Measurement of the Economical and Social Efficiency of OECD Countries by Means of data Envelopment Analysis and Artificial Neural Network

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Abstract

The most efficient Decision Making Units (DMU) are subject to alignment in a way to obtain an efficiency score of 1,00 by way of weighing each input and output separately with Data Envelopment Analysis (DEA), which is an extremely convenient efficiency measurement method for multiple inputs and outputs. Artificial Neural Networks (ANN), which are also based on human thinking system, are such systems that are used to accomplish one or more of operations of learning, relating, classification, generalization and optimization by way of making use of the data at hand in practice. While it is observed in the literature that efficiency analyses are generally applied to economical DMUs, economic and social efficiencies of 34 OECD countries in between 2006 and 2010 are measured in this study by way of using DEA and ANN methods.

Key Words: Efficiency Measurement, Data Envelopment Analysis, Artificial Neural Networks, OECD.

Gel Code: C50, C45

Introduction

Business world and industrial sectors encountered global competition, short product life cycle, alternate products and worldwide market structure. Companies, which adapted themselves to these rapidly changing market conditions with technological renovation, gained great advantages.

Efficiency of a decision unit may be considered as outputs, inputs or the relationship between them (Chang & Chen, 2008). The simple method used in performance analysis is the ratio analysis which applies to single input and single output situations and makes an evaluation in regard to the output-input ratio. Parametric methods, which are developed due to the inadequacy of the results of ratio analysis, is an efficiency measurement method that applies to many input and output situations. In this method, which is generally based on making assumptions with regression technique, DMUs are assumed to possess a production function and parameters of this function are predicted. On the other hand, nonparametric methods, which are based on mathematical programming and commonly used for multiple input and output situations, involve the most convenient efficiency measurement techniques for DMUs that possess today's complicated production functions. The most commonly used nonparametric method is certainly Data Envelopment Analysis (DEA) (Baysal, et al., 2005).

In the majority of the efficiency analysis works conducted with DEA in a macro-economic scope, non-profit public sectors are examined and compared with each other. In a study conducted by Özden in 2011, efficiency was measured by using macro-economic indicators which are comprised of 3 inputs and 3 outputs belonging to European Union countries and some other selected countries, and countries are ranked as efficient and inefficient by taking DEA results as the countries' development levels (Özden, 2011).

In another study carried out by Yaylalı, Oktay, Akan and Kaynak, efficiency of Turkey and European Union countries based on information economy was measured. In the study, 6 inputs and 6 outputs are used about the information economy, and information economy efficiency values are specified for each country separately (Yaylalı et al, 2007).

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In another study carried out by Malhotra among Europen Union countries, 7 variables were used and their efficiency to the given result was especially discussed (Malhotra and Malhotra, 2007).

In their study in which the efficiencies of the governments of developing countries were measured, Rayp and Van De Sijpe used 5 outputs in return for a single input. The study aimed to reveal the factors that determined the government efficiencies (Rayp and Van De Sijpe, 2007).

Çınar and Şahin compared Turkish Telecom industry with those of OECD countries. The study made on 2 inputs and 1 output belonging to 1999-2005 was comprised of two sections, one for fixed lines and one for mobile lines (Çınar and Şahin, 2010).

As it is observed in the above-mentioned studies, DEA is a convenient method in determining countries' efficiencies in economic and social terms. In this study, economic and social efficiencies of OECD countries are determined for each structure separately and by way of using the appropriate inputs and outputs which are deemed as the best representatives of each structure.

Data Envelopment Analysis

Data Envelopment Analysis (DEA) is an efficiency measurement method based on linear programming (Banker et al, 2007). DEA, a multi-dimensional efficiency measurement nonparametric method, was developed by Charnes, Cooper and Rhodes in 1978 based on a study carried out by Farrell in 1957. Study of Charnes et al. was entered into the literature as CCR model, named after the initials of their names. In the model, Charnes et al. assumed fixed return to scale. CCR model was developed by Banker, Charnes and Cooper in consideration of the variable return to scale and entered into the literature as BCC model (Yeşilyurt and Alan, 2003).

DEA assigns its efficient DMUs within its efficiency border as a reference set for its inefficient DMUs, thus showing which inputs of which inefficient DMU should be decreased how much or which outputs of which inefficient DMU should be increased how much. So DEA not only measures efficiency but also contributes in performance improvement by setting targets for inefficient DMUs in order to become efficient.

DEA can be calculated in two ways as input-oriented and output-oriented. Accordingly (Charnes, , et al., 1981);
1. Input-oriented: A DMU is efficient if it can increase one of the outputs without increasing any other input or decreasing another output. This method is based on decreasing the inputs without making any changes on the outputs.

2. Output-oriented: A DMU is inefficient if it can decrease one of the inputs without decreasing any other output or increasing other inputs. This method is based on increasing the outputs without making changes on inputs.
DEA can be formulated mathematically in the following way (Banker, et al., 1984);

$$\text{Weighted Total Input} = \sum_{i=1}^{I} v_i x_i$$

$$\text{Weighted Total Output} = \sum_{j=1}^{J} u_j y_j$$

$$\text{Efficiency} = \text{Weighted Total Output/Weighted Total Input} = \frac{\sum_{j=1}^{J} u_j y_j}{\sum_{i=1}^{I} v_i x_i}$$

DEA has profound advantages during application as well as some weaknesses. For instance, DEA enables to determine the optimum weight for all inputs and outputs of each unit without any limitation. This provides an advantage to DEA; however these weights, determined freely, do not necessarily reflect the reality.

Firstly, DEA makes performance evaluation according to the optimum instead of statistical population. The optimum sample is defined for each DMU and a boundary is established. Efficiency or inefficiency is decided in accordance with the coordinate in parallel with this limit. Together with these features, DEA is preferred as an attractive and convenient method (Mok, et al., 2007).

DEA is commonly used since it incorporates such features as being supported with economic theories and methods, focusing on relative efficiency rather than the absolute one, including multiple inputs and outputs coordinately in the calculation, defining the optimum sample and setting it as a target (Kontodimopoulos, et al., 2007).

Another advantage of DEA is that it can determine the potential development points for inefficient DMUs. Thanks to this method, efficiency level for each one of the inputs and outputs can be determined by way of making a comparison between the DMUs which are located on the boundary and the inefficient DMUs which are enveloped with the efficiency boundary (Şevkli, et al., 2007).

