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Performance comparison of different clustering methods for manufacturing cell formation

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ABSTRACT

This study refers to cell formation, which is the fundamental and important stage of cellular manufacturing system design. Three widely used methods that are K-means clustering algorithm, average-linkage clustering algorithm and fuzzy clustering using expectation maximization algorithm for cell formation problem are studied. A real life application of these methods for the design of cylinder department of a construction equipment manufacturer is performed. The performance of each applied algorithm is evaluated according to intracellular voids, intracellular processing intensity and intercellular transportation measures. The application results indicate that K-means clustering algorithm, which is the most widely applied and most known one of classical clustering algorithms, is still an effective method for cell formation.

Keywords: Cellular Manufacturing, Cell Formation, K-Means Algorithm, Average Linkage Clustering Algorithm, Expectation Maximization Algorithm

İmalat hücresi oluşturulması için farklı kümeleme yöntemlerinin performans karşılaştırması

ÖZ

Bu çalışma, hücresel imalat sistemi tasarımının temel ve önemli aşaması olan hücre oluşturmaya değinmektedir. Çalışmada hücre oluşturma uygulamalarında yaygın olarak kullanılan üç yöntem; k-ortalamalar kümeleme algoritması, ortalama bağlantılı kümeleme algoritması ve beklenti maksimizasyonu algoritmasını kullanan bulanık kümeleme algoritması incelenmektedir. Bir inşaat ekipmanı üreticisinin silindir bölümünün tasarımı için bu yöntemlerin gerçek hayat uygulaması gerçekleştirilmiştir. Uygulanan her algoritmanın performansı hücre içi boşluklar, hücre içi işlem yoğunluğu ve hücreler arası taşıma miktarı ölçütlerine göre değerlendirilmektedir. Uygulama sonuçları, klasik kümeleme algoritmalarından en çok bilinen ve en yaygın olarak uygulanan k-ortalamalar kümeleme algoritmasının hücre oluşturma için hala etkili bir yöntem olduğunu göstermektedir.

Anahtar Kelimeler: Hücresel imalat, Hücre oluşturma, K-ortalamalar algoritması, Ortalama bağlantılı kümeleme algoritması, Beklenti maksimizasyonu algoritması

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1. INTRODUCTION

Global competition, changing market conditions and variability in customer demands, which are causing shorter product life cycles, force manufacturing firms to more focus on flexibility and productivity to be able sustain in such an environment. Group Technology (GT) that was introduced by Mitrofanov [1] is a theory of management based on the principle that similar things should be done similarly [2]. Cellular manufacturing (CM), which is the implementation of group technology, is an important modern manufacturing alternative to achieve mid-volume and high-variety production [3]. CM is a hybrid system, which takes the advantage of flexibility of job shops and efficiency of flow shops [3][4]. Design of CM systems is a three-step process that consists of cell formation, intracellular layout and cell layout [5]. Cell formation (CF), which can also be called as part-machine grouping problem, is the fundamental and crucial step of CM system design. CF requires forming part families according to their processing similarities, grouping machines into manufacturing cells and assigning part families to cells [6]. The objective of CF is forming manufacturing cells, which are independent of other cells. In other words, the transfer between the cells are tried to be minimized so that each part family is finished within the cell it is assigned, which is quite difficult to be achieved in real life applications.

This study handles CF problem and presents three methods that are K-means clustering algorithm, average-linkage clustering algorithm and fuzzy clustering using expectation maximization algorithm. These three efficient and easy to use algorithms are applied for the same problem and their performances are compared according to three performance measures, which are intracellular voids, intracellular processing intensity and intercellular transportation criteria. The organization of the paper can be summarized as follows. CF problems and performance measures for CF with a brief literature review will be introduced. Then, the methods used in the study will be explained and the applications of these methods together with performance measures will be given. Finally, results and conclusions will be presented.

2. CELLULAR MANUFACTURING SYSTEMS (CMS)

Cellular manufacturing, an application of the philosophy of "group technology", seeks to achieve efficiency in production by taking advantage of similarities between parts. In other words, the goal of this system is to get more output with less costs and better quality in shorter time. In a cellular manufacturing system, the cell is composed of part families and similar machine groups [7]. The purpose of cell formation is to create separated machine groups in which parts are processed with maximum interactions than the other cells.

The well-known benefits of the cellular manufacturing systems are given below [8][9]:

- *Material handling is reduced:* In the CMS, the part is processed in a cell. Thus, material handling is reduced due to the simplified workflow.
- *Production time is shortened:* By using the advantage of flow type production in the CMS, the production period of parts can be reduced.
- *The setup time is reduced:* Since similar parts are grouped in CMS, similar configurations are required for these parts, which help to reduce the setup time. With the development of flexible manufacturing systems, automatic tool changers reduce the setting, reduce the machining time and produce high quality products at low cost.
- *Batch size can be minimized:* Since the adjustment period in the CMS is greatly reduced, making small parties is economical.
- *The number of parts in the system is reduced:* The number of parts in the system and the amount of in-process stock will be lower because the production time is reduced in the CMS.
- *The delivery time is determined correctly:* The competence of the cell to produce predefined quantity of a part ensures that delivery time is determined more accurately and reliably.
- *Machine usage is reduced:* The effective capacity of the machine is increased due to the reduction of the setup times, which leads to a lower use.
- *The return on investment is fast:* The costs of lost production and resettlement of the machines can be easily recovered from

inventory, efficient usage of machines, labor and materials.

