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Self Organization Map Applied for the Design of Cell Formation in a Cellular Manufacturing System

تطبيق خارطة الترتيب الذاتي (SOM) لتصميم تكوين الخلايا في نظام التصنيع الخلوي

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Abstract
Cell Formation (CF) problem is considered as the most important issue in the cellular manufacturing system. CF deals with the creation of Machine Cells (MCs) and Part Families (PFs). Numerous methods were proposed in the literature for solving the CF problem. The current paper used a strategy based on one well known method, namely Self Organization Map (SOM). It's used for the products firstly, then rearranged them to form the families. Afterward SOM used for the machines, then rearranged them as cells. The output of the proposed method was compared with the best mentioned results in the literature. Five performance measures were used for the comparison and evaluation, these measures are Percent of Exceptional PE elements, Voids V, Intercellular moves IC, Grouping Efficiency GE and Machine Utilization MU. The results referred to the outperforms of the SOM based method, where it leads to reduce the number of IC moves. The PE values are equal or almost equivalent to the best known results, the MU results are approximately equivalent to the best recognized results and the GE results are better than the best identified results for the most problems.
Keywords: Cell formation, cellular manufacturing, group technology, self organization map, machine utilization, grouping efficiency, exceptional elements

المستخلص:
ان مشكلة تكوين الخلايا تعد هي المسالة الاكثر أهمية في نظام التصنيع الخلوي. ان تكوين الخلايا يتضمن تكوين عوائل الاجزاء وخلايا المكائن. من خلال البحوث السابقة اقترحت طرائق عديدة لحل هذه المشكلة. في البحث الحالي اتبعت ستراتيجية تعتمد على طريقة معروفة تسمى (SOM). تطبق هذه الطريقة على الاجزاء اولا ثم تعيد ترتيبها للحصول على العوائل. بعد ذلك تطبق نفس الطريقة على المكائن ثم تعيد ترتيبها لتكون الخلايا. تمت مناقشة النتائج من هذه الطريقة مع افضل النتائج المنشورة. تم استخدام خمسة معايير لتقييم الاداء لغرض مقارنة وتقييم النتائج؛ هذه المعايير هي نسبة الاجزاء الحرجة (PE)؛ عدد العمليات التي تشير الى توقف المكائن (V) ؛عدد مرات التنقل بين الخلايا (IC)؛ كفاءة التجميع (GE) واستغلال المكائن (MU). اشارت النتائج التي تم الحصول عليها الى كفاءة الطريقة المتبعة (SOM) حيث ادت هذه الطريقة الى تقليل عدد مرات التنقل بين الخلايا؛ تساوي بشكل كامل او تقريبي لنسبة الاجزاء الحرجة مع افضل النتائج؛ نتائج استغلال المكائن كانت تقريبا مكافئة لافضل النتائج اما كفاءة التجميع فكانت افضل من النتائج المنشورة في البحوث السابقة
الكلمات المفتاحيه: تكوين الخلايا؛ التصنيع الخلوي؛ تكنولوجيا المجموعة؛ خارطة الترتيب الذاتي؛ استغلال المكائن؛ كفاءة التجميع؛ الاجزاء الحرجة

1. Introduction
Cellular manufacturing (CM) is considered as one of the best approaches that deals with the customer requirements and the problem of continuous change in the product designs. 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 significant issue in the cellular manufacturing system. It deals with collecting the parts in groups known as families based on similarities in the design or process features. As well as, collecting the dissimilar machines that used to perform the families of parts in groups known as cells.

The present paper focused on the CF issue, where a method based on the SOM was used to create MCs and PFs. In the literature, several methods and algorithms are proposed for solving the CF problem. These methods are based on: similarity coefficient, array based clustering, mathematical programming, artificial intelligence, heuristics, meta-heuristics, etc. Fig. (1) refers to a good classification of the CM methods [1]

Wu and Suzuki [2] have developed a new method for solving CF Problem. The proposed methodology includes two steps. In the first step, a new SC method was developed. This SC involves the number of repeated operations and sequences of operations to create PFs. However, a new mathematical model was used in the second step.

This model contains some features such as: operation time, machine capacity, alternative routing, lot splitting and part demand to assign machines to part families with a minimum operation cost, machine cost and inter-cell movement cost. This method compares between the inter-cell movement cost and the machine's duplication cost. The test data sets showed the effectiveness of the proposed method.

Pradhan and Mishra [3] proposed a method based on the SOM to shape PFs and Minkowski distance to build MCs. They proved the efficiency of their proposed method with GC equal to 96.4 %. Potočnik et al., [4] applied a new method based on the self organizing map for facility layout. Their proposed method divided into two stages, in the first stage the SOM based technique used to build MCs and PFs, while in the second stage the facility layout has been done with the consideration of the material handling method and the application in the real life factory.