In applications to be performed with DEA, inputs and outputs are independent in terms of units of measurement and may be measured with quite different units of measurement. In such a case, there is no need to use various assumptions or make conversions in order to perform these measurements in the same way (Karacaer, 1998).

Besides the above mentioned advantages, according to the results obtained by DEA, such a perception that a DMU, whose efficiency score is determined as 1.0 relatively among the production units in the data set, cannot increase its efficiency any more constitutes an important impediment to performance increase. However, this score indicates that the aforementioned DMU is detected as efficient in the current data set. Besides, there is no need to do hypothesis test to DEA due to its nonparametric structure so the significance level of the observed differences cannot be explained statistically (Pereira, 2006).

Original DEA model cannot make a certain alignment among efficient DMUs (Zzadeh, et al., 2008).

DEA provides a result only in the set at hand. This means that a more efficient DMU may exist outside this set. Thus, an efficient DMU statement determined in consequence of the analysis should be perceived as efficient DMU among those in the current data set.

Artificial Neural Networks

Use of artificial neural networks in such problems whose algorithmic solution could not be found has increased due to the fact that artificial neural networks can find solutions to new occurrences by way of examining former instances and learning the relationship between inputs and outputs of the said occurrence, regardless of whether the relationship is linear or not, from the current instances in hand. The biggest problem in artificial neural networks is that there is a need for such artificial neural networks that contain either very large neurons or multi-layered and a great amount of neurons in order to solve complicated problems (Kohonen,1987). An artificial neural network is an intensively parallel-distributed processor which is comprised of simple processing units, has a natural tendency to collecting experiential information, and enabling them to be used (Haykin, 1999).

The relationship of this processor with the human brain can be explained in two ways:

a) Information obtained by the processor is obtained by means of a certain learning process.
b) Link weights between the artificial neurons composing the processor are used to keep the obtained information.

There are three components as neuron (artificial neural cell), links and learning algorithm within the structure of the artificial neural network. Neuron is the basic processing element of an artificial neural network. Neurons within the network accept one or more inputs as per the factors affecting the problem and give as many inputs as the expected results. Neurons come together via the links and form the artificial neural network. In a general artificial neural network, neurons gather on the same direction and form layers (Yıldız, 2001).

Artificial neural networks is a logic programming technique which is developed by simulating the working mechanism of human brain and aims to do the basic operations that human brain can do biologically with a certain software (Öztemel, 2003). Artificial neural networks are flexible and non-parameter modeling tools (Tang & Chi, 2005). Considering the general structure of ANNs, it is seen that they are formed of 3 layers at the least. Besides the layers in an artificial neural network model, there exist 5 basic elements as inputs, weights, net function, activation function and outputs. The number of cells in input and output layers of the network varies depending on the information defined in the problem. Efficiency and significance of the input layer information in the system is ensured by weights.

İnformation is obtained in these weights, and the intelligence and learning performance of the network depend on the correct determining of the weight values. Net function, which is calculated as the total of weighted inputs, represents the effects of inputs to this cell. These net inputs coming to the cells are converted into outputs or linked to other intermediate cells with the help of an activation function. Activation function can be linear and nonlinear. While an activation function called sigmoid, whose definition range is between 0-1 approximately, is generally used in applications, such functions as hyperbolic, tangent, linear and step can also be used.

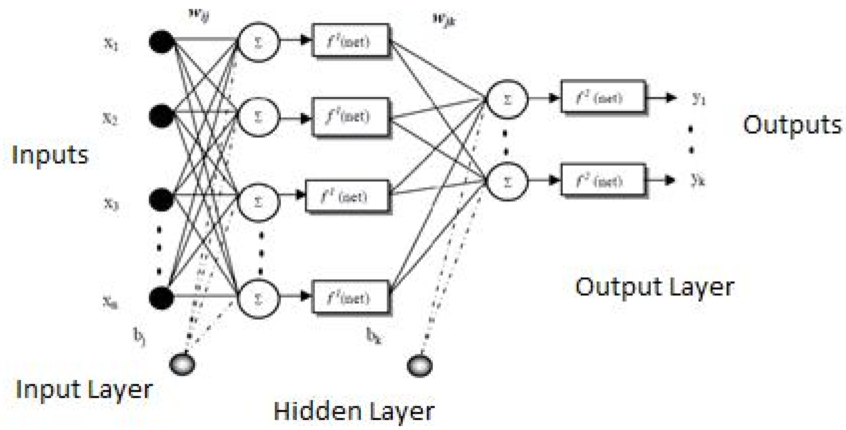

Figure 1: Artificial Neural Network Structure

In Figure 1, each neuron in the input layer is linked to each neuron in the concealed layer via $w_{i,j}$ synaptic weights. Besides, there is no link from the neurons in the input layer to the next concealed layer or output layer. Output values of the neurons in input layer constitute the input values of the neurons in concealed layer.
Accordingly, weighted net input coming to $N_{1,1}$ neuron in concealed layer,

$$v_{1,1} = \sum_{i=1}^{3} x_{i,}w_{i,1} = x_1w_{1,1} + x_2w_{2,t} + x_3w_{3,1} + \cdots$$

Initial values of the synaptic weights ($w_{i,j}$,$b_{i,j}$) of the back propagation networks are generally assigned as random variables between (-1,1) range.

Net input coming to $N_{1,2}$neuron in concealed layer,

$$v_{1,2} = \sum_{i=1}^{3} x_iw_{i,2} = x_1w_{1,2} + x_2w_{2,2} + x_3w_{3,2} + \cdots$$

After this stage, $N_{1,1}$ and $N_{1,2}$ neurons activate the coming inputs. Activation functions chosen for this example are given below;

$$y_{i,k} = f(v_{i,j}) = \frac{1}{1 + e^{-v_{i,j}}}$$

$y_{i,k}$: output of j neuron in i layer
$v_{i,j}$: input of j neuron in i layer
Accordingly, outputs of $N_{1,1}$ and $N_{1,2}$ neurons in the first layer are shown below;

$$f(v_{1,1}) = y_{1,1} = \frac{1}{1 + e^{-v_{1,1}}}$$
$$f(v_{1,2}) = y_{1,2} = \frac{1}{1+e^{-v_{1,2}}}$$

Artificial neural networks can be learned in time. Thus, they have adaptive characteristics. This means that neural networks can develop their problem solving skills from past experiences. This occasion in artificial neural networks happens as `learning`. Learning procedure is the constant updating of the weights of links in order to obtain the required outputs (Yakut, 2012).

