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Exploration into The Effect of The Real Life Production Factors in The Assessment of Cellular Manufacturing System

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Abstract

Cellular Manufacturing (CM) is a production philosophy that operates in view of the Group Technology (GT) morality. CM offers a positive impact in the terms of enhancing the quality and increasing the productivity. One of the earlier and essential stages in the CM is known as a Feasibility Assessment (FA). FA considers as an evaluation stage and its results consider as a prediction results for the next design stage called Cell Formation (CF). The output of the FA includes the predicted number of machine cells, the decision of applying or not the CM and the quality of the expected solution. Most of the previous studies focused on studying the influence of the real life production features on the second stage (CF) and recorded significant results. However, an attempt was carried out in the current paper to study the influence of the real life production features on the first stage FA. For this purpose, 19 data sets, two Similarity Coefficients (SCs) based on the real life production features known as production volume and batch size were selected. The results of these two features compared with the results of one well known General Purpose Similarity Coefficient (GPSC) known as Jaccard. Jaccard works based on using only (0,1) matrix as an input data. The output of the current research referred that there is no significant influence of the real life production features on the FA, where 84% of data sets produced the same number of machine cells by using all the three different types of SCs. However, (16%) of datasets created different solutions Thus, Datasets based on (0,1) matrix and (GPSC), (Jaccard) are sufficient to use in the FA to predict the number of machine cells.

Keywords: Cellular manufacturing, Feasibility assessment, Group technology, General purpose similarity coefficient, Real life production features.

الخلاصة

نظام التصنيع الخلوي هو فلسفة تصنيع تعتمد على اسس تكنولوجيا المجموعة. لنظام التصنيع الخلوي فوائد ايجابية في تحسين النوعية وزيادة الانتاجية. ان احد مراحل التصنيع الخلوي المهمة تسمى مرحلة التقييم (FA). تعتبر نتائج مرحلة التقييم نتائج تنبؤية للمرحلة اللاحقة وهي مرحلة التصميم والتي تسمى تكوين الخلايا (CF). وخلال مرحلة التقييم يتم: تحديد عدد خلايا المكائن المتكونة؛ القرار حول تطبيق نظام التصنيع الخلوي ام لا واخيرا نوعية الحل. ان معظم الدراسات السابقة قد ركزت على دراسة تأثير العوامل الانتاجية على مرحلة التصميم (CF) وسجلت نتائج مهمة لهذه العوامل. هذا البحث يمثل محاولة لدراسة تاثير هذه العوامل الانتاجية على مرحلة التقييم (FA). لهذا الغرض تم اختيار اثنان من معاملات التشابه التي تستند على العوامل الانتاجية (حجم الانتاج وحجم الدفعة). النتائج التي تم استحصالها بأستخدام معاملي التشابه المذكورين تم مقارنتها مع احد معاملات التشابه المعروفة والمستخدمة بشكل واسع وتعرف بمعاملات التشابه ذات الاستخدام العام. ومنها معامل يدعى (جاكارد). ان نتائج البحث اشارت الى عدم وجود تأثير مهم عند استخدام هذه العوامل الانتاجية في مرحلة التقييم حيث ان 84% من المصفوفات انتجت نفس العدد من خلايا المكائن بأستخدام معاملات التشابه الثلاثة المختلفة في حين ان 16% فقط من المصفوفات انتجت عدد مختلف من خلايا المكائن. وبناءا على النتائج المستحصلة فأن مصفوفة (صفر-1) ومعامل التشابه العام (جاكارد) يكفي لاستخدامه في مرحلة التقييم لتحديد عدد خلايا المكائن.

الكلمات المفتاحية: التصنيع الخلوي؛ تقييم التطبيق؛ تكنولوجيا المجموعة؛ معامل التشابه ذو الغرض العام؛ عوامل انتاجية واقعية.

1. Introduction

Feasibility Assessment (FA) is a vital stage in the Cellular Manufacturing (CM) system and considers as an evaluation issue. During the FA, the information of the existing manufacturing system has been studied and analyzed.

The outcomes of the FA used as a guide to decide on the possibility or not for changing the present manufacturing system to CM. Therefore, this is an effortless approach to inspect the system before the application of CM. The output of the FA involves: (i) identify the expected machine cells (ii) recognize the correct decision of CM application and (iii) distinguish the goodness of the clustering (Basher and Karaa, 2008).

