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Integration of the Assessment and Design of Cellular Manufacturing System

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Abstract

Cellular Manufacturing (CM) is a developed manufacturing philosophy that operates based on the principles of Groups Technology (GT) concept. It used to improve the quality and increase the productivity. Through CM, parts are grouped into families in view of their similarities in design /and or manufacturing features. Then again, machines likewise are gathered into cells to satisfy all the required processes on the families of parts. The integration was done with exam the manufacturing system, for example, job shop before applying the CM. Therefore, in the current paper an attempt was carried out firstly, to evaluate the presented production data, then to integrate the results of this step with the results of the next step, Cell Formation (CF) to acquire an effective CM system. In the evaluation part of the present paper, some hierarchical procedures were applied while in the design (cell formation) section, one of the well- known array based clustering method was utilized, this method known as Rank Order Clustering (ROC) and used to shape cells of machines and families of parts. However, some notable measures were utilized to assess the performance of the proposed CM, these measures are: grouping efficiency GE, grouping efficacy GC, voids, exceptional elements EE, percent of exceptional elements PE and machine utilization MU. To validate this work, three data sets (matrices) were chosen from the open literature. The strategy that followed lead to get a powerful CM solution. The outcomes demonstrated a missing of EE, increasing GE, GC, MU to 92%, 84%, 84% respectively.

Keywords: Cellular Manufacturing, Group Technology, Rank Order Clustering, Exceptional Elements, Grouping Efficacy, Machine Utilization

الخلاصه

نظام التصنيع الخلوي هو فلسفة تصنيع حديثة تعتمد على اسس مفهوم تكنولوجيا المجاميع. يؤدي نظام التصنيع الخلوي الى تحسين النوعية وزيادة الانتاجية. من خلال نظام التصنيع الخلوي يتم تجميع الاجزاء المنتجة في عوائل اعتمادا على التشابه فيما بينها في العوامل التصميمية او التصنيعية. وكذلك يتم تجميع المكائن التي تستخدم لانتاج تلك العوائل في مجاميع تسمى الخلايا. ان عملية التكامل تتم لفحص معلومات النظام الموجود مثل نظام التصنيع المعتمد على الوظيفة (Job shop) قبل تطبيق نظام التصنيع الخلوي (CM) . بناءا على ذلك فان الورقة الحالية تحاول اجراء هذا التكامل؛ حيث يتم في البداية فحص معلومات النظام الموجود في مرحلة التقييم ثم اجراء تكامل لنتائج هذه المرحلة مع المرحلة اللاحقة (مرحلة التصميم). في مرحلة التقييم تم استخدام مجموعة من الخطوات المتسلسلة. اما في مرحلة التصميم او تكوين الخلايا (CF) تم استخدام احد الطرق المعروفة وهي (ROC) لتكوين الخلايا والمجاميع. بعد ذلك استخدمت مجموعة من معايير الاداء لتقييم نظام التصنيع الخلوي المقترح. هذه المعايير هي (GE, GC%, Voids, EE, PE, MU). ولتحقيق هذا العمل تم اختيار ثلاثة مصفوفات من البحوث السابقة. ان الستراتيجية المتبعة في البحث الحالي ادت الى الحصول على نظام تصنيع خلوي كفوء وقد ادت النتائج التي تم الحصول عليها الى عدم ظهور اجزاء حرجة (EE) والى زيادة في قيمة معايير الاداء (MU, GC, GE) الى (84%, 84%, 92%) بالتسلسل.

الكلمات المفتاحيه: التصنيع الخلوي؛ تكنولوجيا المجاميع؛ التجميع على اساس الرتبة ROC؛ الاجزاء الحرجة؛ كفاءة التجميع؛ استغلال المكائن .

1. Introduction

Currently CM is observed to be the best alternative manufacturing system to handle most of the production problems and to investigate the customer requirements. Likewise CM considers as the best option that deals with the issue of process based manufacturing systems such as job shop. In brief, CM works based on the GT thought that classifying the products based on the similarities in design and \ or production attributes and located them in groups called families. However, the machines that used to operate these families of parts also located in groups called cells. Each cell responsible to complete all the required process for one family or sometimes more than one.

By applying the CM, the factories and firms can gain several advantages such as reducing the production time through reducing the setup time of machines, the delay times, the throughput times, on the other side, reducing the material handling cost. As well increase the productivity and enhance the quality. Moreover decrease the inter-intra cell movement cost.

Sometimes the CM system after applying failed or not pick up the expected outcomes. This is because it applies straightforwardly, without test and examine the current information, Therefore, the present paper endeavor to approve this issue through assessment and dissect the current information toward the starting at that point to apply the new CM.