- *It saves labor:* Due to the utilization level of the cell is low; it is possible to assign a worker to more than one machine to lead better utilization of the workforce.
- *Quality procedure works easily:* Parts move from one station to another as single units or small parts in CMS. Hence parts are fully processed in a small area, the return of production is fast and the process can be stopped to find out what the error is.
- *Field acquisition:* Due to the reduction in the number of parts in the system, significant amounts of usable space for adding new machines and expanding can be gained.

In addition to its many benefits, CMS has also some weaknesses and objectionable aspects:

- *Difficulties in identifying family members:* The creation of family members and the assignment of machines to cells may not always be easy. Part families determined by considering their designs may not be suitable from the point of view of production operations.
- *Challenges of balancing workload among cells:* Balancing workflow within a cell is more difficult than balancing an assembly line. The parts can follow different orders in the cell, which requires different machines and processing times. Wrongly balanced cells can be very inefficient. It is very important to balance workload among the cells in CMS.
- *Employees need to be trained:* The training of employees for different tasks is costly, time consuming, and requires collaboration among employees.
- *Additional costs incurred by reorganization:* In CMS, multiple small machines are preferred to single large machines. It may be necessary to purchase additional cells for the same type of machines. In addition, the cost of the idle plant due to the relocation of the machines can also be high.

2.1. Cell Formation (CF)

The most important problem encountered in the design of CMS is cell formation. This problem, also referred as part-machine group analysis, influences the basic structure of the CMS and the whole layout.

Cell formation is concerned with determining the part families and the machine groups on which these parts are to be produced [10]. The basic assumption in CF is that the part families can only be produced in certain machines or machine groups. For this, the existence of relations between parts and machines is investigated. This relationship is called as routing [11]. When the relationships are determined, the parts are separated into the part families in which all the parts in the part family are produced in the same machine groups. What is required here is that as much processing as possible is carried out on the machines in which the parts within the desired families are assigned and the interaction between the cells is minimized. Once the part families are determined, the machines that the part families will be processed, are also grouped.

The success of the CF problem depends on considering the constraints that exist in the actual production environment. The most important constraints to consider in CF are as follows [12][13]:

- Available capacity of machines must not be exceeded.
- Safety and technological requirements must be met. The machines that can create dangerous interaction with each other must be physically farther away.
- Number of machines in a cell and number of cells must not exceed an upper bound.
- Inter-cell and intra-cell cost of handling material between machines must be minimized.
- Machine utilization rate must be as high as possible.
- Machine purchase and operating costs must be minimized. In CMS, the machines and equipment on the hands are placed to the cells in the most appropriate way. When necessary, new machinery and equipment are purchased.
- Work-in-process inventory costs must be minimized.

2.2. Cell Formation Methods

During the decades, many research papers have been done in literature about CF methods. Some of them have been introduced the classification of these methods. King and Nakornchai [14] examined the methods for grouping parts and associated machines in four subdivisions:

similarity coefficient methods, set theoretic methods, evaluative methods and other analytical methods.

Wemmerlöv and Hyer [11] divided the CF methods into two major groups based on the main data as either part attributes or machine routings. The latter branch for machine routings is further classified into three divisions, i.e. approaches that identify firstly the machine groups, approaches that identify firstly the part families, and the approaches that identify part families and machine groups simultaneously.

