



SAKARYA ÜNİVERSİTESİ

FEN BİLİMLERİ ENSTİTÜSÜ DERGİSİ

Sakarya University Journal of Science
SAUJS

e-ISSN 2147-835X | Period Bimonthly | Founded: 1997 | Publisher Sakarya University |
<http://www.saujs.sakarya.edu.tr/en/>

Title: Machine-Part Formation for Cellular Manufacturing in Group Technology: An Application for Furniture Company

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Received: 2020-12-17 00:00:00

Accepted: 2021-03-14 12:52:00.995000

Article Type: Research Article

Volume: 25

Issue: 2

Month: April

Year: 2021

Pages: 466-483

How to cite

İlker GÜVEN,Fuat ŞİMŞİR; (2021), Machine-Part Formation for Cellular Manufacturing in Group Technology: An Application for Furniture Company. Sakarya University Journal of Science, 25(2), 466-483, DOI:

<https://doi.org/10.16984/saufenbilder.842423>

Access link

<http://www.saujs.sakarya.edu.tr/en/pub/issue/60672/842423>

New submission to SAUJS

<https://dergipark.org.tr/en/journal/1115/submission/step/manuscript/new>

Machine-Part Formation for Cellular Manufacturing in Group Technology: An Application for Furniture Company

İlker GÜVEN¹, Fuat ŞİMŞİR^{*1}

Abstract

Group technology's basic logic is grouping and producing products of the same type together. An important reason behind Group Technology becoming such an important topic is that nowadays companies have quite an extensive range and workshop type production has increased. Both fuzzy clustering and rank order clustering methods use for grouping parts and machines based on a part-machine matrix created from the production flow technique in order to increase productivity and reduce cost and workmanship required. In this study, Group Technology techniques such as the rank order clustering and fuzzy clustering methods were applied in order to increase the efficiency of the production line, reduce transportation between machines, and form a machine-parts groups in the wood cutting department of a furniture company producing modular furniture in Istanbul. The TOPSIS method was used to determine which products to take into account. According to results of the study, it is shown that fuzzy clustering method has overperformed rank order clustering method based on the evaluation criteria which are group productivity with 21,36%, group efficiency with 43,21% and grouping measure with 82,33%.

Keywords: Group Technology, Fuzzy Clustering, Rank Order Clustering, TOPSIS, Cellular Manufacturing

1. INTRODUCTION

Companies have simple steps to keep themselves in business. According to most people, selling their services or products, in other words making profit, is accepted as the first stage of those steps. Typically, all production plans are designed base on this concept. However, nowadays products' life cycles have become short and variation of

products has increased. Also, production times have started to become shorter along with life cycle. Therefore, companies have to react to changes of variation of products as fast as they can. Otherwise, they may not be able to meet changes of product design and customer demands [1].

Flexible production systems can allow for a shorter adaptation period and make companies

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more responsive against those changes. “Cellular Manufacturing” or “Group Technology”, one of the applications of these systems used especially in the automotive sector, is becoming a widespread concept and has been successful as demonstrated by many studies [2].

In a simple definition, group technology (GT) is a production method that groups products using their similarity within all products to increase productivity.

GT’s basic logic is grouping and producing products together that are same type. One of the biggest reasons that GT is so prominent is that is nowadays companies have quite an extensive range and workshop type production has increased.

Therefore, setting up machines or renewing the assembly line during the changing groups of products has become a problem because of setup process time. Companies cannot build an assembly line for each product. That’s why they are grouped products and they build the assembly line for groups as a solution [3].

The philosophy of GT suggests similarities in repetitive works should be grouped together in three ways [4].

1. When doing similar activities, collecting activities together reduces time loses when passing to independent activities.
2. Standardization of activities that have a close relationship with each other, thus avoiding unnecessary repetition by focusing attention on certain differences
3. Collecting and storing information about repetitive problems, thus shortening the time spent searching for information and preventing attempts to solve previously solved problems

This method aims to combine the productivity of the GT flow line production system, which can be used in all sectors in which the production batch size is small, and the product variety is high, allowing for the flexibility of workshop type production. Products manufactured using GT are grouped according to their similarities in terms of

design, planning and production activities, thereby increasing productivity in terms of time, workmanship and cost.

In this study, GT techniques were applied in order to increase the efficiency of a production line, reduce the transportation between the machines, and form machine-parts groups in the wood cutting department in a furniture company producing modular furniture in Istanbul. In section 2, literature review on the problem has been given. In section 3, methods used in the study have been explained and in section 4, given methods have been carried out with the data obtained from the manufacturer. Finally, in section 5, results and conclusions of the study have been discussed and suggestions have been given.

2. LITERATURE REVIEW

Many methods have been developed to apply cellular production techniques in group technology, which is more important than previous years. In the early era of GT, the main goal was calculating number of part-machine groups. Nowadays, reduced non-grouped and exceptional parts, attention to process priorities or similar machineries, evaluated process times and minimized cost of workload methods have been introduced in the literature. The biggest share in the development of these methods is undoubtedly development of computer technologies and heuristics, or artificial intelligence applications [5].

