Vol. 02, No. 03: June (2014)

Journal of Economic & Financial Studies

Open access available at http://journalofeconomics.org

Efficiency measurement in Turkish manufacturing sector using Data Envelopment Analysis (DEA) and Artificial Neural Networks (ANN)

Ömer Akgöbek[a*], Emre Yakut[b]

[a*] Department of Industry Engineering, Faculty of Engineering, Zirve University.
[b] Department of Management Information Systems, Osmaniye Korkut Ata University.
*Corresponding author's email: e-mail: mer.akgobek@zirve.edu.tr

H I G H L I G H T S:

1. The study measures efficiency of Turkish manufacturing industry for the time period of 1996-2008.
2. Data envelopment analysis (DEA) and artificial neural network (ANN) were employed.
3. Manufacture sector and 14 sub-sectors showed on efficiency score of 78.5-100 out of 100, which subsequently increases to 84.7-100 out of 100 in the last period in 2008.

Article History

Received: 20-05-2014
Accepted: 23-06-2014
Available online: 20-06-2014

Keywords:
Artificial Neural Networks; Data Envelopment Analysis; Efficiency Measurement; Manufacture sector.

JEL Classification:
C45; C53; G17.

ABSTRACT

Data Envelopment Analysis (DEA) is a non-parametric measurement technique based on mathematical programming to measure the efficiency level of the firms by determining multiple input and output variables. Artificial neural network (ANN) is information processing system and computer program that imitates human brain's neural network system. By entering the information from outside, ANN can be trained on examples related to the problem so that modeling of the problem can be provided. This study aims to examine the efficiency level of sectors operating in manufacturing industry in Turkey regarding the years between 1996-2008 via DEA and ANN to evaluate it from the financial aspect.

DOI: http://dx.doi.org/10.18533/jefs.v2i02.138

1.0 Introduction

Provision and efficiency measurement in both real (reel) and finance sectors is a subject that has begun to gain importance in Turkey in recent years. Until 1980, the pushing motive of competition particularly, the development of liberalization tendencies in the economy has increased the attempts and enterprise of both industrial and financial organizations, the impact of this on competition force and effectiveness have come to be observed more closely and sensitively after 1980 naturally pulled the countries info the phenomenon of globalization. This situation has led the subject of effectiveness to gain vital importance for not only the whole system, but also for the organizations making up it (Aras, 2006).

Efficiency measurement is of great importance in evaluating business performance. To assess the effectiveness of different firm policies, it is necessary to observe and measure the effectiveness periodically. Conventional measurement of production limit or active production function (Tarım, 2001) and according to this, the observed performance of the firm is compared to absolute (or perfect) standard of effectiveness. As a result, it is important to determine the standard of effectiveness or active production function correctly. Modern efficiency measurement was developed by Farrell (1957), and it was pointed out that the firm's efficiency had two components, namely technical and appropriation effectiveness (Farrell, 1957; Destafanis and Sena, 2007). It can be said that, technical effectiveness is to be able to obtain the most output for a certain amount of effectiveness. On the other hand, appropriation effectiveness is the ability to use the most appropriate proportion of input considering the costs. Total effectiveness is obtained by incorporating these two (Karacabey, 2001).

DEA is a mathematical programming technique which is used to measure the relative effectiveness of organizational units having many inputs and outputs. Especially, DEA has begun to be used as an active and efficient means of approach in those situations in which more than one input and output cannot be turned into a weighty set of input and output. When this technique is not used, the only solution to be resorted is decision- makers combining inputs and outputs using weights which he or she has determined with the help of subjective criteria. This approach will lead to mistake results and on account of this, decision-makers faulty decisions.

When compared to such conventional methods as performance ratios and regression analysis, DEA has many advantages in performance analysis. The difference of DEA from other techniques, like ratio analysis or regression, is its being a method that can correct et al. (Schaffnit vd., 1997; Shahmahammamdi and Harni 2004). As a result of the studies conducted in the fields of economy, engineering and management, DEA can be defined as a technique which can envisage and analyze the best performance data. DEA's application range covers each unit that exists in the internal and external conditions of production, utility and finance sectors. Initially measuring comparative efficiency in non-profit public organizations, DEA began to be widely used in the measuring of technical efficiency between business in profit-oriented production and utility sectors later.

2.0 Literature review

The most intensively used method of efficiency measurement is the Ratio Analysis. This procedure is applied, in a way, in which mathematical relation formed as a consequence of rating only the inputs and outputs with each other, is observed in time. It is impossible to decide the effectiveness by viewing only one ratio in decision units containing many inputs and outputs, notably banking systems and sectors. Therefore, many interrelated ratios are used. However, in this case some problems arise such as not turning the examined ratios into a meaningful set and thus their not being evaluated and commented together.

In general, there is an observation set in parametric methods. With the assumption that the best performance in this set is on the regression line, the observations not deviating from this line are defined as efficient, and those others that are unsuccessful according to these observations are defined as inefficient. According to this method, it is possible to reach an effectiveness limit in any case. Besides, the method assumes the possibility of a coincidental mistake any time. Wholly effective observations are those in which likelihood of a coincidental mistake is already zero. Hence, inefficiency of an observation can only be decided after its mistakes of measurement have been corrected (Aras, 2006).

