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Assessment of the personnel's efficiency with Neuro/DEA combined model

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ABSTRACT

One of the factors effective on success of the organizations is their human resources which has direct effect on productivity of the organizations. For this reason, performance of human resources is very important. In this paper, efficiency of personnel of Islamic Azad University, Tehran Sciences and Research Branch has been studied with approach of human resources. For efficiency analysis and ranking, two combined models of DEA and artificial neural networks (ANNs) were used. At first, analytical results of two models were compared with DEA and then two trained network models were compared with each others. Results of this research show that training method of the second model compared to the first model show potential of neural networks in identification of model, estimation of function, prediction allow to use it in order to assess the organizations with decision making branches, therefore, it can be presented as top model.

Introduction

Efficiency measurement has been considered by the researchers due to its importance in assessment of performance of an organization. One of the factors which are effective on increase of the organization's efficiency is efficiency of that organization's personnel. If the personnel has desirable efficacy, performance of organization is improved. In this method, efficiency of the organization's efficiency with human resources approach. In 1957, Farrell took action regarding measurement of efficiency for a manufacturing branch with use of a method such as efficiency measurement in engineering issues. The case which Farrell considered for efficiency measurement included an input and output. Farrell used his model for estimating efficiency of American agricultural section in comparison to other countries. However, he was not successful in presentation of different inputs and outputs. Charnes, Cooper, Rhodes developed attitude of Farrell and presented a model which had ability to measure efficiency with some inputs and outputs. This model was named data envelopment analysis and was used in Ph.D. thesis and with cooperation of Cooper as assessment of educational progress of the students of American schools in 1976 in Carnegie University. (Charnes et al. 1978) presented his model as CCR of which the first letters were names of these three persons in an article under title of decision making branches efficiency measurement. Performance of the personnel not only is summarized in general concepts of productivity and effectiveness but also different aspects are effective on performance. In most studies, relationship between performance of the personnel and human resources management have been discussed. In fact, a suitable policy in human resources management can improve performance of the organization. Performance of the organization is measurable with a criterion. As a principle, each decision making branch should be measured and presence of absence of effective and efficient performance assessment system is directly related to death of the unit and its absence is regarded as unit disease. Without measurement, there will not be basis for judgment and comment and assessment. What can't be assessed can't be managed well. Any organization should utilize scientific models of performance assessment so that one can test effort and results of his performance.

As said before, one of the efficient tools is data envelopment analysis which includes stronger framework of performance assessment system. DEA can hardly predict performance and efficiency of the units. As result, artificial neural networks were introduced as a suitable option for helping estimate efficiency (Wang and Wu et al. 2003) declared that weakness of DEA in prediction causes to use ANN. ANN is suitable tool for solving nonlinear problems as well as suitable method for prediction of problems.

Some different variables are effective on efficiency measurement. Relationships between variables and efficiency of the units indicate that there is nonlinear and complex relationship between them. For example, improvement of efficiency from 0.5 to 0.6 should be in result of some inputs increase but efficiency increase from 0.8 to 0.9 may be other reasons and increase of some outputs. ANN is suitable tools for approximating different problems which are available for solving nonlinear and nonparametric problems (Jain, Nag, 1995; Shavlik, Mooney, Towell, 1991). Therefore, we intend to assess efficiency and rank training personnel of one of the known universities in Iran, Islamic Azad University, Tehran Sciences and Research Branch with Neuro/DEA combined approach.

Literature review

As said before, we should be careful in use of DEA for assessing efficiency of other decision making units. This problem caused to use artificial neural networks as a good substitute for estimating efficient borders for decision making and because nature of artificial neural networks is such that it resists more against useless data and turbulences resulting from imprecise measurement of data (Mehrgan, 2006). Many methods have been mentioned for measuring efficiency in the related research but DEA is better method for organizing and analyzing data in comparison to all of the above models. Because it allows to change efficiency over time and no presupposition is needed for efficiency border (Wu et al, 2006). It has been used more than other attitudes in assessment of performance and is a

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suitable technique for comparing units in testing efficiency. However, efficiency border which results from DEA is sensitive to statistical turbulences or useless data due to measurement error or any other factor and if there are statistical or data turbulences , it may displace the achieved efficiency border and divert DEA analyses path(Wu et al, 2006;Bauer, 1990).

Shiravizadeh (2009) with his colleagues measured and analyzed the personnel with use of data envelope analysis. They considered each one of the personnel as a decision making unit with inputs and outputs. Inputs were salary, workplace, lack of job responsibility, work volume of the personnel and outputs were motivation, job satisfaction, organizational commitment, and job displacement of the personnel. In an applied example, this model has been calculated for 20 personnel of a manufacturing organization. Result of this study showed that more efficiency of the personnel is consistent with organizational commitment and workplace. This article shows that salary is not a very important factor in efficiency of the personnel. The personnel who receive high salary don't necessarily have job satisfaction. Therefore, organizations should focus on human aspects in organization.

Azadeh et al. (2011a) used merge of two Analytical Hierarchy Process (AHP) and DEA process in order to assess efficiency and optimize productivity of the personnel. Stages of execution of this article which have been performed in Industries and Mines Bank are as follows:

- *Determining quality indices which have effect on productivity of the personnel.*
- *Converting quality to quantity indices through questionnaire*
- *Weighing and ranking indices through AHP technique*
- *Determining input and output indices for DEA and ranking units*

Revising and validating research results with use of Principal components analysis (PCA) and numeral taxonomy (NT).