These methods ensure that the commonly produced parts are processed in the same cell throughout the production period. To accomplish this, cell creation problems are summarized in three basic steps [4]:

1. Determination of part families
2. Creating of machine cells
3. Assignment of part families to cells

Depending on the technique used, the steps are applied either simultaneously or sequentially. In cellular production, classification techniques or cell formation techniques can be used to create cells. Classification techniques are techniques

which consider part constraints such as shape, size, raw material, processing and processing times. It can be used visually or with the coding systems. There is no need for coding systems or visual evaluation in cell formation techniques,

unlike classification techniques. Parts and machines can be grouped based on production process. A summarized list of clustering techniques is given for creating cells in Table 1 [4].

Table 1
Clustering techniques

Array-Based Clustering Techniques	Hierarchical Clustering Techniques	Non-Hierarchical Clustering Techniques	Mathematical Programming Techniques	Graphic Theory Techniques	Artificial Intelligence Techniques
Production Flow Analysis	Single Link Clustering	Ideal Core Algorithm	P-Median		Artificial Neural Networks
Rank Order Clustering	Average Link Clustering	GRAFICS Technique	Goal Programming		Fuzzy Logic
Direct Clustering			Dynamic Programming		Expert Systems
Bond Energy Algorithm			Assignment Technique		Genetic Algorithm
Cluster Identification Algorithm			Quad Programming		Simulated Annealing
Modified Rank Order Clustering					Tabu Search Algorithm

Numerous studies have been done for creating part-machine families. While many applications have been implemented, many researchers use artificial intelligence techniques such as Tabu search algorithm, genetic algorithm, k-means clustering algorithm, fuzzy set theory [1], [3], [6–31]. In addition to these researchers, a few researchers have used series-based clustering techniques such as modified rank order clustering, goal programming [4], [12], [26], [32–34], and mathematical modeling techniques [18], [35–37]. Other researchers suggest a hybrid solution consisting of a combination of two or more different methods and they created performance evaluation criteria by comparing their methods with others for methods which they suggested in their papers. Also, constraints are generally considered such as ungrouped parts, cluster number, intercell transport costs as performance criteria. One of the recent research areas that gain interest is energy efficient scheduling in cellular manufacturing [38–40].

Another point that draws attention in the literature review is that there is a lack of information in the selection of part-machine for using clustering and

the way the data is obtained. Most researchers have used part-machine matrices and data provided in previous papers in the literature for testing their methods in their papers. Researchers who have prepared datasets themselves have not provided a technique or explanation of why these data were selected. The issues such as which parts will be taken into account for the formation of cells, and why these parts should be selected, are steps to be considered in companies where machine and parts numbers are too numerous. If selected part is different from the production process of other parts in general, it is inevitable that the formed cells are only efficient for a small number of parts, as the cost of transportation intercell increases and production process will become more complicated. Seifoddini and Tjahjana (1999) encountered 300.000 pieces in the Harnischfeger Company in their work. They examined the product properties and determined that there were many parts in different dimensions passing through the same production processes and managed to classify them into 22 part groups by grouping them according to their size. Because so many parts cannot be placed on the part-machine matrix [41].

According to literature review, researchers have tried different approach to overcome high variety in the products and production route. Due to overcome the challenge created by different type of products and their production routes, in this study, TOPSIS method which is one of the ordering techniques, is used to choose the best product by several criteria, thus, the efficiency of production line is expected to be increased in terms of grouping the machines according to selected product. The idea of the logic behind this approach is, if production line is arranged according to the product which is produced most then that production line would represent most of the production.

3. MATERIAL AND METHOD

The fact that there are many product varieties in the company where the application is made poses a problem in the formation of machine part families. As machine cells cannot be formed for all of the products, there may be cases in which the cells formed are not suitable for all products. The parts of the product and the products to be used during the formation of the cells should show similarities with the other products produced in the company on the basis of the production routes and products with high demand. This would mean that the cell to be formed is more efficient. In view of that fact, product to be considered when cell is forming, is a step as important as forming cells. In this respect, necessity of combining TOPSIS with clustering methods is very high.

The use of multi-criteria decision-making methods in cases in which there are many alternatives and more than one evaluation criterion will give more accurate results because it is a scientific method. In this study, the TOPSIS (Technique for Order-Preference by Similarity to Ideal Solution) method, which is one of the multi-criteria decision-making methods, has been used in the determination of machine-parts groups.

Choosing the best multi criteria decision-making techniques is a hard process since each of them have advantages and disadvantages. The reason of using TOPSIS method among other multi criteria decision-making techniques is that, TOPSIS is

one of the most popular and widely used method, its algorithm reliable and simple. Another reason of using the TOPSIS is it's interpretability and applicability in various fields [42]. One of the most important advantage of TOPSIS is that regardless the number of criteria and alternatives, it has same amount of process which provide flexibility[43]. Besides that, TOPSIS has standardization step that allow to use data where data range for each criterion can be various.

Machine-part matrices were created for the selected product with TOPSIS and machine-part cells were formed by using ROC (Rank Order Clustering) algorithm and Fuzzy Clustering algorithm.

3.1. TOPSIS

When the TOPSIS method is used, cases where the ideal solution is the nearest and the negative ideal solution is far away are examined among the alternatives. In this case optimal solution point is the farthest from the negative ideal solution and the closest to the positive ideal solution [44]. Relation of alternatives with positive and negative ideal solution is given in Figure 1.

