An Integrated Artificial Neural Network Fuzzy C-Means-Normalization Algorithm for performance assessment of decision-making units: The cases of auto industry and power plant

A. Azadeh a,⇑, M. Saberi b, M. Anvari c

aDepartment of Industrial Engineering, College of Engineering, University of Tehran, P.O. Box 11365-4563, Iran
bMember of Young Researcher Club, Islamic Azad University, Tafresh Branch, P.O. Box 19585-466, Tafresh, Iran
cDepartment of Industrial Engineering, Iran University of Science and Technology, P.C. 16844, Narmak, Tehran, Iran

Efficiency frontier analysis has been an important approach of evaluating firms’ performance in private and public sectors. There have been many efficiency frontier analysis methods reported in the literature. However, the assumptions made for each of these methods are restrictive. Each of these methodologies has its strength as well as major limitations. This study proposes two non-parametric efficiency frontier analysis sub-algorithms based on (1) Artificial Neural Network (ANN) technique and (2) ANN and Fuzzy C-Means for measuring efficiency as a complementary tool for the common techniques of the efficiency studies in the previous studies. Normal probability plot is used to find the outliers and select from these two methods. The proposed computational algorithms 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 these algorithms, for calculating the efficiency scores, a similar approach to econometric methods 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 the second algorithm, for increasing DMUs’ homogeneity, Fuzzy C-Means method is used to cluster DMUs. Two examples using real data are presented for illustrative purposes. First example which deals with power generation sector shows the superiority of Algorithm 2 while the second example dealing auto industries of various developed countries shows the superiority of Algorithm 1. Overall, we find that the proposed integrated algorithm based on ANN, Fuzzy C-Means and Normalization approach provides more robust results and identifies more efficient units than the conventional methods since better performance patterns are explored.

1. Introduction

The appropriate use of few resources with the available technology is referred to as technical efficiency. Efficiency frontier analysis has been an important approach of evaluating firms’ performance in private and public sectors. 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 competing paradigms on efficiency analysis. Parametric and non-parametric approaches are widely-used in the efficiency measurement. 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 latter include DEA and Free Disposal Hull (FDH) which are based on mathematical programming approaches. 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).

1.1. Problem formulation

There have been several 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). But, 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. For instance, the DEA frontier is very sensitive to the presence of the outliers and statistical noise which indicates that the frontier derived from DEA analysis may be warped if the data are contaminated by statistical noise (Bauer, 1990). On the other hand, DEA can hardly be used to predict the performance of other decision-making units. In summary, it should be mentioned that previous studies have the following drawbacks:

1. Have assumptions about the functional form.
2. Are sensitive to outliers and statistical noise.
3. Do not have forecasting capability.
4. Do not consider a method for increasing the homogenous status of DMUs.

### 1.2. Objective

The main objective of the present study is to propose an Integrated Artificial Neural Network Fuzzy C-Means algorithm that has the following features:

1. Contributes to the use of neuro-fuzzy models in the area of efficiency measurement.
2. Handles environmental complexity.
3. Requires no assumption about the functional form.
4. Handles outliers and statistical noise.
5. Forecasts the future behaviour.
6. Increases the homogenous status of DMUs.

One of the main objectives 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 two distinct algorithms are proposed. Using ANN guides the algorithm to reach the first five objectives. Also, Fuzzy C-Means is used to increase the homogenous status of DMUs as stated in the sixth objective. Previous studies by Azadeh, Ghaderi, Anvari, and Saberi (2006a, 2006c) and Azadeh, Ghaderi, Tarverdian, and Saberi, 2006e, 2006f). 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 and (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 Valin (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 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. ANN has been viewed as a good tool to approximate numerous non-parametric and non-linear problems. Therefore, the proposed algorithm estimates more robust results and more efficient units than the conventional approach because better performance patterns are explored.

### 2.1. Fuzzy C-Means

In Fuzzy C-Means clustering, each data point belongs to a cluster with membership value that indicates the grade of membership. Fuzzy C-Means was proposed as an improvement on traditional clustering methods by Bezdek (1981). Using Fuzzy logic in the proposed clustering method improves its flexibility and is therefore ideal for non-linear situations. Overlapping as one of important problem in clustering is also decreased by the proposed Fuzzy C-Means approach.

### 3. Methodology

Two distinct ANN algorithms are proposed to measure the units’ efficiency in current period. These algorithms can estimate efficiency by considering input (output) oriented by finding production function (cost) function by using ANN approach, same as econometric methods. Also for simplicity, we consider one output (input), but it is easy to extend to various outputs (inputs).

#### 3.1. The proposed algorithm

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 (Sₜ: test data) does not belong to Sₜ. Then, obtain the preprocessed data set (S and Sₜ) after the data are scaled between 0 and 1.

