter-cell movement cost of each part is known, regardless of distance.
- Some machines are multipurpose, and repeated operations are in the manufacturing system.
- Intra-cell movement is ignored.
- Lower and upper bounds of cells are not limited.
- Each operation can be assigned to one machine.
- The part demand should be satisfied totally.

According to the problem assumptions above and notations given in Table 1, the objective functions and constraints of the decomposed model are described below.

To determine operation routing and the required machine in some real-life manufacturing systems, operations can be performed by more than one machine, allowing for alternative operation routing. Therefore, it is necessary to select operation routing based on the minimum machine cost and operation cost. The purpose of the objective function (4) in the following integer programming model is to determine the machine type and quantity for each part family and form independent cells. Moreover, the result can tell us which machines are exceptional.

$$Min = \sum_{j=1}^{J}\sum_{c=1}^{C} c_j . N_{jc} + \sum_{c=1}^{C}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K_i} Y_{ic} . v_i . t_{ijk} . s_j . u_{ijkc} \quad (4)$$

Subject to:

$$\sum_{c=1}^{C}\sum_{j=1}^{J} b_{ijk} . u_{ijkc} = 1 \qquad \forall i,k \quad (5)$$

$$u_{ijkc} \leq b_{ijk} \qquad \forall i,j,k,c \quad (6)$$

$$\frac{\sum_{i=1}^{I}\sum_{k=1}^{k_i} v_i . t_{ijk} . u_{ijkc}}{C_j . N_{jc}} \leq 1 \qquad \forall j,c \quad (7)$$

$$N_{jc} > 0 \text{ , are } (0,1) \text{ integers} \qquad \forall j,c \quad (8)$$

$$u_{ijc} \text{ , are } (0,1) \text{ integers} \qquad \forall j,c \quad (9)$$

Constraints (5) and (6) guarantee that each operation of each part is assigned to only one machine in one cell.

Constraint (7) ensures that machine capacities are not

exceeded. Constraints (8) and (9) represent the binary and non-negativity integer requirements on the decision variables.

Step 2: To calculate the minimum material inter-cell movement cost

Normally, some machines cannot be utilized

completely in cells. The non-exceptional machine assignment is fixed to meet part demand. Nevertheless, it is possible to optimize surplus capacities of exceptional machines by material inter-cell movement among different cells.

The optimized capacity allocation can reduce the demand for exceptional machines while also increasing machine utilization. However, inter-cell movement cost will inevitably be induced. wjc is the minimum inter-cell movement cost caused by cutting relevant exceptional machine j, which is not fully utilized, from cell c.

$$Min = \sum_{c=1}^{C}\sum_{j \epsilon EM} W_{jc} \quad (10)$$

Subject to:

$$W_{jc} = \sum_{i=1}^{I}\sum_{k=1}^{K_i} h_i . V_{ijkc} . u_{ijkc} \qquad \forall j \in EM, c \qquad (11)$$

$$r_{jc} = N_{jc} - \frac{\sum_{i=1}^{I}\sum_{k=1}^{K_i} \nu_i . t_{ijk} . u_{ijkc}}{C_j} \qquad \forall j \in EM \qquad (12)$$

$$\sum_{i=1}^{I}\sum_{k=1}^{k_i} t_{ijk} . V_{ijkc} . u_{ijkc} = (1 - r_{jc}) . C_j \qquad \forall j \in EM, c \qquad (13)$$

$$u_{ijkc} . V_{ijkc} < \nu_i \qquad \forall i, j \in EM, k, c \qquad (14)$$

$$V_{ijkc} > 0 \text{ , are integer variables} \qquad \forall i,\ j \in EM, k, c \qquad (15)$$

EM is the set of exceptional machines. The objective function of Eqs. (10) and (11) account for minimizing inter-cell movement cost. Constraint (12) shows the calculation of r_{jc}, which is the surplus capacity of the exceptional machine j in cell c.

Constraint (13) is to guarantee that the variable V_{ijkc} accords with the surplus capacity of the exceptional machine j in cell c.

Constraint (14) ensures V_{ijkc} cannot exceed part demand.

Constraint (15) is the non-negativity integer requirement.

