



CLASSIFICATION OF LOGISTICS-BASED TRANSPORTATION ACTIVITIES IN OECD COUNTRIES AND SELECTED NON-MEMBER COUNTRIES THROUGH CLUSTER ANALYSIS

KÜMELEME ANALİZİ İLE OECD ÜLKELERİ VE SEÇİLMİŞ ÜYE OLMAYAN ÜLKELERİN LOJİSTİK FAALİYETLERİNE DAYALI TAŞIMACILIK SINIFLANDIRILMASI

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**Öz**

Lojistik, ürünün yalnızca taşınması değil, ürünün üretiminden başlayarak tüketiciye hatasız bir şekilde ulaştırılmasını sağlayan tüm faaliyetleri kapsamaktadır. Lojistik, süreç temelli olup taşıma faaliyeti, bu sürecin temelini oluşturmaktadır. Bu çalışmada, ülkelerin ekonomik gelişmişliğinde önemli rol oynayan taşımacılık faaliyeti göstergeleri temel alınarak “İktisadi İşbirliği ve Gelişme Teşkilatı” olan OECD ülkeleri ve seçilmiş üye olmayan ülkelerin yer aldığı OECD istatistiklerinden yararlanılarak 47 ülke hiyerarşik ve bulanık kümeleme yardımıyla sınıflandırılmaktadır. Çalışmada taşımacılık göstergeleri açısından OECD istatistiklerinde yer alan ülkelerin benzeştiği ve farklılaşma gösterdiği kümeler bulunmuş ve Türkiye'nin ait olduğu küme ortaya konulmuştur.

**Anahtar Kelimeler:** Lojistik, Taşımacılık, Kümeleme Analizi, OECD İstatistikleri

**Abstract**

Logistics involves not only transportation of products, but also all the procedures that make it possible to deliver products to customers without any problems starting from production phase. Transport is the basic component of logistics, which is a process-based activity. This study aims to classify 47 countries according to the statistics about OECD (Organization for Economic Cooperation and Development) countries and selected non-member countries through hierarchical clustering and fuzzy clustering in terms of transportation activity indicators, which play an important role in countries' economic development. The study found that there are clusters in which the countries available in OECD statistics are similar or different in terms of transport indicators. The cluster which Turkey belongs to was also presented within the scope of the study.

**Keywords:** Logistics, Transportation, Cluster Analysis, OECD Statistics

## GENİŞLETİLMİŞ ÖZET

### Çalışmanın Amacı

Bu çalışmada, “İktisadi İşbirliği ve Gelişme Teşkilatı (OECD)” ülkeleri ve seçilmiş üye olmayan ülkelerin, lojistik boyutlu taşımacılık göstergeleri açısından benzerlik gösteren ve farklılaşan ülkeler olarak kümeleme analizi yöntemlerini kullanarak sınıflandırıp, Türkiye’nin bu sınıflandırma içerisindeki yerini belirlemeyi amaçlanmıştır.

### Araştırma Soruları

OECD ülkeleri ve seçilmiş üye olmayan ülkeler lojistik boyutuyla gerçekleştirdikleri taşımacılık faaliyetlerine göre nasıl kümelenebilir? Hangi kümeleme yöntemleri uygulanır? Uygulanan yöntemler arasında, en uygun kümelemeyi hangi yöntem vermiştir? Oluşan kümelerdeki ülkeler hangileridir? Türkiye hangi kümede yer almaktadır?

### Literatür Araştırması

Çalışmada, taşımacılık konusuna ilişkin literatür incelendiğinde akademik değeri yüksek veri tabanlarında taranan 120 dergi incelenmiştir. Türkiye’de taşımacılık konusunda 1986-2019 arası toplamda yapılmış olan 126 tez taranmıştır. Araştırmanın yöntemi ile ilgili birçok kaynak olmasına karşın, Türkiye’de bu konuda yapılmış çalışma bulunmamaktadır. Ancak yurtdışı uygulamalarına ilişkin literatürde konunun farklı boyutları ele alınmış ve benzer uygulamalar çalışmanın içerisinde özetlenmiştir.

### Yöntem

OECD ülkeleri ve seçilmiş üye olmayan ülkelere ilişkin sınıflandırma için kümeleme analizi yöntemleri kullanılmıştır. Analizde, yatay kesit verilerden yararlanılmış ve kümeleme analizinde, hiyerarşik kümeleme ward yöntemi ve hiyerarşik olmayan kümelemede bulanık c-ortalamalar yöntemleri uygulanmıştır.

### Sonuç ve Değerlendirme

Araştırma sonucunda, OECD ülkeleri ve seçilmiş üye olmayan ülkelerin taşımacılık göstergeleri doğrultusunda hiyerarşik kümeleme ward yöntemi ve bulanık kümeleme c-ortalamalar yöntemi sonucunda elde edilen bulgular birbirinden farklılık göstermektedir. Bulanık c-ortalamalar yönteminin, hiyerarşik ortalama ward yöntemine göre daha kararlı sonuçlar ürettiği gözlenmiştir. Türkiye’nin içerisinde yer aldığı kümeler her iki yöntemde de benzerlik göstermekte olup ait olduğu küme yapıları göz önüne alınarak lojistik stratejileri belirlenebilir. Araştırmada 7 göstergeye bağlı analiz yapılmıştır, farklı temel ve alt göstergeler kullanılarak diğer kümeleme algoritmaları ile analiz genişletilebilir. Beklenmeyen durumlara yönelik olarak ülkelerin kümelenebilirliği incelenebilir. Elde edilen bulgular olası kriz durumlarına ilişkin strateji belirlenmesine yardımcı olacaktır.

## **1. INTRODUCTION**

Due to increasing competition in global markets, countries have to minimize production costs to increase their competitive power. Even if they are in the form of raw materials, semi-finished products or finished products, or domestic or imported products, all modes of freight are a component of logistics process until they reach customers through a supply chain. Therefore, high cost of logistics activities is a variable that causes deceleration in economic growth of countries.

Logistics costs include expenses tracked by accountants through fiscal records and coordination of related costs. Types of logistics costs are determined according to functionality during value creation (Siepermann, 2003) and classified as follows: transportation costs, storage costs, inventory costs, order processing costs, costs due to technology use, customer service costs and handling costs; transportation costs being the highest.

Reducing transportation costs increases competitive power of a country and allows it to provide more quality logistics services (Korinek and Sourdin, 2011: 5). A steady competitive power is an advantage to transport a product from one place to another with the lowest cost. Considered as a simple mathematical problem, logistics is the iceberg of logistics activities. Thus, logistics costs change according to various variables such as weight and size of product, whether it is a dangerous product or not, transportation destination and type of transportation. In addition, competitive power of a country in global market depends on the following variables: geographical features, transportation policies, transportation infrastructure and types of transportation.

Following the introduction section, the first section of the paper discusses the importance of transportation in logistics and logistics activities. In the second section, OECD countries and selected non-member countries are examined in terms of their transportation activities. The third section explains Hierarchical and Fuzzy Clustering methods and the fourth one is about OECD countries and selected non-member countries. In this section, logistics-based transportation activities in Turkey, which is the founding member of OECD, was also examined in detail and compared to other countries. The last section presents conclusions and suggestions derived from the study.

