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NEURAL NETWORK BASED APPROACH FOR SHORT-TERM LOAD FORECASTING

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Abstract: This paper proposes a neural network approach for forecasting short-term electricity prices. Almost until the end of last century, electricity supply was considered a public service and any price forecasting which was undertaken tended to be over the longer term, concerning future fuel prices and technical improvements. Nowadays, short-term forecasts have become increasingly important since the rise of the competitive electricity markets. In this new competitive framework, short-term price forecasting is required by producers and consumers to derive their bidding strategies to the electricity market [1]. Accurate forecasting tools are essential for producers to maximize their profits, avowing profit losses over the misjudgment of future price movements, and for consumers to maximize their utilities. Short-term load forecasting plays an important role in electric power system operation and planning [2]. An accurate load forecasting not only reduces the generation cost in a power system, but also provides a good principle of effective operation. It is trained using back propagation algorithm and tested. The results obtained from neural network are presented and the results show that the neural network based approach is more accurate.
Keywords: Artificial Neural Network, Back Propagation Algorithm, Short Term Load Forecasting.

Introduction

The total amount of electric power [in MW] consumed in an electrical power system must be balanced with an equal amount of generated power. There is no efficient way of storing large amounts of electrical energy. To maintain this power balance between production and consumption the power input to the power system must be controlled. By using various methods to forecast (predict) future power needs; the electric power production may be planned. This is called power load adaption. An accurate load forecasting not only reduces the generation cost in a power system, but also provides a good principle of effective operation. Power system forecasting can be divided into load forecasting and electrical consumption predicting According to forecasting matter. Based on different predicting time, it can be divided into long-term load forecasting, mid-term forecasting, short-term forecasting and ultra short-term forecasting. Midterm And long-term forecasting mainly used in power factory macro control, and their forecasting time ranges are respectively from one month to twelve months and from one month to ten months respectively [3]. The short-term forecasting can be used in generators macroeconomic control, power exchange plan and so on. And the prediction is from one day to seven days in the future, or a little longer time. Whereas the ultra short-term forecasting can predict the situation in a day or in an hour, and it's mainly used in Prevention and control emergency treatment and frequency control. With the deepen reform of electricity, the formation of power market and the independent and self-financing of electricity enterprises, power load forecasting becomes more and more important[4]. How to improve the accuracy of power load forecasting is a valuable research. Generally speaking, long-term accuracy of the forecast will be lower, while short-term will be higher.

An accurate forecast of electricity prices has become a very important tool for producers and consumers. In the short-term, a producer needs to forecast electricity prices to derive its bidding strategy in the pool and to optimally schedule its electric energy resources although neural networks are capable of handling nonlinearity between the electric load and the weather factors that affect the load; they somehow lack to fully handle unusual changes that occur in the environment[5]. The topology of a neural network determines the degrees of freedom available to model the data. If the neural network is too simple then the network will not be able to learn the function relating the input to the output and an over-complex network will learn the noise in the data and will not be able to generalize.

Factors influencing System Load: The Four major categories of factors that influence system load are:

Economic Factors: The economic environment in which the utility operates has a clear effect on the electric demand consumption patterns. Economic trends have significant impact on the system load/decline trend. Typically, these economic factors operate with considerably longer time constants than one week and hence need not be considered for STLF.

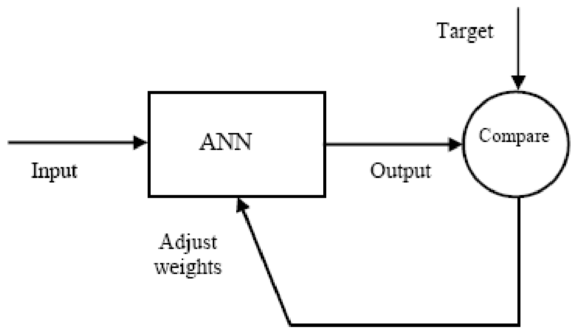
However these factors should be taken in to consideration for long & medium – term forecasting models.

Time factor: The principal of time viz. seasonal effects, weekly – daily cycle legal and religious holidays play an important role in influencing load patterns. Seasonal effects determine utilities peaking (summer/winter) and also bring out structural modifications in electricity consumption pattern. The weekly-daily cycle of the load is consequence of the work-rest pattern of the service is population. The load decreases considerably on holidays the tendency of the people to have extended weekends could also affect the loads on the preceding and following holidays

Weather factor: Significant changes in load pattern are due to metrological factors as most of the utilities have large components of weather sensitive load such as space heating, air conditioning and agricultural irrigation. The load level fluctuates with the climatic conditions and has high correlation with area temperature, rainfall, snowfall etc. Temperature and precipitation are the main meteorological factor considered in load forecasting. Their influence on the system load varies not only between winter and summer, but also between peak and valley of the same day. For a system covering a vast geographical area with wide variations in climate, several weather variables in several areas may need to be considered to account for the variations in the system load. Humidity affects system load in hot and humid areas. Other factors that have impact on load behavior are wind speed, precipitation, cloud cover, light intensity, onset of darkness etc.