3. Divide S into two subsets: training (S₁) and valid (S₂) 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 and (also training errors) will normally decrease during the initial phase of training. 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 lowest scales are returned. The validation data is taken out from the training data and it should be representative across the range of outcomes. It is necessary to strike a balance between the size of training and validation data sets. 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, extrapolation ability of ANN should be calculated. Therefore, the data for validation is chosen for the period which is closer to Sₜ.

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.

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

5. Run ANNₜ for Sₜ.

6. Apply normal probability plot for checking existence of outliers. For this, at first for each index (output (s) and input (s)) (xₖ, k = 1, . . . , m) normalize the data:

$$
\hat{x}_i = (x_i - \mu_k) / \sigma_k, \quad i = 1, \ldots, n
$$

where $\mu_k$ is mean and $\sigma_k$ is standard deviation for data of index $x_i$ in $S_i$. Then use normal probability plot for $\{x_i\}_{i=1}^n$. If p-value <0.05 and you can see some points far from the line go to step 10 Otherwise, do steps 7–9.

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

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

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

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.

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).

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

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 $\text{MAPE} = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{\text{Actual}_i - \text{Predicted}_i}{\text{Actual}_i} \right|$. (N: the number of rows).
8. 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:

\[ E_i' = E_i / P_{ANN,i} \quad i = 1, \ldots, n \] for input oriented model

\[ E_i' = E_i / C_{ANN,i} \quad i = 1, \ldots, n \] for output oriented model

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:

\[ E_k' = \max(E_i) \] (3)

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

\[ Sh_i = E_i' \cdot W_i / W_k \quad i = 1, \ldots, n \] for input oriented model

\[ Sh_i = E_i' \cdot C_{ANN,i} / C_{ANN,k} \quad i = 1, \ldots, n \] for output oriented model

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

\[ F_i = P_i / (P_{ANN,i} + Sh_i) \quad i = 1, \ldots, n \] for input oriented model

\[ F_i = (C_{ANN,i} - Sh_i) / C_i \quad i = 1, \ldots, n \] for output oriented model

10. Cluster DMUs by Fuzzy C-Means method (\( x \) cluster are obtained after running Fuzzy C-Means method which is developed by Dunn and improved by Bezdok) and for each cluster do steps 11–14 (Bezdok, 1981; Dunn, 1973; Windham, 1981).

11. Calculate weigh of DMU: \( W_i \)

\[ V_i = P_i / Ave(P_i, P_{i+1}, P_{i+2}, \ldots, P_n) \quad i = 1, \ldots, n \] for input oriented model

\[ V_i = C_i / Ave(C_i, C_{i+1}, \ldots, C_n) \quad i = 1, \ldots, n \] for output oriented model

\[ W_i = V_i / \text{Sum}(V_i) \]

where \( C_j (1 \leq j \leq x) \) is the number of DMUs which belongs to \( j \)th cluster of \( x \) clusters.

12. Calculate the error between the real output \( P_{\text{real}(i)} \) and ANN model output \( P_{ANN(i)} \) in the period which the efficiency is to be assessed for its DMU \( (S_i) \):

\[ E_i = P_{\text{real}(i)} - P_{ANN(i)} \quad i = 1, \ldots, n \] for input oriented model

\[ E_i = C_{ANN(i)} - C_{real(i)} \quad i = 1, \ldots, n \] for output oriented model

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:

\[ E_i' = E_i / W_i \quad i = 1, \ldots, n \] (8)

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 \( E_i \) which indicates the DMU with best performance. Suppose that DMU \( k \) have the Largest \( E_i \) and we have:

\[ E_k = \max(E_i) \] (9)

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

\[ Sh_i = E_k' \cdot W_i / W_k \quad i = 1, \ldots, n \] (10)

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:

\[ F_i = P_i / (P_{ANN,i} + Sh_i) \quad i = 1, \ldots, n \] for input oriented model

\[ F_i = (C_{ANN,i} - Sh_i) / C_i \quad i = 1, \ldots, n \] for output oriented model

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

\[ F_i = (\Sigma D_{ij} F_{ij}) / \Sigma D_{ij} \quad 1 \geq j \geq x \] if DMU belong to more than one clusters

where \( D_{ij} \) is the DMU’s degree of membership in jth cluster and \( F_{ij} \) the DMU’s efficiency score in jth cluster.

This point is important that the efficient unit in cluster A is not more efficient than the efficient unit in cluster B although it may be better than it. It is noted that, in some cases, perhaps in a particular cluster, the obtained error \( F_i \) for all DMUs is negative. In this situation, by notice of the proposed algorithm, frontier function from neural network is shifted to lower level of production. In such cases, the best unit is the DMU that has the lowest loss with respect to its scale.

