Evaluation of Staff Efficiency Using the Combined Model of Neuro/DEA (Case Study: Operational Unit of Gilan Province Gas Company)

[1]Nabahat Choobdari Namin, [1]Bita Baradaran Jamili, [2]Hojat Allah Kalvandi

[1]Executive Master of Business Administration
[2]Master of Business Management
nabahatchoobdari@yahoo.com

Abstract: Nowadays, human resources are of fundamental importance to organizational success and also have a considerable effect on organizational efficiency. Therefore, it is important to investigate human resources performance in the case of organizational studies. In this study, the operational unit of Gilan Province Gas Company was selected to investigate its personnel efficiency. Two combinational models of Data Envelopment Analysis (DEA) and Artificial Neural Network (ANNs) were used for efficiency analysis and ranking. Firstly, the analysis results obtained from Neuro/DEA were compared to DEA results and then, a comparison was made between the trained networks models. Analysis results show that the training method of second model compared to the first one illustrates the potential ability of neural networks in pattern recognition, function estimation, and efficiency prediction. Furthermore, it can be used to evaluate the organizations with fewer decision making units. On this basis, this study suggests the combinational model of Neuro/DEA 2 as the dominant model.
[Choobdari Namin N, Baradaran Jamili B, Allah Kalvandi H. **Evaluation of Staff Efficiency Using the Combined Model of Neuro/DEA (Case Study: Operational Unit of Gilan Province Gas Company)**. *Life Sci J* 2013;10(185):185-191] (ISSN:1097-8135). http://www.lifesciencesite.com. 29

Keywords: Evaluation, Personnel Efficiency, Gas Company, Combinational Model of Neuro/DEA

1. Introduction

Efficiency measurement has always been paid a lot of attentions by researchers because of its importance to organizational performance evaluation. Any organization should employ scientific models of performance evaluation to achieve the right form of management so that it will be able to evaluate its operation and performance results. Farrel is the first researcher who managed to measure the efficiency of a production unit in 1957. His model of efficiency measurement was composed of an input and an output which was used to estimate the efficiency of American agricultural sector in comparison with other countries'. Nonetheless, he could not provide a suitable method in the case of numerous inputs and outputs. Charn et al developed Farrel's method and finally propounded a model which was able to measure the efficiency with several inputs and outputs. This model is called "Data Envelopment Analysis (DEA)" [12]. Research results show that DEA is hardly capable of measuring units' performance and efficiency. Thus, Artificial Neural Network (ANN) has recently been suggested as an appropriate option for efficiency estimation. Wang et al (2003) have shown the weakness of DEA as the main reason for employing ANN. ANN is an ideal tool of solving non-linear problems and also an appropriate method to make predictions. Numerous variables interfere in efficiency measurement. There is a non-linear and highly complicated relation between variables and efficiency of units. ANN is a very suitable tool of overcoming numerous difficulties with solving non-linear and non-parametric problems [17] [22].

2. Historical Background of the Study

A study has been carried out to measure and analyze the efficiency of employees using data envelopment analysis and results show that personnel efficiency is in accordance with organizational commitment and workplace condition [1]. Another study combined Analytical Hierarchy Process (AHP) technique with DEA to evaluate and optimize personnel efficiency [6]. Furthermore, Saberi et al measured personnel efficiency by combining DEA, ANN, and Rough Set Theory (RST) techniques. This evaluation helps managers to make more effective decisions and to specify personnel's critical characteristics which have considerable impact upon the enhancement of entire organization efficiency [7]. Capaldo employed Fuzzy method to evaluate personnel efficiency in an Italian corporation [11].