Chattopadhyay et al., [5] used SOM for solving the CF problem with the objective to increase the group technology efficiency. They evaluated the proposed SOM by using some benchmark problems selected from the literature. They proved the efficiency of their method. As well as, Chattopadhyay et al., [6] utilized two methods for solving the CF problem. The first method called Principle Component Analysis (PCA) used for data extraction. However, the second method called SOM and used for creating visual clustering. These two methods were applied for part-machine initial matrix with sequence of operations.

Chattopadhyay et al., [7] proposed a new approach for the CF based on using SOM. Their method was applied for binary matrix (0,1) part- machine matrix, where some problems were selected from the literature to apply the proposed method. The output refers to the improvement of the grouping efficacy of 70% of the selected datasets.

Again Chattopadhyay et al., [8] used SOM for solving the 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 their application on 15 problems from the previous literature and recorded an improvement of GC and GTE for 70% of data sets.

Venkumar and Haq [9] have applied a Kohonen Self Organizing Map (KSOM). The effectiveness of the proposed method was identified by the number of voids and exceptional elements. The proposed method was utilized on some benchmarked datasets selected from the literature. GE was used as a performance measure to compare the results of the proposed method with the best known results in the literature. The output was found to be better than or equal to the outputs of other algorithms in the terms of reducing the number of the exceptional elements.

In the current paper SOM was used for parts to form families, then it applied for machines to shape cells. Afterward the proposed method applied on some benchmark problems selected from open literature and evaluated by some well-known performance measures to verify the effectiveness.

2. Self Organization Map

Self Organizing Map (SOM) is an artificial neural network used to convert the high dimensional data to one or two dimensional data. It is trained using unsupervised learning.SOM follows competitive learning with neighborhood function to keep the same topological properties. For the input space, SOM provides a data visualization technique that enables humanity to visualize the high dimensional data in low dimensional data. One major advantage of using SOM is data clustering where SOM capabilities of cluster data in similar groups, SOM clustering done by competing units for current object when data input to the system [10].

The neural network is trained by supplying the input information, one active winning unit is chosen based on the closest weight vector unit to the current object. In the training phase, the input variable values are step by step adjusted trying to keep the neighborhood relationships that exist within the input data set. The neighbors and the winning unit weights are adjusted as it gets closer to the input object. SOM trained with unsupervised learning to classify the data, making it does not need any target vector to do classification [11]. Fig. 2 refers to the SOM idea.

2.1. Similarity

Best Matching Unit is reached by calculating the distance between all input vectors and the sample vector, then getting the weight running through all of them. The winner weight is the one with the shortest distance. There are many ways to calculate the distance.

2.2. Algorithm

The weight vectors are initialized to start SOM mapping. A sample vector is selected randomly and searching the map of weight vectors to find which sample is best represented by the weight, rewarding the weight that is chosen by being able to become more similar to the sample vector that was randomly selected. Neighboring weights are available for each weight vector and are close to it, rewarding the neighbors of that weight also by being able to become more similar to the chosen sample vector. At this point the number of neighbors decreases also weight learning rate decreases over time. This whole process is repeated a large number of times [11].

3. Methodology

The approach that followed in the present paper divided into two sections. In the first section, the SOM was used for creating PFs. Then SOM was applied in the second section to shape MCs. After that, some well-known performance measures that were reported widely in the literature due to their popularity were used to evaluate the results of the proposed method. These performance measures are Inter-cellular moves (IC), Percent of Exceptional elements (PE), Voids (V), Grouping Efficiency (GE) and Machine Utilization (MU).

Three matrices were selected from the published research work to apply the proposed method. These matrices are (5*7, 8*10, 8*20). The first number in each matrix refers to the number of machines, while the second number refers to the number of parts. However, each matrix means a manufacturing system. On the other hand, each matrix was based on a binary number (0, 1), for this purpose this matrix called binary or (0, 1) matrix. Furthermore, the 1 here means the part needs the machine while zero otherwise. Fig. 3 shows the methodology flow chart.

3.1. The application of SOM

To apply the proposed methodology successfully a Matlab R2016b (9.1.0.441655) September 7, 2016 64 bit has been used. The steps of the proposed method are explained as follows:

1. Select three data sets (matrices) from the published research work (5*7, 8*10, 8*20).
2. Apply SOM for the parts in the three selected matrices, for example, in a dataset (5*7), Fig. 3, the inputs 1&3 , 2&4 are similar. 7 is close to 1&3. 6&5 are close to 2&4.
3. Rearrange the matrix accordingly to create PFs.
4. Apply SOM for the machines. Also for the same dataset (5*7), the machines arrange based on the similarities in the distribution of the colors as in step 2.
5. Rearrange the matrix again to find the MCs.
6. The final matrix displays the MCs and PFs, Figs 4, 5, 6 (a, b, c, d, e, f) refer to the steps of the proposed method for datasets (5*7, 8*10, 8*20).

