Prediction of short-term load using artificial neural networks

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Abstract

Neural network can be used for solving the particular problems which are difficult to solve by the human beings or the conventional computational algorithms. The computational meaning of the training comes down to the adjustments of certain weights which are the key elements of the artificial neural netwrok. This is one of the key differences of the neural network approach to problem solving than conventional computational algorithms. This adjustment of the weights takes place when the neural network is presented with the input data records and the corresponding target values. Due to the possibility of training neural networks with off-line data, they are found useful for power system applications. This paper focus on short-term load prediction using three types of neural networks. An accurate short-term forecasting method for load of electric power system can help the electric power system operator to reduce the risk of unreliability of electricity supply. On this paper, radial basis function neural netwrok (RBFNN), Nonlinear Autoregressive model with eXogenous input neural network (NARXNN), and backpropagation neural network (BPNN) were developed to predict the short-term load. Simulation results show that the three types of neural networks can predict the load efficiently. The neural network simulation results were implemented using the Matlab program. The accuracy of load prediction using the neural networks was investigated and assessed in terms of mean absolute percentage error (MAPE).

Keywords: Short-term load prediction, neural networks, RBFNN, NARXNN, BPNN, MAPE, Matlab.

1. Introduction to short-term load prediction using neural networks

Neural networks have been used in a board range of applications including: pattern classification, pattern recognition, optimization, prediction and automatic control. In spite of different structures and training paradigms, all NN applications are special cases of vector mapping. The application of NNs in different power system operation and control strategies has led to acceptable results. During 1990-1996 with them during 2000-2005, the following fields has attracted the most attention in the past five years: load forecasting, fault diagnosis/fault location, economic dispatch, security assessment, and transient stability. The main advantages of using NNs on power system are: its capability of dealing with stochastic variations of the scheduled operating point with increasing data, very fast and on-line processing and classification, and implicit nonlinear modeling and filtering of system data [1]. Commonly and popular problem that has an important role in economic, financial, development, expansion and planning is load forecasting of power systems.

Generally, the load prediction can be categorized into three groups: short-term load prediction over an interval ranging from an hour to a week is important for various applications such as unit commitment, economic dispatch, energy transfer scheduling and real time control.

A lot of studies have been done for using of short-term load prediction with different methods [2], [3], [4], and [5].
Mid-term load prediction that range from one month to five years, used to purchase enough fuel for power plants after electricity tariffs are calculated [6]. Long-term load prediction, covering from 5 to 20 years or more, used by planning engineers and economists to determine the type and the size of generating plants that minimize both fixed and variable costs [7]. Fig. 1 shows the percentage of number of published works during five years in different load prediction types.

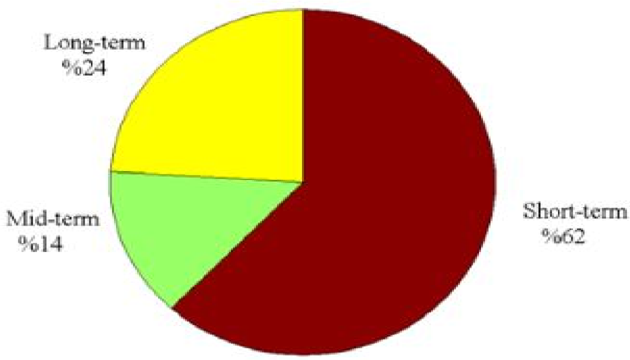

Fig 1 Types of load prediction that done with NN

The load of power grid was predicted using neural networks, and results show that the neural netwrok can predict the load efficiently. The short-term load prediction using neural netwrok carried out on a previous works as: the short-term load predicted using NARXNN [8], and [9]; the short-term load predicted using RBFNN [10]; and the short-term load predicted using BPNN [11], [12]. This paper focus on comparison between the short-term load prediction using the three types of the neural networks (NARXNN, RBFNN, and BPNN) to show the neural networks is a powerful toll to predict the load in power systems, and to show which type of neural netwrok is an accurate to predict the short-term load.

