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CLUSTERING THE MILITARY POWERS OF COUNTRIES USING CRITIC BASED K-MEANS ALGORITHM

Fatma Gül ALTIN*

* Assist. Prof. Dr., Burdur Mehmet Akif Ersoy University, Bucak Zeliha Tolunay School of Applied Technology and Business Administration, Customs Business Administration, gulaltin@mehmetakif.edu.tr, https://orcid.org/0000-0001-9236-0502.

ABSTRACT

Events and developments in the first quarter of the 21st century show that the world will be dragged into a war environment in the near future. The shrinking living spaces of the great powers began to coincide. For this reason, a period has been entered where military power gains importance again. In a possible war, it is not possible for states that are not militarily strong to defend and protect their expatriated national interests. In this study, the list of countries' military powers organized by the Global Firepower site in 2019 was discussed. 21 criteria for 138 countries in the list were determined and the weight values of the criteria were calculated by the Critic method. Then, the required data set for clustering was obtained by multiplying the normalized criteria values with the weight values. By the K-Means algorithm, countries were divided into four clusters and clusters were evaluated.

Keywords: *Military Power, Cluster Analysis, K-Means, Critic Method.*

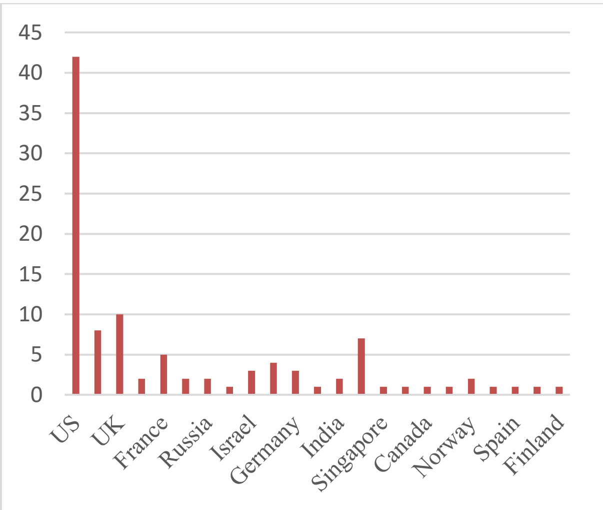
1. INTRODUCTION

In the world, military power has guided the foreign policy of the last two centuries (Tarakçı, 2019). Military power continues to be one of the most important elements of national power in the 21st century as always. For this reason, states that want to be strong against each other are constantly striving to develop and grow their military power (Meydan, 2015: 1).

Military power is the most important element for states to survive and ensure their national security (Aydın, 2004: 39). On the other hand, in terms of international relations, military power differences play an important role in understanding international politics (Balcı & Çelik, 2019: 102). There is an important relationship between a country's military power and its efficiency in foreign policy.

The role of defense industries in countries protecting their military power and turning them into economic and political advantage is great. In Figure 1, the distribution of the world's top 100 defense industry companies, organized by Defense News in 2020, is shown. Lockheed Martin and Boeing companies, known for their air defense technologies, are in the first and second place in the list. When the Defense News Top 100 list is examined, it is seen that the US companies (42) are in the majority. In addition, there are 10 British, 8 Chinese, 7 Turkish and 5 French companies on the list. Russia, which has one of the strongest armies in the world, does not have any companies in the top ten, and there are only two Russian companies in the Defense News Top 100 list.

Figure 1. Distribution of the World's Top 100 Defense Industry Companies by Country



Reference: (Defense News, 2020.)

In this study, the values related to the military power of countries are divided into clusters with the Critic based K-Means algorithm. The rest of this study is created as follows: Literature review, Research methodology, Application, Discussion and Conclusion.

2. LITERATURE REVIEW

When the literature is examined, there are many studies in which various weighting methods and K-Means algorithm are used together. Some of these studies are summarized below:

Ibrahim et al. (2011) evaluated customer trust in mobile commerce using AHP-based K-Means clustering algorithm. Two different questionnaires were designed in the study. The first survey is based on paired comparisons for the judgment of the experts. Factors affecting trust in mobile commerce websites in the survey are divided into three groups and each of these factors consists of sub-factors. By the AHP method, these sub-factors are ranked according to their importance levels and the second questionnaire is designed based on the most important sub-factors. The second survey is used to collect data from three mobile commerce websites. Then, factors are divided into five groups using the K-Means algorithm.

