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Research Article

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The relationship between Neural Networks and DEA-R (Case Study: Companies Stock Exchange)

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Abstract

Evaluate the performance of companies on the Stock Exchange using non-parametric methods is very important. DEA and DEA-R with the strategies for piecewise linear frontier production function and use of available data, assess the stock company. In this study, using a neural network algorithm DEA and DEA-R is suggested to classify the first companies in the stock exchange; Secondly, using the cover models in the nature of input in technology and constant returns to scale Non-decreasing scale performance on each floor with propagation neural network is calculated. Thirdly, neural network training and repetition, scale efficiency is determined at the end of a functional study is presented on the company's stock.

Keywords: DEA; DEA-R; Efficiency; Neural Network.

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1. Introduction

With the availability of new technology and the Internet, more and more organizations are entering some aspect of the banking business and this result in intense competition in the financial services markets. Major domestic banks continue to pursue all the opportunities available to enhance their competitiveness. Consequently, performance analysis in the banking industry has become part of their management practices. Top bank management wants to identify and eliminate the underlying causes of inefficiencies, thus helping their firms to gain competitive advantage, or, at least, meet the challenges from others.

Traditionally, banks have focused on various profitability measures to evaluate their performance. Usually multiple ratios are selected to focus on the different aspects of the operations. However, ratio analysis provides relatively insignificant amount of information when considering the effects of economies of scale, the identification of benchmarking policies, and the estimation of overall performance measures of firms. As alternatives to traditional bank management tools, frontier efficiency analyses allow management to objectively identify best practices in complex operational environments. Five different approaches, namely, data envelopment analysis (DEA) as in Sherman and Gold (1985), Golany and Storbeck (1999), Soteriou and Zenios (1999), Athanassopoulos and Giokas (2000), and, etc. free disposal hull (FDH) as in Tulkens (1993) and Chang (1999), stochastic frontier approach (SFA), also called econometric frontier approach (EFA) as in Kaparakis, Miller, and Noulas (1994), Berger and Humphrey (1997), Hao, Hunter, and Yang (2001), thick frontier approach (TFA) as in Berger and Humphrey (1991), Clark (1996) and Deyoung (1998), and distribution free approach (DFA) as in Berger, Hancock, and Humphrey (1993), Akhavein, Berger, and Humphrey (1997) and Deyoung (1997), have been reported in the literature as methods to evaluate bank efficiency. These approaches primarily differ in how much restriction is imposed on the specification of the best practice frontier and the assumption on random error and inefficiency. Compared to other approaches, DEA is a better way to organize and analyze data since it allows efficiency to change over time and requires no prior assumption on the specification of the best practice frontier. Thus, DEA is a leading approach for the performance analysis in banking industry in literature. However, the DEA frontier is very sensitive to the presence of the outliers and statistical noise (Bauer, 1990), which indicates that the frontier derived from DEA analysis may be warped if the data are contaminated by statistical noise. From the other hand, DEA can hardly be used to predict the performance of other decision-making units. As a result, the artificial neural networks

(ANNs) were introduced recently as good alternatives to assist in estimating efficiency frontiers for decision makers (Wang, 2003). Wang (2003) demonstrated that neural networks assist model developers in finding data envelopes, which are based on the entire data set, rather than some extreme data points from which uncertainty information has been lost. The idea of combination of neural networks and DEA for classification and/or prediction was first introduced by Athanassopoulos and Curram (1996). They treated DEA as a preprocessing methodology to screen training cases in a study of forecasting the number of employees in the health care industry. After selecting samples, the ANNs are then trained as tool to learn a nonlinear forecasting model. In Costa and Markellos (1997), ANNs are compared with corrected ordinary least squares (COLS) and DEA in the application to the London underground efficiency analysis. Their findings reveal that ANNs perform better in regard of the decision making, the impact of constant vs. variable returns to scale or congestion areas.

In order to evaluate the performance of the units and departments, scientific activities have taken place. DEA, including techniques and methods to evaluate the efficiency or productivity measurement units is the decision maker. DEA also provides possibilities for study units with several inputs and output. DEA works on the generalization of Farrell (1957), the introduction of the first non-parameter method. Farrell using the inputs and outputs of the decision and the principles of their units, as a possible set of production, presentation and part of the border as it introduced the production function. DEA was introduced in 1978 for the first time by Charnes, Cooper and Rhodes (Model CCR). Banker, Charnes and Cooper developed CCR model for variable returns to scale and introduced the famous model BCC.

In 2007 Dspyk and colleagues offered ratio data envelopment analysis (DEA-R), DEA ratio is another model for evaluating the performance of decision making units is a combination of two models DEA analysis is deficit. DEA-R model considers input to output ratio as an indicator of the evaluation. We and colleagues (2011) applied DEA-R model for evaluation in hospitals. In the case where the data are ratio involving DEA and DEA-R models is involving a fraction analysis can be very important. In this regard We and his colleagues calculated DEA-R multiple linear models in the form and offered super performance scale.