The evaluation of the current information is an imperative and is considered as an assessment issue. Through this progression, the data of the existing manufacturing system has been analyzed.

The outcomes of the evaluation lead to the decision on the likelihood or not changing over the existing manufacturing system to CM. Thus, this is a simple approach to inspect the system in the beginning periods prior to the design of the CM system. The output of this step incorporates: (i) The anticipated number of the machine cells (ii) the decision of the CM application and (iii) the quality of the expected solution (Basher and Karaa, 2008).

The investigations of the assessment issue are exceptionally constrained, one of the earliest studies was completed by (Maleki, 1991) , he utilized some production factors, for example, product assortment and yearly production amount.

However, (Arvindh and Irani, 1994) presented a more mind boggling technique that incorporates another element known as the index of clustering tendency. This strategy incorporates the using of the Principle Component Analysis (PCA) with the two key measurements: (parts and machines) of the incidence matrix that’s used as an input in solving the CM issue.

(Luong *et.al.,* 2002) presented an approach in view of the yearly time and the yearly amount of production of the verity proportion of the product as a fundamental factor. This factor used for assessing the reasonableness of the CM. Later on, Basher and Karaa (2008) proposed a compelling and basic technique for the assessment issue. This technique based on a specific end goal to judge the plausibility of changing over the current system to CM, figuring the anticipated number of machine cells and developing an equation to recognize the quality of the solution.

(Hamza and Adesta, 2013) compared 19 similarity coefficients (SCs) measures (general purpose similarity coefficients GPSCs and problem oriented) from (Yin and Yasuda, 2006) scientific classification. Afterward, they compared the results of these SCs with the results of Jaccard measure in the assessment stage. In their investigation, they demonstrated the capability of utilizing these 19 SCs measures to foresee the solution.

Also (Hamza and Adesta , 2013) contrasted two strategies to recognize the number of machine cells in the assessment stage. The first one depends on utilizing the number of machines in the matrix and the pre-definable greatest limit of machines in each machine cell. However the second one depends on one of the GPSCs known as Rogers and Tanimoto measure. The outcomes of this investigation alluded to the exactness of the GPSC based strategy.

Again (Hamza and Adesta , 2013) integrated the assessment step with the CF by using three strategies, the first and the second strategy depend on two SCs known as (Baroni-urbane and Buser measure, and Sorenson) and the third strategy depends on the (ROC) technique. These techniques connected to the (0-1) incidence matrix.

(Raja and Anbumalar, 2016) utilized generalized SC strategy to integrate the assessment and CF with the consideration of the sequence of operations. The point of their proposed strategy is to recognize the right number of machine cells in the incidence matrix. They utilized the procedure that used by (Kaiser, 1960) and the Eigenvalues of the SC matrix. At long last, they demonstrated that their proposed strategy more effective than the current strategies.

It can be observed from the above concise literature that the investigations on the assessment of the existing manufacturing system are extremely restricted. Therefore, this is the fundamental inspiration of the present research to focus on this issue. On the other hand, this research focused particularly on the predicted number of machine cells. For this purpose, the present study used hierarchical steps in the evaluation phase, then utilized ROC in the cell formation phase to validate the integration process.

2. Methodology

The strategy that followed in the present paper partitioned into three steps: the initial step is utilized to assess the existing information based on applying some hierarchical procedures. However, the second step (CF) is used to shape the machine cells and part families, thus ROC technique used to investigate this goal. On the other hand, the third step is utilized to measure the performance of the created CM system. Figure 1 refers to the research methodology flow chart. The details about these three steps are as clarified in the following:-

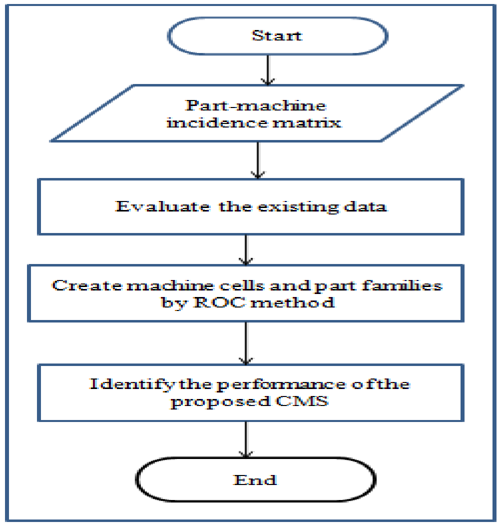

Fig 1: Research methodology flow chart

2.1. Assessment of the existing data

The existing data (initial matrix) that used in this paper as an input was selected from the open literature. It was called (0-1) matrix or binary matrix. This binary matrix includes parts and machines where parts arranged in columns and machines in rows. The selected matrix defined as follows:

M: number of machines; P: number of parts; Xij = 1 if the part i need machine j

Xij =0 otherwise, where j= machine index (j = 1, 2,……,M), while i = part index (i =1, 2,…., p). In the present paper three matrices were selected, the size of these matrices are: (5*6), (6*8) and (7*11), where the first number refers to the number of machines and the second number refers to the number of parts. These matrices as shown in Table 1 (a, b, c).