Learning in an artificial network means finding optimum weight values that shall enable the network to produce the correct outputs in regard to a certain problem. Since information is distributed in the form of weights among the links throughout the network, a single link does not represent any significant information. More precisely, a group of links with processing elements must be designed to construct significant information. The network should have correct weight values of the links so as to solve the problem. This is done by means of a process namely learning or training. Learning is based on a learning rule which tells how to change weight values. There are many learning rules under development. Some of these are feedback networks, squasher functions, radial basis function, ridgelet networks, jump links, multi-layered feedback networks and recurrent networks (Wasserman, 1993).

Learning methods are generally split into counseling and non-counseling learning. In counseling learning, artificial neural network should be trained at first. Training process is carried out by providing input and output information to the neural network. The network obtains the information that shall be used in changing weights, by way of comparing the output value produced as per input information with the required value. Training continues until the difference between input value and required value is smaller than the error value designated beforehand. Once the error value drops down below the required value, all weights are fixed and training process is completed. In non-counseling learning, system does not have any information about the correct output and samples itself according to the inputs. Networks, which can be trained as non-counseling, set the weight values according to the characteristics of input information without the required or target output (Elmas, 2003).

Basic steps to take in order to establish an artificial neural network model are given below (Hawley, 1990):

- Firstly, it should be determined what aim, in other words output, the system shall have.
- The values which are considered to affect this output or shall be accepted as input into the artificial neural network system should be determined.
- A data set should be formed in regard to these inputs, it should be divided as training set and test set, and it should be converted in compliance with the network.
- Network topology should be designated (how many layers, how many neurons in the layers, activation function of neurons).
- Learning algorithm should be designated.
- Network should be trained and tested.
- Previous steps should be repeated until reaching the required level.

Application

Aim of this study is to perform an efficiency analysis on the country level with economic and social indicators. For this purpose, indicators of OECD countries in between 2006 and 2010 have been used.

Data Set

Scope of the study is limited to OECD countries. OECD has a total of 34 member countries as of 2010. OECD countries, a briefing of which is given below, are listed as Germany, America, Australia, Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Netherlands, England, Ireland, Spain, Israel, Sweden, Switzerland, Italy, Iceland, Japan, Canada, Korea, Luxembourg, Hungary, Mexico, Norway, Poland, Portugal, Slovakia, Slovenia, Chili, Turkey, New Zealand and Greece.

An efficiency analysis has been made by using some data including 2006-2010, obtained from various official web sites. In the efficiency analysis, performed separately per year, 6 economic inputs and 6 economic outputs were used and the economic efficiency of the aforementioned countries was determined. Likewise, a social efficiency analysis was conducted with 4 social inputs and 4 social outputs, which are subject to the analysis and obtained for 5 years. 6 economic input data of member countries were used in the analysis as unemployment rate (%), annual average working time (hours), direct foreign investments (million dollar), food production index (1999-2001=100), total import (billion dollar), and tax revenue (% domestic product). In the analysis where social efficiency was measured; 4 social input data were used as population per 1 km^2, rate of service workers to total workers (%), total energy production (petrol equivalent) and total health costs (% domestic product).

6 economic output data were designated for economic efficiency analysis and these data are gross domestic product per capita (dollar), purchasing power parity (dollar), comparative price index (OECD=100), income index, total export (billion dollar) and CO2 emission per capote (ton). For the output of social efficiency analysis, such social output data were included as total energy consumption (petrol equivalent), total number of subscribers to mobile phones (per 100 persons), health index and average life expectancy (year).

Economic and social efficiency scores of the countries were performed with DEA method using Frontier Analyst Professional 2.0 package software. Afterwards, artificial neural network method was chosen to estimate efficiency scores, and Statistica 8.0 software was used to utilize artificial neural network method. Estimated efficiency scores and real efficiency scores were compared and evaluated with R2, MPE, MSPE, RMSPE and MAPE.

Results of Economic Efficiency Analysis

Economic efficiency scores, obtained from the results of the analysis which was performed by using inputs and outputs of 5 years between 2006 and 2010, are given in Table 1;

Table 1: Economic Efficiency Scores

	CCR Efficiency Analysis					BCC Efficiency Analysis				
	2006	**2007**	**2008**	**2009**	**2010**	**2006**	**2007**	**2008**	**2009**	**2010**
Germany	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
America	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Australia	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Austria	**98.20**	**92.79**	**94.14**	**98.19**	100.00	**98.82**	**94.22**	**95.70**	**98.91**	100.00
Belgium	**97.83**	**97.56**	**99.74**	**96.16**	**94.88**	**98.06**	**97.91**	100.0	**96.44**	**95.95**
Czech Rep.	**92.46**	100.00	**91.10**	100.00	**89.07**	**92.88**	100.00	**91,83**	100.00	**91.15**
Denmark	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Estonia	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Finland	100.00	100.00	**90.00**	100.00	**92.86**	100.00	100.00	**97.86**	100.00	**96.43**
France	**97.08**	100.00	**97.93**	**94.54**	**93.50**	**97.33**	100.00	**97.95**	**94.67**	**95.02**
Netherlands	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
England	**93.19**	**93.75**	**93.49**	**94.72**	**94.03**	**95.47**	**94.25**	**94.97**	**96.69**	**96.33**
Ireland	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Spain	**87.92**	**88,52**	**89,96**	**98,51**	**92,63**	**92,61**	**91,60**	**91,55**	100.00	**94.37**
Israel	**88.27**	**90.61**	**86.73**	**94.86**	**94.55**	**92.60**	**95.05**	**92.61**	**97.43**	**98.02**
Sweden	**93.48**	**94.30**	**94.80**	**93.47**	**90.96**	**95.10**	**95.21**	**95.72**	**96.57**	**95.93**
Switzerland	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Italy	**91.80**	**97.26**	**97.57**	**94.08**	**93.04**	**94.00**	**98.08**	100.00	**94.58**	**94.46**
Iceland	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Japan	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Canada	**97.01**	**96.66**	**96.93**	100.00	**96.15**	**97.66**	**97.46**	**98.14**	100.00	100.00
Korea	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Luxembourg	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Hungary	**87.29**	**94.38**	**79.90**	**89.50**	100.00	**87.61**	100.00	**84.54**	**89.65**	100.00
Mexico	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Norway	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Poland	**75.63**	**85.56**	**73.65**	**81.53**	**83,00**	**82,88**	**88.09**	**84.,50**	**87.23**	**85.92**
Portugal	**91.15**	100.00	**86.71**	**98.77**	**97.32**	**91.49**	100.00	**89.96**	100.00	100.00
Slovakia	**97.26**	100.00	**90.80**	100.00	**99.90**	100.00	100.00	**91.40**	100.00	100.00
Slovenia	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Chili	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Turkey	**89.61**	**91.20**	**90.06**	**88.86**	**84.42**	**90.01**	**91.43**	**90.46**	**89.59**	**84.91**
N. Zealand	**97.51**	100.00	**94,75**	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Greece	**98.26**	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Average	**96.29**	**97.72**	**95.54**	**97.74**	**96.95**	**97.25**	**98.33**	**96.98**	**98.29**	**97.90**