As it can be seen the proposed algorithm is more complicated than that of traditional DEA approach. There are however several advantages for using this approach. There have been several efficiency frontier analysis methods reported in the literature. But, the assumptions made for each of these methods are restrictive. The non-parametric approach makes no assumption about the functional form of the frontier. Instead, it specifies certain assumptions that allow the construction of the production set. For instance, DEA frontier is very sensitive to the presence of the outliers and statistical noise which indicates that the frontier derived from DEA analysis may be warped if the data are contaminated by statistical noise. On the other hand, DEA can hardly be used to predict the performance of other decision-making units. In fact, applying ANNs can reduce the restrictive assumptions of each of these methods. Moreover, the efficiency prediction power of ANN is unique and its flexibility mechanism facilitates decision makers to solve complex problems, where the main information lies implicitly in the data.

4. Case studies

The proposed method is applied to data sets of two actual cases: steam power generation and auto industry. Implementation of Algorithms 1 and 2 for steam power generations and auto industry are illustrated step by step in Sections 4.1 and 4.2, respectively. The results of running algorithms for the two actual case studies are
also discussed in each section. Section 4.3 presents discussions on the superiority and robustness of the proposed algorithm.

4.1. Performance assessment of steam power generations

The performance and efficiency of power generation industry is of great importance to researchers and experts considering its complexity and particular requirements. This study deals with an investigation into technical efficiency of the Iranian generation electricity industry. This study presents an Artificial Neural Network approach for performance evaluating of steam power plants by noting their important role in electricity generation and that the DMUs essentially perform the same tasks and are homogeneous. In fact, this selection ensures that plants in the sample constitute a homogenous technology, thus forming a suitable sample for applying the model. In this section the proposed methodology is used to efficiency measurement for evaluating 19 steam power plants in Iran for 2004.

In these two algorithms 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 algorithm

Step 1: As shown by several authors, the production function for conventional thermal steam–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 electrical energy production. But by noting studies about efficiency measurement of thermal power generations in Iran which indicate that labor is not an effective factor in our study, electric power is better than 4th model because stable state of 8–11th models indicates that their low errors are not casual.

Step 2: 133 rows of data are collected from 1997 to 2003. Table 1 shows the real data for the inputs and output used in the model. Detailed information about power generation of thermal power plants such as total output, generation capacity and fuel consumption can be obtained from “Electric Power Industry in Iran” (including transmission and distribution) published by the TAVANIR Management Organization (1997–2004).

Step 3: $S_1$ is data from 1997 to 2002 (114 rows of data) and $S_2$ is 2003 data (19 rows of data).

Step 4: In order to get the best ANN for the electricity production in steam power plants, 20 MLP–LM models are tested to find the best architecture. The architecture of the stated MLP–LM models and their MAPE error values are shown in Table 2. It seems the 8th model (it has eight neurons in single hidden layer) has the lowest MAPE (relative error) and consequently is chosen as the preferred model. In Fig. 1, the ANN architecture for the preferred network (8th model) is shown. Fig. 2 present the MLP–LM performance of each model. Examination of Fig. 2 suggests that 8th model is better than 4th model because stable state of 8–11th models indicate that their low errors are not casual.

Step 5: Therefore, the preferred model from previous step is selected for estimating the electricity production in 2004.

Step 6: Fig. 3 shows the Normal probability plot for power plants in 2004. As seen from the plot some outliers exist and p-value is less than 0.005. Thus we should go to step10.

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 ($c_\ell$) that the entropy value ($S_\ell$) lies below the rising trend and the value for the partition coefficient ($pc$) of $c_\ell$ lies above the falling trend. Fig. 4 shows that, according to these two criteria, the best partitioning of the data is achieved with 3 clusters.

