ANN and ANFIS for Short Term Load Forecasting

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Abstract—**Load forecasting has become one of the major areas of research in electrical engineering. Short term load forecasting (STLF) is essential for power system planning and economic load dispatch. A variety of mathematical methods has been developed for load forecasting. This paper discusses the influencing factors of STLF and an artificial intelligence (AI) based STLF model for MGVCL load. It also includes comparison of various AI models. Our main objective is to develop the best suited model for MGVCL, by critically evaluating the ways in which the AI techniques proposed are designed and tested.**

Keywords-load forecasting; neural network; adaptive neuro fuzzy interface system

I. INTRODUCTION

Electric load forecasting is the process used to forecast future electric load from the given historical load and weather information. In the last few decades, several models have been developed to forecast electric load more accurately than analytical methods. Load forecasting can be divided into three major categories [1]:

1. Long-term electric load forecasting, used to supply electric utility company management with prediction of future needs for future expansion, equipment purchases, or hiring of new staff.
2. Medium-term forecasting, used for the purpose of scheduling fuel supplies and maintenance.
3. Short-term forecasting used to supply necessary information for the system management of day-to-day operations and unit commitment for economic load dispatch.

Short term load forecasting mainly aims at one hour to one week forecast. As daily load pattern is highly non linear and random, it is very difficult to obtain higher accuracy using analytical methods. Application of artificial intelligence (AI) techniques like neural networks and adaptive neuro fuzzy interface systems is an advanced approach for accurate short term load forecasting.

II. ARTIFICIAL NEURAL NETWORKS

A. Introduction

Artificial neural networks (ANNs) have been used for many years in sectors like medical science, defense industry, robotics, electronics, economy, forecasts etc. The learning property of ANNs in solving nonlinear and complex problems is the cause of their application to forecasting problems.

B. Learning Algorithm

ANNs work through optimized weight values [2]. The method by which the optimized weight values are attained is called learning. In the process of learning we present to the neural network pairs of input and output data and try to teach the network how to produce the output when the corresponding input is presented. When learning is complete, the trained neural network, with the updated optimal weights, should be able to produce the output within desired accuracy. There are several learning algorithms. They can be broadly categorized into two classes: supervised and unsupervised. Supervised learning means guided learning, i.e. when the network is trained by showing the input and the desired result side by-side. This is similar to the learning experience in our childhood. As children we learn about things (input) when we see them and simultaneously are told (supervised) their names and the respective functionalities (desired result). This is unlike the unsupervised case where learning takes place from the input pattern itself. In unsupervised learning the system learns about the pattern from the data itself without a priori knowledge. This is similar to our learning experience in adulthood. For example, often in our working environment we are thrown into a project or situation which we know very little about. However, we try to familiarize with the situation as quickly as possible using our previous experiences, education, willingness and similar other factors. This adaptive mechanism is referred to as unsupervised learning.

C. ANN Model Traning Process

Multilayer feed forward neural network (having input layer, hidden layer and output layer) is used for STLF. The training goal was set at 0 in order to ensure zero tolerance to network computational errors [3]. The transfer function used was the tan-sigmoid in the hidden layer while a linear function was used in the output layer neurons so as not to constrain the output's values. The learning function used is the steepest gradient descent method. The Levenberg-Marquardt learning function was used as it has better learning rate compared to the other available functions in forecasting problems. The training function used was the steepest gradient descent function and in some tests the steepest gradient descent method with momentum.

III. Adaptive Neuro Fuzzy Interface System

An adaptive neuro-fuzzy inference system or adaptive network-based fuzzy inference system (ANFIS) is a kind of artificial neural network that is based on Takagi–Sugeno fuzzy inference system. Since it integrates both neural networks and fuzzy logic principles, it has the potential capturing the benefits of both in a single framework. Its inference system corresponds to a set of fuzzy if–then rules that have learning capability to approximate nonlinear functions. Hence, ANFIS is considered to be a universal estimator.

A. ANFIS Architecture

In ANFIS architecture [4] (Figure 1), each joint in the same layer has the analogous function. Level 1 shows that with each input in terms of its association grade a linguistic tag is associated. This is also called membership grade [5] and it can be defined by suitable membership functions with appropriate parameters. The foundation parameters associated with functions are called nonlinear parameters.