In consequence of DEA which was performed by CCR method under fixed return to scale, with economic data subject to the analysis between 2006 and 2010; Germany, America, Australia, Denmark, Estonia, Netherlands, Ireland, Switzerland, Iceland, Japan, Korea, Luxembourg, Mexico, Norway, Slovenia and Chili were determined as among efficient countries. When the analysis was repeated with BCC method under fixed return to scale, New Zealand and Greece joined in efficient countries due to the flexibility provided by the fact that the method gave result under variable return to scale.

As a result of DEA performed with the economic data of 2006, 17 countries were efficient, on the other hand, 17 countries could not reach full efficiency score, and efficiency score was 96.29. When the analysis is repeated with BCC method, the number of full efficient countries increased to 20 and the number of inefficient countries was 14 so efficiency average was 97.25. As a result of the measurement of economic efficiencies of OECD countries for the year of 2007, 23 countries obtained full efficiency score, on the other hand, 11 countries were inefficient. Efficiency average for 2007 was 97.72. By BCC method, 24 full efficient countries were identified in return for 10 inefficient countries. The efficiency average was 98.33 in consequence of the analysis performed with this method.

According to the results of DEA performed by CCR method in the year of 2008, the number of efficient and inefficient countries was 17, efficiency average of this period was 95.54, the lowest score among all periods subject to the efficiency average analysis. By BCC method, the number of efficient and inefficient countries was 20 and 14 respectively, and the efficiency average was 96.98.

In 2009, by CCR method, while 22 countries were efficient, 12 countries could not attain any efficiency score. As a result of this analysis made by CCR method, efficiency score average was 97.74. By BCC method, the number of efficient countries increased to 24, the number of inefficient countries decreased to 10. Efficiency score average obtained with this method was 98.29.

As a result of the analysis made by CCR method in 2010, while 20 countries were full efficient, 14 countries were inefficient. Average efficiency score was 96.95 in consequence of the said analysis made for the years of 2010. By BCC method, 23 countries were regarded as efficient and 11 countries were regarded as inefficient. An efficiency score average of 97.90 was obtained as a result of the analysis made by BCC method.

Results of Social Efficiency Analysis

Social efficiency scores, obtained from the results of the analysis which was performed by using inputs and outputs of 5 years between 2006 and 2010, are given in Table 2;

Table 2: Results of Social Efficiency Analysis

	CCR Efficiency Analysis					BCC Efficiency Analysis				
	2006	2007	2008	2009	2010	2006	2007	2008	2009	2010
Germany	92.18	92.50	93.77	94.45	94.44	97.70	97.76	97.94	97.30	97.68
America	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Australia	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Austria	90.37	87.40	86.40	88.42	87.58	99.15	99.20	99.38	99.53	99.49
Belgium	80.56	78.51	77.60	79.92	81.51	97.57	97.62	97.40	97.14	97.02
Czech Rep.	100.00	99.99	98.79	98.34	96.82	100.00	100.00	100.00	100.00	100.00
Denmark	77.57	76.38	74.83	73.95	72.98	96.31	96.11	96.46	96.22	96.32
Estonia	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Finland	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
France	89.45	87.99	92.06	94.92	95.72	99.19	99.31	99.33	99.06	99.50
Netherlands	74.09	73.67	71.98	72.80	71.31	97.54	97.82	97.78	97.43	97.52
England	81.05	80.15	89.77	80.18	74.64	97.43	97.29	97.20	97.20	97.12
Ireland	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Spain	100.00	100.00	100.00	98.03	97.50	100.00	100.00	100.00	100.00	100.00
Israel	100.00	98.00	98.40	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Sweden	90.72	89.02	89.76	89.00	88.95	100.00	100.00	100.00	100.00	100.00
Switzerland	80.53	80.78	79.03	83.23	82.83	100.00	100.00	100.00	100.00	100.00
Italy	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Iceland	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Japan	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Canada	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Korea	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Luxembourg	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Hungary	85.46	84.55	87.61	93.19	95.61	91.79	92.68	93.90	95.67	96.20
Mexico	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Norway	91.28	90.73	92.32	91.13	90.81	100.00	99.38	99.28	99.22	99.12
Poland	99.97	98.54	96.41	98.05	93.35	100.00	100.00	99.04	100.00	98.70
Portugal	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Slovakia	94.81	94.95	93.34	90.88	88.74	96.11	95.85	94.92	93.94	93.42
Slovenia	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Chili	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Turkey	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
N. Zealand	95.54	95.49	95.39	95.71	96.36	99.98	99.33	99.20	99.60	99.93
Greece	90.15	88.65	88.87	90.86	92.83	98.73	98.74	99.09	99.17	99.48
Average	94.52	94.04	94.29	94.50	94.17	99.13	99.15	99.14	99.16	99.16

In consequence of DEA performed with social data of 2006-2010 by CCR method; America, Australia, Estonia, Finland, Ireland, Italy, Iceland, Japan, Canada, Korea, Luxembourg, Mexico, Portugal, Slovenia, Chili and Turkey achieved full efficient scores for all years subject to the analysis. By BCC method, Spain, Israel, Sweden and Switzerland joined in efficient countries.

As a result of DEA performed by CCR method with the social data of 2006, 19 countries were efficient, whereas 15 countries could not attain full efficiency score and the efficiency average was 94.52. By BCC method, the number of full efficient countries increased to 23 and the number of inefficient countries was 11. Efficiency average was 99.13. As a result of the measurement of social efficiencies of OECD countries by CCR method for the year of 2007, 17 countries achieved full efficiencies scores, whereas 17 countries were found inefficient.