In the studies to efficiency measurement, non-parametric methods, which emerged as on alternative to the parametric ones trying to estimate mostly regression procedures for only one output and many inputs, have adopted mathematical programming as a solution technique. Such methods do not predict the existence of any analytic form behind production function. On account of this quality, they are more elastic than parametric methods. In addition, they have a quite suitable structure for performance measurement within settings of production with many inputs and outputs (Yolalan, 1993),

Data Envelopment Analysis has been widely used in the efficiency measurements of both public and private sectors in recent years. Especially, it is intensively practiced in production, utility and financial sectors in order to evaluate the efficiency of resource use and business performance. A number of studies directed to measure the efficiency of utility and production businesses of different kinds, principally banks, by data envelopment analysis have been carried out.
During 1990-2001 periods in Indonesia, Sabutra (2011) used DEA analysis in the technical efficiency measurement of totally 23 main sectors under the manufacturing sector. As input variables, he dealt with the number of the employees and the core-capital used in the manufacturing sector; as an output variable he dealt with the dollar worth of the manufacturing industry's added value and the amount of production. As a result of his analysis, Saputra found that 3 out of 23 sectors were efficient and the remaining 20 sectors inefficient in a period of twelve years. Sueyoshi and Goto (2009) used DEA and discriminant analysis to investigate if Research Development expenditures of 150 companies in Japan's machine industry and electrical equipment sectors affected the financial performance. As a consequence of their research, they found out that the expenditures of Research – Development have a positive effect on the financial performance of machine industry, whereas they had a negative effect on the financial performance of electrical equipment sector.

To compare the performances of Turkish and Chinese manufacturing firms, Bayyurt and Duzu(2008), used DEA by making use of canonic correlation analysis when calculating the weights of input and output variables. As a result, they showed that the DEA outcomes of the Chinese manufacturing firms had higher efficiency values than those of the Turkish firms. Azadeh, et al.(2007), used DEA, Principal Component Analysis (PCA) and arithmetic taxonomy analysis to evaluate total energy efficiency and optimization belonging to iron and steel, oil refinery, paper, other production sectors in some OECD countries covering the period from 1991 to 1998. As output variables, they considered the amounts of production, the added valve, etc. in the sectors, and as input variables they took fuel and electricity consumption into consideration.

In another study conducted by Mahadevan (2002) the efficiency of 28 industries in Malaysia's manufacturing sectors between the years 1981 and 1996 was calculated by means of DEA, and it was revealed that the development of the manufacturing sector in Malaysia is 0,8 % below the annual total factor efficiency. Destafanis and Ulucan (2000), handled 225 companies dealt in Istanbul Stock-Exchange (IMKB), to determine the relative efficiency of the firms through data envelopment analysis. At the first stage of the study where staff number, assets, and paid capital were chosen as input and on the other land, the market value of the company shares, net sales and net profit after fax were considered as the output, it was seen that 12 out of 225 companies were efficient, and there were groupings on the sectoral base. At the second stage, however, 25 companies operating in the food sector were analyzed, and 5 of those were found relatively efficient.

In their study, Kayalıdere and Kargın (2004) searched the efficiency of the companies belonging to textile and cement sectors at the Istanbul Stock Exchange through DEA with this study the input and output amounts needed for inefficient companies to become effective and efficient was tried to be determined. Esenbel, Erkin and Aydın (2007) examined the efficiency of the performances of the firms, which are quoted to the Istanbul Stock Exchange and operating in the textile, clothing and leather sector, depend on the rates of liquidity and profitability in the year 2000 by means of DEA method. According to the result of the study, it was determined that six firms were relatively efficient, and these efficient companies were the coming ahead ones in the sector. Yalama and Sayim (2007) compared performance of the companies that are in the manufacturing sector and listed to the Istanbul Stock Exchange through DEA method. In the analysis, commonly accepted financial ratios were used as input and output variables and the relative efficiency of the firms was revealed. Aras (2006) examined the efficiency and risk analysis of the Turkish textile and clothing sector on the basis of the years 1992-2003. A negative correlation was observed between efficiency results and risk taking sales calculated through DEA method.

3.0 Materials and methodology

This study is composed of two stages. Firstly, the efficiency of 14 sectors under manufacturing sector, dealt in this research, has been calculated by using DEA, and then the efficiency scores of the sectors have been realized to be estimated by using the techniques of artificial neural networks.

In the study, the data belonging to manufacturing sector and subsectors, from the financial chart which is reported by the central Bank of the Turkish Republic have been used. The efficiency by has been calculated with the help of the ratios estimated by means of these data. Efficiency measurement is analyzed with DEA. Regarding the efficiency measurement of the sectors, the data of balance and revenue chart belonging to the period between 1996 and 2008 and estimated financial ratios balance sheets of the Central Bank of the Turkish Republic includes a period of 13 years and the information of over 8000 companies on average annually. While arranging their financial charts, the companies used inflation accounting in 2004, and in the other years they employed the cost basis method. The data of 2004 contain the effect of the inflation accounting which was applied merely in that year.