3. The Study Methodology

The idea of combining neural networks with DEA was first given by Athanassopoulos and Curram in 1996. Their comparison of DEA with ANNs showed that DEA compared to ANNs gives a better performance when measuring goals and also ANNs function similar to DEA when ranking units based on the resulted efficiency. Flessig and his co-workers managed to estimate cost functions using neural networks and proved that the convergence problems which are faced by some other techniques are not the case for ANN. In 2004, Santin employed a neural network to simulate non-linear production function. The results demonstrated a higher level of stability for neural networks in comparison with various observations and more prevalent methods such as Stochastic Frontier Analysis (SFA) and DEA [20]. This study aims to combine neural networks with DEA in order to measure personnel efficiency. There are two competitive samples in efficiency analysis. The first sample employs mathematical programming techniques on the basis of DEA which are generally applicable for operational researches. The other sample uses regression or Stochastic Frontier Function (SFF) method which is widely used in economy. Either of these methods has its own characteristics. In the main study on DEA by Charenz et al, DEA has been propounded as a mathematical programming model which is indeed a method to empirically estimate the probable procedures of an efficient product. In comparison with SFF, DEA, in its applied form, does not require the concavity of frontier functions. The chief challenge faced in DEA is the fact that the frontiers calculated by DEA may deviate if data undergo any statistical disturbance [25]. ANN is a general non-linear prediction method and has a specific advantage because of its non-parametric manner, that is, it does not require any assumption about probability distribution or product function structures.

Recently, artificial neural networks have been employed as a suitable alternative in order to estimate efficient frontiers for decision making [25]. The nature of neural networks performance makes it resistant to outliers and disturbances resulted from inexact data measurements. This characteristic originates from its generalization and learning power [3]. Among all measurement models, DEA is a better method of data organization and analysis because it allows efficiency to vary with time and does not require any pre-supposition about efficiency frontier [26]. On this basis, it has been used more than other methods to evaluate performance and is a suitable technique to compare units' efficiencies. Nonetheless, the efficiency frontier resulted from DEA is sensitive to statistical disturbances and the outliers which are resulted from measurement errors or external factors. In other words, the resulted efficiency frontier may move and deviate DEA analyses paths if data face a statistical disturbance or include outliers [26] [10].

3.1. Data Envelopment Analysis

DEA is a non-linear non-parametric model which is used to measure production plants' efficiency. Previous researches show that the predictions made by DEA are more reliable than parametric models which consider specific structures such as functions shapes or power of 2. DEA considers the most desirable set of weights for each decision making unit. In other words, DEA is a highly capable tool which is considerably applied to evaluate the performance of the systems with several inputs and outputs [19]. In recent decades, DEA has been being considered as a prevalent methodology to evaluate the decision making units (DMUs) with similar characteristics [21]. Generally, data envelopment analysis models are categorized in two groups of input-oriented ones and output-oriented ones. Input-oriented models are those which require fewer inputs to obtain the same number of outputs, while output-oriented models give more outputs with the same number of inputs [18]. In another categorization, DEA models are divided to two groups of multiple models and envelopment models. To measure the efficiency, DEA uses the ratio of a weighted sum of outputs to a weighted sum of inputs. The CCR model 1 is a preliminary ratio to measure the efficiency of n decision making units (DMU_n, n=1,…,n) with m inputs and s outputs for each one. In model 1, DMU_t is denoted by θ_t, while given weights are symbolized by v_i and u_r. Fractional programming model was used to make the remaining calculations (model 2).

$$\text{Max } \theta = \frac{\sum_{r=1}^{s} u_r y_{rt}}{\sum_{i=1}^{m} v_i x_{it}}$$

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

$$u_r, v_i \ge 0, \qquad i=1,\dots,m, \quad r=1,\dots,s.$$

$$\text{Max} \quad \theta = \sum_{r=1}^{s} u_r y_{rt}$$

$$\text{s} \quad \sum_{r-1}^{s} u_r y_{rj} - \sum_{i-1}^{m} v_i x_{ij} \le 0, \qquad j=1,\dots,n \quad (2)$$

$$\sum_{i=1}^{m} v_i x_{it} = 1$$

$$u_r, v_i \ge , \qquad i=1,\dots,m, \quad r=1,\dots,s.$$

Output-oriented CCR model determines efficiency in order to maximize outputs with a fixed number of inputs. Model 3 (LP) is a secondary model for output-oriented CCR model [9].

$$\text{Max} \quad \theta$$

$$\text{s.t.} \quad x_{it} \ge \sum_{j=1}^{n} \lambda_j x_{ij}, \qquad i=1,\dots,m \qquad (3)$$

$$\theta y_{rt} \le \sum_{j=1}^{n} \lambda_j x_{rj}, \quad r=1,\dots s$$

$$\lambda_j \ge 0$$

Charen et al (1978) have found an empirical relation among the number of evaluated units, number of inputs, and number of outputs, when developing data envelopment analysis model:

Number of evaluated units (DMUs) ≥ 3 × number of inputs + number of outputs.

