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Evaluating the efficiency and productivity of gas units using combined artificial neural networks and data envelope analysis

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Abstract: Since the power industry is one of the economic development bases of each country, and it has an important contribution in other sections, there has been an outstanding effort in power industry in recent years. Considering the importance of this topic, investigation of the efficiency in powerhouses has a high priority and strengths and weaknesses of various sections could be found and their performance could be enhanced by appropriate solutions. In this thesis, regarding the importance of production in power industry of the country, efficiency and productivity of power producing units were evaluated in years 2010 and 2011 using the hybrid ANN and DEA models. The weakness in resolution of decision making units is one of the major problems in Data Envelope Analysis. The little number of units in comparison with the model's input and outputs is the most important reason for that problem. In this regard, evaluation of units' efficiency was performed using DEA and the weakness of model was obtained from the calculation and resolving units' efficiency point of view. Furthermore, Artificial Neural Network efficiency predicting approach was used for analysis and evaluation of units, by using combined ANN and DEA (Neure-DEA) models and the results proved the ANN's high performance for units' efficiency estimation.

Key words: *Efficiency; Productivity; Artificial neural networks; Data envelope analysis; Neuro-DEA*

1. Introduction

Evaluating efficiency is one of the challenging tasks which are highly regarded by researchers. Until 1957 when Farrel proposed a method to evaluate the performance, basic review has been performed in this matter. Parametric and non-parametric views are also widely used in efficiency investigations (Delgado, 2005). It is obvious that creating an efficient system and optimum application of resources, leads to avoid loss of the Financial and intellectual assets, so that a small increase in efficiency and productivity would cause a high amount of thrift.

1.1. Literature review

Thompson et al. (1996) evaluated the efficiency and profitability of 14 big oil companies of the United States between 1980 to 1991using advanced operation research methods such as DEA.

Castaet et al. (2007) analyzed the efficiency of London metro using time series data and founded that ANN and DEA results were very close (casta and Harkellas, 1997). ANNs were used by Fleissing to estimate cost functions (Fleissing et al., 2000). In 2004, Santin used an ANN to simulate non-linear production functions and compared the results with results of more common methods such as DEA and random boundaries. He Found that ANNs has more consistency comparing the other techniques (Santin and Delgad, 2004). ANNs were also used by Delgado in order to measure the productivity of public sectors and better results were obtained for rating the decision making units. Results show that 45 units out of 72 are efficient (Delgado, 2005).

Celebiet et al. in 2007 published an article and combined DEA and ANNs to evaluate suppliers under incomplete information and obtained a new hybrid model (celebi and Bayrakter, 2007).

2. Research Methodology

In this article, productivity of the energy producing gas units was evaluated between 2008 and 2009. There are many methods to investigate the efficiency but, due to being variable in time, and needing no assumption in efficiency frontier, DEA is the most promising tool to organize and analyze data (Dosh and Liang, 2005). In addition, it is an appropriate method to compare units' efficiency. However, the DEA frontier is very sensitive to the presence of statistical noise and outliers which indicate that the frontier derived from DEA analysis may be warped if the data are contaminated by statistical noise (Dosh, 2005). In order to overcome these problems, ANNs are used as effective replacements to estimate efficient frontiers for decision making. This is due to the capability of ANNs to learn and being generalized and also their resistance against outliers and imprecise measurement caused noise in data (Wang, 2003). In

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this article, the efficiency of gas units were measured using combination of DEA and ANNs (Neure-DEA)

2.1 The population

The population which is considered for this study is 8 energy producing units activating in gas power plant. Technical information about gas units were obtained by library studies. Effective factors on efficiency were also determined using literatures.

This information is recorded in each unit's daily log sheet. Every energy producing unit is considered as a DMU. Choosing input and outputs variables is a very important because qualitative and quantitative targets could be presented in energy producing sections.

The variables of this study are: 1- Fuel consumption: One of the most basic inputs, which in Zahedan power plant, is gasoil. 2- The pick temperature: Performance benchmarks of the gas turbine are very much affected by the ambient temperature and every change in temperature of compressor input air would have an important impact on turbine's function. 3-Productivity: The maximum productivity of a gas unit installed at different seasons of the year with regard to environmental conditions is called productivity which is based on MW (Kiameh, 2003)

And outputs are: 1- Gross energy production: The total energy produced by each unit's power generator, measured on the unit's output terminal during a given time period (1 day for example).

