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A Meta heuristic approach for performance assessment of production units

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ABSTRACT

There have been many efficiency frontier analysis methods reported in the literature. However, each of these methodologies has its strength as well as major limitations. This study proposes a Meta heuristic approach based on adaptive neural network (ANN) technique, fuzzy C-means and numerical taxonomy (NT) for measuring efficiency as a complementary tool for the common techniques of the efficiency studies in the previous studies. Homogenous test is done by NT. It is used to determine if the DMUs are homogenous or not. The proposed computational methods are able to find a stochastic frontier based on a set of input–output observational data and do not require explicit assumptions about the functional structure of the stochastic frontier. In this algorithm, for calculating the efficiency scores, a similar approach to za has been used. Moreover, the effect of the return to scale of decision making unit (DMU) on its efficiency is included and the unit used for the correction is selected by notice of its scale (under constant return to scale assumption). Also in non homogenous situation, for increasing DMUs' homogeneousness, fuzzy C-means method is used to cluster DMUs. Two examples using real data are presented for illustrative purposes. Homogenous test result is positive in the first example, which deals with power generation sectors, and is negative in the second example dealing auto industries of various developed countries. Overall, we find that the proposed integrated algorithm based on ANN, fuzzy C-means and numerical taxonomy provides more robust results and identifies more efficient units than the conventional methods since better performance patterns are explored.

1. Introduction

Measuring an organisation's efficiency is about the relationship between the outputs it produces and the inputs it uses. As alternatives to determine the efficiency boundaries, the international experience reports a significant number of methodologies with different approaches and methods to characterize such efficiency (Jamasb & Pollitt, 2001). In rough terms, these methodologies can be classified according to how the frontier is estimated. There are two types of modelling methods of comparative performance. They are the parametric and non-parametric methods. The first include the estimation of both deterministic and stochastic frontier functions (SFF) which is based on the econometric regression theory and has been widely accepted in the econometrics field. The main non-parametric methods include DEA and free disposal hull (FDH) which are based on a mathematical programming approach. Each of these two methodologies has its strength as well as major limitations. In all of these methodologies, the frontier is defined by the most efficient DMU of the sample. Mathematically, the frontier methods are introduced as a high-reliability analysis tool and have been largely used for studies in the electrical field (Pollit, 1995; Sanhueza, Rudnick, & Lagunas, 2004).

The assumptions made for each of these methods are restrictive. Conflicting conclusions of efficiency are often resulted by using the different methods due to the unsuitability of the assumptions. Their frontier sensitive to outliers and will be deterministic. The non-parametric approach makes no assumption about the functional form of the frontier. Instead, it specifies certain assumptions about the underlying technology that in combination with the data set allow the construction of the production set. There have been many efficiency frontier analysis methods reported in the literature (for instance only about power plants Cook & Green, 2005; Golany, Yaakov, & Rybak, 1994; Goto & Tsutsui, 1997; Knittel, 2002; Lam & Shiu, 2001; Olatfubi & Dismukes, 2000; Park & Lesourd, 2000; Sanhueza et al., 2004; Sueyoshi & Goto, 2001).

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The main objective of this paper is to contribute to the use of neural networks in the efficiency measurement. To this end, for estimating production (cost) function, ANN method is applied and for calculating the efficiency scores, a similar approach to econometric methods is used and an algorithm is proposed. Previous studies by (Azadeh, Ghaderi, Anvari, & Saberi, 2006; Azadeh, Ghaderi, Tarverdian, & Saberi, 2006; Azadeh, Ghaderi, Anvari, & Saberi, 2007; Azadeh, Ghaderi, & Sohrabkhani, 2007) show the applicability approach of ANN and ANN-fuzzy C-means in selected power plants. However, this study presents an algorithm which is not only based on ANN-fuzzy C-means but also in this method one of the ANN-fuzzy C-means or ANN algorithm is selected based on the homogeneity of DMUs. In addition ANN-fuzzy C-means which is proposed in previous studies (Azadeh, Ghaderi, Anvari, Saberi, & Izadbakhsh, 2007; Azadeh et al., 2006; Azadeh et al., 2007) is expanded for output oriented models.

The paper is organized as follows. Section 2 provides an introduction to ANNs in efficiency analysis, where Neural Networks form a promising analysis tool together with known econometric models and non-parametric methods. This section concludes with a review of some published papers about ANNs and efficiency. Section 3 is dedicated to ANNs in efficiency analysis and an algorithm is proposed in this section for assessing efficiency of DMUs and a method is proposed to select between them. Two empirical illustrations for measuring performance of power generation in the world and auto industries are carried out in Section 4. The final section of the paper offers conclusions and suggests areas for the future research.

2. Literature review

Artificial neural networks (ANNs) are a promising alternative to econometric models and they are information processing paradigms that are inspired by the way biological nervous systems, such as the brain, process information. ANNs, like people, learn by example. ANNs are configured for specific applications, such as pattern recognition, function approximator, through learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true for ANNs as well. They are made up simple processing units which are linked by weighted connections to form structures that are able to learn relationships between sets of variables.

Among the different networks, the feed forward neural networks or multi layer perceptron (MLP) are the most commonly used in engineering science (Chavarnakul & Enke, 2008; Chen, Tai, Deng, & Hsieh, 2008; Cheng & Titterington, 1994; Coelli, 1995; Deng, Chen, & Pei, 2008; Fleissig, Kastens, & Terrell, 2000; Geman, Bienenstock, & Doursat, 1992; Hornik, Stinchcombe, & White, 1989; Karthikeyan, Gopal, & Venkatesh, 2008; Kose, 2008; Lee, Shih, & Chung, 2008). MLP networks are normally arranged in three layers of neurons, the input layer and output layer represent the input and output variables of the model and between them lay one or more hidden layers which hold the networks ability to learn non-linear relationships. Architecture selection is one major issue with implications on the empirical results and consists of:

1. Input and output variables number.
2. Hidden layers' number and number of units in each layer.
3. Hidden and output activation function.
4. Learning algorithm

All of the above issues are open questions today and there are several answers to each one. The hidden units' number is determined by a trial-error process considering $m = 1, 2, 3, 4\ldots$ (White, 1989). Too few neurons in hidden layers (hidden units) can lead to under fitting. However, too many neurons can cause over fitting. The actual number of neurons required in the hidden layer must be found by trial and error. Moreover, the inputs are used by the network must be effective on the value of output(s), in fact the input and output variables should be identified carefully, because enable the network to learn relationships quicker and use fewer hidden units.

Another critical issue in ANNs is the neural learning or model estimation based upon searching the weights that minimize some cost function such as square error

$$\mathrm{Min}[E(y - f(\mathrm{x},\theta))^2]\theta\epsilon\Theta \tag{1}$$

The most popular learning algorithm is the back proportion (BP). BP learning is a kind of supervised learning introduced by Werbos (1974) and later developed by Rumelhart and McClelland (1986). Desirable output for input set is made by this algorithm. Error in each neuron is the difference between ANN output and real output. The interconnections weight and threshold value in each neuron is adjusted to minimize the error. After neural training (training set), new observations (test sets) are presented to the network to verify the so-called generalization capability (Schiffmann, Joost, & Werner, 1992).