- *The input indices which were used in order to assess efficiency and ranking including number of personnel, time of training the personnel. Costs of research and education*
- *Output indices include motivation , responsibility , creativity , innovation , public relations , ability of the operational personnel , working quality , skill and ability , order and discipline of personnel*

Results of this research showed that most of the indices which caused inefficiency of the branches were low working quality and high training hours and indices which caused efficiency of the branches were motivation, skill and ability of the personnel in the organization. Azadeh et al. (2011) assessed efficiency of the personnel by merging DEA, ANN and RST techniques. This article included 6 stages which help the managers make more effective decisions and identify critical characteristics of the personnel which have considerable effect on increase of the entire efficiency of the organization. In this article, effect of efficient characteristics of the personnel on efficiency of the organization is studied through DEA ‹ANN ‹ RST. Stages of execution of this research are as follows:

- *Calculating efficiency of DMUs with DEA*
- *Determining a set of personnel's characteristics through RST*
- *Calculating performance of ANN for each set with CVTT*
- *Selecting the best set with ANN results through DEA*
- *Predicting efficiency of DMUs by selecting the best set through ANN*

Results of this set help the managers make useful and suitable system for predicting efficiency of DMUs. Capaldo and Zollo (2001) assess efficiency of the personnel in an Italian private company which included 850 personnel. They performed this work with fuzzy logic.

Research methodology

Idea of combination of neural networks and DEA was raised for the first time by Athanassopoulos and Curram (1996). They compared DEA with ANNs and the results of simulation showed that DEA acts better in measurement of goals than ANNs act and ANNs are similar to DEA in ranking of units on the basis of efficiency point. In 1997, efficiency of subway in London was analyzed with time series data and the result showed that results of ANNs with Corrected Ordinary Least Sequels (COLS) and DEA are similar to each other (Costa and Markellos, 1997;Fleissig, Kastens and Terrell ,2000) estimated cost functions with use of neural networks. They also showed that there are convergence problems in some techniques which are solved in ANN. In 2004, Santin used a neural network for simulation of nonlinear production function and compared its results with common methods such as random borders and DEA with different observations and turbulence and showed that neural networks have more stability in comparison to the above methods (Santin et al, 2004). This research tries to use combination of neural networks and DEA in measurement of the personnel's efficiency.

There are two competitive samples in efficiency analysis. The first sample uses mathematical planning techniques or data envelope analysis (DEA) which is in the field of operational research (OR). Other samples are regression approach or SFF which is widely applied in economic fields. Each one of these two methodologies has specifications which have been discussed as follows (Ajali, 2009). In main study of DEA done by Charnes et al (CCR), DEA method has been regarded as mathematical planning model which allows experimental estimation method (impractical ,experimental) from efficient production procedures (levels). Instead of trying to make regression compatible through observational data center, DEA is directed to linear level which is upper envelope of the observational data set. Relative efficiency is provided with another data point which is analyzed through mathematical planning. In comparison to SFF approach, DEA doesn't need any assumption in applied forms (functional) regarding concavity of border functions. Main challenge in DEA is that if statistical turbulence penetrates into data, the calculated borders may divert with DEA (Wang, 2003). For example, it is natural in definite prediction to assume that prediction function will have uniform characteristics. For example, personal demand has increased with income in the financial prediction models. In laser and transportation industries, price of the perishable goods such as chambers and aircraft position increase uniformly with demand of the consumer (Celebi , Bayrraktar, 2007).

ANN is a general nonlinear prediction method and has specified advantages on the basis of nonparametric approach that no hypothesis about probable distribution or structures of product function is needed. Hypotheses of using this method are global hypotheses of the efficiency borders. It means that efficiency border is concavity. External diversion in data has a unilateral distribution and internal diversion in data has bilateral distribution. In fact, that method can specify lot of information about indefinite state internal and external diversion for decision making (Wang, 2003).

- **Data envelope analysis**

DEA model is a nonparametric and nonlinear model which is used for measuring efficiency of the manufacturing units. Pendharkar and Rodger (2003) declare that DEA estimates are much better and stronger than parametrical models which consider definite structure such as forms of functions or square forms. For each decision making unit, consider DEA of the moist desirable set of weights. It means the set of weights which maximizes efficiency ratio of the decision making units without increase of efficiency ratio of other decision making units. On the other hand, DEA helps the deciders classify decision making units into two efficient and inefficient units. DEA is a powerful tool which has been used considerably for assessing function of the systems with some inputs and outputs (Jahanshaloo et al, 2008). Two decades before, DEA is a common methodology for assessing decision making units (DMUs) with similar specifications (Sun , Lu, 2005).

Generally, data envelope analysis models are classified into two (input oriented) and (output oriented) groups. Input oriented models are the models which used the fewer inputs in order to obtain the same output without any change in outputs and output oriented models are the ones which obtain more outputs without ant change (Neto and Lins, 2004). In another classification, DEA models are classified into two groups of multiplicative models and envelope models. In DEA, outputs balanced set to inputs balanced set ration is used.

Primary fractional Model1 CCR is used for assessing efficiency of n decision making unit (DMU_t) ، (j=1,…, n) each having m input and s output. θ_t و ، u_r ، v_i are given weights. In order to perform remainder of calculations, fractional planning model is used which is found in model no. 2.

$$\begin{aligned} & Max \quad \theta = \frac{\sum_{r=1}^{s} u_r y_{rt}}{\sum_{i=1}^{m} v_i x_{it}} \\ & s.t: \\ & \frac{\sum_{r=1}^{s} u_r y_{rt}}{\sum_{i=1}^{m} v_i x_{it}} \le 1 \qquad j = 1,\dots,n \quad r = 1,\dots,s \\ & u_r, v_i \ge 0 \qquad i = 1,\dots,m \quad r = 1,\dots,s \end{aligned} \tag{1}$$

$$\begin{aligned} & Max \quad \theta = \sum_{r=1}^{s} u_r y_{rt} \\ & s.t: \\ & \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \qquad j = 1,\dots,n \\ & \sum_{i=1}^{m} v_i x_{ij} = 1 \\ & u_r, v_i \ge 0 \qquad i = 1,\dots,m \quad r = 1,\dots,s \end{aligned} \tag{2}$$