<table>
<thead>
<tr>
<th>Power plant name</th>
<th>Install capacity (MW)</th>
<th>Internal consumption (MWh)</th>
<th>Fuel consumption (TJ)</th>
<th>Gross production (MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Montazerghaem</td>
<td>625.88</td>
<td>241,139</td>
<td>30.95308</td>
<td>3,297,100</td>
</tr>
<tr>
<td>Besat</td>
<td>247.5</td>
<td>139,505</td>
<td>17.00441</td>
<td>1,500,253</td>
</tr>
<tr>
<td>Firoozi</td>
<td>50</td>
<td>13,039</td>
<td>3.412765</td>
<td>200,103</td>
</tr>
<tr>
<td>Salimi</td>
<td>1760</td>
<td>311,276</td>
<td>117.1448</td>
<td>13,190,817</td>
</tr>
<tr>
<td>Shazand</td>
<td>1300</td>
<td>642,909</td>
<td>57.30782</td>
<td>7,438,002</td>
</tr>
<tr>
<td>Rajaee</td>
<td>1000</td>
<td>421,015</td>
<td>54.61188</td>
<td>6,342,203</td>
</tr>
<tr>
<td>Beheshti</td>
<td>240</td>
<td>85,307</td>
<td>14.06063</td>
<td>1,435,991</td>
</tr>
<tr>
<td>Tabriz</td>
<td>736</td>
<td>361,080</td>
<td>42.82585</td>
<td>4,341,330</td>
</tr>
<tr>
<td>Mofatteh</td>
<td>1000</td>
<td>390,708</td>
<td>46.37235</td>
<td>5,134,547</td>
</tr>
<tr>
<td>Bistoon</td>
<td>640</td>
<td>350,154</td>
<td>38.2554</td>
<td>4,210,280</td>
</tr>
<tr>
<td>Ramin</td>
<td>1890</td>
<td>686,643</td>
<td>95.29557</td>
<td>12,561,867</td>
</tr>
<tr>
<td>Madjah</td>
<td>290</td>
<td>81,674</td>
<td>7.885659</td>
<td>992,587</td>
</tr>
<tr>
<td>Bandar Abbas</td>
<td>1280</td>
<td>588,855</td>
<td>73.2442</td>
<td>7,196,540</td>
</tr>
<tr>
<td>Zarand</td>
<td>60</td>
<td>69,698</td>
<td>6.322743</td>
<td>691,402</td>
</tr>
<tr>
<td>Esfahan</td>
<td>835</td>
<td>422,673</td>
<td>32.77859</td>
<td>5,621,431</td>
</tr>
<tr>
<td>Montazeri</td>
<td>1600</td>
<td>796,262</td>
<td>112,4223</td>
<td>13,037,177</td>
</tr>
<tr>
<td>Toos</td>
<td>600</td>
<td>271,901</td>
<td>37.45617</td>
<td>3,831,065</td>
</tr>
<tr>
<td>Mashhad</td>
<td>120</td>
<td>73,050</td>
<td>7.955432</td>
<td>865,887</td>
</tr>
<tr>
<td>Iranshahr</td>
<td>256</td>
<td>140,940</td>
<td>15.76105</td>
<td>1,492,847</td>
</tr>
<tr>
<td>Average</td>
<td>764.7568</td>
<td>314,622.5</td>
<td>42.47745</td>
<td>4,914,812</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>583.8156</td>
<td>231,103.9</td>
<td>32.92167</td>
<td>4,209,986</td>
</tr>
<tr>
<td>Min</td>
<td>50</td>
<td>13,039</td>
<td>3.412765</td>
<td>200,103</td>
</tr>
<tr>
<td>Max</td>
<td>1890</td>
<td>796,262</td>
<td>117.1448</td>
<td>13,190,817</td>
</tr>
</tbody>
</table>

Various natural elements have been used as fuel in the production of electric power in various steam plants in Iran (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. Internal power is the amount of energy consumed (in megawatt hour) within the site (for electrically powered equipment etc.).
Then the Fuzzy C-Means algorithm is run for the three clusters (A, B, C). The degrees of membership of the power plants in each of the three clusters (A–C) are shown in Fig. 5. The reader should note the high degree of membership of Montazerghaem, Shazand and Bandarabbas in clusters (A and C), (A and B) and (A and B), respectively. Thus, these DMUs are considered in the two of these clusters. In Table 5 (column1), the DMUs which belong to each of these clusters are shown.

Steps 11–14: The results of these steps for each of the clusters are shown in Table 3. It is observed that middle, large and small plants belong to clusters A–C, respectively. It should be noted that some units may belong to two or more clusters and their efficiency scores in the cluster with large scale units are less than clusters with smaller scale units. For instance, Montazerghaem plant belong to both clusters A and C but its efficiency score in cluster C is approximately 5% less than its calculated efficiency in cluster A. This point indicates the importance of clustering of units before evaluating their performance. For calculating a unique efficiency score for Montazerghaem plant by the proposed algorithm, the degree of membership in each of clusters A and B is used:

\[
\frac{(\text{Montazerghaem's efficiency score in cluster A (0.943)}}{C2} + \text{Montazerghaem's degree of membership in cluster A (0.59)}) + \frac{(\text{Montazerghaem's efficiency score in cluster C (0.891)}}{C2} + \text{Montazerghaem's degree of membership in cluster C (0.36)})}{(\text{Montazerghaem's degree of membership in cluster A (0.59)} + \text{Montazerghaem's degree of membership in cluster C (0.36)}) = 0.923.\]

Table 4 provides rankings of the plants by common method which is similar to COLS (presented by: Athanassopoulos and Curram (1996) who called this measure "standardized efficiency") (Costa & Markellos, 1997; Delgado, 2005).

Step 15: Based on the best estimated neural networks for the dataset for power plants in 2004, unique efficiency scores for all plants by the algorithm are calculated. The main results of proposed algorithm are summarized in the Table 5.

### 4.1.2. Results and analysis

From Table 5 presents the results of both conventional and proposed algorithm. It can be seen that the conventional algorithm produces smaller mean technical efficiency while the proposed algorithms produce distinctly higher mean technical efficiency for the steam power plants 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 the algorithm are significantly different.

Conflicting conclusions of DMUs efficiency are often resulted by using the different methods due to the unsuitability and difference of their assumptions. Besides, it has been noted that comparing various units with various scales and capitals is not logical. For example, increasing 100,000 MWh in the production of 2000 MW and 50 MW plants is more feasible for the 2000 MW plant. In fact, if a 50 MW plant can produce 100,000 MWh more than predicted
value of the ANN algorithm, its efficiency is more than a plant with the same added production of 2000 MW plant. Therefore, in order to increase DMUs’ homogeneousness, Fuzzy C-means method is used to cluster DMUs and this is the cause of different results in the conventional and proposed algorithms.

