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Short Term Load Forecasting Using Functional Link Network

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Abstract

Short Term Load Forecasting (STLF) is an important tool for successful planning and operation of power generating stations. This paper proposes neural network algorithm for STLF using Functional Link Neural Network (FLN) with Slope Parameter. This Neural Network Algorithm includes peak and minimum loads and load factors as additional inputs for the final forecast. The Proposed Functional Link Network with Slope Parameter (FLNSP) is tested for the Tamilnadu state, (India) grid data and the results are compared with the Conventional Back Propagation (CBP) method. Simulation results indicate that the proposed forecasting techniques are effective.

Keywords: Load Forecasting, Back Propagation, Functional Link Network, Slope Parameter

1. Introduction

Accurate models for electric power load forecasting are essential for the operation and planning of a utility company. Load forecasts are extremely important for energy suppliers, financial institutions and other participants in electric energy generation, transmission, distribution and markets. It is also required for unit commitment, energy transfer scheduling and load dispatch. Load forecasting is vitally important as there is fluctuation in supply and demand, unpredictable weather leading to increase of energy price in many folds.

Load forecasts can be divided into three categories: short-term forecasts which are usually from one hour to one week, medium forecasts which are usually from a week to a year, and long-term forecasts which are longer than a year. Short-term load forecasting can help to estimate load flows and to make decisions that can prevent overloading. Timely implementation of such decisions leads to the improvement of network reliability and to the reduced occurrences of equipment failures and blackouts. Load forecasting is also important for contract evaluations and evaluations of various sophisticated financial products on energy pricing offered by the market.

This paper presents a novel approach to STLF using back propagation algorithm with Functional Link and slope parameter scheme to predict hourly load on the power system. The Networks are trained with one-year data and tested for the next year data pertaining to the electric power system of Tamilnadu grid for all types. The network also includes weather data obtained from the Statistical Department. Comparison of results between conventional and the proposed approach indicate that the proposed neural net offer an accurate alternative to classical methods.

2. Forecasting Overview

The existing methodologies for load forecasting can be categorized as time series approach, regression models, knowledge based approach, state space and Kalman Filtering. Time-Series model employs the historical load data for extrapolation to predict future load. General problems with the time series approach are the inaccuracy in predictions and numerical instability. Since these models do not utilize weather information, they often give inaccurate results as there is a strong correlation between the behavior of power consumption and weather variables such as temperature, humidity, cloud cover and wind speed. Regression models analyze the relationship between weather variables and loads. The regression approach uses linear or piece-wise linear representations. The regression approach finds the functional relationships between selected weather variables and load demands. Regression models are computationally intensive and linearization of weather terms is unsatisfied.

The knowledge based approach develops load forecasting by emulating the experience and thought process of the experienced system operators. The problem with Knowledge Based technique is the deviation of the rules from the on-job training. State space and Kalman Filtering model require historical databases for 3 to 10 years to model the periodic load variation. Though perfect prediction is hardly ever possible, Artificial Neural Network (ANN) can be used to obtain reasonably good predictions in number of cases. The advantages of ANN over statistical methods include the ability to perform reasonably well using incomplete database.

3. Data Formulation

The load forecasting for the next 24 hours is generally a function of various factors such as load of the previous day and weather data. The number of neurons used in the input layer is determined by the number of load hours, number of hourly temperature data and the type of the day. Since there are different load shapes for different types of the day, they are split into six categories. They are National holidays, Religious festivals, Saturday, Sunday and working day. Further a working day is classified into a working day in summer and a working day in winter. The effect of climatic condition on the system load can be considered by including the temperatures as additional inputs along with historical load input. In addition to temperature, humidity is also considered as an additional input for the network. The additional weather parameter data are used to improve the accuracy of the forecasting model.

3.1. Normalization

Since the activation function used in the above network is binary sigmoidal, the network requires the input and the target values to lie within the range from 0 to 1. The hourly load of each day is normalized.

