The Iraqi Journal For Mechanical And Material Engineering, Vol.19, No1,March 2019

HEURISTIC METHOD FOR SOLVING CELL FORMATION PROBLEM IN CELLULAR MANUFACTURING SYSTEM BASED ON HAMMING DISTANCE

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ABSTRACT

Cell Formation (CF) problem considers as the most important issue in the Cellular Manufacturing (CM) system particularly the design step. CF deals with the creation of machine cells (MCs) and part families (PFs). Numerous methods, algorithms and mathematical models were proposed and used in the literature for solving the CF problem. The current paper used a heuristic method based on the hamming distance to form MCs &PFs, this proposed method calculates the hamming distance for the parts, firstly then rearranges them based on the results to shape the PFs. Afterward, the hamming distance was calculated for machines, then the machines rearranged based on the results to form the MCs. Three datasets from the literature were utilized to validate the proposed method. Five performance measures were used for comparison and evaluation, these measures are Exceptional Elements EE, Percent of Exceptional elements PE, Voids, Grouping Efficiency GE and Machine Utilization MU. The results referred to the outperforms of the hamming distance based method comparing with the best known results in the literature. Among the total 20 performance indexes: three are better than, twelve are equal to and five are almost equivalent to the best known results. On the other hand, the proposed hamming distance based method is effectual particularly in terms of the number of machine cells and PE.

KEYWORDS: Cell formation, Cellular manufacturing, hamming distance, machine utilization, grouping efficiency

طريقة عملية لحل مشكلة تكوين الخلايا في نظام التصنيع الخلوي باستخدام مسافة Hamming

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الخلاصة

ان تكوين الخلايا هي القضية الاكثر اهمية في نظام التصنيع الخلوي وخاصة في مرحلة التصميم. ان تكوين الخلايا يرتبط بتكوين عوائل الاجزاء وخلايا المكائن . ان عدد كبير من الطرق والخوارزميات قد اقترحت لحل مشكلة تكوين الخلايا. البحث الحالي يستخدم طريقة تعتمد على مسافة Hamming لحل مشكلة تكوين الخلايا. هذه الطريقة تبدا بتطبيق هذه المسافة على الاجزاء ثم تعيد ترتيبها لتكوين العوائل. بعد ذلك تطبق هذه المسافة على المكائن واعتمادا على النتائج تعيد ترتيبها لتكوين خلايا المكائن. ولتطبيق هذه الطريقة تم اختيار ثلاث مصفوفات من البحوث السابقة. خمسة معايير اداء تم استخدامها لاغراض التقييم والمقارنة؛ هذه المعايير هي (الاجزاء الحرجة؛ نسبة الاجزاء الحرجة؛ كفاءة التجميع و استغلال المكائن). النتائج اشارت الى كفاءة الطريقة المقترحة المعتمدة على (مسافة Hamming) مقارنة مع احسن النتائج المنشورة في البحوث السابقة. من بين 20 مؤشر اداء؛ ثلاثة كانت افضل؛ 12 مساوية و5 تقريبا مساوية الى افضل النتائج المنشورة.من جانب اخر؛ ان الطريقة المقترحة المعتمدة على مسافة Hamming اظهرت نتائج كفوءة خاصة من ناحية عدد خلايا المكائن ونسبة الاجزاء الحرجة.

الكلمات المفتاحيه : تكوين الخلايا؛ التصنيع الخلوي؛ مسافة (Hamming)؛ استغلال المكائن؛ كفاءة التجميع