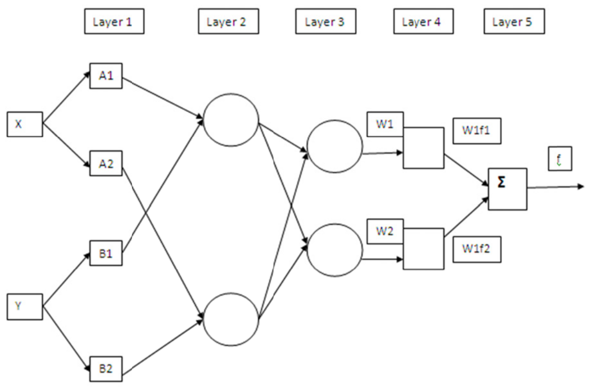

Fig. 1. ANFIS architecture

Layer 2 shows fuzzy AND operations using an appropriate operator on the input signals to generate the output can be given as

$$\mathrm{Oi}^2 = \mathrm{Wi} = \mu\mathrm{pi}(x)\mu\mathrm{qi}(x); \qquad i = 1, 2 \qquad (1)$$

The output of this level is normally known as the analogous rule of firing power. The ratio of a rule's firing strength is the summation of the firing strengths of all the rules and is calculated in layer 3. This is known as firing strengths of normalization. The throughput of layer 3 can be given by:

$$\mathrm{Oi}^3 = \mathrm{Wi} = \frac{\mathrm{Wi}}{\mathrm{W1}+\mathrm{W2}}; \qquad i = 1, 2 \qquad (2)$$

The output of layer 4 is given by:

$$\mathrm{Oi}^4 = \mathrm{W1d1} = \mathrm{w1}(\mathrm{aix} + \mathrm{biy} + \mathrm{ci}); \qquad i = 1, 2 \quad (3)$$

In this, resulting parameters are ai, bi and ci where i=1, 2 of the ANFIS. The amount of parameters of ANFIS is the sum of premise and resultant parameters. In layer 5, overall output of ANFIS which can be given below is the summation of incoming signals.

$$\mathrm{Oi}^5 = \sum_i \mathrm{w1di} = \frac{\sum_i \mathrm{widi}}{\sum_i \mathrm{wi}} \qquad (4)$$

The ANFIS structure is a meaningful assignment of node functions and because of this several configurations are possible. ANFIS is an amalgamation of fuzzy logic and neural network holding the benefits of both.

B. Learning Process

As mentioned above, both the premise (non-linear) and consequent (linear) parameters of the ANFIS should be tuned, utilizing the learning process, to optimally represent the factual mathematical relationships between the input space and output space. Normally, as a first step, an approximate fuzzy model is initiated by the system and then improved through an iterative adaptive learning process. Basically, ANFIS takes the initial fuzzy model and tunes it by means of a hybrid technique combining gradient descent back propagation and mean least-squares optimization algorithms. At each epoch, an error measure, usually defined as the sum of the squared difference between actual and desired output, is reduced. Training stops when either the predefined epoch number or error rate is obtained. There are two passes in the hybrid learning procedure for ANFIS. In the forward pass of the hybrid learning algorithm, functional signals go forward till layer 4 and the consequent parameters are identified by the least squares estimate. In the backward pass, the error rates propagate backward and the premise parameters are updated by the gradient descent. When the values of the premise parameters are learned, the overall output (f) can be expressed as a linear combination of the consequent parameters as:

$$\begin{aligned} f &= \frac{w_1}{w_1+w_2} f_1 + \frac{w_2}{w_1+w_2} f_2 = \overrightarrow{w_1} f_1 + \overrightarrow{w_2} f_2 \\ &= (w_1 x_1) m_1 + (w_1 x_1) n_1 + w_1 q_1 + (w_2 x_2) m_2 \qquad (5) \\ &+ (w_2 x_2) n_2 + w_2 q_2 \end{aligned}$$

which is linear. In the forward pass of the learning algorithm, consequent parameters are identified by the least squares estimate. In the backward pass, the error signals, which are the derivatives of the squared error with respect to each node output, propagate backward from the output layer to the input layer. In this backward pass, the premise parameters are updated by the gradient descent algorithm.

IV. Results

A. ANN Model Results

Table I shows the comparison of ANN model error and forecasted error. Average ANN error for 6th January is 0.05% and forecasted error is -1.346% while for 7th January average ANN error is 0.134% and forecasted error is -1.566%. Figure 2 shows the comparison of ANN error and forecasted error for November and December. It shows that ANN error is very small compared to forecasted error. Figure 2 also shows the comparison of errors for the entire year which varies between -0.3% to 0.5%. It indicates that application of ANN for STLF improves the accuracy of forecasting. The ANFIS error for February and March (Figure 2) varies up to 0.07%. A model for the entire year could be similarly developed. A comparison between errors is also shown in Figure 2.