In this study application of ANNs in efficiency analysis is discussed. Within the efficiency literature, few applications have been made in this field. Commonly, neural network technique is used as a complementary tool for parametric and non-parametric methods such as DEA, to fit production functions and measure efficiency under non-linear contexts. In fact, applying ANNs can reduce the restrictive assumptions each of these methods. This heuristic method can be useful for non-linear process that has an unknown functional form (Enders 2004) and There has been a vast literature about ANNs, basically in the empirical field, showed that ANNs comparability or superiority to conventional methods for estimating functions (Azadeh, Ghaderi, Tarverdian, et al., 2006; Azadeh et al., 2007; Azadeh, Ghaderi, Tarverdian, & Sarberi, 2007; Brian Hwarng, 2001; Chiang, Urban, & Baldridge, 1996; Hill, O'Connor, & Remus, 1996; Indro, Jiang, Patuwo, & Zhang, 1999; Jhee & Lee, 1993; Kohzadi, Boyd, Kermanshahi, & Kaastra, 1996; Stern, 1996; Tang, Almeida, & Fishwick, 1991; Tang & Fishwick, 1993). So in this study, ANNs is selected for estimating production function and then performance evaluation.

For instance consider DEA approach, a basic principle to use ANNs is for generalizing efficiency frontier functions which concavity is an important characteristic of them and they may be applied to frontier analysis (Wang, 2003). Moreover, the efficiency prediction power of ANNs is unique and the flexibility of it to solve complex problems, where the main information lies implicitly in the data, is very applicable (Wu, Yang, & Liang, 2006).

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. Their application is bank with multi-output: 4 inputs, 3 outputs. After selecting samples, the ANNs are then trained as tools to learn a non-linear forecasting model. They assume that inefficiency distributions are semi-normal and exponential and conclude that DEA is superior to ANN for measurement purpose. Their study indicates that ANN results are more similar with the constant returns to scale and less with the variable returns to scale results. The latter, is a consequence of the implicit assumption of constant returns to scale adopted by the ANN models.

Costa and Markellos (1997) analysed the London underground efficiency with time series data for 1970–1994 where there are 2 inputs – fleet and workers – and 1 output – kms. They explain how the ANNs results are similar to COLS and DEA. They proposed two procedures: (a) similar way to COLS after neural training; (b) by an oversized network until some signal to noise ratio is reached. Then, inefficiency is determined as observation-frontier distance. However, ANNs offer advantages in the decision making, the impact of constant versus variable returns to scale or congestion areas (Costa & Markellos, 1997). Santin and Valino (2000) study on education efficiency by a two-level model: student-production function is estimated by ANNs – and school. They infer that ANN is superior to econometric approach at frontier estimation. Pendharkar and Rodger (2003) used DEA as a data screening approach to create a sub sample training data set that is 'approximately' monotonic, which is a key property assumed in certain forecasting problems. Their results indicate that the predictive power of an ANN trained on the 'efficient' training data subset is stronger than the predictive performance of an ANN trained on the 'inefficient' training data subset. Santin, Delgado, and Valino (2004) used a neural network approach for a simulated non-linear production function and compared its performance with conventional alternatives such as stochastic frontier and DEA in different observations and noise scenarios. The results suggested that ANNs are a promising alternative to conventional approaches, to fit production functions and measure efficiency under non-linear contexts. Wu et al. (2006) presented a DEA-NN[1] study for performance assessment of branches of a large Canadian bank. The results are operable to the normal DEA results on the whole. They concluded that the DEA-NN approach produces a more robust frontier and identifies more efficient units because better performance patterns are explored. Furthermore, for worse performers, it provides the guidance on how to improve their performance to different efficiency ratings. Ultimately, they concluded the neural network approach requires no assumptions about the production function (the major drawback of the parametric approach) and it is highly flexible. ANNs have been viewed as a good tool to approximate numerous non-parametric and non-linear problems.

3. The Meta heuristic approach

A Meta heuristic approach is proposed to measure the units' efficiency in current period. Numerical taxonomy and homogenous test are used to determine if the DMUs are homogenous or not. This intelligent approach can estimate efficiency by considering input (output) oriented by finding production (cost) function by using ANN approach, same as econometric methods. Also for simplicity, we consider one output (input), but it is easy to extend it to various outputs (inputs). The approach is composed of the following steps:

1. Determination of input(s) and output (P) variables under input oriented assumption (input (C) and output(s) variables under output oriented assumption) of the model.

2. Collect data set S in all available previous periods which describes the input–output relationship for DMUs. Assume that there are n DMUs to be evaluated. Note that the current period data (S_c: test data[2]) does not belong to S. Then obtain the preprocessed data set (S and S_c) after the data are scaled between 0 and 1.

3. Divide S in to two subsets: training (S_1) and valid (S_2) data. The first subset is the training set, which is used for computing the gradient and updating the network weights and biases. The second subset is the validation set. The error on the validation set is monitored during the training process. The validation error will normally decrease during the initial phase of training, as does the training set error. However, when the network begins to overfit the data, the error on the validation set will typically begin to rise. When the validation error increases for a specified number of iterations, the training is stopped, and the weights and biases at the minimum of the validation error are returned. Take validation data out from the training data and should be representative across the range of outcomes.[3] It is necessary to strike a balance between the training and validation data set sizes. When large amounts of data are available the selection of validation data can be done using a simple random choice. But according to our problem, extrapolate ability of ANN should be calculated, therefore the data for validation is chosen of the period which is closer to the period data S_c.

4. Use ANN method to estimate relation between input(s) and output(s). For this reason select architecture and training parameters. All networks used in this study have a single hidden layer because the single hidden layer network is found to be sufficient to model any function (Cybenko, 1989; Patuwo, Hu, & Hung, 1993). To find the appropriate number of hidden nodes, following steps are performed for networks with one to q nodes in their hidden layer. When the value of q is optional and should be changed if after following next steps, the goal error has not met.[4]

- Train the model using the training data (S). In this study Levenberg–Marquardt (LM) training algorithm is used[5]
- Evaluate the model using the test data (S_c) and obtaining MAPE[6] error.

Then the model which has the lowest error is selected for estimating production function.

5. Run ANN* for S_c.

6. Apply homogenous test by numerical taxonomy (this test is applied in NT method for clustering analysis) as follows (Azadeh & Ebrahimipour, 2002; Azadeh & Jalal, 2001; Azadeh, Ebrahimipour, & Ataei, 2003):

6-1: It is assumed there are m inputs and output of ANN* (P_{ANN^*}) variables under input oriented assumption (output of ANN* (C_{ANN^*}) and m outputs variables under output oriented assumption) and n DMUs which can be shown by a $n^*(m+1)$ data matrix.

6-2: The n by $m+1$ matrix is standardized such that all variables have mean of 0 and variance of 1.

6-3: The distance of every two DMUs for each variable is computed. This is done to homogenize the DMUs. Therefore, the distance matrix $D = [d_{ij}]_{n^*n}$ and vector $d = d[d_i]_{nx1}$, where d_i is the minimum of ith row of matrix D are identified. To identify homogenous DMUs, the upper (L1) and lower (L2) limits of vector d is computed as $L1 = \bar{d} + 2s_d$ and $L2 = \bar{d} - 2s_d$, where $\bar{d}$ and s_d are the mean and standard deviation of vector d, respectively. If all d_i are within L1 and L2, homogeneity is achieved, do steps 7–9 (do sub-alg.I). Otherwise, go to step 10 (do sub-alg.II).

7. Calculate the error between the real output ($P_{\mathrm{real}(i)}$ for input oriented model and $C_{\mathrm{real}(i)}$ for output oriented model) and ANN

[1] To implement the DEA-ANN model, they defined an algorithm. In this algorithm after collecting a data set, CCR method (Charnes, Cooper, & Rhodes, 1978) is used to calculate efficiency score of DMUs. The preprocessed data set is obtained and is grouped into four categories based on the efficiency scores and the neural network is trained with some groups of data subset until the pre-specified epochs or accuracy is satisfied. Then the trained neural network model is applied to calculate efficiency scores of all DMUs and post process the calculated efficiency scores by regress analysis between DEA-NN results and CCR DEA results.