Table 1 (a, b, c): Machine/part matrices for the three selected datasets (5*6, 6*8, 9*11)

M\P	P1	P2	P3	P4	P5	P6
A	0	0	1	0	1	0
B	0	1	1	0	0	0
C	1	0	0	1	0	0
D	0	1	1	0	1	0
E	1	0	0	1	0	1

a: Machine/Part matrix (5*6)

M\P	P1	P2	P3	P4	P5	P6	P7	P8
1	1	1	0	1	1	0	0	0
2	0	1	0	1	0	1	1	1
3	1	0	0	1	0	1	1	1
4	1	0	1	0	1	0	1	1
5	1	1	1	0	1	1	1	1
6	1	1	0	0	0	1	1	0

b: Machine/Part matrix (6*8)

M\P	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11
M1	1	0	0	1	0	1	1	0	0	0	0
M2	0	1	0	0	0	0	0	1	0	0	1
M3	0	0	1	0	1	0	0	0	0	1	0
M4	1	0	0	1	0	1	0	0	1	0	0
M5	0	0	1	0	1	0	0	0	0	1	0
M6	0	1	0	0	0	0	0	1	0	0	1
M7	0	0	1	0	1	0	0	0	0	0	0
M8	0	0	0	1	0	1	1	0	1	0	0
M9	0	0	1	0	0	0	0	0	0	1	0

c: Machine/Part matrix (9*11)

Then the similarity coefficient matrices for the three selected datasets have been computed by using Jaccard measure. Jaccard measure classifies as a general purpose similarity coefficient (GPSC). Eq.1 refers to the Jaccard measure. It needs only the information of the part-machine matrix with (0-1) entries , Table 2 (a, b, c) refer to the similarity coefficient matrices.

$$S_{ij} = \frac{\sum_{k=1}^{n} X_{ijk}}{\sum_{k=1}^{n} Y_{ijk}} \qquad (1)$$

Where, S_{ij}: similarity coefficient between machines *i* and *j;* X_{ijk} = 1 if part type *k* visits both machines *i* and *j;* X_{ijk}= 0 otherwise, Y_{ijk}= 1 if part type *k* visits either machine *i* or *j;* Y_{ijk}= 0 otherwise.

Table 2 (a, b, c): The similarity coefficient matrices for the three selected datasets (5*6, 6*8, 9*11)

	M1	M2	M3	M4	M5
M1	1.00	0.50	0.00	2.00	0.00
M2	0.50	1.00	0.00	2.00	0.00
M3	0.00	0.00	1.00	0.00	2.00
M4	2.00	2.00	0.00	1.00	0.00
M5	0.00	0.00	2.00	0.00	1.00

a: The similarity coefficient matrix for dataset 5*6

	M1	M2	M3	M4	M5	M6
M1	1.00	0.29	0.29	0.29	0.38	0.33
M2	0.29	1.00	0.67	0.25	0.50	0.50
M3	0.29	0.67	1.00	0.43	0.50	0.50
M4	0.29	0.25	0.43	1.00	0.71	0.29
M5	0.38	0.50	0.50	0.71	1.00	0.57
M6	0.33	0.50	0.50	0.29	0.57	1.00

b: The similarity coefficient matrix for dataset (6*8)

	M1	M2	M3	M4	M5	M6	M7	M8	M9
M1	1.00	0.00	0.00	0.60	0.00	0.00	0.00	0.60	0.00
M2	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
M3	0.00	0.00	1.00	0.00	1.00	0.00	0.67	0.00	0.67
M4	0.60	0.00	0.00	1.00	0.00	0.00	0.00	0.60	0.00
M5	0.00	0.00	1.00	0.00	1.00	0.00	0.67	0.00	0.67
M6	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
M7	0.00	0.00	0.67	0.00	0.67	0.00	1.00	0.00	0.33
M8	0.60	0.00	0.00	0.60	0.00	0.00	0.00	1.00	0.00
M9	0.00	0.00	0.67	0.00	0.67	0.00	0.33	0.00	1.00

c: The similarity coefficient matrix for dataset (9*11)

Then the Eigenvalues of the similarity coefficient matrices have been calculated by utilizing Eq. 2.

$$(S - I\lambda)Y = 0 \qquad (2)$$

Where: S: denotes the matrix of similarity; I: refers to the identity matrix; λ: defines the Eigenvalue of the Eq. 1; Y: is the n numbers of Eigenvectors.