Step 3: Determine if the exceptional machine, j, should be assigned to cell c, even if it is not fully utilized. Obviously, if the cost savings by cutting machines are less than the accompanying material inter-cell movement cost, the machine cutting will be irrational. Otherwise, it is feasible.

$$Max = \sum_{c=1}^{C}\sum_{j \in EM} \left[(1 - q) . W_{jc} - q . c_j\right] . a_{jc} \qquad (16)$$

Subject to:

$$\frac{\sum_{c=1}^{C}(1 - r_{jc})}{\sum_{c=1}^{C} a_{jc}} \leq 1 \qquad \forall j \in EM \qquad (17)$$

$$q = \{0 \text{ or } 1\} \qquad (18)$$

$$a_{jc} \text{ , are } (0,1) \text{ integers} \qquad \forall j \in EM, c \qquad (19)$$

The objective function of Eq. (16) means the potential benefit caused by assigning exceptional machine j, which is not fully utilized to cell c. Constraint (17) specifies that the final utilization of each machine is covered by its capacity.

Constraint (18), (19) is the limitation of the user-specified weight q.

Step 4: To distribute extra parts caused by the merging machine capacity

The extra parts will become available if some exceptional machines are cut down due to the merger of machine capacities. They should be transferred to other cells to meet the total demand.

Thereby, the last sub-problem is to determine the type and quantity of parts that should be transferred to each cell. The lot splitting design is based on optimizing utilization and minimizing workload imbalance of exceptional machines across different cells.

$$\text{Min}= \sum_{\forall\ J\in EM} \frac{\max_{c\in C} Q_{jc}}{\sum_{c=1}^{C} Q_{jc}} \tag{20}$$

subject to:

$$Q_{jc} = a_{jc}.(1\text{-}r_{jc} + \frac{\sum_{i=1}^{I}\sum_{k=1}^{k_i} f_{ijkc}.t_{ijk}}{C_j}) \tag{21}$$

$$if\ \frac{\sum_{c=1}^{C} r_{jc}}{\sum_{c=1}^{C} a_{jc}.r_{jc}} > 1\ and\ \sum_{c=1}^{C} a_{jc} \neq 1 \qquad \forall j \in EM, c \tag{22}$$

$$Q_{jc} = a_{jc}.(1\text{-}\ r_{jc});\ \ if\ \frac{\sum_{c=1}^{C} r_{jc}}{\sum_{c=1}^{C} a_{jc}.r_{jc}} = 1 \qquad \forall j \in EM, c \tag{23}$$

$$\sum_{c=1}^{C} f_{ijkc} = V_{ijkc} \qquad \forall i, j \in EM, k\ , c \tag{24}$$

$$\sum_{i=1}^{I}\sum_{k=1}^{K_i} f_{ijkc}.\,t_{ijk} < r_{jc}\,.\,C_j \qquad \forall j \in EM, c \tag{25}$$

$$f_{ijkc} > 0\ , are\ integer\ variables \qquad \forall i, j \in EM, k, c \tag{26}$$

The objective function expressed by Eq. (20) minimizes the total workload imbalance of exceptional machines in each cell. Equations (21)– (23) are to calculate the final utilization of exceptional machine j in cell c. Constraint (24) ensures the transferred part and amount as requested by step 3. Constraint (25) indicates that added parts from other cells do not exceed the capacity of exceptional machine j in cell c.

3- Computational experiments

In this example, we consider 11-part types and 10 different types of machines. All the part types and machine types are to be grouped into three cells.

Nine operation types are needed among the 11-part types in the experimental manufacturing system, as shown in Table 3. A series of sequential operations processes each part. It is worth noting that some parts include repeated operations in their operation sequence. In part P1, both the third and fifth operations are processed by operation Op3.

Table 3: Part operations incidence matrix

Part / Operation	Part1	Part2	Part3	Part4	Part5	Part6	Part7	Part8	Part9	Part10	Part11
Op1	1			1		1					1
Op2	2	1	1	2	1	2	2	1	2		
Op3	3, 5		2	3, 5		3					
Op4	4	2,4	3		2		1,3		1	1, 3	3
Op5		3		4	3			2,4			
Op6	6	5						3, 5			
Op7		6					4	6		2, 4	2
Op8							5			5	
Op9										6	

Based on the rule of step 2 in phase I, part groups are identified as shown in Table 4. Hence, the number of part types could be reduced to 8 from 11.