[2] The test set error is not used during the training, but it is used to compare different ANN models.

[3] In our problem, each period have all range of outcomes. Therefore, all of the data of this period can be selected for test or the data of this period can be sorted by the value of the output variable, partitioned and one validation data point is chosen at random from each partition. In this way the stratification tries to ensure that validation data is chosen across the range of outcomes.

[4] In this study the value of the desired minimum error has been defined between 2 and 4% (96–98% confidence) and the value of q has been defined 20. The error is estimated by mean absolute percentage error (MAPE).

[5] LM algorithm is selected by noting of reaching the goal error in appropriate time and using of this algorithm in previous similar studies.

[6] Mean absolute percentage error $\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\text{Actual value}_i - \text{Set point value}_i}{\text{Set point value}_i}\right|$ (N: the number of rows).

model output ($P_{ANN^*(i)}$ for input oriented model and $C_{ANN^*(i)}$ for output oriented model) in the period which you want to assess the efficiency of its DMUs (S_c)

$$E_i = P_{real(i)} - P_{ANN^*(i)} \quad i = 1, \ldots, n \text{ for input oriented model} \tag{2}$$

$$E_i = C_{ANN^*(i)} - C_{real(i)} \quad i = 1, \ldots, n \text{ for output oriented model} \tag{3}$$

8. Shift frontier function from neural network for obtaining the effect of the largest positive error which is one of the unique feature of this algorithm

$$E'_i = E_i / P_{(ANN^*)i} \quad i = 1, \ldots, n \text{ for input oriented model} \tag{4}$$

$$E'_i = E_i / C_{(ANN^*)i} \quad i = 1, \ldots, n \text{ for output oriented model} \tag{5}$$

This option consists of not considering the largest error, but calculates by noting the DMU scale (constant returns to scale (CRS)). To this end find the largest E'_i indicate the DMU with the best performance. Suppose that DMU_k have the Largest E'_i and we have

$$E'_k = \max(E'_i) \tag{6}$$

So, the value of the shift for each of the DMUs is different and is calculated by

$$Sh_i = E_k * P_{(ANN^*)i} i / P_{(ANN^*)k}$$
$$i = 1, \ldots, n \text{ for input oriented model} \tag{7}$$

$$Sh_i = E_k * C_{(ANN^*)i} i / C_{(ANN^*)k}$$
$$i = 1, \ldots, n \text{ for output oriented model} \tag{8}$$

In this approach in spite of the previous studies (Athanassopoulos & Curram, 1996) called this measure "standardized efficiency") the effect of the scale of DMUs on its efficiency is considered and the unit used for the correction is selected by notice of its scale (CRS) (Costa and Markellos (1997), Delgado, 2005).

9. *Calculate efficiency scores*

The efficiency scores take values between 0 and 1. This maximum score is assigned to the unit used for the correction

$$F_i = P_i / (P_{(ANN^*)i} + Sh_i) \quad i = 1, \ldots, n \text{ for input oriented model} \tag{9}$$

$$F_i = (C_{(ANN^*)i} - Sh_i) / C_i \quad i = 1, \ldots, n \text{ for output oriented model} \tag{10}$$

10. Cluster DMUs by fuzzy C-means method (x cluster are obtained after running fuzzy C-means method) and for each of the clusters do steps 11–14. Appendix A discusses fuzzy C-means method.

11. *Calculate weigh of* DMU_i:W_i

$$V_i = P_i / \mathrm{Ave}(P_1, \ldots, P_{i-1}, P_{i+1}, \ldots, P_{cj}) \quad i = 1, \ldots, n \text{ for input oriented model}$$
$$V_i = C_i / \mathrm{Ave}(C_1, \ldots, C_{i-1}, C_{i+1}, \ldots, C_{cj}) \quad i = 1, \ldots, n \text{ for output oriented model}$$
$$W_i = V_i / \mathrm{Sum}(V_i) \tag{11}$$

where c_j ($1 \leqslant j \leqslant x$) is the number of DMUs which belong to jth cluster of x clusters.

12. Calculate the error between the real output ($P_{real(i)}$) and ANN model output ($P_{ANN^*(i)}$) in the period which you want to assess the efficiency of its DMUs (S_c)

$$E_i = P_{real(i)} - P_{ANN^*(i)} \quad i = 1, \ldots, n \text{ for input oriented model} \tag{12}$$

$$E_i = C_{ANN^*(i)} - C_{real(i)} \quad i = 1, \ldots, n \text{ for output oriented model} \tag{13}$$

13. Shift frontier function from neural network for obtaining the effect of the largest positive error which is one of the unique features of this algorithm

$$E'_i = E_i / W_i \quad i = 1, \ldots, n \tag{14}$$

This option consists of not considering the largest error, but calculates by noting the DMU scale (constant returns to scale (CRS)). To this end find.

The largest E'_i indicate the DMU with the best performance. Suppose that DMU_k have the Largest E'_i and we have

$$E'_k = \max(E'_i) \tag{15}$$

So, the value of the shift for each of the DMUs is different and is calculated by

$$Sh_i = E_k * W_i / W_k \quad i = 1, \ldots, n \tag{16}$$

In this approach in spite of the previous studies (Athanassopoulos & Curram, 1996) called this measure "standardized efficiency") the effect of the scale of DMUs on its efficiency is considered and the unit used for the correction is selected by notice of its scale (CRS).

14. *Calculate efficiency scores*

The efficiency scores take values between 0 and 1. This maximum score is assigned to the unit used for the correction in each cluster:

$$F_i = P_i / (P_{(ANN^*)i} + Sh_i) \quad i = 1, \ldots, n \text{ for input oriented model}$$
$$F_i = (C_{(ANN^*)i} - Sh_i) / C_i \quad i = 1, \ldots, n \text{ for output oriented model} \tag{17}$$

15. *Calculate unique efficiency score for all DMUs*

It should be noted that some units may belong to two or more clusters and of curse, their efficiency scores in the cluster with large scale units are less than the time their efficiency are calculated in the cluster with smaller scale units. For calculating a unique efficiency score for theses units by means of proposed algorithm, the degree of membership in each of the clusters is used

$$F^*_i = \left(\sum D_{ij} * F_{ij}\right) / \sum D_{ij} \quad 1 \leq j \leq x \quad \text{if } DMU_i \text{ belong to more than one clusters} \tag{18}$$

where D_{ij} is the DMU_i's degree of membership in jth cluster and F_{ij} is the DMU_i's efficiency score in jth cluster.

It is noted that, in some cases, perhaps in a particular cluster, the error E_i for all of the DMUs is obtained negative. In this situation, by notice of the proposed algorithm, frontier function from neural network is shifted to lower level of production. In real, in this case the best unit is the DMU that has the lowest loss with respect to its scale.

4. The case studies

The proposed Meta heuristic approach is applied to two actual cases: (1) power generation units and (2) auto industries each of which is discussed in Sections 4.1 and 4.2, respectively. The results of applying the proposed algorithm in these two actual case studies are analyzed in Section 4.3.

4.1. Performance assessment of power generations

The approach is illustrated by means of the data set which is concerned with power generation system of 10 countries in the world. It is assumed that the model is input oriented because of the selected application which DMUs (power plants) have particular orders to fill (e.g. electricity generation) and hence the input quantities appear to be the primary decision variables.