Received : 2018 -6 - 20
Accepted : 2018 - 9 –3

INTRODUCTION

Cellular manufacturing (CM) is considered as one of the best strategy that deals with the global manufacturing needs. Some of manufacturing needs are: high variety of production, short cycles of production life, changeable demand, and short times for delivery. CM works based on the group technology thought. It gains positive impact in the terms of the productivity and quality. Cell formation (CF) is the most essential and complex part of the CM system. It deals with gathering similar parts in groups called families and dissimilar machines also in groups called cells. The early two methods that were used to create machine cells (MCs) and part families (PFs) are known as: Classification and Coding system (C&C) Mitravanov [1966] and Production Flow Analysis (PFA) Burbidge [1971]. The PFA was used more than C&C because it has less complexity. Murugan and Selladurai [2005] have proposed a new approach for simultaneous arrangement of machine-part grouping with the consideration of some production features. CF based Genetic Algorithm (GA) developed by Ponnambalam et al., [2007] with and considering operational time information. The proposed algorithm exchanges the (0-1) incidence matrix by the workload data matrix.Hachicha et al., [2008] have formulated a multivariate method using a correlation investigation to solve the CF problem. The proposed method is applied in three steps. In the first step, the matrix of correlation is calculated and utilized as a matrix of similarity coefficient. The Principal Component Analysis (PCA) is utilized in the second step to identify the eigenvectors and eigenvalues of the correlation matrix. The scatter plot is applied to form concurrently part families and machine cells while maximizing the correlation between the elements. In the third step, an algorithm is enhanced to allocate the exceptional parts and machines utilizing Euclidian distance and respectively angle measure. Murugan and Selladurai [2011] proposed an Art Modified Single Linkage Clustering approach (ART-MOD-SLC) to solve the cell formation problems in the CM. The Machine Utilization (MU), Grouping Efficacy (GC), Percentage of Exceptional Elements (PE), and Grouping Efficiency (GE) utilized as performance factors. This proposed method, first creates a CF is applying an ART1, then refines the (MOD-SLC) procedures. ART1 Modified Single Linkage Clustering applied to the most well-known datasets in the literature, involving a real time production information. The computational outcome showed that the proposed method creates the best outcome in most of the problems. Then the proposed approach compared with some popular clustering methods chosen from the published research work.Additionally, different methods were developed with more concentration on the design issue (CF) of the CM. These methods were based on different approaches such as: similarity coefficients, array based, mathematical programming, artificial intelligence, etc. Arora [2011]. Ghosh et al., [2011, a; 2011, b] introduced a new approach known as Heuristic Part Family by Opitz Coding System (HPFOCS) to form part families. The proposed algorithm exchanges the (0-1) incidence matrix by the workload data matrix. Hamza and Adesta [2013] introduced a brief investigation of the literature on the integration of the basic decisions on the design of Cellular Manufacturing (CM) system. These basic decisions are: (i) cell formation; (ii) cell layout and (iii) cell scheduling. The objectives and limitations of the integration of these fundamental decisions have been recognized. Future study guidelines are suggested by taking into consideration the integration of another important issue in CM, this is the Feasibility Assessment (FA). Again Hamza and Adesta [2013] applied particular method to integrate the assessment step with the design step. The proposed method depends on three strategies. The same SCs (Sorenson) used in both steps in the first strategy. While, in the second strategy two different SCs (Baroni-urbane and Buser, and Sorenson) are used. However, different technique based (ROC) algorithm was used in the third strategy.

Chattopadhyay et al., [2014] used Self Organization Map (SOM) for solving CF problem, then for large size datasets they used SOM in a hierarchical style called Growing Hierarchical Self-Organizing Map (GHSOM). Afterward, they compared the two proposed algorithms after applied on 15 problems from previous literature and recorded an improvement of GC and GTE for 70% of data sets.Yan et al., [2014] applied two-phases clustering algorithm for part family and machine cells for the design of CM. The proposed algorithm involves two phases: the first phase includes the identification of the determination of preliminary group centers by means of the determination of preliminary group centers via a method based a linear assignment utilizing the least similar cluster representatives. However, in the second phase a technique based on a fuzzy C-means clustering is applied to create MCs and PFs. Experimental outcome on many standard problems based on several performance measures demonstrate the effectiveness of the proposed technique.kumar et al., [2014] compared five CF methods known as Direct Clustering Analysis (DCA), single linkage clustering (SLC), Modified-Single Linkage Clustering (MOD-SLC), Rank Order Clustering (ROC) and Rank Order Clustering-2 (ROC-2) for analyzing the real time production delay with the manufacturing CF. In this paper, (MOD-SLC) method is found to be outperforming the further four approaches, regardless of the measures utilized, irrespective of any other prevalence of exceptional elements in the data set. The outcomes are validated with the real time data of the manufacturing systems.Pradhan and Mishra [2015] proposed a method based on SOM to shape PFs and Minkowski distance to build MCs. They proved the efficiency of their proposed method with GC equal to 96.4 %. Kumar and Sharma [2015] developed a simple and easy heuristic procedure for cell formation with the considerations of some production features. The proposed procedure minimizes inter-cell movement time and cost. Moreover, the proposed method is modified for the application of Taguchi’s method and Principal Component Analysis (PCA). To demonstrate the proposed method, a numerical example is explained. The application of the PCA and Taguchi’s approach leads to the modification in the results.Shunmugasundaram and Anbumalar [2016] proposed a new similarity coefficient algorithm to create machine cells and part families. They used some benchmark problems for validation and comparison with the results of other CF methods. The performance of the proposed algorithm is tested by two measures known as grouping efficiency GE and grouping efficacy GC. The proposed algorithm is found to be powerful for reducing the inter-intra movement time.Giri and Moulick [2016] tested the benefits of the ART method of CF via the array based clustering algorithms, known as DCA and ROC-2. The evaluation and comparison of the CF methods have been carried out in the paper. The most suitable method is chosen and utilized to shape the CM system. The evaluation and comparison is made based on using the grouping efficiency as a performance measure. The output of the proposed method is outperform of the existing CF methods.Shunmugasundaram et al., [2017] developed a combined algorithm for solving the CF problem in the CM system. The proposed algorithm involves two steps. PFs identified by using Bond Energy Algorithm (BEA) and Rank Order Clustering (ROC) in the first step. However, in the second step, MCs created also by using Bond Energy Algorithm (BEA) and Rank Order Clustering (ROC). The aim of this study is to minimize the machine cost, operation cost, and inter-intra cell movement cost. The proposed method is tested by using some benchmark problems and compared with the results of other methods. Grouping efficacy is used to measure the performance of the proposed method in CM System.Hamza [2018] evaluated the presented production data, and then integrated the results of this step with the results of Cell Formation (CF) to acquire an effective CM system. In the evaluation part some hierarchical procedures were applied while in the design (CF) part, one of the well- known array based clustering method was utilized, this method known as Rank Order Clustering (ROC) and used to form groups of parts and machines. However, some important measures were utilized to evaluate 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 selected. The approach that followed led to get a powerful CM solution.The majority of the previous studies have focused more on creating MCs and PFs or CF issue in CM. In the current study, a particular methodology followed to create PFs and MCs; this methodology is based on using hamming distance in solving the CF problem. Based on our knowledge, researchers referred to the hamming distance, but haven't applied it in the CF problem.