The result of this step is as displayed in Table 3. As well as in this Table, the predicted number of machine cells was identified based on the number of positive eigenvalues equal to or greater than one. This number should be equal two at least, otherwise the predicted number of machine cells will be equal zero as shown with the result of data set 2 for matrix (6*8) (Kaiser, 1960).

Table 3: The results of the assessment step

Dataset	Matrix Size	Eigenvalues	No of positive eigenvalues equal to or greater than one	No of cells	Decision of applying CM
1	5*6	4.089, 0.500, -1.589, 3.000, -1.000	2	2	Yes, possible
2	6*8	3.211, 0.920, 0.778, 0.564, 0.348, 0.180	1	0	No, impossible
3	9*11	0.400, 2.200, 2.000, 0.000, 3.046, 0.000, 0.284, 0.400, 0.670	3	3	Yes, possible

2.2. Cell Formation

In this step, rank order clustering (ROC) method was used to identify the part families and machine cells. This method is classified as one type of the array based clustering methods and used here to obtain better performance for the new CM system as shown in Fig 2. In the ROC, the columns and rows are rearranged to form the final CM matrix. More details about this algorithm are as follows:

2.2.1. Rank Order Clustering (ROC)

ROC is a well known clustering method that attempts to build cells and families by reallocating rows and columns of the initial part-machine matrix based on the binary values (King, 1980). ROC is considered as the most acceptable algorithm for solving the CF issue to create cells and families simultaneously. Steps of applying ROC algorithm are given below:

2.2.2. ROC Algorithm:

Stage 1: Allocate binary weight and ascertain the decimal comparable for each column of the machine part initial matrix

Stage 2: Arrange columns of the binary matrix in dropping order of the comparing decimal weights

Stage 3: Replicate the previous two stages for every row

Stage 4: Repeat the previous strides until the point when the position of every component in every row and column does not change. A weight of each row i and column j are computed in equations 3 and 4:

$$Row i = Wi = \sum_{k=1}^{n} a_{ik} 2^{n-k} \qquad (3)$$

$$Column\ j = Wj = \sum_{k=1}^{m} a_{jk} 2^{n-k} \qquad (4)$$

In the last matrix that created by ROC algorithm, clusters are recognized visually. The results of the cell formation step are as shown in Figures (2, 3, 4).

```
---- Try No. 1----
  1   1   1   0   0   0  37   5 Machine No
  1   1   0   0   0   0  36   3
  0   0   0   1   1   1  26   4
  0   0   0   1   1   0  24   2
  0   0   0   1   0   1  10   1
 24  24  16   7   6   5   0   0 power
  1   4   6   3   2   5   0   0 product No:

---- Try No. 2----
  1   1   1   0   0   0  56   5 Machine No
  1   1   0   0   0   0  48   3
  0   0   0   1   1   1   7   4
  0   0   0   1   1   0   6   2
  0   0   0   1   0   1   5   1
 24  24  16   7   6   5   0   0 power
  1   4   6   3   2   5   0   0 product No:

-----------------------------------------
Final Result

---- Try No. 3----
  1   1   1   0   0   0  56   5 Machine No
  1   1   0   0   0   0  48   3
  0   0   0   1   1   1   7   4
  0   0   0   1   1   0   6   2
  0   0   0   1   0   1   5   1
 24  24  16   7   6   5   0   0 power
  1   4   6   3   2   5   0   0 product No:
```