2. Artificial Neural Networks (ANNs)

2.1 Introduction to artificial neural networks

The concept of a neural network was originally conceived as an attempt to model the biophysiology of the brain. At the same time, research engineers were concerned with how to use Artificial neural networks (ANNs) to form controllers from neurons with interesting and powerful computational capabilities. ANNs offer a potential solution for problems which require complex data analysis and promise to form the future basis of an improved alternative to current engineering practice. Many researchers found that neural networks have many applications in various fields of study including modeling and control of linear and nonlinear systems. Neural networks have been developed in different ways, where various algorithms and methods have been applied, such as backpropagation (BP) rule and Radial Basis Function (RBF) [8], and [13].

In most cases the structure of the MLPs is carried out in a fairly heuristic way, so far a certain problem a reasonable number of layers and neurons in each layer are initially selected, based on experience. However, if incorrect number of nodes are selected, then adjustments can be made on a trial and error basis. Moreover, the backpropagation algorithm (BP) suffers from several deficiencies, such as slow convergence and construction complexity. An alternative approach to overcome the limitations associated with the BP algorithm is to use the Radial Basis Function (RBF) network which is discussed in details in the following sections.

2.2 Radial Basis Function Network

The RBF network can be regarded as a special three-layer network including input, hidden and output layers. Full explanations of the connections of these layers together with the activation function are given in the next sections. The performance of the RBF depends on the proper selection of three important parameters, centers, widths and the weights. The radial basis function has been shown to able to solve many problems in different fields, one example is the modeling and controlling of non-linear systems. The RBF neural network has a feed forward structure consisting of three layers as shown in Fig. 2 [14].

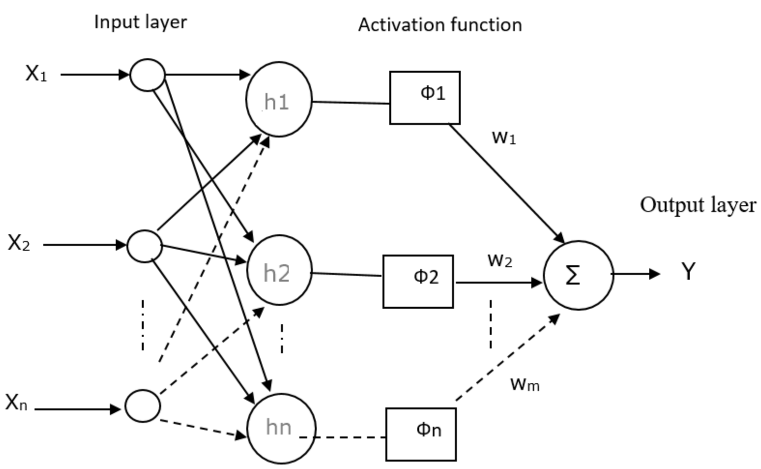

Fig 2 The radial basis function neural network structure

The Radial Basis Function Network consists of three important parameters, centers *(c)*, widths *(σ)* and weights *(w)*. The value of these parameters are generally unknown and may be found during the learning process of the network. There are a variety of methods to allow the RBF network to learn. These processes are generally divided into two stages, as each layers of the RBF perform a different task. The first learning stage involves selecting the centers and the widths in the hidden layer. The second stage is to adjusting the weights in the output layer [5].

2.3 Nonlinear Autoregressive model with eXogenous input neural network (NARXNN)

A Nonlinear Autoregressive model with eXogenous input neural network (NARXNN) was used in this project for wheel wear and rail wear prediction. The NARXNN can be implemented using a feedforward neural network [15]. Fig. 3 shows the structure of the NARXNN which are called NARX recurrent neural networks. This network simply uses a TDL-type network (Tapped delay line) with a feedback connection from the output of the network to the input. The function of the delay line (TDL) or taps is to feed the neural network with the past values of inputs [16].