Output oriented CCR model obtains efficiency in order to maximize outputs when inputs are fixed. Model no. 3 is the secondary LP for output oriented CCR (Azadeh et al, 2011a)

$$\begin{aligned} & Max \quad \theta \\ & s.t: \\ & x_{it} \ge \sum_{j=1}^{n} \lambda_j x_{ij} \qquad i = 1,\dots,m \\ & \theta \; y_{rt} \ge \sum_{j=1}^{n} \lambda_j x_{rj} \qquad r = 1,\dots,s \\ & \lambda_j \ge 0 \end{aligned} \tag{3}$$

Charnes, Cooper, Rohdes achieved an experimental relation for making data envelope analysis model indicating the number of assessed units and number of inputs and outputs as follows:

((Outputs) +inputs) 3≤ (DMUs), the number of assessed units

Failure to apply causes many units on the envelopment model and it will obtain efficiency point 1 on the other hand. Therefore, ability to separate model is decreased. Since a constraint should be written for each unit , linear planning model will be obtained and the number of constraints is more than the number of its variables and since volume of operations for solving simplex depends more on the number of constraints than variables, therefore, solving the secondary problem requires less operations volume. Banker, Charnes, and Cooper (1984) use BCC model in order to estimate efficiency of the decision making units (DMUs) with variable return relative to scale that is outputs changes rate is not consistent with inputs changes rate. Therefore, we can say that CCR models are a special type of BCC models (Toloo , Sohrabi, Nalchigar, 2009).

Reasons for use of output-oriented CCR model instead of BBC model in this research are the BCC model not only doesn’t solve problem of DMUs, but also introduces more units in comparison to CCR model, therefore, the available problem will be worsened. Since input-oriented models try to fix outputs, it is evident that the present research tries to increase outputs as main priority. Most organizations don’t intend to reduce inputs and try t fix the input and increase more outputs and CCR models are among the fixed return models relative to the scale. It is suitable when all units act in optimal scale. In the present research, result showed that ratio of outputs to inputs changes follows fixed value; therefore, CCR model has been used.

- **Artificial neural networks**

Artificial network is the network which has been created out of connection of some factors to each other. In order to prepare these factors, biological study of neural systems of living creatures especially human being have been used. On the other hand, neural networks try to make machines which act similarly to human brain. Some components are used to make these machines which are similar to biological neurons. Function of a neural network is such that when an input model is defined for it, it should be able to produce an output model (Toloie and Radfar, 2008). Power of an ANN depends on adjustment of its weights and procedure of adjusting weights which are specified on the basis of training data is called network training. ANN can be given with supervision and without supervision. Only difference between Supervised Learning and Unsupervised Learning are in that the former includes comparison of desirable outputs with real outputs while the later includes giving desirable outputs (target) to the network so that ANN can adjust the weights in such a manner that outputs of the network conform to desirable outputs. In supervised training stage, data is paired with desirable outputs of the network. After passing training stage, ANN is tested only by giving input values to the network. Output values obtained from output layer are compared with desirable output values and difference between them is called output error. The essential belief in training stage is that network adjusts the weights in such a manner that it learns the available models between data of the test group. This stage starts with allocating random weights to each one of the relations between neuron, and unseen layer and outputs layer values are determined with input feeding in the system. If output gets close to desirable output (target), process will stop (Iskandar, 2005). Trained network is able to generalize unseen data. In any way, if the network is not able to do this work, weights will be readjusted and this stage will continue until output gets close to desirable output (target). Since there are unseen layers in an ANN, algorithm for monolayer PERCEPTRON will not be successful. Solution of this problem is use of Back Propagation learning algorithm (BP) (Zirili, 1997). Instead of error propagation of correcting values of weights, errors are fed into the network in reverse route. Multilayer PERCEPTRON networks with Back Propagation learning are considered as an example of standard networks for prediction modeling. Multilayer PERCEPTRON networks with Back Propagation learning uses two main routes. The first route is called departure route in which input vector route is applied to MLP network and its effects are propagated through middle layers (unseen) to the output layers. Output vectors formed in output layer make real response of MLP network. In this route, parameters of the network are fixed and are considered uncharged. The second route is return route. In this route, parameters of MLP network are changed and adjusted. This adjustment is done according to error correction law. Error signal is formed in network output layer. Error vector equals to difference between desirable response and real response of the network. Error value is distributed in the entire network after calculation in return route from output layer and through network layers. Because this later distribution is opposite to synapses communication route, the word back propagation has been selected for explaining behavioral correction of the network. Network parameters are selected in such a manner that real response gets closer to the desirable route (Poorzaker Arabani, 2006).

A perfect cycle of calculation includes completing all forward and reverse routes of the training vectors and this cycle is named epoch. Therefore, number of epoch will equal to frequency of feeding training data to the network. When other variables are fixed, the number of epoch can be regarded as criterion for training. Transfer function (stimulus) used in unseen layers should be nonlinear so that it can identify nonlinear relations between data. Without use of such functions, the network is like a simple Perceptron which follows linear relations. But this is nonlinear structure of ANN which strengthens multilayer networks (Iskandar, 2005). Standard BP algorithm which is used for ANN training is based on the maximum descending gradient which is used for minimizing cost function (network weights function) (Azoff, 1994). LM algorithm has high speed of convergence like quasi-Newton algorithms because there is no need for calculation of Hessian matrix and it is approximated with Jacobin matrix. It is necessary to note that when Jacobin matrix has large dimensions, some problems such as calculation problems will occur, however, there are methods on which basis there is no need for calculation of all Jacobin matrix elements. In MATLAB, *trainlm* function is one of the applied learning functions which have been developed on the basis of LM learning (Farasat, 2007). After data preprocessing, another important problem which should be considered is normalization of data. Different scales in different variables will affect final results in different aspects. For this purpose, all data should be normalized and transformed. In order to standardize effect of each variable on result, numerical variables should be normalized. There are different methods for normalizing data. We can arrange data in each desirable interval with use of the above method. This is done as follows (Farasat, 2007):

$$X^* = mX_i + b$$

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

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

In this relation, X is normalized variable and X is main variable. In this research, four scales of MSE ،MAD ،Bias and Tracking Signal were used in order to compare and estimate network training trend (Ghaffari, 2011).