Neglecting the above relation in practice may cause a lot of units to locate on the efficient frontier or in other words, their efficiency point will equal 1. This reduces model's resolution power and since the operations size, when solving simplex, is rather dependent on the number of limitations than variables, the solution of the model's secondary problem will require smaller operations size. Banker et al used BCC to estimate the efficiency of decision making units (DMUs) with variable-efficiency-of-scale, that is, outputs variations are not proportional to inputs variations. Therefore it can be said that CCR models are a special type of BCC models [24]. The reason of using output-oriented CCR model instead of BCC model in this study is that BCC not only is unable to solve the problem of having few DMUs, but also it introduces some other efficient units compared to CCR model and hence even intensifies existing problems. Since input-oriented models try to keep outputs constant, CCR model is a constant-efficiency-of-scale model and is suitable when all units function at optimum scale. In the present study, the research on the number of inputs and outputs revealed that the ratio of outputs' variations to inputs' is almost a constant value, thus CCR model was employed.

3.2. Artificial Neural Networks

Artificial neural network (ANN) is a network of connections between some factors with each other. It performs to produce an output pattern when an input pattern is set up for it [2]. The power of an ANN depends on the manner by which its weights are arranged. The process of weights arrangement based on special training data is called network training. ANN can be taught with or without supervision. In training with supervision, the desirable outputs are compared with real outputs, while this is not the case for training without supervision. Desirable outputs are given to network during training process in order for ANN to arrange the weights so that network outputs accord with desirable outputs. During the process of training with supervision, data are paired with network's desirable outputs. After training, ANN is tested just by defining input values. The output values resulted from output layer are compared to desirable output values. The difference between these two values is called output error. The process stops when output well matches its desirable value [16]. Trained network should be able to generalize hidden data, otherwise weights must be arranged again and the process continues until resulted output reaches its desirable value. Since an ANN has some hidden layers, the algorithm for single-layer perceptron may not succeed. Application of the Back Propagation (BP) error training algorithm can solve this problem. Instead of error propagation to correct the values of weights, network is fed with errors in opposite direction. Multilayer perceptron networks with Back propagation training are generally considered as a sample of standard networks for prediction modeling. The term "back propagation error" has been chosen to explain the behavioral modification of network. Network parameters are arranged so that the real outputs of the network further match desirable values [27].

A complete cycle of calculation includes the completion of all forward and backward paths of training vectors. This cycle is indeed called repetition. Therefore, number of the repetition times equals number of the times the network is fed with training data. If other variables are constant, number of repetitions can act as a training criterion. The transfer function used in hidden layers should also be non-linear in order to specify the non-linear relations between data. But in fact it is the non-linear structure of ANN which makes multilayer networks more capable [16]. The standard BP algorithm being used for ANN training is based on the maximum descending gradient which is used to minimize the cost function (network weights function) [8]. LM algorithm like quasi-Newtonian algorithms has a very high convergence rate because it does not require the calculation of Hessian matrix and makes an approximation of it by means of Jacobian matrix. The Trainlm function is one of those widely-used functions in MATLAB which has been developed based on LM learning. Another important point after data preprocessing is data normalization. Numerical variables should be normalized to standardize the impact of each variable on result. Using the above method, data can be arranged at any desired interval such as [L, H]. The approach is as following [14]:

$$X^{*} = m\, X_i + b$$

$$m = \frac{H - L}{Max(X) - Min(X)}$$

$$b = \frac{Max(X)L - Min(X)H}{Max(X)\ \ Min(X)}$$

Where X^* and X_i are the normalized and the main variables, respectively. In addition, this study employs four criteria of MSE, MAD, Bias, and Tracking Signal to compare and estimate network training procedure.