The results of t-test are reported in Table 6. The test rejects the null hypothesis that mean technical efficiencies of the conventional algorithm is larger than that of the proposed algorithm. Consequently, the proposed algorithm provides more robust results and identifies more efficient units than the conventional methods since better performance patterns are explored (Wu et al., 2006).

4.2. Performance assessment of auto industries

Automotive industries play an important role in the overall economic development. Due to the ever-increasing growth and development of automotive industry in the world, determining the position of automotive industry is very important. Therefore, the need for an integrated approach for continuous assessment and improvement of automotive industries based on economic performance becomes essential. Consequently, it will enable predictions to be made about manufacturing system behaviour.

In summary, there are economical and non-economical approaches to measure performance. Economical approach is mostly used in export performance studies and is concerned with such factors as export intensity (export to sales), profitability, return on investment (ROI), export growth and market share. Non-economical approach is concerned with number of exports to international markets, product characteristics, export of new products and share of export in product development. Noting that the non-economical criteria affect economic criteria in one way or another, this study will only consider the economical criteria. In
fact, export performance studies either use single indicators or multiple indicators. Furthermore, it is concluded from the previous studies that export performance indicators are dependent to one another. Therefore, the need for an integrated approach for continuous assessment and improvement of auto industries based on export and economics performance becomes essential.

Export plays an important role in the overall performance of auto industries. In fact, export activities are correlated with expansion of industrial products and also are an important factor in influencing foreign markets. Those countries that achieve a high level of economic growth have also been successful in expanding their industrial exports. Export performance assessment is still the least comprehended aspects of international marketing. This may be due to theoretical issues, implementing and assessing export performance models, which often result in inadequate or contradictory results. Export growth is also reported to be correlated with R&D expenditure.

This study has identified major indicators, which impact the performance of auto industries. Auto industries are categorized and selected according to International Standard for Industrial Classification (ISIC). Only industrial units with more than 50 personnel are considered in this study. Furthermore, industries in the bottom of the ranking may enhance their performance by improving the most important principal components. Managers may use this type of modelling approach to assess the performance for various sites with respect to economic indicators in a particular industry. In turn, the selected sites would be ranked based on an integrated scientific approach, which reveals the standing of each industry. In turn, the selected sites would be ranked based on an integrated scientific approach, which reveals the standing of each industry. In turn, the selected sites would be ranked based on an integrated scientific approach, which reveals the standing of each industry. In turn, the selected sites would be ranked based on an integrated scientific approach, which reveals the standing of each industry.
Table 5

<table>
<thead>
<tr>
<th>DMU</th>
<th>Efficiency scores by conventional algorithm</th>
<th>Efficiency scores by proposed algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandarabbas</td>
<td>0.940</td>
<td>0.939</td>
</tr>
<tr>
<td>Beheshti</td>
<td>0.819</td>
<td>1.000</td>
</tr>
<tr>
<td>Besat</td>
<td>0.646</td>
<td>0.726</td>
</tr>
<tr>
<td>Bistoon</td>
<td>0.919</td>
<td>0.961</td>
</tr>
<tr>
<td>Esfahan</td>
<td>0.866</td>
<td>0.875</td>
</tr>
<tr>
<td>Firoozie</td>
<td>0.195</td>
<td>0.379</td>
</tr>
<tr>
<td>Iranshahr</td>
<td>0.664</td>
<td>0.753</td>
</tr>
<tr>
<td>Madhaj</td>
<td>0.621</td>
<td>0.818</td>
</tr>
<tr>
<td>Mashhad</td>
<td>0.489</td>
<td>0.679</td>
</tr>
<tr>
<td>Mofatteh</td>
<td>0.885</td>
<td>0.902</td>
</tr>
<tr>
<td>Montazerghaem</td>
<td>0.880</td>
<td>0.923</td>
</tr>
<tr>
<td>Montazeri</td>
<td>0.967</td>
<td>0.940</td>
</tr>
<tr>
<td>Rajaei</td>
<td>0.945</td>
<td>0.953</td>
</tr>
<tr>
<td>Ramin</td>
<td>0.930</td>
<td>0.904</td>
</tr>
<tr>
<td>Salimi</td>
<td>0.993</td>
<td>0.967</td>
</tr>
<tr>
<td>Shazand</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Tabriz</td>
<td>0.851</td>
<td>0.880</td>
</tr>
<tr>
<td>Toos</td>
<td>0.902</td>
<td>0.950</td>
</tr>
<tr>
<td>Zarand</td>
<td>0.310</td>
<td>0.527</td>
</tr>
<tr>
<td>Mean (µTE)</td>
<td>0.780</td>
<td>0.846</td>
</tr>
</tbody>
</table>

Table 6
Hypothesis testing of means technical efficiencies (µTE) of the conventional and proposed algorithm for power plants in 2004.