The input and output variables to be selected for the efficiency measurement of the sectors should have the best representative quality in estimating the efficiency. Considering this matter, input and output variables have been identified as following:

Input Variables	Output Variables
Current Ratio	Stocks/Current Asset
Total Debt/Equity Capital	Net Profit Margin
Tangible Fixed Assets / (Long-term liabilities + Equity Capital)	Active Rate of Return
	Interest expense/Net Sales

DEA calculates the efficiency scores relatively, determines the units with the best scores as efficient and the efficiency scores of these units are calculated as 100. Those units which are inefficient have a relative efficiency score between 0 and 100. The classification of the artificial neural networks, the second stage of our study, is a method which requires classification of the input data to be analyzed, as efficient or inefficient. In DEA the units whose efficiency score is not 100, even if it is quite close to 100 (e.g.,. 99.5), are called technically inefficient units. On the other hand, considering the units, with or efficiency score very close to 100, as inefficient will encounter problems at the stage of classification of the efficient and inefficient units through application of artificial neural network. Because, in that case, the distinguishing power at the classification to be applied will diminish. Therefore, by deciding that there should be a difference of at least 5 units between the efficiency scores of efficient and inefficient units, the sectors whose DEA score is 100 have been classified as efficient, whereas those with a DEA score of 95 or below have been considered as inefficient sectors.

Defining information belonging to the manufacturing industry, and 14 sub-sectors within the scope of the analysis are given in the following chart.

The List of manufacturing industry and sub-sectors

Sector	Abbreviation	Sectors
1	D	MANUFACTURING INDUSTRY
2	DA	Food, Drinks And Tobacco Products Manufacturing
3	DB	Textile And Textile ProductionManufacturing
4	DC	Leather and Leather Products Manufacturing
5	DD	Wood Products Manufacturing
6	DE	Manufacture of Cellulose, Paper And Paper Products, Production of Printing and PublishingManufacturing
7	DF	Manufacturing of Coke, Refined Petroleum Products And Nuclear Fuel
8	DG	ManufacturingProducts A Of Chemical Substances and Products And Artificial Fiber
9	DH	Plastics and Rubber Products Manufacturing
10	DI	Non-Metallic, Manufacture of other Metal Products
11	DJ	Basic Metals and Fabricated Metal Products Manufacturing
12	DK	Machinery and Equipment Manufacturing
13	DL	Manufacture Of Electrical And Optical Equipment
14	DM	Manufacture Of Transport Equipment
15	DN	Non-Classified Manufactures In Another Place (Furniture industry)

3.01 Data enveloping analysis (DEA)

DEA is used as a method which evaluates the efficiency of the decision making unit together with many inputs and outputs on the strength of weighted input and output ratios and compares it to the efficiency of other decision-making units (Charnes,et al., 1978).The basis in the DEA method is the measuring of the efficiency of a decision unit in comparison with another one operating in the same market. The constraint in this analysis is a necessity for all decision-making units to be above or below the efficiency limit. As a result, while efficient units take the value 1, the value of the inefficient ones is smaller than 1. The difference between 1 and the efficiency valve indicates that the same amount of output will be obtained in proportion to the difference with less input (Ulucan, 2000).

The mathematical model of this method: the organizational expression of input/output ratio to be maximized for in decision unit within input and s output is given below:

$$\max \ h_k = \frac{\sum_{i=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \qquad (1)$$

In this expression x_{ik}>0 parameter shows i amount of input used by k decision unit, where as y_{rk}>0 parameter shows r amount of output used by k decision unit. The variables for this decision problem are the weights which k decision unit will give for i inputs and r outputs. The weights are indicated as v_{ik} and u_{rk} respectively. The following expression is the limit preventing the efficiency from exceeding 100% when other decision units used the weights of k organizational unit.

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \quad j=1,\dots,n \qquad (2)$$

Finally, the limit rendering the weights of the inputs, which will be used, not to be negative is given below.

$$u_r \geq 0; \qquad r = 1\dots,s \qquad (3)$$

$$v_i \geq 0; \qquad i = 1\dots,m \qquad (4)$$

In order to reach a solution with simplex or similar algorithms by transforming these inequalities into linear programmes form, it is enough to equalize the denominator of the objective function to 1 and make it a limit in the form of maximization. The linear programming model belonging to the data enveloping analysis is given below:

Model VZA (CCR):

$$
\begin{aligned}
& Maxh_k = \sum_{r=1}^{s} u_{rk} y_{rk} \\
& \sum_{r=1}^{s} u_{rk} y_{rj} - \sum_{i=1}^{m} v_{ik} x_{ij} \leq 0; \qquad j = 1,\dots,n \\
& \sum_{i=1}^{m} v_{ik} x_{ik} = 1 \\
& u_{rk} \geq 0; \qquad r = 1,\dots\dots s \\
& v_{ik} \geq 0; \qquad i = 1,\dots,m
\end{aligned} \tag{5}
$$

The model above should be prepared for number organizational decision units with their own parameters and it should be solved n times. The dual model which particularly supports the determining of efficient reference sets is shown below.