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

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

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

$$TrackingSignal = \frac{Bias}{MAD}$$

MSE shows error between target and output. Bias value if positive or negative will show upper estimate and under estimate of the model. Tracking Signal expresses prediction trend in terms of percentage and this scale can contribute to prediction.

Presented model algorithm

- **Presented model**

The present research includes two stages for assessing efficiency of the personnel. The first stage is calculation of unit's efficiency with DEA method (output oriented CCR model) and stage of model identification and prediction of model with neural networks. This model helps optimize the personnel in order to increase outputs with desirable inputs with human resources approach. Neuro/DEA model diagram is found in figure 1. The first stage is identification of the variables which have considerable effect on efficiency of the personnel. With regard to the present research, three input variables and four output variables were identified on the basis of human resources approach, broad studies on the previous articles and consultation with experts of this field.

- **data analysis**

After identification of variables, quality variables with semi-metric spectrum were converted to quantity ones with use of standard questionnaire. The gathered data for 67 personnel is shown in table 1. In order to determine data reliability, SPSS software and Konbach alpha scale were used and α value 0.925 was obtained which indicates high reliability of data and questionnaire.

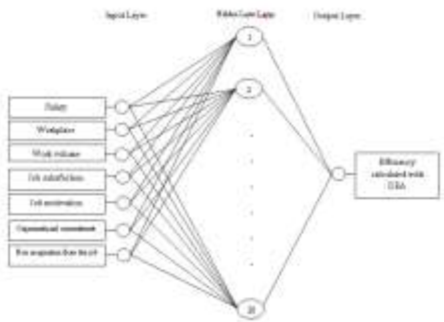

Figure 1: Neuro/DEAModel

- **DEA results**

In order to calculate efficiency, assess performance and rank the units, output oriented CCR model with DEA approach was used. For this purpose, EMS software was used. This software is able to rank efficient units in addition to classification of the inefficient and efficient units so that it shows efficiency of the efficient units well. Final results are seen in table 2. This table shows the obtained weights slacks of input and output variables as well as Benchmarks units. In this regard, the numbers shown in this column indicate inefficient units, efficient units which have been used as Benchmarks as well as efficient units, the frequency which has been used for inefficient units as benchmarks.

- **Results of Neuro/DEA combined model**

In this research, the use d network is three-layered PERCEPOTRON of which input neurons are based on the number of inputs and outputs of DEA. Output layer in this network has one neuron which shows efficiency calculated with DEA. The number of hidden layer neurons was calculated with use of trial and error method. Accurate number of middle layer neurons is not easy to determine and depends on nature of the problem. In order to determine middle layer neurons, an upper bound of the neuron number (30 neurons) was used and error of network was observed with decrease of neurons to specify the desirable neuron number. With decrease of neuron, error of the network was reduced until error of network was increased resulting from some neurons ($n=n_1$) with decrease of neuron and n_1 was considered as n^{*}. In this topology, all functions of hidden layer are *tan-sigmoid* transfer function or *tansig*. Output function is Positive linear transfer function or *poslin*. Linearization of output layer means creation of a one-to-one mapping between input and output of the last layer neuron which shows efficiency which is larger than 0. Table 3 shows parameters of neural network structure designed in software MATLAB.

In order to achieve desirable results, we normalized data from the minimum and maximum data method and their range was obtained to be between [0, 1] to increase speed of convergence of the network and access to optimal answer. In such way, we show difference between variables and learn neural networks with binary and bipolar variables. The normalized data is given in table 4.

○ **Neuro/DEA1 algorithm**

Goal of network training is to adjust weights so that desirable cluster of outputs can be produced with use of a cluster of inputs. Training stages of this network with BP algorithm are as follows:

✓ *We divide input vector into three classes of learning, test and training vectors. In this network, this data was classified with use of divider and function with the software.*
✓ *Calculating output of the network*
✓ *Repeating steps 1 to 3 so that error of network can be reduced acceptably.*

○ **Neuro/DEA2 model algorithm**

This model was trained like the second model with similar hypotheses with this difference that 67 times of network training were used of which executive steps are as follows:

✓ *Selecting vector (personnel) n for test and the rest of vectors i.e. 66 personnel for training and learning by determining valRatio = 25% ‹(n=1,2,...,67)*
✓ *Designed network training*
✓ *Personnel n efficiency simulation*
✓ Repeating steps 1 to 3 by changing input vector to n+1

○ comparing results of two Neuro/DEA models with DEA

After training two designed models units efficiency simulation, they were ranked of which results are shown in table 5.

Results

- **top model selection**

In order to compare two presented models and select the top model, different scales are used according to table 6. Results of Neuro/DEA2 model indicate its improvement compared to the first model. Generally, we can conclude from comparison of two models that the second designed model (Neuro/DEA2) can be implemented for assessing the organizations which have fewer decision making units because the number of test and training units may be reduced for training the networks with few samples and may not show result of the test data simulation .

As observed in table 6, Bias rate in the second model indicates its upper estimate due to its positivity that is this model (Neuro/DEA 2) shows higher efficiency than target values (DEA). Tracking Signal value shows prediction trend for 17% more than the target value (DEA).

Conclusion

In this research, case study of training personnel efficiency assessment in Islamic Azad University, Tehran Sciences and Research Branch was considered and basic models of DEA is not able to analyze and predict efficiency alone , therefore, neural networks were used. Research results showed that neural networks are able to learn efficiency models. But it is necessary to note that the network should be trained properly. One can apply neural networks and its combination with DEA in case those basic models don't have ability to separate and distinguish units. In comparison with mathematical and combined methods of efficiency analysis, neural networks presented acceptable results. Two models were used for training input data. The second model (Neuro/DEA2) was recognized as top model for assessing the organizations which have few decision making units in order to minimize error because the number of test and training units is reduced in order to train the networks with few samples and may not show test data simulation result well. For this reason, this approach can be executed in order to rank the units finally, analyze and assess the personnel and a model for prediction of units for future data in the similar organizations.