Table 4: part groups

Part / Operation	PG1	PG2	PG3	PG4	PG5	PG6	PG7	PG8
	P1	P2(P5)	P3	P4(P6)	P7(P9)	P8	P10	P11
Op1	1			1(1)				1
Op2	2	1(1)	1	2(2)	2(2)	1		
Op3	3, 5		2	3, 5(3)				
Op4	4	2, 4(2)	3		1, 3(1)		1, 3	3
Op5		3(3)		4		2, 4		
Op6	6	5				3, 5		
Op7		6			4	6	2, 4	2
Op8					5		5	
Op9							6	

According to the similarity coefficients, we can identify part families by the P-median model.

Table 5: similarity coefficient

	PG2	PG3	PG4	PG5	PG6	PG7	PG8
PG1	0.3086	0.2857	0.6306	0.2701	0.1886	0.1273	0.2681

	PG2	PG3	PG4	PG5	PG6	PG7	PG8
PG2		0.3077	0.1538	0.3153	0.4837	0.2874	0.2308
PG3			0.2400	0.3201	0.2146	0.2481	0.2727
PG4				0.1945	0.2667	0	0.2329
PG5					0.1540	0.6048	0.3201
PG6						0.1333	0.1073
PG7							0.4000

part family 1— {P1, P4, P6},

part family 2— {P2, P5, P8},

part family 3— {P3, P7, P9, P10, P11}

After part family identification, the next step is to assign machines into corresponding families so as to form manufacturing cells.

Tables 6–10 present input data generated randomly within the ranges of data found in most published articles and case studies, showing that there are 10 machine types to perform nine operations in the given manufacturing system.

Computational experiments in the method are operationalized using software on a PC with a 2.94-GHz processor and 2 GB of memory.

Table 6: Assign machines to operations

Machine/ Operation	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
Op1	1									
Op2	1	1								
Op3						1				
Op4			1							
Op5				1	1					
Op6								1		
Op7				1			1			
Op8									1	
Op9										1

The element "1" indicates that the corresponding machine is capable of operating.

Table 7: machine information

Machine j	Machine cost cj ($)	Machine capacity Cj (min)	Machine operation cost sj ($)
M1	1300	1224	1.1
M2	1500	1224	1.3
M3	1150	1224	1.3
M4	1600	1224	1.0
M5	1100	1224	1.2
M6	1800	1224	1.5
M7	1500	1224	0.6
M8	1000	1224	1.1
M9	1100	1224	1.1
M10	1250	1224	1.2

Table 8: Operation sequence, time

Part i	Operation number K_i	Operation data	Operation sequence					
			1	**2**	**3**	**4**	**5**	**6**
P1	6	Machine j	M1	M1/M2	M6	M3	M6	M8
		Processing time t_{ijk} (min)	0.5	0.9/0.7	1.2	1.0	1	0.8
P2	6	Machine j	M1/M2	M3	M4/M5	M3	M8	M4/M7
		Processing time t_{ijk} (min)	1.0/1.2	0.8	0.4/0.6	0.8	1.3	1.4/1.3
P3	3	Machine j	M1/M2	M6	M3			
		Processing time t_{ijk} (min)	1.0/1.2	0.8	1.5			
P4	5	Machine j	M1	M1/M2	M6	M4/M5	M6	
		Processing time t_{ijk} (min)	0.7	1.2/0.9	1.3	0.9/1.1	1	
P5	3	Machine j	M1/M2	M3	M4/M5			

Part i	Operation number K_i	Operation data	Operation sequence					
			1	**2**	**3**	**4**	**5**	**6**
		Processing time tijk (min)	0.8/1.1	1.0	1.2/1.4			
P6	3	Machine j	M1	M1/M2	M6			
		Processing time tijk (min)	1.1	1.5/1.3	1.5			
P7	5	Machine j	M3	M1/M2	M3	M4/M7	M9	
		Processing time tijk (min.)	0.9	1.4/1.2	0.9	1.3/1.7	2.2	
P8	6	Machine j	M1/M2	M4/M5	M8	M4/M5	M8	M4/M7
		Processing time tijk (min)	0.8/0.8	1/1.4	1.0	0.6/0.9	1.3	1.6/1.1
P9	2	Machine j	M3	M1/M2				
		Processing time tijk (min)	1.0	1.5/1.3				
P10	6	Machine j	M3	M4/M7	M3	M4/M7	M9	M10
		Processing time tijk (min)	1.0	1.6/1.3	0.8	1.6/0.9	1.9	2.1
P11	3	Machine j	M1	M4/M7	M3			
		Processing time tijk (min)	0.9	1.4/1.6	1.2			