Model Dual CCR:

$$
\begin{aligned}
& \min w_k = q_k \\
& \sum_{j=1}^{n} \lambda_{kj} y_{rj} \geq y_{rk;r=1,\dots\dots s} \\
& -\sum_{j=1}^{n} \lambda_{kj} x_{ij} + q_k x_{ik} \geq 0; i = 1,\dots\dots m \\
& \lambda_{kj} \geq 0;\ j = 1,\dots\dots n \\
& -\infty \leq q_k \leq +\infty
\end{aligned} \tag{6}
$$

The mathematical model mentioned above is the first-CCR method of DEA model, initially developed by Charnes, et al. (1978). As CCR method is a scale with fixed yield, it could not disclose the difference between the scale efficiency and pure technical efficiency clearly (Park et al., 2007). Banker, Charnes and Cooper (1984) suggested a new method with variable yield and called BCC model. DEA can be separated in accordance with input and output. While the output directed model tries to maximize the outputs with given inputs, the input directed model minimizes the inputs together with the given outputs (Park et al.2007; Adler, vd. 2002).

3.02 Artificial neural networks (ANN)

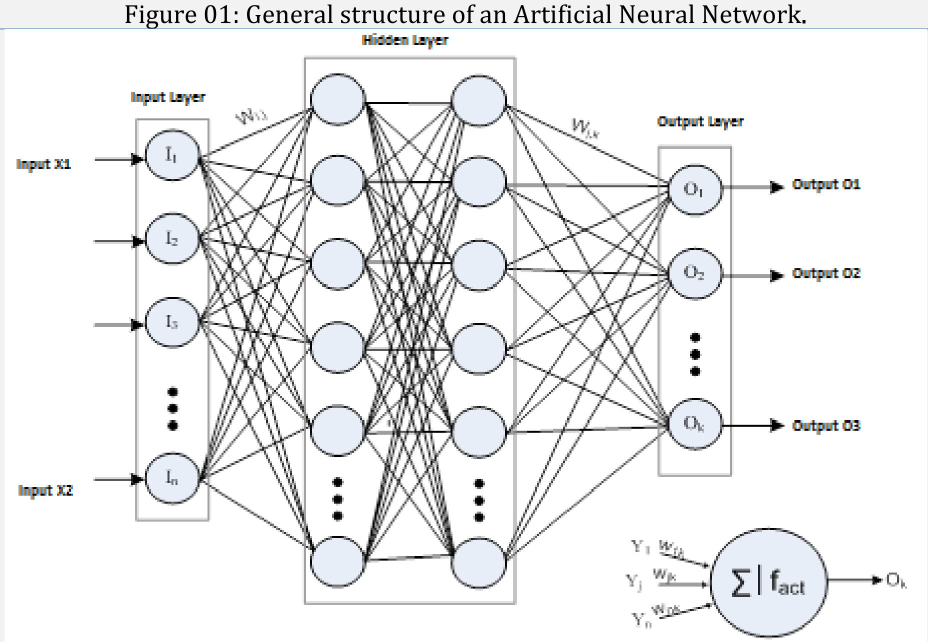
ANNs are cellular systems that can receive, store and use data. ANNs are parallel systems which are formed by connecting many dependent elements with the connections of variable weights. Of the most artificial neural networks, the multi-layer neural network is the most popular (Lippman, 1987). ANN is a system built on basic neural networks that can take the data connected together in the input cells, give it to the other units as input after processing it and can even use the output as input once again (Pissarenko,2001-2002). With ANN, the working pattern of the basic biological neural system is simulated. ANNs produces solutions to the problems which normally require a person's natural skills of thinking and observing.

Artificial neural networks were computer systems which have been developed in order to perform such brain features automatically as deriving new data, forming new data and discovery skills without any help (Öztemel, 2003). In practice, by making use of the data at hand, artificial of the functions are used to achieve one or more as an association, classification, generalization, and optimization (Şen,2004).In a common artificial neural network gathering of neurons in the same direction forms layers (Yıldız, 2001). Within an architectural structure, there is a parallel flow of information from the entrance layer towards the exit. Such a flow is provided via cells that are placed parallel.

Entrance layer was the first layer and helps the data coming outside to be received the artificial neural network. These data correspond to independent variables in statistics. The last layer is called the exit layer and performs the function of transmitting the information outside. Output variables, on the other hand, correspond to dependent variables in statistics. The other layers in this model are located between the input layer and output layer and are called as a hidden layer. The neurons in the hidden layer have no connection with the outside setting. They only receive signals from the input layer and send signals to the output layer (Küçük Kocaoğlu, et al., 2005).

Single-layer artificial neural network is composed of only input and output layers. Each network has one or more input and output. In 1982 Hopfield laid, the foundation of multi-layer artificial neural networks with hopfield networks which the named after himself and Rumelhart and Fumelhart et al. (1986) developed the multi-layer artificial neural networks with delta learning rule through their studies in 1985. A multi-layer network consists of an input layer, interval layer and output layer. Multi-layer networks function in accordance with the strategy of teacher learning (Öztemel, 2003).

Figure 01: General structure of an Artificial Neural Network.



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 the input layer constitute the input values of the neurons in concealed layer.

Accordingly, weighted net input coming to $N_{1,1}$ neuron in a hidden layer,

$$v_{1,1} = \sum_{i=1}^{3} x_i, w_{i,1} = x_1 w_{1,1} + x_2 w_{2,t} + x_3 w_{3,1} + \cdots \quad (7)$$

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

$$v_{1,2} = \sum_{i=1}^{3} x_i w_{i,2} = x_1 w_{1,2} + x_2 w_{2,2} + x_3 w_{3,2} + \cdots \quad (8)$$

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

$$y_{i,k} = f(v_{i,j}) = \frac{1}{1 + e^{-v_{i,j}}} \quad (9)$$

$y_{i,k}$: 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;

$$f(v_{1,1}) = y_{1,1} = \frac{1}{1 + e^{-v_{1,1}}} \tag{10}$$

$$f(v_{1,2}) = y_{1,2} = \frac{1}{1 + e^{-v_{1,2}}} \tag{11}$$

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).