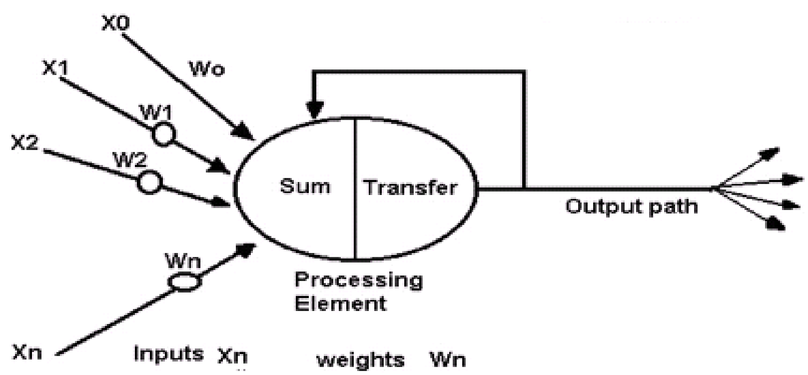
4. Back Propagation Technique

An artificial neuron is a computational model inspired by the natural neuron. Natural neurons receive signals through synapse located on the dendrites of the neuron. When the signals received are strong enough, surpass a certain threshold then the neuron is activated and sends the signal through the axon.

This signal might be sent to another synapse, and might activate other neurons. These inputs are multiplied by weights and then computed by a mathematical function which determines the activation of the neuron.

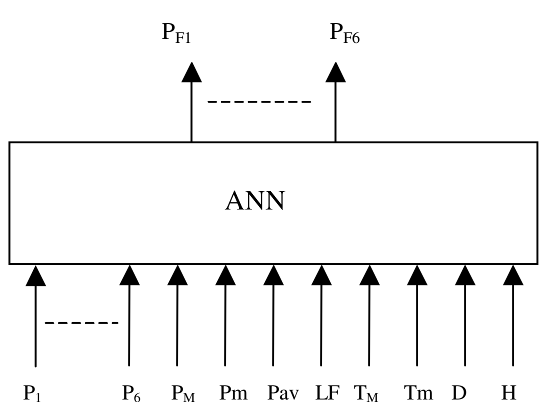
The Back propagation algorithm is a multi-layer network, which may contain one or more internal representation units known as hidden layer. These hidden layers lie between the input and the output layers. The back propagation technique is useful for training multilayer artificial neural network. Back propagation is a systematic method for training multilayer artificial neural networks and it has a strong mathematical foundation. Back propagation has dramatically expanded the range of problems to which artificial neural networks can be applied. A set of inputs are applied either from outside or from a previous layer. Each of these is multiplied by a weight and the products are summed. This summation is termed as "NET" and must be calculated for each neuron in the network. After "NET" is calculated the activation function 'f' is applied to modify it, there by producing the output.

Figure 1: Structure of Artificial Neural Network



The 24 hourly loads are split into 4 sets. Each set containing 6 hourly loads along with maximum load (P_M), minimum load (P_m), average load of the day (P_{av}), load factor (LF), type of day (D), maximum and minimum temperatures (T_M &T_m) and humidity (H), which forms the 14 input variables. The six output variables (P_{F1}-P_{F6}) of the neural network are the forecasted six hourly loads for the next day. All the 4 networks are provided with corresponding normalized inputs and the output patterns are obtained from all the 4 networks using back propagation algorithm.

Figure 2: Structure of Neural Network with various parameters for CBP



P_1 - P_6 - Hourly Load (MW)
P_M - Maximum Load (MW)
P_m - Minimum Load (MW)

P_{av} - Average Load (MW)
LF - Load Factor (MW)
T_M - Maximum Temperature (^oC)
T_m - Minimum Temperature (^oC)
D - Type of day
H - Humidity
P_{F1}- P_F - Forecasted hourly Load (MW)

The activation function used is binary sigmoidal function and is given as,

$$f(x)=\frac{1}{1+e^{-x}} \quad (1)$$

Where,
x is the net input

The sigmoid compress the range of NET so that 'OUT' lies between zero and one. Multilayer networks have greater representational power than single layer network only if non-linearity is introduced. The back propagation algorithm requires the function differentiable. The sigmoid satisfies these requirements.

The objective of training the network is to adjust the weight, So that the application of a set of inputs produces the desired set of outputs. These input output sets can be referred to as vectors. Training assumes that each input vector is paired with a target vector representing the desired output and these are called a training pair. Usually, a network is trained over a number of training pairs. This group of training pairs is called a training set. Before starting the training process, all the weights must be initialized to small random numbers. This ensures that the network is not saturated by large values of the weights and prevents certain other training pathologies.

