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Electricity Demand Estimation Using an Adaptive Neuro-Fuzzy Network: A Case Study from the State of Johor, Malaysia

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Abstract

Electricity is one of the energy types that have attracted a lotof interest due to its versatility.Rigorous analysis of the determinants of electricity demand as well as its accurate forecasting are of vital importance in the design of an effective energy policy to deal with current and future electricity needs.Several load forecasting models have been used inelectric power systems for achieving accuracy. Most studies have focused on the relationship between electricity demand and economicparameters such as gross domestic product (GDP), Gross National Product (GNP), national income, and the rate of employment as well as unemployment. Various studies have investigated the influence of ambient airtemperature, most times represented by heating and coolingdegree-days, on electrical energy consumption. Many studies have been conducted on short/long term electricity demand/load forecasting, but application of neuro fuzzy logic for forecasting electricity demand based on combined economic and climate conditions is still unexplored. In this paper, an ANFIS network (adaptive neuro fuzzy inference system) was designed to map six parameters as input data for State of Johor, Malaysia including four demographic& economic parameters (i.e. Employment, GDP, Industry Efficiency and Population), and two meteorological parameters related to annual weather temperature (i.e. minimum and maximum average annual temperature).to electricity demand as output variable.

Keywords: Electricity demand; Neuro-Fuzzy; ANIFS; Forecasting

1. Introduction

The current electricity demand/load forecasting methods are mostly based on: data mining, multivariate analysis and time series analysis [1-10]. Multivariate analysis establishes the relationship between dependent and independent variables and fashions a causal model for dependent variable forecasting in term of independent variable. The forecasting precision of this model depends on the selection of independent variables. If the variation of the dependent variables cannot effectively explain, then it will produce a forecast model with high variance. On the other hand, time series models require only the historical data of the variable of interest to forecast its future progression. For example, the autoregressive integrated moving average (ARIMA) models have been widely used in energy demand forecasting. However, a large number of observations have been usually required to produce accurate forecasting results. Data mining techniques, such as artificial neural networks and support vector regression, are widely used as forecasting approaches and have extremely good forecasting performance. However, the forecasting results depend on the number of training data and their representativeness, and these limitations have not yet been overcome.

In all the above methods, the key element that affects forecasting performance is the sample size, which limits their applicability to certain forecasting situations. Forecasting the energy demand in rapidly developing countries is an example of this. Although a considerable amount of historical data is available, it usually differs significantly from the actual growth in electricity consumption. Since electricity consumption is generally represented as following an exponential trend, the usual methods of forecasting with limited data, such as basic time-series approaches like the moving average, exponential smoothing, and linear regression, are not suitable. Therefore, for a non-deterministic condition, it is helpful to establish new models using limited samples to conduct electricity consumption forecasting. The currently applied theories and methods for non-deterministic data or uncertainties can be divided into three categories: probability theory, fuzzy mathematics, and grey system theory [11-15]. Where probability theory focuses on the stochastic phenomena [16], fuzzy mathematics studies the situation of cognitive uncertainties [17], and grey system theory is developed to deal with the problems of small samples and insufficient information [18]. Probability theory usually requires quite a lot of observations to produce accurate and stable results, and the performance of fuzzy mathematics is heavily related to human experience. These characteristics are why the probability theory and fuzzy mathematics are not very suitable when dealing with problems with small sample sets [19].

Several load forecasting models have been used in electric power systems for achieving accuracy. Among the models are statistical, linear regressions, ARMA, Box-Jenkins, filter model of Kalman. In addition, artificial intelligence has been introduced based on neural network, fuzzy logic, neuro-fuzzy system and genetic algorithm. Forecasting short, medium and long term electric load consumption with artificial neural network has received more attention because of its easy implementation, accuracy and good performance [20-25]. James et al. [26] in their study compare the accuracy and performance of several methods for load forecasting for lead times up to a day-ahead. They describe six approaches: double seasonal ARMA modeling, exponential smoothing for double seasonality, artificial neural network, a regression method with Principal Component Analysis (PCA) and two simplistic benchmark methods using a time series of hourly demand for Rio de Janeiro and a series of half-hourly demand for England and Wales. They conclude that in addition to its forecasting performance smoothing method is simplest and quickest to implement. Espinoza et al. [27] used a fixed-size least squares support vector machines for nonlinear estimation in NARX model for prediction the load at a given hour by the evolution of the load at previous hours. They conclude that the forecasting performance assessed for different load series is satisfactory with a mean square error less than 3% on the test data. Chen et al. [28] and all in their study are also used support vector machine techniques for med-term load forecasting by constructing models on relative information such as climate and previous electric load data. They recommend the use of available complete information for medium-term load forecasting because taking climate factors into account may lead to imprecise prediction and that the use of time-series concept may improve the forecasting. Song et al. [29] present a new fuzzy linear regression method for the short term 24 hourly electric loads forecasting of the holidays. Results shows relatively big load forecasting errors are significantly enhanced due to the dissimilar electric load pattern of the special days compared of regular weekdays. The use of neural network for short term load forecasting provides errors in case of speedy fluctuations in load and temperature. To overcome this problem, Jain et al. [30] uses an adaptive neuro-fuzzy to adjust the load curves on selected similar days which takes into account the effect of humidity and temperature. Results obtained show a good prediction with a small mean absolute percentage error. Furthermore, Neuro-fuzzy approaches have been used in short, medium and long term load forecasting [31].

