SHORT-TERM LOAD FORECASTING USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS) APPLICATION TO ALEPPO LOAD DEMAND

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Abstract: The huge consumption of electric energy in these days has given the load forecasting a big attention from researchers and utility operators. Forecasting electric load will aid the electric company in optimal energy generation, dispatching and unit commitment.

This paper introduces the preliminary results of applying Adaptive Neuro-Fuzzy inference System (ANFIS) to short term load forecasting The theoretical foundations are introduced and details of the adaptive fuzzy system are presented. The results of its application on Aleppo 24 hours load demand are included.

Keywords: Power System, Adaptive Neuro-Fuzzy Inference System, Load Forecasting.

1. Introduction

The rapid growth of demand for energy in the last three decades and the exhaustion of fossil fuel resources have given an impulse to the development of optimal energy planning and forecasting of electrical loads in power systems.

Forecasting electrical loads in power system up to 24-hour lead-time has obvious economic as well as other advantages. The forecast information can be used to aid optimal energy interchange between utilities, thereby saving valuable fuel costs. Forecast also significantly influences important system operating decisions such as dispatch, unit commitment, and maintenance scheduling [1]. For these reasons, considerable efforts are being invested.

Most of the traditional techniques used in load forecasting can be categorized under two approaches. One treats the load demand as a time series and predicts the load using different time-series analysis technique. The second method is a regression-based technique [2]. However, such traditional techniques often do not give sufficiently accurate results. One major drawback of the time series is that it does not utilize weather conditions [1,3,7,9]. Whereas, the main problem with regression approach is that it unjustifiably assumes a linear relationship between weather conditions and load demand [3]. ANFIS, in the contrary, uses indirectly the weather conditions and does not assume a specific relationship between weather and load conditions.

In this paper, ANFIS is first introduced then applied to forecast the Aleppo daily load demand. The output from ANFIS forecast results are compared to actual loads and the results are very encouraging

2. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

ANFIS are relatively new Artificial Intelligence (AI) tools derived from a general category of intelligent networks known as adaptive networks. An adaptive network is a network structure consisting of a number of nodes connected by directional links [4]. Each node represents a process unit and the links specify the relationship between the nodes. All or some of the nodes are adaptive, which means the output of these nodes depends on modifiable parameters relevant to the nodes. The learning rule specifies how these parameters should be updated to minimize a prescribed error that measures the difference between the actual output and a desired (target) output. In the general case, each node in an adaptive network may have a node weights or parameters associated with them. The main learning rule applied to adaptive network is the Backpropagation learning rule that may be combined with other learning mechanisms to accelerate the convergence of the learning process [5].

ANFIS are a class of adaptive networks functionally equivalent to fuzzy inference systems[4]. The shape of a fuzzy membership function depends on a set of parameters, and changing these parameters changes the shape of the membership function. Hence, the nodes of an adaptive network are well suited to the representation of the fuzzy system membership functions, and an adaptive network type structure can be adapted to represent the fuzzy inference system. Using any of the learning rules related to adaptive networks, the parameters associated with the membership functions will be automatically modified through the learning process to model closely the relation described by a set of known input/output pairs.

3. ANFIS AND LOAD FORECASTING

This work involves exposing the potential of using ANFIS in load forecasting. The basic idea behind ANFIS is very simple. ANFIS provides a method for the fuzzy modeling procedure to learn information about the historic data in order to compute the membership function parameters that best allow the associated fuzzy inference system to track (learn) the historic data input/output[2,5,8]. This learning method works similarly to that of neural networks as shown in Figure 1.

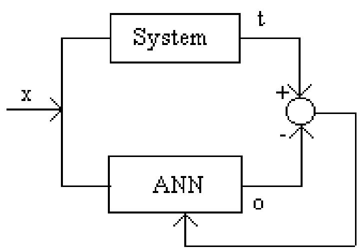


Figure 1 training Block Diagram

The steps for the application of ANFIS can be summarized as follows:

1. Initialization:

Get ANFIS structure that specifies the structure (rules) and initial parameters of the FIS for learning purposes. The MATLAB Fuzzy Toolbox includes 11 built-in membership function types. In this application, bell membership functions are used.