4.0 Results and discussion

4.01 Result of DEA

In this part of the study, the analyses related to the results of DEA and ANN carried out by using the sectoral data are given.

In the study, the efficiency analysis of the sectors reported by the central Bank of the Turkish Republic within the period from 1996 to 2008 was conducted on the basis of input and output variables, pre-determined with the help of the sectors financial ratios, and efficiency scores of each sector were calculated. The present data within the extent of evaluation were calculated, and the efficiency scores were obtained by identifying weighted co-efficiency corresponding input and output variables.

Assessments regarding efficiency have been carried out whether the efficiency value is 100 or not in the study. The fact that the efficiency score is 100 means that the efficiency has been provided relatively. Also, the values whose efficiency score of manufacture sector is 100 have been indicated as efficient sectors, on the other hand, values smaller than 100 have been indicated as inefficient sectors. According to the obtained data, efficiency scores of all sectors, calculated by means of DEA in the period between 1996 and 2008 are shown in the table1.

Table 01: Efficiency scores

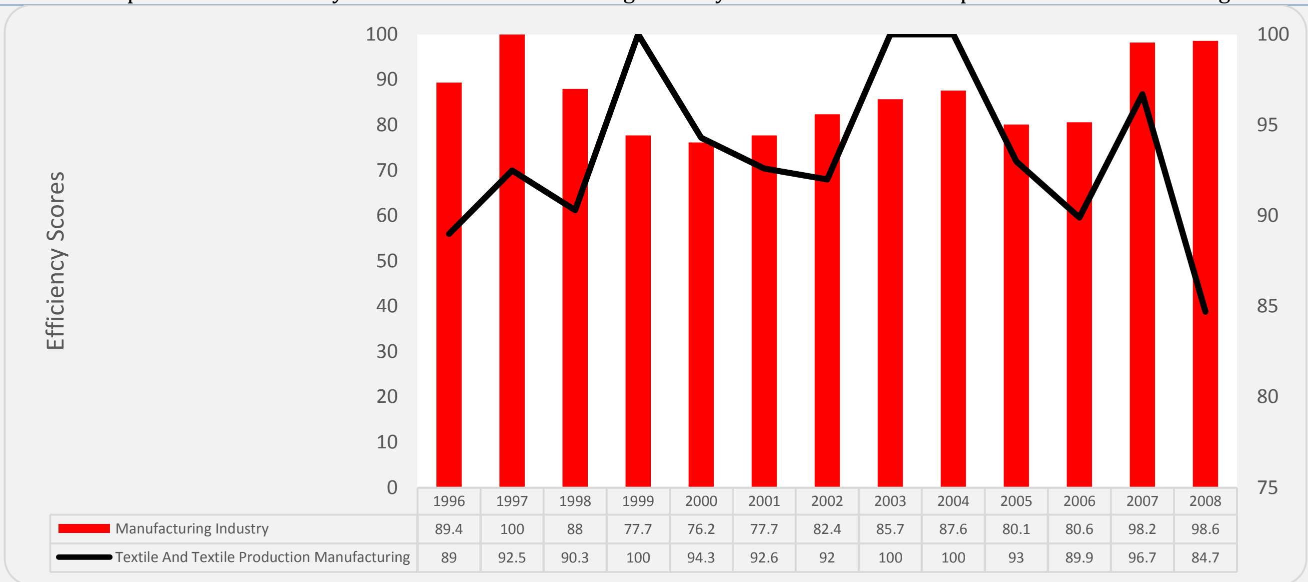
Manufacturing Sectors		Efficiency Criterion	2008	2007	2006	2005	2004	2003	2002	2001	2000	1999	1998	1997	1996
EFFICIENCY SCORES	D	100	100	98.6	98.2	80.6	80.1	87.6	85.7	82.4	77.7	76.2	77.7	88.0	100
	DA	100	100	99.8	100	100	100	100	100	100	96.8	100	100	100	100
	DB	100	100	84.7	96.7	89.9	93.0	100	100	92.0	92.6	94.3	100	90.3	92.5
	DC	100	100	100	100	100	100	100	100	100	100	100	100	100	100
	DD	100	100	100	100	100	100	100	100	100	100	100	100	100	100
	DE	100	100	100	94.8	81.9	74.5	100	100	79.2	100	67.2	67.0	72.9	83.6
	DF	100	100	100	100	100	100	100	100	100	100	100	100	100	77.4
	DG	100	100	100	100	96.6	90.6	96.6	99.9	86.4	100	100	90.2	97.7	100
	DH	100	100	90.1	95.7	63.6	73.4	79.8	100	93.3	100	82.5	80.9	93.4	100
	DI	100	100	100	100	100	100	100	100	100	100	100	100	100	100
	DJ	100	100	100	100	100	100	100	100	94.0	93.8	88.1	74.3	100	88.5
	DK	100	100	99.9	97.8	100	100	100	100	89.7	100	100	100	100	100
	DL	100	100	100	100	77.0	78.4	100	98.5	75.5	75.3	80.4	84.8	80.7	83.7
	DM	100	100	100	100	78.8	92.5	100	86.3	71.9	84.6	89.3	73.1	100	100
	DN	100	100	93.9	100	100	85.5	100	95.1	95.3	100	92.9	98.6	100	100
The number of Efficient Sectors			9	10	8	7	12	10	5	9	7	7	9	10	10
The number of Inefficient Sectors			6	5	7	8	3	5	10	6	8	8	6	5	5