Efficiency average of 2007 was 94.04. By BCC method, there were identified 22 full efficient and 12 inefficient countries. In consequence of the analysis made by this method, efficiency average was found as 99.15.

According to the results of DEA carried out by CCR model using social data of 2008, the number of efficient and inefficient countries was 17, efficiency average for this period was 95.54. When the analysis was repeated by BCC method for the same year, the number of efficient and inefficient countries was 21 and 13 respectively. Efficiency average was 99.16.

According to the results of DEA carried out by CCR method using social data of 2009, 17 countries were efficient, whereas 17 countries could not achieve any efficiency score. Efficiency score average obtained as a result of this analysis made by CCR method was 94.50. The analysis was repeated by BCC method. As a result, the number of efficient countries increased to 22, on the other hand the number of inefficient countries decreased to 12. Efficiency score average obtained by this method was 99.16.

As a result of the analysis conducted by CCR method using social data of OECD countries for the year of 2010, 17 countries were full efficient, whereas 17 countries were inefficient. In consequence of this analysis or the years of 2010, average efficiency score was 94.17. The same data was analyzed by BCC method. As a result, 20 countries were efficient; on the other hand 14 countries were regarded as inefficient. In consequence of the analysis made by BCC method, efficiency score average was 99.16.

ANN Network Parameters

In contrast to statistical methods, artificial neural networks do not need any presupposition on data set (Kaynar&Taştan, 2009:141). During this ANN step of the research, 170 entries, including 6 input and 6 outputs variables of economic efficiency analyses on the input layer and economic efficiency scores on the output layer and 4 inputs and 4 outputs variables of social efficiency analyses on the input layer and social efficiency scores on the output layer, were entered into Statistica 8.0 software in order to be used in the artificial neural network analysis. Data between 2006 and 2009 (80%) were used for the training of models, the rest part belonging to 2010 (20%) were assigned for the validity of the models.

Table 3: ANN Network Parameters

Type of Network		**Multi-layered Perceptron**
Learning Algorithm		Back Propagation
Learning Rule		Momentum
Economic Efficiency	**Number of Nodes in Input Layer**	12
	Number of Concealed Layer	1
	Number of Nodes in Concealed Layer	10-11
Social Efficiency	**Number of Nodes in Input Layer**	8
	Number of Concealed Layer	1
	Number of Nodes in Concealed Layer	5-10
Number of Nodes in Output Layer		1
Learning Rate		0,01
Number of Cycles		10000
Transfer Function for Concealed Layers		Tansig
Transfer Function for Output Layer		Purelin
Training Function of Back Propagation Network		Trainlm

In Table 3, there are given network structures of the models which include the optimum layer and number of nodes for ANN that is used to estimate efficiency scores. In the estimation of economic data, 10 and 11 nodes were used in concealed layer to analyze efficiency scores, obtained by CCR and BCC methods respectively, with ANN. In the estimation of social data, 5 and 10 nodes were used in concealed layer to analyze efficiency scores, obtained by CCR and BCC methods respectively, with ANN.

10000 iteration were done for training the established artificial neural network. In this study, input and output variables used in efficiency analysis are included in the input layer of ANN analysis, and efficiency scores to be estimated are included in the output layer of ANN analysis.

Results of ANN Models

Estimated performance criteria are considered when making a decision in regard to ANN. The most frequently used formulas in the literature to measure estimated performances are MPE (Mean Performance Error), MSPE (Mean Square Percentage Error), RMSPE (Root Mean Square Percentage Error), MAPE (Mean Absolute Percentage Error), MSE (Mean Square Error) and RMSE (Root Mean Square Error) (Zhang and Hu, 1998:500). Statistical representations of measurements are given below.

Table 4. Truth Criteria and formulas

$MSE = \frac{1}{n}\sum[e(t)]^2$	Mean Square Error
$MAE = \frac{1}{n}\sum\lvert e(t)\rvert$	Mean Absolute Error
$MPE = \frac{1}{n}\sum p(t)$	Mean Percentage Error
$MSPE = \frac{1}{n}\sum[p(t)]^2$	Mean Square Percentage Error
$RMSPE = \sqrt{\frac{1}{n}\sum[p(t)]^2}$	Root Mean Square Percentage Error
$MAPE = \frac{1}{n}\sum\lvert p(t)\rvert$	Mean Absolute Percentage Error

Table 5. For Economic Efficiency: ANN Coefficient of Determination (R^2) and Truth Criteria Percentage Values

ANN Analysis		R^2	MPE	MSPE	RMSPE	MAPE	MSE	RMSE
Economic Efficiency	CCR	0.83	0.00012	0.00052	0.02279	0.01421	4.33013	2.08090
	BCC	0.88	-0.00032	0.00018	0.01360	0.00780	1.65487	1.28642

In Table 5, there are given the coefficient of determination, mean percentage error, mean square percentage error, root mean square percentage error, mean absolute percentage error, mean square errors and root mean square errors, which are all used in comparing artificial neural network performances. In the estimation of economic efficiency, R^2 values were found as 0.83 and 0.88 for the models which are established by means of ANN model that used efficiency scores obtained by CCR and BCC methods. On the other hand, it was determined that MPE values were between 0.00012 and 0.00032, MSPE values were between 0.00052 and 0.00018, RMSPER values were 0.02279 and 0.01360, MAPE values were between 0.01421 and 0.00780, MSE values were between 4.33013 and 1.65487, and RMSE values were between 2.08090 and 1.28642. Lewis (2002) classified models whose MAPE values are below 10% as \`very good\`, between 10% and 20% as \`good\`, between 20% and 50% as \`acceptable\` and below 50% as \`false and corrupt\`(Lewis, 1982: 509). Thus, it can be said that the models are very good since MAPE values are below 1%.