2- CC/KW which is fuel consumption to gross energy production ratio. Lower values of this ratio are a sign for higher efficiency. 3- Coefficient of emergency exits: In some emergency cases, power producing units are not able to generate energy and they may be removed from the production circuit and this may have a direct impact on the unit's efficiency and would be estimated in terms of coefficient of emergency exits (Kiameh, 2003)

2.2. Data Envelope Analysis

SBM method was used in this article to analyze data and solve DEA patterns. The importance of SBM compared with the others in DEA is calculating covariates and also the unit's efficiency. It uses S^- and S^+ and focuses on inputs reduction and outputs increase simultaneously (Tone, 2001).

The reason for that choice in data preparation stage is lack of some input and output indices for some decision making units so their value is set to zero.

The CCR and BCC patterns identified in DEM literature are not stable against this increase and decrease and their results are being varied. But SBM pattern is stable with the variations (Cooper et.al.2002). SBM model formula is shown in equation (1)

$$.\ \rho_0 = min\frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{S_i^-}{X_i}}{1+\frac{1}{S}\sum_{r=1}^{S}\frac{S_r^+}{Y_r}} \qquad (1)$$

$$\text{St.}\sum_{j=1}^{n}\lambda_j X_j + S^- = X_0$$

$$\sum_{j=1}^{n}\lambda_j Y_{j+S^+=Y_0} S^-, S^+ \geq 0, \lambda_j \geq \circ\ \forall_j$$

After solving the SBM pattern, values for P_0 and S^- and S^+ covariates were obtained. The pattern is effective when $\rho_{0\ =1}$ or all values of S^+ and S^- are being zero (Cooper et.al.2002).

2.3. Neural Networks (ANNs)

A supervised neural network with back propagation learning algorithm (BPNN) was used in this study. In supervised learning, the network is trained based on a target, so that to learn the patterns and adapt itself closely to desired outputs (Rolon, 2004).

2.4. Neuro –DEA model

A multilayer perceptron Artificial Neural Network with error back propagation algorithm was used. The network inputs were the inputs and outputs of each DMU and the target was efficiency of each DMU obtained by DEA method. Firstly a proper network was created and then trained by applying pre-processed data in order to learn data patterns and predict the units' efficiency. Networks' output was compared with DEA- SBM models afterwards.

In evaluation of efficiency analysis using Neuro-DEA, data are gathered firstly and then units' efficiency is estimated using DEA model. To obtain a network with higher efficiency some pre-processing are going to be applied on data using special functions. 70% of the total data are chosen for training, 15% for validation and the remaining for testing the network.

The network is trained with training data afterwards and if the output data is close to targets then the next step would be applied if not, training step would be applied again.

Once the network training is finished, efficiency of the units would be estimated using trained Neuro-DEA Network for 2010 and 2011 and finally the DEA and Neuro-DEA results would be compared to each other. The algorithm flowchart is shown in Fig. 1.

3. Results and discussion

In this study, in order to measure efficiencies and comparing units, 2010 and 2011power plant were used. Efficiency of each of these units is calculated based on their inputs and outputs. The unit efficienciesfor the average of inputs and outputs for every year is shown in tables 1 and 2. They were calculated by DEA and using Lingo software for better comparison, DEA obtained efficiencies in 2010 and 2011 are shown in Fig. 2.

As can be seen all units' efficiencies have increased in 2011. Due to impossibility of the increasing efficiency for all units in one year, it can be concluded that the DEA is not able to analyze the units in this study.