As can be seen in the table 01, the efficiency values belonging to the sectors follow a fluctuating trend. The lowest efficiency ratio in the manufacturing industry occurred 79.2 out of 100 in the year 2000. In that year, the number of the efficient sectors was 7, and the number of inefficient ones was 8, including manufacture industry. In 2008, the efficiency ratio of the manufacturing industry was found 98.6out of 100. In 2008, the number of the efficient sectors was 9, and the number of the inefficient sectors was 6, including manufacture industry. During the period between

1996 and 2008 the most efficiency sectors were Leather and Leather Products Manufacturing, Wood Products Manufacturing, Non-Metallic, Manufacture of other Metal Products, Manufacturing of Coke, Refined Petroleum Products and Nuclear and Food, Drinks and Tobacco Products Manufacturing; on the contrary the least efficient one was found to be Textile and Textile Production Manufacturing.

The graph above shows the efficiency values of the subsector with the lowest efficiency along with the manufacturing industry in general within the period 1996 and 2008. During that thirteen-year period, the manufacturing industry became efficient once, and the least efficient sub-sector, textile and textile production manufacturing became efficient three times. The years 1999-2003 and 2004 show the efficient times of Textile and Textile Production Manufacturing, and 1997 shows a year in which manufacturing industry was efficient.

Graph 4.1: The efficiency scores of the manufacturing industry and textile and textile production manufacturing



The period during which the lowest efficiency value took place covers the years from 1999 to 2001. One of the reasons of its occurring in that way can be stated as the impact of the 2001 crisis on the manufacturing industry. The lowest efficiency value of the construction industry occurred in the year 2001, with on efficiency score of 76.2. Ever since 2002, a remarkable increase has been observed inefficiency of the manufacturing industry and it reached its highest efficiency scores in the years 2007 and 2008.

Fluctuations can be observed in the efficiency values of the textile and textile production, manufacturing in the period between 1996 and 2008. While the efficiency scores had displayed a positive increase until 2000, it showed a decline in the years 2001 and 2002. This can be stated as the decrease in the net profit of the sector, an increase in the Total Debt/Equity Capital and Tangible Fixed Assets / (Long-term liabilities + Equity Capital) to gather with the reflection of the crisis in 2001.It was observed that it reached the highest efficiency values again due to the improvements in the economy in 2003 and 2004. We can say that the decline of the sectoral profit, the increase of the expenditures of interest together with the crisis in the year 2008, though partially,had on effect on the decline in the efficiency of the textile and textile production manufacturing again in 2008.

4.02 Result of ANN

The parameters of the artificial neural network with the best performance, determined after trial and error method, are given in table 02.

Table 02: The parameters of the artificial neural network with the best performance, determined after trial and error

Network	Multilayered Perceptron
Learning Algorithm	Back Propagation
Learning Rule	Momentum
Number of Nodes in Input Layer	7
Hidden Layers	3
1 Number of Nodes in Hidden Layer	18
2 Number of Nodes in Hidden Layer	24
3 Number of Nodes in Hidden Layer	28
Number of Nodes in Output Layer	1
Momentum Coefficient	0.20
Learning Rate	0.60

Speed	5000
Transfer Function for Hidden Layers	Sigmoid
Transfer Function for Output Layer	Sigmoid

Figure 02: General Architectural Structure of the Artificial Neural Networks.

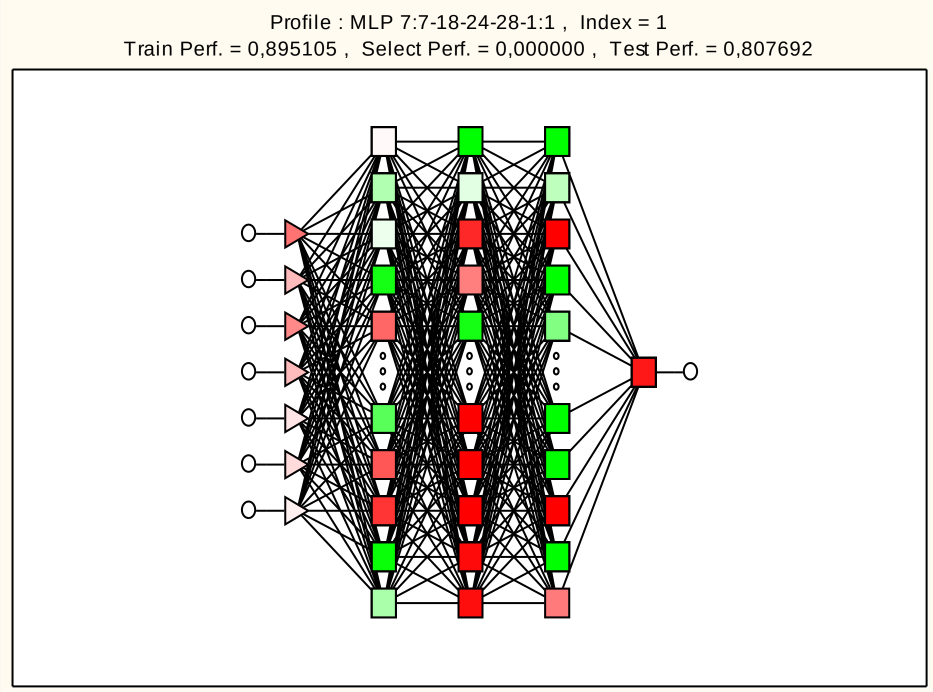


Table 3: The classification success of the efficiency scores belonging to 1996-2008 period for theexperimental set of Data