## **2. LITERATURE REVIEW**

Transportation has been examined with an academic perspective in many fields of science due to its significant role in economy. The literature review revealed that there are 120 journals focusing on transportation (<https://mjl.clarivate.com>), and approximately 130.000 articles were published in 2019 ([www.sciencedirect.com](http://www.sciencedirect.com)). In Turkish context, 126 dissertations on transportation were written between 1986 and 2019. As for the distribution of these dissertations according to fields of science, it was found that transportation was mainly examined under the key word “transportation” in the field of business administration, under the key word “optimization” in industrial engineering field and in terms of “infrastructure” in the field of civil engineering field. In social sciences, sea, air and land transportation

were examined with reference to logistics. In addition, there are dissertations focusing on transportation in law, economy and other fields of engineering (<https://tez.yok.gov.tr/UlusalTezMerkezi/giris.jsp>). Academic studies in other countries have similar distribution patterns according to fields of science; especially the USA has a rich literature on transportation.

The study uses cluster analysis as methodology. Although there are many dissertations and articles related to this type of analysis, the literature did not reveal any studies using cluster analysis in logistics and transportation.

Ren, Yong-Chan et.al used fuzzy cluster analysis for logistic center settlement plan (Ren, et.al 2010: 504). Similarly, Fu and Yin, in their dissertation, tried to develop an evaluation model based on fuzzy cluster algorithm of logistics companies. Seven companies were classified through fuzzy cluster analysis according to 8 variables (Fu and Yin, 2012: 1583).

Meng, in his performance evaluation for supply chain, tried to optimize e-trade supply chain based on fuzzy cluster analysis. The study introduced a sample analysis, and various supply chain options were classified through fuzzy clustering. The aim of the study was to develop an evaluation method combining qualitative and quantitative analysis (Meng, 2007).

Hirschinger et.al wrote an article focusing on fuzzy clustering scenarios. They suggested that decision makers in transportation and logistics industry are likely to use fuzzy clustering analysis in order to group scenarios related to the development of transportation and logistics in developing countries until 2030 (Hirschinger et.al, 2015).

Lima et.al (2014), in their research article titled “Humanitarian Logistics: A Clustering Methodology for Assisting Humanitarian Operations”, suggest a method to define and classify regions according to the type and frequency of disasters. The results show that classification through cluster analysis considerably contributes to decision-making process during Humanitarian Logistics intervention phase (Lima et.al, 2014).

Trappey et.al (2010) applied a clustering approach to supply chain partners in automobile industry, prioritizing the services offered by third-party logistics service (3PL) providers. By applying a two-stage clustering approach combined with Ward's minimum-variance method and the K-means algorithm, the logistics companies prioritize their services to satisfy groups of customers with specific preferences more effectively (Trappey et.al, 2010:731).

Wang and Wei carried out a cluster analysis for dangerous goods transportation in logistics by using k-mean algorithm. Accessing the data from Chinese logistics information platform, the authors did a cluster analysis involving 9 types of dangerous goods and 571 Logistics company. In corrected algorithm, distance similarity between clusters was used to calculate cluster coefficient (k). The analysis revealed some key points in dangerous goods transportation, and it was recommended that these points should be focused on so that potential disasters can be avoided (Wang, 2016).

This study aims to classify 47 countries involving OECD (Organization for Economic Cooperation and Development) countries according to 7 variables through hierarchical ward method

and fuzzy cluster c-means) algorithm in terms of their transportation activity indicators. The clusters formed after the analysis and the cluster that includes Turkey were interpreted accordingly.

The next section will examine OECD statistics and transportation parameters of the organization.

### **3. CONCEPTUAL FRAMEWORK**

#### **3.1. Logistics and Transportation**

The most basic function of logistics in business world is to make profit just like in other related activities. For instance, humanitarian aid logistics aims to ensure sustainability of life with the lowest cost; urban logistics deals with delivering tons of freight to users and costumers despite the presence of serious problems such as undesired environmental conditions and heavy traffic; the function of military logistics is to provide necessary ammunitions on time during a war when needed; and finally, health logistics serves human beings by providing services regarding the transportation of medical equipment, medicine and blood as well as organs to be transplanted for people and health institutions (Keskin, 2015). Nature itself has such a perfect logistics organization that it even inspires human beings for possible solutions to problems encountered in logistics activities (Çekerol, 2019).

The definition of logistics should take into consideration the dynamics of the field where it will be applied. In this respect, a comprehensive general definition of logistic in business world has been made by Council of Supply Chain Management Professionals-CSCMP, which is a leading non-governmental organization in the world. According to the council, logistics refers to the process of planning, implementing, and controlling procedures for the efficient and effective transportation and storage of goods which includes various services and related information used in different phases starting from production until consumption phase for the purpose of meeting customer demands and needs. This definition includes inbound, outbound, internal, and external movements.

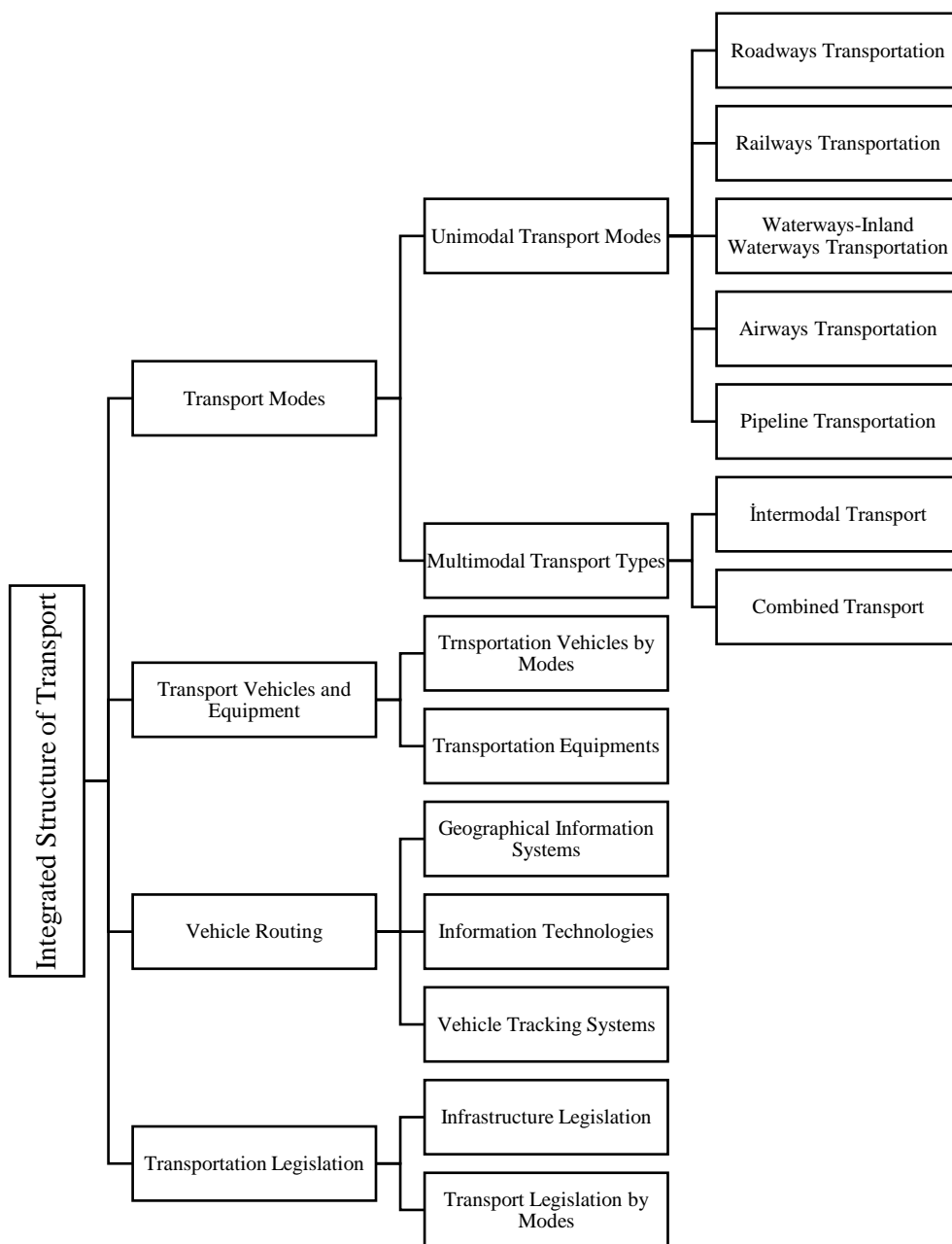
Transportation is the main component of logistics, and it has recently played more extensive roles due the increasing importance given to customer satisfaction and integration of computer systems into the field. Logistics is not a unit or an activity; it is a comprehensive process involving many activities starting from order of product until its final delivery to customers such as transport, storage, forecasting, customer services, packaging etc. However, certain variables including market conditions, competition, sector, geography and culture also play significant roles in logistics activities and affect the coordination and management of these activities.