3.2. Performance measures

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

3.2.1. Number of the Intercellular Moves (IC)

Inter-cellular moves refer to the number of operations (1's) that are located outside the diagonal blocks. These 1's are known as Exceptional Elements (EE) and need to visit more than one cell to complete their operations. The EE are operated by some machines known as bottleneck machines. The bottleneck machines and EE are considered as an expensive problem in the CMS because the solution of these problems needs to either duplicate the machines or subcontract the parts. EE can be computed as in Eq. 1:

$$E = eo \qquad (1)$$

Where, eo: is the number of EEs or the off-diagonal positive entries [12]. 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 3.2.2.

3.2.2. Percentage of the Exceptional Elements (PE)

The grouping quality can be calculated by the number of parts which remain outside the block diagonals [13, 14]. 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. [15] reported that the lower PE refers to better clustering results. Eq. 1 represented the PE [12, 16]:

$$\mathrm{PE} = \frac{\mathrm{EE}}{\mathrm{UE}} * 100 \qquad (2)$$

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).

3.2.3. 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 do not need to operate on some machines or some machines have idle times and do not use all the available capacity.

3.2.4. Machine Utilization (MU)

Machine Utilization refers to the percentage of utilizing the machines inside the cells obtained in the production. [12, 16] proposed Eq. 2 to compute MU as follows:

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

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 [15].

3.2.5. Grouping Efficiency (GE)

Grouping Efficiency GE can be defined in Eq. (4):

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

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 [12, 16].

3.3.The Performance measures results

Five performance measures have been used to assess the performance of the final solution for the five selected datasets (5*7, 7*11, 10*10, 10*15, 8*20). These well-known performance measures are: Voids, Machine Utilization, Inter-Cellular movement, Grouping Efficiency, Percentage of Exceptional elements, (Voids, MU, IC, GE, PE,) respectively. The results of utilizing these performance measures and the source of datasets are shown in Table 1 and Table 2.

4. Results and discussion

The results on several benchmark problems are summarized in Table (2). This Table displays the results of the proposed method in comparison with the best known results in the literature. Table (2) involves five benchmark problems and four performance measures for each one. Among the total twenty performance indexes, three are better than, eight are equal to and nine are almost equivalent to the best known results.

From Fig 7 (a, b) three of the five selected datasets produced PE results equal to the best known results while the rest two datasets produced different results. In the terms of the MU, Fig 7 (c, d) reveals that one dataset from five recorded MU equal to the best mentioned results in the literature. However, the results of the rest four data sets are almost equivalent to the best known results. For the GE Fig 7 (e, f), the proposed method produced results better than for three data sets and two results less than the best known results. The output reveals that the SOM based method is effective and efficient for solving the cell formation problem particularly in the terms of the number of machine cells C, grouping efficiency GE and machine utilization MU.

5. Conclusions

In the current paper, a SOM based method is proposed for creating machine-cells and part-families. The proposed method applied SOM firstly for the parts, then rearranged them based on the results to form PFs. However, again SOM applied, but for the machines and rearranged them based on the results to shape MCs. The effectiveness of the proposed method was examined by some performance measures. The present method is demonstrated to be an effective and efficient according to the obtained results of the comparative study with the previously published results in the literature. In conclusion, the results of the proposed methodology investigated the following:

1. Missing or reducing the number of inter-cellular moves (IC).
2. The PE values are equal to or almost equivalent to the best known results.
3. The MU results are approximately equivalent to the best recognized results.
4. The GE results are better than the best identified results for the most problems.

For the future work, it is suggested to use large size datasets (matrices) and compare the results of the proposed method with the results of other methods such as Rank order clustering (ROC) based methods, Similarity Cofficient based methods, Heurestic-Meta heuristic based methods, etc.