The studies in the (FA) stage are very restricted, one of the initial research work was carried out by (Maleki, 1991), he used two real life production features known as product variety and annual production quantity. On the other hand, (Arvindh and Irani , 1994) introduced a more complicated approach that includes another feature called the index of clustering tendency. They utilized the Principle Component Analysis (PCA) with the two essential dimensions (machines and parts) that utilize as an information in to deal with the issue of CM.

(Luong *et.al.,*2002) proposed a method based on the annual time and annual quantity of the product. They used the verity ratio for the product as a basic aspect for evaluating the suitability of the CM. Afterward, Basher and Karaa, 2008 proposed an effective and simple method for the FA in order to judge the possibility of converting the existing system to CM. Furthermore, they identified the number of machine cells and formulated an equation to identify the value of the obtained solution.

(Hamza and Adesta, 2013, a) applied nineteen Similarity Coefficients (SCs) (General Purpose Similarity Coefficient (GPSC) and problem oriented) from (Yin and Yasuda, 2006), then compared their results with the Jaccard measure in the FA stage. They proved the ability of utilizing these nineteen measures to predict the solution for the next stage Cell Formation (CF). As well,(Hamza and Adesta, 2013, b) compared two methods to identify the number of machine cells in the FA. The first method is based on using the number of machines in the initial matrix and the pre-determinable maximum limit of machines in each machine cell. However, the second method is based on one of the GPSCs called Rogers and Tanimoto. The results of this study referred to the accuracy of the GPSC based method.

Additionally, Hamza and Adesta in the same year (2013, c) integrated the FA with the CF by utilizing three methods, the first and the second method are based on the SC called (Baroni-urbane and Buser, and Sorenson). However, the third method is based on the rank order clustering. These methods applied to the (0,1) initial matrix. The outcomes of this investigation referred to a similar results by all the three proposed strategies, consequently the specialists advised to utilize similar SCs in the two phases, FA and CF to diminish the time and exertion of the calculations.

(Raja and Anbumalar , 2016) applied the generalized SC method to integrate the FA and CF with the incorporating of the operation sequence. The aim of their proposed method is to identify the correct number of machine cells. To verify this objective, they used the methodology of (Kaiser, 1960) and the eigenvalues of the SC matrix. Finally, they proved that their proposed method more efficient than the existing methods.

It can be observed from the above brief literature that the studies on the FA are very limited and this is the basic motivation of the current research to center of attention on this topic. On the other hand, this paper focused mainly on the effect of the real life production features on the predicted number of machine cells in the FA. For this reason, two well known SCs based on the real life production features called production volume and batch size were used in the present study.

2. Real life production features in the proposed method

In order to study the influence of the similarity coefficients (SCs) that involve the real life production features on the FA, two types of the SCs (SC based on the production volume and SC based on the batch size) were selected. However, these two SCs and further SC which classifies as a general purpose similarity coefficient (GPSC) and called Jaccard were utilized in the FA. The equations of these three SCs formulated by (Seifoddini and Djassemi, 1991; Seifoddini and Djassemi, 1996; Seifoddini and Tjahana, 1999) and displayed in the following:

2.1. **Jaccard Measure**

Equation 1 refers to the Jaccard measure which classifies as a general purpose SC. It needs only the information of the part-machine matrix (0,1 matrix), Table 1.

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

2.2. **Production Volume based Measure**

Equation 2 refers to the SC based on the production volume of the products. It classifies as a SC based on the real life production factors which needs the values of the production volume in addition to the information of the (0,1) matrix, Table 2.

$$S_{ij} = \frac{\sum_{k=1}^{n} V_k X_{ijk}}{\sum_{k=1}^{n} V_k Y_{ijk}} \qquad (2)$$

2.3. **Batch Size based Measure**

Equation 3 refers to the SC based on the batch size of the products. It also classifies as a SC based on the real life production factors and needs the values of the batch size in addition to the information of the (0,1) matrix, Table 3.

$$BS_{ij} = \frac{\sum_{k=1}^{n} \left(\frac{V_k}{b_k}\right) * X_{ijk}}{\sum_{k=1}^{n} \left(\frac{V_k}{b_k}\right) * Y_{ijk}} \qquad (3)$$

Where, S_{ij}: similarity coefficient between machines *i* and *j;* V_k: production volume for part type *k*, n: number of part types; 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; B_{Sij}: batch similarity coefficient; b_k: batch size.