Table 9: Part demand

Demand—vi	**Parts**										
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11
	500	400	550	500	700	600	800	1000	450	500	550
Material inter-cell movement cost hi ($)	0.7	1.0	0.5	0.7	0.5	1.0	0.7	0.7	1.1	0.5	1.0

Table 10: Machine quantity in each cell

Machine	**Cell**			
	Cell 1	**Cell 2**	**Cell 3**	**Total**
M1	2	2	3	7
M2	1	0	0	1
M3	1	2	4	7
M4	1	3	2	6
M5	0	0	0	0
M6	3	0	1	4
M7	0	1	1	2
M8	1	3	0	4
M9	0	0	3	3
M10	0	0	1	1

Table11: Minimum utilization of exception

Exceptional	**Independent cell**	**Dependent cell**
machines	system (q=0)	system (q=1)
M1	0.32	0.76
M3	0.09	1
M4	0.37	0.71
M6	0.36	0.93
M7	0.9	0.9
M8	0.3	0.63

Table 12: Maximum workload imbalances of exceptional machines

Exceptional	**Independent cell**	**Dependent cell**
machines	system (q=0)	system (q=1)
M1	0.68	0.24
M3	0.91	0
M4	0.63	0.29
M6	0.64	0.07

M7	0.21	0.21
M8	0.7	0.37

Table 13: Comparison between independent and dependent cell systems

	Independent cell system (q=0)	Dependent cell system (q=1)	Improvement
Machine cost ($)	47,000	39,000	
Inter-cell movement	0	1049	
Total cost ($)	47,000	40,049	14.8 %
System utilization	73.6 %	90.1 %	16.5 %

This section evaluates the performance of independent and dependent cell systems formed by applying the proposed algorithm to the experiment.

In the independent cell system (q=0), despite the absence of material inter-cell movements, some machines' utilization is so low that a significant amount of capacity will be wasted. In the dependent cell system (q=1), parts are transferred between cells, allowing for the elimination of underutilized machines and improving overall machine utilization. Not only that, but it also decreases the workload imbalance of exceptional machines, as shown in Table 13. However, just like the two sides of a seesaw, the increase in material inter-cell movement cost is the price of the benefits. The cost of the machine is reduced sharply, but the inter-cell movement cost is increased as a trade-off. It is a relief that the total cost of both has dropped by 14.8%. Moreover, system utilization in the dependent cell system is enhanced by 16.5 %. By eliminating superfluous and underutilized machines from the manufacturing system, a more reasonable workload assignment can be achieved among cells.

4- Conclusions and future research

In this paper, a two-phase approach was proposed for CF in the cellular manufacturing system. In the first phase, an improved SCM was presented for identifying part families. The main difference of the improved method from existing research is that the operation sequence and the number of repeated operations are considered simultaneously in part similarity measurement. Based on the similarity coefficients, the part family identification would serve as the foundation for the next phase. In the second phase, a decomposed mathematical model was presented, considering various crucial operational aspects such as machine cost, operation cost, inter-cell movement cost, alternative routing, part demand, processing time, lot splitting, and machine available capacity, to assign machines into part families. The model decomposes the NP-complete problem into several simple sub-problems, thereby facilitating the cell formation problem and reducing computational efforts. The ultimate aim of the two-phase approach is to form promising manufacturing cells with minimum machine investment, operation cost, and inter-cell movement cost, as well as maximum machine utilization and workload balance.

It also leads to effective production scheduling with optimum system utilization in the complex cellular manufacturing system. Moreover, to reduce problem size, our model focuses on exceptional machines rather than all the mentioned machines. Computational experiments demonstrated that significant cost savings and system utilization improvements can be achieved by considering the trade-off between machine duplication and material inter-cell movement. To continue the research direction outlined in this paper, two major directions are suggested. First, the proposed method in our research was confirmed by some small-scale problems

, but its limitation is that a long computational time will be needed for solving large-scale problems. Therefore, future work will focus on developing metaheuristics to solve the proposed problem with more reasonable computational efforts. Furthermore, we will consider additional variables such as layout design, cross-trained workers, and setup time in the applied CF problem.

References Format:

[1] Batsyn, Mikhail & Batsyna, Ekaterina & Bychkov, I. (2019). NP-completeness of cell formation problem with grouping efficacy objective. International Journal of Production Research. 58. 1-11. 10.1080/00207543.2019.1668072.