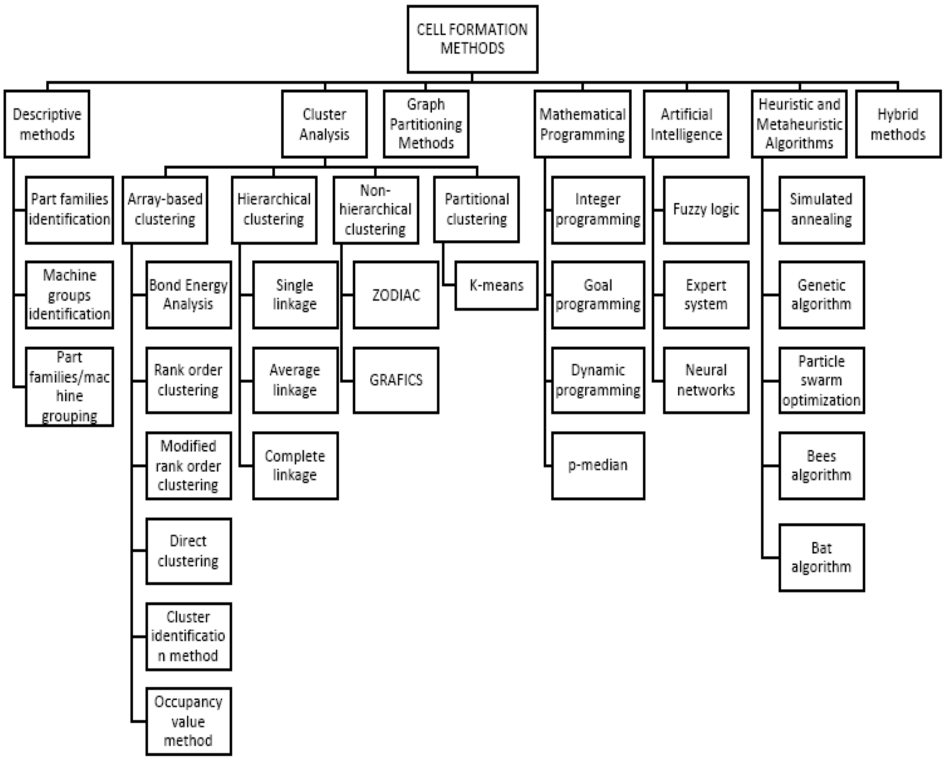


Fig. (1). Classification of the CM methods.

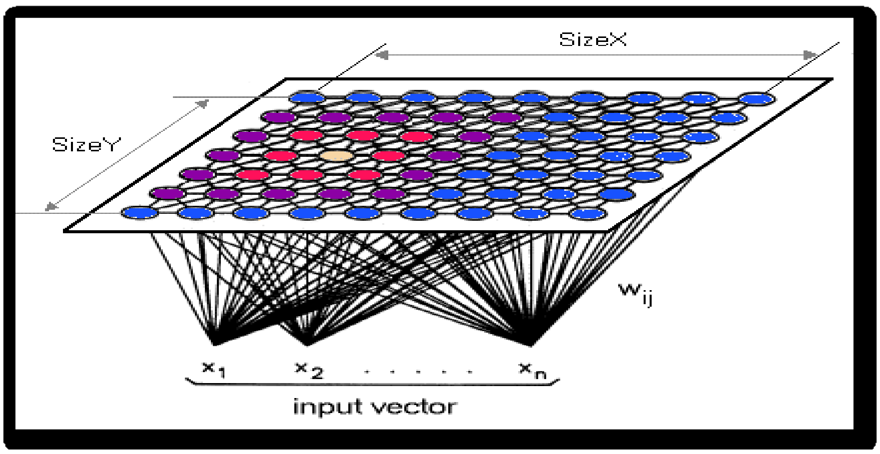


Fig. 2. The SOM idea.