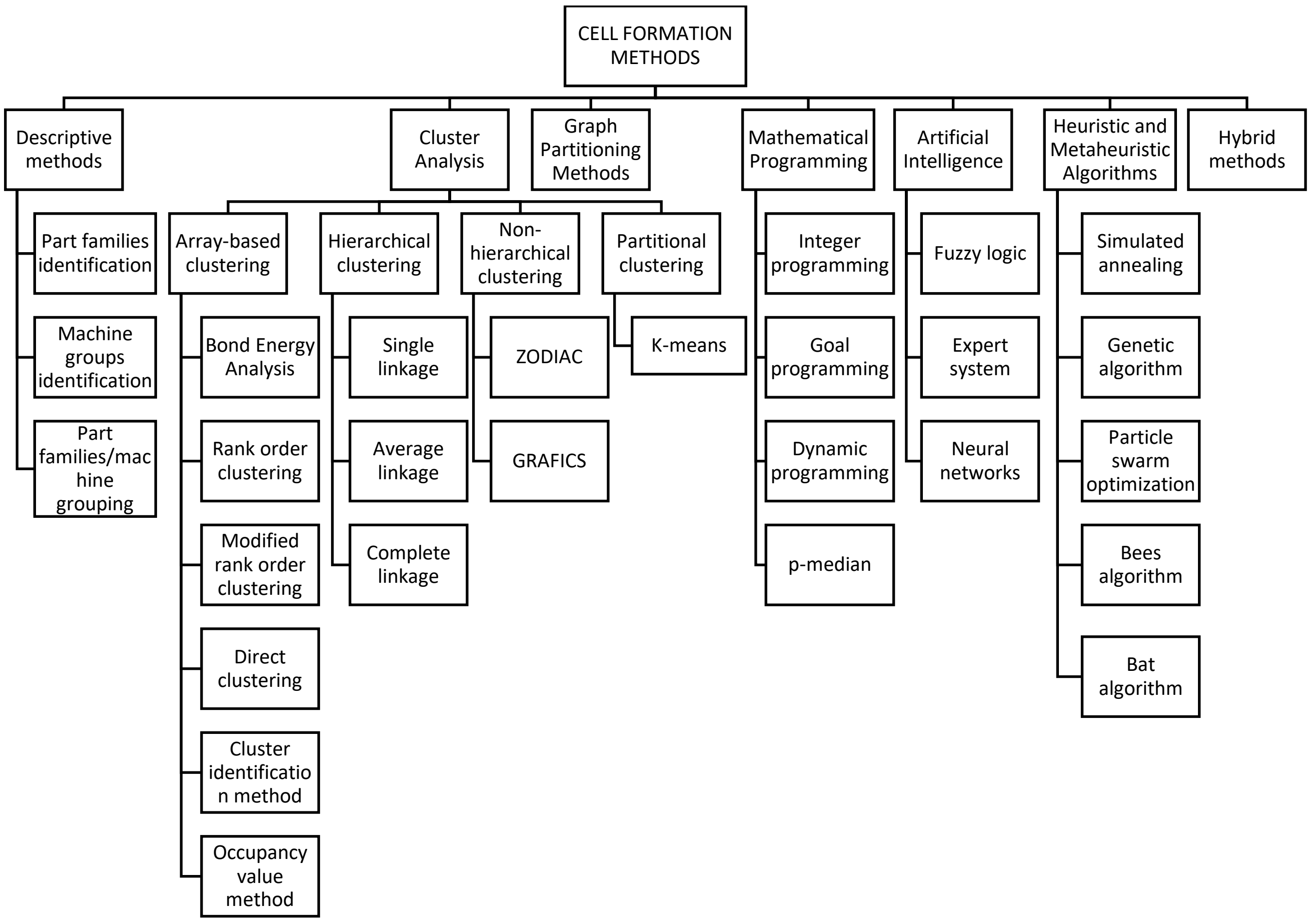
Selim et al. [10] categorized these approaches into five subsections that are descriptive procedures, cluster analysis, graph partitioning, artificial intelligence and mathematical programming.

Adenso-Díaz et al. [15] classified the approaches as hierarchical, simultaneous and iterative. They also considered the use of information about the sequence of operations or not in their classification. Another issue they marked for their classification is use of a machine-process plans binary incidence matrix or a machine-operation processing time matrix.

Papaioannou and Wilson [6] presented a detailed review about the evaluation of cell formation problem methodologies. They firstly categorized the approaches under three main headings: informal methods, part coding analysis methods and production-based methods. Then the production-based methods are classified as cluster analysis, graph-partitioning approaches, mathematical programming methods, heuristic and metaheuristic algorithms and artificial intelligence methodologies.

According to previous research papers, the CF methods can be summarized as shown in Figure 1 [7].

Figure 1. Classification of cell formation methods



2.3. Performance Measures

In literature, there have been a variety approaches that used the performance measures for appropriate machine/part clustering. Mosier [16] focused on four performance measures in their study, which are simple matching measure, generalized matching measure, product moment correlation coefficient measure and intercellular transportation measure.

Shafer and Meredith [17] compared the numerous cell formation techniques by using three companies' data with regard to average flow time, maximum flow time, average distance travelled, number of extra-cellular operations, average work-in-process (WIP) parts, maximum WIP and longest average queue.

Chu and Tsai [18] compared the rank order clustering algorithm, the direct clustering algorithm and the bond energy algorithm using the four performance measures: 1) total bond energy, 2) percentage of exceptional elements, 3) machine utilization and 4) grouping efficiency.

Morris and Tersine [19] presented a simulation model for layout choice, which examines the impact of changes in setup time, transfer time, material handling speed and flow within cell. They used mean throughput time and mean level of work-in-process (WIP) inventory as performance measures for their observations.

Miltenburg and Zhang [20] presented a comprehensive comparison of nine clustering methods. The final solutions were evaluated by using three independent measures that are grouping measure, clustering measure and bond energy measure.

Burgess et al. [21] compared the traditional job shop environment with the cellular manufacturing unit by different simulation combinations. They computed the ratio of actual flow time to optimum flow time and the ratio of machine delay time to optimum flow time for performance evaluation.

Rogers and Shafer [22] gave a detailed review and critique for the performance measures that were used in literature for comparing cell formation procedures. They categorized the performance measures into four subgroups: part volumes and sequencing not considered, part volumes considered, part sequencing considered and both part volumes and sequencing considered.

Sarker [23] provided information for different measures such as grouping efficiency, grouping efficacy, weighted grouping efficacy, grouping index, grouping capability index, and grouping measure. Sarker (2001) also introduced a new performance measure that is called doubly weighted grouping efficiency measure. This new measure showed better performance than some of the existing measures in order to capture both inter-cell and intra-cell movements in cellular manufacturing system.

Keeling et al. [24] examined optimal machine and part grouping for several problems from the literature using grouping genetic algorithm. Through their application, they investigated the impact of four efficiency measure that are grouping efficacy, grouping index, grouping capability index, doubly weighted grouping efficiency on various factory measures, such as flow time, wait time, throughput, machine utilization etc.