4.1.1. Running the Meta heuristic

Step 1: As shown by several authors, the production function for conventional thermal electric production may be described conveniently within an engineering framework. In this framework, pertinent inputs are the fuel quantity consumed and installed power, which is the maximum nominal power the plants are initially designed for. On the other hand, labor inputs contribute to production through control and maintenance services, which also require some capital. The output is, of course, electrical energy production. But by noting studies about efficiency measurement of thermal power generations which indicate that labor isn't an effective factor (for instance, Emami Meibodi, 1998), in our study, electric power (in megawatt hour) generated from thermal power plants in each DMU (P) is used as the output variable, while capital (C) and fuel (F) are two inputs used for power generation. Capital is measured in terms of installed thermal generating capacity in megawatt (MW) (Fare, Grosskopf, & Lovell, 1983; Hawdon, 1997). Various natural elements have been used as fuel in the production of electric power in various steam plants (natural gas, gas oil and Mazute). The choice of fuel depends on many factors such as availability, cost and environmental concerns and each fuel has its limitations. Our figures measure fuel consumption in terms of Tera Joule (TJ). In other words, our figures have already adjusted for the quality of fuel used in different plants.

Step 2: 105 rows of data are collected from 1997 to 2003. Table 1 shows the real data for the inputs and output of 2003 used in the model.

Step 3: S_1 is data from 1997 to 2002 (90 rows of data) and S_2 is 2003 data (15 rows of data).

Step 4: In order to get the best ANN for the electricity production in power plants, 20 MLP-LM models are tested to find the best architecture. The architecture of the mentioned MLP-LM models and their MAPE error values are shown in Table 2.

It seems the 9th model (it has 9 neurons in single hidden layer) has the lowest MAPE error and consequently is chosen as the preferred model. In Fig. 1, the ANN architecture for the preferred network (9th model) is shown. Fig. 2 present the MLP-LM performance of each model.

Step 5: Therefore, this model is selected for estimating the electricity production in 2003.

Step 6: Homogenous test is performed and show that the data set is homogeneous.

Steps 7, 8 and 9: the results of these steps are shown in Table 3 for assessing performance of the electricity production in 2003.

Table 1
Real data indicators for evaluating performance of power generations in 2003

Country name	Install capacity (MW)	Fuel consumption (TJ)	Gross production (MWh)
Austria	40,028	2,732	197,950
Indonesia	19,944	901	94,818
Republic of Korea	38,871	1,644	185,883
Malaysia	13,565	742	73,452
Mexico	33,956	1,908	173,327
Philippine	10,253	273	31,192
Singapore	8,919	297	34,665
Thailand	21,221	1,152	101540
United Kingdom	58,716	2,600	273,728
Iran	32,375	1,267	132,348
Average	27,785	1,352	129,890
Standard deviation	15,842	866	77,730
Max	58,716	2,732	273,728
Min	8,919	273	31,192

Table 2
Architecture of the 20 models and network's error for evaluating performance of power plants in 2003

Model	Number of neurons in hidden layer[a]	MAPE error
1	1	0.116
2	2	0.107
3	3	0.022
4	4	0.012
5	5	0.011
6	6	0.011
7	7	0.009
8	8	0.010
9	9	0.008
10	10	0.012
11	11	0.011
12	12	0.009
13	13	0.021
14	14	0.012
15	15	0.014
16	16	0.011
17	17	0.019
18	18	0.011
19	19	0.010
20	20	0.009

[a] Hidden layer activation function which is defined for this single layer is Tan-Sigmoid. This non-linear feature is introduced at the hidden transfer function. From the previous universal approximation studies, these transfer function must have mild regularity conditions: continuous, bounded, differentiable and monotonic increasing. The most popular transfer function is sigmoid or tanh. TanSig (n) calculates its output according to: $n = 2/(1 + \exp(-2 * n)) - 1$.This is mathematically equivalent to $\tanh(n)$. This transfer functions bound the output to a finite range $[-1, 1]$.

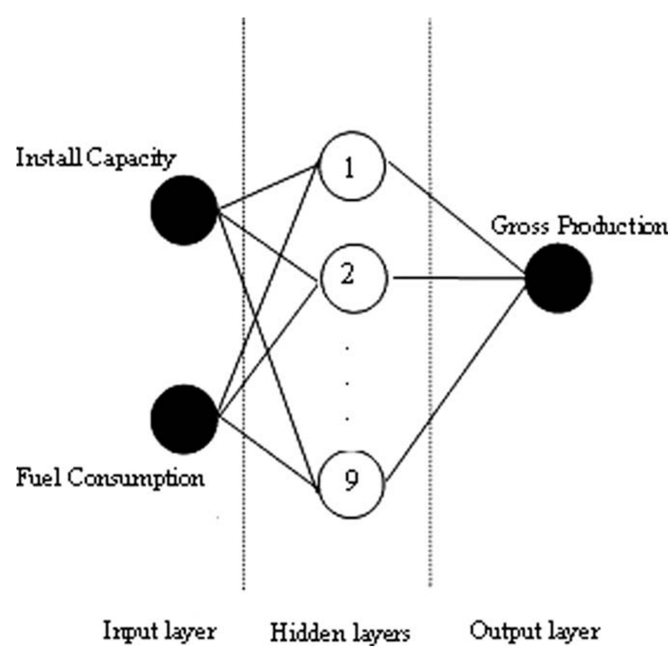

Fig. 1. The architecture of the selected ANN model (9th model).

4.2. Performance assessment of auto industries

Ever-increasing growth and development of automotive industry in the world requires continuous assessment through robust scientific methodologies. The objective of this section is to assess and analyze automotive industries on the basis of international and standard indicators. The economic indicators are identified by an extensive international review. This study considers auto industries of 12 countries with respect to the selected indicators

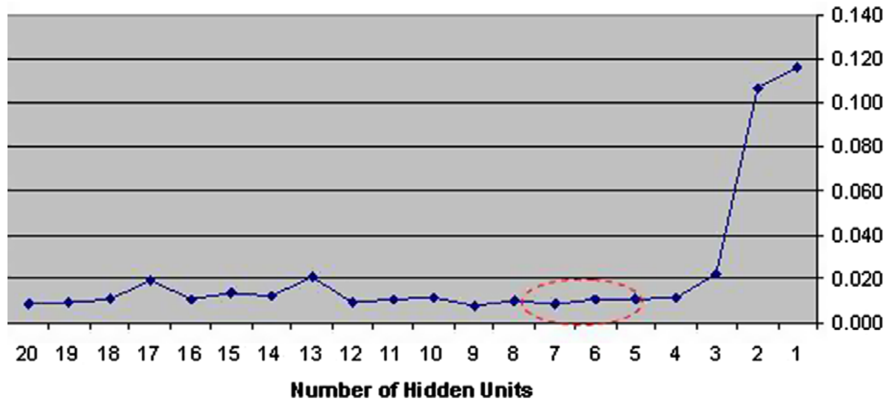

Fig. 2. MLP-LM performance of each model.

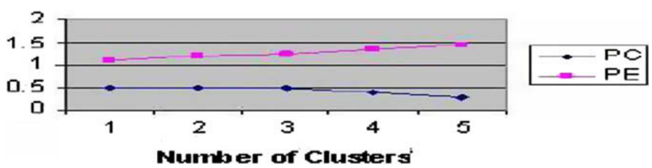

Fig. 3. The result values of PC and PE for clustering.

for 2000. In addition for estimating cost function five years period (1995–2000) is considered.

Four indicators were identified as major economic performance factors in automotive industries. These indicators are influenced by such shaping factors as export value (output), production value (output), value added (output) and human cost (input), so the model is output oriented. The automotive industry sectors are selected according to the format of International Standard for Industrial Classification (ISIC) from 1995 to 2000.

According to complete illustration of running steps 1–5 for power generations in Section 4.1, in this section other steps for evaluating efficiency scores and rankings auto industries of 12 countries by considering output oriented assumption are prescribed.