2. Subtractive Clustering

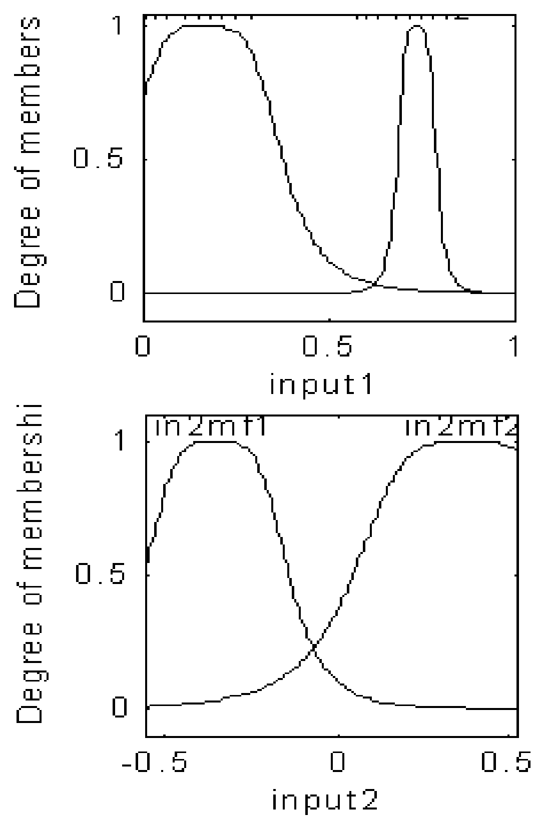
When the number of inputs is more than four, the number of rules will be large and invokes the so-called curse of dimensionality. Subtractive Clustering techniques solve this problem by partitioning the data into groups called clusters, and generates a FIS with a minimum number of rules required to distinguish the fuzzy qualities associated with each of the clusters.

3. Fuzzy C-Mean Clustering

Fuzzy C-means FCM is a data clustering technique wherein each data point belongs to a cluster to some degree that is specified by a membership grade. The output of FCM helps us building a fuzzy inference system by creating membership functions to represent the fuzzy qualities of each cluster.

3. Training ANFIS

Using the historic data, ANFIS adjusts the membership function parameters using either a backpropagation algorithm alone or in combination with a least square estimation so as to reduce some error measure defined by the sum of the squared difference between actual and desired outputs. Figure 2 shows the adjusted membership functions. This means that the fuzzy system has learned from the historic data they are modeling.



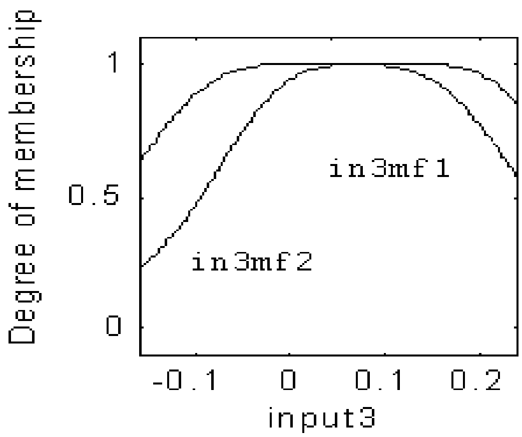


Figure 2 Adjusted Membership Functions

4. Application to Aleppo Load Forecasting

The application procedure involves five steps:

- Gathering the data
- Normalizing the data
- Selection of ANFIS structure
- Training step
- Testing step

4.1 Data Collection

From Aleppo Electric Company, Aleppo, Syria, the Aleppo hourly consumption for the last three years (1997 - 1999) was obtained.

4.2 Normalization

After the historical data is gathered, the next step is to normalize all the data so that each value falls between 0 and 1 where a normalization routine was written using MATLAB Platform. The normalization is done because the membership function must vary between 0 and 1.

4.3 ANFIS Structure

You can choose any type and number of membership function. The ANFIS used in this paper consists of two generalized bell membership functions on each input. Figure 3 shows the ANFIS structure to the system under study (after training).

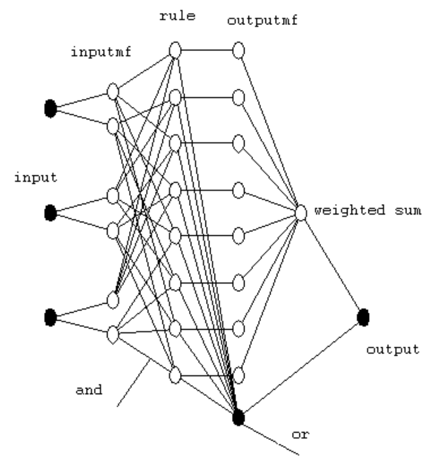


Figure3 ANFIS Structure

ANFIS are characterized by two steps known as *training* and *testing*. During *training*, membership function parameters (membership function shapes) are modified in a manner that causes the desired input/output relationship to be learned. The training set is shown to the network many times (iterations or epochs), until converge is obtained (usually, a mean-square error between output and target is minimized). During *testing*, the used data should not be seen during the training process. The selected input/output pair variables for the ANN are given in Table 1 [9]. The chosen input variables are very informative because they implicitly reflect possible weather changes.