HAMMING DISTANCE

Hamming distance is a distance function to measure the distance between two equal length vectors in a metric set of vectors, it is widely used in coding and decoding in the information theory to detect errors and correct them.

Let R be a set of vectors and Q a subset of Rn, the set of vectors of length n over A. Let u=(u1, … , un) and v=(v1,…,vn) be vectors in Q. The Hamming distance d (u, v) is defined as the number of places in which u and v differ: that is, $\sharp\{i: u_i \neq v_i, i=1,\dots, n\}$.

The application of hamming distance in Binary vectors is to find the difference between the two vectors after applying the XOR binary function on the vectors which will then the number of ones from the result is the Hamming distance between the two vectors. In the current paper the hamming distance applied by using a Matlab R2016b (9.1.0.441655) September 7, 2016 64 bit. Figure(1) refers to the Veen diagram of XOR and Table 1 refers to the XOR truth Table

METHODOLOGY

The strategy that followed in the current paper used the hamming distance based method for creating PFs and MCs. Then some well-known performance measures were used to evaluate the results of the mentioned method. These performance measures are (PE, voids, GE, GC, MU). Three matrices were selected from the literature to apply the proposed method, these matrices are (7*11, 10*10, 10*15). Figure(2) refers to the methodology procedures.

The steps of the proposed method are as follows:-

1. Select some datasets arranged as a binary matrix with (0-1) entries
2. Find the hamming distance for the parts
3. Rearrange the matrix according to the above results in step 2
4. Find the hamming distance for the machines
5. Rearrange the matrix according to the hamming distance results in step 4
6. The final matrix in step 5 gives PFs and MCs
7. Evaluate the performance of the proposed method

NUMERICAL EXAMPLES

Three numerical examples (datasets) were selected from the published literature to apply the proposed method, these datasets includes parts and machines that display the factory information. The parts arranged in columns while the machines in rows, when the part needs the particular machine, it takes 1 otherwise it takes 0.

Problem 1: Dataset (7*11)

In order to explain the steps of the proposed method, a binary matrix is considered with eleven parts (labeled P1-P11) and seven machines (labeled M1-M7). This data set is provided by Boctor (1991). Figure (3- a, b, c, d, e) refers to the steps of applying hamming distance for dataset 7*11.

Problem 2: Dataset (10*10)

In the second numerical example, a binary matrix is considered with ten parts (labeled P1-P10) and ten machines (labeled M1-M10). This data set is provided by Mosier and Taube (1985). Figure (4- a, b, c, d, e) refers to the steps of applying hamming distance for dataset 10*10

Problem 3: Dataset (10*15)

In the third example, a binary matrix is considered with ten parts (labeled P1-P10) and fifteen machines (labeled M1-M15). This data set is provided by Chang and Milner (1982). Figure (5- a, b, c, d, e) refers to the steps of applying hamming distance for dataset 10*15

PERFORMANCE MEASURES

Five well-known measures were used to identify the performance of the proposed method, these measures known as (Voids, EE, PE, GE, and MU). These performance measures explained as follows:

Number of the Exceptional Elements (EE)

The off-diagonal positive entries (1's) which are 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. 1:

$$E = eo \tag{1}$$

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.2 represented the PE (Chandrasekharan and Rajagopalan, 1986a, 1986b):

$$PE = \frac{EE}{UE} * 100 \tag{2}$$

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 Equation(3) to compute MU as follows:

$$MU = \frac{N1}{\sum_{k=1}^{K} m_k n_k} * 100 \quad (3)$$

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).

Grouping Efficiency (GE)

Grouping Efficiency GE can be defined in Equation (4):

$$GE = \rho \frac{N1}{\sum_{K=1}^{K} mk.\,nk} + (1-\rho)\left[1 - \frac{NE}{MN - \sum_{K=1}^{K} mk.\,nk}\right] \quad (4)$$

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).

Table 2: refers to the results of the hamming distance of the selected datasets, using the number of cells, EE and Voids. However, Table (3) illustrated summary of the hamming distance based method results in comparison with the best recognized results on the benchmark datasets in the literature.