a: ROC steps for matrix 5*6

Famil y	P 1	P 2	P 3	P 4	P 5	P 6
1	√			√		√
2		√	√		√	

c: The created families for matrix 5*6

M\P	P1	P 4	P 6	P 3	P 2	P 5
M5	1	1	0			
M 3	1	1	1			
M 4				1	1	1
M 2				1	1	0
M 1				1	0	1

b: Cells and Families for matrix 5*6

Cell	M1	M2	M3	M4	M5
1			√		√
2	√	√		√	

d: The created Cells for matrix 5*6

Fig 2 (a, b, c, d): The results of the cell formation step for dataset 5*6

```
---- Try No. 1----
   1    1    1    1    1    1   63    7 Machine No
   1    1    1    1    1    0   62    6
   1    1    1    1    0    0   54    1
   1    1    0    0    1    0   42    5
   1    0    1    1    1    0   30    3
   1    0    1    1    0    1   23    4
   1    0    1    0    0    0    6    8
   0    0    1    0    0    1    5    2
 254  240  239  236  216  133    0    0 power
   5    1    4    2    3    6    0    0 product No:

---- Try No. 2----
   1    1    1    1    1    1   63    7 Machine No
   1    1    1    1    1    0   62    6
   1    1    1    1    0    0   60    1
   1    1    0    0    1    0   50    5
   1    0    1    1    1    0   46    3
   1    0    1    1    0    1   45    4
   1    0    1    0    0    0   40    8
   0    0    1    0    0    1    9    2
 254  240  239  236  216  133    0    0 power
   5    1    4    2    3    6    0    0 product No:

---------------------------------------
Final Result

---- Try No. 3----
   1    1    1    1    1    1   63    7 Machine No
   1    1    1    1    1    0   62    6
   1    1    1    1    0    0   60    1
   1    1    0    0    1    0   50    5
   1    0    1    1    1    0   46    3
   1    0    1    1    0    1   45    4
   1    0    1    0    0    0   40    8
   0    0    1    0    0    1    9    2
 254  240  239  236  216  133    0    0 power
   5    1    4    2    3    6    0    0 product No:
```

a: ROC steps for matrix 6*8

Family	P1	P2	P3	P4	P5	P6	P7	P8
1	√		√		√	√	√	
2		√		√				√

c: The created families for matrix 6*8

M\P	P7	P6	P1	P5	P3	P4	P8	P2
M5	1	1	1	1	1		1	1
M1	0	0	1	1	0	1	1	1
M4	1	0	1	1	1		1	
M2	1	1				1	1	1
M3	1	1	1			1	1	0
M6	1	1	1			0	0	1

b: Cells and Families for matrix 6*8

Cell	M1	M2	M3	M4	M5	M6
1	√			√	√	
2		√	√			√

d: The created Cells for matrix 6*8

Fig 3 (a, b, c, d): The results of the cell formation step for dataset 6*8

```
---Try No. 1---
 1 1 1 1 0 0 0 0 0 0 0 1200 1 Machine No
 1 1 1 0 1 0 0 0 0 0 0 1188 4
 0 0 0 0 0 1 1 1 0 0 0 521 2
 0 0 0 0 0 1 1 1 0 0 0 521 6
 0 0 0 0 0 0 0 0 1 1 1 322 5
 0 0 0 0 0 0 0 0 1 1 1 322 3
 0 0 0 0 0 0 0 0 1 1 0 320 7
 0 0 0 0 0 0 0 0 1 0 1 258 9
 1 1 0 1 1 0 0 0 0 0 0 180 8
385 385 388 257 129 96 96 96 30 28 26 0 0 power
 4 6 1 7 9 8 2 11 3 5 10 0 0 product No
---Try No. 2---
 1 1 1 1 0 0 0 0 0 0 0 1920 1 Machine No
 1 1 1 0 1 0 0 0 0 0 0 1856 4
 1 1 0 1 1 0 0 0 0 0 0 1728 8
 0 0 0 0 0 1 1 1 0 0 0 56 6
 0 0 0 0 0 1 1 1 0 0 0 56 2
 0 0 0 0 0 0 0 0 1 1 1 7 3
 0 0 0 0 0 0 0 0 1 1 1 7 5
 0 0 0 0 0 0 0 0 1 1 0 6 7
 0 0 0 0 0 0 0 0 1 0 1 5 9
448 448 384 320 192 48 48 48 15 14 13 0 0 power
  4 6 1 7 9 8 2 11 3 5 10 0 0     product No
---Try No. 3---
 1 1 1 1 0 0 0 0 0 0 0 1920 1 Machine No
 1 1 1 0 1 0 0 0 0 0 0 1856 4
 1 1 0 1 1 0 0 0 0 0 0 1728 8
 0 0 0 0 0 1 1 1 0 0 0 56 6
 0 0 0 0 0 1 1 1 0 0 0 56 2
 0 0 0 0 0 0 0 0 1 1 1 7 3
 0 0 0 0 0 0 0 0 1 1 1 7 5
 0 0 0 0 0 0 0 0 1 1 0 6 7
 0 0 0 0 0 0 0 0 1 0 1 5 9
448 448 384 320 192 48 48 48 15 14 13 0 0 power
  4 6 1 7 9 8 2 11 3 5 10 0 0     product No
-----------------------------------
Final Result
---Try No. 4---
 1 1 1 1 0 0 0 0 0 0 0 1920 1 Machine No
 1 1 1 0 1 0 0 0 0 0 0 1856 4
 1 1 0 1 1 0 0 0 0 0 0 1728 8
 0 0 0 0 0 1 1 1 0 0 0 56 6
 0 0 0 0 0 1 1 1 0 0 0 56 2
 0 0 0 0 0 0 0 0 1 1 1 7 3
 0 0 0 0 0 0 0 0 1 1 1 7 5
 0 0 0 0 0 0 0 0 1 1 0 6 7
 0 0 0 0 0 0 0 0 1 0 1 5 8
448 448 384 320 192 48 48 48 15 14 13 0 0 power
 4  6 1 7 9 8 2 11 3 5 10 0 0     product No
```