ANN Model		Estimated group			
		Inefficient	Efficient	Total	Accuracy Percentage
Observed group	Inefficient	52	0	52	100
	Efficient	15	76	91	83.5
	Total	67	76	143	89.5

When we look at table 3, in the experimental set of data covering 143 sectors in total belonging to the period between 1996 and 2008, the model of artificial neural network made accurate classification, 100% for inefficient sectors, 83.5 % for efficient sectors, by correctly anticipating 52 of the 52 inefficient sectors and 76 of the 91 efficient sectors. 89.5% total classification success for the experimental set of data was obtained.

Table 4. The classification success of the efficiency scores belonging to 1996-2008 period for the control set of data

ANN Model		Estimated group			
		Inefficient	Efficient	Total	Accuracy Percentage
Observed group	Inefficient	11	2	13	84.6
	Efficient	8	31	39	79.5
	Total	19	33	52	80.8

When we look at table 4. in the test set of data covering 52 sectors belonging to the period between 1996 and 2008, the model of artificial neural network model accurate classification, 84.6% for inefficient sectors and 79.5% for efficient sectors, by predicting 11 of the 13 inefficient sectors and 31 of the 39 efficient sectors. The total classificationsuccess for the test set of data was obtained as 80.8%.

5.0 Conclusion

In the study, carried out to measure the efficiency of the firms based on financial performance in the manufacturing sector, efficiency scores have been calculated through data enveloping analysis, sectoral efficiency analysis throughout years has been fulfilled and then the accurate classification success of the efficiency scores has been identified by means of the model of an artificial neural network, by using the data of financial chart of the period from 1996 to 2008 belonging to manufacture industry and sub-sectors reported by the Central Bank of the Turkish Republic.In this study, under the assumption of fixed yield according to scale, the efficiency levels of each sector have been estimated with respect to years on the strength of decision variables of the output-oriented data enveloping analysis models, which were formed to measure efficiency. Manufacture sector and 14 sub-sectors showed on efficiency score of 78.5-100 out of 100 in the first period of the term in 1996 and 84.7-100 out of 100 in the last period of the term in 2008. As a result of the analysed DEA, 3 wholly efficient sectors have been identified every year (efficiency score:100). These sectors are Leather and Leather Products Manufacturing, Wood Products Manufacturing Non-Metallic, Manufacture of other Metal Products.

In the performed efficiency analysis, while the most efficient sectors were Leather and Leather Products Manufacturing, Wood Products Manufacturing,Non-Metallic, Manufacture of other Metal Products, Manufacturing of Coke, Refined Petroleum Products And Nuclear Fuel and Food, Drinks And Tobacco Products Manufacturing, the least efficient ones were Textile And Textile Production Manufacturing.

Table 5. Efficiency value means of the sectors and their standarddeviations

Years	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Mean	96.5	95.0	94.9	89.8	91.4	94.7	90.6	97.7	97.6	91.2	91.2	98.9	97.8
Std.Deviation	6.5	7.9	8.4	12.2	10.6	8.6	9.6	4.9	5.9	10.2	11.9	1.8	4.6

As can be seen in the table 5, within the period between 1996 and 2001, the efficiency means of the sectors proceeded around 90, started to decline owing to the impact of 2001 crisis, yet beginning with 2002 along with the revival in the economy some improvements were observed again in the efficiency values.While the lowest efficiency averagesoccured in 1999 with an efficiency score of 89.8the highest efficiency occurred in the year 2007 with a score of 98.9. Low standard deviation is a desirable condition, and from 2006 on the developments in the efficiency levels of totally 14 sectors have come true, as a result, of this condition.

In the second analysis of the study, a model has been developed by means of artificial neural network method for the experimental set of data made up of totally 143 sectors belonging to the period from 1996 to 2008, and it was established that the obtained model discriminated this group with on accuracy of 89.5%. With the foresight obtained from the experimental group, the model was found to predict on the control group, consisting of 52 sectors, with on accuracy of 80.8%.In this study, it has been shown that DEA and ANN are effective techniques which can be used for the measurement of organizational performances of the firms operating in the manufacturing sector. After this, it seems possible that studies can be carried out in two different fields. First, studies can be done as to what variables can be used as input and output. By using different input and output sets and comparing the results of prepared and solved models, it can be determined what inputsand outputs are the most appropriate. Second, according to the results of this study performed with the data from the years between 1996 and 2008, predictions can be made for the upcoming years by using ANN.

Reference

Adler, N., Friedman, L., & Sinuany-Stern, Z., 2002. Review of ranking methods in the data envelopment analysis context. European Journal of Operational Research, 140: 249–265.