RESULTS AND DISCUSSION

The results on several benchmark problems are summarized in Table (3) where the values of the performance measures in the right columns refer to the best known results recorded in the literature. However, the results on the left hand column refer to the hamming distance based method. Table (3) consists five benchmark datasets with four performance parameters for each one. The results demonstrate that the hamming distance based method is effective and efficient for solving part-family and machine-cell problems. Among the total twenty performance indexes: three are better than, twelve are equal to and five are approximately equal to the best recognized results. Particularly, the hamming distance based method is effective in terms of the number of machine cells and percent of exceptional elements. From Table (4), 4 datasets (80%) of the 5 selected datasets produced same PE results of the best known results while just one data set produced different solution. This results also appeared in Figure (6). In terms of the MU, Table (5) reveals that 2 datasets from 5 recorded MU equal to the best mentioned results in the literature. However, the results of the rest 3 datasets are almost equivalent to the best known results. Figure (7) illustrated the above results. For the GE Table (6), the proposed method produced better results for 3 data sets, one equal to and one is approximately equal to the best known results. Figure (8) displayed the obtained results.

CONCLUSIONS

In this paper, a hamming distance based method is proposed for creating machine-cells and part-families. The proposed method calculated the hamming distance for parts, then rearranged the parts based on the results to form PFs. However, the hamming distance was calculated for the machines and rearranged them based on the results to shape MCs.

The effectiveness of the proposed method is examined by some performance measures. The present method is demonstrated to be an effective and efficient according to the obtained results of comparative study with the previous research work in the literature. In conclusion, the results of the proposed methodology investigated the followings:

1. Miss or reduce the number of exceptional elements (EE)
2. The PE values are equal to the best known values
3. The MU results are almost equivalent to the best recognized results
4. The GE results are better than the best identified results

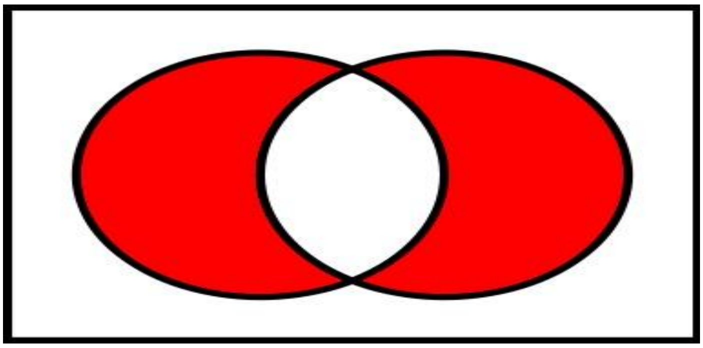

Fig. 1: Veen diagram of XOR

Table 1: XOR truth table

XOR truth table		
Input		**Output**
A	**B**	
0	0	0
0	1	1
1	0	1
1	1	0

Where 0: false and 1: true. The same principle was applied to the part/machine matrix individually once on the parts to find the hamming distance between the parts vectors and once on the machines to find the hamming distance between the machines vectors.

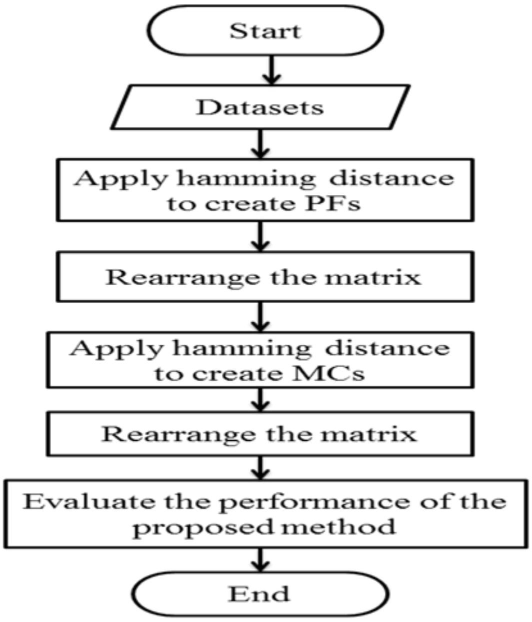

Fig. 2: The methodology procedures

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

(a): Part-machine matrix (7*11)

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11
P1	0	0.2857	0.4286	0.5714	0.5714	0.2857	0.2857	0.4286	0.4286	0.5714	0.2857
P2	0.2857	0	0.7143	0.5714	0.5714	0.0000	0.5714	0.4286	0.1429	0.5714	0.5714
P3	0.4286	0.7143	0	0.4286	0.7143	0.7143	0.1429	0.5714	0.5714	0.7143	0.1429
P4	0.5714	0.5714	0.4286	0	0.2857	0.5714	0.5714	0.4286	0.4286	0.2857	0.2857
P5	0.5714	0.5714	0.7143	0.2857	0	0.5714	0.5714	0.1429	0.4286	0.0000	0.5714
P6	0.2857	0.0000	0.7143	0.5714	0.5714	0	0.5714	0.4286	0.1429	0.5714	0.5714
P7	0.2857	0.5714	0.1429	0.5714	0.5714	0.5714	0	0.4286	0.4286	0.5714	0.2857
P8	0.4286	0.4286	0.5714	0.4286	0.1429	0.4286	0.4286	0	0.2857	0.1429	0.4286
P9	0.4286	0.1429	0.5714	0.4286	0.4286	0.1429	0.4286	0.2857	0	0.4286	0.4286
P10	0.5714	0.5714	0.7143	0.2857	0.0000	0.5714	0.5714	0.1429	0.4286	0	0.5714
P11	0.2857	0.5714	0.1429	0.2857	0.5714	0.5714	0.2857	0.4286	0.4286	0.5714	0