The fuzzy theory combined with neural network by soft computing algorithms, have found a variety of applications in various fields including industrial environment control system, process parameters, semi-conductor machine capacity forecasting, business environment forecasting, financial analysis, stock index fluctuation forecasting, consumer loan, medical diagnosis and electricity demand forecasting. Lin and George-Lee [32] conducted to combine the fuzzy theory with neural network. They proposed a hybrid model which combines the idea of fuzzy logic controller, neural network structure and learning abilities into an integrated neural-network based fuzzy logic control and decision system. Subsequently, several researchers investigated some studies related to the application of this combined approach and then developed several kinds of approaches [33-40].

- The commonly used methods are as follows [41]:
- Fuzzy adaptive learning control systems (FALCON)
- Fuzzy back-propagation network (FBPN)
- Adaptive neuro-fuzzy inference systems. (ANFIS)
- Fuzzy hyper rectangular composite neural networks (FHRCNNs)
- Fuzzy neural network (FuNN).

Recently, Mordjaoui and Boudjema[31] presents an application of neuro fuzzy model with a high forecasting accuracy that depends on previous weekly load data and concluded that the ANFIS approach can accurately predict weekly load consumption and the performance of the proposed model is not affected by rapid fluctuations in power demand which is the main drawback of neural networks models.

The main purpose of this study is to develop and test a model for short term electric load forecasting in order to cross the bypass of existing model based on large scale of data and much time consuming and complexity. The rest of this paper is organized as follows. Section 2 introduces the building procedure of the grey forecasting model, while Section 3 presents its performance and compares it with that of other forecasting methods. Finally, Section 4 concludes this study.

2. Material and Method

2.1. Input parameters

In this paper, an ANFIS network (adaptive neuro fuzzy inference system) was designed to map six parameters as input data for State of Johor, Malaysia including four demographic& economic parameters (i.e. Employment, GDP, Industry Efficiency and Population), and two meteorological parameters related to annual weather temperature (i.e. lowest average annual temperature (CDD), and highest average annual temperature (HDD)).to electricity demand as output variable.

2.1.1. Metrological Factors

Various studies have investigated the influence of ambient air temperature, most times represented by heating and cooling degree-days, on electrical energy consumption [42-51]. However, temperature is not the only variable considered in the literature. Other primitive independent variables, such as relative humidity, clearness index, cloudiness, rainfall, solar radiation and wind speed[52-56], and derived variables including latent enthalpy-days, temperature–humidity index, Steadman's indoor apparent temperature, cooling radiation-days and clothing insulation units 'clo'[51, 57-59] have also been used by other researchers for the development of statistical models for energy consumption. In many cases modeling of electric energy consumption is multivariate, consisting in a mix between climate and other important economic factors. The main constituents of these economic factors are energy prices, income, Gross National Product (GNP), import and export values and energy demand index[54, 60-66]. Population and production in total manufacturing, together with temperature, have also been used by Bessec and Fouquau [67] for modeling monthly electricity consumption to a panel of 15 member states of the European Union over the last two decades. Moral-Carcedo and Vice´ns-Otero [68] in their analysis, proposed a logistic smooth threshold regression model with the temperature as a threshold variable. This allows the relationship between electricity consumption and temperature to depend on the level of the threshold variable i.e. the temperature. Time series analysis of daily electricity demand data reviles a ''U'' shape relation between outdoor temperature and electricity demand [42, 44, 48, 53, 56, 60, 67-70].According to Henley and Peirson [45], this response is caused by the differences between the ambient or outdoor temperature and the comfort or indoor temperature. When the differential between outdoor and indoor temperatures increases, the starting-up of the corresponding heating or cooling equipment immediately raises the demand for electricity. Naturally, the curve of the response of demand to temperatures depends especially on the climate characteristics of the geographical area to which the demand data refer[71].

While variations in temperatures are an important determinant in electricity demand (especially by the residential sector), Pouris [72] notes that in studies using annual data from countries where residential sector accounts for a small share of total electricity consumed, changes in temperatures tend to exhibit less explanatory power. This evidence is augmented by Diabi [73] who argues that if temperature exhibits less variation between years, then it will matter very little in explaining variability in electricity demand[74].

2.1.2. Economic Factors

Higher real incomes should result in higher levels of economic activity and accelerate purchases of electrical goods and services. Across the world, the electricity supply industry is a highly capital intensive venture requiring generating plants that are expensive to construct and take relatively long lead times before being operational. For this reason, rigorous analysis of the determinants of electricity demand as well as its accurate forecasting are of vital importance in the design of an effective energy policy to deal with current and future electricity needs[74].