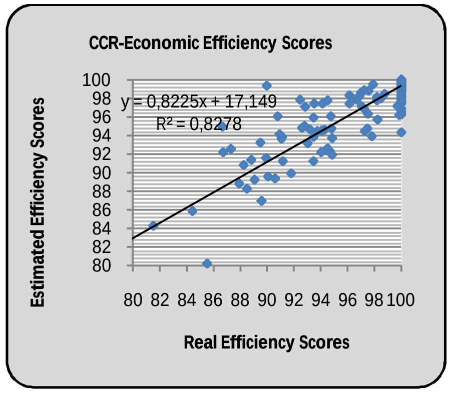

Diagram 1: CCR: Economic Efficiency Scores

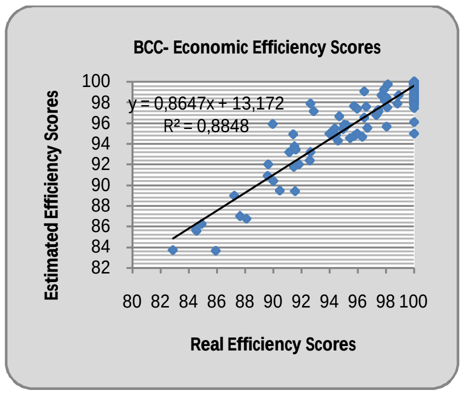

Diagram 2: BCC: Economic EfficiencyANN Estimated Real Values

Scores - ANN Estimated Real Values

Above, there are given comparative diagrams of the estimated economic efficiency scores obtained by ANN and the real economic efficiency scores obtained by CCR and BCC methods. We can say that ANN models derived from these diagrams have high R^2 values. Diagrams show that there is no significant difference between real data and estimated results obtained from ANN for the period of 2006-2010. Accordingly, it was deduced that there is a strong relationship between these two groups of data (Measured data – ANN data). When diagrams are analyzed, it is seen that data obtained from ANN are similar to the measured values. We can say that ANN model developed for BCC is much better with a R^2 of 6.89% than the ANN model developed for CCR.

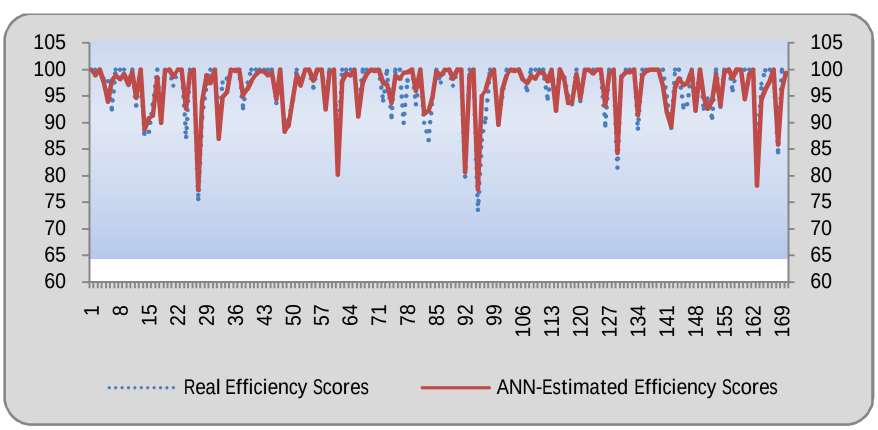

Diagram 3: CCR: Real Economic Efficiency Scores and ANN Dispersion Diagram of ANN Estimated Efficiency Values

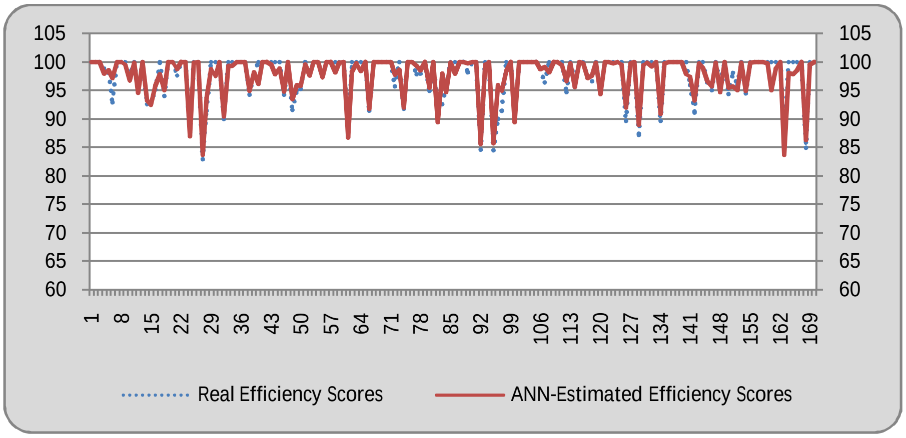

Diagram 4: BCC: Real Economic Efficiency Scores and Dispersion Diagram of ANN Estimated Efficiency Values

Table 6: For Social Efficiency: ANN Coefficient of Determination (R^2) and Truth Criteria Percentage Values

ANN Analysis		R^2	MPE	MSPE	RMSPE	MAPE	MSE	RMSE
Social Efficiency	CCR	0.89	-0.00214	0.00083	0.02887	0.02122	6.97863	2.64171
	BCC	0.94	-0.00049	0.00002	0.00404	0.00290	0.15642	0.39551

Values obtained for ANN models are presented in Table 6. In the estimation of social efficiency, R^2 values were found as 0.89 and 0.94 for the models which are established by means of ANN model that used efficiency scores obtained by CCR and BCC methods. On the other hand, it was determined by ANN that MPE values were between 0.00214 and 0.00049, MSPE values were between 0.00083 and 0.00002, RMSPE values were between 0.02887 and 0.00404, MAPE values were between 0.02122 and 0.00290, MSE values were between 6.97863 and 0.15642, and RMSE values were between 2.64171 and 0.39551. We can deduce that the models are very good since MAPE values are below 3%.