Momeni et al. (2015) evaluated firms listed on the Tehran Stock Exchange to assist investors, creditors and shareholders. 87 firms from three different sectors were included in the study. In the study, financial data were collected from the firms' 2012 financial statements. For the analysis, five criteria related to profitability were determined and then the weights of these criteria were calculated by the AHP method. Then, using the weighted criteria, the firms were divided into two clusters by the K-Means algorithm.

Li et al. (2016) conducted a risk assessment of water pollution in sources using Entropy-based K-Means and Set Pair analysis methods for the Shiyan region of China. Shiyan is the source water district for the South to North water transfer project. The reservoir in the Shiyan area, 292 industries and 65 agricultural companies are included in the study. The data used in the study were collected in 2011. According to the K-Means cluster analysis results, nine sources of industrial water pollution and two agricultural water pollution sources were identified.

Xu et al. (2018) evaluate urban flood risk in the Haikou region of China using an integrated improved Entropy weight method and K-Means clustering algorithm. In the proposed approach, seven assessment indexes are determined by combining the natural disaster index system and hydrological models. Index weights are calculated by an advanced Entropy weight method. Then, the flood risk map in Haikou region is developed by the K-Means clustering algorithm.

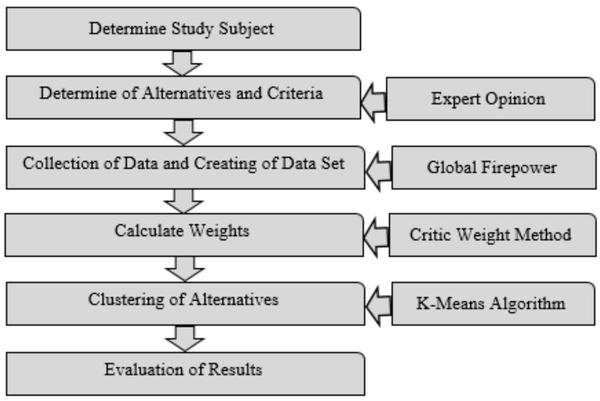
Eghtesadifard et al. (2020) developed an integrated method for the selection of urban solid waste storage area in Shiraz, one of the major cities of Iran. First of all, in the study, the dependencies among the 13 criteria were determined by the DEMATEL method. Then, criterion weights were calculated using the ANP method. Candidate regions were divided into six using the K-Means algorithm. To determine the best regions, rankings were obtained using MOORA, WASPAS and COPRAS methods.

Kılıç et al. (2020) evaluated the municipality's 81 cities in Turkey in terms of environmental services. In the study, statistics related to municipal services organized by the Turkey Statistical Institute was used. Six criteria have been determined for the environmental services of the municipalities regarding the years of 2001-2016. The weights of the criteria were calculated by the AHP method. Later, municipalities were divided into five clusters in terms of environmental services using the K-Means algorithm.

3. METHODOLOGY

In this section, information was given about the Critic Method and K-Means algorithm used in the study. The methodological framework of the study was shown in Figure 2.

Figure 2. Methodological Framework



3.1. Critic Method

Critic (Criteria Importance Through Intercriteria Correlation) is a method developed by Diakoulaki (1995) that uses correlation analysis to measure the significance of each criterion (Odu, 2019:1456). The weights obtained with the Critic include both contrast intensity and conflict inherent in the decision problem. The method developed is based on analytical examination of the evaluation matrix to extract all the information included in the evaluation criteria (Diakoulaki et al., 1995:764). The main idea of this method is to measure the contradictory characteristics of contrast density and evaluation criteria, two basic concepts of a multi-criteria decision making method. In the method, contrast density is measured with standard deviation and is based on the correlation between the contradictory characters of the criteria (Guo et al., 2009:1362).

For each criterion, the xij membership function rij is defined, which converts all values of the fij criteria to the range [0, 1] (Vujicic et al., 2017:425).

$$r_{ij} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}} \qquad \text{(for utility criterion)} \qquad (1)$$

$$r_{ij} = \frac{x_j^{max} - x_{ij}}{x_j^{max} - x_j^{min}} \qquad \text{(for the cost criterion)} \qquad (2)$$

This transformation is based on the concept of an ideal point. In this way, the starting matrix is converted into a matrix by generic elements rij.