<table>
<thead>
<tr>
<th>Hypothesis:</th>
<th>H₀: µTE Algorithm 2 - µTE C. algorithm = 0</th>
<th>H₁: µTE Algorithm 2 - µTE C. algorithm &gt; 0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calculated t-statistic</td>
<td>4.21</td>
<td>0.0003</td>
</tr>
<tr>
<td>P-value</td>
<td></td>
<td>0.0003</td>
</tr>
<tr>
<td>Decision</td>
<td>Reject H₀ at the 1% level of significance</td>
<td></td>
</tr>
</tbody>
</table>

would help policy makers and top managers to have better understanding and improve existing systems with respect to integrated performance of auto industries.

The framework presented in this paper may be used by top managers to compare the economic performance of auto industries. This may be accomplished by defining the target units (say n sectors) and ranking them with respect to the four economic indicators discussed in this paper. Therefore, they will have standard and scientific results about the standings of all units. Second, the modelling approach may be extended to include external units (competitors) to identify standings and weak and strong export factors in the big picture.

This study considers auto industries of 12 countries with respect to the selected indicators for 2000. In addition for estimating cost function 5 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

Table 7
Estimation of efficiency scores for all DMUs by the proposed algorithm for evaluating performance of auto industries in 2000.

<table>
<thead>
<tr>
<th>DMU</th>
<th>Pₑₑₑₑₑₑ after normalization</th>
<th>Pₑₑₑₑₑₑ</th>
<th>Eₑₑ</th>
<th>Eₑₑₑₑ</th>
<th>Sₑₑ</th>
<th>Fₑₑ</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Austria</td>
<td>0.010</td>
<td>0.008</td>
<td>-0.001</td>
<td>-0.171</td>
<td>0.004</td>
<td>0.422</td>
<td>12</td>
</tr>
<tr>
<td>Brazil</td>
<td>0.036</td>
<td>0.031</td>
<td>-0.004</td>
<td>-0.134</td>
<td>0.016</td>
<td>0.435</td>
<td>10</td>
</tr>
<tr>
<td>Canada</td>
<td>0.052</td>
<td>0.074</td>
<td>0.022</td>
<td>0.297</td>
<td>0.038</td>
<td>0.702</td>
<td>3</td>
</tr>
<tr>
<td>France</td>
<td>0.105</td>
<td>0.133</td>
<td>0.027</td>
<td>0.207</td>
<td>0.067</td>
<td>0.623</td>
<td>5</td>
</tr>
<tr>
<td>Germany</td>
<td>0.581</td>
<td>0.505</td>
<td>-0.076</td>
<td>-0.150</td>
<td>0.255</td>
<td>0.429</td>
<td>11</td>
</tr>
<tr>
<td>Italy</td>
<td>0.942</td>
<td>0.966</td>
<td>0.024</td>
<td>0.364</td>
<td>0.033</td>
<td>0.776</td>
<td>2</td>
</tr>
<tr>
<td>Japan</td>
<td>0.258</td>
<td>0.289</td>
<td>0.031</td>
<td>0.107</td>
<td>0.146</td>
<td>0.553</td>
<td>8</td>
</tr>
<tr>
<td>Malaysia</td>
<td>0.004</td>
<td>0.008</td>
<td>0.004</td>
<td>0.506</td>
<td>0.004</td>
<td>1.000</td>
<td>1</td>
</tr>
<tr>
<td>Republic of Korea</td>
<td>0.045</td>
<td>0.062</td>
<td>0.017</td>
<td>0.270</td>
<td>0.031</td>
<td>0.677</td>
<td>4</td>
</tr>
<tr>
<td>Spain</td>
<td>0.098</td>
<td>0.099</td>
<td>0.012</td>
<td>0.200</td>
<td>0.030</td>
<td>0.617</td>
<td>6</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>0.096</td>
<td>0.098</td>
<td>0.003</td>
<td>0.026</td>
<td>0.050</td>
<td>0.507</td>
<td>9</td>
</tr>
<tr>
<td>United States</td>
<td>0.503</td>
<td>0.570</td>
<td>0.067</td>
<td>0.118</td>
<td>0.289</td>
<td>0.560</td>
<td>7</td>
</tr>
</tbody>
</table>

Table 8
The impact of outlier and corrupted data on the results of proposed algorithm.