Adom et al. [75] investigated for the factors responsible for the historical growth trends in aggregate domestic electricity demand quantifying their effects both in the short-run and long-run periods using the ARDL Bounds co-integration approach and the sample period 1975 to2005. In the long-run, real per capita GDP, industry efficiency, structural changes in the economy, and degree of urbanization are identified as the main driving force behind the historical growth trend in aggregated domestic electricity demand. However, in the short-run, real per capita GDP, industry efficiency, and degree of urbanization are the main drivers of aggregate domestic electricity demand. Industry efficiency is the only factor that drives aggregate domestic electricity demand downwards. However, the negative efficiency effect is insufficient to have outweighed the positive income, output, and demographic effects, hence the continual growth in aggregate domestic electricity demand.

Electricity is one of the energy types that have attracted a lot of interest due to its versatility. Literature on empirical analysis of electricity demand abounds but most of these studies are micro based with special focus on developed countries [71, 76-84].

Most studies have focused on the relationship between electricity demand and economical parameters such as gross domestic product (GDP), Gross National Product (GNP), national income, and the rate of employment as well as unemployment. Sari and Soytas [85] studied the relationship between different sources of electricity consumption, employment and national income growth in Turkey. Narayan and Smyth [86]carried out the same study in Australia. They evaluated both long and short term relationship between electricity consumption, employment and real income. Relationships between GDP and electricity consumption in ten newly industrialized Asian countries were estimated by Chen et al.[87]. They studied long run relationship in China, Hong Kong, India, Indonesia, Korea, Malaysia, Philippines, Singapore, Taiwan and Thailand. In another attempt, German Institute for Economic Research (DIW) was commissioned by "German Advisory Group on Economic Reform in Ukraine" in 1998 to predict electricity demand in Ukraine until the year 2010. A comparison of the relationship between renewable and non-renewable electricity consumption and real GDP in the US using annual data from 1949 to 2006 was done by Payne[88]. Bowden and Payne[89]used these data in 2008 to check the causal relationship between electricity consumption and real GDP. Studying the time series properties of electricity consumption of G-7 countries was the subject of Soytas and Sari [90]. In Pakistan, Aqeel and Butt [91] found out that economic growth affects the total electricity consumption. They also discovered that economic growth leads to growth in petroleum consumption but however electricity consumption leads to economic growth without feedback. De Vita et al. [92] found the same results for Namibia. Their research for the period between the year 1980 to 2002 showed that electricity consumption respond positively to changes in GDP and negatively to changes in electricity price and air temperature. Hainoun et al. [93] found that both electricity and electricity demand growth rates are lower than the corresponding GDP growth rates in Syria. In some literatures, other parameters which are not economical are also selected. For example Valor et al. [94] tried to analyze the relationship between electricity load and daily air temperature in Spain. More recently many studies have been conducted on short/long term electricity demand/load forecasting [95-107], but application of neuro fuzzy logic for forecasting electricity demand based on combined economic and climate conditions is still unexplored. In this paper, an ANFIS network (adaptive neuro fuzzy inference system) was designed to map six parameters as input data including for demographic parameters (i.e. Employment, GDP, Industry Efficiency and Population), and two meteorological parameters related to annual weather temperature (i.e. HDD and CDD) to electricity demand as output variable.

The measure of industry efficiency follows from Lin [108] and Zuresh& Peter[109] where the ratio of industry value added as a percent of GDP to industry consumption of electricity is used to capture the efficiency effect in their model. However, our measure of structural changes in the economy follows from Zuresh and Pete r[109] where the share of industry output in total output is used as a proxy. Using this approach we focus on the impact on electricity consumption as the economy move towards the more energy intensive sectors which we capture by increases in industry value added as a percent of GDP. We expect this to have a positive effect on aggregate domestic electricity consumption.

3. Neuro-fuzzy model formulation

Neuro-Fuzzy is combination of two approaches: ANN and fuzzy logic. In this case, a brief description of ANN is presented which is followed by fuzzy systems description.

3.1.Artificial Neural Network

The history of ANN begins with the pioneering work of McCulloch and Pitss [1] who first introduced the idea of ANN as computing machines. Ability to find nonlinear and complex relationships has been the main reason for the popularity of ANN applications in various branches of science and also in industrial managements [2-3]. Image processing [4], document analysis [5], engineering tasks [6-7], financial modeling[8], biomedical ([9]) and optimization[10] could be perfect examples of the various applications of ANN in different branches of sciences.

One of the serious problems with ANN is lack of interpretation. Wieland et al. [11] claimed that ANN fails to improve the explicit knowledge of the user. Limitations in catching casual relationships between major system components were mentioned as the main reason. ANN is also poor in extrapolation. It fails to deal properly with data out of training range.