Each vector has a standard deviation representing the degree of deviation of the variant values for the criteria of a given mean value. The amount of information Cj in j criteria is determined by using equation (3):

$$C_j = \sigma_j \sum_{i=1}^{m} (1 - r_{ij}) \qquad (3)$$

According to the previous equation (3), the higher the value of Cj, the greater the amount of information transmitted by the corresponding criterion and the higher its relative importance for the decision making process. Objective criterion weights are obtained by normalizing Cj values using equation (4) to obtain wj values:

$$w_j = \frac{c_j}{\sum_{i=1}^{m} c_j} \qquad (4)$$

3.2. Cluster Analysis

Clustering is an unsupervised learning approach used to group data sets by similar characteristics by the help of determined mathematical criteria. The mathematical criterion is called the objective function. A cluster analysis is done to fulfill objective functions (Chowdhury et al., 2020:1). Cluster Analysis is at the center of many data-driven application areas and provides a comprehensive analysis of data in terms of distance functions and grouping algorithms (Xie et al., 2016:1). Clustering is an important data mining function that separates data sets based on similarities between data. This technique plays a pivotal role in the rapidly growing field known as exploratory data analysis. One of the main challenges of effective clustering is defining appropriate grouping criteria for good clustering (Armano & Farmani, 2016:184).

Clustering algorithms are basically divided into two categories, Hierarchical algorithms and Division algorithms. A hierarchical clustering algorithm divides the considered data set into smaller subsets in a hierarchical manner. On the other hand, a partition clustering algorithm divides the data set into any number of clusters in a single step (Ibrahim et al., 2011:1450). In this study, one of the division clustering algorithms K-Means is used.

- **K-Means Clustering Algorithm**

K-Means clustering is a popular algorithm used for iterative calculations to divide a data set into clusters. The algorithm has the advantage of simple implementation and obtaining optimal clustering (Nasution et al., 2019:39).

This algorithm, first introduced by Mac Queen in 1967, is a cyclic algorithm in which clusters are continuously refreshed until the optimal solution is reached. The basic logic of the K-Means algorithm is the process of dividing a data set consisting of n data objects into k sets determined based on the prior knowledge and experience of the researcher. The aim is to ensure high similarity between clusters but low similarity between clusters. The similarity of clusters is calculated by the mean value of the objects (Selvi & Caglar, 2016:343).

The four stages of the K-Means algorithm are as follows (Babrdelbonab et al., 2014: 52):

Step 1: k data items are randomly selected.

$X=\{x_1,x_2,\ldots x_n\}$ as cluster centers $(m_1,m_2,\ldots m_k)$ 5)

Step 2: Based on relation (6), each data item is added to a related set. In other words, if the following relation (6) is provided, element xi is added from the data set X = {x1, x2,… xn} to the set cj.

$$\|xi - mj\| < \|xi - mp\| \qquad 1 \leq p \leq k, \quad j \neq p \qquad (6)$$

Step 3: At this stage, based on the clustering process in step 2, new cluster centers (m1 *, m2 *…, mk *) are calculated using the following equation (7) (ni refers to the number of objects in the set i):

$$m_i^* = \frac{1}{n_i} \sum_{x_j \in c_i} x_j \qquad 1 \leq i \leq k \tag{7}$$

Step 4: If the cluster centers are changed, the algorithm is repeated from Step 2. Otherwise, clustering is done according to the resulting centers.

Although K-Means is one of the widely used clustering techniques, it is known that the solution it provides depends on the selection of the initial cluster centers. The random selection of the first cluster centers causes this algorithm to give different results in different studies on the same data sets. This situation is considered as one of the potential weak points of the algorithm (Bandyopadhyay & Maulik, 2002:224).

4. APPLICATION

In this section, evaluations were made about the purpose of the study, alternatives, criteria, weight values of criteria and clustering of countries.

4.1. Purpose of Research and Data

In the study, the list of countries' military powers prepared by the Global Firepower site in 2019 was discussed. 21 criteria were determined by taking expert opinions of the military powers of 138 countries in the list. These criteria were shown in Table 1.