The basic aim of logistics is to achieve targeted customer satisfaction with minimum cost (Bowersox and Cooper, 2002). In this respect, focusing on activities with high cost enables companies to minimize their expenses. Therefore, the main activity to focus on in logistics activities should be transportation.

Transportation simply refers to the activity of dispatching people, goods etc. with a vehicle from one place to another. As for business world, transportation is inevitably necessary when potential markets and customers are geographically far away from each other.

In a broader sense, transportation is a comprehensive and complex process involving various services ranging from preparation of necessary documents for transportation (freight, driver, customs etc.) to the delivery of products to certain regions and centers to meet customers' needs and demands (Taşkın&Durmaz, 2012: 41-42). In addition, transportation is a combination of activities that require collaboration of different disciplines such as engineering, management and law (Figure 1).

**Figure 1.** Integrated Structure of Transport



Transportation sector is one of the main components of economy. The roles it plays in the production of goods and services determine its current position. It also helps economic systems to improve and function effectively and provides added value to economy, which makes it a basic component of economic activities (Çancı and Güngören, 2013: 199).

### **3.2. OECD Statistics and Transportation Variables**

Established in September 30th, 1961, OECD is an organization in which 36 member countries collaboratively try to solve their economic, social and administrative problems due to globalization and benefit from the positive consequences of this problem solution process. Turkey is the founding member of the organization and other member countries are as follows: the USA, Austria, Australia, Canada, France, Holland, Luxemburg, Germany, Greece, Italia, England, Belgium, Denmark, Ireland, Finland, Swiss, Sweden, Spain, Iceland, Norway, Portugal, Czechia, Estonia, Japan, Korea, Latvia, Lithuania, Israel, Hungary, Mexico, Poland, Slovakia, Slovenia, Chili, and New Zealand (MFA, 2020).

The website that publishes data about OECD countries and selected non-member countries (<https://stats.oecd.org/> ) provides rich data for the purposes of the study. The non-member countries selected for this study are as follows: Albania, Armenia, Bulgaria, China, Croatia, Georgia, India, Malta, Moldova, Montenegro, Romania, and Serbia.

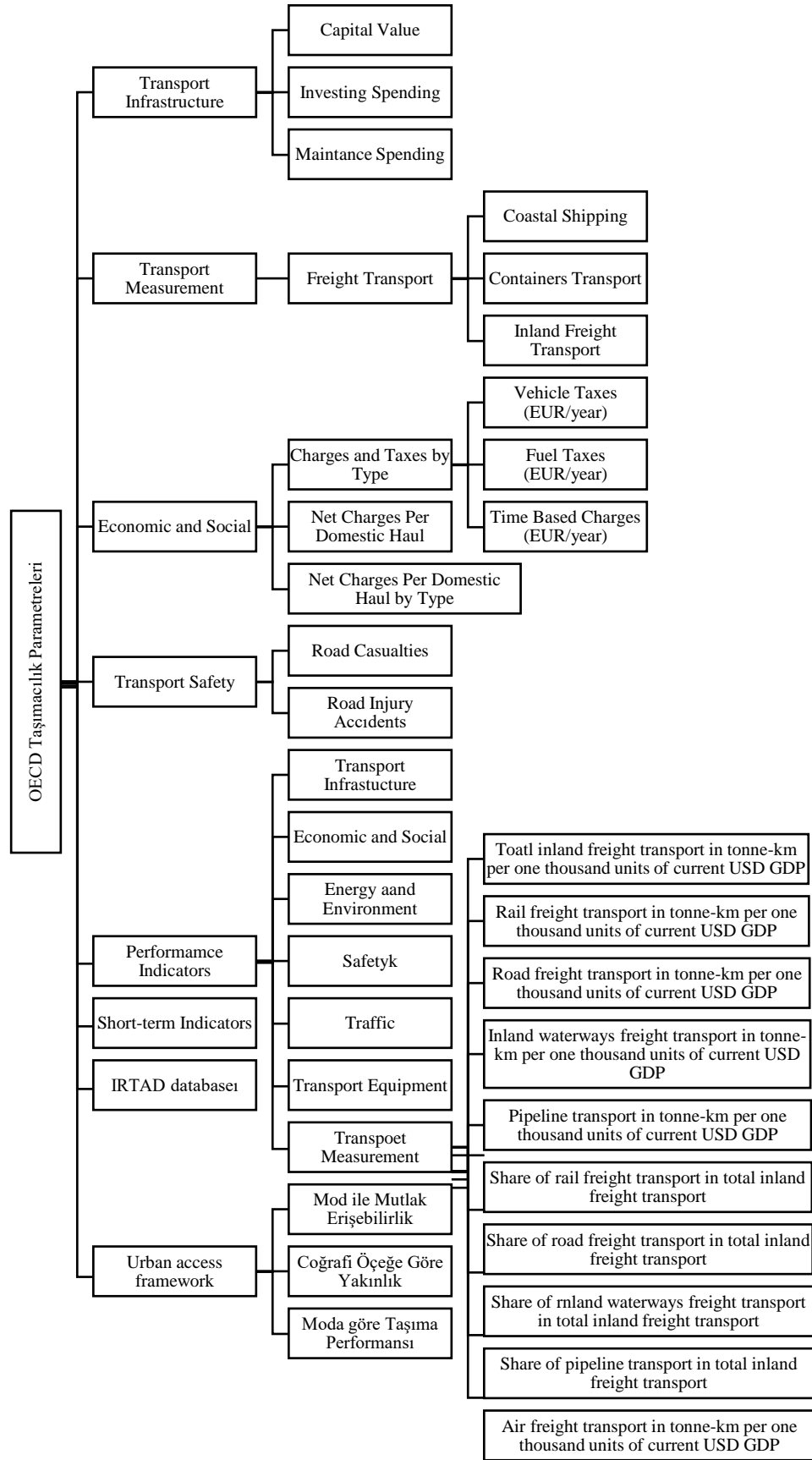
The first article of the organization's bylaws stipulates that the aim of the organization is to develop politics that;

will maintain economic stability, increase life standards and ensure economic growth and high levels of employment in member countries

will contribute to the development of world economy, healthy economic development in member or non-member countries and the growth of multi-party world trade in conformity with international liabilities. (MFA, 2020)

OECD is recognized as a reference organization in terms of economic analyses and statistical data by the leading institutions such as IMF and World Bank, which take these references as bases for their own activities. The variables related to logistics-based transportation indices were determined by collecting up-to-date data from the website that publish statistical figures (<https://stats.oecd.org/>) (Figure 2);

**Figure 2. OECD Transportation Variables**





However, it is not possible to use all the variables displayed in Figure 2 above. The common indicators of OECD member countries were taken as the basis for clustering. For instance, although it is important for logistics activities, coastal transportation was not used since not all the countries have coastal regions; however, container transportation was taken as a variable since it is a common indicator for each country. The study-specific variables were determined as follows after they were analyzed within the algorithms used (Table 1).