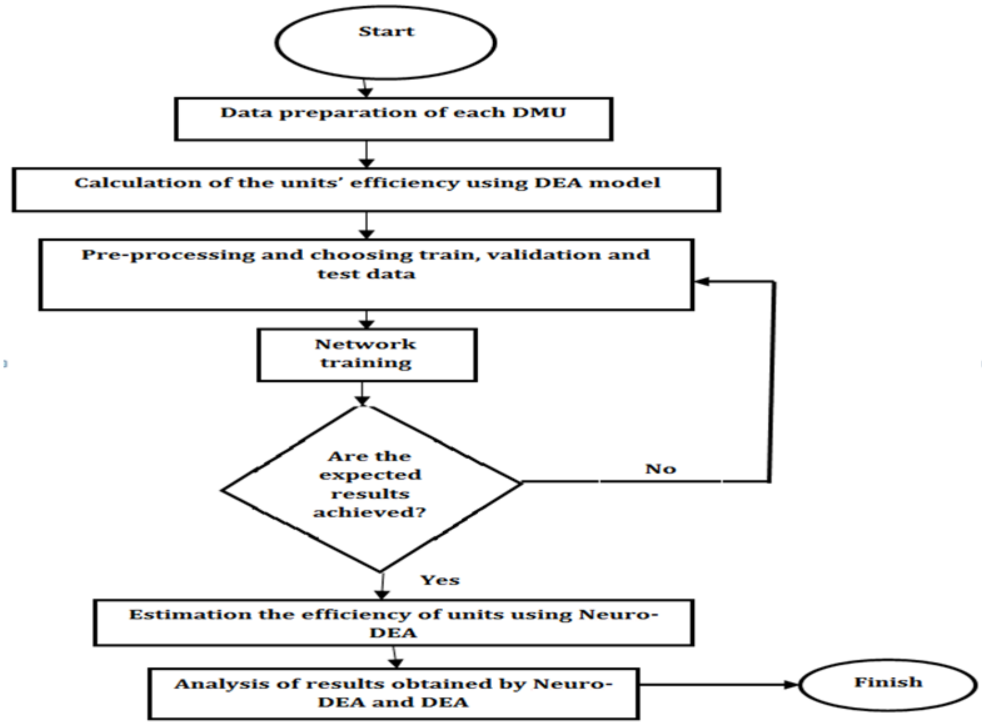


Fig. 1: The efficiency analysis algorithm using Neuro-DEA

Table1: Average efficiency data for DEA in 2010

Unit 9	Unit 8	Unit 7	Unit 6	Unit 5	Unit 3	Unit 2	Unit 1	
0.745249	***0.540393***	***0.559322***	***0.746245***	***0.827364***	***0.454671***	***0.455187***	***0.0810207***	**Efficiency**

Table2: Average efficiency data for DEA in 2011

Unit 9	Unit 8	Unit 7	Unit 6	Unit 5	Unit 3	Unit 2	Unit 1	
0.976808	*0.849594*	*0.740303*	*0.926065*	*0.967111*	*0.447514*	*0.760206*	*0.438753*	Efficiency

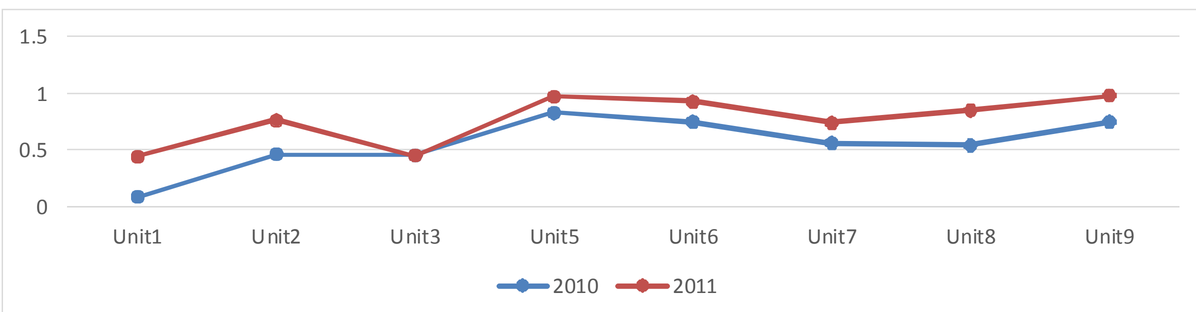


Fig. 2: Comparison between units' efficiency using DEA mode

3.1. Estimating the efficiency based on Neuro-DEA model

Matlab multipurpose software was used to design a multilayer perceptron network to evaluate the units' efficiency. The network was trained using a supervised learning back propagation algorithm. The training rate of the network was also evaluated and finally the network with minimum error and the best regression coefficients. Mean Square Error and Root Mean Square errors were used to evaluate the optimum network.