Not only Neurophysiologists but also psychologists and engineers, had an impact in the development of neural network simulation. Perceptron by Rosenblatt was introduced in 1958. Athanassopoulos and Kurram (1996) Offered neural networks as a tool for measuring performance, to evaluate the performance of a number of bank branches in

Canada and comparing the results of neural networks and model-based results of the analysis carried out. In 1997, London Underground was analyzed the time series data and calculation efficiency. Neural Networks in 2000 was used to estimate cost functions. Santin in 2004 uses a neural network to simulate nonlinear production function. In 2005, the number of municipal departments in Spain Delgado performance using the basic model of data envelopment analysis and evaluated neural networks. Wu and colleagues in 2005, evaluated the efficiency of Canada's big banks using a combination of neural network and data envelopment analysis. Mustafa in 2006 using the same procedure Wu and colleagues (2006) evaluated the performance of banks Arabic. Celibi and Byrktr in 2007, using a combination of data envelopment analysis and artificial neural network offered model for supplier evaluation under incomplete information. Sri Kvmad and Maha Patra in 2011 in a study to evaluate the performance of educational institutions India using a combination approach of DEA's neural network model. In this study, using the model of DEA and DEA-R in the variable returns to scale technology (decreasing) is calculated scale performance inspired by the methods of neural network. Overall integration of DEA-R models and neural networks of the view that it is important to have the unique ability for ratio data. The idea of this research is as follows:

First, calculated the scale efficiency of DMUs in DEA and DEA-R and units are classified according to the scale efficiency.

Secondly, using neural network classifier training units are re-evaluation and classification is determined based on the performance scale.

In the second part the basic concepts presented in Part III DEA and DEA neural network algorithm is proposed in Section IV DEA-R models are offered and a case study will be presented at the end.

2. The basic concepts of DEA

In this section we briefly review the basic concepts of the DEA.

Suppose n decision making unit by using m inputs $X_j = (x_{ij}, \dots, x_{mj})$, produce s outputs $Y_j = (y_{1j}, \dots, y_{sj})$. Production possible set made possible by the following set of principles and frontier production function approximates a linear piece.

a) $(X_j, Y_j) \epsilon T \; j = 1, \dots, n$

b) $X \geq X_j \;\&\; Y \leq Y_j$

c) $(\sum_{j=1}^{n} \lambda_j X_j \;, \sum_{j=1}^{n} \lambda_j Y_j) \epsilon\, T$

d) $(X, Y) \epsilon T \longrightarrow (\lambda X, \lambda Y) \epsilon T \;, \lambda \geq 0$

Obviously, the smallest set that satisfies the four principles set out above that the input of X to Y to produce outputs, namely:

$$T_C = \left\{ \begin{array}{c} (x,y) \mid \sum_{j=1}^{n} \lambda_j X_j \leq x \,, \sum_{j=1}^{n} \lambda_j Y_j \geq y \,, \\ \lambda_j \geq 0 \,, \qquad j = 1, \dots, n \end{array} \right\} \quad (1)$$

T_C set is constant returns to scale and CCR cover model can be built as follows:

$$\min \theta$$
$$\text{s.t} \quad (\theta X_0, Y_0) \in T_C$$

In (2) with the aim of reducing all entries equally and keep the output constant returns to scale technology performance scale (CRS) is obtained.

If use the model (2) optimal solution that $\theta^*$and paste in the model (3) we can obtain the Pareto efficient DMUs.

$$\max\,(1s^- + 1s^+)$$
$$\text{s.t.} \quad \sum_{j=1}^{n} \lambda_j X_j + s^- = \theta_c^* X_0$$
$$\sum_{j=1}^{n} \lambda_j Y_j - s^+ = Y_0$$
$$\lambda_j \geq 0\,, \quad j = 1, \dots, n$$
$$s^- \geq 0\,, s^+ \geq 0$$

Model (3) is known as a two-phase model is a linear programming problem was proposed by Charnes and colleagues. If the set (1) indicating $\sum_{j=1}^{n} \lambda_j \geq 1$ obtained $T_{BCC-CCR}$ or T_{ND} set. The technology returns to scale additive or ND production function frontier is include BCC frontier and CCR frontier. If indicating $\sum_{j=1}^{n} \lambda_j \geq 1$ the models (2) and (3) is achieved T_{ND} efficiency scale. The BCC-CCR-phase model to evaluate the DMU_0 is as follows:

$$\max\,(1s^- + 1s^+)$$
$$\text{s.t.} \quad \sum_{j=1}^{n} \lambda_j x_j + s^- = \theta^*_{ND} X_0$$
$$\sum_{j=1}^{n} \lambda_j Y_j - s^+ = Y_0$$
$$\sum_{j=1}^{n} \lambda_j \geq 1 \quad , \quad \lambda_j \geq 0\,, j = 1, \dots, n$$
$$s^- \geq 0\,, s^+ \geq 0$$

It should be noted that θ^*_{ND} obtained on of the optimal solution (2) on T_{ND}.

3. Neural network algorithm in DEA

Neural networks provide a new way for feature extraction (using hidden layers) and classification (e.g. multilayer perceptrons). In addition, existing feature extraction and classification algorithms can also be mapped into neural network architectures for efficient (hardware) implementation. Backpropagation neural network (BPNN) is the most widely used neural network technique for classificaiton or prediction (Hecht, 1990; Shavlik et al., 1991; Liang & Wu, 2005). Fig. 1 provides the structure of the backpropagation neural network. With backpropagation the related input data are repeatedly presented to the neural network. The output of the neural network is compared to the desired output and an error is calculated in each iteration. This error is then backpropagated to the neural network and used to adjust the weights so that the error decreases with each iteration and the

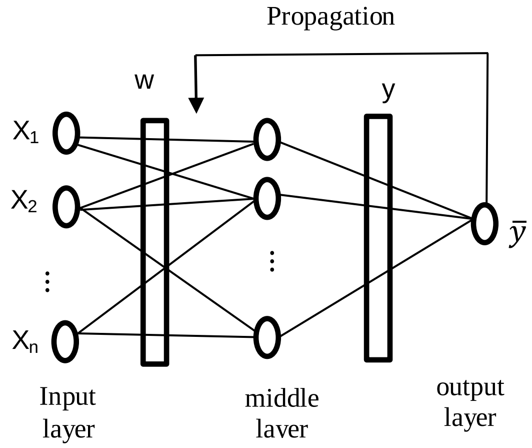

Figure 1. Propagation neural network.

neural model gets closer and closer to produce the desired output.