3.1.1.Fuzzy Systems

Fuzzy sets are basic concepts of fuzzy logic which was proposed by Prof. Lotfi A. Zadeh in 1965. Unlike Boolean logic, fuzzy logic believes one element can belong to more than one set at a same time [12]. A simple example can help to compare the set types in these two logics. Set A is assumed to be the universal set which included all numbers from 0 to 10. Numbers between 2 to 8 stand in set B. Borders of sets are completely clear. In order to recognize the members of set B, all numbers in set A which exist in set B are valued by 1 and others take 0 (Figure 1).

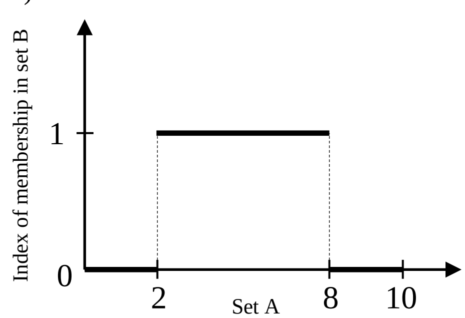

Figure 1: Boolean sets

The problem however lies in showing some vague subsets like subset of "big numbers". What would be the correct criteria to recognize the big numbers among 0 to 10? Boolean logic defines specific borders for such cases. If 8 be the set point, the numbers below and above 8 will be categorized as small and big numbers, respectively.

Problem arises as some numbers like 7.9 and 8.1 are studied. Fuzzy logic believes 0.2 difference between two numbers cannot make one big and the other small. In this case, fuzzy logic defines specific membership degrees which determine the degree by which, each element belongs to different sets. These sets are known as fuzzy sets. Figure 2 shows the fuzzy sets of the discussed example. Numbers below 7 have membership degree of zero which means they do not belong to the set and numbers between 7 to 10 receive degrees based on their values.

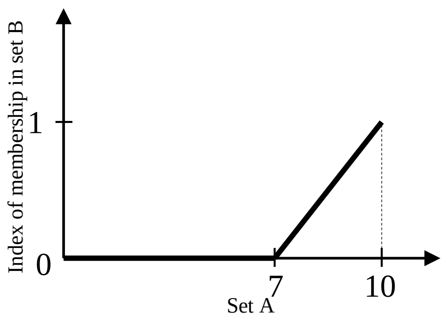

Figure 2: Fuzzy sets

Graphs like that in Figure 2 are known as "Membership Function (MF)" in fuzzy logic. Membership functions present different categories of different inputs by fuzzy sets.

Fuzzy rules are used to combine defined concepts (like big, small, hot, cool and etc.) in order to catch the relationships between the data. The application of fuzzy rules is shown by an example:

If pressure is high, and temperature is high, then system is in critical condition

This rule combines pressure, temperature, and system variables together with concepts like high and critical condition (which should be defined in different MFs for applying in fuzzy logic). Rules are generated by an expert who has the knowledge and experience over the subject. Fuzzy rules combine variables and fuzzy sets (membership functions) together based on expert decisions. A general form of a fuzzy rule (known as if-then rules) is

If x is A and y is B, then z is C

Where A, B and C are pointing out fuzzy subsets (membership functions) and x, y and z are variables. Word "and" in this phrase needs to be determined with special equation. There are different equations to define operators "OR" and "AND" in fuzzy rules.

There are specific issues regarding fuzzy inference system (FIS) which demands better understanding. The main problem with FIS is inadaptability. Unlike ANN, FIS cannot adapt itself with new environment or data. An expert has to define rules for FIS. The generated rules deal with relationships between the data and FIS fails to perform as it faces a new condition which has not been defined in terms of fuzzy rules [13].

The idea of ANFIS arises from the limitations and drawbacks of ANN and FIS and tries to design more reliable approach by combining ANN and FIS.

3.1.2. Adaptive Neuro-Fuzzy Inference System

ANFIS, which used to stand for adaptive network-based fuzzy inference system was proposed by Jang [14].

Hybrid learning method and back propagations are the main choices for learning methods. In fuzzy section, only zero or first-order Sugeno inference system or Tsukamoto inference system can be used, and output variables are achieved by applying fuzzy rules to fuzzy sets of input variables [13, 15-17]:

Rule 1: if x is A_1 and y is B_1, then $f_1 = p_1 x + q_1 y + r_1$ (1)

Rule 2: if x is A_2 and y is B_2, then $f_2 = p_2 x + q_2 y + r_2$ (2)

Where p_1, p_2, q_1, and q_2 are linear parameters and A_1, A_2, B_1, and B_2 nonlinear. Figure 3 shows architecture of a two input first-order Sugeno FIS model with two inputs and rules. Architecture includes five layers: fuzzy layer, product layer, normalized layer, defuzzifier layer, and total output layer.