Nineteen numerical examples were selected from the open literature as shown in Table 4 to verify the proposed method in the FA. Firstly, the two selected SCs based on the (production volume and batch size) were used. Then the results of these two SCs compared with the results of Jaccard measure. Afterward, the performance of each of the three SC was evaluated. The values of production volume and batch size of the parts in the (0,1) incidence matrix (part- machine) matrix were generated randomly.

Table 1: Jaccard SC, using only (0,1) matrix of data set (7*8)

M\P	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**
M1	0	1	0	1	0	0	0	0
M2	1	1	0	0	0	1	1	1
M3	0	0	1	0	0	1	0	1
M4	0	0	0	1	0	0	1	0
M5	1	0	1	0	1	1	0	1
M6	0	0	0	1	0	0	1	0
M7	1	1	0	0	0	1	1	1

Table 2: SC, using (0,1) matrix and production volume of data set (7*8)

M\P	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**
M1	0	1	0	1	0	0	0	0
M2	1	1	0	0	0	1	1	1
M3	0	0	1	0	0	1	0	1
M4	0	0	0	1	0	0	1	0
M5	1	0	1	0	1	1	0	1
M6	0	0	0	1	0	0	1	0
M7	1	1	0	0	0	1	1	1
Prod-uction volume	**150**	**120**	**100**	**120**	**100**	**140**	**160**	**150**

Table 3: SC, using (0,1) matrix and batch size of data set (7*8)

M\P	P1	P2	P3	P4	P5	P6	P7	P8
M1	0	1	0	1	0	0	0	0
M2	1	1	0	0	0	1	1	1
M3	0	0	1	0	0	1	0	1
M4	0	0	0	1	0	0	1	0
M5	1	0	1	0	1	1	0	1
M6	0	0	0	1	0	0	1	0
M7	1	1	0	0	0	1	1	1
Batch size	**50**	**60**	**50**	**40**	**20**	**70**	**80**	**30**

Table 4: The selected datasets from open literature

Data set	Matrix	Matrix Size	Reference	Year
1	4*4	16	Singh and Rajamani	1996
2	4*5	20	Singh and Rajamani	1996
3	5*5	25	Singh and Rajamani	1996
4	5*6	30	Singh and Rajamani	1996
5	5*7	35	Waghodekar and Sahu	1984
6	6*7	42	Waghodekar and Sahu	1984
7	6*8	48	Basher and Karaa	2008
8	7*8	56	Chen et al	1996
9	7*11	77	Bocter	1991
10	8*10	80	Arikaran and Jayabalan	2011
11	7*14	98	Mahdavi et al	2010
12	9*11	99	Salehi and Moghaddam	2009
13	10*10	100	Chattopadhyay et al	2011
14	12*10	120	McAuley	1972
15	15*10	150	Chan and Milner	1982
16	8*20	160	Chandraasekharan and Rajagopalan	1986
17	14*24	336	King	1980
18	16*30	480	Bocter	1991
19	16*43	688	King and Nakornchai	1982

3. Methodology

The applied methodology in the current study displayed in Fig 1 and explained in the following, Firstly the SC matrices calculated for all the datasets in Table 4, utilizing the three types of the selected SCs (Equations 1, 2, 3), the results of this step illustrated in Tables (5, 6 and 7) for one data set (7*8) from Table 4. Then the eigenvalues of the SC matrices computed for the same dataset, using Equation 4:

$$(S - I\lambda)Y = 0 \qquad (4)$$

Where: S: denotes the similarity matrix; I: refers to the identity matrix; λ: defines the Eigenvalue of the Eq. 4; Y: is the n numbers of Eigenvectors.

After that, the predicted number of machine cells identified based on the number of positive eigenvalues equal to or greater than one (Kaiser, 1960) Table 8 referred to the eigenvalues and the number of machine cells for data set (7*8). Then the same procedure followed to calculate the eigenvalues and the predicted number of machine cells for all datasets in Table 4, using the same three types of the SCs. The recorded results displayed in Table 9.