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Table 1: Inputs and outputs of model

DMU name	Salary (I1)	Workplace)I2(	Work volume) I3(	Job satisfaction)O1(	Job motivation)O2(	Organizational commitment) O3 (	Non resignation from job (O4)
1	4000000	40	25	40.43	35	45	86.67
2	4700000	69	5	50.7	38.88	41.8	5.33
3	4280000	1.5	1.5	29.96	41.25	20	1.5
4	7000000	65	40	54.79	72.5	82	96.67
5	4670000	60	10	30	23.75	51	73.33
6	4500000	65	20	34.48	19.13	18.8	9

7	6800000	55	70	46.09	58.75	54	90
8	4000000	90	95	36.96	41.25	37	63.33
9	3800000	70	75	56.09	46.25	16	50
10	4200000	1.5	95	15.65	33.75	8	3.33
11	6500000	50	10	58.04	70	84	90
12	7000000	60	50	53.04	70	68	60
13	6600000	55	5	41.3	65	63	100
14	5100000	10	1.5	28.7	63.75	66	80
15	5000000	25	1.5	21.43	36.63	16	1.5
16	5300000	90	50	20.26	42.5	52.6	60
17	5500000	95	50	32.17	35.88	45.8	63.33
18	4000000	45	65	54.78	45	55.8	50
19	5000000	85	25	39.35	13.75	38	43.33
20	5000000	40	15	40.43	51.25	39	70
21	4000000	30	25	38.04	52.5	42	86.67
22	6100000	49.5	70.5	46.3	53.25	18.2	4.67
23	6200000	45	25	20.43	14.38	10	16.67
24	6000000	56.5	50	18.26	31.25	15	46.67
25	5000000	50.5	40.5	28.7	35.75	53.7	50.33
26	5800000	1.5	36	7.52	18.75	14.1	1.5
27	5300000	35	2.5	25.21	32.5	4	20
28	4500000	73.5	85	34.7	40.13	58	56.67
29	5000000	51	40	52.52	51.13	64.3	74.67
30	4500000	40	5	15.65	6.25	12	1.5
31	6300000	40	20	32.17	50	37	20
32	6000000	39	27.5	32.96	42.13	39	25
33	4750000	82	55	44.61	36	67.6	71
34	5000000	50	15	46.83	39.25	57.3	79.33
35	5200000	35	15	44.22	35.63	42.9	66.67
36	4900000	1.5	1.5	13.04	12.5	60	33.33
37	4900000	57.5	2.5	30.43	43.75	57	90
38	4550000	45	25	39.78	40	46	81.67
39	4650000	65	10	50.91	39.25	40.9	10
40	4270000	10	7.5	27.87	42.25	20.8	10
41	7100000	57.5	37.5	53.17	70.25	76.8	95
42	4670000	60	13.5	32.48	28.38	51.2	67
43	6770000	55	31	35.78	20.88	18	5.33
44	6400000	60.5	65	47.22	56.88	54.6	90
45	4300000	90	98	38.52	41.63	36.8	60.67
46	3900000	75	75	55.09	49.38	19.3	53.67
47	4100000	11	94.5	20.52	42.5	11.6	11
48	6400000	49.5	7	56.26	66.25	81.5	85

49	6900000	61	51	52.26	71.63	66	60
50	5300000	55	7.5	41.09	66	63.1	93.33
51	5100000	15	7.5	31.09	62.63	65.9	76.67
52	5450000	20	1.5	21.43	36.63	16	1.5
53	5600000	96.5	60	21.35	45.25	53.2	53.33
54	5550000	96.5	55.5	32.43	34.88	46.8	60.67
55	4800000	49.5	58.5	53.35	46.38	54.4	53.33
56	5900000	87	19	41.74	15.25	40.4	42.67
57	6700000	21	12	41.65	53.63	38.1	65.33
58	4400000	23	28.5	36.74	54	40.9	89.33
59	4800000	57	69.5	45.61	51.5	20.1	9.67
60	6200000	50	29	23.39	15.38	11	18.33
61	6000000	58	56.5	20.26	35.5	18.1	42
62	5700000	52.5	39.5	30.04	36	52.7	47.67
63	5800000	1.5	32	9.22	19.38	16	1.5
64	5370000	42	2.5	25.91	31.25	9.1	18.67
65	4600000	74	84.5	34.09	39.75	57.8	57.67
66	6900000	51	49	52.65	51.38	61.8	71.33
67	5200000	37.5	12	19.26	7.5	13.6	3.33

Table 2: Calculation of unit's efficiency

DMU name	score	the weights (virtual inputs/outputs)							slacks							Benchmarks
		I1	I2	I3	O1	O2	O3	O4	I1	I2	I3	O1	O2	O3	O4	
1	1.0478	0.8	0	0.1	0.6	0	0.2	0.3	-	-	-	-	-	-	-	-
2	1.2373	0.6	0	0.2	1	0	0	0	-	-	-	-	-	-	-	-
3	3.4083	0.1	0.2	0	0	1	0	0	-	-	-	-	-	-	-	-
4	0.8986	1.1	0	0	0.1	0.1	0.6	0.2	0	22	0	0	0	0	0	33,18,14,11,1
5	0.8883	1.1	0	0	0.1	0	0.6	0.4	0	34	0	0	27	0	0	50,37,14,1
6	0.6685	1.3	0.1	0.1	1	0	0	0	0	0	0	0	12	14	2.5	2, 9,18
7	0.6902	1.5	0	0	0	0.1	0.5	0.3	0	1	19	0	0	0	0	33,21,18,14
8	0.8425	1.2	0	0	0.5	0.1	0.1	0.4	0	52	56	0	0	0	0	21,18,9,1
9	1.0482	0.9	0.1	0	1	0	0	0	-	-	-	-	-	-	-	-
10	0.8781	0.7	0.5	0	0	0.9	0	0.1	0	0	94	10	0	13	0	3,14,36
11	1.018	0.9	0	0	0.3	0.4	0.3	0	-	-	-	-	-	-	-	-
12	0.8026	1.3	0	0	0.1	0.7	0.3	0	0	12	0.6	0	0	0	48	21,18,14