Table 1. Criteria Used in the Study

Code	*Criteria Name*	*Code*	*Criteria Name*	*Code*	*Criteria Name*
C1	Available manpower	***C8***	Helicopters	***C15***	Aircraft carriers
C2	Total military personnel	***C9***	Attack helicopters	***C16***	Destroyers
C3	Fighters	***C10***	Tanks	***C17***	Frigates
C4	Dedicated attack	***C11***	Armored vehicles	***C18***	Corvettes
C5	Transports	***C12***	Self-propelled artillery	***C19***	Submarines
C6	Trainers	***C13***	Towed artillery	***C20***	Patrol
C7	Special-mission	***C14***	Rocket projectors	***C21***	Mine warfare

In the study, first, the weights of the criteria were calculated by the Critic method. Then, the criterion values for the military power of the countries were normalized. The required data set for clustering was obtained by multiplying the normalized criteria values with the weight values. By the K-Means algorithm, data set of 138 countries' military powers were clustered. Evaluations were made on the clusters obtained.

4.2. Calculation of Critic Weights

Before clustering the criteria related to the military powers of the countries, the weight values were calculated by the Critic method. Critic weights of the criteria were shown in Table 2 and the most important criterion was determined to be C20 (patrol) with a weight value of 0.11. On the other hand, the lowest criterion for weight value was C3 (fighters) with 0.028.

Table 2. Critic Weights of Criteria *(w_j)*

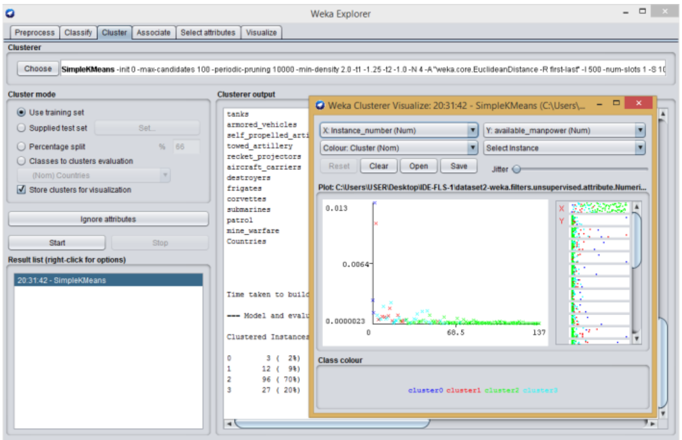
	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**
w_j	0.060	0.065	0.028	0.036	0.030	0.033	0.034	0.031	0.030	0.041	0.036

	C12	**C13**	**C14**	**C15**	**C16**	**C17**	**C18**	**C19**	**C20**	**C21**
w_j	0.043	0.068	0.047	0.040	0.037	0.065	0.043	0.048	0.110	0.072

4.3. Clustering of Countries' Military Powers

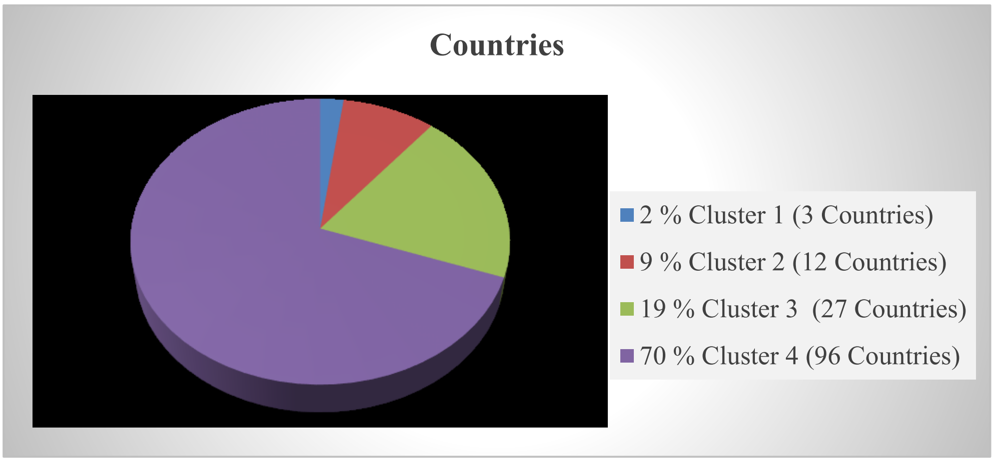
Clustering analysis allows countries to be divided into groups in line by determined variables and to evaluate the differences between groups. After obtaining the data set on the military powers of 138 countries, countries were divided into clusters using the WEKA program. Many algorithms were tried in the WEKA program, but it was decided that the K-Means algorithm was suitable for the study. The screenshot of the clustering tool of the WEKA program was shown in Figure 3.