**Table 1.** The Selected Variables

Variables
X1: Investment Spending
X2: Maintenance Spending
X3: Containers Spending
X4: Inland Freight Transport
X5: Share of Value Added by the Transport Sector
X6: Total Inland Freight Transport in Tonne - km per One Thousand Units of Current USD GDP
X7: Road Freight Transport in Tonne - km per One Thousand Units of Current USD GDP

The International Transport Forum collects, on a quarterly basis, monthly data from all its Member countries. When monthly information is not available, then quarterly data are provided. The survey contains a dozen variables selected for their quarterly availability among reporting countries. Data are collected from Transport Ministries, statistical offices and other institution designated as official data source. The variables of this study include the followings (<https://stats.oecd.org/>):

**X<sub>1</sub>:** Investment Spending includes the following variables: Transport gross investment spending, total inland transport infrastructure investment, rail infrastructure investment, road infrastructure investment, road infrastructure investment: of which motorway, inland waterway infrastructure investment, maritime port infrastructure investment, airport infrastructure investment, transport maintenance expenditures, capital value at the end of the year, total road spending.

**X<sub>2</sub>:** Maintenance Spending includes the following variables: Transport gross investment spending, total inland transport infrastructure investment, rail infrastructure investment, road infrastructure investment, road infrastructure investment: of which motorway, inland waterway infrastructure investment, maritime port infrastructure investment, airport infrastructure investment, transport maintenance expenditures, capital value at the end of the year, total road spending.

**X<sub>3</sub>:** Containers Spending includes the following variables: Information rail containers transport (TEU: Twenty-foot Equivalent Unit), information rail containers transport (weight), information maritime containers transport (TEU), information maritime containers transport (weight).

**X<sub>4</sub>:** Inland Freight Transport includes the following variables: Information Total inland freight transport, Information Rail freight transport, Information Road freight transport, Information Road freight transport for hire and reward, Information Road freight transport on own account, Information Inland waterways freight transport, Information Pipelines transport.

**X<sub>5</sub>:** Share of Value Added by the Transport Sector

**X<sub>6</sub>:** Total Inland Freight Transport in Tonne - km per One Thousand Units of Current USD GDP

**X<sub>7</sub>: Road Freight Transport in Tonne - km per One Thousand Units of Current USD GDP**

## **4. METHODOLOGY**

### **4.1. Cluster Analysis**

This study uses hierarchical clustering Ward method and fuzzy c-means algorithm in order to compare OECD countries and selected non-member countries in terms of transportation indicators and to determine Turkey's position in this comparison. Cluster analysis has a wide range of usage in various disciplines such as economy, sociology, medicine, engineering, archeology and agriculture (Alpar, 2011, p, 30).

Cluster analysis is a multi-variable analysis technique aiming to classify data according to certain criteria. Also known as numerical classification or classification analysis, cluster analysis uses distance matrix to determine intra-cluster homogeneity and inter-cluster heterogeneity (Hair, 1998: 473). In other words, cluster analysis starts with data sets containing information about a sampling that composes of units and rearranges these units as homogenous groups (Aldenderfer&Blashfield,1984).

The functions of cluster analysis (Özdamar, 2004; 279-280) are

to group "n" number of cases, objects, phenomena based on the criteria determined according to p variable into intra-homogenous and inter-heterogeneous subgroups.

to group "p" number variables according to values identified in "n" number of cases into sub-clusters that are assumed to account for common features and to determine common factor structures.

to split both cases and variables into sub-clusters having common characteristics.

to make biological and typological classification of cases according to values determined in terms of "p" variable

In a broad sense, cluster analysis involves four steps:

Determining data matrix,  
Selecting Clustering Algorithm,  
Validity of Results,  
Interpreting Results

In cluster analysis, there are two types of clustering process: hierarchical clustering and nonhierarchical clustering (Malhotra, 2007). In hierarchical cluster analysis, clustering is carried out according to similarity criteria for cases and variables without determining a specific number of clusters in advance (Koyuncugil, 2006, s. 57). In contrast, non-hierarchical clustering methods are preferred when number of clusters is known beforehand; the number of clusters is also determined in advance in this method (Alpar, 2011, p. 314, 333).

#### **4.1.1. Hierarchical Clustering**

Hierarchical clustering aims to combine objects by considering their similarities according to cluster distance measurement (Özdamar,2004). Basically, it has two approaches: agglomerative and divisive (Rafsanjani et.al, 2012). The methods used while calculating distance between two clusters are as follows: single linkage, complete linkage, average linkage, centroid linkage, Ward method, neighbor joining and adjusted complete linkage.

The current study uses Ward method, which employs an agglomerative approach. This method aims to minimize centroid-cluster variance by taking average distance as reference. In other words, it is based on calculating the sum of squared errors by using centroid cluster squares deviations (Murtagh&Contreras, 2017).

The method starts with “n” number of clusters each of which has a single case. Since each observation becomes a cluster in the first step, sum of squared errors is zero (Everitt, 1974). In each following phase, two subclusters are combined to form the next level. In this case, it is assumed that  $k(k-1)$  is a subcluster. The sum of Euclid distances of “ni” point in k cluster to means vector of k cluster is the sum of squared errors ( $W_i$ ) and it is calculated as follows:

$$W_k = \sum_{i=1}^p \sum_{j=1}^{n_k} (x_{ijk} - \bar{x}_{ik})^2 = \sum_{i=1}^p \sum_{j=1}^{n_k} (x_{ijk})^2 - n_k \sum_{i=1}^p (\bar{x}_{ik})^2$$

Here,  $W_k$  value is calculated for  $k = 1, 2, 3 \dots \dots \dots, n$  clusters and the sum of centroid cluster squared errors is calculated as:

$$W = \sum_{i=1}^n W_k$$

Later, p and q clusters, which cause the lowest increase in W, are combined to obtain t cluster. This increase in W is calculated by using the following equation:

$$DW_{pq} = W_t - W_p - W_q$$

By doing so, “n” number of cases is split into (n-1) cluster and W increase values are calculated until the number of clusters reach  $k=1$  so that cases are hierarchically joined together. When Ward Method is used in analysis, cases are displayed in a diagram called “dendrogram”, where these cases are combined successfully at different levels (Dibb, 1998).