a: ROC steps for matrix 9*11

Family	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11
1	√			√		√	√		√		
2		√						√			√
3			√		√					√	

c: The created families for matrix 9*11

M\P	4	6	1	7	9	8	2	11	3	5	10
M1	1	1	1	1	0						
M4	1	1	1	0	1						
M8	1	1	0	1	1						
M6						1	1	1			
M2						1	1	1			
M3									1	0	1
M5									1	1	1
M7									1	1	0
M9									1	1	1

b: Cells and Families for matrix 9*11

Cell	M1	M2	M3	M4	M5	M6	M7	M8	M9
1	√			√				√	
2		√				√			
3			√		√		√		√

d: The created Cells for matrix 9*11

Fig 4 (a, b, c, d): The results of the cell formation step for dataset 9*11

2.3. Programs developed:

In the current research two programs were developed for calculating the similarity coefficient matrix in the first step (assessment) and for ROC method in the second step (CF). These two programs developed by using C++ language, they create the results automatically after inter the information in the (0-1) matrix to them as an input data. It is very essential to use these programs for many reasons as follows:

1. To avoid the blunder that occurs with the manual calculations
2. To save time and exertion, particularly with the substantial size matrices
3. These algorithms may require numerous cycle to pick up the last outcomes

2.4. Structure of the programs

Two programs were developed through the present research work, the first one for calculating the similarity coefficient matrix by Jaccard measure and the second one for utilizing ROC method. The first part of each program is to enter the initial binary matrix, the second part is to enter the number of machines and parts, however the third part is to display the results.

3. The performance measures

The six performance measures that used to evaluate the proposed cellular manufacturing solutions in this paper are:

Grouping Efficiency (GE)

Grouping Efficiency GE can be defined in Eq. (5):

$$GE = \rho \frac{N1}{\sum_{K=1}^{K} mk.nk} + (1-\rho)\left[1 - \frac{NE}{MN - \sum_{K=1}^{K} mk.nk}\right] \quad (5)$$

Where, MN: refers to the (0-1) matrix size; NE: denotes the number of exceptional elements; N1: refers to the number of 1's inside the clusters; k: denotes the number of clusters; m: refers to the number of machines in kth group; n: is the number of parts in kth group; ρ: is the weight factor ranging between 0 and 1, usually 0.5 is used widely Chandrasekharan and Rajagopalan (1986a, 1986b).

Grouping Efficacy (GC)

This measure is proposed to conquer the GE restriction. GC has some positive properties, for example, (i) leads to acquire nonnegative values (ii) It ranges from zero to one and (iii) does not have any limitation against the matrix size. GC can be found in Eq. 6:

$$GC = \frac{N_1 - N_1^{out}}{N_1 + N_o^{in}} * 100 \quad (6)$$

Where, N1: refers to the whole 1's numbers in (0-1) matrix; N1out: denotes the total number of 1's located outside the cells; N0 in: refers to the total number of 0's located inside cells, Tariq et al. (2007).