Step 6: Homogenous test is performed and show that the data set is non homogeneous. Therefore, we continue the algorithm from step 10.

Step 10: First we determine the best number of clusters. The values of pc and pe are shown in Fig. 3. The "best" number of clusters is the point on the horizontal axis (c^*) that the entropy value (pe) of c^* lies below the rising trend and the value for the partition coefficient (pc) of c^* lies above the falling trend. Fig. 3 shows that, according to these two criteria, the best partitioning of the data is achieved with 2 clusters.

Then the fuzzy C-means algorithm runs for two clusters (A and B). The degrees of membership of the units in each of the two clusters (A and B) are shown in Fig. 4. By notice of the high degree of membership of Canada in clusters (A and B), this DMU is considered in both of these clusters. In Table 4 (column1), the DMUs which are belonged to each of these clusters are shown.

Steps 11–14: The results of these steps for each of the clusters are shown in Table 4. It should be noted that some units may belong to two or more clusters and of curse, their efficiency scores in the cluster with large scale units are less than the time their efficiency are calculated in the cluster with smaller scale units. For instance, Canada belongs to both of the clusters A and B but its efficiency score in cluster B approximately 10% less than its calculated efficiency in cluster A. This point indicates the importance of units clustering before evaluating performance of them.

For calculating a unique efficiency score for Canada by means of proposed algorithm, the degree of membership in each of the A and B clusters is used:

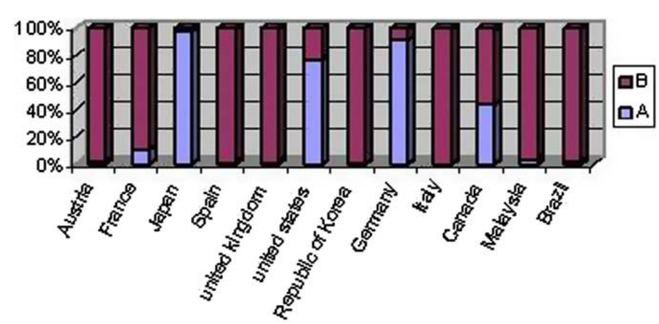

Fig. 4. The degree of membership of the units in each of the two clusters (A and B).

Table 3
Estimation of efficiency scores for evaluating performance of power generations in 2003

DMU	$P_{real(i)}$ after normalization	$P_{ANN(i)}$	E_i	E'_i	Sh_i	F_i (%)	Rank
Austria	0.1241	0.1278	−0.0037	−0.0289	0.0091	90.62	7
Indonesia	0.0588	0.0599	−0.0011	−0.0177	0.0043	91.67	6
Republic of Korea	0.1165	0.1087	0.0078	0.0716	0.0078	100.00	1
Malaysia	0.0453	0.0459	−0.0006	−0.0138	0.0033	92.03	5
Mexico	0.1085	0.1077	0.0008	0.0078	0.0077	94.05	4
Philippine	0.0185	0.0194	−0.0009	−0.0464	0.0014	88.99	8
Singapore	0.0207	0.0204	0.0003	0.0125	0.0015	94.48	2
Thailand	0.0630	0.0696	−0.0066	−0.0947	0.0050	84.49	10
United Kingdom	0.1721	0.1701	0.0020	0.0117	0.0122	94.42	3
Iran	0.0826	0.0869	−0.0043	−0.0496	0.0062	88.69	9

Table 4
Estimation of efficiency scores for evaluating performance of auto industries in 2000

	DMU name	$P_{\mathrm{real}(i)}$	$P_{\mathrm{ANN}(i)}$	E_i	W_i	E_i'	Sh_i	F_i	Ranking
Cluster A	Japan	10,652,741,514	14,807,241,339	4154499824.46	0.2146	19363748522.89	4948432823.69	92.55	2
	United States	20,654,000,000	18,555,999,987	−2098000012.86	0.2925	−7172364285.71	6746546452.91	57.18	4
	Germany	23,832,000,000	24,799,158,543	967158542.54	0.4580	2111695572.85	10563424449.23	59.73	3
	Canada	2,218,000,000	3,023,794,813	805794812.89	0.0349	23064198538.73	805794812.89	100.00	1
Cluster B	Austria	483177570.1	690728886.9	207551316.79	0.0264	7870866025.82	209842272.14	99.53	2
	France	4,385,378,505	5,535,565,535	1150187029.87	0.2702	4257453963.79	2149851748.57	77.20	6
	Spain	2,029,103,991	2,400,085,943	370981951.33	0.0993	3737764102.38	789825042.67	79.36	5
	United Kingdom	4,001,492,537	4,592,329,598	590837060.82	0.2126	2779076046.24	1691832273.15	72.49	7
	Republic of Korea	1,941,083,432	2,505,895,315	564811883.06	0.1042	5422301810.92	828915279.61	86.39	4
	Italy	1,789,345,794	2,685,579,289	896233494.66	0.1126	7957744793.51	896233494.65	100.00	1
	Canada	2,218,000,000	3,023,794,813	805794812.89	0.1290	6248350403.92	1026240377.44	90.06	3
	Brazil	1,541,025,641	1,175,300,936	−365724705.14	0.0459	−7973450795.86	365004305.25	52.58	8

((Canada's efficiency score in cluster A (1) * Canada's degree of membership in cluster A (0.437)) + (Canada's efficiency score in cluster B (0.9) * Canada's degree of membership in cluster B (0.563)))/(Canada's degree of membership in cluster A (0.437) + Canada's degree of membership in cluster B (0.563)) = 0.944.

Table 5
Efficiency scores for evaluating performance of auto industries and power generation

DMU	Sub-alg.I		Sub-alg.II	
	F_i (%)	Rank	F_i (%)	Rank
Austria	90.621	7	97.432	3
Indonesia	91.669	6	92.556	8
Iran	88.694	1	97.584	2
Malaysia	92.034	5	92.691	7
Mexico	94.054	4	94.094	5
Philippine	88.989	8	96.707	4
Republic of Korea	100.00	2	88.489	10
Singapore	94.485	10	91.053	9
Thailand	84.488	3	100.00	1
United Kingdom	94.417	9	92.992	6
Average	91.945		94.360	

4.3. Result analysis

In this section the results of applying the proposed approach will be analyzed. As it was seen the result of homogenous test for power generations was positive so sub-alg.I was applied. But note that if by clustering the situation is changed, to more homogenous space (sub-alg.II is applied) then efficiency means rate will be changed in an increasing manner or not. If this increasing manner occurred then using sub-alg.I is invalid. For considering this, homogenous rate (Hr) is defined as below

$$Hr = \mathrm{Average}\{[(\bar{d} + 2 * s_d) - \mathrm{Max}(di)]/(\bar{d} + 2 * s_d) \quad \text{and} \quad [\mathrm{Min}(di) - (\bar{d} - 2 * s_d)]/(\bar{d} - 2 * s_d)\} \tag{19}$$

where $\bar{d}$ and s_d are the mean and standard deviation of vector d, respectively (see Step 6 of proposed algorithm). For this case Hr is equal to 0.28.