This process is known as 'training'. When the neural networks are trained, three problems should be taken into consideration. Firstly, it is very challenging to select the learning rate for the nonlinear network. If the learning rate is too large, it leads to unstable learning. On the contrary, if the learning rate is too small, it results in incredibly long training iterations. Secondly, settling in a local minimum may be good or bad depending on how close the local minimum is to the global minimum and how accurate an error is required. In either case, backpropagation may not always find the correct weights for the optimum solution. We may reinitialize the network for several times to guarantee the optimal solution. Finally, the network is sensitive to the number of neurons in its hidden layers. Too few neurons can lead to underfitting. However, too many neurons can cause overfitting. Although all training points are well fit, the fitting curve takes wild oscillations between these points. In order to solve these problems, we preprocess the data before training. The scale of input data values is bounded to 10 and 100 by dividing a constant value, e.g. 10 or 100. The weights are initialized with random decimal fraction ranging from -1 to 1. Moreover, there are about twelve training algorithms for BPNN. After preliminary analyses and trial, we chose the fastest training algorithm, Levenberg–Marquardt algorithm, which can be considered as a trust-region modification of the Gauss–Newton algorithm.

Model DEA-NN (BCC-CCR) is used to measure the performance of the stock exchange. The modules aim to minimize costs to achieve the desired output level. DEA-NN model there are two inputs and nine outputs.

Start: In the first step scale of performance are calculated from both models (3) and (4), using data classification neural network and trained several times with propagation network. the algorithm is as follows:

Step1. Collect a data set k in the first quarter 2015 on Stock Exchange which describes the inputoutput relationship for DMUs. Obtain the preprocessed data set $\bar{k}$ after the data in k are divided by an integer 1000 for the purpose of neural network training and simulation.

Step 2. CCR method is used to calculate efficiency score of DMUs in k. The data set $\bar{k}$ is grouped into four categories k_1 , k_2 , k_3 , and k_4 based on the efficiency scores. The efficiency score intervals of $k_1 \epsilon$ (0.98, 1] are referred as 'strong relative efficient interval'. The efficiency score intervals of $k_2 \epsilon$ (0.8, 0.98] are referred as 'relative efficient interval'. The efficiency score intervals of $k_3 \epsilon$ (0.5, 0.8] are referred as 'relative inefficient interval' and the efficiencies of $k_4 \epsilon$ (0, 0.5] are referred as 'very inefficient interval'.

Step 3. Train neural network NN1 with S1 and any other two groups of data subset (e.g $k_1 \cup k_2 \cup k_3$ or $k_1 \cup k_2 \cup k_4$ or $k_1 \cup k_3 \cup k_4$) . If the pre-specified epochs or accuracy is satisfied, STOP; go to Step 5.Otherwise, change one training subset and go to Step 3.

Step 4. Apply the trained neural network model to the data set $\bar{k}$ to calculate efficiency scores of all DMUs.

4. Neural network algorithm on the DEA-R

This section DEA-R models suggested that the neural network algorithms to run on DEA-R models.

Despic and colleagues in 2007 with the integration of DEA and DEA-R offered the deficit analysis. We and colleagues are offered models to calculate the scale and efficiency supper in 2011. In the case where the data are ratio DEA models is not accountable for the performance scale. Thus, by definition input-output model of DEA-R at constant returns to scale technology is proposed as follows:

Min θ

s.t. $\sum_{j=1}^{n} \lambda_j \left(\frac{x_{ij}}{y_{rj}}\right) \leq \theta \left(\frac{x_{i0}}{y_{r0}}\right)$

i=1,..,m & r=1,..,s.

$\sum_{j=1}^{n} \lambda_j = 1$

$\lambda_j \geq 0$ j=1,…,n. (5)

By defining a set:

$$T_{RND} = \left\{ \begin{array}{c} (\frac{X}{Y}, X) \mid \sum_{j=1}^{n} \lambda_j (\frac{X_j}{Y_j}) \leq \frac{X}{Y} \,, \\ \sum_{j=1}^{n} \lambda_j \,(X_j) \leq X, \sum_{j=1}^{n} \lambda_j = 1 \\ , \lambda_j \geq 0 \,, j = 1, \dots, n \end{array} \right\}$$

In view of the axioms as following is recommended the BCC-CCR coverage model in DEA-R for ratio data.

a. (including observations) : $\left(\frac{x_j}{y_j}\right)$ $j = 1, \dots, n$

b. (the convexity) :

$$\sum_{j=1}^{n} \lambda_j (\frac{x_j}{y_j}) \quad \sum_{j=1}^{n} \lambda_j = 1 \text{ و } j = 1, \dots, n$$

c. (the possibility) : $\frac{X}{Y} \geq \sum_{j=1}^{n} \lambda_j (\frac{x_j}{y_j})$

So by taking the ratio of input to output and the produce set T_{RND} is proposed model as following:

min θ

s.t $(\frac{\theta X_0}{Y_0}, \theta X_0) \epsilon T_{RND}$

And using the definition the possibility of production set BCC-CCR model of DEA-R with input oriented is recommended of the following:

Min θ

s.t. $\sum_{j=1}^{n} \lambda_j \left(\frac{x_{ij}}{y_{rj}}\right) \leq \theta \left(\frac{x_{i0}}{y_{r0}}\right)$

i=1,…,m& r=1,…,s.