Each node in this Figure represents a node function which has adjustable parameter, and nodes in same layers follow same functions. The learning algorithm of neural network seeks for the best values of model parameters, and performance of the network is evaluated based on training and testing data. The main task of the mentioned learning algorithms (back propagation and hybrid learning) is to reach the minimized errors like Root Mean Square Error (RMSE). Next section discusses the procedure of transforming input to output in ANFIS based on the five mentioned layers. Figure 3 represents schematic of an ANFIS. In this Figure, fuzzy layer consists of nodes A_1, A_2, B_1, and B_2, which receive the inputs x and y, respectively. A_1, A_2, B_1, and B_2 represent linguistic labels or fuzzy sets (like fast, big, etc), which apply fuzzy membership functions and determine by which degree each input belongs to the sets. This mapping can be shown as:

$Q_{1,i} = \mu_{A_i}(x)$, for i= 1,2 (3)

$Q_{1,i} = \mu_{B_j}(y)$, for j= 1,2 (4)

in which x (or y) is input to node I and A_i (or B_j) is the fuzzy set. $Q_{1,i}$ determines the degree to which the input belongs to the set. Guassian curve or the generalized bell-shaped membership functions are usually used for $\mu_{A_i}(x)$ and $\mu_{B_j}(y)$ [13, 18]:

$$\mu_{A_i}(x) = \frac{1}{1+[(x-\frac{c_i}{a_i})^2]b_i} \quad (5)$$

$$\mu_{A_i}(x) = \exp\left[-\left(\frac{x-c_i}{a_i}\right)^2\right] \quad (6)$$

Where $\{a_i, b_i, \text{ and } c_i\}$ is the parameter set. The bell-shaped functions changes based on changes of the parameter set, resulting in different forms of membership functions.

There are two nodes labeled "Π" in product layer. As they receive the signals, they multiply it and make the layer outputs (w_1 and w_2) which will be the weight functions of next layer. The output of this layer can be expressed as [13, 15, 19]:

$$Q_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y) \quad \text{for } i = 1,2 \quad (7)$$

where $Q_{2,i}$ stands for the product layer output.

The layer with nodes labeled "N" is the normalized layer. The outputs of the previous layer nodes represented the firing strength of a rule [13, 18]. The i[th] node calculates the ratio of the i[th] rules firing strength to the sum of all rule's firing strengths [20]. The weight function gets normalized by [13, 15, 18-19]:

$$Q_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad \text{for } i = 1,2 \quad (8)$$

Therefore, the output of this layer ($Q_{3,i}$) is called the normalized firing strengths.

The fourth layer with adaptive nodes is the defuzzification layer. In fact, the signals which have been fuzzified at the beginning of the process get defuzzifed and return to normal form. The relationship in this layer can be written as [13, 15, 18-19]:

$$Q_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i), \text{ for } i = 1,2 \quad (9)$$

The output of layer four is $Q_{4,i}$, while $\bar{w}_i$ stands for normalized firing strength from layer 3, and $\{p_i x + q_i y + r_i\}$ represents the parameter set.

The last layer with a single node labeled "Σ" is total output layer, which represents the final decision according to [13, 15, 18-19]:

$$Q_{5,i} = \text{overall output} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (10)$$

Here $Q_{5,i}$ refers to the output of last layer.

ANFIS combines ANN and fuzzy-logic in order to benefit their advantages. It follows ANN topology with fuzzy-logic, and aims to remove the disadvantages of both which enables this method to deal with complex and nonlinear cases Unlike ANN, there is no vagueness in ANFIS [16, 21]. In addition, since learning duration in ANFIS is shorter than ANN, ANFIS can approach the demanded target faster. So, it can be concluded that using ANFIS instead of ANN in sophisticated and complex systems can be more effective in order to overcome the complexity of the problem [22].

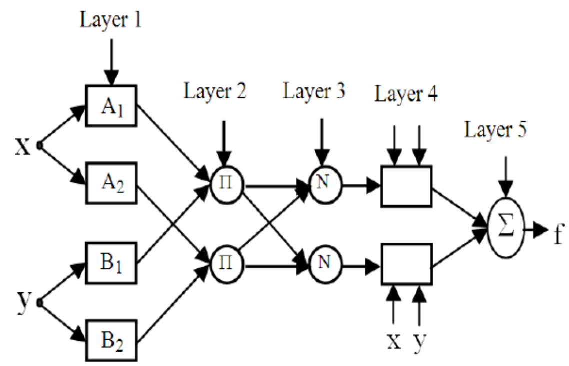

Figure 3: ANFIS structure with two inputs and two rules

4. Results and discussion

4.1. Designed network structure

As mentioned in the previous section, Employment, GDP, Industry Efficiency, Population, HDD, and CDD are the input variables of the model. Based on these data, an ANFIS network with Sugeno-style inference system has been designed which maps these six independent variables as input data to electricity demand as output. MATLAB 2010a was employed for model building. Three Gaussian membership functions have been considered for each input data. Figure 4 shows the final and best obtained membership functions.