Table 6
conventional and the proposed algorithm results

Auto industries			Power generation		
DMU	Algorithm II	Conventional algorithm	DMU	Conventional algorithm	Algorithm I
Japan	0.9255	0.6301	Austria	0.9151	0.9062
United States	0.5718	1	Indonesia	0.8685	0.9167
Germany	0.5973	0.8860	Republic of Korea	1	1
Canada	1	0.4330	Malaysia	0.8435	0.9203
Austria	0.9953	0.1732	Mexico	0.9393	0.9405
France	0.772	0.5744	Philippine	0.6801	0.8899
Spain	0.7936	0.4511	Singapore	0.7340	0.9448
United Kingdom	0.7249	0.5981	Thailand	0.8139	0.8449
Republic of Korea	0.8639	0.4216	United Kingdom	0.9673	0.9442
Italy	1	0.3740	Iran	0.8722	0.8869
Canada	0.9006	0.4330	Average	0.8634	0.9194
Brazil	0.5258	0.4707			
Average	0.8058	0.5371			

Table 7
Hypothesis testing for conventional and the proposed algorithm

	Power generation	Auto industries
Hypothesis: H_0:	$\mu_{\mathrm{TE\ Proposed\ Algorithm}} - \mu_{\mathrm{TE\ Conventional\ Algorithm}} = 0$	$\mu_{\mathrm{TE\ Proposed\ Algorithm}} - \mu_{\mathrm{TE\ Conventional\ Algorithm}} = 0$
H_1:	$\mu_{\mathrm{TE\ Proposed\ Algorithm}} - \mu_{\mathrm{TE\ Conventional\ Algorithm}} \neq 0$	$\mu_{\mathrm{TE\ Proposed\ Algorithm}} - \mu_{\mathrm{TE\ Conventional\ Algorithm}} \neq 0$
Calculated t-statistic	2.05	2.55
P-value	0.07	0.027
Decision	Reject H_0 at the 1% level of significance	Reject H_0 at the 1% level of significance

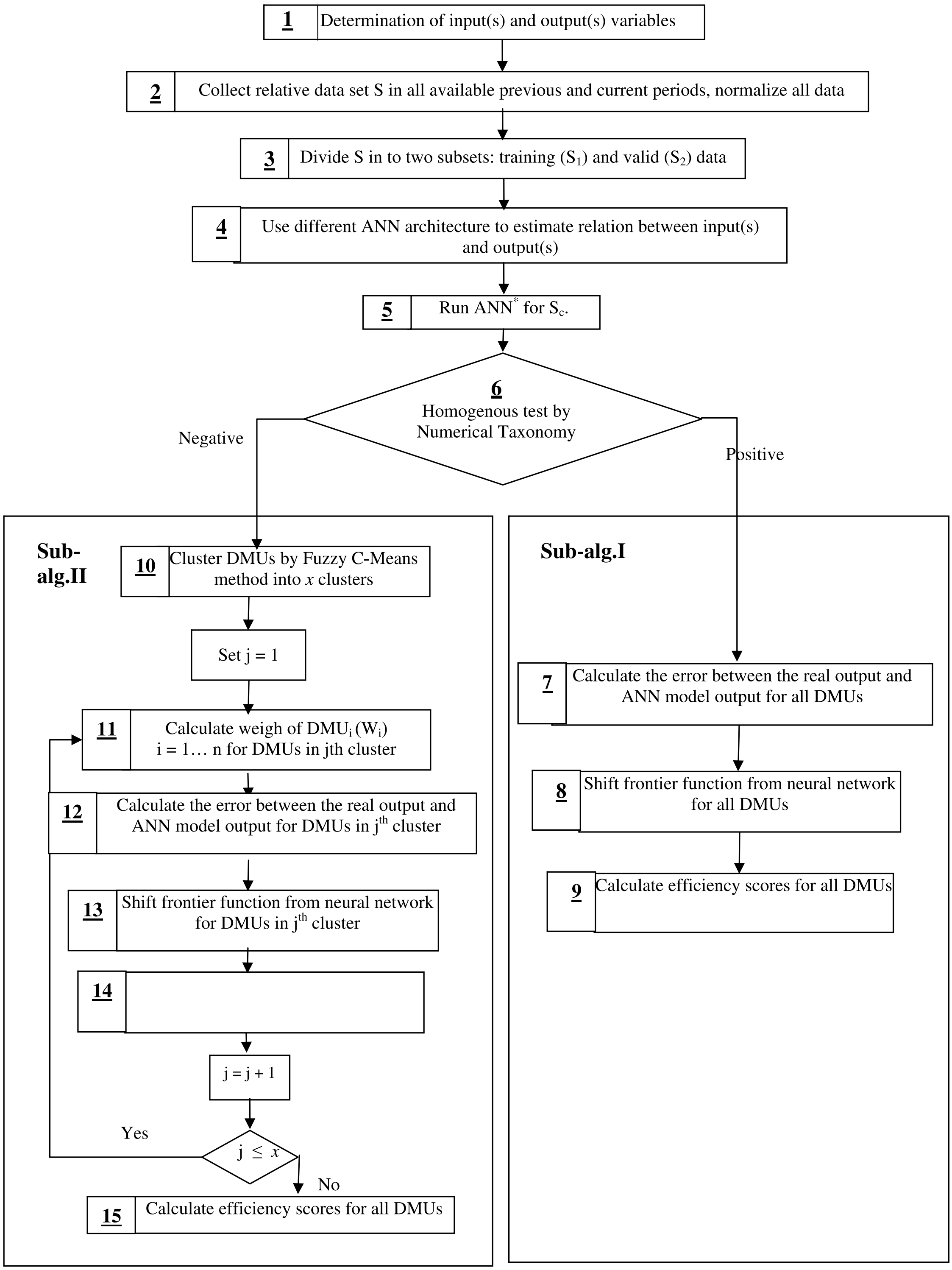

Fig. 5. The meta heuristic approach for performance assessment of production units.

After clustering and applying sub-alg.II for this case (Table 5) change in efficiency means rate is obtained 0.026.[7] This value indicates that change in efficiency values is insignificant and using sub-alg.II only increase complicity and calculation amount without notable effect on efficiency values. Note that if change in efficiency means rate were grater than Hr then using sub-alg.II had been meaningful.

As described in the literature of performance assessment it is so better that homogenous DMUs are compared with themselves (Azadeh & Ebrahimipour, 2002; Azadeh et al., 2003; Azadeh & Jalal, 2001; Azadeh Ghaderi, Tarverdian, et al., 2006; Charnes et al., 1978), therefore in second case study (auto industries), which the result of homogenous test is negative, using sub-alg.I is opposite of the above fact.

[7] Efficiency means rate = (efficiency mean by sub-alg. II – efficiency mean by sub-alg. I)/efficiency mean by sub-alg. I.

5. Comparisons with conventional algorithm

Following formula shows the main process of conventional algorithm:

$$F_i = \mathrm{Preal}(i)/(\mathrm{PANN}(i) + \max Ei|Ei >= 0) \quad (20)$$

The main results of proposed algorithm and conventional algorithm are summarized in the Table 6, several differences are clearly appreciated. From Table 6, it can be seen that the conventional algorithm produces smaller mean technical efficiency while the proposed algorithm produce distinctly higher mean technical efficiency for the power generations and auto industries under constant returns to scale assumption. Statistical t-test has been conducted in order to test whether the mean technical efficiencies obtained from the conventional algorithm and proposed algorithm is significantly different.

The results of t-test are reported in Table 7. The test rejects the null hypothesis that mean technical efficiencies of the conventional algorithm is larger than mean technical efficiencies of the proposed algorithm. Consequently, proposed algorithm provide more robust results and identified more efficient units than the conventional method since more good performance patterns are explored (Pollit, 1995).

6. Conclusion

A highly unique flexible ANN algorithm was proposed to measure and rank the DMUs efficiency scores which are composed of fifteen distinct steps. Fig. 5 represents the Meta heuristic approach for performance assessment of DMUs.

Because of non-linearity of the neural networks in addition to its universal approximations of functions and its derivates which makes the algorithms highly flexible. To show their applicability and superiority they were applied to two case studies (10 countries power generation in 2003 and 11 countries auto industries in 2000). Homogenous test is used to determine if the DMUs are homogenous or not. Result of this test is important in algorithm's process.