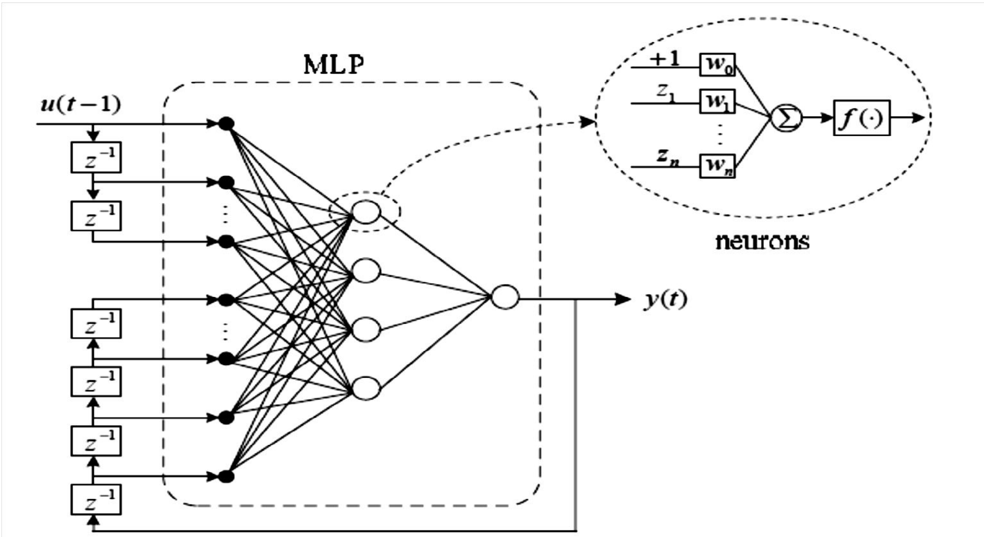

Fig 3 The structure of NARXNN [16], [15]

The output of the NARXNN is represented using the following equation:

$$y(t) = f(u(t-1), u(t-2), \ldots, u(t-n), y(t-1), y(t-2), \ldots, y(t-m, W \quad (1)$$

Where $u(t)$ is the input and $y(t)$ is the output of the network at time t, n and m are the input-memory and output-memory order, W is a weights matrix, and f is a nonlinear function.

The output at time t depends on both its past m values and the past n values of the input as well. The Lavenberg-marquardt backpropagation algorithm was used on this work to train the NARXNN. The training of NARXNN automatically stops when the validation error (MSE) begins to increase [17].

2.4 Backpropagation Neural Network (BPNN)

This section describes one of the most common types of artificial neural network. Multilayer feedforward (MLFF) neural network with backpropagation (BP) learning (multilayer perceptron). A general multilayer feedforward (MLFF) network is illustrated in Fig. 4. The MLFF consists of three layers: Input layer, hidden layers, and output layer. The hidden layer is sometimes called the internal layer because it only receives internal inputs then produces internal outputs. It consists of one or more hidden layers [18].

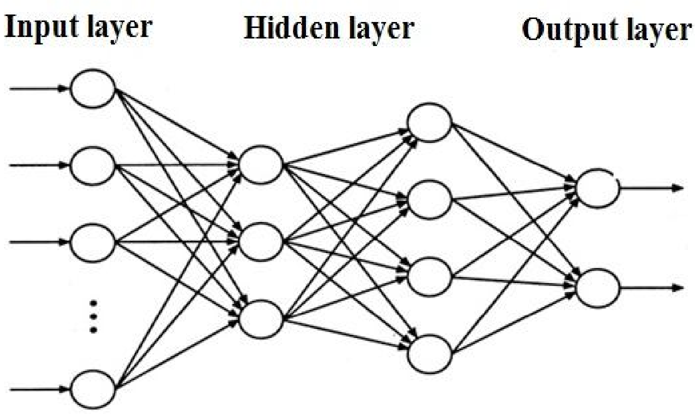

Fig 4 MLFF Backpropagation Neural Network (BPNN) [18]

The backpropagation training process requires an activation function. One of the most common activation functions is the sigmoid function. The most common training algorithm which is used on this work for training of BPNN is a Levenberg-Marquardt algorithm which adjusts the weights to reduce the error [18].