Number of the Exceptional Elements (EE)

The off-diagonal positive entries (1’s) which is called the exceptional elements EE in the final CF solution can be used to measure the performance of the selected CF method. The EEs are the foundation of the outside cell travels of the products. One of the CF aims is to decrease the overall material handling cost. Thus, EE is considered as the simplest measure to evaluate the final CF solution. EE can be computed as in Eq. 7:

$$E = eo \tag{7}$$

Where, eo: is the number of EEs or the off-diagonal positive entries. Some researchers used the percentage of exceptional elements instead of the number of exceptional elements as a performance measure and formulated it as presented in the following:

Percentage of the Exceptional Elements (PE)

The grouping quality can be also calculated by the number of parts which remain outside the block diagonals (King, 1980; Chan and Milner, 1982). These outside diagonal parts are known as the EEs. The PE is obtained from dividing the number of EE on the total number of (1’s) in the incidence matrix UE. Chu and Tsai (1990) reported that the lower PE refers to better clustering results. Eq. 8 represented the PE (Chandrasekharan and Rajagopalan, 1986a, 1986b):

$$\mathrm{PE} = \frac{\mathrm{EE}}{\mathrm{UE}} * 100 \tag{8}$$

Where, EE: is the number of (parts or 1’s that are located outside the block diagonal), UE: refers to the number of 1’s inside the incidence matrix (for example, the overall number of operations in the initial matrix).

Number of Voids (V)

Voids refer to the number of zero’s entries in the final created cells, these zero’s refer that some parts no need to operate on some machines or some machines have idle times and don’t use all the available capacity.

Machine Utilization (MU)

Machine Utilization refers to the percentage of utilizing the machines inside the cells obtained in the production. Chandrasekharan and Rajagopalan (1986a, 1986b) proposed Eq. 9 to compute MU as follows:

$$\mathrm{MU} = \frac{\mathrm{N1}}{\sum_{k=1}^{K} m_k n_k} * 100 \tag{9}$$

Where, N1: denotes the whole number of one's inside clusters; K: is the number of groups; m: is the number of machines in the kth group; n: is the number of products in the kth group.

The higher value of MU refers to better clustering results (Chu and Tsai, 1990).

4. Performance measurement results

Six performance measures have been used to evaluate the performance of the final solution for the three selected datasets ((5*6, 6*8, 9*11). These well-known performance measures are: machine utilization, grouping efficacy, grouping efficiency, a number of exceptional elements, percentage of exceptional elements and number of voids (MU, GC, GE, EE, PE, Voids) respectively. The results of utilizing these performance measures are as shown in Table 4, and Figs 5 and 6.

Table 4: The results of performance measures for the three selected datasets

Dataset	Voids	EE	PE%	GE%	GC%	MU%
5*6	3	0	0	90%	80%	80%
6*8	7	14	45%	56%	44.7%	70%
9*11	5	0	0%	92.42%	84.84%	84.84%