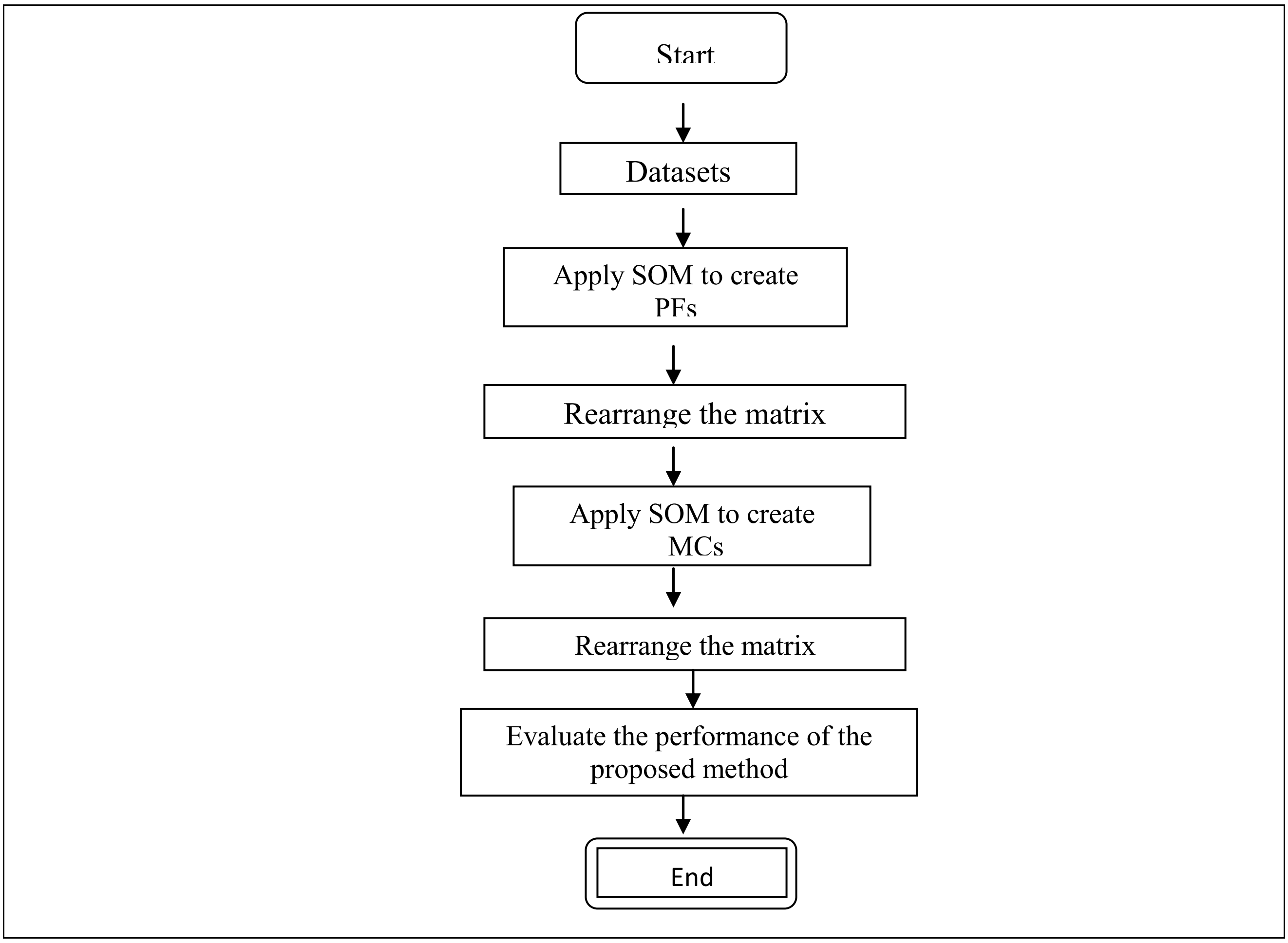
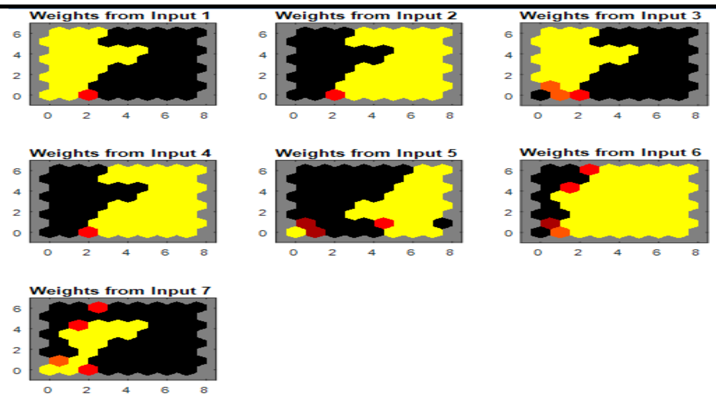


Fig. 3. The methodology flow chart.

	P1	P2	P3	P4	P5	P6	P7
M1	0	1	0	1	1	1	0
M2	1	0	1	0	0	0	0
M3	1	0	1	0	0	1	1
M4	0	1	0	1	0	1	0
M5	1	0	0	0	1	0	1

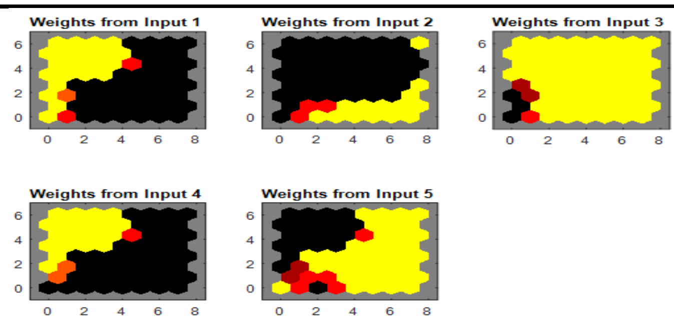
(a): Part-machine matrix (5*7).



(b): Apply SOM for parts.