3. MATERIALS AND METHODS

In this study, the design of the cylinder department is dealt with in a new facility of a company that manufactures construction equipment that is taken from [25]. It is desired to see which of the different cell formation methods will be more suitable for the cylinder department. For this purpose, k-means clustering algorithm, average linkage clustering method and fuzzy clustering method with expectation maximization algorithm are applied to machine-part matrix of this department to obtain first clusters. Subsequently, clusters were tried to reach more understandable and stable machine-parts clusters by applying rank order clustering method. During the execution of the algorithms, attention has been paid to the formation of three cells and the prioritization of machine groups. The performance of the results was then assessed according to the intracellular voids, intracellular processing intensity and intercellular transportation criteria.

The machine-part matrix consisting of 12 machines and 19 parts, obtained for use in the study, is given in Table 1. The 1's on the table indicate that the part is processed on that machine whereas 0's indicate that is not.

Table 1. Machine-parts matrix for cylinder department

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16	P17	P18	P19
M1	1	0	0	0	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0
M2	0	1	0	0	0	1	0	0	1	0	0	1	0	0	1	0	0	1	0
M3	0	1	0	0	0	1	0	0	1	0	0	1	0	0	1	0	0	1	0
M4	1	1	0	0	0	1	0	1	0	0	0	1	0	1	0	0	0	0	0
M5	0	0	0	0	1	0	0	0	1	0	1	0	0	0	1	0	1	1	0
M6	1	0	0	0	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0
M7	0	1	0	0	0	1	0	0	1	0	0	1	0	0	1	0	0	1	0
M8	0	1	0	0	0	1	0	0	1	0	0	1	0	0	1	0	0	1	0
M9	0	1	0	0	0	1	0	0	1	0	0	1	0	0	1	0	0	1	0
M10	0	1	1	1	0	1	1	0	1	1	0	1	1	0	1	1	0	1	1
M11	1	0	1	1	1	0	1	1	0	1	1	0	1	1	0	1	1	0	1
M12	0	1	0	0	0	1	0	0	1	0	0	1	0	0	1	0	0	1	0

Details of the methods used in this study are given below.

3.1. K-Means Clustering Algorithm

K-Means clustering algorithm, which is the most commonly used and known one of classical clustering algorithms, was developed by J. MacQueen [26]. The general logic of the algorithm is to divide a data set consisting of *n* data objects into *K* sets that is given as an input parameter. The goal is to maximize the intra-cluster similarities of the clusters obtained at the end of the partitioning process while minimizing the inter-cluster similarities. Cluster similarity is measured by the mean value of the distances between the center of gravity of the cluster and other objects in the cluster. The cluster similarity is defined as Eq. 1 [27].

$$J(c_k) = \sum_{x_i \in c_k} \|x_i - \mu_k\|^2 \tag{1}$$

where μ_k is the center of gravity of the k^{th} cluster, x_i is the data object $(i = 1,2, \dots n)$. The objective function of the K-Means clustering algorithm is as follows:

$$J(C) = \sum_{k=1}^{K} \sum_{x_i \in c_k} \|x_i - \mu_k\|^2 \tag{2}$$

The higher the value of the objective function indicates that the objects in the cluster are far from the cluster center. Likewise the lower value is the indicator that the objects are closer to the cluster center.

The steps of the K-Means clustering algorithm are given below:

Step 1: Initial cluster centers are chosen randomly or by various methods according to the given cluster number of *K*.
Step 2: Calculate the distance of each object to cluster centers and assign it to that cluster where it is closer.
Step 3: After all objects have been assigned, recalculate the new cluster centers in the direction of the objects included in that cluster.
Step 4: Repeat steps 2 and 3 until the cluster assignments of objects have not changed.

3.2. Average-Linkage Clustering Algorithm

Average Linkage Clustering (ALC) algorithm is one of the algorithms based on similarity coefficient. The selected similarity coefficient and the methodology used in the clustering process play an important role for accuracy of the final clusters. In this study the "Jaccard Similarity Coefficient" is used in ALC algorithm.

Calculation of the Jaccard similarity coefficient is given in Eq. 3 [28].

$$S_{ij} = \frac{c}{(a+b-c)} \qquad 0 \le S_{ij} \le 1 \tag{3}$$

where S_{ij} is the Jaccard Similarity Coefficient between machine i and machine j, c is the number of parts processed both machine i and machine j, a and b are the number of parts processed machine i and machine j, respectively.

The steps of the ALC algorithm are as follows [9][29]:

Step 1: Calculate the similarity coefficients for all machine pairs and then create the similarity matrix.
Step 2: Group the two objects (two machines, a machine and a machine group or two machine

group) with the highest similarity coefficient.

Step 3: Update the similarity coefficient matrix according to Eq. 4.

$$S_{tv} = \frac{\sum_{i\in t}\sum_{j\in v} S_{ij}}{N_t \times N_v} \tag{4}$$

where N_t is the number of machines in group t, and N_v is the number of machines in group v.

Step 4: Go to step 5 if all the machines are grouped into a single machine group or predetermined number of machine groups has been obtained. Otherwise go back to step 2.

