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Short Term Load Forecasting for Shiraz Region Using Adaptive Back Propagation Neural Network

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Abstract. In this paper, the goal is to develop a model to forecast 24 hours ahead electrical load of Shiraz which located in Iran. To achieve this goal, the adaptive back propagation neural network has been studied. It should be noted that only climate and time factors have been taken into account as input causal factors in load forecasting. This model has been tested on the hourly electrical load data between March 21, 2009 and March 20, 2010 for Shiraz region. Experimental results demonstrate that the proposed model has favorable performance.

Keywords : Load forecasting, Neural network, Adaptive.

1. Introduction

Short-term load forecasting (STLF) refers to forecast electrical loads for a period of minutes, hours, days, or weeks. In contrast to other sources of energy such as coal and oil, electricity cannot be stored in large and in most uses, it cannot be replaced by any other sources of energy. Therefore, it is obvious the importance of knowing in advance the demand (or load) curve so electrical producers are able to plan the most effective way of producing electrical energy.

A large number of works have been published in the last decade on this subject. The traditional models for STLF such as linear or multiple regression [1], ARMAX [2] cannot always deal with the nonlinear characteristics of electrical loads. After the invention of artificial intelligence algorithms, artificial neural network [3], radial basis function network [4] and neuro-fuzzy model [5] are widely used in the STLF. These algorithms can deal with the nonlinear relation between the influencing factors and the load output, so the forecasting performance is raised.

For developing the forecasting model, I used the actual hourly electrical load data for Shiraz state located in Iran. In this paper I will only focus on the problem of short term forecasting up to 24 hours ahead. This kind of load forecasting play a vital role in optimum buying and selling of power in interconnected systems. The parameters that are taken into account as input causal factors are as follows:

- Minimum temperature
- Maximum temperature
- Average temperature
- Minimum humidity
- Maximum humidity
- Rain
- Sunshine
- Maximum wind velocity
- Day-of-week indicator
- Hour-of-day indicator

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For the day-of-week and hour-of-day indicators, one input neuron was assigned to each possible value. Therefore, for the day-of-week indicator was assigned 7 possible input neurons and for the hour-of-day indicator was assigned 24 possible input neurons.

The rest of the paper is organized as follows. Section 2 describes the adaptive back propagation neural network followed by experiments in section 3. Section 4 concludes the paper.

2. Adaptive Back Propagation Neural Network

The Back Propagation neural network (BP) is shown in Fig.1. This network is normally called multilayer perceptron (MLP) type. It uses error back propagation supervised training algorithm which was first described by Paul Werbos in 1974. The example BP shown in Fig. 1 has three inputs (X1, X2, X3), and one output (Y1). The circles represent the neurons which have associated transfer function (not shown), and the weights are indicated by lines between two neurons.

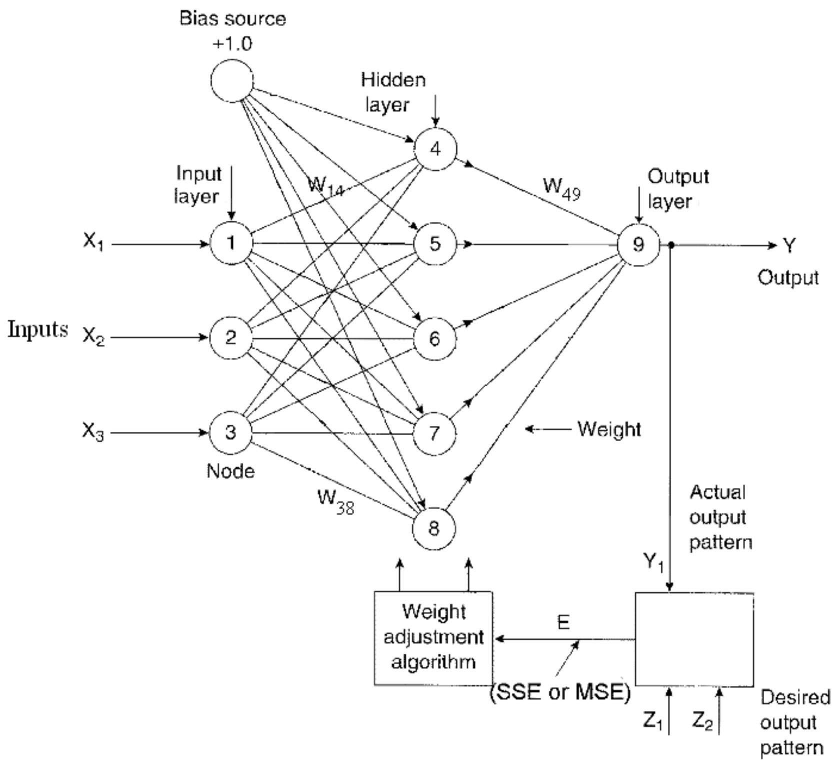

Fig. 1. Three layer back propagation neural network.

Each neuron accumulates all the input-weighted signals, adds to the input-weighted signals bias signal, and then passes to the output through the nonlinear (or linear) activation or transfer function (TF) as shown in Fig. 2. The network shown has three layers: input layer, hidden layer, and output layer. With five neurons in the hidden layer as indicated, it is normally defined as 3–5–1 neural network. The input layer is nothing but the nodes that distribute the signals to the middle. For the simplicity, The bias source is only coupled to the hidden layer and it is eliminated for the output layer neuron. The BP neural network is actually an input–output mapper. To achieve the mapping property, the weights are adjusted by back propagation algorithm until the error between the output pattern and the desired pattern is very small and acceptable.

A direct adaptive learning method for BP neural network called RPROP learning algorithm [6] was used in this paper. The following pseudo-code gives the RPROP learning algorithm.