$\sum_{j=1}^{n} \lambda_j \left(\frac{x_{ij}}{x_{i0}}\right) \leq \theta$ i=1,…,m.

$\sum_{j=1}^{n} \lambda_j = 1$

$\lambda_j \geq 0$ j=1,…,n. (6)

The proposed models (5) and (6) has the following properties:

a. A performance scale in model (5) specifies evaluation DMU_0 with rates $\frac{X_0}{Y_0}$.

b. If the model (5) optimal solution λ^*_t is positive, then DMU_t is efficient.

c. If the model (5) added s_{ir} auxiliary variables to constraint handle and in terms of the objective function we can identify strong and weak Pareto efficient.

d. If the data be ratio just models (5) and (6) can calculate the efficiency scale and model of DEA's (3) and (4) cannot determine the scale efficiency.

5. Case Study

In this section we consider the 252 companies on the Stock Exchange in the first quarter of 2015 with personnel inputs and outputs of debt and demand, the purchase price, the number of supply, turnover, number of shares, the number of transactions and value of stock and network algorithm. Also in the case where all market can offer performance scale using models (3) and (4) in the DEA and the neural of the rates input to the output of such personnel to the demand of debt to turnover and the $\frac{X_j}{Y_j}$ specifying evaluated the ratio of input to output of 252 companies. The diagram below shows the inputs and outputs are now displayed.

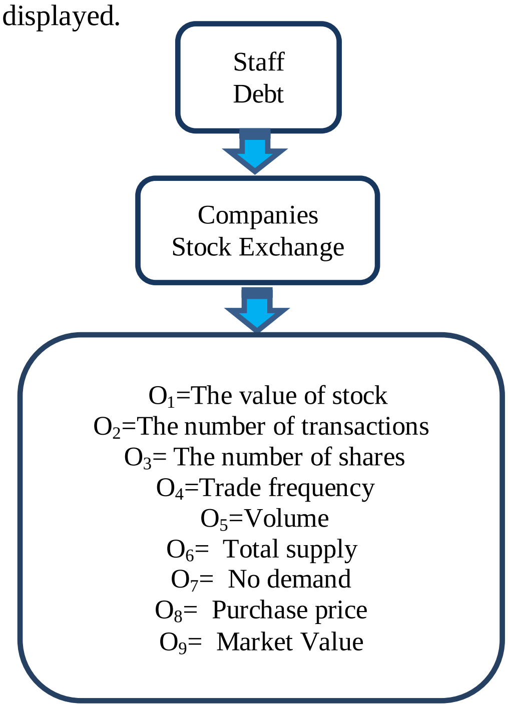

Figure2. Diagrams of inputs and outputs in DEA-NN.

Since is not possible to provide all the inputs and outputs of 252 companies therefore top 20 companies in the data exchange with the input and output data displayed is specified in Table1.

Table1:20 first input data

20 First	Debt	Staff
1	678	**1392783505**
2	591	1198550725
3	508	1195256917
4	510	1194402036
5	535	1193665158
6	545	1192553622
7	960	1146789488
8	572	1137323177
9	493	1048070562
10	627	1043802779
11	581	9780693533
12	501	958492823
13	477	9103920822
14	494	8690690691
15	472	864516129
16	494	8634132892
17	526	8457961484
18	473	8455871627
19	460	8415656391
20	457	8270432692

Output data of the first 20 companies of 252 companies on the stock exchange is shown below. To see all the entrances and exits to the site www.seo.ir see. (Data for the first quarter of 2015).

So the 252 companies on the Stock Exchange with two input and output using neural networks DEA-R and DEA evaluated then proposed algorithm was carried out on models (3), (4), (5) and (6). The results data 252 is shown in table(3):

Table 2: Output data 20 of the Stock Exchange

20 First	Market value	Total demand	purchase price	No release	Turnover	Read Deal	number of shares	The number of transactions	The value of stock
1	1747	65326203	21	3766	4800	4225	23	429	104462
2	1698	65287109	224	3759	7428	3731	16	350	93854
3	1429	64493827	35	377	1740	1578	19	398	252642
4	974	5029245	98	3823	1810	1634	179	5314	3252344
5	1366	7076111	335	3768	2720	2298	275	6882	2996571
6	947	472552	25	3762	4400	2569	290	6237	2428557
7	2920	66809689	382	3768	17990	15354	78	1410	92338
8	1839	63819296	462	3773	4210	3823	93	940	247462
9	1186	58	112	38	1880	1821	511	5876	3160738
10	1559	7816354	226	3752	37016	7635	6	111	14626
11	2537	63626943	152	3799	9200	7767	343	6689	879983
12	1895	62791255	567	376	3632	3477	257	4665	137346
13	1187	2714	398	375	2828	2621	17	134	49896
14	2418	63443182	443	3747	9299	6600	17	103	15248
15	1668	65767635	107	3755	3865	3750	67	1313	350798
16	3074	61866525	641	3749	7404	7016	29	538	73712
17	3054	67159529	254	3766	17713	17713	15	239	13524
18	1631	7037978	129	3753	6210	5703	4	120	21059
19	1186	58	638	374	3000	2760	4	44	15500
20	1486	6912333	247	3741	3400	1	5	57	17000