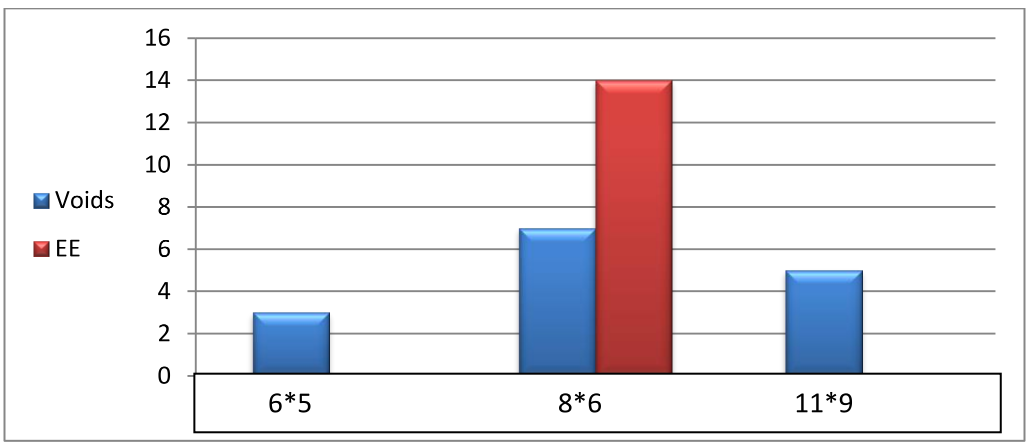

Fig 5: Voids and exceptional elements EE for the three selected datasets

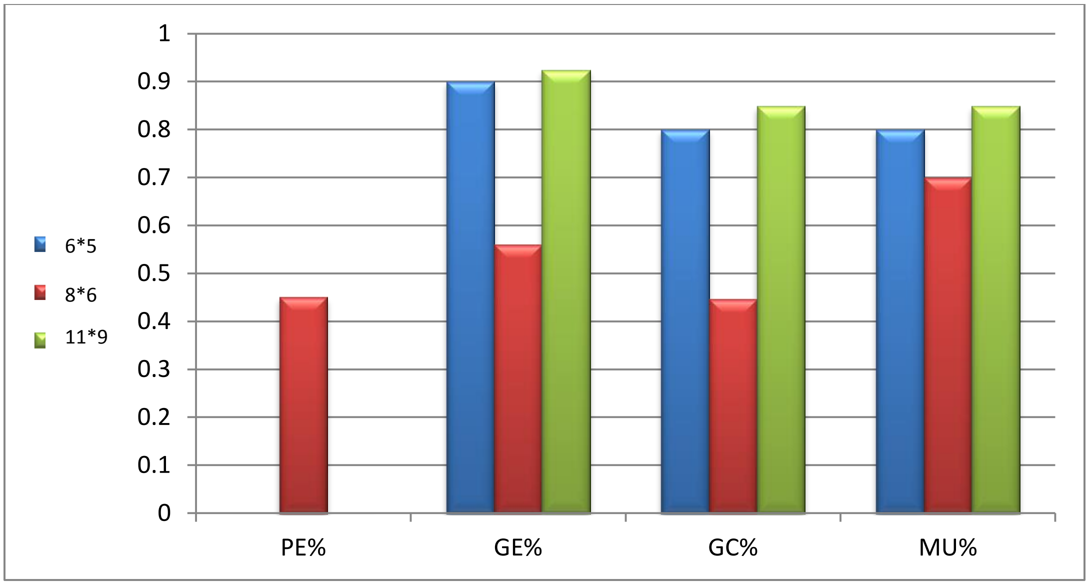

Fig 6: The PE%, GE%, GC% and MU% for the three selected datasets

5. Results and Discussion

From the results, Table 3 shows two positive eigenvalues equal to or greater than one for dataset 5*6. This means that, the predicted number of machine cells equal two and it is feasible to change the existing manufacturing system to CM. However, the number of positive eigenvalues, is equal 1 with dataset 6*8 which means: (i) zero predicted number of machine cells (ii) it is unfeasible to change the manufacturing system to CM and (iii) it can be change with bad outcomes.

On the other hand, in case of dataset 9*11, it is strongly recommended to apply the CM with three predicted numbers of machine cells. Figs 2, 3, and 4 reveal the steps of the ROC method for datasets (5*6, 6*8, 9*11) which take three, three and four iterations respectively to obtain the final solution. The results of ROC showed two cells and families with good arrangement with dataset 5*6, where no exceptional elements (which means low material handling cost), and just three void elements (which means the machine utilization for machines 1, 2, 5 less than other machines)

However, with dataset 6*8, two cells and families with bad arrangement has been formed, this bad solution produced 14 exceptional elements (high material handling cost) and 7 void elements (which means the utilization of available capacity for machines 1, 3, 4 and 6 less than other machines). Finally, three cells and families with good arrangement with dataset 9*11 have been obtained. In addition, this solution created zero exceptional elements and 5 voids elements (machines 1, 3, 4, 7, and 8 have idle times). However, Table 8, Figs 5 and 6 display the results of applying the performance measures. For PE%, datasets 5*6 and 9*11 recorded zero while dataset 6*8 recorded 45%.

In terms of the GE%, datasets 5*6 and 9*11 resulted 90%, 92%, respectively but dataset 6*8 resulted 56%. For GC%, dataset 6*8 created 44%, while 80% and 84% shaped with datasets 5*6 and 9*11 respectively. Finally, in terms of the MU% still dataset 6*8 recorded less percent than datasets 5*6 and 9*11 with 70%, 80% and 84% respectively. In conclusion, the good performance of data sets (5*6 and 9*11) is as these datasets investigated similar results in both steps (evaluation and cell formation), particularly in terms of the number of machine cells and the related decision of applying the CM which is mentioned clearly in Table 3.

6. Conclusions

In the present article, the existing manufacturing data that are arranged in a binary matrix with (0-1) entries were examined. The main reason for this step is to ensure if it is feasible or not to apply the CM system on the shop floor. After ensuring that is feasible and the predicted number of machine cells is known, The second step is starting which is called the design step or CF.

It is very essential in the CF to create the same number of machine cells that is predicted in the assessment step. In the current research, the ROC method was used and produced the same number of machine cells as in the first step for two datasets from three. Six measures of performance, namely: voids, EE, PE, MU, GE and GC were used to investigate the effectiveness of the obtained CM solution. The recorded results of the selected methodology investigate the followings:

1. Miss the exceptional elements (EE)
2. Decrease the number of void elements
3. Increase the percent of GE%
4. Increase the percent of GC%
5. Increase the percent of MU%

Therefore, it is very essential to assess the existing data of job shop system before applying the CM on the shop floor. This issue is very essential to enhance the performance and to reduce the material handling cost by decreasing the inter cell movement cost.

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