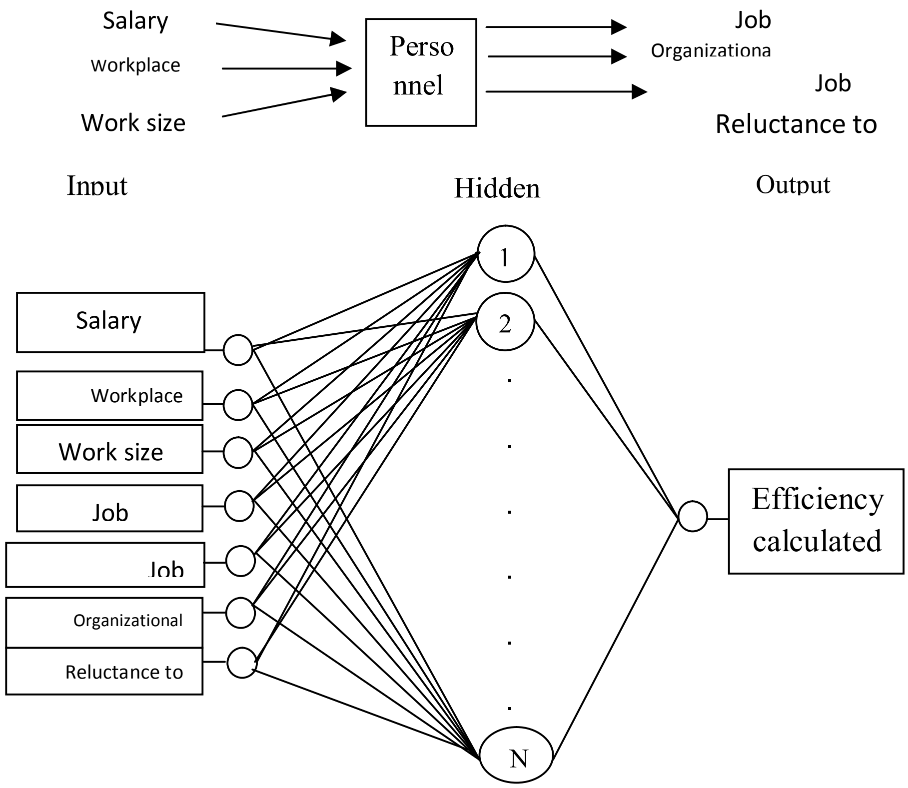

Figure 1. Neuro/DEA model

$$MSE=\frac{1}{N}\sum_{i=1}^{n}(O-T)^2$$

$$MAD=\frac{1}{N}\sum_{t=1}^{n}|O-T|$$

$$Bias=\frac{1}{N}\sum_{t=1}^{n}(O-T)$$

$$Tracking\ Signal=\frac{Bias}{MAD}$$

MSE denotes the error level between output and target values. A negative value of Bias illustrates that result is smaller than real value, while a positive Bias means the resulted value is greater than real value. Tracking Signal expresses the prediction procedure in terms of percent and is a great help to make predictions.

4. The Presented Model's Algorithm

4.1. The Presented Model

Present study evaluates personnel efficiency in two steps. During first step, units' efficiency is calculated using output-oriented CCR model. Then, pattern is specified and model is predicted using neural networks during the second step. This model optimizes personnel in order to increase outputs having a set of inputs desired by human resources policy. Figure 1 illustrates Neuro/DEA model. First step is to specify the variables which quite impact upon personnel efficiency. Considering the human resource policy of this study, the comprehensive review of previous reports and consultation with experts and professors resulted in the specification of three input variables and four output variables.

4.2. DEA Results

Output-oriented CCR model was employed to calculate the efficiency, evaluate performance and rank units. The applied software was EMS which is capable of ranking efficient units in addition to the classification of efficient and inefficient units. It also shows the efficiency of efficient units. Table 1 lists the final results. As it is obvious, the table lists the resulted weights, the shortage level of input and output variable, and reference units. The reference units column shows the number of times that efficient and inefficient units have served as reference for each other.

Table 1. Units' Efficiency Calculation (Omit)

4.3. The Results of Neuro/DEA Combinational Model

The network used in this study is a three-layer perceptron which the number of its input neurons equals the sum of DEA inputs and outputs. The output layer of this network includes one neuron which illustrates the efficiency calculated by DEA. The number of hidden layer neurons in this model was calculated using try and error method. Determination of the exact number of median layer neurons is quite difficult and depends on the nature of problem. Here again, an upper limit of 30 neurons was considered to determine the median layer neurons and network error was observed via reducing neurons till the desirable amount of neurons was eventually specified. Firstly, network error decreased by reducing neurons till the neuron number reached a specific amount ($n=n_1$) where further reduction of neuron numbers resulted in an increase in network error. Thus, n_1 was taken as n^*. In this topology, all hidden layer functions are sigmoid functions and output function is a linear function. Output layer linearization is indeed a one-to-one mapping between input and output of the last layer neuron which shows the efficiency that has a value greater than zero. Table 2 shows the structural parameters of the neural network which has been designed using MATLAB (7.11.0) software.