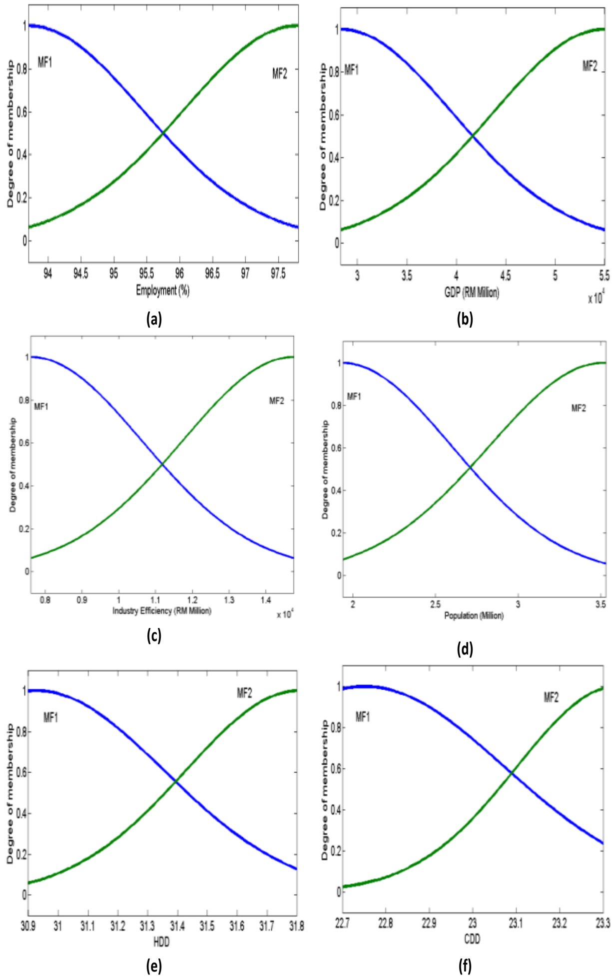

Figure 4: Membership functions of (a) Employment, (b) GDP, (c) Industry Efficiency, (d) Population, (e) HDD and (f) CDD

From 21 available data sets, 15 sets were selected to train the network. Five data sets were applied to test the trained network, and one set which is related to the electricity demand in 2011 is used for validating the network. The procedure ensures that the designed network produces good results for any range of data.

After training the network, a mean square error (MSE) of 2.954 × 10-5 was obtained for training the data. The low training error enabled the trained network to estimate unseen data with high precision (Fig.5).

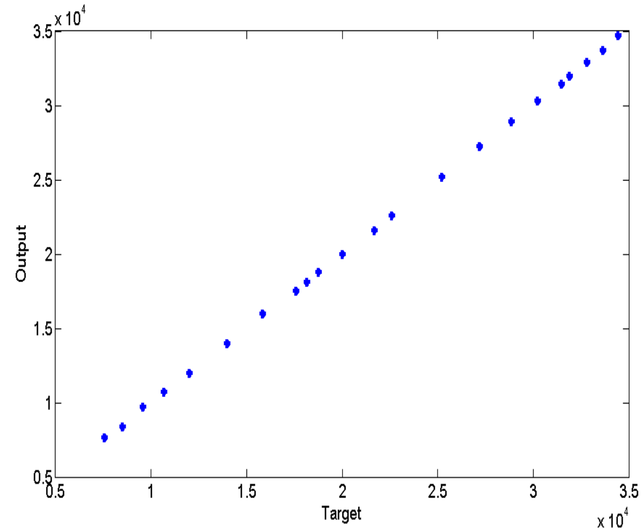

Figure 5: Targets vs. outputs for training data

The best obtained network MSE is 0.0016 for test data. Figure 6 depicts network estimation for the test data.

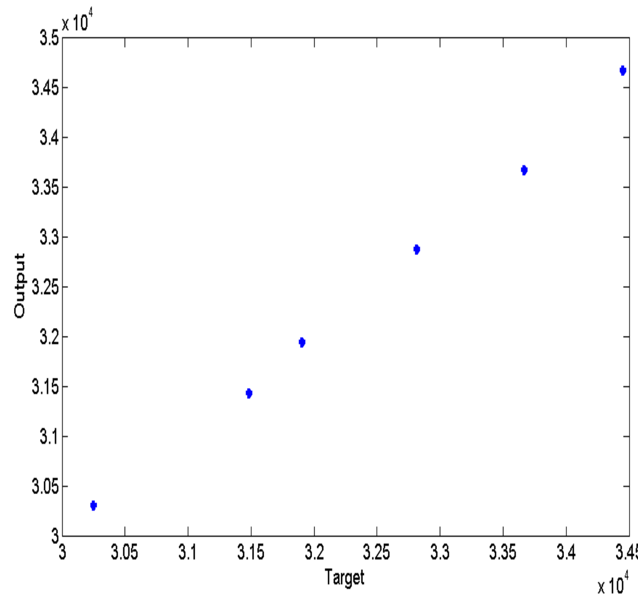

Figure 6: Targets vs. network outputs for testing data

4.2.Model Validation

In order to build a forecasting model to the year 2030, a linear trend was assumed. These lines are shown in Figures 7 and 8 and their equations are listed in Table 1.