#### 4.1.2. Non-Hierarchical Clustering

Non-hierarchical clustering techniques have been developed to combine cases rather than variables in “k” number of clusters. The number of clusters (k) can be given as a certain value or determined as a part of clustering technique because it is not obligatory to determine distance (similarity) and to store main data when computer functions. Non-hierarchical clustering techniques can be applied to bigger data clusters when compared to hierarchical techniques (Johnson & Wichern, 1988).

The most common non-hierarchical clustering methods are k-means clustering, medoids clustering and fuzzy clustering (Özdamar, 2010, p. 311). This study uses fuzzy clustering method in the analysis

##### 4.1.2.1. Fuzzy Cluster Analysis

Fuzzy sets theory was developed in 1965 by L.A. Zadeh as a method to represent uncertainty. It defines the terms and concepts expressing a sort of uncertainty within the framework of cluster theory by assigning a certainty level for these uncertainties without applying random splitting (Aksoy, et.al., 2014).

Fuzzy clustering approach is appropriate when clusters are not clearly classified, or some objects are inconsistent in terms of cluster membership. Being a flexible method, fuzzy clustering method provides information about uncertain cluster memberships, which helps to identify complex relationships among objects and clusters (Mansoori, 2011). All the cases in the data may become a member of more than one cluster at the same time depending on various membership values thanks to fuzzy clustering analysis.

Fuzzy clustering is based on distance measurements, and the use of distance criteria depends on the structure of clusters and the algorithm used. Some useful features of fuzzy clustering are as follows:

- it provides useful membership values so that accurate interpretation can be made
- it is flexible in terms of distance use
- when some of membership values are known, they might be combined with numerical optimization (Naes& Mevik, 1999).

This study uses fuzzy c-means clustering method since it examines the situations in which OECD member countries belong to more than one cluster rather than only one cluster.

Fuzzy c-means algorithm is the most common and the most popular fuzzy clustering method. It was introduced by Dunn in 1973 and developed by Bezdek in 1981. Hierarchical clustering method is the fuzzy version of k-means clustering algorithm. It tries to minimize objective function and uses distance criteria like other algorithms. Which distance criterion will be used depends on cluster structure and algorithm. Fuzzy c-means algorithm uses Euclid distance. When c-means algorithm is completed, points in p-dimensioned space form global shapes. Therefore, algorithm gives the optimum result for globally distributed data. Margin of error for the algorithm, which can also be used for ellipsoidal data, should not be preferred for scattered data (Höppner et.al., 1999).

Fuzzy c means is a method of clustering which allows one piece of data to belong to two or more clusters. This method is frequently used in pattern recognition. It is based on minimization of the following objective function:

$$J(u, v) = \sum_{i=1}^c \sum_{j=1}^n (u_{ij})^m \|x_j - v_i\|^2$$

There is a restriction for this objective function. Due to the principles of fuzzy logic, each data belongs to a cluster with a membership value ranging between 0 and 1. The sum of membership values of data for each cluster should be “1” (Ruspini, 1973).

$$u_{ij} \geq 0, \sum_{i=1}^c u_{ij} = 1, 1 \leq j \leq n$$

Here;

X:  $\{x_1, x_2, \dots, x_n\} \subset R^n$  = the data,

n: number of data

c: number of clusters in X;  $2 \leq c \leq n$

$u_{ij}$ : Fuzzy Membership level for j unit of i cluster

$v_i$ : centroid vector of cluster

$V = [v_1, v_2, \dots, v_c]$ ,  $v_i \in R_n$  cluster centroid vector to be determined

$\|x_j - v_i\|^2$ ,  $x_j$  Euclid distance between  $x_j$  value and  $v_i$

$m$ : weighting exponent  $1 \leq m \leq \infty$

Objective function, which refers to Weighted least squares function, is the sum of weighted squared error. Fuzzy c-means method, which is based on the principle of minimization of the given objective function, is applied by following the steps below (Şen, 2004);

Step 1: Initial values are determined: number of clusters  $c$ , parameter that determines fuzziness  $m$ , cluster centroids  $v_i$  ( $i = 1, \dots, c$ ) and stop criterion  $\varepsilon$

Step 2: Membership degrees matrix is determined by using initial cluster centroid  $v_i$  as follows

$$u_{ij} = \frac{1}{\sum_{k=1}^c \left( \frac{\|x_i - v_j\|}{\|x_i - v_k\|} \right)^{\frac{2}{m-1}}} \quad (i = 1, \dots, c)$$

Step 3: cluster centroids are updated by using the following formula.

$$v_i = \frac{\sum_{j=1}^n u_{ij}^m x_j}{\sum_{j=1}^n u_{ij}^m} \quad (i = 1, \dots, c)$$

Step 4: New membership values are compared to previous ones, If improvement in  $\|V_{yeni} - V_{eski}\| < \varepsilon$ , iteration is terminated. Otherwise step 2 is repeated. Fuzzy c-means algorithm depends on initial values. Initial parameters mustn't be lower and higher than actual number of clusters. It is necessary to find accurate number of clusters.

Fuzziness parameter ( $m$ ) choice checks how many clusters will overlap, and it takes the value "2" to make calculation easier.

Stop criterion ( $\varepsilon$ ), terminates repeats when the difference between membership values are lower than stop criterion, which is generally taken as 0,01 but lower values can also be chosen to shorten calculation time.

Initial membership criterion ( $V$ ) is generated in a way that membership matrix will be random. It is necessary to start  $v_i$  cluster centroids randomly and calculate corresponding  $V$  values accordingly in order to obtain this matrix.

In summary, although Ward technique and k-means are classical clustering methods, it is necessary to assign each case to a cluster. Since cases are placed in clusters by taking 0 and 1 membership values, clusters accurately split from each other. However, such a clear-cut distinction might give wrong results because homogenous clusters might have observation units that are equally distant from each other (Döring, et a.l., 2006: 192).

Unlike definite splits in classical clustering method, fuzzy clustering assign cases according to membership degrees, i.e. cases might belong to more than one cluster. Membership degrees of cases range between 0 and 1, and the sum of membership degree values is 1. In addition, due to definite splits in classical cluster analysis, possible relationships between cases or cluster may not be noticed; however,

fuzzy clustering method provides more detailed information by eliminating this problem to some extent (Mansoori, 2011, p. 961).

Fuzzy sets can be examined in three groups: normal fuzzy sets, non-normal fuzzy sets and convex fuzzy sets. If at least one of the cases in a set has a set membership equal to 1, it is called normal fuzzy set. If the membership of all cases is lower than 1, it is non-normal fuzzy set. Finally, convex fuzzy set occurs when membership values for increasing values in a set is monotonously increasing and decreasing (Koyuncugil, 2006: 98).

## 5. FINDINGS

When means and variances of variables in a data matrix are largely different from each other, those with high means and variances considerably affect the contribution of other variables to analysis. Sometimes, extreme values of variables have negative effects on cluster analysis. In such cases, data should be standardized or transformed (Özdamar, 2004: 291). Although there are many methods for data standardization, this study used z point transformation and transformation to  $-1 \leq x \leq 1$  range. This technique is preferred when there are extreme values and / or heterogeneous values with positive and negative signs.