Aras, G., 2006. Avrupa Birliği Açısından ve Dünya Pazarlarına Uyum Açısından Türk Tekstil ve Konfeksiyon Sektörünün Rekabet Yeteneği (Finansal Yaklaşım), Mart Matbaası, İstanbul.

Azadeh, A., Amalnick, M.S., Ghaderi, S.F. and Asadzadeh, S.M., 2001. An integrated DEA PCA numerical taxonomy approach for energy efficiency assessment and consumption optimization in energy-intensive manufacturing sectors. Energy Policy, 35: 3792-3806.

Banker, R., Charnes, A., & Cooper, W. W. 1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management Science, 30: 1078–1092.

Bayyurt, N. &Duzu, G., 2008. Performance measurement of Turkish and Chinese manufacturing firms: A comparative analysis, Eurasian Journal of Business and Economics 2008, 1 (2): 71-83.

Charnes, A., Cooper, W. W., & Rhodes, E., 1978. Measuring the efficiency of decision making units. European Journal of Operation Research, 2: 429–444.

Destafanis, S. ve Sena, V., 2007. Patterns of corporate governance and technical efficiency in Italian manufacturing. Published Online in Wiley Inter Science, 28: 27-40.

Esenbel, M., Erkin, M. O., Aydın, F.K., 2007. Veri Zarflama Analizi ile Dokuma, Giyim Eşyası ve Deri Sektöründe Faaliyet Gösteren Firmaların Etkinliğinin Karşılaştırılması", (http://www.analiz.com/eğitim/gazi/001.html).

Farrel, M.J. 1957. The measurement of productive efficiency.Journal of Royal Statistical Society, A, 120: 253-281.

Hopfield, J.J., 1982.Neural networks and physical systems with emergent collective computational abilities. Proceedings of the National Academy Of Sciences,79: 2554-2558.

Karacabey, A. A., 2001. Veri Zarflama Analizi, Tartışma Metinleri, Ankara Üniversitesi Siyasal Bilgiler Fakültesi, Ankara, No 33: 1-4.

Kargın, S. ve Kayalıdere, K., 2004. Çimento ve Tekstil Sektörlerinde Etkinlik Çalışması ve Veri Zarflama Analizi. Dokuz Eylül Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, 6(1): 199-201.

Lippman, R., 1987. An introduction to computing with neural nets. IEEE ASSP Mag., 4: 4-22.

Mahadevan, R., 2002. A DEA approach to understanding the productivity growth of Malaysia's manufacturing industries. Asia Journal of Management, 19: 587-600.

Öztemel E., 2003. Yapay Sinir Ağları, Papatya Yayıncılık, Istanbul.

Park, Y., Choi, J., Seol, H., and Park, G., 2007. A framework for benchmarking service process using data envelopment analysis and decision tree.Expert Systems with Applications, 32: 432-440.

Pissarenko, Dimitri, 2002. Neural networks for financial time series prediction: overview over recent research. Accessed from http://members.inode.at/d.pissarenko/fyp/Pissarenko2002.pdf

Rumelhart, D.E., Hinton, D.E. and Williams R.J., 1986.Learning representation by back-propagating errors. Nature 323(9): 533-536.

Sabutra, P.M.A, 2011. Analysis of technical efficiency of Indonesian manufacturing industries: An application of DEA. International Research Journal of Finance and Economics, 66:1450-2887.

Sayım, M. ve Yalama, A., 2006. Veri Zarflama Analizi (VZA) Yöntemi İle Temel Analiz: Türkiye'de IMKB' ye Kote İmalat Sektörü Üzerine Ampirik Bir Uygulama,10. Ulusal Finans Sempozyumu, İzmir.

Schaffnit, Claire; Dan Rosen; Joseph C. Paradi, 1997. Best practice analysis of bank branches: An application of DEA in a large Canadian bank.European Journal of Operational Research, 98: 269–289.

Şen Z., 2004. Yapay Sinir Ağlarının İlkeleri, Özener Matbacılık, İstanbul.

Shahmohammadi, Faramarz; Morteza Charmi, 2004. Using DEA to measure performance of science parks: case of Iran. Data Envelopment Analysis and Performance Management, 4th International Symposium of DEA, Aston University, 5–6 September 2004, pp. 396–402. (www.DEAzone.com/DEA2004).

Sueyoshi, T.& Goto, M., 2009. Can R&D expenditure avoid corporate bankruptcy? Comparison between Japanese machinery and electric equipment industries using DEA–discriminant analysis. European Journal of Operational Research, 196: 289–311.

Tarım, A., 2001. Veri Zarflama Analizi Matematiksel Programlama Tabanlı Göre Etkinlik Ölçüm Yaklaşımı, Sayıştay Yayınları, Ankara.

Ulucan, A., 2000. Şirket Performanslarının Ölçülmesinde Veri Zarflama Analizi Yaklaşımı: Genel ve Sektörel Bazda Değerlendirmeler, Hacettepe Üniversitesi İktisadi ve İdari Bilimler Dergisi, 18(1): 406-407.

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.

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

Yolalan, R. 1993. İşletmeler Arası Göreceli Etkinlik Ölçümü, Ankara: Milli Prodüktivite Merkezi Yayınları, No 483.