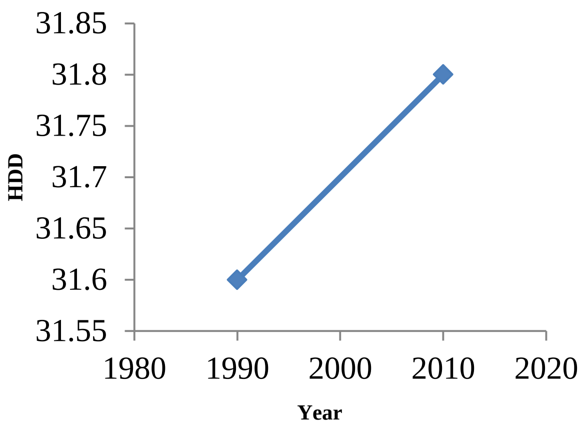

Figure 7: Trend of HDD 20 year average change in period 1990-2010

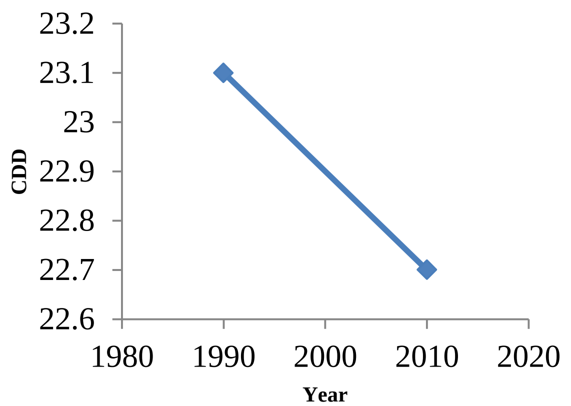

Figure 8: Trend of CDD 20 year average changing in period 1990-2010

Table 1: Average changing for HDD and CDD for 20 years

Parameter	Equation of fit curve
HDD	y = 0.01 X + 11.7
CDD	y = -0.02 X + 62.9

These equations can be used to find the average values for the next 19 years period from 2012 to 2030. Having the values of all input parameters for the year 2011, the electricity demand for the year can be predicted. The calculated value is 35210.33 Wh while the real reported value is 34450.2. It means an acceptable validation for the model and confirms its ability to predict electricity demand in future years. It is important to note that the year 2011 is out of the data set used to design the network, and that the HDD and CDD parameters were calculated and not measured.

4.3. Prediction of electricity demand until 2030

After validating the model, it can be used to forecast the electricity demand in future. In this case, future inputs are needed. In this regard, the average values for every 5 years have been calculated to find out whether they have a special trend. Figures 9 to 14 illustrate the trend of changes in employment, GDP, industry efficiency, population, HDD, and CDD from 1990 to 2010.

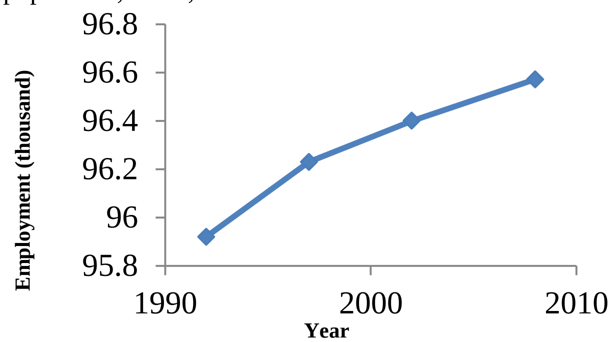

Figure 9: Trend of five years average employment change from 1990-2010

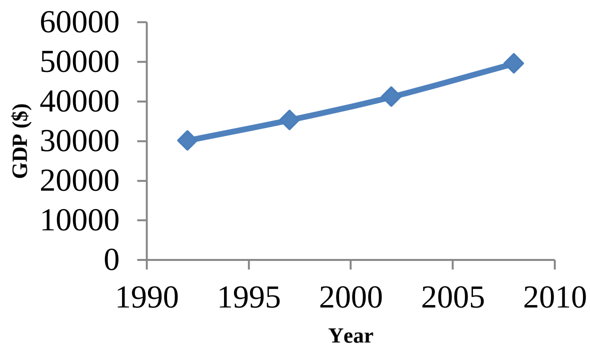

Figure 10: Trend of five years average GDP change from 1990 to 2010

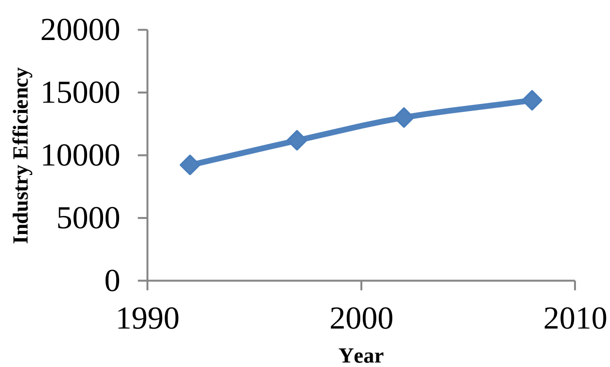

Figure 11: Trend of five years average industry efficiency change from 1990 to 2010