Step 5: Assign each part to the cell.

3.3. Fuzzy Clustering Using Expectation Maximization Algorithm

Expectation maximization (EM) algorithm, which works with the maximization principle of similarity, was first introduced by Dempster et al. [30]. The algorithm shows the probability that an object belongs to one of the existing clusters using probabilistic criteria rather than using definite distance criteria. At each iteration the EM algorithm first finds an optimal lower bound and then maximizes this bound to obtain an improved estimate. Hence the algorithm includes two steps that are called E-step (expectation-step) and M-step (maximization-step) respectively [31].

In the context of fuzzy clustering, an EM algorithm starts with an initial set of parameters and iterates until the cluster centers converge or the change is sufficiently small. Each iteration also consists of two steps [32].

E-step: Objects are assigned to clusters according to the existing fuzzy clusters or parameters of probabilistic clusters. In this step, the membership degree of each point in each cluster is calculated with Eq. 5.

$$w_{o,c_j} = \frac{\frac{1}{dist(o,c_j)^2}}{\frac{1}{dist(o,c_1)^2} + \frac{1}{dist(o,c_2)^2} + \cdots + \frac{1}{dist(o,c_K)^2}}$$

$$j = 1,2,\ldots,K \tag{5}$$

where $dist()$ is Euclidean distance, o is any point, c_j is cluster center and K is set of clusters. This means if the distance of the point to the cluster j is small, the membership degree of that point to the cluster j should be high.

M-step: Find the new clusters or the parameters that will maximize the expected probability or the sum of error squares. The equation used in that step is given below.

$$c_j = \frac{\sum_{each\ point\ o} w_{o,c_j}^2 o}{\sum_{each\ point\ o} w_{o,c_j}^2} \quad j = 1,2,\ldots,K \tag{6}$$

3.4. Rank Order Clustering Method

Rank order clustering (ROC) method is one of the most common methods for generating cells that take the machine-part matrix as input. The computational simplicity of the ROC method plays a big role in its preference. First developed in 1980 by the King, the ROC method has changed over time in such a way that the shortcomings are removed. In this study, the original state of the method is used and the steps are as follows [33]:

Step 1: Assign weights for each column of the initial matrix starting from the rightmost column. The assignment weights are twice as high as the previous one. If number of columns is represented by m, each column by j and its weights by W, Eq. 7 calculates weight.

$$W_j = 2^{m-j} \tag{7}$$

Step 2: Write the sum of the column weights corresponding to the inputs "1" in the rows in lines. The sum of the weights is calculated with Eq. 8.

$$TW_i = \sum_{j=1}^{m} 2^{m-j} a_{ij} \tag{8}$$

where i is rows, j is columns, a_{ij} is binary (0,1) entries of matrix.

Step 3: Sort rows by top down so that TW_i values are decreasing.

Step 4: Assign the weights to the sorted rows from bottom to top so that each one is twice as big as the bottom one. The number of rows is represented by n.

$$W_j = 2^{n-i} \tag{9}$$

Step 5: Write the sum of the row weights corresponding to the inputs "1" in the columns in lines. The sum of the weights is calculated as follows.

$$TW_j = \sum_{j=1}^{n} 2^{n-i} a_{ij} \tag{10}$$

Step 6: Sort columns from left to right so that TW_j values are decreasing.

Step 7: It is checked whether block-diagonal structure is formed. If not, go to step 1 and repeat the algorithm. After a certain number of iterations of the algorithm, the result is the same as the previous iteration. This indicates that the best solution is achieved according to the ROC algorithm and stop.

4. RESULTS AND DISCUSSION

The K-Means algorithm is used first and the given machine-part matrix is allocated to the appropriate cells with paying attention to the formation of the three cells and the grouping of the machines.

The initial machine cells for the K-means algorithm are determined as follows:

Cell 1: M1, M2, M3, M4

Cell 2: M5, M6, M7, M8

Cell 3: M9, M10, M11, M12

As a result of the iterations carried out in EXCEL in line with this initial information, the cells, the machines placed in the cells and the parts processed by these machines are given in Table 2.

Table 2. Cells, machines and parts for K-Means clustering algorithm

CELLS	MACHINES	PARTS
1	M1, M4, M6	P1, P2, P5, P6, P8, P11, P12, P14, P17
2	M2, M3, M5, M7, M8, M9, M12	P2, P5, P6, P9, P11, P12, P15, P17, P18
3	M10, M11	P1, P2, P3, P4, P5, P6, P7, P8, P9, P10, P11, P12, P13, P14, P15, P16, P17, P18, P19

After the formation of these cells, rank order clustering method is carried out in each of the cells for more regular structure in the machine-part matrix.

Matrix structures of each cell with the K-Means algorithm are shown in Table 3, 4 and 5 respectively.