Figure 3. Screenshot from the WEKA Window



In Figure 4, the number of countries in each cluster was shown with a pie chart. The table includes 2 % in Cluster 1, 9 % in Cluster 2, 19 % in Cluster 3 and 70 % in Cluster 4.

Figure 4. Number of Countries in Each Cluster



According to the findings obtained from the K-Means Algorithm, there are 3 countries in Cluster 1, 12 countries in Cluster 2, 96 countries in Cluster 3 and 27 countries in Cluster 4. The countries in each cluster are shown in Table 3.

Tablo 3. Clusters

Clusters	Countries
Clusters 1	United States, Russia, China
Clusters 2	South Korea, Egypt, Iran, Turkey, Saudi Arabia, Vietnam, Ukraine, Taiwan, North Korea, Syria, Pakistan, India

Clusters 3	Japan, Brazil, Indonesia, France, United Kingdom, Italy, Germany, Australia, Israil, Poland, Spain, Thailand, Greece, Nigeria, Bangladesh, Mexico, Myanmar, Bulgaria, Chile, Cuba, Finland, Denmark, Morocco, Colombia, Sweden, Malaysia, Algeria
Clusters 4	Canada, South Africa, Switzerland, Norway, Czechia, Netherlands, Romania, Peru, Venezuela, Argentina, United Arab Emirates, Philippines, Iraq, Singapore, Uzbekistan, Belarus, Hungary, Angola, Slovakia, Ethiopia, Portugal, Kazakhstan, Azerbaijan, Serbia, Austria, Bolivia, Ecuador, Croatia, Belgium, Democratic Republic of The Cango, Jordan, Yemen, Oman, Sudan, Turkmenistan, Afganistan, New Zealand, Libya, Tunisia, Sri Lanka, Lithuania, Kenya, Kuwait, Uganda, Chad, Zambia, Georgia, Qatar, Zimbabwe Guatemala, Bahrain, Tajikistan, Uruguay, Mali, Burkina Faso, Kyrgyzstan, Ireland, Slovenia , Cameroon Latvia, Niger, Ivory Coast, Mongolia, Ghana, Cambodia, Botswana, Tanzania, Honduras, Armenia, Moldova, Paraguay, Nicaragua, Albania, Mozambique, South Sudan, Lebanon, Estonia, Dominican Republic, Republic of The Congo, Nepal, Montenegro, Mauritani Madagascar, El Salvador, North Macedonia, Namibia, Central African Republic, Gabon, Laos, Panama, Bosnia and Herzegovina, Sierre Leone, Suriname, Somalia, Liberia, Bhutan

After clustering, the Kruskal Wallis test was used to examine whether there was a statistically significant difference between clusters. Kruskal Wallis-H Test results were shown in Table 4.