For all weight and biases{

if $(\frac{\partial E}{\partial w_{ij}}(t-1)\times\frac{\partial E}{\partial w_{ij}}(t)>0)$ then{

$\Delta_{ij}(t)=$ minimum $(\Delta_{ij}(t-1)\times\eta^{+},\Delta_{max})$

$\Delta w_{ij}(t)=-sign\ (\frac{\partial E}{\partial w_{ij}}(t))\times\Delta_{ij}(t)$

$w_{ij}(t+1)=w_{ij}(t)+\Delta w_{ij}(t)$

}

else if $(\frac{\partial E}{\partial w_{ij}}(t-1)\times\frac{\partial E}{\partial w_{ij}}(t)<0)$ then{

$\Delta_{ij}(t)=$ maximum $(\Delta_{ij}(t-1)\times\eta^{-},\Delta_{min})$

$w_{ij}(t+1)=w_{ij}(t)-\Delta w_{ij}(t-1)$

$\frac{\partial E}{\partial w_{ij}}(t)=0$

}

else if $(\frac{\partial E}{\partial w_{ij}}(t-1)\times\frac{\partial E}{\partial w_{ij}}(t)=0)$ then{

$\Delta w_{ij}(t)=-sign\ (\frac{\partial E}{\partial w_{ij}}(t))\times\Delta_{ij}(t-1)$

$w_{ij}(t+1)=w_{ij}(t)+\Delta w_{ij}(t)$

}

}

In the pseudo-code, w_{ij} is the weight from neuron j to neuron i, E is the error function, $\eta^{+}$and η^{-} are the increase and decrease factors respectively, Δ_{ij} is the update-value of the weight, w_{ij}, and Δ_{max} and Δ_{min} are the upper and lower limits of the update-values respectively.

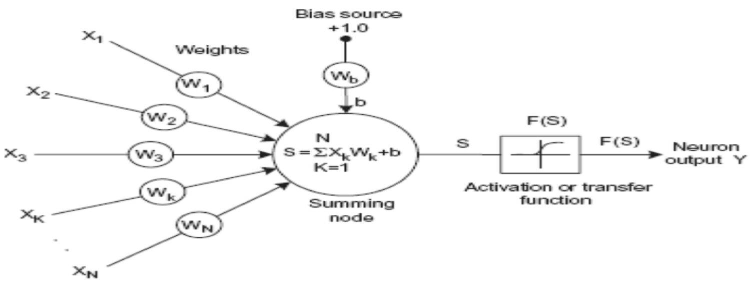

Fig. 2. Structure of a neuron

3. Experimental Results

It was determined that the optimal learning sequence for short-term load forecasting is 20 days. In order to forecast the load for the 21st day, the previous 20 days of loads must be learned. Similarly, to forecast the 145th day's load, the previous 20 days (i.e. days 125-144) must be learned. In order to incorporate this, the hourly electrical load data have been broken up into blocks of 20 days, and have been used to predict the following day's load.

The BP neural network architecture is as follows: 39 input neurons that represent causal factors, 200 hidden neurons, which have been experimentally determined, and one output neuron, representing the load consuption. The hidden and output layer neurons have log-sigmoid and linear transfer function respectively. To show the system performance, it was evaluated by the Root Mean Square Percentage Error (RMSPE) measure using (1).

$$RMSPE = \sqrt{\frac{1}{days}\sum_{d=1}^{days}\frac{1}{24}\sum_{i=1}^{24}[1-\frac{Predicted\, Y_{di}}{Actual\, Y_{di}}]^2} \quad (1)$$

Based on the experimental results, the RMSPE between March 21, 2009 and March 20, 2010 is 7.89%. The best result was obtained for day 147 (Fig. 3), which had an error of 0.95%. Day 282 with an error of 38% was the worst day (Fig. 4).

4. Summaries

In this paper, a new model is developed to forecast 24 hours ahead load demands for Shiraz state located in Iran using adaptive back propagation neural network. To evaluate the forecasting accuracy, the developed model was tested on the actual hourly electrical load data between March 21, 2009 and March 20, 2010. Experimental results show that the short term load forecasting error rate (RMSPE) of 7.89% can be achieved.

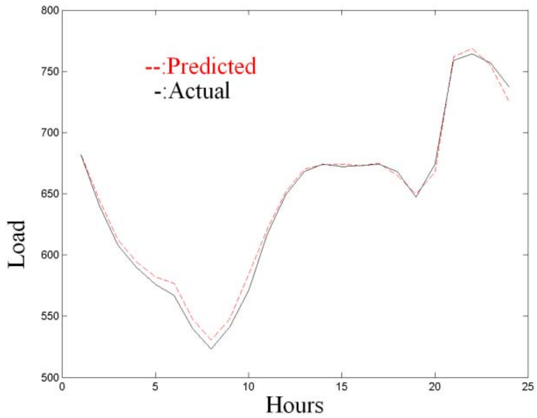

Fig. 3. The best 24 hours ahead load forecasting using the proposed model

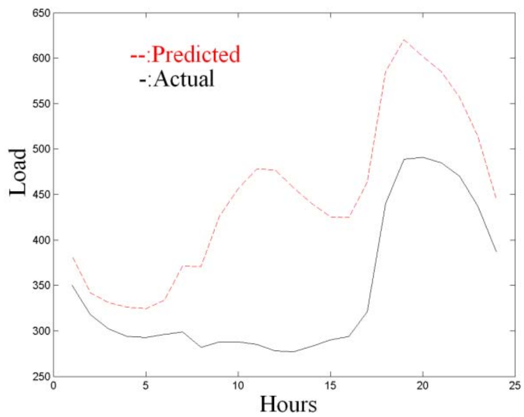

Fig. 4. The worst 24 hours ahead load forecasting using the proposed model

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