The network is trained by Back Propagation algorithm for one year data and tested with the next year data. The training time is more due to large number of input neurons. The network is trained by CBP. Table-1 shows the experimental training results.

5. Functional Link Network with Slope Parameter

The functional Link Network enhances the computing power of the neural network. In the back propagation algorithm, there is a hidden layer between the output layer and the input layer this poses several problems. This could be done by adding a link, which enhances the inputs depending upon the type of output to be approximated. Therefore this link functionally enhances the input and establishes a functional relationship between output and enhanced input. Thus the network is named as Functional Link Network. By functional transformation, an input pattern (vector) is enhanced in its representation. In the Functional Link Network the input units pass their data through a functional link before distributing the data to other units. The purpose of the functional link is to produce multiple data elements from each individual input element by using the input elements as arguments to certain functions or by multiplying certain data elements together.

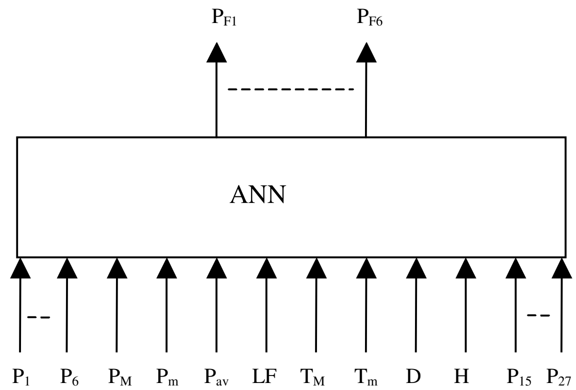
In this approach, 24 hourly load data are split into 4 sets as in conventional back propagation making 14 input variables. Here 13 additional inputs are generated using Functional Link Concept which is the functions of 14 input variables. The input generation is as follows

$$I_{15} = I_1 * I_2$$
$$I_{16} = I_2 * I_3$$
$$I_{27} = I_{13} * I_{14}$$

where,

I_1 to I_{14} – Load and weather parameters
I_{15} to I_{27} – Additional generated inputs

Figure 3: Structure of Neural Network with various parameters for FLNSP



$P_{15} - P_{27}$ – Additional inputs generated using Functional Link Concept.

The normalized network consists of 27 input neurons and 6 output neurons. The hidden and the output neurons are activated by binary sigmoidal function

$$f(x) = \frac{1}{1 + e^{-(x/q)}} \tag{2}$$

where,

q – Slope parameter

x – Net Input

The values of the slope parameter are chosen randomly so that it gives better convergence. The training is carried by Back Propagation algorithm also by fixing proper value for learning rate, momentum factor, training tolerance and slope parameter. The network is trained for one-year data and tested with next year data. Tested results are given in Table-1 also the forecasted error using functional link network is less compared with the conventional Back propagation network. This shows that by using slope parameter we get better results than in CBP and the time taken for training the network is less compared with CBP.

Table 1: Training Results for Conventional Back propagation and Slope Parameter

Data Set	Parameter	CBP	FLNSP
	No of epoch	82,500	30,000
For 1st 6 hours	Computational Time (Sec)	3093.75	1425.0
	Misclassification	81	85
	No of epoch	2,32,500	53,500
For 2nd 6 hours	Computational Time (Sec)	8718.75	2541.25
	Misclassification	149	128
	No of epoch	1,15,500	76,000
For 3rd 6 hours	Computational Time (Sec)	4312.5	3610
	Misclassification	144	142
	No of epoch	1,48,500	60,500
For 4th 6 hours	Computational Time (Sec)	5568.75	2873.25
	Misclassification	138	140

6. Conclusion

An Artificial Neural Network based Short Term Load Forecasting model for an autonomous power system has been developed. The proposed model using Functional Link Network can provide hourly load forecast for a week which would be useful for scheduling and security analysis.

Input data pre-processing is introduced to improve forecast accuracy. Weather data has been taken to enhance the forecasting results. The training time and the percentage of error are minimized in the proposed methods of Functional Link Network using Slope Parameter and systole Activation Function. As a future work, the effect of slope parameters in the activation function has to be investigated.

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