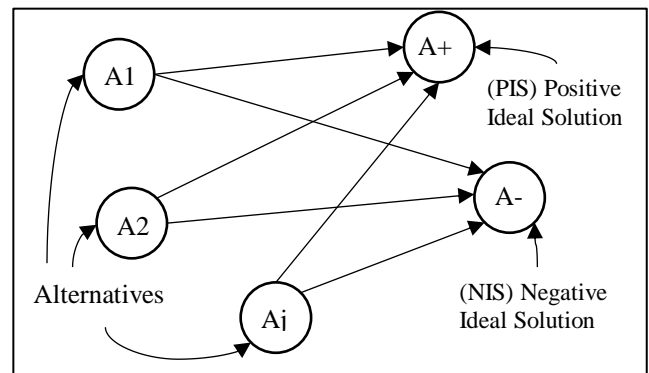


Figure 1 Distance of alternatives to ideal solutions

The general algorithm for TOPSIS is given below [45];

Step 1: The decision matrix is generated by the decision maker. The size of the matrix consists of m alternatives and n criteria. Alternatives are in rows, and criteria are in columns.

Step 2: After the decision matrix is formed, the standard matrix is formed by

using decision matrix. TOPSIS allows researchers to use different normalization techniques to form standard matrix which is important when range of values for each criterion is various. In this study vector normalization method is used to normalize decision matrix according to the equation (1). Where i is the alternative, j is the criteria.

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^m a_{ij}^2}} \quad (i = 1, \dots, m \text{ and } j = 1, \dots, n) \quad (1)$$

Step 3: The weighted standard matrix is calculated using the equation (2). Here, the weight of i th criterion is expressed by w_i . Total weights must equal one. ($\sum_{i=1}^n w_i = 1$).

$$V_{ij} = w_i * r_{ij} \quad (i = 1, \dots, m \text{ and } j = 1, \dots, n) \quad (2)$$

Step 4: In order to obtain a positive ideal solution, maximum values are taken for each column in the V matrix obtained by considering the structure of the problem. In order to obtain a negative ideal solution in the same way, the minimum values in each column are taken. Related equations are given at equations (3) and (4). J cluster is used for benefit criteria while J' cluster is used for cost criteria. The largest best rule in cluster J is valid, while the smallest best rule is in cluster J' .

$$A^* = \begin{cases} \max_i \{v_{ij} | j \in J\} \\ \min_i \{v_{ij} | j \in J'\} \end{cases} \quad (3)$$

$$A^- = \begin{cases} \min_i \{v_{ij} | j \in J\} \\ \max_i \{v_{ij} | j \in J'\} \end{cases} \quad (4)$$

Step 5: The distance of i th alternative to positive ideal solution (s_i^*) and the distance to negative ideal solution (s_i^-) are calculated using equations (5) and (6).

$$S_i^* = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^*)^2} \quad (5)$$

$$S_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2} \quad (6)$$

Step 6: In the calculation of the distance of the alternatives to ideal solution point, distance of alternative to positive and negative solution is used and indicated by C_i^* . The calculated ideal solution takes a value between $0 \leq C_i^* \leq 1$. It is calculated according to the equation (7).

$$C_i^* = \frac{s_i^-}{s_i^- + s_i^+} \quad (7)$$

An alternative with a higher C_i^* value is a better.

3.2. Rank Order Clustering

The Rank Order Clustering (ROC) technique is a method developed by King on the basis of a production flow technique for the formation of machine-part cells. In this technique, a machine-part matrix is formed according to the information on which machines the parts are processed.

Then, this matrix is applied to the King algorithm given in the following steps to formation machine-parts cells [46].

Step 1: After the formation of the machine-part matrix, the values in the binary system decreasing from left to right for each row are calculated. The values of 1 on each line are summed to calculate the decimal value of the line.

Step 2: Go to Step 6 if the calculated row order is the same as the current row order, otherwise go to Step 3.

Step 3: Rows of the machine-part matrix are rearranged in descending order according to the decimal values obtained in Step 1. The values are calculated for each part that has 1 value in matrix, which goes down from top to bottom decreasingly for the columns. The decimal sum of columns is calculated by the sum of those values.

Step 4: Go to Step 6 if the calculated column order is the same as the current column order, otherwise go to Step 5.

Step 5: Columns of the machine-part matrix are rearranged in descending order according to the decimal values obtained in Step 4. Go to Step 1.

Step 6: Stop

3.3. Fuzzy Clustering

Fuzzy clustering is a clustering method which allows a single variable to be a member of multiple clusters in part by generalizing clustering methods such as K-Means or Medoid. In this method, the membership function of the clusters is distributed among all the clusters. In the fuzzification step, which is the classic fuzzy logic step, that membership function can take a value between 0 and 1, provided that sums are 1.

In the literature, there are two methods of fuzzy clustering. One of them is Fuzzy C-Means as known as FCM which follows c-partition logic. Other one is FANNY, hierarchical clustering method which based on fuzzy equality principle [47].

The algorithm used for Fuzzy Clustering, FANNY, was created by Kaufman and Rousseeuw [48]. The purpose of the algorithm is to minimize the goal function (8) consisting of cluster membership and distance.

$$C = \sum_{v=1}^k \frac{\sum_{i,j=1}^n u_{iv}^2 u_{jv}^2 d_{ij}}{2 \sum_{j=1}^n u_{jv}^2} \quad (8)$$

d_{ij} gives the distance between i and j in the equation, while u_{iv} gives the coefficient of the unknown membership of the i unit to v cluster. Similarly, u_{jv} gives the coefficient of the unknown membership of the j unit to v cluster. Here k is the number of clusters and n is the total number of units. One of the constraints here is that the membership function cannot have a negative value and sum of membership function must be 1 in total for cluster.