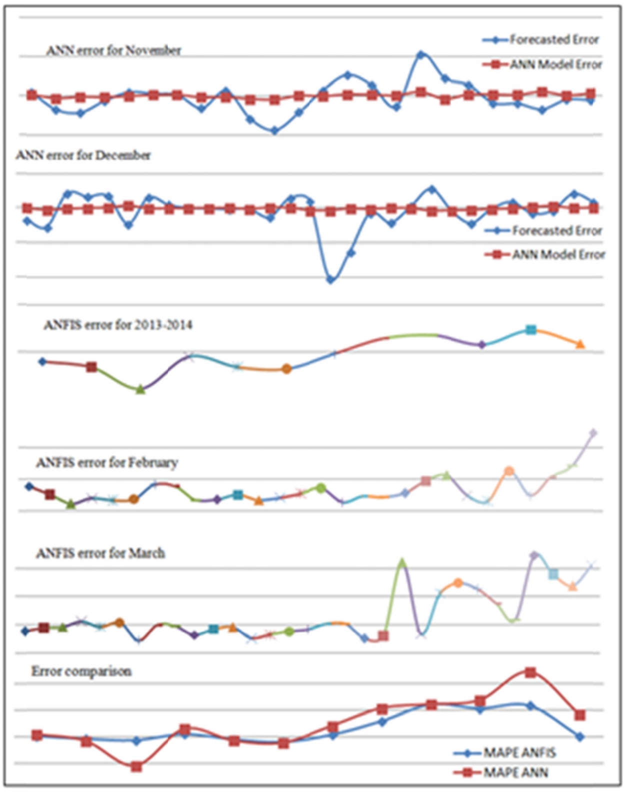

Fig. 2. Error graphs

TABLE I. ANN RESULTS FOR JANUARY.

Hour	6th Jan Error (ANN)	6th Jan Error (Forecast)	7th Jan Error (ANN)	7th Jan Error (Forecast)
1	0.390	-2.181	-0.046	-1.899
2	-0.986	-0.658	0.047	-1.129
3	0.050	-0.695	-0.024	-1.335
4	0.056	-0.823	0.048	-1.278
5	0.089	-0.060	2.178	-2.683
6	0.324	0.178	-1.512	-1.351
7	0.904	-2.935	0.000	-2.145
8	0.872	-3.281	0.019	-1.780
9	0.422	-6.404	0.000	-3.800
10	0.285	-6.142	0.000	1.042
11	-0.413	-4.782	1.948	-0.842
12	0.779	-2.515	0.036	-2.504
13	-0.577	-3.640	0.019	-3.656
14	-1.671	-2.938	0.018	1.575
15	1.366	-2.647	-1.877	2.217
16	-0.407	-0.455	-3.287	0.263
17	1.429	0.839	-5.021	0.436
18	-0.394	2.270	-0.037	-0.405
19	-0.809	-2.777	0.018	-0.339
20	-2.410	-1.692	0.036	-2.123
21	1.091	4.114	-1.018	-3.306
22	0.275	2.745	-0.040	-6.583
23	0.383	0.192	11.677	-3.935
24	0.240	1.943	0.021	-2.019

REFERENCES

[1] K. Kalaitzakis, G. S. Stavrakakis, E. M. Anagnostakis, "Short-term load forecasting based on artificial neural networks parallel implementation", Electric Power Systems Research, Vol. 63, No. 3, pp. 185-196, 2002

[2] M. Markou, E. Kyriakides, M. Polycarpou "24-Hour Ahead Short Term Load Forecasting Using Multiple MLP', International Workshop on Deregulated Electricity Market Issues in South-Eastern Europe, pp. 1-6, 2008

[3] E. Banda, K. A. Folly, "Short-Term Load Forecasting Using Artificial Neural Network", IEEE Lausanne Power Tech, Lausanne, Switzerland, pp. 108-112, July 1-5, 2007

[4] Z. Souzanchi-K, H. Fanaee-T, M. Yaghoubi, M. R. Akbarzadeh-T, "A Multi Adaptive Neuro Fuzzy Inference System for Short Term Load Forecasting by Using Previous Day Features", International Conference on Electronics and Information Engineering, Kyoto, Japan, Vol. 2, pp. 54-57, August 1-3, 2010

[5] H. P. Oak, S. J. Honade, 'ANFIS Based Short Term Load Forecasting', International Journal of Current Engineering and Technology, Vol. 5, No.3, pp. 1878-1880, 2015