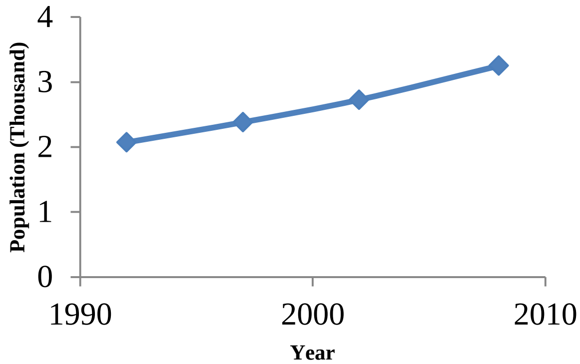

Figure 12: Population five years average change from 1990 to 2010

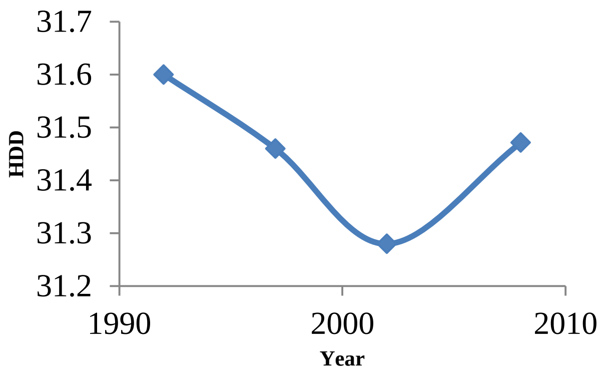

Figure 13: Trend of HDD five year average change from 1990 to 2010

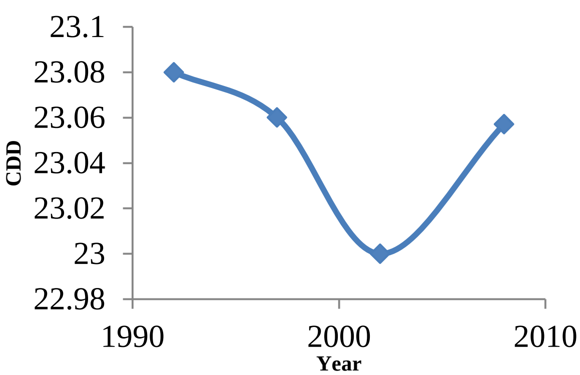

Figure 14: Trend of CDD five year average change from 1990 to 2010

Noting the figures, a linear line was fitted to the data based on the linear trend of the data. Table 2 provides the linear equation form.

Table 2: Input parameters trends

Parameter	Equation of fitted curve[a]
Employment	Y= 141.4 X + 0.2217
GDP	Y= 15628 X + 22712
Industry Efficiency	Y= 322.7875 X - 633782
Population	Y= 0.0331 X – 63.265
HDD	$Y= 6.9 X^2 + 15.5 X + 0.7$
CDD	$Y= 12 X^2 - 16.5 X + 3$

By using these equations, it is possible to predict the values of these parameters in the future (in this paper 2012-2030).

In this case, using the fitted equations, all six independent variables for the next nineteen years (2012-2030) were obtained. Using these inputs, ANFIS network can provide estimations. Figure 15 depicts electricity demand value from 1990 to 2030. In this figure, blue markers refer to recorded data and red markers correspond to the model estimations.

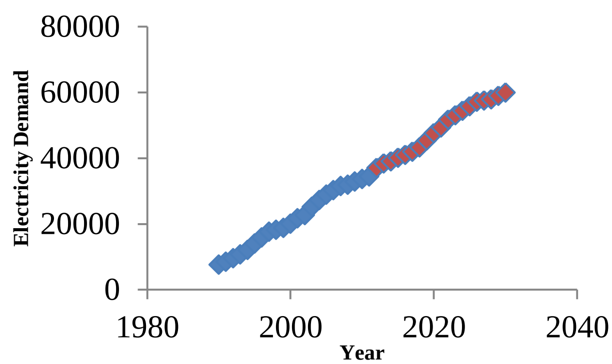

Figure 15: Estimation of electricity demand from 1990 to 2030

5. Conclusion and Remarks

In this paper, an ANFIS network (adaptive neuro fuzzy inference system) was designed to map six parameters as input data (i.e. Employment, GDP, Industry Efficiency, Population, HDD, and CDD) to electricity demand as output variable. The network had excellent forecasting capacity with MSE of 0.0016. In the last part, electricity demand was predicted until 2030.

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