<table>
<thead>
<tr>
<th>DMU name</th>
<th>Efficiency score after Besat noise (%)</th>
<th>Efficiency score after Bandarabbas noise (%)</th>
<th>Original efficiency score (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Montazerghaem</td>
<td>0.916</td>
<td>0.916</td>
<td>0.916</td>
</tr>
<tr>
<td>Bistoon</td>
<td>0.934</td>
<td>0.934</td>
<td>0.934</td>
</tr>
<tr>
<td>Toos</td>
<td>0.925</td>
<td>0.925</td>
<td>0.925</td>
</tr>
<tr>
<td>Tabriz</td>
<td>0.862</td>
<td>0.862</td>
<td>0.862</td>
</tr>
<tr>
<td>Besat</td>
<td>0.964</td>
<td>0.760</td>
<td>0.760</td>
</tr>
<tr>
<td>Firoozie</td>
<td>0.381</td>
<td>0.381</td>
<td>0.381</td>
</tr>
<tr>
<td>Beheshti</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Madhaj</td>
<td>0.831</td>
<td>0.831</td>
<td>0.831</td>
</tr>
<tr>
<td>Zarand</td>
<td>0.554</td>
<td>0.554</td>
<td>0.554</td>
</tr>
<tr>
<td>Mashhad</td>
<td>0.702</td>
<td>0.702</td>
<td>0.702</td>
</tr>
<tr>
<td>Iranshahr</td>
<td>0.773</td>
<td>0.773</td>
<td>0.773</td>
</tr>
<tr>
<td>Salimi</td>
<td>0.950</td>
<td>0.950</td>
<td>0.950</td>
</tr>
<tr>
<td>Shazand</td>
<td>0.973</td>
<td>0.973</td>
<td>0.973</td>
</tr>
<tr>
<td>Rajaei</td>
<td>0.930</td>
<td>0.930</td>
<td>0.930</td>
</tr>
<tr>
<td>Mofatteh</td>
<td>0.883</td>
<td>0.883</td>
<td>0.883</td>
</tr>
<tr>
<td>Ramin</td>
<td>0.892</td>
<td>0.892</td>
<td>0.892</td>
</tr>
<tr>
<td>Bandarabbas</td>
<td>0.738</td>
<td>0.738</td>
<td>0.918</td>
</tr>
<tr>
<td>Esfahan</td>
<td>0.860</td>
<td>0.860</td>
<td>0.860</td>
</tr>
</tbody>
</table>

Table 9
MAPE values for simulated noisy DMUs in the proposed algorithm vs. DEA.

<table>
<thead>
<tr>
<th>DMU name</th>
<th>Proposed algorithm</th>
<th>DEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Besat</td>
<td>0.024</td>
<td>0.14</td>
</tr>
<tr>
<td>Bandarabbas</td>
<td>0.011</td>
<td>0.13</td>
</tr>
</tbody>
</table>
according to the format of International Standard for Industrial Classification (ISIC) from 1995 to 2000.

The Normal probability plot for auto industries in 2000 shows that there are no outliers and p-value is <0.05. Thus, steps 7–9 are performed. In this section only the main results of steps 7–9 for evaluating efficiency scores and rankings of auto industries in 12 countries are presented since the detailed results are quite similar to the first case study presented in Section 4.1. Hence, by considering output oriented assumption, the efficiency values and ranking results are shown in Table 7.

4.3. Superiority of the proposed algorithm

The proposed method can find a stochastic frontier with a set of inputs and outputs. Finding frontier and stochastic features are two important features of the integrated algorithm of this study. There have been several studies in the empirical and experimental field. Moreover, they have shown that ANN is superior to conventional methods in estimating production functions (Brian Hwarng, 2001; Chiang et al., 1996; Hill, O’Connor, & Remus, 1996; Indro et al., 1999; Jhee & Lee, 1993; Kohzadi et al., 1996; Stern, 1996;
Tang & Fishwick, 1993; Tang et al., 1991; Azadeh et al., 2006). Furthermore, non-linearity of ANN in addition to its universal approximations of production functions makes it highly flexible. Also, ANN as an intelligent method can be useful for non-linear process that has an unknown functional form (Enders, 2004). Therefore, ANN could find frontier based on some of the historical data when sufficient data is available.

Similar to other intelligent and heuristic approaches, ANN provides semi-optimum solutions. This is because ANN uses various and different initial weights in its structure. Therefore, even if the given ANN is trained several times without change in its structure then different solution and output is yielded in each iteration. Thus, as a first conclusion, ANN can find the stochastic frontier. In other words, if ANN structure remains the same, initial weights and learning algorithm are two important factors on frontier structure. Consequently, the stochastic frontier will be constructed.

Therefore, in this study, ANN is selected for estimating production function and performance evaluation of DMUs. ANN could learn chaotic behaviour of a complex system which in turn could reduce noise and bias. Fig. 6 shows an example of such situations with respect to the obtained stochastic frontier of this study.

4.3.1. Quantification of robustness

Robustness is defined in various areas such as economics, computer science, and control theory. Also, robustness could be an essential part of performance assessment in various areas. One of the drawbacks of DEA is its lack of robustness due to existence of noise and complexity. However, due to intelligent, flexible and non-linear mechanism of ANN, noise and complexity could be considerably reduced and hence robustness increases consequently. An example is given to quantify and show the robustness of ANN versus DEA. Suppose that imaginary outlier data is yielded from human error. Also, it is assumed that outlier or corrupted data is occurred in inputs variable. Let us suppose that one of input variable of Besat DMU (Fuel Consumption) is changed from 0.13 to 0.013 that is yielded from human error. The result of the proposed algorithm after occurrence of this error is shown in Table 8. Mean absolute percentage error (MAPE) is used to compare the results.