[2] Fardis F, Zandi A, Ghezavati V (2013) Stochastic extension of cellular manufacturing systems: a queuing-based analysis. J Ind Eng Int 9:20.

[3] Wu, Lang & Shen, Yifan & Niu, Ben & Li, Li & Yang, Congcong & Feng, Yuanyue. (2021). Similarity coefficient-based cell formation method considering operation sequence with repeated operations. Engineering Optimization. 54. 989-1003. 10.1080/0305215X.2021.1904917.

[4] Janis S. Neufeld, Jatinder N.D. Gupta, Udo Buscher, A comprehensive review of flow shop group scheduling literature, Computers & Operations Research, Volume 70, 2016, Pages 56-74, ISSN 0305-0548, https://doi.org/10.1016/j.cor.2015.12.006.

[5] Kia R, Shirazi H, Javadian N, Tavakkoli-Moghaddam R (2013) A multi-objective model for designing a group layout of a dynamic cellular manufacturing system. J Ind Eng Int 9:8.

[6] KusiakA, ChoM (1992) Similarity coefficient algorithms for solving the group technology problem. Int J Prod Res 30(11):2633–2646.

[7] Kumar, Shailendra & Sharma, Rajiv. (2015). Development of a cell formation heuristic by considering realistic data using principal component analysis and Taguchi's method. Journal of Industrial Engineering International. 11. 10.1007/s40092-014-0093-3

[8] McAuley J (1972) Machine grouping for efficiency production. Prod Eng 51(2):53–57.

[9] Pandian, R. & Ramalingam, Kamalakannan & Poruran, Sivakumar. (2019). Heuristic and meta-heuristic algorithms for solving medium and large scale sized cellular manufacturing system NP-hard problems: A comprehensive review. Materials today: proceedings.

[10] Ramesh, S. & Natesan, Arun Kumar & Vijaya raj, R. (2021). Cellular manufacturing layout design using heuristic clustering algorithm and LPP model. The South African Journal of Industrial Engineering. 32. 10.7166/32-2-2340.

[11] Reisman A, Kumar A, Motwani J, Cheng CH (1997) Cellular manufacturing: a statistical review of the literature (1965–1995). Oper Res 45(4):508–520. doi:10.1287/opre.45.4.508.

[12] Sharma, Rajiv & Kumar, Love. (2021). An Efficient Algorithm for Solving Cell Formation Problem in Cellular Manufacturing. 10.1007/978-981-15-4550-4_19.

[13] Voznesenski, Rohullah & Sadeghi, Azadeh & Mosadegh, Hadi & Almasarwah, Najat & Süer, Gürsel. (2022). Cellular manufacturing design 1996–2021: a review and introduction to applications of Industry 4.0. International Journal of Production Research. 61. 1-52. 10.1080/00207543.2022. 2105763.

[14] Aghakhani, S., Pourmand, P., & Zarreh, M. (2023). A Mathematical Optimization Model for the Pharmaceutical Waste Location-Routing Problem Using Genetic Algorithm and Particle Swarm Optimization. Mathematical Problems in Engineering, 2023(1), 6165495.

[15] Aghakhani, S., & Rajabi, M. S. (2022). A new hybrid multi-objective scheduling model for hierarchical hub and flexible flow shop problems. AppliedMath, 2(4), 721-737.

[16] Aghakhani, S., Larijani, A., Sadeghi, F., Martín, D., & Shahrakht, A. A. (2023). A Novel hybrid artificial bee colony-based deep convolutional neural network to improve the detection performance of backscatter communication systems. Electronics, 12(10), 2263.

[17] Vahidi, M., Aghakhani, S., Martín, D., Aminzadeh, H., & Kaveh, M. (2023). Optimal band selection using evolutionary machine learning to improve the accuracy of hyper-spectral images classification: A novel migration-based particle swarm optimization. Journal of Classification, 40(3), 552-587.

[18] Ghasemi, F., & Keihani, H. (2025). Application of machine learning and data science in project construction scheduling. International journal of sustainable applied science and engineering, 2(2), 39-52.

[19] Havigh, E. A., & Chobar, A. P. (2025). Elaborating a Management Model for Sustainable Development in Cellulosic Industries. International journal of sustainable applied science and engineering, 2(2), 11-24.