In normal clustering algorithm, each object must have only one membership coefficient and this

coefficient must be different from 0, in case no value other than 1 can be taken. Therefore, fuzzy objects also limited in normal clustering. Dunn's partition coefficient (9) can quantify the amount of fuzzification in the fuzzy clustering solution by measuring similarity between fuzzy clustering solution and corresponding normal clustering solution.

$$F_k(U) = \sum_{i=1}^n \sum_{v=1}^k u_{iv}^2 / n \quad (9)$$

U indicates the membership matrix and n indicates the number of objects in equation (9). Coefficient range is limited to between 1 and $1/k$. When an object receives a value, which is $1/k$, all objects get the same value. If this coefficient is to be standardized, it can be expressed as 0 (fully fuzzy) and 1 (not fuzzy). Standardized equation is given below (10). This process also known as defuzzification.

$$F'_k(U) = \frac{F_k(U) - (1/k)}{1 - (1/k)} \quad (10)$$

As a second function other than Dunn's partitioning coefficient, the mean square error can be used.

$$D_k(U) = \sum_{v=1}^k \sum_{i=1}^n (w_{iv} - u_{iv})^2 / n \quad (11)$$

The object expressed by w which is formed by normal clustering, is the most similar object to fuzzy object u . $D_k(U)$ is calculates the mean square error of fuzzy clustering in the closest way to normal clustering. Unlike Dunn's partitioning coefficient, it is expressed as 0 (not fuzzy) and $1 - 1/k$ (fully fuzzy). Standardized version of the equation is given equation (12).

$$D'_k(U) = \frac{D_k(U)}{1 - 1/k} \quad (12)$$

The general steps of algorithm are as shown below [1];

- Step 1: Determine the number of clusters to be formed
- Step 2: Select the membership function
- Step 3: Determine the stopping criterion
- Step 4: Find the starting matrix and calculate the membership value

Step 5: Calculate the initial values of cluster centers

Step 6: Updating membership functions according to initial values

Step 7: Continue until the difference between the calculated membership function and the current function is less than the stopping criterion

The biggest disadvantage of the fuzzy clustering method is that the number of clusters to be formed must be determined in advance. It is impossible to estimate it where companies with lots of parts and machines. For this reason, these algorithms experiment on various cluster numbers and calculate the results and error rates. Thus, the cluster number is determined where the error rate is lowest, the standardized version of Dunn's partition coefficient $F'_k(U)$ in equation 10 is the highest, and the standardized Kaufman coefficient $D'_k(U)$ in equation 12 is the lowest.

4. APPLICATION

In the scope of this study, a wood cutting workshop was taken into consideration in the production department of modular furniture manufacturer. The cells to be formed are evaluated according to the processes that parts undergo in the wood cutting workshop.

The study has three steps of implementation. First is determining which product parts were to be used to form machine-part matrix by TOPSIS method, then implementation of ROC method, and finally implementation of Fuzzy Clustering method. Steps of approach are illustrated in Figure 2.

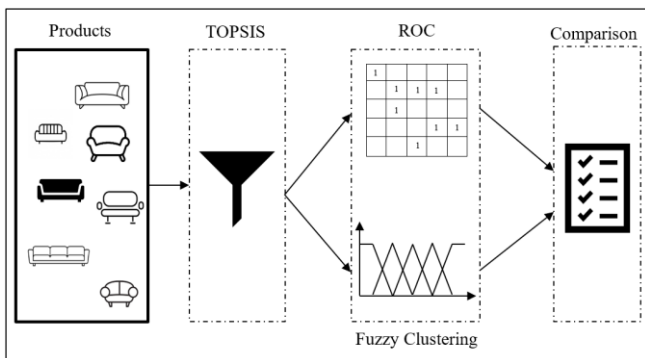


Figure 2 Proposed approach

Dataset for TOPSIS method is created based on the all products that company produce which are 277 products in total. Then, criteria are determined by the production planning team of the company considering the factors that might affect the production routes. Thus, information regarding criteria has been obtained for each product from production planning resources and dataset is finalized for TOPSIS.

After selection of the most suitable product with TOPSIS method, datasets which contains machine-part information of the product has been used to carry out grouping algorithms.

Considering 277 products that would be manufactured in the company, it is quite impossible to arrange production line for each of them. Therefore, decision makers need to choose a reference product that reflects the company's daily production route, which means that product could be the most seller one. Hence, there might be some other criteria that should be considered to choose right product. That is why TOPSIS is used to make a decision based on multi-criteria and choices.

4.1. TOPSIS Application

In the first step of the application, the selection of the product to be used is included. The TOPSIS algorithm given in section 3.1 will be used for this. The algorithm of the given TOPSIS method is coded and executed in the Microsoft Excel 2010 program using the Visual Basic for Applications (VBA) language.

A number of criteria must be assessed in order to choose which product parts to use. In order to cells to be efficient, some variables are defined as key roles, such as how many machines are used for the product to be processed, how many parts it has, size of product, production time and number of orders. Therefore, the criteria to be used in TOPSIS are as follows:

- Production time
- Number of parts
- Number of orders
- Size of product

- Number of machines

Expert opinions have been finalized to determine which of these criteria is more important by using Delphi method. Weights of the criteria are given in Table 2.