Table 9 shows MAPE value for the proposed algorithm. The same procedure is done for Bandarabbas DMU. Second input variable of Bandaabbas DMU (Internal Consumption) is changed from 0.71 to 0.071. MAPE values in the stated examples (2% and 1.1%) show the capability of proposed algorithm in handling outliers and corrupted data. These two examples show the superiority of the proposed approach versus DEA with respect to robustness.

5. Conclusion

Two highly unique flexible ANN algorithms were proposed to measure and rank the DMUs efficiency scores which are composed of eight and eleven distinct steps, respectively. Fig. 7 presents the flow chart for the Integrated ANN-Fuzzy C-Means-Normalization Algorithm for performance assessment of DMUs. Because of non-linearity of the neural networks in addition to its universal approximations of functions and its derivatives which makes the algorithms highly flexible. To show their applicability and superiority they were applied to two case actual studies (steam power plants of Iran in 2004 and 12 auto industries in the world in 2000). Normal probability plot is used to select from the two sub-algorithms from the main algorithm by referring to existence of outliers in dataset. Moreover, if the dataset has outlier(s) sub-algorithm 1 will be selected and otherwise sub-algorithm 2 will be selected for performance assessment of DMUs.

The first application showed that sub-algorithm 2 is more appropriate and efficient for assessing performance of steam power generation. This may be due to none-homogeneity of DMUs and existence of few outliers. Also, in the second case study which was concerned with auto industries, it was concluded that sub-algorithm 1 is more appropriate to performance evaluation of auto industries than sub-algorithm 1.

Furthermore, in the first study the results and rankings were compared with the conventional approach. Results indicated that the proposed algorithm estimates the values of efficiency scores closer to the ideal efficiency but rankings of DMUs remain the same. Therefore, the proposed algorithm estimates more robust results and more efficient units than the conventional approach because better performance patterns are explored.

The proposed ANN- Fuzzy C-means approach was also compared with DEA which is one of the well-known methods in efficiency literature. Its features were compared with DEA to show its advantages over DEA (Table 10). The two methods are non-parametric and make no assumption about the functional form of the frontier. The ANN-Fuzzy C-means provides great flexibility, whereas DEA has medium flexibility. The DEA frontier is very sensitive to the presence of the outliers and statistical noise which indicates that the frontier derived from DEA analysis may be warped if the data are contaminated by statistical noise (Bauer, 1990) while one of main feature of ANN is its high flexibility and could handle the statistical noise and outliers. Another attractive feature of ANN-Fuzzy C-Means approach is its forecasting ability while DEA can hardly be used for forecasting purpose. Moreover, by using Fuzzy C-Means method, homogeneity of DMUs is increased by proper clustering. Sensitivity analysis and optimization ability are other main features of ANN-Fuzzy C-Means Algorithm (Azadeh, Saberi, & Anvari, in press).

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.

Acknowledgement

The authors are grateful for the valuable comments and suggestions from the respected reviewers. Their valuable comments and suggestions have enhanced the strength and significance of our paper.
Appendix A. Artificial Neural Networks

An ANN is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. Among the different networks, the feed forward neural networks or multi layer perceptron (MLP) are the most commonly used in engineering science. In these networks, the output function is the linear combination of hidden units’ activations; each one is a non-linear function of the weighted sum of inputs. MLPs are mathematical models often equivalent to conventional models in econometrics (linear regression, auto regressive moving average (ARMA) models for time series analysis), but with specific estimation methods (Cheng & Titterington, 1994).

The activation function for output layer is generally linear. The non-linear feature is introduced at the hidden transfer function. From the previous universal approximation studies, these transfer functions must have mild regularity conditions: continuous, bounded, differentiable and monotonic increasing (Hornik, Stinchcombe, & White 1989). The most popular transfer function is sigmoid or logistic, nearly linear in the central part. 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.
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 $m = 1, 2, 3, 4$. Finally, it is common to eliminate ‘irrelevant’ inputs or hidden units (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. 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. BP is an iterative process. Parameters are revised from the error function gradient by the learning rate, constant or variable. The error propagates backwards to correct the weights until some stop page criterion – epoch, error goals – is reached.

After neural training (training set), new observations (validation and/or test sets) are presented to the network to verify the so-called generalization capability (Schiffmann, Joost, & Werner, 1992). ANNs have advantages, but logically they also have several drawbacks. ANNs have an important role when these relationships are unknown (non-parametric method) or non-linear (non-linear method), provided there are enough observations with flexible form and universal approximation property. Algorithm convergence and trial and error process are also some relevant drawbacks.

References