Table 4. Results of Kruskal Wallis-H Test

Criteria	KRUSKAL WALLIS-H TEST						Criteria	KRUSKAL WALLIS-H TEST					
C1	**Cluster**	**N**	**Mean Rank**	**sd**	**X^2**	**p**	**C12**	**Cluster**	**N**	**Mean Rank**	**sd**	**X^2**	**p**
	Cluster1	3	134.67	3		0.000		**Cluster1**	3	136.67	3		0.000
	Cluster2	11	112.27	3	47.25	0.000		**Cluster2**	11	125.68	3	54.88	0.000
	Cluster3	27	97.78	3		0.000		**Cluster3**	27	92.19	3		0.000
	Cluster4	97	54.76	3		0.000		**Cluster4**	97	54.74	3		0.000
	Total	138						**Total**	138				
C2	**Cluster**	**N**	**Mean Rank**	**sd**	**X^2**	**p**	**C13**	**Cluster**	**N**	**Mean Rank**	**sd**	**X^2**	**p**
	Cluster1	3	134.00	3		0.000		**Cluster1**	3	135.67	3		0.000
	Cluster2	11	125.73	3	62.53	0.000		**Cluster2**	11	129.73	3	45.80	0.000
	Cluster3	27	100.00	3		0.000		**Cluster3**	27	82.56	3		0.000
	Cluster4	97	52.64	3		0.000		**Cluster4**	97	56.99	3		0.000
	Total	138						**Total**	138				
C3	**Cluster**	**N**	**Mean Rank**	**sd**	**X^2**	**p**	**C14**	**Cluster**	**N**	**Mean Rank**	**sd**	**X^2**	**p**
	Cluster1	3	137.00	3		0.000		**Cluster1**	3	136.33	3		0.000
	Cluster2	11	124.50	3	66.07	0.000		**Cluster2**	11	124.59	3	38.94	0.000
	Cluster3	27	100.85	3		0.000		**Cluster3**	27	78.13	3		0.000
	Cluster4	97	52.45	3		0.000		**Cluster4**	97	58.78	3		0.000
	Total	138						**Total**	138				
C4	**Cluster**	**N**	**Mean Rank**	**sd**	**X^2**	**p**	**C15**	**Cluster**	**N**	**Mean Rank**	**sd**	**X^2**	**p**
	Cluster1	3	137.00	3		0.000		**Cluster1**	3	132.67	3		0.000
	Cluster2	11	101.45	3	28.79	0.000		**Cluster2**	11	81.50	3	51.63	0.000
	Cluster3	27	83.09	3		0.000		**Cluster3**	27	80.94	3		0.000
	Cluster4	97	60.01	3		0.000		**Cluster4**	97	63.00	3		0.000
	Total	138						**Total**	138				
C5	**Cluster**	**N**	**Mean Rank**	**sd**	**X^2**	**p**	**C16**	**Cluster**	**N**	**Mean Rank**	**sd**	**X^2**	**p**
	Cluster1	3	136.67	3		0.000		**Cluster1**	3	136.33	3		0.000
	Cluster2	11	106.73	3	49.98	0.000		**Cluster2**	11	82.09	3	49.93	0.000
	Cluster3	27	101.81	3		0.000		**Cluster3**	27	76.07	3		0.000
	Cluster4	97	54.21	3		0.000		**Cluster4**	97	64.18	3		0.000
	Total	138						**Total**	138				
C6	**Cluster**	**N**	**Mean Rank**	**sd**	**X^2**	**p**	**C17**	**Cluster**	**N**	**Mean Rank**	**sd**	**X^2**	**p**
	Cluster1	3	135.33	3		0.000		**Cluster1**	3	102.00	3		0.000
	Cluster2	11	117.82	3	67.24	0.000		**Cluster2**	11	118.36	3	65.17	0.000
	Cluster3	27	106.63	3		0.000		**Cluster3**	27	101.65	3		0.000
	Cluster4	97	51.65	3		0.000		**Cluster4**	97	54.01	3		0.000
	Total	138						**Total**	138				