	P7	P1	P3	P2	P4	P6	P5
M1	0	0	0	1	1	1	1
M2	0	1	1	0	0	0	0
M3	1	1	1	0	0	1	0
M4	0	0	0	1	1	1	0
M5	1	1	0	0	0	0	1

(c) Rearrange parts based on the SOM results.



(d): Apply SOM for machines.

	P7	P1	P3	P2	P4	P6	P5
M1	0	0	0	1	1	1	1
M4	0	0	0	1	1	1	0
M5	1	1	0	0	0	0	1
M2	0	1	1	0	0	0	0
M3	1	1	1	0	0	1	0

(e): Rearrange machines based on the SOM. results.

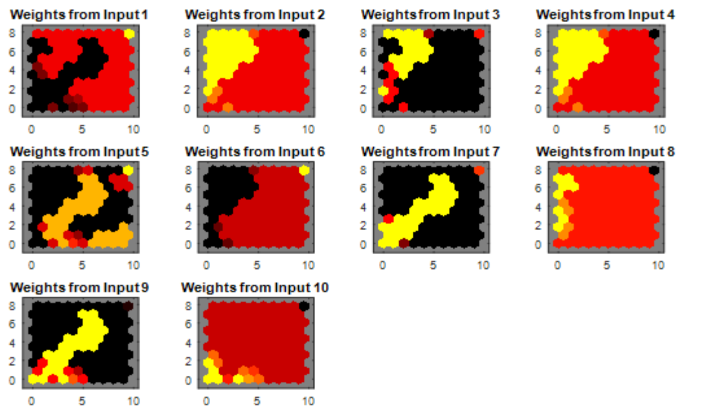
	P7	P1	P3	P2	P4	P6	P5
M1	0	0	0	1	1	1	1
M4	0	0	0	1	1	1	0
M5	1	1	0	0	0	0	1
M2	0	1	1	0	0	0	0
M3	1	1	1	0	0	1	0

(f): Identify MCs and PFs

Fig. (4- a, b, c, d, e, f). Steps of the proposed method for data set (5*7).

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

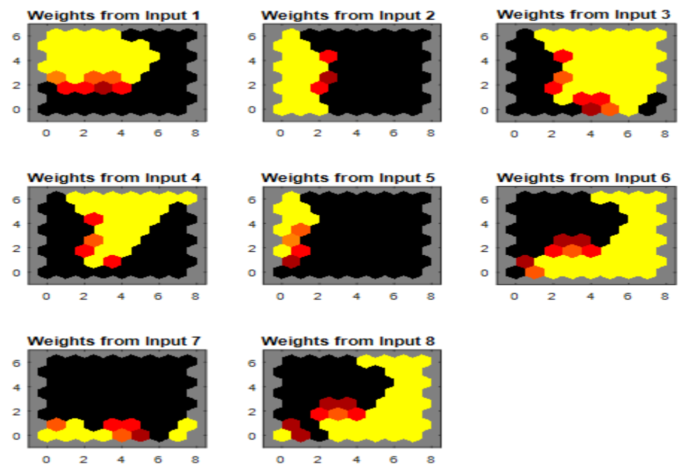
(a): Part-machine matrix (8*10).



(b): Apply SOM for parts.

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

(c) Rearrange parts based on the SOM results.



(d): Apply SOM for machines.

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

(e): Rearrange machines based on the SOM results.

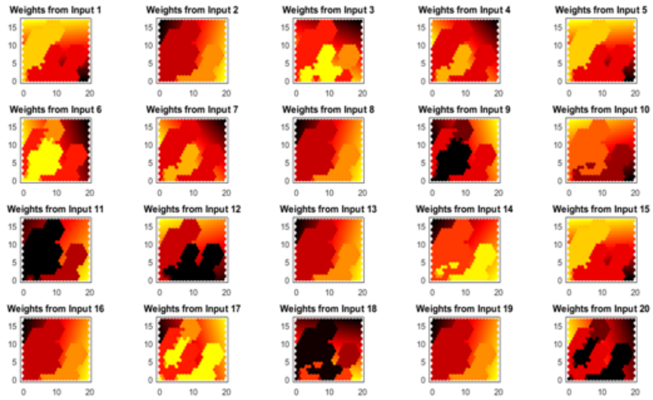
	P2	P4	P8	P3	P10	P7	P9	P5	P6	P1
M2	1	1	1	1	1	1	0	0	0	0
M5	1	1	1	0	0	0	0	0	0	0
M1	1	1	0	1	0	0	0	0	0	1
M6	0	0	0	0	0	1	1	1	1	0
M8	0	0	0	0	1	0	1	1	1	0
M3	0	0	0	0	0	0	0	1	1	1
M4	0	0	0	0	0	0	0	0	1	1
M7	0	0	0	0	1	1	1	0	0	0

(f): Identify MCs and PFs.