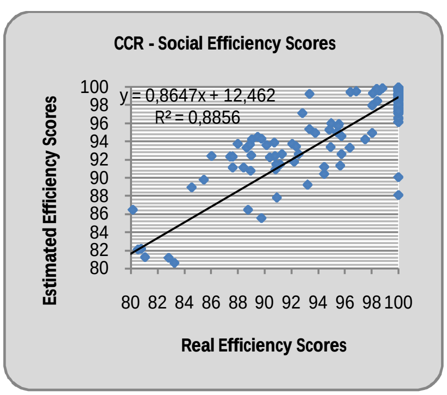

Diagram 5: CCR: Social Efficiency Scores Estimated-Real Values

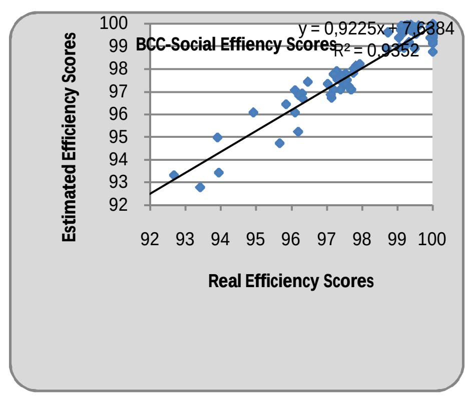

Diagram 6: BCC: Social Efficiency Scores ANN ANN Estimated-Real Values

Above, there are given the comparative diagrams of the estimated social efficiency scores obtained from ANN and real social efficiency scores belonging to CCR and BCC methods. We can say that ANN models deduced from these diagrams have high R2 values. As in the estimation of economic efficiency scores, we can say that there is no significant difference between real data and estimated social efficiency results of 2006-2010 obtained by ANN. There is a strong relationship between these two groups of data (measured data – ANN data). When the diagrams are analyzed, we can say that ANN model established for BCC is much better with a R^2 of 5,6% than the ANN model established for CCR.

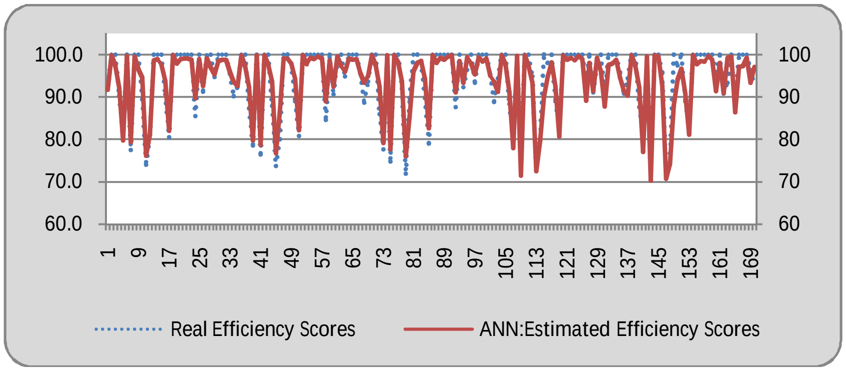

Diagram 7: CCR: Real Social Efficiency Scores and ANN Dispersion Diagram of Estimated Efficiency Values

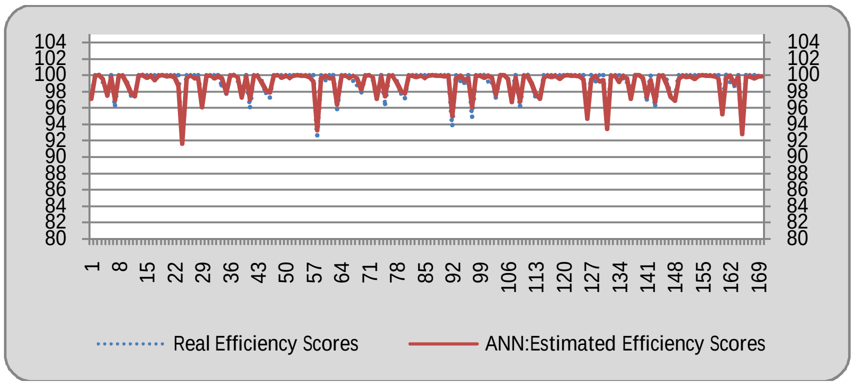

Diagram 8: BCC: Real Social Efficiency Scores and ANN Dispersion Diagram of Estimated Efficiency Values

Conclusion

In this study, macroeconomic efficiencies of 34 OECD countries for the period of 2006-2010 have been identified by DEA, and it has been determined whether some designated inputs were able to fully convert into outputs or not, and finally efficiency scores have been estimated by way of using artificial neural networks. Economically efficient countries are generally expected to be socially efficient also in parallel with their level of welfare. For this purpose, both efficiency indicators have been compared separately. As a result of the comparison of economic and social efficiencies, it has been determined that there is not any linear relationship between both efficiency indicators. In consequence of the analyses performed with both economic and social data, the number of efficient countries was 11 according to CCR method and 12 according to BCC method. It has been understood that there is no such condition that every country with full economic efficiency must have full social efficiency and vice versa. In the study, we encountered a data reliability issue which constitutes an important weakness of the analysis. In particular, economic efficiency scores gained by Greece contradict with the reliability of data of Greece which has gone through a hard economic process in recent years.

DEA is a static efficiency analysis method essentially. It enables an efficiency in a certain period to be defined and necessary actions to be taken in the subsequent period. However, since this study is conducted with five-year data, it is significant in terms of presenting the change expending over years. Economic and social efficiency scores have been estimated by ANN which is another method used in this study. It has been observed that MAPE (Mean Absolute Percentage Error) was below 1% and 3% for the estimation of economic efficiency and social efficiency, respectively. When the estimations made from this point of view are compared with real values, it is seen that generally estimated efficiency scores are close to the realized efficiency values. It has been observed that the estimated social efficiency scores obtained by ANN have a little higher R2 value than economic efficiency scores. Likewise, it has been observed that the ANN model created for BCC makes estimation with a better R2 percentage of average 6.2% than the ANN model created for CCR. In conclusion, it is anticipated that efficiency scores of the countries can be estimated by using ANN method in determining future economic and social efficiencies. The next section of this study shall discuss which inputs inefficient countries should reduce or which outputs they should increase at what rate, in order for them to become efficient relatively.

References

Banker R.D.,Charnes A., Cooper W.W., (1984). "SomeModelsForEstimating Technical andScaleEfficiencies in Data Envelopment Analysis", Management Science, Vol. 30, No. 9, September.

Banker Rajiv D.,ChangHsihui, Natarajan Ram. (2007). "Estimating DEA Technical andAllocativeInefficiency Using AggregateCostorRevenue Data", Journal of Productivity Analysis, 27, 115-121.

Baysal Mehmet Emin, Alçıcılar Bahriye, Çerçioğlu Hakan, Toklu Bilal, (2005). "Türkiye'deki Devlet Üniversitelerinin 2004 Yılı Performanslarının, Veri Zarflama Analizi Yöntemiyle Belirlenip Buna Göre 2005 Yılı Bütçe Tahsislerinin Yapılması", SAÜ Fen Bilimleri Enstitüsü Dergisi, 9. Cilt, 1. Sayı.

Chang S.Y.,Chen T.H., (2008). "PerformanceRanking of AsiaLeadrameFirms: A Slack-BasedMethod in Data Envelopment Analysis", International Journal of ProductionResearch, Vol. 46, No. 14, 3875-3885.