(b): Hamming distance for the parts

The numbers above represent the difference percentage between parts vectors

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

(c): Rearranging the parts based on the hamming results

The matrix rearranged according to the difference percentage, the smaller difference percentage the more parts similarity

	M1	M2	M3	M4	M5	M6	M7
M1	0	0.4545	0.6364	0.6364	0.1818	0.2727	0.6364
M2	0.4545	0	0.1818	0.5455	0.4545	0.5455	0.5455
M3	0.6364	0.1818	0	0.5455	0.4545	0.5455	0.5455
M4	0.6364	0.5455	0.5455	0	0.4545	0.3636	0.1818
M5	0.1818	0.4545	0.4545	0.4545	0	0.2727	0.4545
M6	0.2727	0.5455	0.5455	0.3636	0.2727	0	0.5455
M7	0.6364	0.5455	0.5455	0.1818	0.4545	0.5455	0

(d): Hamming distance for the machines

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

(e): Rearranging the machines based on the hamming results and identify PFs & MCs

Fig. (3- a, b, c, d, e): The steps of applying hamming distance on dataset 7*11

P/M	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
M1	1	0	0	0	0	1	0	0	0	0
M2	0	0	0	0	0	0	0	0	1	1
M3	0	1	0	0	0	0	1	0	1	1
M4	0	0	0	1	0	0	0	0	1	1
M5	0	0	1	0	0	0	0	0	0	0
M6	0	0	1	0	0	0	0	1	0	0
M7	0	0	0	0	1	1	0	0	0	0
M8	0	1	0	0	0	0	1	0	1	0
M9	0	0	0	0	0	0	0	1	0	0
M10	1	0	0	0	1	1	0	0	0	0

(a): Part-machine matrix (10*10)

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
P1	0	0.4000	0.4000	0.3000	0.2000	0.1000	0.4000	0.4000	0.6000	0.5000
P2	0.4000	0	0.4000	0.3000	0.4000	0.5000	0.000	0.4000	0.2000	0.3000
P3	0.4000	0.4000	0	0.3000	0.4000	0.5000	0.4000	0.2000	0.6000	0.5000
P4	0.3000	0.3000	0.3000	0	0.3000	0.4000	0.3000	0.3000	0.3000	0.2000
P5	0.2000	0.4000	0.4000	0.3000	0	0.1000	0.4000	0.4000	0.6000	0.5000
P6	0.1000	0.5000	0.5000	0.4000	0.1000	0	0.5000	0.5000	0.7000	0.6000
P7	0.4000	0.000	0.4000	0.3000	0.4000	0.5000	0	0.4000	0.2000	0.3000
P8	0.4000	0.4000	0.2000	0.3000	0.4000	0.5000	0.4000	0	0.6000	0.5000
P9	0.6000	0.2000	0.6000	0.3000	0.6000	0.7000	0.2000	0.6000	0	0.1000
P10	0.5000	0.3000	0.5000	0.2000	0.5000	0.6000	0.3000	0.5000	0.1000	0

(b): Hamming distance for the parts

P/M	P1	P6	P5	P4	P2	P7	P9	P10	P4	P3	P8
M1	1	1	0	0	0	0	0	0	0	0	0
M2	0	0	0	0	0	0	1	1	0	0	0
M3	0	0	0	0	1	1	1	1	0	0	0
M4	0	0	0	1	0	0	1	1	1	0	0
M5	0	0	0	0	0	0	0	0	0	1	0
M6	0	0	0	0	0	0	0	0	0	1	1
M7	0	1	1	0	0	0	0	0	0	0	0
M8	0	0	0	0	1	1	1	0	0	0	0
M9	0	0	0	0	0	0	0	0	0	0	1
M10	1	1	1	0	0	0	0	0	0	0	0

(c): Rearranging the parts based on the hamming results

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M110
M1	0	0.3636	0.5455	0.5455	0.2727	0.3636	0.1818	0.4545	0.2727	0.0909
M2	0.3636	0	0.1818	0.1818	0.2727	0.3636	0.3636	0.2727	0.2727	0.4545
M3	0.5455	0.1818	0	0.3636	0.4545	0.5455	0.5455	0.0909	0.4545	0.6364
M4	0.5455	0.1818	0.3636	0	0.4545	0.5455	0.5455	0.4545	0.4545	0.6364
M5	0.2727	0.2727	0.4545	0.4545	0	0.0909	0.2727	0.3636	0.1818	0.3636
M6	0.3636	0.3636	0.5455	0.5455	0.0909	0	0.3636	0.4545	0.0909	0.4545
M7	0.1818	0.3636	0.5455	0.5455	0.2727	0.3636	0	0.4545	0.2727	0.0909
M8	0.4545	0.2727	0.0909	0.4545	0.3636	0.4545	0.4545	0	0.3636	0.5455
M9	0.2727	0.2727	0.4545	0.4545	0.1818	0.0909	0.2727	0.3636	0	0.3636
M10	0.0909	0.4545	0.6364	0.6364	0.3636	0.4545	0.0909	0.5455	0.3636	0