13	0.9112	0.9	0.1	0.1	0.5	0	0	0.5	0	0	0	0	0	11	0	50,48,37,14
14	2.6695	0	0.1	0.3	0	0.5	0	0.5	-	-	-	-	-	-	-	-
15	0.7276	0	0	1.4	0.9	0.1	0	0	38872	20	0	0	0	17	31	14,3
16	0.7401	1.4	0	0	0	0.1	0.7	0.2	0	51	25	11	0	0	0	33,18,14
17	0.6546	1.5	0	0	0	0.1	0.6	0.3	0	25	0.7	1.8	0	0	0	33,21,14
18	1.224	0.8	0.1	0	0.7	0	0.3	0	-	-	-	-	-	-	-	-
19	0.7313	1.2	0	0.2	0.9	0	0	0.1	0	24	0	0	25	0	0	18,9,2,1
20	0.8887	1	0	0.1	0.5	0.5	0	0	0	0	0	0	0	16	2	50,21,11,2
21	1.0961	0.8	0	0.1	0.4	0.3	0	0.3	-	-	-	-	-	-	-	-
22	0.7132	1	0.4	0	0.5	0.5	0	0	0	0	16	0	0	42	97	3,18, 21
23	0.3437	2	0.6	0.3	1	0	0	0	0	0	0	0	21	33	0	39,18,11,3
24	0.3968	2.5	0	0	0	1	0	0	0	12	13	11	0	25	12	21
25	0.7855	1.2	0.1	0	0	0	1	0	0	0	0	7.3	5.6	0	9.7	33,18,14
26	0.5193	0	1.9	0	0	0.7	0.4	0	140912	0	35	12	0	0	4.3	3,36
27	0.6538	1	0	0.5	1	0	0	0.1	0	15	0	0	5.2	38	0	2,3,14
28	0.9188	1.1	0	0	0	0.1	0.7	0.2	0	13	24	14	0	0	0	33-18-14
29	0.9876	1	0	0.1	0.1	0.1	0.6	0.2	0	2	0	0	0	0	0	33-18-14-11-1
30	0.3715	2	0.6	0.1	1	0	0	0	0	0	0	0	23	0.2	1.1	2,3,39
31	0.634	1.3	0.1	0.2	0.4	0.6	0	0	0	0	0	0	0	16	84	50,21,14,11
32	0.6014	1.2	0.3	0.1	0.6	0.3	0.1	0	0	0	0	0	0	0	47	21,18,14,11,3
33	1.0579	0.9	0	0	0	0	0.8	0.2	-	-	-	-	-	-	-	-
34	1.0003	0.9	0	0.1	0.8	0	0	0.2	-	-	-	-	-	-	-	-
35	0.9504	0.7	0.2	0.1	0.9	0	0	0.1	0	0	0	0	20	13	0	21,18,11,3
36	4.2937	0	0.2	0	0	0	0.7	0.4	-	-	-	-	-	-	-	-
37	1.1439	0.8	0	0.1	0	0	0	1	-	-	-	-	-	-	-	-
38	0.8893	1	0	0.1	0.7	0.1	0.1	0.1	0	3.1	0	0	0	0	0	21,18,11,2,1
39	1.0065	0.6	0.3	0.1	1	0	0	0	-	-	-	-	-	-	-	-
40	0.8955	1	0.1	0	0.4	0.6	0	0	0	0	0.2	0	0	10	25	3,14,21
41	0.8465	1.1	0	0	0.1	0.1	0.6	0.2	0	4.1	0	0	0	0	0	50,18,14,11,1
42	0.8692	1.1	0	0	0.1	0	0.7	0.2	0	29	0	0	17	0	0	33,14,11,1
43	0.5266	1.3	0.4	0.2	1	0	0	0	0	0	0	0	25	22	15	3,18,39
44	0.7348	1.4	0	0	0	0.1	0.5	0.3	0	1.8	12	0	0	0	0	33,21,18,14
45	0.7868	1.3	0	0	0.5	0.1	0.1	0.4	0	47	52	0	0	0	0	21,18,9,1
46	1.0252	1	0	0	0.2	0.8	0	0	-	-	-	-	-	-	-	-
47	0.8239	1.2	0	0	0	1	0	0	0	0	90	0.2	0	38	54	21,14
48	1.0637	0.7	0	0.2	0.8	0	0	0.2	-	-	-	-	-	-	-	-
49	0.8198	1.2	0	0	0.1	0.7	0.3	0	0	14	6.7	0	0	0	56	21,18,14
50	1.0819	0.9	0	0.1	0.3	0.3	0	0.4	-	-	-	-	-	-	-	-
51	0.9925	1	0	0	0	0.1	0.9	0	0	1.1	0	0.3	0	0	1.6	33,18,14
52	0.7276	0	0	1.4	0.9	0.1	0	0	83872	15	0	0	0	17	31	3,14
53	0.6978	1.4	0	0	0	0.1	0.7	0.2	0	50	0.1	30	0	0	0	33,18,14
54	0.6468	1.6	0	0	0	0.1	0.6	0.3	0	26	6.4	0	0	0	0	33,21,18,14
55	0.8963	0.6	0.2	0.3	1	0	0	0	0	0	0	0	1.3	3.9	0	39,18,11,3
56	0.6833	1.3	0	0.2	0.9	0	0	0.1	0	14	0	0	27	0.4	0	1,2,34