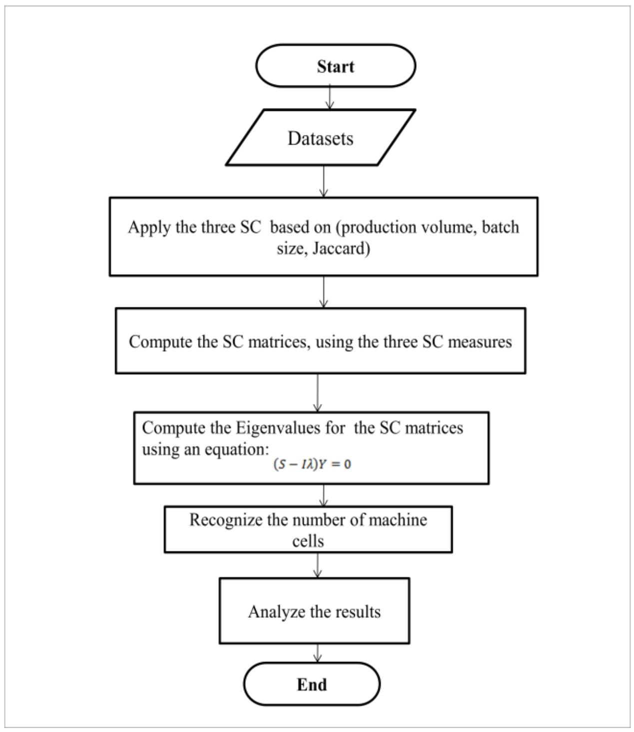

Fig. 1. The methodology flow chart

Table 5: The SC matrix for data set (7*8), using Jaccard SC

	M1	M2	M3	M4	M5	M6	M7
M1	1.00	0.20	0.00	0.50	0.00	0.50	0.20
M2	0.20	1.00	0.50	0.20	0.75	0.20	1.00
M3	0.00	0.50	1.00	0.00	1.50	0.00	0.50
M4	0.50	0.20	0.00	1.00	0.00	1.00	0.20
M5	0.00	0.75	1.50	0.00	1.00	0.00	0.75
M6	0.50	0.20	0.00	1.00	0.00	1.00	0.20
M7	0.20	1.00	0.50	0.20	0.75	0.20	1.00

Table 6: The SC matrix for data set (7*8), using production volume based SC

	M1	M2	M3	M4	M5	M6	M7
M1	1.00	0.16	0.00	0.42	0.00	0.42	0.16
M2	0.16	1.00	0.54	0.23	0.91	0.23	1.00
M3	0.00	0.54	1.00	0.00	1.56	0.00	0.54
M4	0.42	0.23	0.00	1.00	0.00	1.00	0.23
M5	0.00	0.91	1.56	0.00	1.00	0.00	0.91
M6	0.42	0.23	0.00	1.00	0.00	1.00	0.23
M7	0.16	1.00	0.54	0.23	0.91	0.23	1.00

Table 7: The SC matrix for data set (7*8), using batch size based SC

	M1	M2	M3	M4	M5	M6	M7
M1	1.00	0.22	0.00	0.28	0.00	0.28	0.22
M2	0.22	1.00	0.41	0.32	0.71	0.32	1.00
M3	0.00	0.41	1.00	0.00	2.14	0.00	0.41
M4	0.28	0.32	0.00	1.00	0.00	1.00	0.32
M5	0.00	0.71	2.14	0.00	1.00	0.00	0.71
M6	0.28	0.32	0.00	1.00	0.00	1.00	0.32
M7	0.22	1.00	0.41	0.32	0.71	0.32	1.00

Table 8: The eigenvalues for data set (7*8), using the three types of SCs

The eigenvalues		
(Jaccard) SC	**SC based on production volume**	**SC based on batch size**
3.612	3.841	3.916
2.383	2.307	2.385
-0.532	-0.633	-1.173
0.624	0.722	0.837
0.913	0.763	1.034
0.000	0.000	0.000
0.000	0.000	0.000
The predicted number of machine cells =2	**The predicted number of machine cells =2**	**The predicted number of machine cells =3**

4. Results and Discussion

The results of applying the three different types of SCs in the FA were shown in Table 9, These results involve the influence of incorporating the real life production features on the predicted number of machine cells.

The outcomes of Table 9 showed that there is no significant difference in the predicted number of machine cells with or without using the production factors. For instance: 16 data sets from 19 (84%) produced the same number of machine cells by using all the three different types of SCs

However, three data sets from 19 (16%) formed different solution: datasets (6*7) and (16*30) created a number of machine cells by using Jaccard less than the number by using the SC based on the production volume or batch size. On the other hand, dataset (7*8) shaped a number of machine cells by using SC based on batch size more than the same number by using Jaccard or SC based on the production volume.