Table 3. The machine-part matrix for cell 1 with the K-Means clustering algorithm

	P1	P8	P14	P2	P6	P12	P5	P11	P17
M4	1	1	1	1	1	1			
M1	1	1	1				1	1	1
M6	1	1	1				1	1	1

Table 4. The machine-part matrix for cell 2 with the K-Means clustering algorithm

	P9	P15	P18	P2	P6	P12	P5	P11	P17
M2	1	1	1	1	1	1			
M3	1	1	1	1	1	1			
M7	1	1	1	1	1	1			
M8	1	1	1	1	1	1			
M9	1	1	1	1	1	1			
M12	1	1	1	1	1	1			
M5	1	1	1				1	1	1

Table 5. The machine-part matrix for cell 3 with the K-Means clustering algorithm

	P3	P4	P7	P10	P13	P16	P19	P1	P5	P8	P11	P14	P17	P2	P6	P9	P12	P15	P18
M11	1	1	1	1	1	1	1	1	1	1	1	1	1						
M10	1	1	1	1	1	1	1							1	1	1	1	1	1

As seen in Table 3, P1, P8 and P14 coded parts must be supplied together with the machines. When P2, P6 and P12 parts are processing on machine M4, the assignment of parts P5, P11 and P17 to machines M1 and M6 will minimize the idle conditions of the machines. In the cell 2, minimizing the idle conditions of the machines is done as follows: P9, P15 and P18 coded parts must be given to all machines as a group. P2, P6 and P12 must be given as a group to all machines except the M5, and the M5 machine must process the P5, P11 and P17 coded parts.

The cells, the machines placed in the cells and the parts processed by these machine generated by the application of the average linkage clustering algorithm are given in Table 6.

Table 6. Cells, machines and parts for average linkage clustering algorithm

CELLS	**MACHINES**	**PARTS**
1	M1, M6, M11	P1, P3, P4, P5, P7, P8, P10, P11, P13, P14, P16, P17, P19
2	M2, M3, M7, M8, M9, M10, M12	P2, P3, P4, P6, P7, P9, P10, P12, P13, P15, P16, P18, P19
3	M4, M5	P1, P2, P5, P6, P8, P9, P11, P12, P14, P15, P17, P18

After the formation of these cells, rank order clustering method is carried out in each of the cells for more regular structure in the machine-part matrix.

Matrix structures of each cell with the average-linkage clustering algorithm are shown in Table 7, 8 and 9 respectively.

Table 7. The machine-part matrix for cell 1 with the average-linkage clustering algorithm

	P1	P5	P8	P11	P14	P17	P3	P4	P7	P10	P13	P16	P19
M11	1	1	1	1	1	1	1	1	1	1	1	1	1
M1	1	1	1	1	1	1							
M6	1	1	1	1	1	1							

Table 8. The machine-part matrix for cell 2 with the average-linkage clustering algorithm

	P2	P6	P9	P12	P15	P18	P3	P4	P7	P10	P13	P16	P19
M10	1	1	1	1	1	1	1	1	1	1	1	1	1
M2	1	1	1	1	1	1							
M3	1	1	1	1	1	1							
M7	1	1	1	1	1	1							
M8	1	1	1	1	1	1							
M9	1	1	1	1	1	1							
M12	1	1	1	1	1	1							

Table 9. The machine-part matrix for cell 3 with the average-linkage clustering algorithm

	P1	P2	P6	P8	P12	P14	P5	P9	P11	P15	P17	P18
M4	1	1	1	1	1	1						
M5							1	1	1	1	1	1

For fuzzy clustering using expectation maximization algorithm, three random cluster centers were determined to form three clusters:

Center of Cluster 1: M7
Center of Cluster 2: M4

Center of Cluster 3: M11

Then, the distances of each point to these centers and the probabilities of each point being included in the clusters are calculated.

The cells, the machines placed in the cells and the parts processed by these machine resulting from repeated iterations of the fuzzy clustering using expectation maximization algorithm are given in Table 10.

Table 10. Cells, machines and parts for fuzzy clustering using expectation maximization algorithm

CELLS	**MACHINES**	**PARTS**
1	M2, M3, M7, M8, M9, M12	P2, P6, P9, P12, P15, P18
2	M10	P2, P3, P4, P6, P7, P9, P10, P12, P13, P15, P16, P18, P19
3	M1, M4, M5, M6, M11	P1, P3, P4, P5, P7, P8, P10, P11, P13, P14, P16, P17, P19

After the formation of these cells, rank order clustering method is carried out in each of the cells for more regular structure in the machine-part matrix. Matrix structures of each cell with fuzzy clustering using expectation maximization algorithm are shown in Table 11, 12 and 13 respectively.

Table 11. The machine-part matrix for cell 1 with the fuzzy clustering using expectation maximization algorithm

	P2	P6	P9	P12	P15	P18
M2	1	1	1	1	1	1
M3	1	1	1	1	1	1
M7	1	1	1	1	1	1
M8	1	1	1	1	1	1
M9	1	1	1	1	1	1
M12	1	1	1	1	1	1

Table 12. The machine-part matrix for cell 2 with the fuzzy clustering using expectation maximization algorithm

	P2	P3	P4	P6	P7	P9	P10	P12	P13	P15	P16	P18	P19
M10	1	1	1	1	1	1	1	1	1	1	1	1	1

Table 13. The machine-part matrix for cell 3 with the fuzzy clustering using expectation maximization algorithm

	P1	P8	P14	P2	P6	P12	P5	P11	P17	P3	P4	P7	P10	P13	P16	P19	P9	P15	P18
M4	1	1	1	1	1	1													
M11	1	1	1				1	1	1	1	1	1	1	1	1	1			
M1	1	1	1				1	1	1										
M6	1	1	1				1	1	1										
M5							1	1	1								1	1	1

Following the creation of the individual machine-part matrices by three algorithms, the performance of the algorithms was evaluated according to the intracellular voids, intracellular processing intensity and intercellular transportation criteria.