Table 2. Structural parameters of the designed network

concept	Result
Network architecture	Back-propagation
Epochs (max)	10000
Algorithm	Levenberg–Marquardt(trainlm)
Performance Function	MSE
Transfer function(hidden layer)	Tansig
Transfer function(output layer)	Poslin

To achieve desirable results, data were normalized using minimum and maximum data method and their variation range was taken between 0 and 1 to enhance the rate of network divergence and receiving the optimum answer. In such a condition, the differences between variables are better illustrated and neural networks with binary and dipolar variables are better trained. The gathered data were normalized using the relations mentioned in section 3.2.

4.3.1. The Algorithm of Neuro/DEA 1 Model

The aim of training a network is to arrange its weights so that the desired set of outputs is produced using a set of inputs. The steps of training this network using BP algorithm are as follows:

1- Input vector is divided to three groups of learning, testing, and training vectors. In this network, data are classified using stochastic function by means of software itself.
2- Calculation of network output
3- Calculation of the error between network output and real output
4- Repetition of steps 1 to 3 until the network error decreases to an acceptable level.

4.3.2. The Algorithm of Neuro/DEA 2 Model

This model is also trained using the assumptions similar to those of model 1. The only difference is that network training was carried out for 70 times. Its operational steps of are as follows [23]:

1- Selection of the n^{th} vector (personnel) for testing and other 69 vectors for training and learning, n=1,2,3,…,69 and valRation=25%
2- Training of the designed network
3- Simulation of the efficiency of n^{th} personnel
4- Repetition of steps 1 to 3 by varying input vectors number to n+1

4.3.3. Comparison of the results obtained by two Neuro/DEA models with results of DEA

After training two designed models and simulation of the units' efficiency, they can be ranked. The results are shown in table 3.

Table 3. The calculation results for three models (Omit)

5. Results

5.1. Selection of the Dominant Model

Results show an improvement for Neuro/DEA 2 compared to Neuro/DEA 1. Generally, comparison of these two models reveals that the designed second model (Neuro/DEA 2) is applicable for evaluation of the organizations with fewer decision making units because training of the networks with few samples decreases the number of training and testing units and simulation result may not show the testing data properly.

Table 4. Comparison of two presented models

CRITERION	Neuro/ DEA 1	Neuro/ DEA 2
no. tests	37	77
MSE	0.011	0.002
MAD	0.053	0.031
BIAS	-0.012	-0.004
Tracking Signal	-0.24	-0.11
$R^2_{\text{Coefficient}}$(scores)	0.97	0.99
$R^2_{\text{Coefficient}}$(ranking)	0.95	0.98

As it is obvious from table 4, a negative Bias value for model 2 demonstrates an underestimation, that is, the value of efficiency by Neuro/DEA 2 model is averagely smaller than the target value determined by DEA. Moreover, the value of Tracking Signal shows the prediction procedure to averagely be 11% smaller than the target value determined by DEA.

5.2. Conclusion

This study evaluates the personnel efficiency in operation unit of Gilan province gas company. Results demonstrated that the fundamental DEA models were not capable of predicting and analyzing the efficiency by their own, thus neural networks were employed. Based on the results, neural networks are highly capable of learning efficiency patterns but it is worth mentioning that network should be trained properly. Neural networks and their combination with DEA can be used when the fundamental models are not able to resolve and specify units. The comparisons made by mathematical and combinational efficiency analysis methods revealed that neural networks produce acceptable results. At the next stage, two models were used to train input data and based on the results, the second model (Neuro/DEA 2) was chosen as the dominant model for evaluation of the organizations with limited number of decision making units since this model reduces the errors to their minimum level. This is because training of the networks with few samples decreases the number of training and testing units and simulation result may not show the testing data properly. On this basis, this model is applicable to the upcoming data in similar organizations for final ranking of units and personnel efficiency analysis and evaluation. It is also provides a pattern for prediction of units' efficiency.

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