(d): Hamming distance for the machines

P/M	P1	P6	P5	P4	P2	P7	P9	P10	P3	P8
M1	1	1	0	0	0	0	0	0	0	0
M10	1	1	1	0	0	0	0	0	0	0
M7	0	1	1	0	0	0	0	0	0	0
M2	0	0	0	0	0	0	1	1	0	0
M4	0	0	0	1	0	0	1	1	0	0
M3	0	0	0	0	1	1	1	1	0	0
M8	0	0	0	0	1	1	1	0	0	0
M5	0	0	0	0	0	0	0	0	1	0
M6	0	0	0	0	0	0	0	0	1	1
M9	0	0	0	0	0	0	0	0	0	1

(e): Rearranging the machines based on the hamming results and identify PFs & MCs

Fig. (4- a, b, c, d, e): The steps of applying hamming distance on dataset 10*10

P/M	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
M1	0	0	1	1	0	1	0	0	0	0
M2	1	0	0	0	0	0	1	0	0	1
M3	0	1	0	0	1	0	0	1	0	0
M4	0	0	0	1	0	1	0	0	1	0
M5	0	1	0	0	1	0	0	1	0	0
M6	0	0	1	0	0	1	0	0	1	0
M7	0	0	0	0	0	0	0	0	0	1
M8	0	1	0	0	1	0	0	1	0	0
M9	0	0	1	1	0	1	0	0	1	0
M10	1	0	0	0	0	0	1	0	0	1
M11	1	0	0	0	0	0	1	0	0	1
M12	1	0	0	0	0	0	1	0	0	1
M13	0	1	0	0	1	0	0	1	0	0
M14	0	0	1	1	0	1	0	0	1	0
M15	0	1	0	0	1	0	0	1	0	0

(a): Part-machine matrix (10*15)

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
P1	0	0.6000	0.5333	0.5333	0.6000	0.6000	0	0.6000	0.5333	0.0667
P2	0.6000	0	0.6000	0.6000	0.0000	0.6667	0.6000	0.0000	0.6000	0.6667
P3	0.5333	0.6000	0	0.1333	0.6000	0.0667	0.5333	0.6000	0.1333	0.6000
P4	0.5333	0.6000	0.1333	0	0.6000	0.0667	0.5333	0.6000	0.1333	0.6000
P5	0.6000	0.0000	0.6000	0.6000	0	0.6667	0.6000	0.0000	0.6000	0.6667
P6	0.6000	0.6667	0.0667	0.0667	0.6667	0	0.6000	0.6667	0.0667	0.6667
P7	0.0000	0.6000	0.5333	0.5333	0.6000	0.6000	0	0.6000	0.5333	0.0667
P8	0.6000	0.0000	0.6000	0.6000	0.0000	0.6667	0.6000	0	0.6000	0.6667
P9	0.5333	0.6000	0.1333	0.1333	0.6000	0.0667	0.5333	0.6000	0	0.6000
P10	0.0667	0.6667	0.6000	0.6000	0.6667	0.6667	0.0667	0.6667	0.6000	0

(b): Hamming distance for the parts

P/M	P1	P7	P10	P2	P5	P8	P3	P4	P6	P9
M1	0	0	0	0	0	0	1	1	1	0
M2	1	1	1	0	0	0	0	0	0	0
M3	0	0	0	1	1	1	0	0	0	0
M4	0	0	0	0	0	0	0	1	1	1
M5	0	0	0	1	1	1	0	0	0	0
M6	0	0	0	0	0	0	1	0	1	1
M7	0	0	1	0	0	0	0	0	0	0
M8	0	0	0	1	1	1	0	0	0	0
M9	0	0	0	0	0	0	1	1	1	1
M10	1	1	1	0	0	0	0	0	0	0
M11	1	1	1	0	0	0	0	0	0	0
M12	1	1	1	0	0	0	0	0	0	0
M13	0	0	0	1	1	1	0	0	0	0
M14	0	0	0	0	0	0	1	1	1	1
M15	0	0	0	1	1	1	0	0	0	0