Table 2
Criteria and weights

Criteria	Weights(w)
Production Time	0,1
Number of parts	0,3
Number of orders	0,2
Size of product	0,15
Number of machines	0,25

The values of the products taken into consideration for the determined criteria and the decision matrix are given in Table 3.

Table 3
TOPSIS decision matrix

No	Product Code	Production Time (Min)	Number of Parts (PCS)	Number of Order (PCS)	Machine Number (PCS)	Size of Product (CM)
1	PKT.0001	423	45	8	7	120
2	PKT.0002	482	45	7	7	140
3	PKT.0003	312,5	31	11	10	60
4	PKT.0005	386,4	33	8	10	140
5	PKT.0006	415,5	34	10	10	180
6	PKT.0007	288	22	7	12	60
7	PKT.0009	388,9	34	6	12	140
.
56	PKT.0116	647	56	20	11	200
.
276	PKT.0966	245	55	5	10	70
277	PKT.0967	245	55	5	10	70

The results obtained after running the TOPSIS algorithm in the Microsoft Excel 2010 program are given in Table 4. According to TOPSIS algorithm each product has its C_i^* point and products can be listed based on these points. As

we mentioned in the section 3.1. higher point indicates the most suitable products.

When results were examined, the product with the highest C_i^* values, was product PRD.0116.

Table 4
 C_i^* values obtained after TOPSIS application

No	Product Code	C_i^* Value	No	Product Code	C_i^* Value	No	Product Code	C_i^* Value
1	PRD.0001	0,291476	55	PRD.0115	0,360284	78	PRD.0186	0,243217
2	PRD.0002	0,286407	56	PRD.0116	0,640292	79	PRD.0187	0,249414
3	PRD.0003	0,266665	57	PRD.0117	0,143348	80	PRD.0188	0,260233
4	PRD.0005	0,240191	58	PRD.0119	0,441315	81	PRD.0189	0,325993
5	PRD.0006	0,293847	59	PRD.0120	0,293266	82	PRD.0190	0,272331
6	PRD.0007	0,172323	60	PRD.0121	0,112321	83	PRD.0191	0,33493
7	PRD.0009	0,239567	61	PRD.0122	0,145293	84	PRD.0192	0,283935

8	PRD.0010	0,258862	62	PRD.0123	0,166797	85	PRD.0193	0,34425
.
.
53	PRD.0113	0,341918	76	PRD.0180	0,204487	276	PRD.0966	0,315148
54	PRD.0114	0,146228	77	PRD.0185	0,237553	277	PRD.0967	0,315148

4.2. Rank Order Clustering (ROC) Application

In order to implement the ROC algorithm, a machine-part matrix of the product must be created. A machine-part matrix is shown in Table 5. It includes parts of PRD.0116 and the machines

used for processing in the wood cutting workshop, along with the information obtained after examining bill of materials and route of product PRD.0116. In this matrix, 0 indicates that the parts are not processed in the corresponding machine, and 1 indicates that the parts are processed by the corresponding machine.

Table 5
Machine-part matrix of PRD.0116

PARTS / MACHINES	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
P1	0	0	1	0	0	0	0	0	0	0	0	1
P2 – P4	0	0	1	0	0	0	0	0	0	0	0	0
P5 – P8	0	0	0	0	0	0	0	1	1	0	0	0
P9	0	0	1	0	0	0	0	0	0	0	0	0
P10, P11, P13	1	1	0	0	0	0	0	0	0	0	0	0
P12, P14 –P16	0	0	1	0	0	0	0	0	0	0	0	0
P17, P39	1	1	0	0	0	0	0	0	0	0	0	0
P18 – P21	0	0	0	0	0	0	0	1	1	0	0	0
P22	0	0	0	0	1	1	1	0	0	0	1	0
P23	0	1	0	0	1	1	1	0	0	0	1	0
P24	0	0	0	0	1	1	1	0	1	0	0	0
P25	1	1	0	1	0	0	0	0	0	0	0	0
P26, P27	0	0	1	0	0	0	0	0	0	0	0	0
P28, P29	1	1	0	0	0	0	0	0	0	0	0	0
P30 – P32	0	0	1	0	0	0	0	0	0	0	0	0
P33	0	1	0	0	0	0	0	1	1	1	1	0
P34	0	1	0	0	0	0	0	1	1	0	1	0
P35	0	0	0	0	0	0	0	1	1	1	0	0
P36 – P38	0	0	0	0	0	0	0	1	1	0	0	0
P40 – P44	0	0	1	0	0	0	0	0	0	0	0	0
P45	0	0	1	0	0	0	0	0	0	1	0	0
P46	1	1	0	0	0	0	0	0	0	0	0	0
P47	0	0	1	0	0	0	0	0	0	0	0	0
P48, P49	0	0	1	0	0	0	0	0	0	0	0	1
P50	1	1	0	0	0	0	0	0	0	0	0	0
P51, P52	0	1	0	0	1	1	1	0	1	1	1	0
P53	0	0	1	1	0	0	0	0	0	0	0	0
P54	0	0	1	1	0	0	0	0	0	0	0	1
P55	0	0	0	0	1	1	1	0	1	0	1	0
P56	0	0	1	0	0	0	0	0	0	0	0	0

In implementing the ROC algorithm, the algorithm steps given in section 3.2 have been coded and executed in Microsoft Excel 2010

program using VBA. The obtained machine-part cells are given in Table 6.