RMSE was calculated using equation 3:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} e_i^2}{n}} \quad (1)$$

Where n is the number of data and e is the difference between true and network's estimated value.

In this study, the main problem was optimizing the network structure and finding the best transfer and training functions. After 20 runs for each designed network, a 3 layers network with 1 hidden layer and 19 neurons in the hidden layer and also Tansig and Purelin transfer functions for the hidden and output Layershad the best results. Trainlm training function was also found to have the least error between the others.

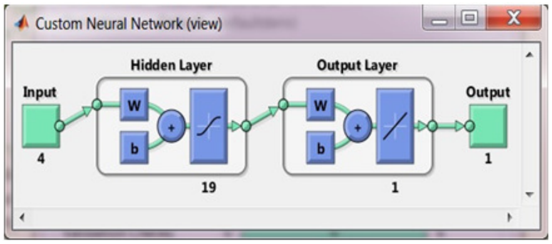
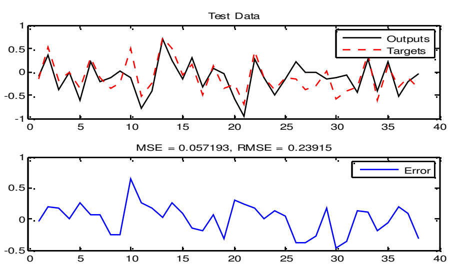


Fig. 3: The structure of the total optimum

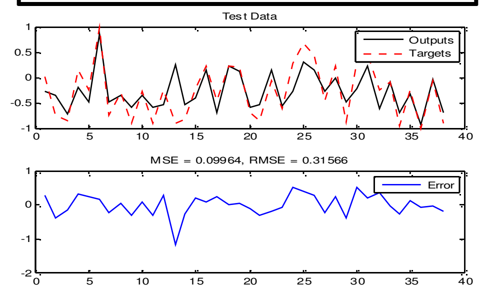
In Fig. 4 the network response and DEA results of year 2010 are compared with each other for test data. MSE and RMSE for each unit are shown.

In Fig. 5 the network's DEA outputs in 2011 for test data are compared to each other. MSE and RMSE values are seen for each unit. It is obvious that lower MSE and RMSE values show the better performing network.

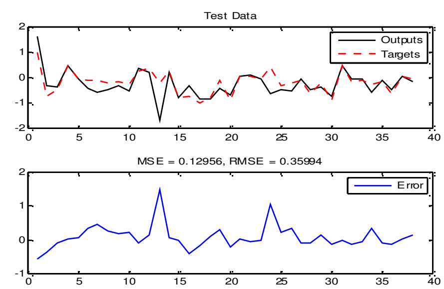
Comparison between DEA and ANNs for Unit 2



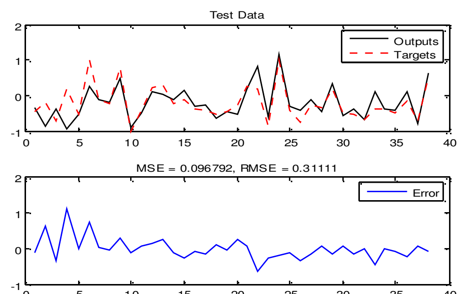
Comparison between DEA and ANNs for Unit 1



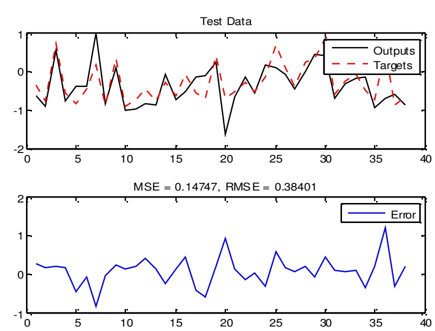
Comparison between DEA and ANNs for Unit 5