C7	**Cluster**	**N**	**Mean Rank**	**sd**	**X^2**	**p**	**C18**	**Cluster**	**N**	**Mean Rank**	**sd**	**X^2**	**p**
	Cluster1	3	136.33	3		0.000		**Cluster1**	3	136.50	3		0.000
	Cluster2	11	99.41	3	53.91	0.000		**Cluster2**	11	108.00	3	49.74	0.000
	Cluster3	27	103.57	3		0.000		**Cluster3**	27	86.80	3		0.000
	Cluster4	97	54.56	3		0.000		**Cluster4**	97	58.25	3		0.000
	Total	138						**Total**	138				
C8	**Cluster**	**N**	**Mean Rank**	**sd**	**X^2**	**p**	**C19**	**Cluster**	**N**	**Mean Rank**	**sd**	**X^2**	**p**
	Cluster1	3	137.00	3		0.000		**Cluster1**	3	136.00	3		0.000
	Cluster2	11	118.50	3	59.92	0.000		**Cluster2**	11	106.05	3	62.94	0.000
	Cluster3	27	102.06	3		0.000		**Cluster3**	27	96.39	3		0.000
	Cluster4	97	52.79	3		0.000		**Cluster4**	97	55.81	3		0.000
	Total	138						**Total**	138				
C9	**Cluster**	**N**	**Mean Rank**	**sd**	**X^2**	**p**	**C20**	**Cluster**	**N**	**Mean Rank**	**sd**	**X^2**	**p**
	Cluster1	3	137.00	3		0.000		**Cluster1**	3	109.50	3		0.000
	Cluster2	11	118.73	3	39.88	0.000		**Cluster2**	11	110.36	3	41.40	0.000
	Cluster3	27	82.81	3		0.000		**Cluster3**	27	98.69	3		0.000
	Cluster4	97	58.12	3		0.000		**Cluster4**	97	55.51	3		0.000
	Total	138						**Total**	138				
C10	**Cluster**	**N**	**Mean Rank**	**sd**	**X^2**	**p**	**C21**	**Cluster**	**N**	**Mean Rank**	**sd**	**X^2**	**p**
	Cluster1	3	135.67	3		0.000		**Cluster1**	3	133.00	3		0.000
	Cluster2	11	128.59	3	49.99	0.000		**Cluster2**	11	114.64	3	65.24	0.000
	Cluster3	27	87.98	3		0.000		**Cluster3**	27	99.35	3		0.000
	Cluster4	97	55.61	3		0.000		**Cluster4**	97	54.11	3		0.000
	Total	138						**Total**	138				
C11	**Cluster**	**N**	**Mean Rank**	**sd**	**X^2**	**p**	**$p<0.05$**						
	Cluster1	3	137.00	3		0.000							
	Cluster2	11	124.77	3	67.63	0.000							
	Cluster3	27	103.07	3		0.000							
	Cluster4	97	51.80	3		0.000							
	Total	138											

According to the Kruskal Wallis test results in Table 4, it is seen that the p value for all variables (C1, C2,… C21) is below 5%. Therefore, it can be said that there is a significant difference between clusters. In addition, when cluster averages are analyzed, Cluster 1 ranks first in all variables except C17. Cluster 2 is in second rank except C7, Cluster 4 is in third rank and Cluster 3 is in last rank.

5. CONCLUSION

In the study, the 2019 list of countries' military powers organized by the Global Firepower site was used. 21 criteria for 138 countries in the list were determined and the weight values of the criteria were calculated by the Critic method. Then, using the WEKA program, countries were divided into four groups by the K-Means algorithm.

As seen in Table 3, Cluster 1 includes United States, Russia and China. These three countries are in the top three in the Global Firepower 2019 list. On the other hand, American companies (42) take the first place in the graph of the distribution of the world's 100 top defense industry companies by countries in Figure 2. According to the Kruskal Wallis test results in Table 4, the cluster average of Cluster 1 is greater than the others, except for C17. In line with the findings obtained, it is possible to say that these three countries are the countries with top military power in the world.

Cluster 2 includes South Korea, Egypt, Iran, Turkey, Saudi Arabia, Vietnam, Ukraine, Taiwan, North Korea, Syria, Pakistan and India. Ten of the countries in this cluster are among the top 27 in the Global Firepower 2019 list. According to the Global Firepower 2019 list, the most powerful countries of the cluster are India (4) and South Korea (6). It can be said that the most surprising country in the cluster is Syria. The reason for this may be that while the Global Firepower list was created with 50 criteria, 21 criteria were used in the study.

Cluster 3 includes Japan, Brazil, Indonesia, France, United Kingdom, Italy, Germany, Australia, Israel, Poland, Spain, Thailand, Greece, Nigeria, Bangladesh, Mexico, Myanmar, Bulgaria, Chile, Cuba, Finland, Denmark, Morocco, Colombia, Sweden, Malaysia and Algeria. 12 of the countries in this cluster are among the top 25 of the Global

Firepower 2019 list. The most powerful countries of this cluster are Japan (5), France (7) and United Kingdom (8).

Cluster 4 includes the remaining 96 countries. Most of the countries in this cluster are at the bottom of the list and are considered underdeveloped countries. The most powerful country in the cluster is Canada, ranked 25th on the Global Firepower 2019 list.

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