Table 6
Formed machine-part cells

PARTS / MACHINES	M3	M12	M4	M10	M2	M1	M9	M11	M8	M5	M6	M7
P54	1	1	1	0	0	0	0	0	0	0	0	0
P1	1	1	0	0	0	0	0	0	0	0	0	0
P48	1	1	0	0	0	0	0	0	0	0	0	0
P49	1	1	0	0	0	0	0	0	0	0	0	0
P53	1	0	1	0	0	0	0	0	0	0	0	0
P45	1	0	0	1	0	0	0	0	0	0	0	0
P2	1	0	0	0	0	0	0	0	0	0	0	0
...
P56	1	0	0	0	0	0	0	0	0	0	0	0
P25	0	0	1	0	1	1	0	0	0	0	0	0
P33	0	0	0	1	1	0	1	1	1	0	0	0
P51	0	0	0	1	1	0	1	1	0	1	1	1
P52	0	0	0	1	1	0	1	1	0	1	1	1
P35	0	0	0	1	0	0	1	0	1	0	0	0
P10	0	0	0	0	1	1	0	0	0	0	0	0
P11	0	0	0	0	1	1	0	0	0	0	0	0
...
P50	0	0	0	0	1	1	0	0	0	0	0	0
P34	0	0	0	0	1	0	1	1	1	0	0	0
P23	0	0	0	0	1	0	0	1	0	1	1	1
P55	0	0	0	0	0	0	1	1	0	1	1	1
P5	0	0	0	0	0	0	1	0	1	0	0	0
...
P38	0	0	0	0	0	0	1	0	1	0	0	0
P24	0	0	0	0	0	0	1	0	0	1	1	1
P22	0	0	0	0	0	0	0	1	0	1	1	1

As a result of the ROC algorithm, three groups are formed. Part groups are shown in Figure 3 and machine groups are shown in Figure 4.

Figure 3 Part groups according to ROC results

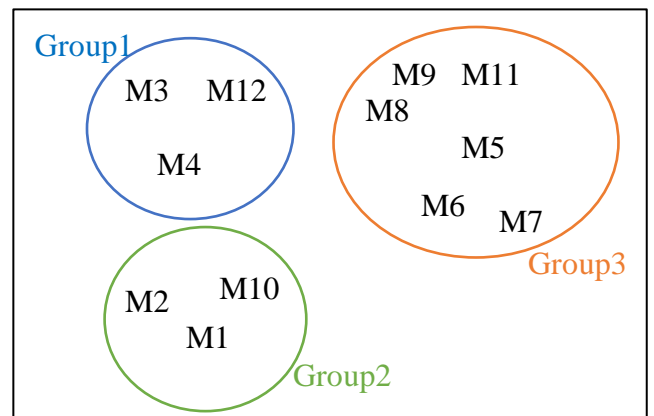
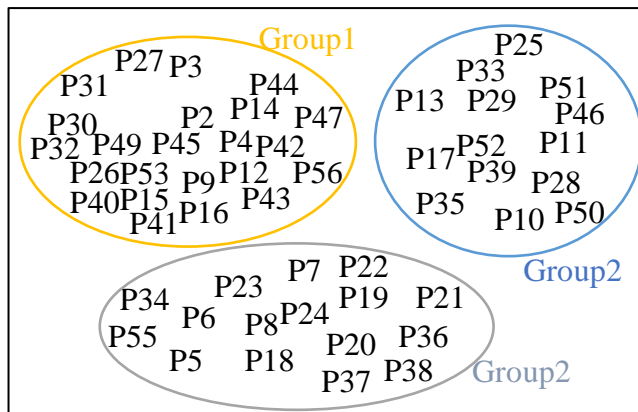


Figure 4 Machine groups according to ROC results

4.3. Fuzzy Clustering Application

In order to implement the fuzzy clustering algorithm, we need the machine-part matrix as in the ROC algorithm. For this reason, the machine-part matrix in Table 5, which is used in the application phase of the ROC algorithm, will also be used for fuzzy clustering in the same way.

For the fuzzy clustering algorithm, version 1.3.1093 of the R Studio was used free license. The steps to be followed when fuzzy clustering is applied are given below [1].

Step 1: Machine-part matrix is entered into the package program while machines are on the lines and parts are on the columns.

Step 2: Fuzzification level is determined.

Step 3: Cluster number is determined.

Step 4: Algorithm is executed for clustering

Step 5: Groups of machines and parts are written in matrix format.

The machine and part cells obtained after applying the steps are given in Table 7. Euclidean distance is used as distance criterion, and the fuzzification level is set to 2. Cluster number is set to be 4 after tried few different cluster numbers.

Table 7
Obtained machine-part cells after fuzzy clustering applied

Machine	Cluster	Part	Cluster	Part	Cluster	Part	Cluster	Part	Cluster	Part	Cluster
M1	1	P1	1	P13	3	P25	3	P37	2	P49	1
M2	1	P2	1	P14	1	P26	1	P38	2	P50	3
M3	2	P3	1	P15	1	P27	1	P39	3	P51	4
M4	1	P4	1	P16	1	P28	3	P40	1	P52	4
M5	3	P5	2	P17	3	P29	3	P41	1	P53	1
M6	3	P6	2	P18	2	P30	1	P42	1	P54	1
M7	3	P7	2	P19	2	P31	1	P43	1	P55	4
M8	4	P8	2	P20	2	P32	1	P44	1	P56	1
M9	4	P9	1	P21	2	P33	4	P45	1		
M10	1	P10	3	P22	4	P34	4	P46	3		
M11	3	P11	3	P23	4	P35	2	P47	1		
M12	1	P12	1	P24	4	P36	2	P48	1		

In order to be able to compare the formed cells with the ROC algorithm, the machines and parts are placed in the machine-part matrix in Table 8.