Charnes A., Cooper W.W., Rhodes E., (1981). "Evaluating Program andManagerialEfficiency: An Application of Data Envelopment Analysis to Program Follow Through", Management Science, Vol. 27, No. 6.

Çınar Yetkin, Şahin Hasan, (2010). "Türk Telekom Endüstrisinin OECD Ülkeleri ile Karşılaştırmalı Etkinlik Analizi: 1999-2005 Dönemi İçin Firma Bazlı Değerlendirme", Atatürk Üniversitesi İktisadi ve İdari Bilimler Dergisi, Cilt 24, Sayı 3.

Elmas, Ç. (2003). Yapay Sinir Ağları (Kuram, Mimari, Eğitim, Uygulama). Ankara: Seçkin Yayıncılık.

Hawley, Delvin.D.,Johson, J.D., andRaina, D., (1990). "ArtificialNeuralSystems: A newtoolforFinacialDecisionMaking" [Yapay Sinir Ağları Sistemleri: Yeni Bir Finansal Karar Verme Aracı], Financial AnaylystJournal, 46(6), 63-72.

Haykin S., (1999). "Neural Networks: A Comprehensive Foundation" [Elektronik Sürüm], PrenticeHallInc, New Jersey.

http://oecd.pr.mfa.gov.tr, Türkiye Cumhuriyeti OECD Daimî Temsilciliği Resmî İnternet Sitesi, Erişim Tarihi: 04.02.2012

Karacaer, Ş., (1998). "Antalya Yöresindeki 4 ve 5 Yıldızlı Otellerde Toplam Etkinlik Ölçümü: Bir Veri Zarflama Analizi Uygulaması", Hacettepe Üniversitesi, Sosyal Bilimler Enstitüsü.

Kaynar, O.,& Taştan, S. (2009). Zaman serileri tahmininde arıma-mlp melez modeli. Atatürk Üniversitesi İktisadi ve İdari Bilimler Dergisi, 23 (3), 141-149.

Kohonen, T. (1987) : State of the Art in Neural Computing. "Int. Conf. on AI", pp.1-79, 1-90.

Kontodimopoulos, Nick, Moschovakis, Giorgos, Aletras, Vassilis, Niakas, Dimitris, (2007). "TheEffectof EnvironmentalFactors on Technical andScaleEfficiency of PrimaryHealthCare Providers in Greece", CostEffectivenessand Resource Allocation, BioMed Central Publishes.

Lewis,. C.D., (1982). Industrialand Business ForecastingMethods. Londra: Butterworths Publishing.

Malhotra D.K.,MalhotraRashmi, (2007). "Using Data Envelopment Analysis toAnalyzeEuropeanUnion Nations", ICFAI Journal of International Business, Vol. II, No. 4.

Mok, Vincent, Yeung, Godfrey, Han, Zhaozhou, Li, Zongzhang, (2007). "Leverage, Technical EfficiencyandProfitability: An Application of DEA toForeign-Invested Toy ManufactoringFirms in China", Journal of ContemporaryChina, 16 (51).

Özden Ünal H., (2011). "Faktör Analizi ve Veri Zarflama Analizi ile AB'ye Üye ve Seçilmiş Bazı Ülkelerin Karşılaştırmalı Analizi", Trakya Üniversitesi Sosyal Bilimler Dergisi, Cilt 13, Sayı 1.

Öztemel, E., (2003) Yapay Sinir Agları, Papatya Yayıncılık.

Pereira, Artura, (2006). Economies of Scale in Blood Banking: A StudyBased on Data Envelopment Analysis, VoxSanguinis, 90.

RaypGlenn, Van De Sijpe Nicolas, (2007). "MeasuringandExplainingGovernmentEfficiency in DevelopingCountries", Journal of Development Studies, Vol. 43, No. 2.

Şevkli, Mehmet, Koh, S.C. Lenny, Zaim, Selim, Demirbağ, Mehmet, Tatoğlu, Ekrem, (2007). "An Application of Data EnvelopmentAnalyticHierarchyProcessforSupplierSelection: A Case Study of BEKO in Turkey", International Journal of ProductionResearch, 45 (9).

Tang, T. C.,&Chi, L. C. (2005). Neuralnetworksanalysis in businessfailureprediction of chineseimporters: a between-countriesapproach. ExpertSystemswith Applications, 29, 244–255.

Wasserman, P.D., (1993). "Advanced Methods in Neural Computing" [Elektronik Sürüm], Van NostrandReinhold, New York.

Yakut, E., (2012). "Veri Madenciliği Tekniklerinden C5.0 Algoritması, Destek Vektör Makineleri ile Yapay Sinir Ağlarının Sınıflandırma Başarılarının Karşılaştırılması: İmalat Sektöründe Bir Uygulama", (Yayımlanmamış Doktora Tezi), Atatürk Üniversitesi Sosyal Bilimleri Enstitütüsü, Erzurum.

Yaylalı Muammer, Oktay Erkan, Akan Yusuf, Kaynak Selahattin, (2007). "Türkiye ve Avrupa Birliğine Üye Ülkelerin Bilgi Ekonomisi Performanslarının Veri Zarflama Analizi Metoduyla Karşılaştırılması", Marmara Üniversitesi İ.İ.B.F. Dergisi, Cilt. XXII, Sayı 1.

Yeşilyurt Cavit ve Alan M. Ali, (2003). "Fen Liselerinin 2002 Yılı Göreceli Etkinliğinin Veri Zarflama Analizi (VZA) Yöntemi İle Ölçülmesi", C.Ü. İktisadi ve İdari Bilimler Dergisi, Cilt 4, Sayı 2.

Yıldız, B. (2001). Finansal Başarısızlığın Öngörülmesinde Yapay Sinir Ağı Kullanımı ve Halka Açık Şirketlerde Ampirik Bir Uygulama, İMKB Dergisi, 5 (17): 51-67.

Zhang, G.,& Hu, M. Y. (1998). Neural network forecasting of thebritish pound/US Dollarexchange rate, Omega International journal of Management Science, 26(4), 495-506.

Zzadeh, A.,Ghaderi, S.F., Javaheri, Z., Saberi, M., (2008). "A Fuzzy Mathematical Programming Approachto DEA Models", AmericanJournal of AppliedSciences, 5 (10).