57	0.8532	0.9	0.2	0.1	0.8	0	0	0.2	0	0	0	0	14	18	0	21,14,11,3
58	1.0566	0.7	0.3	0	0	0	0	1	-	-	-	-	-	-	-	-
59	0.834	1.1	0.1	0	0.3	0.7	0	0	0	0	15	0	0	15	77	9,21,46
60	0.3787	1.8	0.5	0.3	1	0	0	0	0	0	0	0	22	35	0	39,18,11,3
61	0.4508	2.2	0	0	0	1	0	0	0	13	19	12	0	23	37	21
62	0.6806	1.4	0.1	0	0	0	1	0	0	0	0	2.8	6.5	0	15	33,18,14
63	0.5552	0	1.8	0	0	0.6	0.4	0	138327	0	31	9.6	0	0	5.8	3,36
64	0.6629	1	0	0.5	1	0	0	0.1	0	23	0	0	8	29	0	2,3,14
65	0.8981	1.1	0	0	0	0.1	0.7	0.2	0	13	27	12	0	0	0	33,18,14
66	0.7584	0.8	0.4	0.2	0.8	0	0.1	0.1	0	0	0	0	11	0	0	21,18,14,11,3
67	0.4006	1.8	0.5	0.2	1	0	0	0	0	0	0	0	29	3.4	2.3	3,18,39

Table 3: Parameters of designed network structure

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*

Table 4: Normalized inputs and outputs

DMU name	Salary (I1)	Workplace)I2(	Work volume)I3(	Job satisfaction)O1(	Job motivation)O2(	Organizational commitment)O3 (	Non resignation from job (O4)
2	0.272727	0.710526	0.036269	0.854711	0.492528	0.4725	0.038883
3	0.145455	0	0	0.444181	0.528302	0.2	0
4	0.969697	0.668421	0.398964	0.935669	1	0.975	0.966193
5	0.263636	0.615789	0.088083	0.444972	0.264151	0.5875	0.729239
6	0.212121	0.668421	0.19171	0.53365	0.194415	0.185	0.076142
7	0.909091	0.563158	0.709845	0.76346	0.792453	0.625	0.898477
8	0.060606	0.931579	0.968912	0.58274	0.528302	0.4125	0.627716
9	0	0.721053	0.761658	0.961401	0.603774	0.15	0.492386
10	0.121212	0	0.968912	0.160926	0.415094	0.05	0.018579
11	0.818182	0.510526	0.088083	1	0.962264	1	0.898477
12	0.969697	0.615789	0.502591	0.901029	0.962264	0.8	0.593909
13	0.848485	0.563158	0.036269	0.668646	0.886792	0.7375	1
14	0.393939	0.089474	0	0.41924	0.867925	0.775	0.796954
15	0.363636	0.247368	0	0.275337	0.458566	0.15	0
16	0.454545	0.931579	0.502591	0.252177	0.54717	0.6075	0.593909
17	0.515152	0.984211	0.502591	0.487926	0.447245	0.5225	0.627716
18	0.060606	0.457895	0.658031	0.935471	0.584906	0.6475	0.492386
19	0.363636	0.878947	0.243523	0.630048	0.113208	0.425	0.42467
20	0.363636	0.405263	0.139896	0.651425	0.679245	0.4375	0.695431
21	0.060606	0.3	0.243523	0.604117	0.698113	0.475	0.86467
22	0.69697	0.505263	0.715026	0.767617	0.709434	0.1775	0.032183
23	0.727273	0.457895	0.243523	0.255542	0.122717	0.075	0.15401

24	0.666667	0.578947	0.502591	0.212589	0.377358	0.1375	0.458579
25	0.363636	0.515789	0.404145	0.41924	0.445283	0.62125	0.495736
26	0.606061	0	0.357513	0	0.188679	0.12625	0
27	0.454545	0.352632	0.010363	0.350158	0.396226	0	0.187817
28	0.212121	0.757895	0.865285	0.538005	0.511396	0.675	0.560102
29	0.363636	0.521053	0.398964	0.890736	0.677434	0.75375	0.742843
30	0.212121	0.405263	0.036269	0.160926	0	0.1	0
31	0.757576	0.405263	0.19171	0.487926	0.660377	0.4125	0.187817
32	0.666667	0.394737	0.26943	0.503563	0.541585	0.4375	0.238579
33	0.287879	0.847368	0.554404	0.734165	0.449057	0.795	0.705584
34	0.363636	0.510526	0.139896	0.778108	0.498113	0.66625	0.790152
35	0.424242	0.352632	0.139896	0.726445	0.443472	0.48625	0.661624
36	0.333333	0	0	0.109264	0.09434	0.7	0.323147
37	0.333333	0.589474	0.010363	0.453484	0.566038	0.6625	0.898477
38	0.227273	0.457895	0.243523	0.638559	0.509434	0.525	0.813909
39	0.257576	0.668421	0.088083	0.858868	0.498113	0.46125	0.086294
40	0.142424	0.089474	0.062176	0.402811	0.543396	0.21	0.086294
41	1	0.589474	0.373057	0.903603	0.966038	0.91	0.949239
42	0.263636	0.615789	0.124352	0.494062	0.334038	0.59	0.664975
43	0.9	0.563158	0.305699	0.559382	0.22083	0.175	0.038883
44	0.787879	0.621053	0.658031	0.785827	0.764226	0.6325	0.898477
45	0.151515	0.931579	1	0.613618	0.534038	0.41	0.600711
46	0.030303	0.773684	0.761658	0.941607	0.651019	0.19125	0.529645
47	0.090909	0.1	0.963731	0.257324	0.54717	0.095	0.096447
48	0.787879	0.505263	0.056995	0.964766	0.90566	0.96875	0.847716
49	0.939394	0.626316	0.512953	0.88559	0.986868	0.775	0.593909
50	0.454545	0.563158	0.062176	0.664489	0.901887	0.73875	0.932284
51	0.393939	0.142105	0.062176	0.466548	0.851019	0.77375	0.763147
52	0.5	0.194737	0	0.275337	0.458566	0.15	0
53	0.545455	1	0.606218	0.273753	0.588679	0.615	0.526193
54	0.530303	1	0.559585	0.493072	0.432151	0.535	0.600711
55	0.30303	0.505263	0.590674	0.907165	0.605736	0.63	0.526193
56	0.636364	0.9	0.181347	0.677356	0.135849	0.455	0.41797
57	0.878788	0.205263	0.108808	0.675574	0.71517	0.42625	0.64802
58	0.181818	0.226316	0.279793	0.578385	0.720755	0.46125	0.891675
59	0.30303	0.584211	0.704663	0.753959	0.683019	0.20125	0.082944
60	0.727273	0.510526	0.284974	0.314133	0.137811	0.0875	0.170863
61	0.666667	0.594737	0.569948	0.252177	0.441509	0.17625	0.411168
62	0.575758	0.536842	0.393782	0.445764	0.449057	0.60875	0.468731
63	0.606061	0	0.316062	0.03365	0.198189	0.15	0
64	0.475758	0.426316	0.010363	0.364014	0.377358	0.06375	0.174315
65	0.242424	0.763158	0.860104	0.52593	0.50566	0.6725	0.570254
66	0.939394	0.521053	0.492228	0.89331	0.681208	0.7225	0.708934
67	0.424242	0.378947	0.108808	0.232383	0.018868	0.12	0.018579