(c): Rearranging the parts based on the hamming results

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15
M1	0	0.6000	0.6000	0.2000	0.6000	0.2000	0.4000	0.6000	0.1000	0.6000	0.6000	0.6000	0.6000	0.1000	0.6000
M2	0.6000	0	0.6000	0.6000	0.6000	0.6000	0.2000	0.6000	0.7000	0.0000	0.0000	0.0000	0.6000	0.7000	0.6000
M3	0.6000	0.6000	0	0.6000	0.0000	0.6000	0.4000	0.0000	0.7000	0.6000	0.6000	0.6000	0.0000	0.7000	0.0000
M4	0.2000	0.6000	0.6000	0	0.6000	0.2000	0.4000	0.6000	0.1000	0.6000	0.6000	0.6000	0.6000	0.1000	0.6000
M5	0.6000	0.6000	0.0000	0.6000	0	0.6000	0.4000	0.0000	0.7000	0.6000	0.6000	0.6000	0.0000	0.7000	0.0000
M6	0.2000	0.6000	0.6000	0.2000	0.6000	0	0.4000	0.6000	0.1000	0.6000	0.6000	0.6000	0.6000	0.1000	0.6000
M7	0.4000	0.2000	0.4000	0.4000	0.4000	0.4000	0	0.4000	0.5000	0.2000	0.2000	0.2000	0.4000	0.5000	0.4000
M8	0.6000	0.6000	0.0000	0.6000	0.0000	0.6000	0.4000	0	0.7000	0.6000	0.6000	0.6000	0.0000	0.7000	0.0000
M9	0.1000	0.7000	0.7000	0.1000	0.7000	0.1000	0.5000	0.7000	0	0.7000	0.7000	0.7000	0.7000	0.0000	0.7000
M10	0.6000	0.0000	0.6000	0.6000	0.6000	0.6000	0.2000	0.6000	0.7000	0	0.0000	0.0000	0.6000	0.7000	0.6000
M11	0.6000	0.0000	0.6000	0.6000	0.6000	0.6000	0.2000	0.6000	0.7000	0.0000	0	0.0000	0.6000	0.7000	0.6000
M12	0.6000	0.0000	0.6000	0.6000	0.6000	0.6000	0.2000	0.6000	0.7000	0.0000	0	0	0.6000	0.7000	0.6000
M13	0.6000	0.6000	0.0000	0.6000	0.0000	0.6000	0.4000	0.0000	0.7000	0.6000	0.6000	0.6000	0	0.7000	0.0000
M14	0.1000	0.7000	0.7000	0.1000	0.7000	0.1000	0.5000	0.7000	0.0000	0.7000	0.7000	0.7000	0.7000	0	0.7000
M15	0.6000	0.6000	0.0000	0.6000	0.0000	0.6000	0.4000	0.0000	0.7000	0.6000	0.6000	0.6000	0.0000	0.7000	0

(d): Hamming distance for the machines

P/M	P1	P7	P10	P2	P5	P8	P3	P4	P6	P9
M2	1	1	1	0	0	0	0	0	0	0
M10	1	1	1	0	0	0	0	0	0	0
M11	1	1	1	0	0	0	0	0	0	0
M12	1	1	1	0	0	0	0	0	0	0
M7	0	0	1	0	0	0	0	0	0	0
M3	0	0	0	1	1	1	0	0	0	0
M5	0	0	0	1	1	1	0	0	0	0
M8	0	0	0	1	1	1	0	0	0	0
M13	0	0	0	1	1	1	0	0	0	0
M15	0	0	0	1	1	1	0	0	0	0
M4	0	0	0	0	0	0	0	1	1	1
M9	0	0	0	0	0	0	1	1	1	1
M14	0	0	0	0	0	0	1	1	1	1
M1	0	0	0	0	0	0	1	1	1	0
M6	0	0	0	0	0	0	1	0	1	1

(e): Rearranging the machines based on the hamming results and identify PFs & MCs

Fig. (5- a, b, c, d, e): The steps of applying hamming distance on dataset 10*15

Table 2: The results of the hamming distance of the selected datasets, using the number of cells, EE and Voids

Dataset	Performance measures		
	Number of cells (C)	**EE**	**Voids**
7*11	3	2	7
10*10	3	0	12
10*15	3	0	5

Table 3: Summary of the proposed method results in comparison with the best known results in the literature

Dataset	Hamming distance based method results				The best known results				Reference
	Performance measures								
	PE	**C**	**MU**	**GE**	**PE**	**C**	**MU**	**GE**	
5*7	0.1250	2	0.8235	0.8500	0.1250	2	0.8235	0.8256	Waghodekar and Sahu (1984)
7*11	0.0952	3	0.7307	0.8457	0.0952	3	0.7307	0.8457	Boctor (1991)
10*10	0.0000	3	0.6571	0.8285	0.0000	3	0.7059	0.8029	Mosier and Taube (1985)
10*15	0.0000	3	0.9000	0.9500	0.0000	3	0.9200	0.8710	Chan and Milner (1982)
8*20	0.1800	3	0.9615	0.9300	0.1475	3	1.0000	0.9583	Chandrasekharan and Rajagopalan (1986)

Table 4: The PE results by hamming distance with a comparison of the best known results in the literature

Dataset	Hamming distance	Best known results
	PE	PE*
5*7	0.1250	0.125
7*11	0.0952	0.0952
10*10	0.0000	0.0000
10*15	0.0000	0.0000
8*20	0.1800	0.1475