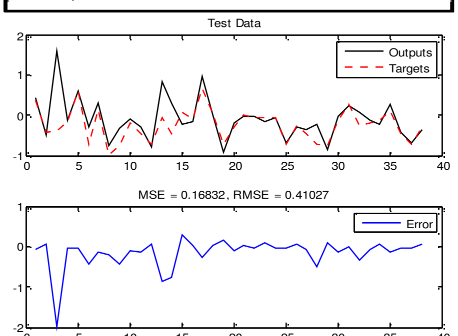
Comparison between DEA and ANNs for Unit



Comparison between DEA and ANNs for Unit



Comparison between DEA and ANNs for Unit 6



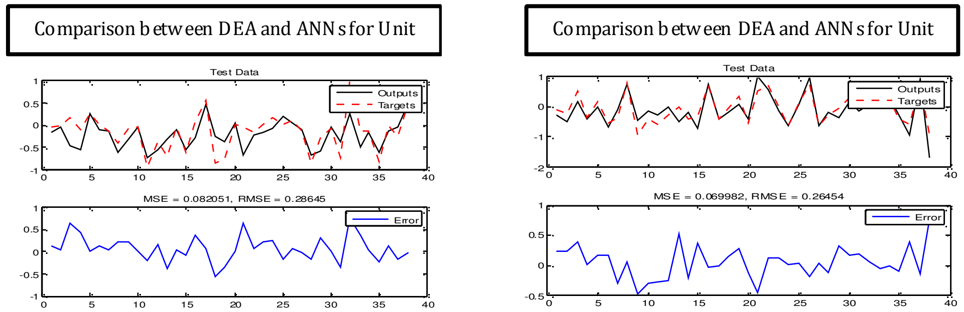
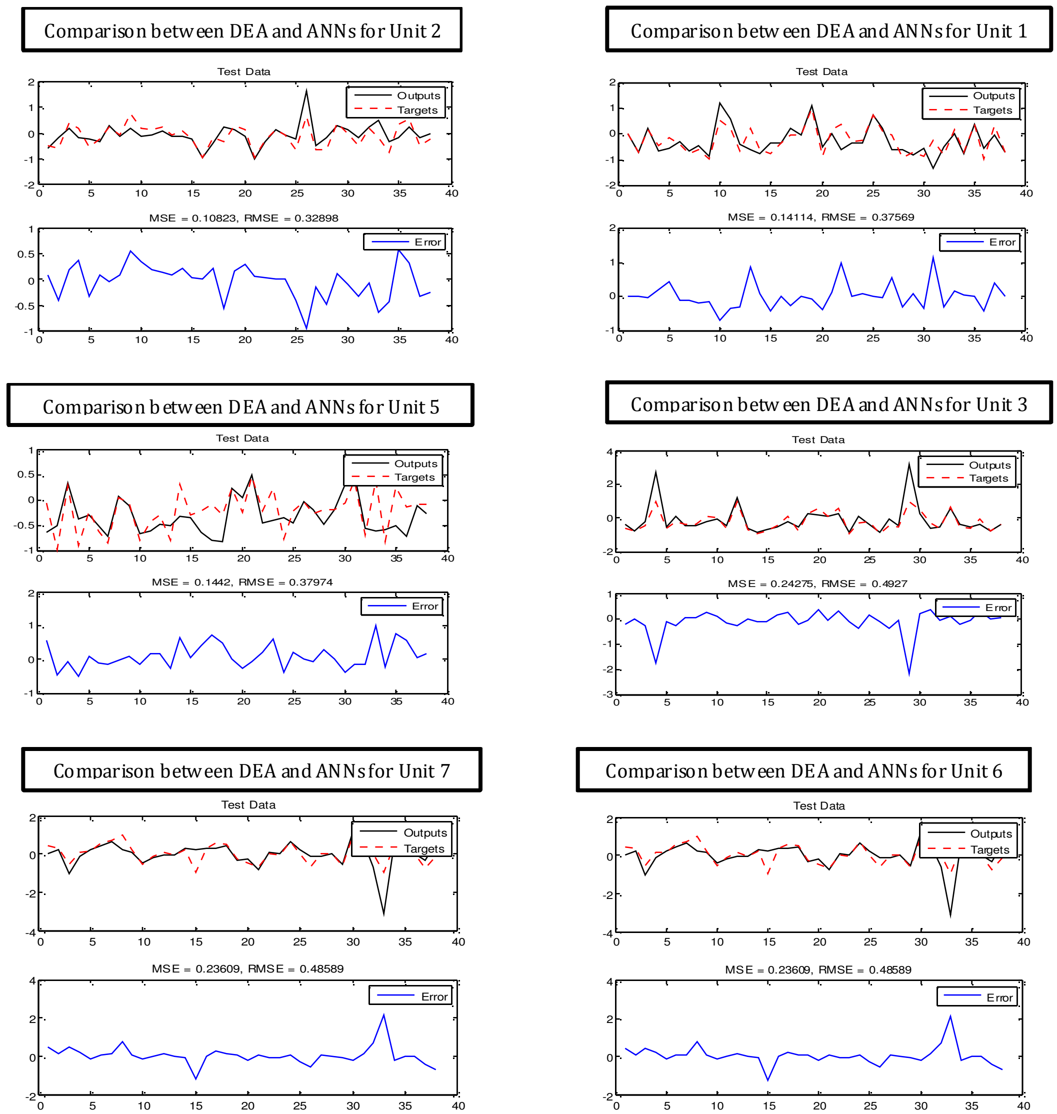