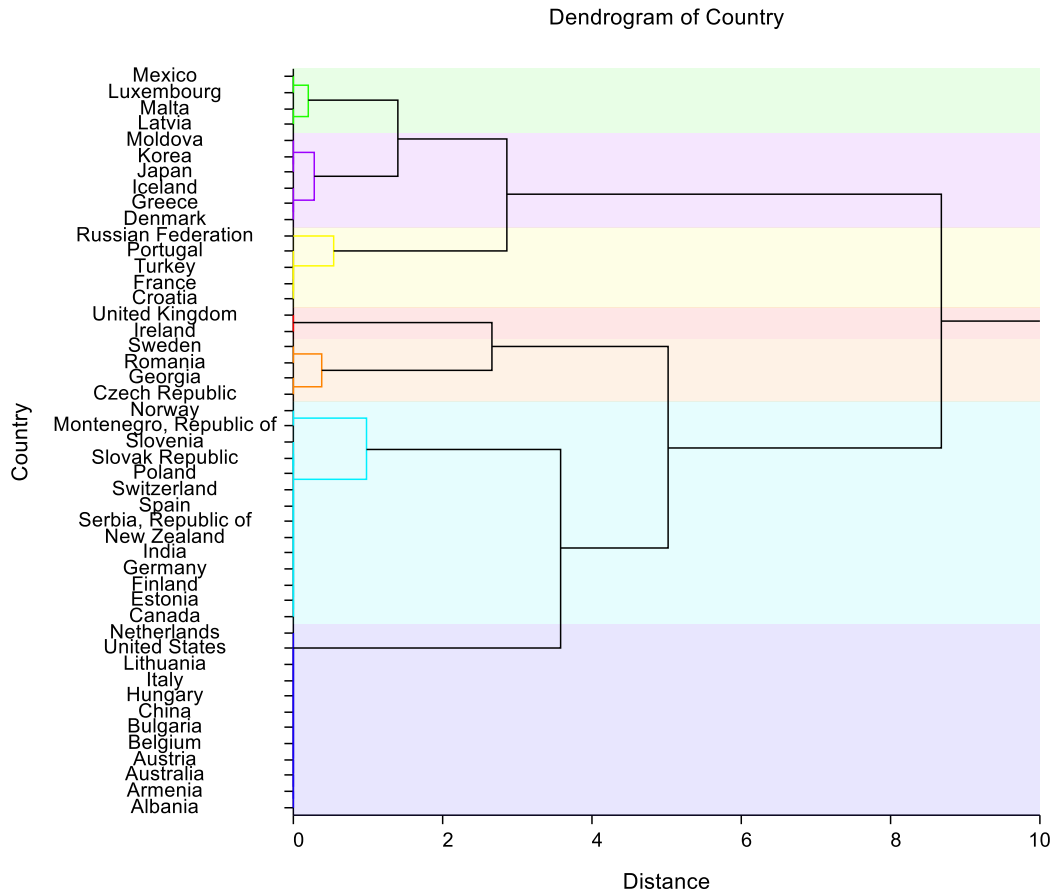
Minitab 19 software was used for standardization. After the standardization, seven clusters were obtained by using Ward method and NCSS 2019 software. These clusters are presented in Table 2.

**Table 2.** Results of Clustering through Ward Method

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7
Ireland	Albania,	Latvia	Denmark	Czech Rep.	Croatia	Canada
United Kingdom	Armenia	Luxembourg	Greece	Georgia	France	Estonia
	Australia	Malta	Iceland	Romania	Portugal	Finland
	Austria	Mexico	Japan	Sweden	Russian Fed.	Germany
	Belgium		Korea		Turkey	India
	Bulgaria		Moldova			Montenegro
	China					New Zealand
	Hungary					Norway
	Italy					Poland
	Lithuania					Serbia
	Netherlands					Slovak Rep.
	United States					Slovenia
						Spain
						Switzerland

The results of clustering were displayed graphically through the dendrogram in Figure 3. This dendrogram is scaled as 0-10 from left to right in equal distances between the units. Horizontal lines show “distance” and vertical ones “intersecting clusters”.

**Figure 3.** Cluster Dendrogram for Countries through Ward Method



Testing the results of cluster analysis through statistical methods will provide more useful and meaningful results (Kurtuluş, 2004:417).

When p values of variables in variance homogeneity test (Levene Test) are examined, it is seen that variances for “Share of Value Added by The Transport Sector” variable are not homogenous ( $p < 0,05$ ) while variances for other variables are homogenous ( $p > 0,05$ ).

The researchers later examined the results of one-way ANOVA for variables confirming homogeneity assumption and Welch test for those that did not confirm this assumption and found that there were differences between the means of the clusters. Post-hoc tests were done to determine which cluster(s) caused this difference. Bonferonni test was used for variables confirming homogeneity assumption and DunnetT3 test for those that did not. According to the results, the variance for “share of value added by the transport sector” variable is due to the second cluster. It might be concluded that the countries in the second cluster is weaker than those in other clusters in terms of added value.

Finally, the countries were classified by using fuzzy c-means method. In this step, the results displayed in Table 3 below were used to determine how many clusters the countries will be split into.

NCSS 2019 program was used for fuzzy c-means clustering algorithm. Table 3 below displays mean silhouette statistics obtained for different cluster numbers  $k= 2, 3, 4, 5$  in the classification of 46

countries and Turkey by fuzzy clustering method according to basic education indicators, and  $D_c(U)$  values, which includes Dunn's partition coefficient, normalized Dunn coefficient.

**Table 3.** The Cluster Analysis Results according to Median Algorithm

Cluster	$\overline{SC}$	$F(U)$	$F_c(U)$	$D(U)$	$D_c(U)$
2	0,371462	0,7036	0,4072	0,1776	0,3551
3	0,423130	0,6820	0,5230	0,1909	0,2864
4	0,548646	0,6983	0,5977	0,1823	0,2431
<b>5</b>	<b>0,514399</b>	0,7267	<b>0,6584</b>	0,1700	<b>0,2125</b>

The table shows that the ideal number of clusters is  $k=5$  according to the data used in the analysis since more than one validity indicators are taken as reference in fuzzy c-means method: partition coefficient  $F(U)$ , Dunn coefficient (standardized partition coefficient)  $F_c(U)$ , Kaufman coefficient  $D(U)$ , standardized Kaufman coefficient  $D_c(U)$ .

The ideal number of clusters is determined according to the highest value of  $F_c(U)$  and the lowest value of  $D_c(U)$ . When Dunn coefficient is normalized in a way to take a value between 0 and 1, the value “0” displays fuzziness while “1” means lack of fuzziness and a strong clustering (Yılancı, 2010: 457). The value which is the closest to “1” is  $F_c(U) = 0,6584$  for  $k = 5$ .

In contrast to Dunn coefficient, standardized Kaufmann coefficient shows strong clustering when it gets closer to “0”. For  $k=5$ ,  $D_c(U) = 0.2125$  is the closest value to 0 and shows strong clustering.

In silhouette statistics, which shows stability structure of clusters,  $\overline{SC}$  (Silhouette Coefficient) takes a value between “-1” and “+1”, and a value closer to +1 implies accurate clustering. In fuzzy cluster analysis,  $\overline{SC}$  should be at least 0.50 when ideal number of clusters are determined.  $\overline{SC}$  for  $k=5$  is 0.514399.

The examination of cluster structure revealed that there are differences when compared to cluster structures obtained by using Ward method. When probability values are examined, it can be concluded that a normal fuzzy cluster was obtained, and the countries are quite likely to be assigned to clusters (Table 4).