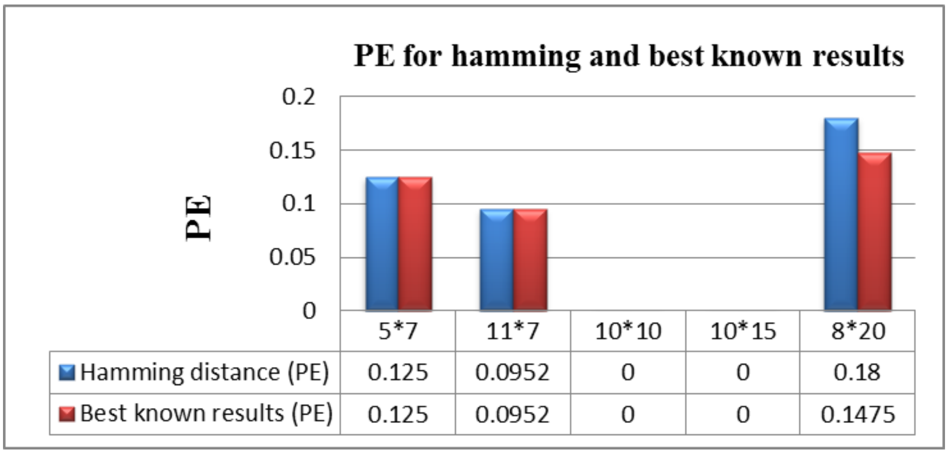

Fig. 6: The PE results by hamming distance with a comparison of the best known results in the literature

Table 5:The MU results of hamming distance with a comparison of the best known results in the literature

Dataset	Hamming distance	Best known results
	MU	MU*
5*7	0.8235	0.8235
7*11	0.7307	0.7307
10*10	0.6571	0.7059
10*15	0.9000	0.9200
8*20	0.9615	1.0000

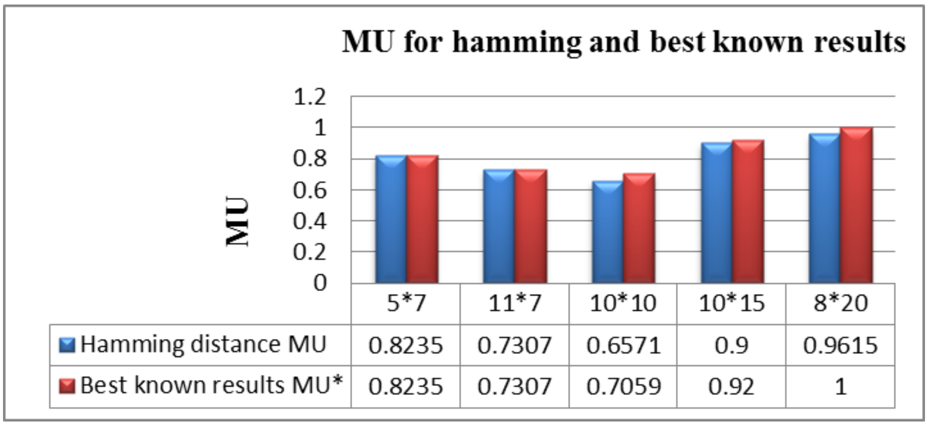

Fig. 7: The MU results by hamming distance with a comparison of the best known results in the literature

Table 6: The GE results by hamming distance with a comparison of the best known results in the literature

Dataset	**Hamming distance**	**Best known results**
	GE	**GE***
5*7	0.8500	0.8256
7*11	0.8457	0.8457
10*10	0.8285	0.8029
10*15	0.9500	0.8710
8*20	0.9300	0.9583

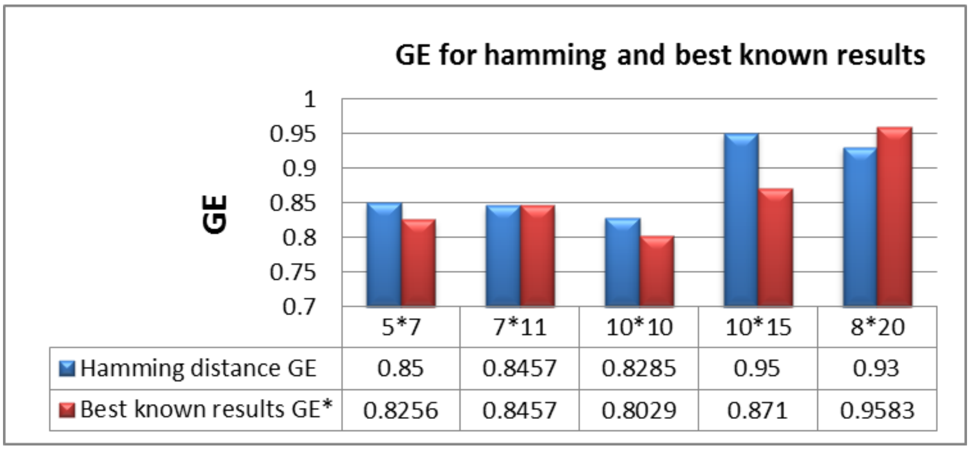

Fig. 8: The GE results by hamming distance with a comparison of the best known results in the literature

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