The intracellular voids are the input of "0" in the formed cells and means that part is not processed in that machine. This is not desirable in the cells because it reduces the utilization of the machines and it is targeted that the least possible number of voids occurs while cells are being created. The numbers of intracellular voids of each cell obtained from the three algorithm results are given in Table 14.

Table 14. The numbers of intracellular voids obtained from used algorithms

	The numbers of intracellular voids			
	Cell 1	Cell 2	Cell 3	TOTAL
K-Means Clustering Algorithm	9	21	12	42
Average-linkage clustering algorithm	14	42	12	68
Fuzzy clustering using expectation maximization algorithm	0	0	58	58

As shown in Table 14, the K-means clustering algorithm is more advantageous in terms of intracellular voids than the other two methods.

In machine-parts matrices, each part is not processed on every machine. This causes the resulting cells to vary in process intensity. Intracellular processing intensity is calculated by the following equation.

$$H = \frac{x}{w} \tag{11}$$

where H is intracellular processing intensity, x is total number of operations in the cell and w is the total number of elements in the cell. The intracellular processing intensities obtained by Equation 11 are presented in Table 15.

Table 15. The numbers of intracellular processing intensities obtained from used algorithms

	The intracellular processing intensities			
	Cell 1	Cell 2	Cell 3	AVERAGE
K-Means Clustering Algorithm	0.667	0.667	0.684	0,673
Average-linkage clustering algorithm	0,641	0,538	0,5	0,560
Fuzzy clustering using expectation maximization algorithm	1	1	0,411	0,804

As seen in Table 15, with fuzzy clustering using expectation maximization algorithm, the machines in the cells are working with a higher average.

During the formation of cells, it may not be possible to produce each part in a single cell. Therefore, the parts that need to be processed in different cells will have to go through. During these movements a transport cost arises. Thus, when the cells are being created, it is aimed that the part will be released from the cell where it started to be processed. The intercellular transportations resulting from the three applied algorithms are given in Table 16.

Table 16.The numbers of intercellular transportations obtained from used algorithms

	The number of intercellular transportations
K-Means Clustering Algorithm	18
Average-linkage clustering algorithm	19
Fuzzy clustering using expectation maximization algorithm	19

5. CONCLUSION

In this study, CF that is the fundamental and important step in the design of CM system is investigated. Three methods, which are K-means clustering algorithm, average-linkage clustering algorithm and fuzzy clustering using expectation maximization algorithm for CF problem are studied. A real life application of these methods for the design of cylinder department of a construction equipment manufacturer is performed. The performance of each applied algorithm is evaluated according to 3 performance measures that are intracellular voids, intracellular processing intensity and intercellular transportation criteria. According to the results, average-linkage clustering algorithm gives the least performance with respect to the three performance measures. K-means clustering algorithm performs best with respect to intracellular voids and intercellular transportation criteria in terms of average. Fuzzy clustering using expectation maximization algorithm is the best with respect to intracellular processing intensity measure in terms of average. Although K-means algorithm is behind fuzzy clustering using expectation maximization algorithm according to intracellular processing intensity measure, as it can be seen in Table 15, it gives a more balanced cell formation. It can be concluded that K-means clustering algorithm which is the most widely applied and known one of classical clustering algorithms is still an effective method for CF. Since there have been developed many methods and techniques in literature for CF problem, for further research, the comparison of these methods with respect to developed performance measures can be a promising area for both better understanding the strengths and weaknesses of these methods and for developing a common approach to CF problem.

REFERENCES

[1] S. P. Mitrofanov, *The scientific principles of group technology*. Boston Spa, Yorks, UK: National Lending Library Translation, 1966.

[2] R. G. Askin and C. R. Standridge, C. R., *Modeling and analysis of manufacturing systems*. John Wiley & Sons Inc, 1993.

[3] B. Bootaki, I. Mahdavi and M. M. Paydar, "New criteria for configuration of cellular manufacturing considering product mix variation," *Computers & Industrial Engineering*, vol. 98, pp. 413-426, August 2016.

[4] M. Mohammadi and K. Forghani, "A hybrid method based on genetic algorithm and dynamic programming for solving a bi-objective cell formation problem considering alternative process routings and machine duplication," *Applied Soft Computing*, vol. 53, pp. 97-110, April 2017.

[5] I. Mahdavi, E. Teymourian, N. T. Baher and V. Kayvanfar, "An integrated model for solving cell formation and cell layout problem simultaneously considering new situations," *Journal of Manufacturing Systems*, vol. 32, no. 4, pp. 655-663, October 2013.

[6] G. Papaioannou, J. M. Wilson, "The evolution of cell formation problem methodologies based on recent studies (1997–2008): Review and directions for future research," *European journal of operational research*, vol. *206*, no. 3, pp. 509-521, November 2010.

[7] V. Modrák, P. Semančo, "Developments in Modern Operations Management and Cellular Manufacturing," in *Operations Management Research and Cellular Manufacturing Systems: Innovative Methods and Approaches: Innovative Methods and Approaches*, V. Modrák, Ed., IGI Global, 2011.