Table 1: Inputs - output pair for the 24-hour training period

INPUT	OUTPUT
X_{11}=L(d, t)	
X_{12}=L(d, t)-L(d-1, t)	Y =L(d+1,t)
$X_{13}=L_M(d+1)-L_M(d, t)$	

Where:

$$L_M(d,t) = \frac{L(d-7,t) + L(d-14,t) + L(d-21,t)}{3}$$

t hour
L(d,t) load on day d and hour t
L(d-7,t) load on day d-7 (one week ahead) and hour t
X_{11} reflects the load demand on a day d at hour t
X_{12} indicates the daily load change.
X_{13} provides the weekly trend of demand changes on day d at hour t

Back propagation and least square learning techniques are used to train the network. It requires a set of input and output (target) pairs. Basically, an output vector can be produced by presenting an input pattern to the network. According to the difference between the produced output and the target vector , membership function shapes are adjusted to reduce the output error (Figure 1).

5. Simulation Results

In this research, ANFIS is trained and then used to predict the load demand for Aleppo City. In this respect, Figure 4 shows the load demand over 24-hour period for 4 day from each of the four seasons. It is clear that the most obvious difference in load demand occurs in summer and winter. The daily peak load in winter can be as high as 500 MW as compared to 480 MW in summer. The difference in load demand for autumn and spring are not that discernible since they represent transitional periods in which there is a gradual change in load conditions from one season to the other. In addition, the weekday (Saturday to Thursday) electricity demands are much higher than for the weekends (Friday).
The trained ANFIS is then used to forecast the load demand over a 24-hour period. Figure 5 shows the load demand, actual and forecast (with lead times of 24 hours). It is observed that, the ANFIS forecast closely matches the actual demand. The mean square error (mse) was found to be around 0.5%.

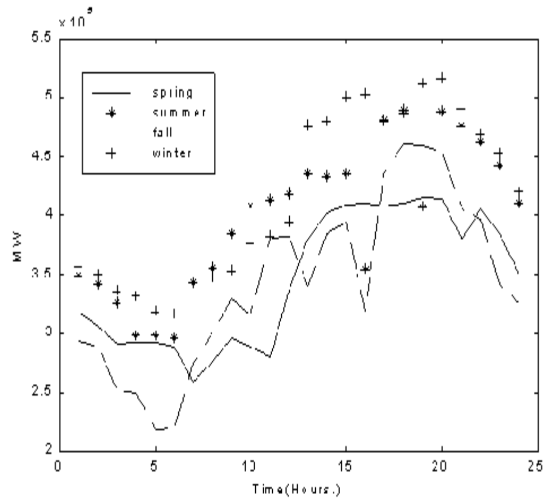


Figure 4 Pattern for one day for 4 seasons

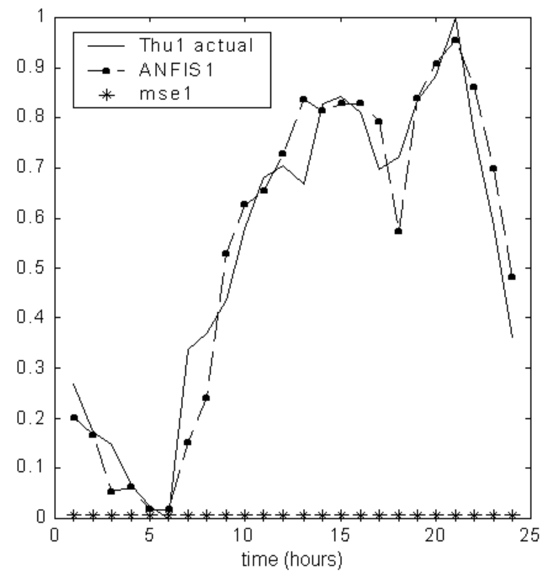


Figure 5 Forecast and Actual daily Load profiles for Thursday (a week Ahead)

6. Conclusion

In this paper, ANFIS is first introduced then applied to forecast the Aleppo daily load demand (the 24-hour load demand) using realistic data. Even though the error was acceptable, at least for the time being, it could be reduced further by trying to improve the ANFIS structure. More work is in fact needed in this respect.

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