Fig. 4: Comparison between outputs of two models in 2010



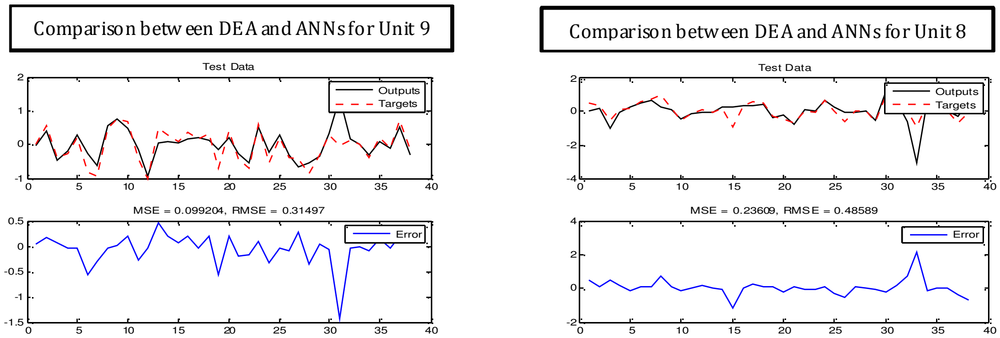


Fig.5: Comparison between outputs of two models in 2011

Table 3: efficiency of average data with ANNs model in 2010

	Unit 1	Unit 2	Unit 3	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9
Efficiency ANNs	*0.58856*	*0.520915*	*0.658852*	*0.695968*	*0.7803*	*0.569686*	*0.874175*	*0.896946*

Table 4: efficiency of average data with ANNs model in 2011

	Unit 1	Unit 2	Unit 3	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9
Efficiency ANNs	*0.433833*	*0.793434*	*0.58402*	*0.610401*	*0.98618*	*0.925031*	*0.668639*	*0.865755*

