Application of Neural Networks for Very Short-Term Load Forecasting in Power Systems

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Abstract. Load forecasting has become in recent years one of the major areas of research in electrical engineering. In a deregulated, competitive power market, utilities tend to maintain their generation reserve close to the minimum required by an independent system operator. This creates a need for an accurate instantaneous-load forecast for the next several minutes. An accurate forecast eases the problem of generation and load management to a great extent. This paper presents a novel artificial neural network (ANN) for very short-term load forecasting. The model with tapped delay line input is simple, fast, and accurate. Obtained results from extensive testing on Taipower System load data confirm the validity of the proposed approach.

1 Introduction

Reliable operation of a power system and economical utilization of its resources require load forecasting in a wide range of time leads, from minutes to several days. Accurate short-term load forecasting (STLF) is essential for planning startup and shut-down schedules of generating units, reserve planning and load management. In addition, the load frequency control and economic dispatch in power system require load forecasts within shorter time leads, from single minutes to several dozen minutes. They are referred to as very short-time load forecasts (VSTLF). These forecasts, integrated with the information about generation cost, spot market energy pricing, transmission availability, and spinning reserving requirements imposed by an independent system operator, are used to determine the best strategy for the utility resources. Very short-term load forecasting has become of much greater importance in today's deregulated power industry.

Many methods have been developed for short-term load forecasting [1],[2],[3]. These methods are mainly classified into two categories: classical approaches [4],[5] and artificial intelligence based techniques [6],[7]. Recently, artificial intelligence based methods using artificial neural networks have been applied to STLF. The main advantage of using neural networks lies in their abilities to team the mentioned dependencies directly from the historical data without the necessity of selecting an appropriate model. There are a few types of neural networks that have been applied for

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load forecasting. A multilayer feedforward network with one hidden neuron layer is most commonly used [8],[9].

Very short-term load forecasting requires a different approach [10]. Instead of modeling relationships between load, time, weather conditions and other load affecting factors we are rather focused on extrapolating the recently observed load pattern to the nearest future. This paper presents a novel ANN for very short-term load forecasting by the application of ANN to modeling load dynamics. When actual loads are forecasted and used as input variables the proposed model with the tapped delay line input is more simple, fast, and accurate. It is less sensitive to the requirement of having the training data representative of the entire spectrum of possible load and weather conditions. The method has been successfully implemented and tested for on-line load forecasting in Taipower system. The results will testify the availability of the application of artificial neural networks to very short-term load forecasting.

2 The Artificial Neural Networks

An ANN can be defined as a highly connected ensemble of processing elements (PEs) called neurons or nodes. A neuron shown in Fig. 1 is a multi-input-single-output PE consisting of a summation operation and an activation function. PEs can be interconnected in various network topologies and can be globally programmed (trained) for various purposes such as pattern recognition, combinatorial optimization, estimation of sampled function whose form is not known, etc.

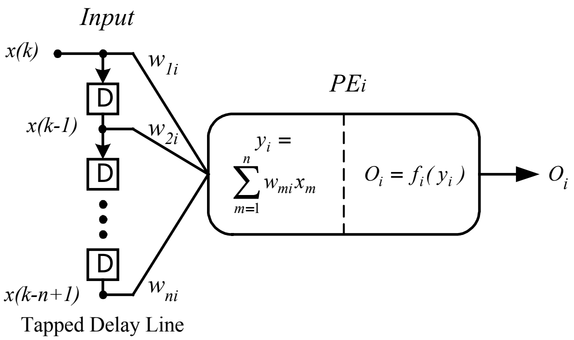

Fig. 1. Processing element with the tapped delay line input

As seen from Figure 1, each PE performs two functions: (i) sum the weighted input signal to the PE, and (ii) produce an output that is a function of the weighted sum. We are rather focused on extrapolating the recently observed load pattern to the nearest future for VSTLF. The input signals enter from the left. At the output of the tapped delay line we have an R-dimensional vector, consisting of the input signal at the current time and at delays of from 1 to n-1 time steps. The actual loads are forecasted and used as input variables. It is less sensitive to the requirement of having the training data representative of the entire spectrum of possible load and weather conditions.

The PEs produce output that is a function of sum of the weighted inputs. The PE function, also called activation function or squashing function, map the unbounded activation (sum of weighted inputs) into a bounded output signal. Among the infinite number of possible PE functions, generally sigmoidal or hyperbolic tangent function is preferred. Linear functions are not preferred because linear functions do not suppress noise. Non-linearity increases computational richness and facilitates noise suppression but also introduces computationa1 intractability as well as dynamical instability. Monotonic continuous nonlinear function appear to be the natures compromise. Most biological neurons have sigmoidal signal characteristics.

3 Implementation of ANN-Based VSTLF

The implementation of the load forecasting system required carrying out several tasks such as selection of ANN architecture, selection of input variables, data normalization, and training of the design networks. These issues are briefly discussed below:

3.1 Selection of ANN Architecture

The three-layer fully connected feedforward neural network is used here. It includes an input layer, a hidden layer and an output layer. Signal propagation is allowed only from the input layer to the hidden layer and from the hidden layer to the output layer. The actual loads are forecasted and used as input variables. The output is the desired forecasting load at 6-min ahead. The number of inputs, the number of hidden nodes, transfer functions, scaling schemes, and training methods affect the forecasting performance and hence need to be chosen carefully.