From the obtained results, it can be concluded that (0,1) matrix that's used with Jaccard measure is sufficient to predict the number of machine cells. This implies there is no critical impact to the production features on the outcomes of the FA stage. Figure 2 displays the results of Table 9.

Table 9: The predicted number of machine cells, using the three SCs in the FA

Dataset	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Matrix	4*4	4*5	5*5	5*6	5*7	6*7	6*8	7*8	7*11	8*10	7*14	9*11	10*10	12*10	15*10	8*20	14*24	16*30	16*43
(Jaccard) SC	2	2	2	2	2	2	2	2	3	3	3	3	3	5	4	5	3	4	6
SC based on the production volume	2	2	2	2	2	3	2	2	3	3	3	3	3	5	4	5	3	5	6
SC based on the batch size	2	2	2	2	2	3	2	3	3	3	3	3	3	5	4	5	3	5	6

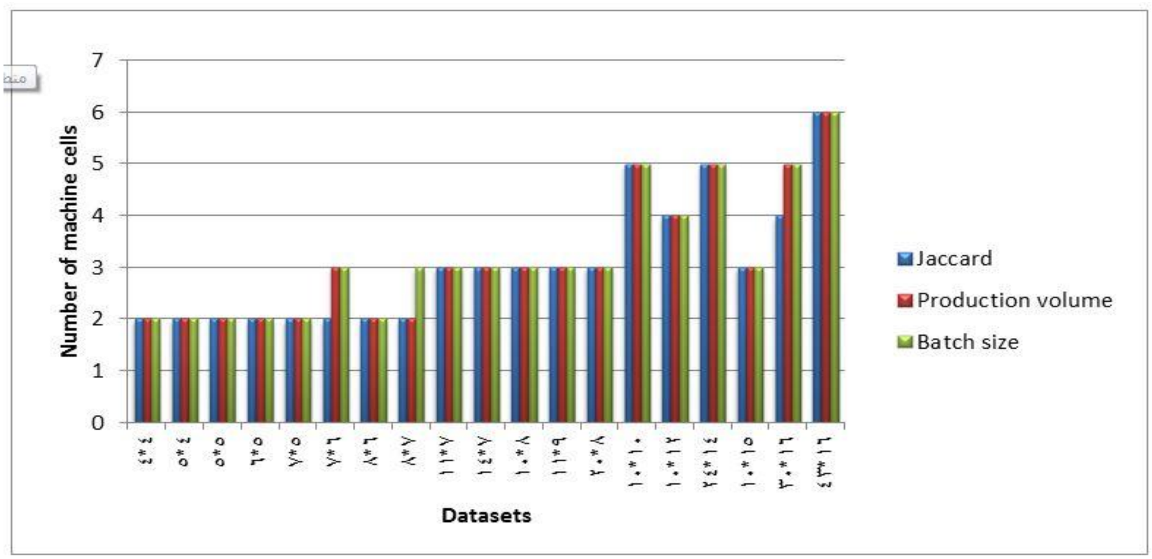

Figure 2 The predicted number of machine cells, using the three SC in the FA

5. Conclusions

Jaccard and two other SCs based on the real life production features: (production volume and batch size) have been used in the FA to predict the number of machine cells. This number of machine cells should be also produced in the next design stage called cell formation. The outcomes of utilizing the SCs based on the real life production features after compared with Jaccard referred to the following:-

1. (84%) of data sets produced similar solutions (the same number of machine cells) by using all the three different types of SCs
2. (16%) of datasets created different solutions (different number of machine cells) by using the same three selected types of SCs.
3. Datasets based on only (0,1) matrix is sufficient to use in the FA
4. General Purpose Similarity Coefficient (GPSC) known as Jaccard is sufficient to use in the FA

References

Arikaran P. and Jayabalan V. , 2011 . A Grouping Genetic Algorithm for Solving the Machine Component Grouping Problem. *European Journal of Scientific Research*, *Vol. 63* (Issue 3): *347-357.*

Arvindh B. and Irani S.A., 1994 . Principal component analysis for evaluating the feasibility of cellular manufacturing without initial machine-part matrix clustering. *International Journal of Production Research, Vol. 32 (*Issue 8*): 1909-1938.*

Basher H.A. and Karaa S., 2008 . Assessment of clustering tendency for the design of cellular manufacturing systems. *Journal of Manufacturing Technology Management, Vol.19 (*Issue 8*): 1004-1014.*

Boctor F.F., 1991 . A linear formulation of the machine-part cell formation problem. *International Journal of Production Research, Vol. 29: 343-356.*

Chan H.M. and Milner D.A., 1982 . Direct clustering algorithm for group formation in cellular manufacture, *.Journal of Manufacturing Systems, Vol.* 1: 64-76.