Table 8
Fuzzy clustering resultant machine-part matrix

PARTS / MACHINES	M3	M8	M9	M1	M2	M4	M10	M12	M5	M6	M7	M11
P1	1	0	0	0	0	0	0	1	0	0	0	0
..
P4	1	0	0	0	0	0	0	0	0	0	0	0
P9	1	0	0	0	0	0	0	0	0	0	0	0
P12	1	0	0	0	0	0	0	0	0	0	0	0
P14	1	0	0	0	0	0	0	0	0	0	0	0
P15	1	0	0	0	0	0	0	0	0	0	0	0
P16	1	0	0	0	0	0	0	0	0	0	0	0
P26	1	0	0	0	0	0	0	0	0	0	0	0
P27	1	0	0	0	0	0	0	0	0	0	0	0
P30	1	0	0	0	0	0	0	0	0	0	0	0
P31	1	0	0	0	0	0	0	0	0	0	0	0

P32	1	0	0	0	0	0	0	0	0	0	0	0
P40	1	0	0	0	0	0	0	0	0	0	0	0
...
P49	1	0	0	0	0	0	0	1	0	0	0	0
P53	1	0	0	0	0	1	0	0	0	0	0	0
P54	1	0	0	0	0	1	0	1	0	0	0	0
P56	1	0	0	0	0	0	0	0	0	0	0	0
P5	0	1	1	0	0	0	0	0	0	0	0	0
...
P8	0	1	1	0	0	0	0	0	0	0	0	0
P18	0	1	1	0	0	0	0	0	0	0	0	0
...
P21	0	1	1	0	0	0	0	0	0	0	0	0
P35	0	1	1	0	0	0	1	0	0	0	0	0
...
P38	0	1	1	0	0	0	0	0	0	0	0	0
P10	0	0	0	1	1	0	0	0	0	0	0	0
P11	0	0	0	1	1	0	0	0	0	0	0	0
P13	0	0	0	1	1	0	0	0	0	0	0	0
P17	0	0	0	1	1	0	0	0	0	0	0	0
P25	0	0	0	1	1	1	0	0	0	0	0	0
P28	0	0	0	1	1	0	0	0	0	0	0	0
P29	0	0	0	1	1	0	0	0	0	0	0	0
P39	0	0	0	1	1	0	0	0	0	0	0	0
P46	0	0	0	1	1	0	0	0	0	0	0	0
P50	0	0	0	1	1	0	0	0	0	0	0	0
P22	0	0	0	0	0	0	0	0	1	1	1	1
P23	0	0	0	0	1	0	0	0	1	1	1	1
P24	0	0	1	0	0	0	0	0	1	1	1	0
P33	0	1	1	0	1	0	1	0	0	0	0	1
P34	0	1	1	0	1	0	0	0	0	0	0	1
P51	0	0	1	0	1	0	1	0	1	1	1	1
P52	0	0	1	0	1	0	1	0	1	1	1	1
P55	0	0	1	0	0	0	0	0	1	1	1	1

Fuzzy clustering resulted in 4 groups. Part groups are shown in Figure 5 and machine groups are shown in Figure 6. Part and machine locations on the graphs are extracted from the Fuzzy Clustering algorithm.

Figure 5 Part groups according to Fuzzy Clustering results

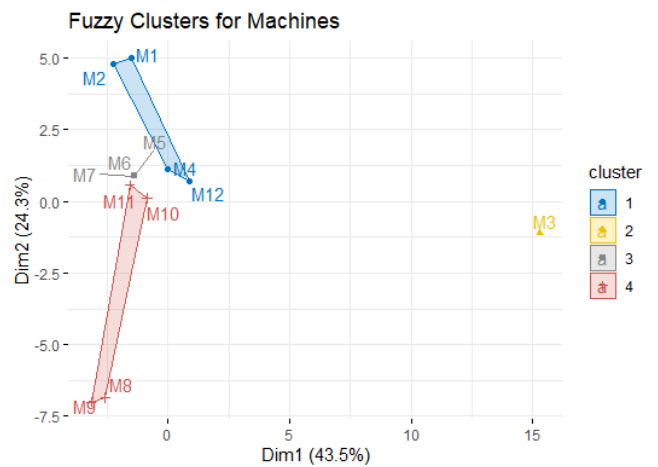
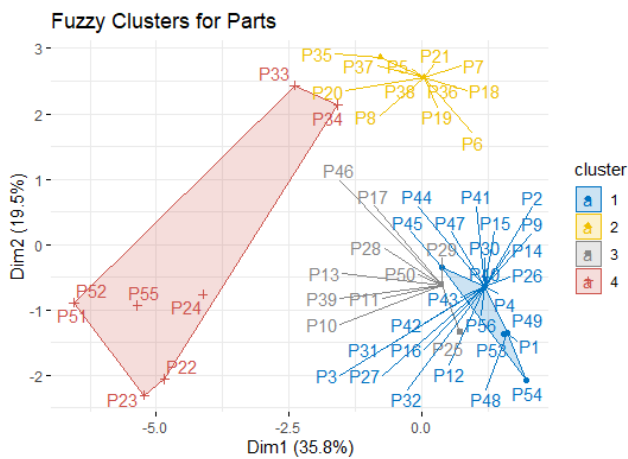


Figure 6 Machine groups according to Fuzzy Clustering results

The membership degrees of the machines to clusters are given in Table 9.