3.2 Selection of Input Variables

We are rather focused on extrapolating the recently observed load pattern to the nearest future for VSTLF. The input variables are consisted of the actual loads at the current time and at delays of from 1 to 9 time steps.

3.3 Data Normalization

Once the historical data are gathered, the next step in training is to normalize all the data so that each value falls within the range from 0 to 1. This is done to prevent the simulated neurons from being derived too far into saturation.

3.4 Training of the Design Networks

Learning in ANN means change in its parameters based on training data. Learning methods determine how the system parameters change when presented with new samples. Among the different learning methods available, the error back-propagation learning algorithm is a supervised learning method. It is the most popular and almost universally used because of its computational simplicity, ease in implementation and good results generally obtained for large number of problems in many different areas of application. The back-propagation learning algorithm was used as training method here.

4 Test Results

The historical data of a substation load in Taipower system for June 2004 was used for testing the proposed ANN-based VSTLF. A neural network with 10 inputs, 10 hidden node, and one output was used here. The forecaster was trained using the data from recent week and then used to forecast the 6-min ahead load for next week. A tangent sigmoid function was chosen as the transfer function for the hidden layer, and a linear function for the output layer. The training performance for a learning rate and a momentum set at 0.55 and 0.85 respectively is shown in Fig. 2. The fast convergence without oscillation is due to the relative large values of the learning rate and the momentum, which were chosen based on multiple tests carried out with different values of these two parameters.

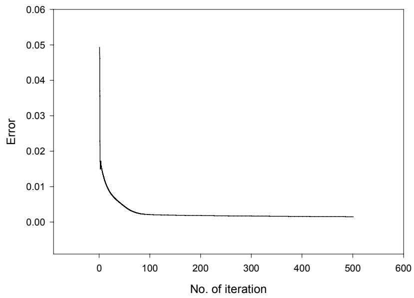

Fig. 2. Training performance of the proposed ANN

The VSTLF results for Monday July 21, 2004 and Saturday July 26, 2004 are depicted in Figs. 3 and 4 along with the actual load. The adequate performance of the proposed VSTLF is also illustrated in the mean absolute percentage error (MAPE) for 1,670 data forecasted per 6-minute ahead on a week shown in Table 1. The MAPE of the whole week, including holidays, is 0.0264 (2064%). These results indicate that the proposed ANN provides a good application to very short-term load forecasting in power system.

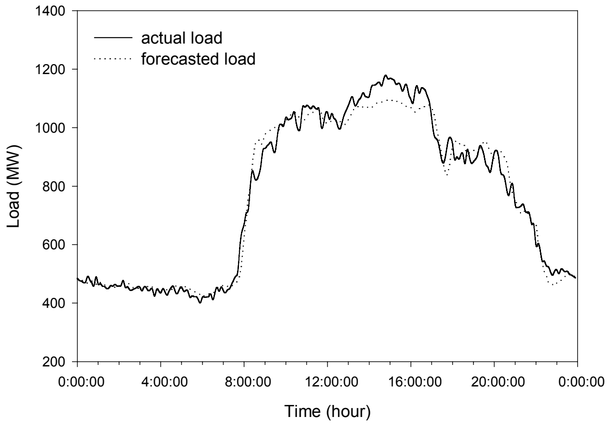

Fig. 3. Forecasting results for Monday June 21, 2004

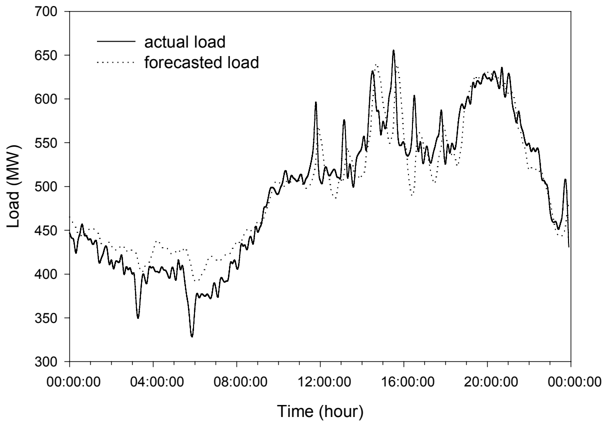

Fig. 4. Forecasting results for Saturday June 26, 2004

Table 1. Forecasting results including holidays

Weekday	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Average
MAPE%	2.98	2.80	2.57	2.40	2.43	2.37	2.98	2.64

5 Conclusions

A novel ANN-based VSTLF method that uses a three-layer feedforward neural network with the tapped delay line input and a back-propagation training method is presented. Instead of dealing with actual loads, neural networks focus on modeling load dynamics. The forecasting results indicate that this model can meet the need of improving forecast accuracy and enhancing the performance of the network. Artificial neural networks have been successfully used for instantaneous-load forecasting with time leads in a range of several to several dozen minutes. It proves the effectiveness of the application of artificial neural networks to very short-term load forecasting.

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