Table 3: Scale performance with the proposed models

20 First	BCC-CCR DEA-R model	CCR DEA-R model	BCC-CCR DEA model	CCR DEA model
1	1.9504	0.6596	0.0558	0.2481
2	1.9043	0.6328	0.0504	0.3054
3	1.3968	0.5663	0.0658	0.3352
4	1.564	0.7681	0.716	0.7006
5	1.5621	0.6736	0.1114	0.4213
6	1.877	0.58	0.0443	0.3636
7	1.124	0.7446	0.5602	0.4013
8	1.3277	0.6901	0.0845	0.3881
9	2.1023	0.7423	0.0624	0.3650
10	1.5239	0.6974	0.0753	0.6951
11	1.5991	0.7337	-0.0115	0.4075
12	1.3614	0.8109	0.0797	0.4614
13	1.1956	0.8071	0.0231	1.0686
14	1.1625	0.6703	0.0721	0.4633
15	1.9341	0.742	0.0289	0.4145
16	1.3164	0.7861	0.2079	0.5367
17	1.2506	0.6554	0.1398	0.6142
18	1.9423	0.9346	0.0248	0.4303
19	1.2783	0.6373	0.0501	0.5219
20	0.6537	0.5033	0.0527	0.4041

The table 3 scale of the performance of neural networks and DEA and DEA-R is offered. Column CCR-DEA scale efficiency DEA model with constant returns to scale in oreinted is input. For example DMU_1 and DMU_5 and DMU_{19} and DMU_{20} scale performance respectively are 0.24, 0.42, 0.52 and 0.40.

Column BCC-CCR DEA scale efficiency radial model with RTS technology is non descending.

For example scale perfomance of DMU_1 and DMU_5 and DMU_{19} and DMU_{20} are 0.50, 0.11, 0.05 and 0.05. Column CCR-DEA-R scale performance radial model in DEA or DEA-R ratio analysis technology is constant returns to scale. For example scale performance by DMU_1 and $DMU_5$and DMU_{19} and DMU_{20} are 0.65, 0.67, 0.63 and 0.50.

Column BCC-CCR DEA-R scale performance radial model with RTS technology is non descending in DEA-R. For example scale performance by DMU_1 and DMU_5 and DMU_{19} and DMU_{20} are 1.95, 1.56, 1.27 and 0.65.

Obviously, in table 3, column values of CCR DEA less than or equal to CCR DEA-R column and column values of BCC-CCR DEA less than or equal column values of BCC-CCR DEA-R. If you consider the scale of output-oriented model, efficiency scale in DEA-R is less than or equal DEA efficiency scale.

Results data for 252 companies in the DEA and DEA-R without the neural network shown in the following table:

Table 4: DEA and DEA-R scale performance without network

20 First	DEA-R	DEA
1	0.3101	0.2243
2	0.3817	0.2562
3	0.4182	0.2811
4	0.8844	0.6391
5	0.6175	0.3644
6	0.5727	0.3270
7	0.6514	0.3879
8	0.3858	0.3122
9	0.6670	0.3928
10	0.9747	0.6354
11	0.7092	0.3561
12	0.6530	0.4121
13	۱	۱
14	0.5554	0.3822
15	0.4787	0.3493
16	0.6268	0.4925
17	0.6873	0.5857
18	0.5139	0.3625
19	0.4888	0.4596
20	0.4158	0.3283

Generally without the use of neural networks to solve the DEA and DEA-R models with software GAMS will be difficult. The performance measures Table 4-4 with GAMS software under DOS operating system has achieved a lot of time and computational form. Decision-maker 13 in DEA and DEA-R has 1 is a performance scale. In general efficiency scale to 252 companies in the DEA-R greater than or equal efficiency scale DEA.

In the charts below compare the performance scale model used in this study is shown:

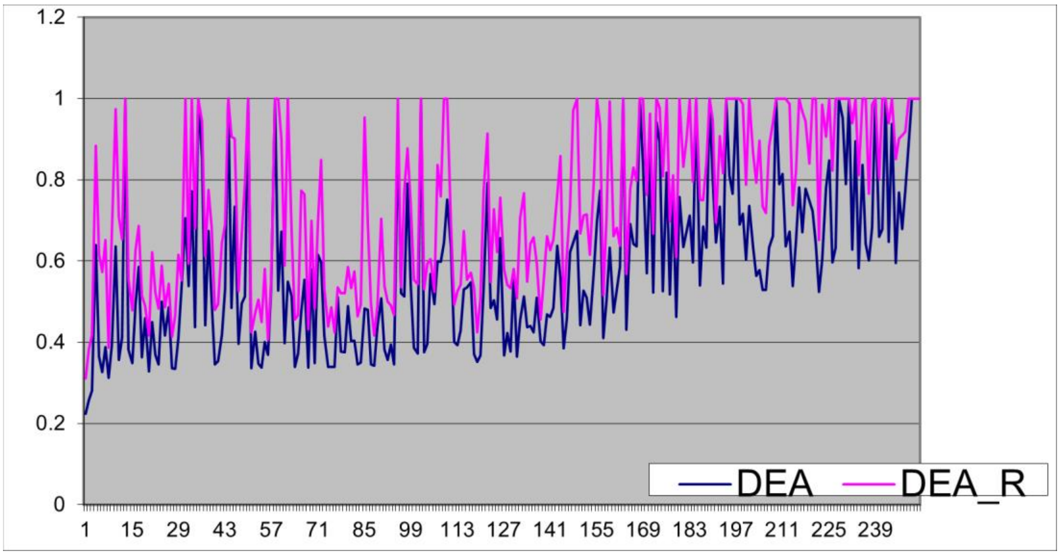

Figure 3. Comparison of the results of DEA and DEA-R without ANN

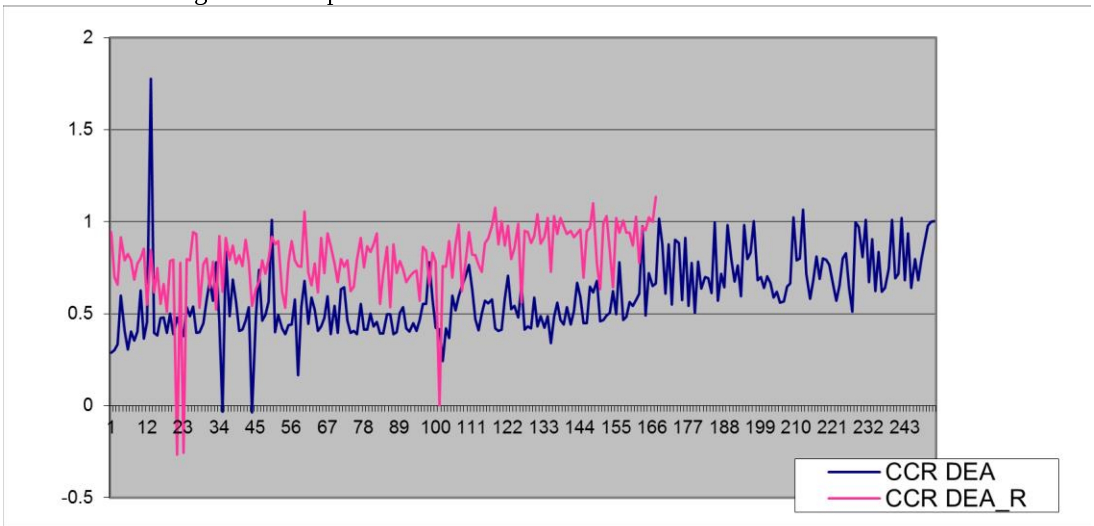

Figure 4. Comparison of the results of CCR DEA and CCR DEA-R with neural network

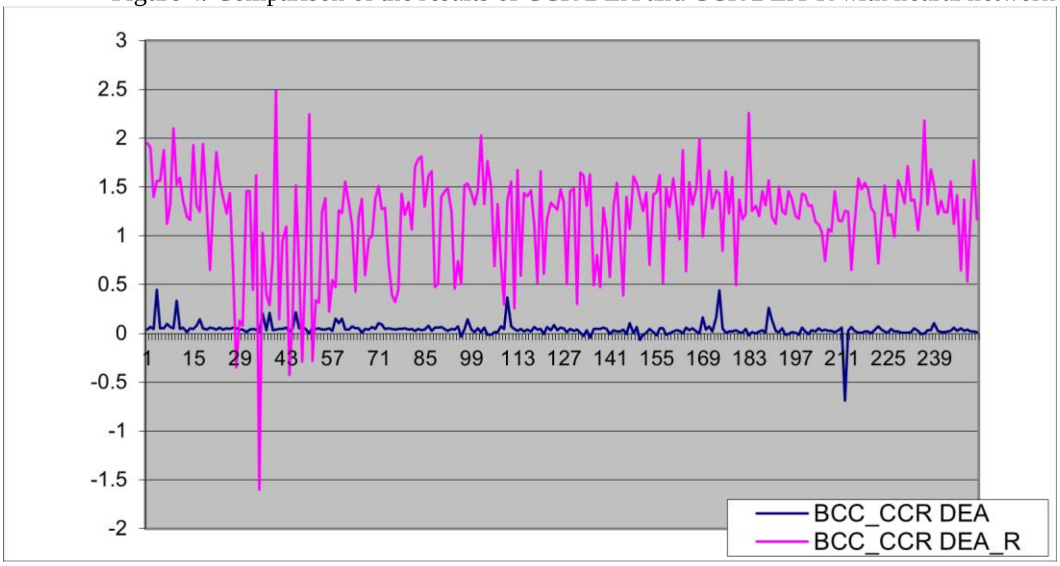

Figure 5. Comparison of the results of BCC-CCR DEA and BCC-CCR DEA-R with neural network

In Figure 3 the results of performance measures in the nature of models covering the entrance with constant returns to scale DEA and DEA-R is displayed without neural networks. Generally supper performance scales in DEA-R is greater than or equal DEA efficiency scale. The scale of efficiency in the DEA and DEA-R due to the increasing number of constraints and variables is a computational problem. Therefore, the use of neural networks and classification units are sometimes useful for performance scale.

In Figure 4 and 5 compared the scale of efficiency in DEA and DEA-R in fixed and non-decreasing returns to scale technology.

Scale efficiency in the input oriented of the DEA-R is greater than or equal scale in DEA efficiency. In Figure 4 scale efficiency except unit 13 is established. It should be noted that the use of neural networks first unit are sorted, second the efficiency scale in each category are determined, thirdly performance scale computing problem has been fixed.