Table 9
Membership degrees of the machines

Machine	Cluster	Membership Degree
M1	1	0.5901
M2	1	0.5406
M3	2	0.9720
M4	1	0.4096
M5	3	0.9791
M6	3	0.9791
M7	3	0.9791
M8	4	0.7132
M9	4	0.6556
M10	1	0.3557
M11	3	0.3787
M12	1	0.3700

Obtained Dunn’s coefficient for part clustering is 0.77 and standardized version of it is 0.69. On the other hand, Dunn’s coefficient for machine clustering is 0.45 and standardized version is 0.26. Thus, fuzzy clustering for machine was successful than fuzzy clustering for parts.

4.4. Calculation of Evaluation Criteria

When the evaluation methods used for the success of the obtained machine-part matrix are examined, the three different evaluation criteria are found as stated in the literature. The most commonly used of these criteria is group productivity [1], [3], [13], [49].

- Group efficiency (%)
- Group productivity (%)
- Grouping measure (%)

The equations used to calculate these criteria are given below.

Group productivity (η);

$$\eta = q \cdot \eta_1 + (1 - q) \cdot \eta_2 \tag{13}$$

$$\eta_1 = \frac{e_d}{\sum_{r=1}^k M_r \cdot N_r} \tag{14}$$

$$\eta_2 = 1 - \left[\frac{e_0}{M \cdot N - \sum_{r=1}^k M_r \cdot N_r} \right] \tag{15}$$

Group efficiency (r);

$$r = 1 - \frac{e_0 + e_v}{e + e_v} \tag{16}$$

Grouping measure (η_p);

$$\eta_p = \eta_u - \eta_m \tag{17}$$

$$\eta_u = \eta_1, \eta_m = \frac{e_0}{e_d} \tag{18}$$

Here;

e_d = Number of 1 in diagonal blocks

e_0 = Number of 1 out of diagonal blocks

q = Equation constant (0,5)

k = Cell number

M = Machine number

N = Part number

M_r = Machine number in r th cell, N_r = Part number in r th cell

e = Total process number

e_v = Number of 0 in diagonal blocks

The group productivity, group efficiency and grouping measure resultant from the ROC algorithm and Fuzzy Clustering are given in Table 10.

Table 10
Comparing of ROC and Fuzzy Clustering methods

Evaluation Criteria	ROC Algorithm	Fuzzy Clustering
Cell Number (k)	3	4
Group Productivity (η)	0,7129	0,8652
Group Efficiency (r)	0,4297	0,6154
Grouping Measure (η_p)	0,2875	0,5242
Number of 1 in diagonal blocks (e_d)	101	96
Number of 1 out of diagonal blocks (e_0)	19	24
Equation constant (q)	0,5	0,5
Number of 0 in diagonal blocks (e_v)	115	36
Total process number (e)	120	120

5. CONCLUSIONS AND DISCUSSION

In this study, it was realized that product selection is a multi-criteria decision-making problem. TOPSIS, one of the most effective methods used in multi-criteria decision making problems, has been used [44], [45], [50]. The products in the sofa group produced by the manufacturer have been evaluated according to the four criteria determined in the selection of the most suitable product. Thus, contrary to previous studies in the literature, a scientific approach has been adopted, as in the case of Seifoddini and Tjahjana, only differing in the process of selecting parts in the problems of forming machine-parts families [41].

Comparing the ROC algorithm and the Fuzzy Clustering method, the Fuzzy Clustering method showed better results as shown in Table 11.

Table 11
Advantages of Fuzzy Clustering Algorithm over ROC

Evaluation Criteria	Fuzzy Clustering > ROC
Group Productivity (η)	21,36%
Group Efficiency (r)	43,21%
Grouping Measure (η_p)	82,33%

Four production cells were created with the Fuzzy Clustering algorithm, while three production cells were created with the ROC algorithm. In the ROC algorithm, there are 101 operations included in the production cell, while in the Fuzzy Clustering algorithm this number decreases to 96 operations. While the success of the ROC algorithm reached 84.16%, because the grouping success covers 101 of 120 operations, the Fuzzy Clustering algorithm grouped 96 of 120 operations and remained at 80%. In evaluating of two methods group productivity, group efficiency, and grouping measure are important criteria, in addition to grouping the operations. These three criteria are taken into account in the literature. For this reason, the Fuzzy Clustering algorithm would be a better choice.

Funding

The author (s) has no received any financial support for the research, authorship or publication of this study.

The Declaration of Conflict of Interest/ Common Interest

No conflict of interest or common interest has been declared by the authors.

Authors' Contribution

The first author contributed 50%, the second author 50%.

The Declaration of Ethics Committee Approval

This study does not require ethics committee permission or any special permission

The Declaration of Research and Publication Ethics

The authors of the paper declare that they comply with the scientific, ethical and quotation rules of SAUJS in all processes of the paper and that they do not make any falsification on the data collected. In addition, they declare that Sakarya University Journal of Science and its editorial board have no responsibility for any ethical violations that may be encountered, and that this study has not been evaluated in any academic publication environment other than Sakarya University Journal of Science.

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