[8] A. I. Shahrukh, *Handbook of cellular manufacturing systems*. New York, John Wiley & Sons, 1999.

[9] N. Singh and D. Rajamani, D., *Cellular manufacturing systems: design, planning and control*. Springer Science & Business Media, 2012.

[10] H. M. Selim, R. G. Askin and A. J. Vakharia, "Cell formation in group technology: review, evaluation and directions for future research," *Computers & Industrial Engineering*, vol. 34, no. 1, pp. 3-20, January 1998.

[11] U. Wemmerlöv and N. L. Hyer, "Procedures for the part family/machine group identification problem in cellular manufacturing," *Journal of Operations*

Management, vol. *6, no.* 2, pp. 125-147, February 1986.

[12] S. S. Heragu, "Group technology and cellular manufacturing," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 24, no. 2, pp. 203-215, February 1994.

[13] S. S. Heragu and Y. P. Gupta, "A heuristic for designing cellular manufacturing facilities," *The International Journal of Production Research*, vol. *32*, no. 1, pp. 125-140, 1994.

[14] J. R. King and V. Nakornchai, "Machine-component group formation in group technology: review and extension," *The International Journal of Production Research*, vol. 20, no. 2, pp. 117-133, 1982.

[15] B. Adenso-Díaz, S. Lozano, J. Racero and F. Guerrero, "Machine cell formation in generalized group technology," *Computers & Industrial Engineering*, vol. *41, no.* 2, pp. 227-240, November 2001.

[16] C. T. Mosier, "An experiment investigating the application of clustering procedures and similarity coefficients to the GT machine cell formation problem," *The International Journal Of Production Research*, vol. *27*, no. 10, pp.1811-1835, 1989.

[17] S. M. Shafer and J. R. Meredith, "A comparison of selected manufacturing cell formation techniques," *The International Journal of Production Research*, vol. *28*, no. 4, pp.661-673, 1990.

[18] C. H. Chu and M. Tsai, "A comparison of three array-based clustering techniques for manufacturing cell formation," *The International Journal of Production Research*, vol. 28, no. 8, pp.1417-1433, 1990.

[19] J. S. Morris and R. J. Tersine, "A simulation analysis of factors influencing the attractiveness of group technology cellular layouts," *Management Science*, vol. 36, no. 12, pp. 1567-1578, 1990.

[20] J. Miltenburg and W. Zhang, "A comparative evaluation of nine well-known algorithms for solving the cell formation problem in group technology," *Journal of operations management*, vol. *10*, no. 1, pp. 44-72, 1991.

[21] A. G. Burgess, I. Morgan and T. E. Vollmann, "Cellular manufacturing: its impact on the total factory," *The International Journal of Production Research*, vol. 31, no. 9, pp. 2059-2077, 1993.

[22] D. F. Rogers and S. M. Shafer, "Measuring cellular manufacturing performance," in *Planning, Design and Analysis of Cellular Manufacturing Systems*, A.K. Kamrani, H.R. Parsaei and D.H. Liles Ed., Elsevier Science, B.V., pp.147-165, 1995.

[23] B. R. Sarker, "Measures of grouping efficiency in cellular manufacturing systems," *European Journal of Operational Research*, vol. *130*, no. 3, pp. 588-611, May 2001.

[24] K. B. Keeling, E. C. Brown and T. L. James, "Grouping efficiency measures and their impact on factory measures for the machine-part cell formation problem: A simulation study," *Engineering Applications of Artificial Intelligence*, vol. 20, no. 1, pp. 63-78, February 2007.

[25] H. C. Babacan, "Çok Amaçlı Hücresel İmalat Tasarımı ve Hidromek Silindir Üretim Tesisinde Bir Uygulama," Graduate Thesis, Gazi University, Ankara, Turkey, 2008.

[26] J. MacQueen, "Some methods for classification and analysis of multivariate observations," In *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability*, vol. 1, no. 14, pp. 281-297, 1967.

[27] A. K. Jain, "Data clustering: 50 years beyond K-means," *Pattern recognition letters*, vol. 31, no. 8, pp. 651-666, 2010.

[28] R. Real and J. M. Vargas, "The probabilistic basis of Jaccard's index of similarity," *Systematic biology*, vol. *45*, no. 3, pp. 380-385, 1996.

[29] Y. Yin and K. Yasuda, "Similarity coefficient methods applied to the cell formation problem: a comparative investigation," *Computers & industrial engineering*, vol. *48*, no. 3, pp. 471-489, May 2005.

[30] A. P. Dempster, N. M. Laird and D. B. Rubin, "Maximum likelihood from

incomplete data via the EM algorithm," *Journal of the Royal Statistical Society. Series B (methodological)*, vol. 39, no. 1, pp. 1-38, 1977.

[31] F. Dellaert, *The expectation maximization algorithm*. Georgia Institute of Technology, 2002.

[32] J. Han, M. Kamber and J. Pei, *Data mining: concepts and techniques*. 3rd Edition, Elsevier, 2012.

[33] J. R. King, "Machine-component grouping in production flow analysis: an approach using a rank order clustering algorithm," *International Journal of Production Research*, vol. *18*, no. 2, pp. 213-232, 1980.