**Table 4.** Cluster Membership and Assignment Probabilities

Row	Country	Cluster	Prob in 1	Prob in 2	Prob in 3	Prob in 4	Prob in 5
1	Albania	5	0,1844	0,1760	0,1665	0,1689	0,3041
2	Armenia	5	0,1058	0,1795	0,0988	0,1462	0,4697
3	Australia	5	0,1848	0,3022	0,1670	0,1694	0,1765
4	Austria	1	0,0074	0,0074	0,9666	0,0073	0,0113
5	Belgium	4	0,0037	0,0044	0,0044	0,9821	0,0054
6	Bulgaria	3	0,0005	0,0005	0,9977	0,0005	0,0008
7	Canada	2	0,0000	1,0000	0,0000	0,0000	0,0000
8	China	2	0,0053	0,9741	0,0068	0,0056	0,0083
9	Croatia	3	0,6879	0,0000	0,0000	0,3121	0,0000
10	Czech Republic	3	0,0005	0,0311	0,9673	0,0004	0,0007
11	Denmark	4	0,2708	0,1455	0,0034	0,5772	0,0031
12	Estonia	1	0,0114	0,0074	0,0074	0,0073	0,9665
13	Finland	4	0,0037	0,0035	0,0044	0,9831	0,0054
14	France	2	0,0138	0,9371	0,0161	0,0129	0,0201
15	Georgia	4	0,0000	0,0000	0,0000	1,0000	0,0000
16	Germany	3	0,0005	0,9978	0,0005	0,0005	0,0008
17	Greece	3	0,0005	0,0005	0,9978	0,0005	0,0008
18	Hungary	5	0,3022	0,1765	0,1670	0,1694	0,1849
19	Iceland	5	0,1040	0,1756	0,0972	0,1437	0,4794
20	India	5	0,1726	0,2751	0,1680	0,1775	0,2067
21	Ireland	3	0,0004	0,0285	0,8584	0,1122	0,0006



22	Italy	5	0,1855	0,3000	0,1676	0,1699	0,1770
23	Japan	4	0,0000	0,0000	0,0000	1,0000	0,0000
24	Korea	3	0,0005	0,0005	0,9977	0,0005	0,0008
25	Latvia	3	0,0592	0,0005	0,9392	0,0005	0,0007
26	Lithuania	5	0,1855	0,1770	0,1676	0,1700	0,2999
27	Luxembourg	3	0,0005	0,0323	0,9662	0,0004	0,0007
28	Malta	4	0,0036	0,0043	0,0043	0,0052	0,9826
29	Mexico	4	0,0000	0,0000	0,0000	0,0000	1,0000
30	Moldova	2	0,0135	0,0194	0,0157	0,0126	0,9388
31	Montenegro, Rep	4	0,0000	0,0000	0,0000	1,0000	0,0000
32	Netherlands	3	0,0005	0,0005	0,8747	0,1236	0,0007
33	New Zealand	5	0,1856	0,1770	0,1676	0,1700	0,2998
34	Norway	3	0,0005	0,0005	0,9978	0,0005	0,0008
35	Poland	3	0,0005	0,0005	0,9977	0,0005	0,0008
36	Portugal	3	0,0005	0,0005	0,8742	0,1242	0,0007
37	Romania	3	0,0005	0,0005	0,9977	0,0005	0,0008
38	Russian Fed.	3	0,0004	0,0289	0,8565	0,1136	0,0006
39	Serbia, Republic	5	0,1856	0,1771	0,1676	0,1700	0,2997
40	Slovak Republic	4	0,0036	0,0034	0,0043	0,9835	0,0052
41	Slovenia	2	0,0000	0,0000	0,0000	1,0000	0,0000
42	Spain	5	0,1857	0,2996	0,1676	0,1700	0,1771
43	Sweden	4	0,0036	0,0043	0,0043	0,9826	0,0052
44	Switzerland	5	0,1857	0,1771	0,1677	0,1700	0,2995
45	Turkey	1	0,9661	0,0075	0,0075	0,0074	0,0114
46	United Kingdom	5	0,1012	0,4942	0,0946	0,1396	0,1704
47	United States	3	0,0000	0,0000	1,0000	0,0000	0,0000

When membership degrees of Albania, Armenia, Australia, Denmark, Hungary, Iceland, India, Italy, Lithuania, New Zealand, Serbia Republic, Spain, Switzerland, and the United Kingdom for five clusters are examined, it can be said that they have fuzzier structure when compared to other countries.

The medoid values for variables used for transportation statistics of OECD countries and selected non-member countries are displayed in Table 5. Medoid values, also known as cluster centers, should be determined through the objects that are the closest to the center of cluster; not through means of cases that form clusters. Although it is not a very sensitive measurement, it enables decision makers to make an overall evaluation.

**Table 5.** Medoid Values of the Variables

Variable	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Qualification
$X_1$	-0,24949	-0,19297	0,87819	-0,27025	0,00425	High
$X_2$	-0,33752	1,92154	-0,10215	-0,3379	-0,33752	High
$X_3$	-0,43108	2,64454	-0,62372	4,39039	2,64454	High
$X_4$	0,554	-0,21288	-0,27877	-0,29223	-0,29117	High
$X_5$	-0,50443	-0,50443	-0,64565	-0,0647	-0,52081	Low
$X_6$	-0,68086	-0,60424	-0,76216	0,25847	-0,56418	High
$X_7$	0,57907	-0,46268	3,04733	-0,43818	-0,47494	High

According to Table 5, the countries in cluster 3 have the highest value in “investment spending” variable and those in cluster 2 in “maintenance spending” variable. As for the variables “container transportation”, “share of value by the transport sector” and “total inland freight transport in tonne-km per one thousand unite of current USD GDP”, the countries in cluster 4 have the highest value. Cluster 1, to which Turkey belongs to, includes countries that have the highest value for the variable “inland freight transport”. The cluster with the highest value for “road freight transport in tonne-km per one thousand units of current USD GDP” variable is cluster 2. When medoid values are examined, all the clusters except cluster 5 can be labelled as “high”.

Five clusters were obtained according to fuzzy c-means analysis (Table 6);

**Table 6.** Clustering according to fuzzy c-means method for k=5

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster5
Croatia,	Australia	Austria	Belgium	Albania
Hungary	Canada	Bulgaria	Denmark	Armenia
Portugal	China	Czech Rep.	Finland	Estonia
Turkey	France	Greece	Georgia	Iceland
	Germany	Ireland	Japan	Latvia
	India	Korea	Montenegro	Lithuania
	Italy	Latvia	Slovak	Malta
	Spain	Luxembourg	Slovenia, Rep.	Mexico
	United Kingdom	Netherlands	Sweden	Moldova
		Norway		New Zealand
		Poland		Serbia
		Romania		Switzerland
		Russian Fed.		
		United States		

The findings obtained from hierarchical clustering Ward method and from fuzzy clustering c-means method have considerable differences; fuzzy c-means method producing more stable results and affected by extreme data and initial values less.