In general, the use of neural networks can be classified as units to be trained several times and using propagation, scale and efficiency can be achieved in less time. Generally, in the case of non-decreasing returns to scale models of the proposed are technology between the DEA and DEA-R's properties. Neural network diagrams that the proposed model is implemented as follows:

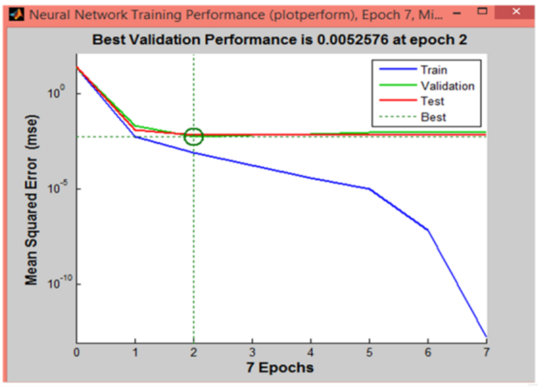

Figure 7. Graph best performance of CCR DEA

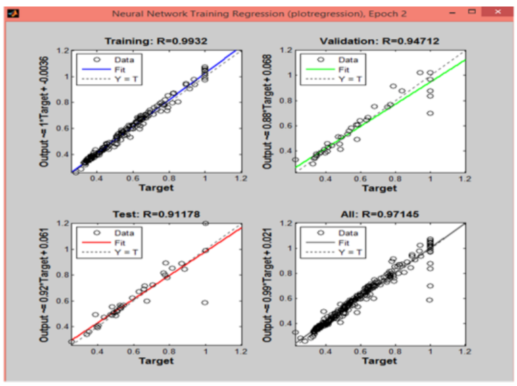

Figure 6. Regression graph data results CCR DEA

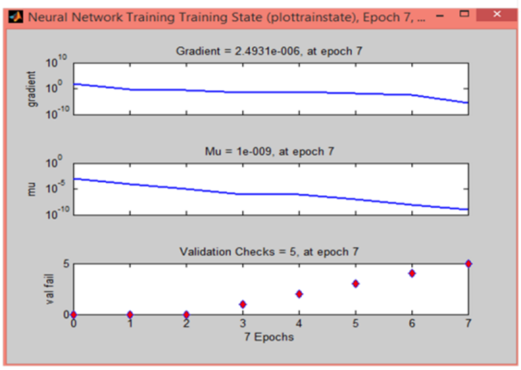

Figure 9. Network status graph CCR DEA

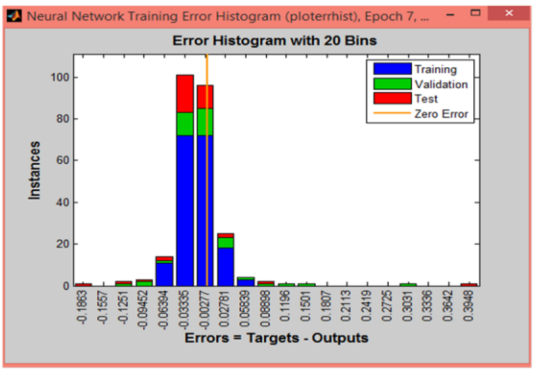

Figure 8. Histograms data CCR DEA

Figure 6 shows CCR DEA model neural network regression graph, which for four separate charts according to the data processing, evaluation, and testing generally is shown. The chart shows that we have done well and regression neural network data to a value of 1 are very close.

Figure 7 shows the best value performance assessment data and the optimal point or milestone gives us. CCR DEA model is achieved at the optimal value 0.0052576. In this diagram, the neural network to seven consecutive repetition does not improve and stops. Color lines category specific data, including data processing, evaluation and testing.

Figure 8 shows a histogram of errors. That show actually belongs in any category of data for various errors. Due to the color category in the chart specified. The left side shows the least amount of errors in other words 0.1863- to error is 0.3948, which -0.00277 point as a vertical line on the right is specified, the error rate than the actual value shows that, as you can see, most data related to education and the right data, test data and evaluation show. Due to the color category in the chart specified. The left side shows the least amount of errors in other words -0.1863 to error is 0.3948, which -0.00277 point as a vertical line on the right is specified, the error rate than the actual value shows that, as you can see, most data related to education and the right data, test data and evaluation.

Figure 9 shows the network status of three graphs that chart the rise and fall of the gradient. The second graph shows the μ algorithm and the graph of improvement and no improvement assessment data shows you can see in this diagram repeated after seven neural networks has been stopped and the four repeat fail to improve.

Chart BCC-CCR DEA model and BCC-CCR DEA-R, respectively, as follows in next page.

According to BCC-CCR DEA model charts the optimal value with respect to Figure 11, is 0.030194. The least amount of error according to the chart histogram -0.8368 and 0.3792 is the greatest amount of error and the actual error is -0.06897. In this model, according to the diagram network, neural network after seven repeat and repeat four stops of improvement.

According to figures BCC-CCR DEA-R model the optimal value with respect to Figure 15, is 0.31095. The least amount of errors due to histogram graph of -3.838 and the greatest amount of error is 2.468 and the actual amount of error between -0.1873 and 0.1446 is. In this model, according to the diagram network, neural network stops after thirty repeat and no improvement repeat five.