Chandrasekharan M.P. and Rajagopalan R., 1986 . An ideal seed non-hierarchical clustering algorithm for cellular manufacturing. *International Journal of Production Research, Vol. 24: 451–464.*

Chattopadhyay M., Sengupta S. and Dan P.K., 2011 . Machine-Part cell formation through visual decipherable clustering of Self Organizing Map. *International Journal of Advanced Manufacturing Technology, Vol. 52* (Issue 9-12): *1019-1030.*

Chen D.S. Chen H.C. and Part J.M., 1996 . An improved ART neural net for machine cell formation, *Journal of Materials Processing Technology, Vol. 61: 1-6.*

Hamza S.A., and Adesta E.Y.T. , 2013,a . Similarity Coefficient Measures Applied to Assessment the Cell Formation Problem: A Comparative Investigation. *International Review on Modeling and Simulations [IREMOS], Vol. 6* (Issue 2): *608-612.*

Hamza S.A., and Adesta E.Y.T. , 2013,b . A Comparative Study on Predicting Methods for Cell Formation Problem, *International Review of Mechanical Engineering [IREME], Vol.7* (Issue 5): *750-756.*

Hamza S.A., and Adesta E.Y.T., 2013,c . Similarity Coefficient Measures Applied to integrate feasibility assessment and the design of cellular manufacturing systems, *Australian Journal of Basic and Applied Sciences*, *Vol.7* (Issue 6): *257-266.*

Kaiser H.F., 1960 . The application of electronic computers to factor analysis, *Educational and psychological Measurement*, *Vol. 20:141-151*.

King J.R., 1980 . Machine-component grouping in production flow analysis: An approach using rank order clustering algorithm, *International Journal of Production Research, Vol. 18: 213-232.*

King J.R. and Nakornchai V., 1982 . Machine-component group formation in group technology: Review and extension. *International Journal of Production Research, Vol. 20: 117-133.*

Luong L., He J., Abhary K. and Qiu L., 2002 . A decision support system for cellular manufacturing system design, *Comput.Ind. Eng*, *Vol.42 (*Issue 2-4*): 457-470.*

Mahdavi I., Paydar M.M., Solimanpur M. and Saidi-Mehrabad M., 2010. A mathematical model for integrating cell formation problem with machine layout. *International Journal of Industrial Engineering & Production Research, Vol. 21* (Issue 2): *61-70.*

Maleki R.A., 1991 . *Flexible Manufacturing Systems: The Technology and Management* (Prentice- Hall).

McAuley J., 1972 . Machine grouping for efficient production, *Production Engineer*, *Vol. 52: 53–57.*

Raja S. and Anbumalar V., 2016 . A new method for integrating feasibility assessment and cell formation problem considering operation sequence, *International Journal of Advanced Engineering Technology*, *Vol.VII* (Issue 1): *544-551*.

Salehi M. and Moghaddam R.T., 2009 . A grouping genetic algorithm for the cell formation problem. *International Journal of Natural and Engineering Sciences, Vol. 3* (Issue 1): *73-78.*

Seifoddini H. and Djassemi M., 1991 . The production data-based similarity coefficient versus Jaccard's similarity coefficient, *Computers & Industrial Engineering, Vol. 21, 263-266.*

Seifoddini H. and Djassemi M., 1996 . A new grouping measure for evaluation of machine-component matrice, *International Journal of Production Research*, Vol. 34 (Issue 5): 1179–1193.

Seifoddini H. and Tjahana B. , 1999 . Part-family formation for cellular manufacturing: A case study at Harnischfeger, *International Journal of Production Research, Vol.* 37**:** 3263-3273.

Singh N. and Rajamani D. , 1996, Cellular Manufacturing Systems: Design Planning and Control (London: Chapman and Hall Press, PP. 73-81).

Waghodekar, P.H. and Sahu, S., 1984. Machine-component cell formation in group technology: MACE, *International Journal of Production Research*, *Vol. 22* (Issue 6): *937–948.*

Yin, Y. and Yasuda, K., 2006 . Similarity coefficient methods applied to the cell formation problem: A taxonomy and review. *International Journal of Production Economics*, Vol.101 (Issue 2): 329-352.