Fig. (5- a, b, c, d, e, f). Steps of the proposed method for data set (8*10).

Machines	Parts																			
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	1	1	0	0	0	0	1	1	0	1	0	1	1	0	1	1	0	1	0
2	0	0	1	1	0	1	1	0	0	0	0	0	0	1	0	0	0	1	0	1
3	0	1	0	0	0	0	0	1	1	0	1	0	1	1	0	1	1	1	1	0
4	0	0	1	1	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	1
5	1	0	0	0	1	1	0	0	0	1	0	1	0	0	1	0	1	0	0	0
6	1	0	0	0	1	0	0	0	1	1	0	1	0	0	1	0	0	0	0	1
7	0	0	1	1	0	1	1	0	0	0	1	1	0	0	0	0	0	1	0	1
8	0	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	1	0	1

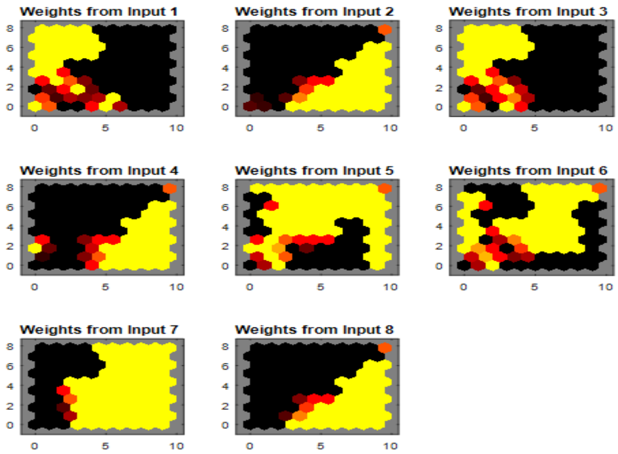
(a): Part-machine matrix (8*20).



(b): Apply SOM for parts.

Machines	Parts																			
	2	8	13	16	19	14	11	9	17	12	10	1	5	15	3	4	7	6	20	18
1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	1	0	0	0	0	0
2	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1	1	1	1	1
3	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	1
4	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	1	1	1	0
5	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	1	0	0
6	0	0	0	0	0	0	0	1	0	1	1	1	1	1	0	0	0	0	1	0
7	0	0	0	0	0	0	1	0	0	1	0	0	0	0	1	1	1	1	1	1
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1

(c) Rearrange parts based on the SOM results.



(d): Apply SOM for machines.

Machines	Parts																			
	2	8	13	16	19	14	11	9	17	12	10	1	5	15	3	4	7	6	20	18
1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	1	0	0	0	0	0
3	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	1
5	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	1	0	0
6	0	0	0	0	0	0	0	1	0	1	1	1	1	1	0	0	0	0	1	0
7	0	0	0	0	0	0	1	0	0	1	0	0	0	0	1	1	1	1	1	1
4	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	1	1	1	0
2	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1	1	1	1	1
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1

(e): Rearrange machines based on the SOM results.

Machines	Parts																			
	2	8	13	16	19	14	11	9	17	12	10	1	5	15	3	4	7	6	20	18
1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	1	0	0	0	0	0
3	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	1
5	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	1	0	0
6	0	0	0	0	0	0	0	1	0	1	1	1	1	1	0	0	0	0	1	0
7	0	0	0	0	0	0	1	0	0	1	0	0	0	0	1	1	1	1	1	1
4	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	1	1	1	0
2	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1	1	1	1	1
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1

(f): Identify MCs and PFs.

Fig. (6- a, b, c, d, e, f). Steps of the proposed method for data set (8*20).

Table (1). The results of the proposed method in the terms of (V and IC).

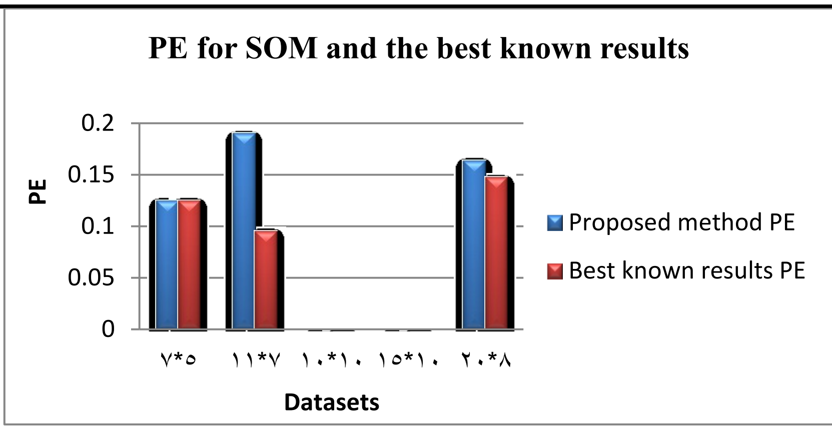
Dataset	V	IC	Reference
5*7	3	2	[17]
7*11	10	4	[18]
10*10	14	0	[19]
10*15	5	0	[14]
8*20	1	10	[12]

Table (2). The results of the proposed method in comparison with the best known results.