In the first application the data set was homogeneous. But in the second case study, it was concluded that the result of homogenous test was negative. At the end the results and selected sub algorithm for each case were analyzed.

The proposed algorithm estimates more robust results and more efficient units than the conventional approach because better performance patterns are explored.

Although it is believed that ANNs can be a potential alternative for measuring technical efficiency and can outperform other techniques when the production process is unknown, there is still a lack of both theoretical and empirical work in efficiency analysis and consequently optimization analysis. Nevertheless, future research with neural networks in efficiency and optimization analysis is proposed. Also, future studies can use more output or input indicators to reach a realistic model.

Appendix A. Fuzzy C-means algorithm

Fuzzy C-means (FCM) (developed by Dunn and improved by Bezdek) is frequently used in pattern recognition. It is based on minimization of the following objective function (Bezdek, 1981; Dunn, 1973)

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^m \|x_i - c_j\|^2 1 \leqslant m \prec \infty \quad (A.1)$$

where m is any real number greater than 1, u_{ij} is the degree of membership of x_i in the cluster j, x_i is the ith of d-dimensional measured data, c_j is the d-dimension center of the cluster, and $\|^*\|$ is any norm expressing the similarity between any measured data and the center.

Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership u_{ij} and the cluster centers c_j by

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{\frac{2}{m-1}}}, \quad c_j = \frac{\sum_{i=1}^{N} u_{ij}^m . x_i}{\sum_{i=1}^{N} u_{ij}^m} \quad (A.2)$$

This iteration will stop when

$$\max_{ij}\left\{\left|u_{ij}^{(k+1)} - u_{ij}^{(k)}\right|\right\} < \epsilon \quad (A.3)$$

where ε is a termination criterion between 0 and 1 and k are the iteration steps. This procedure converges to a local minimum or a saddle point of J_m. The algorithm is composed of the following steps:

1. Initialize U = $[u_{ij}]$ matrix, $U(0)$
2. At k-step: calculate the centers vectors $C(k) = [c_j]$ with $U(k)$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m . x_i}{\sum_{i=1}^{N} u_{ij}^m} \quad (A.4)$$

3. Update $U(k)$, $U(k+1)$

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{\frac{2}{m-1}}} \quad (A.5)$$

4. If $\|U(k+1) - U(k)\| < \varepsilon$ then STOP; otherwise return to step 2.

A.1. Assessment of clustering results

The classes which are found through clustering, should as far as possible be able to be interpreted meaningfully. As a means of checking this, the found classes should be judged by some means of quality criteria. Among other measures proposed in the literature, the following can be found (Windham, 1981).

- *Partition coefficient (PC):*

$$\sum_{i=1}^{N}\sum_{j=1}^{c}\frac{(\mu_{ij})^2}{N} \quad (A.6)$$

- *Partition entropy (PE):*

$$-\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{c}\mu_{ij}\ln(\mu_{ij}) \quad (A.7)$$

- *Proportion exponent (PEX):*

$$-\ln\prod_{i=1}^{N}\sum_{j=1}^{C}(-1)^{j+1}\binom{c}{j}(1 - j\mu_{ij})^{c-1} \quad (A.8)$$

And these variables have bellow relations

$$\begin{aligned} &\tfrac{1}{c} \leqslant pc \leqslant 1 \\ &0 \leqslant pe \leqslant \ln(c) \\ &0 \leqslant PEX \leqslant \infty \end{aligned} \quad (A.9)$$

A cluster result will be crisper, the greater pc and the smaller pe. At $pc = 1$ and $pe = 0$ crisp clusters apply. If the values of pc and pe are shown in a chart then the "best" number of clusters is the point on the horizontal axis (c^*) that the entropy value (pe) of c^* lies below the rising trend and the value for the partition coefficient (pc) of c^* lies above the falling trend.

References

Athanassopoulos, A. D., & Curram, S. P. (1996). A comparison of data envelopment analysis and artificial neural networks as tool for assessing the efficiency of decision making units. *Journal of the Operational Research Society, 47*(8), 1000–1016.

Azadeh, A., Ebrahimipour, V., Ataei, G. H. (2003). A total machine productivity model for assessment and improvement of electrical manufacturing systems. In *Proceedings of the international conference on computers and industrial engineering*. Ireland.

Azadeh, A., & Ebrahimipour, V. (2002). An integrated approach for assessment of manufacturing sectors based on machine performance: The cases of automotive and food and beverages industries. In *Proceedings of the international conference on manufacturing complexity*. UK: University of Cambridge.

Azadeh, A., Ghaderi, S. F., Anvari, M., & Saberi, M. (2006). Measuring performance electric power generations using artificial neural networks and fuzzy clustering. In *Proceeding of the 32nd annual conference of the IEEE industrial electronics society*. Paris, France: IECON.

Azadeh, A., Ghaderi, S. F., Tarverdian, S., & Saberi, M. (2006). Integration of artificial neural networks and genetic algorithm to predict electrical energy consumption. In *Proceeding of the 32nd annual conference of the IEEE industrial electronics society – IECON'06*. Paris France: Conservatoire National des Arts & Metiers.

Azadeh, A., Ghaderi, S. F., Anvari, M., Saberi, M., & Izadbakhsh, H. (2007). An integrated artificial neural network and fuzzy clustering algorithm for performance assessment of decision making units. *Applied Mathematics and Computation, 187*(2), 584–599.

Azadeh, A., Ghaderi, S. F., Anvari, M., & Saberi, M. (2007). Performance assessment of electric power generations using an adaptive neural network algorithm. *Energy Policy, 35*(6), 3155–3166.

Azadeh, A., Ghaderi, S. F., & Sohrabkhani, S. (2007). Forecasting electrical consumption by integration of neural network, time series and ANOVA. *Applied Mathematics and Computation, 186*(2), 1753–1761.

Azadeh, A., Ghaderi, S. F., Tarverdian, S., & Saberi, M. (2007). Integration of artificial neural networks and genetic algorithm to predict electrical energy consumption. *Applied Mathematics and Computation, 186*(2), 1731–1741.

Azadeh, A., & Jalal, S. (2001). Identifying the economic importance of industrial sectors by multivariate analysis. *Journal of the Faculty of Engineering (University of Tehran, Iran), 35*(3), 437–449.

Bezdek, J. C. (1981). *Pattern recognition with fuzzy objective function algorithms*. New York: Plenum Press.

Brian Hwarng, H. (2001). Insights into neural-network forecasting of time series corresponding to ARMA (p;q) structures. *Omega, 29*, 273–289.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429–444.

Chavarnakul, T., & Enke, D. (2008). Intelligent technical analysis based equivolume charting for stock trading using neural networks. *Expert Systems with Applications, 34*(2), 1004–1017.

Chen, W. C., Tai, P. H., Deng, W. J., & Hsieh, L. F. (2008). A three-stage integrated approach for assembly sequence planning using neural networks. *Expert Systems with Applications, 34*(3), 1777–1786.

Cheng, B., & Titterington, D. M. (1994). Neural networks: A review from a statistical perspective. *Statistical Science, 9*(1), 2–54.

Chiang, W. C., Urban, T. L., & Baldridge, G. W. (1996). A neural network approach to mutual fund net asset value forecasting. *Omega, The International Journal of Management Science, 24*, 205–215.

Coelli, T. J. (1995). Recent developments in frontier modeling and efficiency measurement. *Australian Journal of Agricultural Economics, 39*(3), 219–245.

Cook, W. D., & Green, R. H. (2005). Evaluating power plant efficiency: A hierarchical model. *Computers & Operations Research, 32*(4), 813–823.