3. Load prediction using RBFNN, NARXNN, and BPNN

This section describes the procedures for training the neural network to learn from the Year 2005 hourly load data published on a previous work were used to train the neural netwrok in order to predict the next day load demand [11]. The Matlab ANN toolbox was utilized in designing the neural networks architecture. The input consists of daily 24-hour load data for 12 months of the year 2005 and daily average maximum temperature altogether making 25 inputs rows by 365 days. The output layer will be a day's 24 hours load forecast for the utility company. The Target data is the same as the input's daily 24 hours load data. The following equation was used to calculate the mean absolute percentage error (MAPE) [19], [20]:

$$\mathrm{MAPE} = \frac{1}{N} \sum_{i=1}^{N} \frac{|A_i - P_i|}{Ai} \text{ X } 100 \tag{2}$$

Where A_i is the actual load, P_i is the predicted load, i is time period, and N is the number of time periods (number of observed values). MATLAB has been recognised as an effective neural network modelling tool and is subsequently used in this paper to implement the three types of neural networks for load prediction. The actual load and load predicted using RBFNN, NARXNN, and BPNN are shown in Fig. 5. Matlab tool box was used on this work to design, train, and test the RBFNN, NARXNN, and BPNN to predict the load.

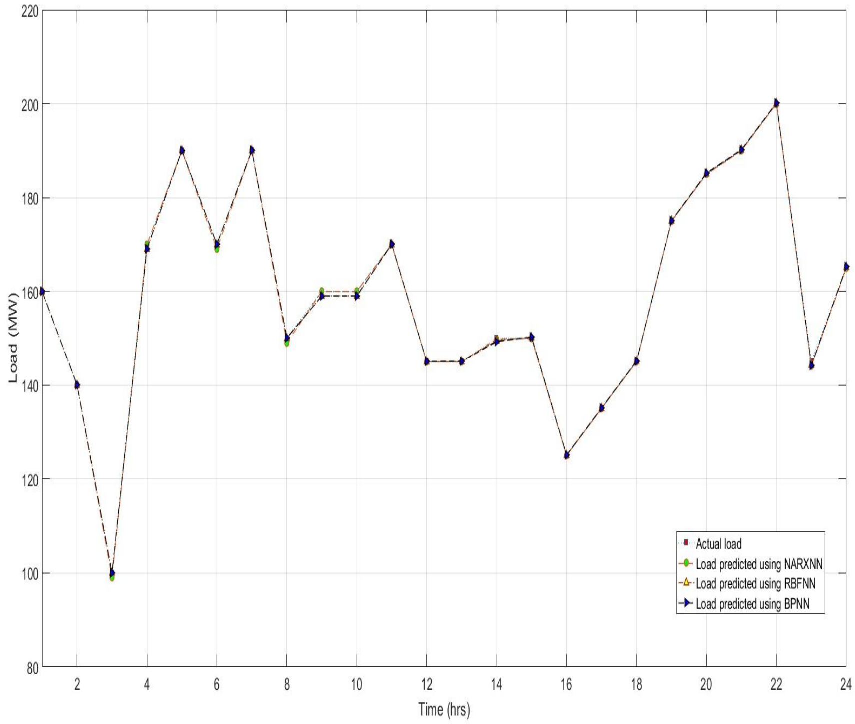

Fig 5 Actual load and load predicted using NARXNN, RBFNN, and BPNN

The simulation results shown in Fig. 5 show that the three types of neural networks achieved good short-term load prediction as: The MAPE was 1.12% for NARXNN, 1.45% for RBFN, and 1.67% for BPNN. Therefore, the accuracy of a three type of neural network for load prediction was greater than 98%. The accuracy of the neural network model was assessed by mean absolute percentage error (MAPE), the accuracy of NARXNN was the best, followed respectively by the RBFNN and BPNN. The NARXNN have an advantage over RBFNN and BPNN, where the output of NARXNN is fed back to the input (closed loop).

4. CONCLUSIONS

This paper has proposed a three types of neural networks to accurately and reliably predict the load of an electric power system. A load prediction using the three neural networks was designed using Matlab program (ANN Toolbox). The implementation of the network architecture, training of the Neural Network and simulation of test results were all successful with a very high degree of accuracy resulting into 24 hourly load output. The simulation results show that the RBFNN, NARXNN, and BPNN can predict the short-term load efficiently with accuracy of 98%. It can therefore be concluded that the RBFNN, NARXNN, and BPNN are accurate models for short-term load prediction. The accuracy of the neural network model was assessed by mean absolute percentage error (MAPE), the accuracy of NARXNN was the best, followed respectively by the RBFNN and BPNN.

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