Dataset	SOM based method results				The best known- results			
	Performance measures							
	C	PE	MU	GE	C	PE	MU	GE
5*7	2	0.1250	0.8235	0.8561	2	0.1250	0.8235	0.8256
7*11	3	0.1904	0.6296	0.7748	3	0.0952	0.7307	0.8457
10*10	3	0.0000	0.6216	0.8108	3	0.0000	0.7059	0.8029
10*15	3	0.0000	0.9000	0.9500	3	0.0000	0.9200	0.8710
8*20	3	0.1639	0.9807	0.8941	3	0.1475	1.0000	0.9583

Dataset	Proposed method	Best known results
	PE	PE
5*7	0.1250	0.1250
7*11	0.1904	0.0952
10*10	0.0000	0.0000
10*15	0.0000	0.0000
8*20	0.1639	0.1475

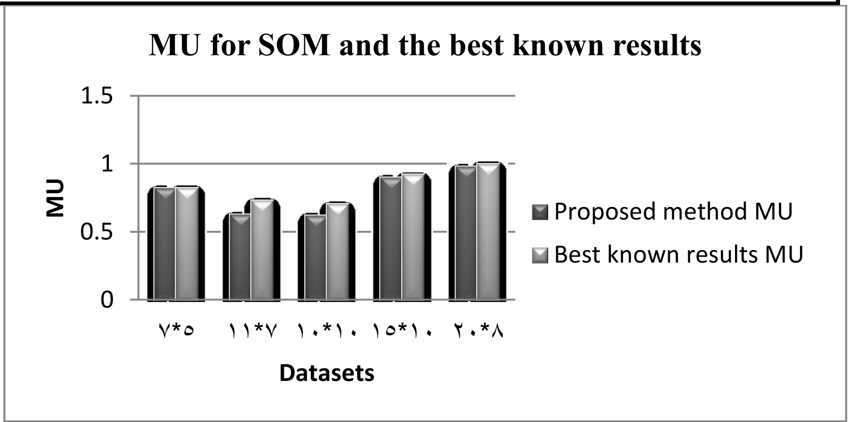
(a): The PE results of SOM with a comparison of the best known results in the literature



(b): The PE results of SOM with a comparison of the best known results in the literature

Dataset	Proposed method	Best known results
	MU	MU
5*7	0.8235	0.8235
7*11	0.6296	0.7307
10*10	0.6216	0.7059
10*15	0.9000	0.9200
8*20	0.9807	1.0000

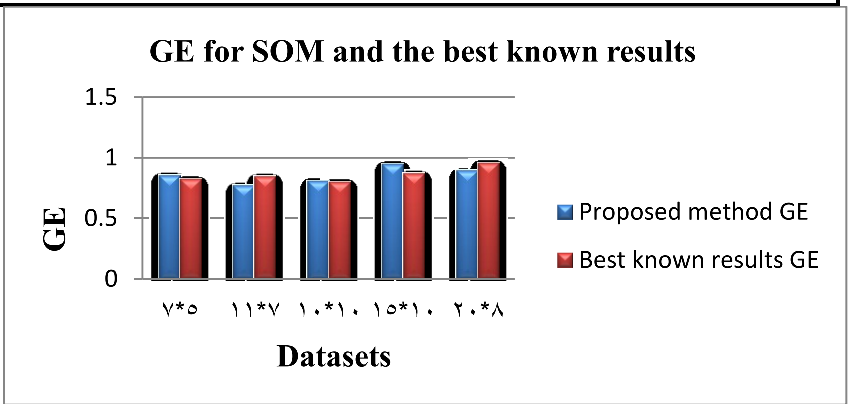
(c): The MU results of SOM with a comparison of the best known results in the literature



(d): The MU results of SOM with a comparison of the best known results in the literature

Dataset	Proposed method	Best known results
	GE	GE
5*7	0.8561	0.8256
7*11	0.7748	0.8457
10*10	0.8108	0.8029
10*15	0.9500	0.8710
8*20	0.8941	0.9583

(e): The GE results of SOM with a comparison of the best known results in the literature



(f): The GE results of SOM with a comparison of the best known results in the literature

Fig. (7, a, b, c, d, e, f). The proposed method results in comparison with the best known

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