Table 5: Results of three approaches calculations

DMU name	DEA		Neuro/DEA 1		Neuro/DEA 2	
	score	ranking	score	ranking	score	ranking
1	1.0478	13	1.0397	11	1.0572	11
2	1.2373	4	1.1104	8	1.519	4
3	3.4083	2	3.3564	2	3.2145	2
4	0.8986	23	0.7486	43	0.9199	25
5	0.8883	29	0.9067	24	0.7729	40
6	0.6685	52	0.7694	40	0.7635	41
7	0.6902	49	0.6298	50	0.6959	50
8	0.8425	34	0.8209	31	0.8268	36
9	1.0482	12	0.9683	16	1.0347	14
10	0.8781	30	0.7963	35	0.8843	31
11	1.018	15	0.9609	17	1.0007	18
12	0.8026	38	0.7792	37	0.8592	33
13	0.9112	22	0.9367	20	0.9325	20
14	2.6695	3	2.4181	3	2.3061	3
15	0.7276	45	0.6686	47	0.6723	52
16	0.7401	42	0.8209	32	0.8296	35
17	0.6546	54	0.6815	45	0.6393	56
18	1.224	5	1.3164	5	1.4402	5
19	0.7313	44	0.7223	44	0.7321	45
20	0.8887	28	0.9186	22	0.9238	22
21	1.0961	7	1.1331	7	1.2057	8
22	0.7132	47	0.5573	57	0.7491	43
23	0.3437	67	0.2681	67	0.2077	67
24	0.3968	64	0.3418	65	0.3547	65
25	0.7855	40	0.7585	42	0.7757	39
26	0.5193	61	0.4994	61	0.5784	61
27	0.6538	55	0.5876	54	0.6589	55
28	0.9188	21	0.8684	27	0.9216	23
29	0.9876	19	0.9768	14	0.9343	19
30	0.3715	66	0.5842	55	0.4578	63
31	0.634	57	0.5899	53	0.6762	51
32	0.6014	58	0.5273	59	0.6239	58
33	1.0579	10	1.0817	9	1.0591	10
34	1.0003	17	0.9544	18	1.0124	16
35	0.9504	20	0.9125	23	0.9082	28
36	4.2937	1	4.2241	1	4.1004	1
37	1.1439	6	1.1656	6	1.3534	6
38	0.8893	27	0.8673	28	0.9136	26
39	1.0065	16	0.9361	21	1.0566	12
40	0.8955	26	0.858	29	0.8868	30
41	0.8465	33	0.8049	34	0.8636	32
42	0.8692	31	0.8765	26	0.8876	29

43	0.5266	60	0.5023	60	0.6055	59
44	0.7348	43	0.6757	46	0.719	47
45	0.7868	39	0.7716	38	0.7985	38
46	1.0252	14	0.969	15	1.0045	17
47	0.8239	36	0.5462	58	0.6315	57
48	1.0637	9	0.9911	13	1.1918	9
49	0.8198	37	0.7699	39	0.8208	37
50	1.0819	8	1.0285	12	1.2159	7
51	0.9925	18	1.4092	4	1.0303	15
52	0.7276	46	0.6258	52	0.7547	42
53	0.6978	48	0.762	41	0.6701	53
54	0.6468	56	0.6665	48	0.667	54
55	0.8963	25	0.8786	25	0.9205	24
56	0.6833	50	0.6623	49	0.7051	48
57	0.8532	32	0.9382	19	0.9309	21
58	1.0566	11	1.0737	10	1.0446	13
59	0.834	35	0.583	56	0.8349	34
60	0.3787	65	0.2805	66	0.3363	66
61	0.4508	62	0.3831	63	0.517	62
62	0.6806	51	0.629	51	0.7381	44
63	0.5552	59	0.4816	62	0.5918	60
64	0.6629	53	0.7825	36	0.7003	49
65	0.8981	24	0.8303	30	0.9111	27
66	0.7584	41	0.8056	33	0.731	46
67	0.4006	63	0.3825	64	0.3659	64

Table 6: Comparing two presented models

CRITERION	Neuro/ DEA 1	Neuro/ DEA 2
no. tests	27	67
MSE	0.018	0.009
MAD	0.1	0.06
BIAS	-0.015	0.01
Tracking Signal	-0.15	0.17
$R^2_{\mathrm{Coefficient}}$(scores)	0.94	0.99
$R^2_{\mathrm{Coefficient}}$(ranking)	0.94	0.97