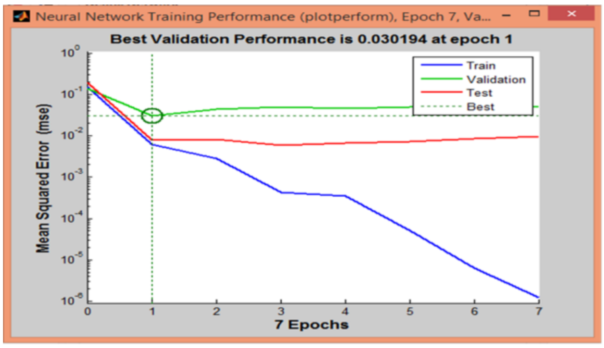

Figure 11. Graph best performance of BCC-CCR DEA

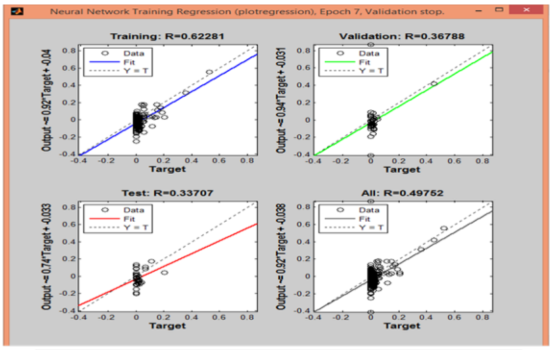

Figure 10. Regression graph data results BCC-CCR DEA

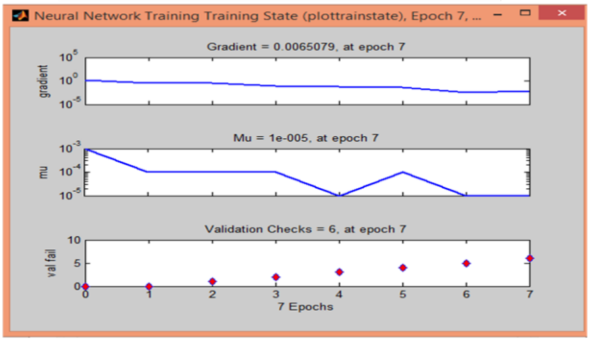

Figure 13. Network status graph BCC-CCR DEA

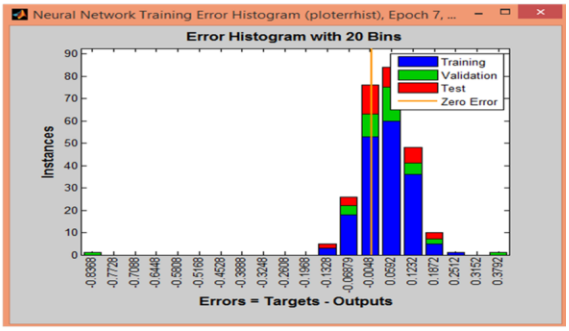

Figure 12. Histograms data BCC-CCR DEA

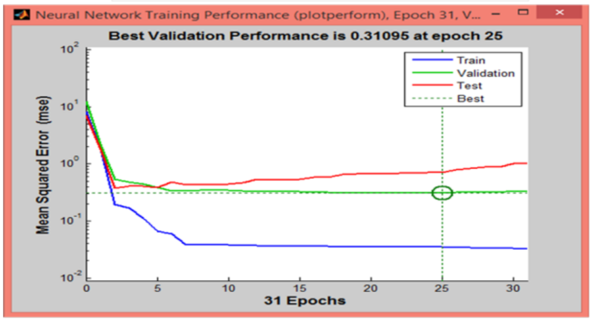

Figure 15. Graph best performance of BCC-CCR DEA-R

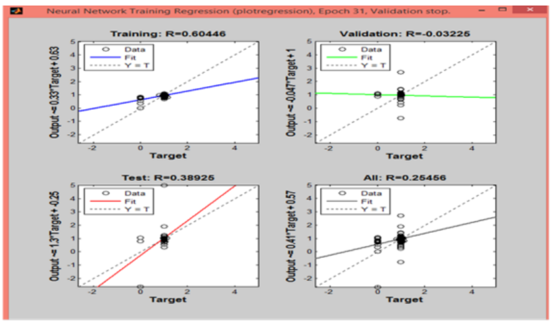

Figure 14. Regression graph data results BCC-CCR DEA-R

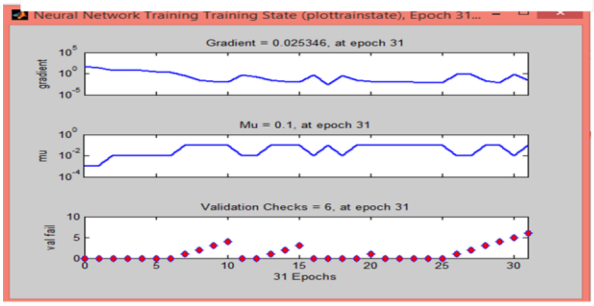

Figure 17. Network status graph BCC-CCR DEA-R

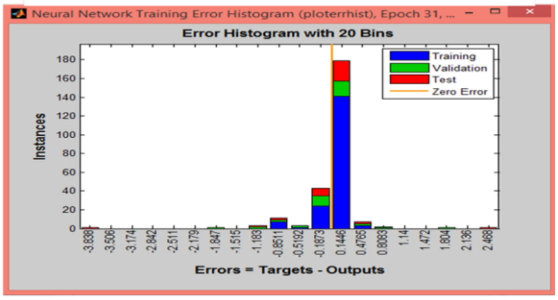

Figure 16. Histograms data BCC-CCR DEA-R

6. Conclusion

In this study, Understanding the basic concepts of neural networks and data envelopment analysis was performed to evaluate DMUs. The combination of neural networks and data envelopment analysis algorithm for evaluation of bank branches were presented. Generally, the use of neural networks and data envelopment analysis in the case of data input and output is large and linear models do not meet the assessment and efficiency is very important. Obviously, calculating performance, choose the best product and forecast performance and then ranked them only with the integration of DEA and neural networks is possible. In this thesis, in which the data relative to assessment of the Stock Exchange of DEA-R and neural networks to predict the scale of performance and rating of companies have already used. The border closure by the method of DEA or DEA-R and neural networks can be built stronger border and to predict performance and non-linear approximation of functions used. 252 Case Study thesis company on the stock exchange by integrating DEA and DEA-R and neural networks have been evaluated.

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