According to the findings;

Cluster 1 (Croatia, Hungary, Portugal, Turkey), which was obtained from fuzzy c-means method and Cluster 6 (Croatia, France, Portugal, Russian Federation, Turkey), which was obtained from hierarchical ward method, have similar structures. The countries in Cluster 1 - especially 3 countries - have similar structures for the following variables: “inland freight transport”, “maintenance spending” and “share of value added by the transport sector”. These countries were clustered according to their similarities by hierarchical clustering Ward method as follows:

Cluster 2 (Hungary)

Cluster 6 (Croatia, Portugal, Turkey),

Cluster 2 (Australia, Canada, China, France, Germany, India, Italy, United Kingdom, United States), which was obtained through c-means method, consists of leading countries in terms of trade volume at global level. They have high expenses for investment and maintenance as indicated by the results obtained for “investment spending” and “maintenance spending” variables. The clusters obtained for these countries by using Hierarchical clustering Ward method are as follows:

Cluster 1 (United Kingdom)

Cluster 2 (Australia, China, Italy, United States),

Cluster 6 (France),

Cluster 7 (Canada, Germany, India)

It can be seen that the countries were split in different ways when this method was used.

Cluster 3, which was obtained through c-means method, involves the highest number of countries (Bulgaria, Czech Republic, Greece, Ireland, Russian Federation, Korea, Luxembourg, Netherlands, Norway, Poland, Romania). They show similarities for the following variables: “maintenance spending”, “total inland freight transport in tonne-km per one thousand units of current USD GDP”, “road freight transport in tonne-km per one thousand units of current USD GDP”

The clusters obtained for these countries by using Hierarchical clustering Ward method are as follows:

- Cluster 1 (Ireland)
- Cluster 2 (Austria, Bulgaria, Netherlands)
- Cluster 3 (Luxembourg)
- Cluster 4 (Greece, Korea)
- Cluster 5 (Czech Republic, Romania)
- Cluster 6 (Russian Fed.)
- Cluster 7 (Norway, Poland)

It can be seen that the countries were split in different ways when this method was used.

Cluster 4, which was obtained through c-means method, mostly consists of European countries (Belgium, Denmark, Finland, Georgia, Japan, Montenegro, Slovak, Slovenia, Spain, Switzerland, Sweden). These countries are similar in terms of the following variables: “share of value added by the transport sector”, “total inland freight transport in tonne-km per one thousand units of Current USD GDP”, “road freight transport in tonne-km per one thousand units of Current USD GDP”.

follows:

- Cluster 2 (Belgium)
- Cluster 4 (Denmark, Japan,)
- Cluster 5 (Georgia, Sweden)
- Cluster 7 (Finland, Montenegro, Slovak, Slovenia Spain, Switzerland)

It can be seen that the countries were split in different ways when this method was used.

Cluster 5 obtained through c-means method involves countries that have relatively fewer logistics activities and related transportation activities (Albania, Armenia, Hungary, Iceland, Latvia, Lithuania, New Zealand, Serbia).

The clusters obtained for these countries by using Hierarchical clustering Ward method are as follows:

- Cluster2 ( Albania, Armenia, Lithuania, United States)
- Cluster3 ( Latvia, Malta, Mexico)
- Cluster4 (Iceland, Moldova)
- Cluster7 (Estonia, New Zealand, Serbia)

It can be seen that the countries were split in different ways when this method was used.

## **6. CONCLUSION**

Logistics sector, which is the fundamental part of economy, and transportation, which is the most important activity of this sector, are based on 7/24 service. In addition, increasing competition in the globalized market requires efficient planning in transportation activities by taking into consideration variables that affect performance of these activities. Transportation is a multi-disciplinary field, and

there are many variables affecting transportation performance such as transportation infrastructure of the country, types of transportation, transportation fares and taxes, transportation safety, equipment and regulations and effective use of information technologies.

This study examined clustering of OECD countries and selected non-member countries according to their logistics-based transportation activities. The variables related to transportation activities and 47 countries were examined through the data obtained from the available database.

For the purposes of the study, the author also collected time-based cross-sectional data related to sub-variables such as transportation infrastructure, transportation measures, economic and social indicators, safety, performance indicators and short-term indicators.

The basic aim of the study is to determine clusters for these countries according to basic transportation variables. Therefore, it explained the idea behind clustering and clustering methods as well.

Hierarchical clustering, also known as hierarchical cluster analysis, is an algorithm that groups similar object into groups called clusters. The endpoint is a set of clusters, where each cluster is distinct from each other cluster and the objects within each cluster are broadly similar to each other. A dendrogram is a type of tree diagram showing hierarchical clustering relationships between similar sets of data.

Other method is fuzzy clustering method, which is used when clusters are not clearly formed or some objects are inconsistent in cluster membership. Fuzzy clustering methods provide information about uncertainty cluster memberships. The current study used fuzzy clustering c-means algorithm.

Under the light of the data obtained from the database regarding OECD countries and selected non-member countries, the following variables were determined after a series of attempts: Investment Spending, Maintenance Spending, Containers Transport, Inland Freight Transport, Share of Value Added by The Transport Sector, Total Inland Freight Transport in Tonne-Km Per One Thousand Units of Current USD GDP, Road Freight Transport in Tonne-Km Per One Thousand Units of Current USD GDP.

Cross-sectional data were used in the analysis; however, it was not possible to access data providing complete information about all the countries. The gaps in the data were eliminated through the use of means. Since the extreme values of the variables have different structures, they have negative effects on cluster analysis. In this case, data should be standardized or transformed. Here, the data set was standardized.

Because the number of clusters was not known in advance, the analysis started by using Ward technique and seven clusters were obtained accordingly. Fuzzy c-means method was used to examine clustering structures of 47 countries. The ideal number of clusters was determined as 5 with the help of indices in fuzzy c-means method.

The findings showed that the clusters obtained through these two methods are different from each other. When the clusters of countries obtained from two methods according to the variables were

examined, it was concluded that those obtained through fuzzy clustering c-means algorithm were more appropriate.

When the clusters obtained from hierarchical clustering Ward method and fuzzy c-means algorithm are examined, it can be said that there are fewer number of clusters obtained from fuzzy c-means algorithm and the countries in these clusters have similar structures.

Cluster 1 and Cluster 6 are similar in terms of grouping according to both methods, and both clusters involve Turkey. The countries in these clusters have similarities for the following variables: inland freight transport, maintenance spending and Share of Value Added by The Transport Sector. In addition, they are all developing economies and have extensive land transportation fleets since they mainly prefer land transportation for domestic shipping activities.

Cluster 2 consists of developed countries in terms of trade volume which have high expenses for “investment spending” and “maintenance spending”. The countries in one single cluster according to fuzzy clustering were split in different clusters according to the results of the hierarchical clustering method.

Clusters 3, which has the highest number of countries, involves countries having similar structures in terms of the following variables: Maintenance Spending, Total Inland Freight Transport in Tonne-Km Per One Thousand Units of Current USD GDP, Road Freight Transport in Tonne-Km Per One Thousand Units of Current USD GDP.

Cluster 4 involves mostly European countries and the countries in the cluster have similar structures for the following variables: Share of Value Added by The Transport Sector, Total Inland Freight Transport in Tonne-Km Per One Thousand Units of Current USD GDP, Road Freight Transport in Tonne-Km Per One Thousand Units of Current USD GDP.

Cluster 5 consists of developing countries with low population density, and their transportation activities are limited due to limited economic activities.

“Investing Spending and Maintenance Spending” are two effective variables for transportation indicators of OECD countries and selected non-member countries. Since economic volume determines transportation indicators, here investment and transportation rates functioned as a determining factor in clustering. The future studies might examine clustering according to different characteristics of countries in terms of economy and through different algorithms in terms of statistical data.

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