Costa, A., & Markellos, R. N. (1997). Evaluating public transport efficiency with neural network models. *Transportation Research C, 5*(5), 301–312.

Cybenko, G. (1989). Approximation by superpositions of a sigmoidal function. *Mathematics of Control, Signals and Systems, 2*, 303–314.

Delgado, F. J. (2005). Measuring efficiency with neural networks, an application to the public sector. *Economics Bulletin, 3*(15), 1–10.

Deng, W. J., Chen, W. C., & Pei, W. (2008). Back-propagation neural network based importance–performance analysis for determining critical service attributes. *Expert Systems with Applications, 34*(2), 1115–1125.

Dunn, J. C. (1973). A fuzzy relative of the ISODATA process and its use in detecting compact well-separated clusters. *Journal of Cybernetics, 3*, 32–57.

Emami Meibodi, A. (1998). *Efficiency considerations in the electricity supply industry: The case of Iran*". A thesis submitted to university of Surrey for the degree of Doctor of Philosophy.

Enders, W. (2004). *Applied econometric time series*. John Wiley & Sons.

Fare, R., Grosskopf, S., & Lovell, C. A. K. (1983). *The measurement of efficiency of production*. Kluwer: Boston.

Fleissig, A., Kastens, T., & Terrell, D. (2000). Evaluating the semi-nonparametric Fourier, AIM, and neural networks cost functions. *Economics Letters, 68*(3), 235–244.

Geman, S., Bienenstock, E., & Doursat, R. (1992). Neural networks and the bias/variance dilemma. *Neural Computation, 4*, 1–58.

Golany, B., Yaakov, R., & Rybak, D. (1994). Measuring efficiency of power plants in Israel by data envelopment analysis. *IEEE Transactions on Engineering Management, 41*(3), 291–301.

Goto, M., & Tsutsui, M. (1997). *Comparison of productive and cost efficiencies among Japanese and US electric utilities*. Tokyo, Japan: Central Research Institute of Electric Power Industry.

Hawdon, D. (1997). Improving the performance of electricity industries in developing countries: Is World Bank policy on deregulation the way forward. *Economics Departmental Research Seminar*, University of Surrey.

Hill, T., O'Connor, M., & Remus, W. (1996). Neural network models for time series forecasts. *Management Science, 42*(7), 1082–1092.

Hornik, K., Stinchcombe, M., & White, H. (1989). Multilayer feed forward networks are universal approximators. *Neural Networks, 2*, 359–366.

Indro, D. C., Jiang, C. X., Patuwo, B. E., & Zhang, G. P. (1999). Predicting mutual fund performance using artificial neural networks. *Omega, The International Journal of Management Science, 27*, 373–380.

Jamasb, T., Pollitt, M. (2001). Benchmarking and regulation of electricity distribution and transmission utilities: Lessons from international experience. In *DEA working paper*. Cambridge, UK: Department of Applied Economics, University of Cambridge.

Jhee, W. C., & Lee, J. K. (1993). Performance of neural networks in managerial forecasting. *Intelligent Systems in Accounting, Finance and Management, 2*, 55–71.

Karthikeyan, B., Gopal, S., & Venkatesh, S. (2008). Partial discharge pattern classification using composite versions of probabilistic neural network inference engine. *Expert Systems with Applications, 34*(3), 1938–1947.

Knittel, C. R. (2002). Alternative regulatory methods and firm efficiency: Stochastic frontier evidence from the US electricity industry. *The Review of Economics and Statistics, 84*(3), 530–540.

Kohzadi, N., Boyd, M. S., Kermanshahi, B., & Kaastra, I. (1996). A comparison of artificial neural network and time series models for forecasting commodity prices. *Neurocomputing, 10*(3), 169–181.

Kose, E. (2008). Modelling of colour perception of different age groups using artificial neural networks. *Expert Systems with Applications, 34*(3), 2129–2139.

Lam, P., & Shiu, A. (2001). A data envelopment analysis of the efficiency of China's thermal power generation. *Utilities Policy, 10*, 75–83.

Lee, W. I., Shih, B. Y., & Chung, Y. S. (2008). The exploration of consumers' behavior in choosing hospital by the application of neural network. *Expert Systems with Applications, 34*(2), 806–816.

Olatfubi, W. O., & Dismukes, D. E. (2000). A data envelopment analysis of the level and determinants of coal-fired electric power generation performance. *Utilities Policy, 9*, 47–59.

Park, S., & Lesourd, J. (2000). The efficiency of conventional fuel power plants in South Korea: A comparison of parametric and non-parametric approaches. *International Journal of Production Economics, 63*, 59–67.

Patuwo, E., Hu, M. Y., & Hung, M. S. (1993). Two-group classification using neural networks. *Decision Sciences, 24*(4), 825–845.

Pendharkar, P. C., & Rodger, J. A. (2003). Technical efficiency-based selection of learning cases to improve forecasting accuracy of neural networks under monotonicity assumption. *Decision Support Systems, 36*(1), 117–136.

Pollit, M. G. (1995). *Ownership and performance in electric utilities*. Oxford, UK: Oxford University Press.

Rumelhart, D. E., & McClelland, J. L. (1986). *Parallel distributed processing: Explorations in the microstructure of cognition. Foundations* (Vol. 1). Cambridge, MA: MIT Press.

Sanhueza, R., Rudnick, H., & Lagunas, H. (2004). DEA efficiency for the determination of the electric power distribution added value. *IEEE Transactions on Power Systems, 19*(2).

Santin, D., Delgado, F. J., & Valino, A. (2004). The measurement of technical efficiency: A neural network approach. *Applied Economics, 36*, 627–635.

Santin, D., & Valino, A. (2000). *Artificial neural networks for measuring technical efficiency in schools with a two-level model: An alternative approach, II Oviedo Workshop on Efficiency and Productivity*. Oviedo, Spain: Universidad de Oviedo, May 22–24.

Schiffmann, W., Joost, M., & Werner, R. (1992). *Optimization of the backpropagation algorithm for training multilayer perceptrons*. Institute of Physics, University of Koblenz.

Stern, H. S. (1996). Neural networks in applied statistics. *Technometrics, 38*(3), 205–214.

Sueyoshi, T., & Goto, M. (2001). Slack-adjusted DEA for time series analysis: Performance measurement of Japanese electric power generation industry in 1984–1993. *European Journal of Operation Research, 133*, 232–259.

Tang, Z., Almeida, C., & Fishwick, P. (1991). A time series forecasting using neural networks vs. Box–Jenkins methodology. *Simulation, 57*(5), 303–310.

Tang, Z., & Fishwick, P. A. (1993). Back-propagation neural nets as models for time series forecasting. *ORSA Journal on Computing, 5*(4), 374–385.

UN (1995–2000). *International standard industries classification of all economic activities*. Series M No. 4/Rev. 3, 20, New York, USA.

Wang, S. (2003). Adaptive non-parametric efficiency frontier analysis: A neural-network-based model. *Computers & Operations Research, 30*, 279–295.

Werbos, P. I. (1974). *Beyond regression: New tools for prediction and analysis in the behavior sciences*. Ph.D. Thesis, Harvard University, Cambridge, MA.

White, H. (1989). Some asymptotic results for learning in single hidden-layer feedforward network models. *Journal of the American Statistical Association, 84*(408), 1003–1013.

Windham, M. P. (1981). Cluster validity for fuzzy clustering algorithms. *Fuzzy Sets and Systems, 5*, 177–185.

Wu, D., Yang, Z., & Liang, L. (2006). Using DEA-neural network approach to evaluate branch efficiency of a large Canadian bank. *Expert Systems with Applications, 31*, 108–115.