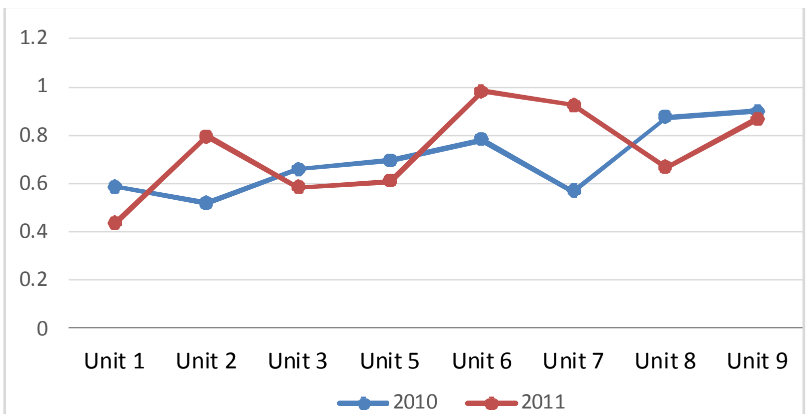


Fig. 6: Results of Neuro-DEA for 2010 and 2011

Table 5: Comparison between results of DEA and Neuro-DEA models for 2010

	Unit 1	Unit 2	Unit 3	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9
Efficiency DEA	*0.081021*	*0.455187*	*0.454671*	*0.827364*	*0.746245*	*0.559322*	*0.540393*	*0.745249*
Efficiency ANNs	*0.58856*	*0.520915*	*0.658852*	*0.695968*	*0.7803*	*0.569686*	*0.874175*	*0.896946*

Table 6: Comparison between results of DEA and Neuro-DEA models for 2011

	Unit 1	Unit 2	Unit 3	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9
Efficiency DEA	*0.438753*	*0.760206*	*0.447514*	*0.967111*	*0.926065*	*0.740303*	*0.849594*	*0.976808*
Efficiency ANNs	*0.433833*	*0.793434*	*0.58402*	*0.610401*	*0.980618*	*0.925031*	*0.668639*	*0.865755*

The network was trained using daily data in each year and for each unit. The optimum network was used for prediction purposes. So, the average of each input variables for each unit- year was given to the network and the network's output was the efficiency of the unit in intended year. Finally the result of the network prediction can be compared to DEA obtained efficiency.

Units' efficiencies for the average of inputs and outputs calculated by the optimum ANN model is listed in Tables 3 and 4.

In Fig. 6 the Neuro-DEA efficiency of the units are presented for 2010 and 2011

As can be seen, the efficiency of the units has variations in 1389 and 2011. By technical investigation of the power plant's units, it is observed that the network's prediction and variety in obtained efficiencies are closer to reality. This is due to the basic service in units which caused them to perform better.

Efficiency of the units using Neuro-DEA and DEA are compared afterwards. Results are tabulated in Table 5.

As seen in the table 6, estimated efficiency of unit 6 is the same in both models while they are different for unit 1. In 2011 estimated efficiencies are far from each other.

4. Conclusions

In this study, DEA and Neuro-DEA were used to measure the efficiency of gas units. In the first step the efficiency of each unit was calculated in DEA model and efficiency diagrams were plotted. Analyzing the plots showed that due to the lower number of decision making units compared to number of inputs and outputs, DEA is not able to separate and determine the efficiency. Thus to solve this problem a neural network with an optimum topology and learning algorithm and also high capability in approximate relations and non-linear functions was used. After training the network, data average of 2010-2011 were given to predict the units' efficiency. In table 7 and 8 the DEA and network's output were compared to each other.

As can be seen in 2010 units 8 and 9 have the highest efficiency in the network. There were units that had been undergone of major or semi-major overhaul. Unit 6 which was in the 3rd place in 2010 had semi-major overhaul in 2009 on the other hand unit 6 which had the lowest rate in 2010 was not undergone any overhaul in 2009. Based on the network's prediction unit 6 had the highest efficiency in 2011 mainly due to semi-major overhaul at the beginning of the year. Although there performed an overhaul on unit one in 2010, it had the lowest rating which may be due to using used parts in overhaul and this shows in addition repairs using new parts is an important factor for enhancing the efficiency.

Table 7: Comparing the efficiency rating with DEA and Neuro-DEA model in 2011

DEA	Rate	Neuro -DEA
Unit 9	1	Unit 6
Unit 5	2	Unit 7
Unit 6	3	Unit 9
Unit 8	4	Unit 2
Unit 2	5	Unit 8
Unit 7	6	Unit 5
Unit 3	7	Unit 3
Unit 1	8	Unit 1

Table 8: Comparing the efficiency rating with DEA and Neuro-DEA model in 2010

DEA	Rate	Neuro – DEA
Unit 5	1	Unit 9
Unit 6	2	Unit 8
Unit 9	3	Unit 6
Unit 7	4	Unit 5
Unit 8	5	Unit 3
Unit 2	6	Unit 1
Unit 3	7	Unit 7
Unit 1	8	Unit 2

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