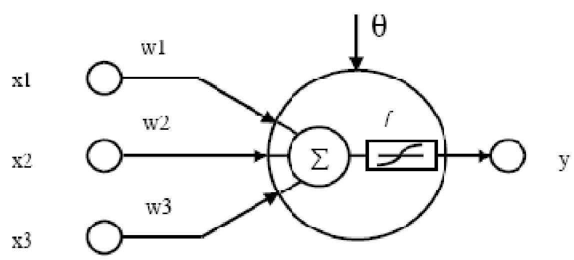
Random disturbances: These include loads such as steel mills, wind tunnels whose operations can cause large variations in electricity usage. Widespread strikes, bands', special TV programs whose effect on the load is not known a – priori could cause sudden and unpredictable variations in load.

Introduction to ANN: ANN's are mathematical tools originally inspired by the way the human brain processes information. They are composed of simple elements operating in parallel. These elements are stimulated by biological uneasy systems. As in nature, the network function is determined largely by the connections between elements. You can train an ANN to perform a particular function by adjusting the values of the connections (weights) between elements.



Simple ANN concept

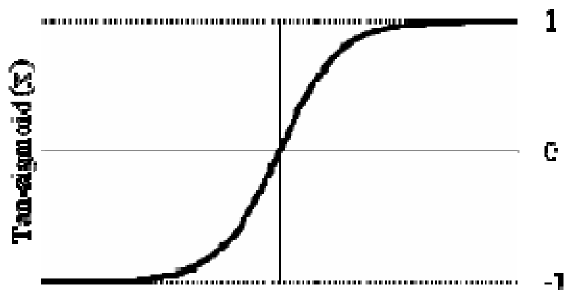
Commonly ANN’s are adjusted, or trained, so that a particular input leads to a specific target output. Therefore, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are needed to train a network. Their basic unit is the artificial neuron. The neuron receives (numerical) information through a number of input nodes, processes it internally, and puts out a response [6]. The processing is usually done in two stages: first, the input values are linearly combined, and then the result is used as the argument of a nonlinear activation function. The combination uses the weights attributed to each connection, and a constant biasterm. One of the most used schemes for a neuron.



An artificial neuron

The neuron output is given by: $Y = f\,(\sum wt - xt)$-$\boldsymbol{\Phi}$ ……..(1)

Where xt is the neuron input multiplied by weight link wt, is the characteristic neuron offset (bias), and f is the activation function. The most common choice for the activation functionin multilayer networks is tan-sigmoid activation function.

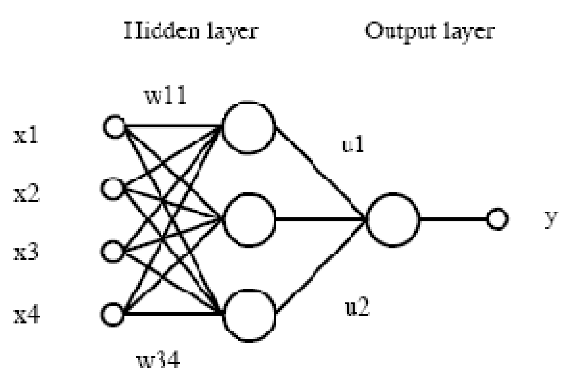


Tan-sigmoid activation function

the tan-sigmoid activation function output is limited between [-1, 1], the output of the function is formulated in (2).

$$F(x) = \frac{2}{1+\exp(-2x)} - 1 \qquad \text{........ (2)}$$

The neurons are organized in a way that defines the network structure. The most concerned structure is the multilayer perceptron (MLP) type, in which the neurons are organized in Layers. The neurons in each layer may share the same inputs, but are not connected to each other. If the architecture is feed forward, the outputs of one layer are used as the inputs to the following layer. The layers between the input neurons and the output layer are called the hidden layer. Fig. 4 shows an example of a tow-layers feed- forward perceptron network, with four input neuron, three neurons in the hidden layer and one neuron in the output layer. Each layer has a specifiednumber of nodes; the interconnections are only betweenneurons of adjacent layers, and each neuron belonging to alayer is connected to all the neurons of adjacent layers. Notethat ANN may contain more than one hidden layer; thenumber of neuron in each layer should be carefully selecteddepends on the application requirements. The parameters of this network are the weight matrix, and the bias.



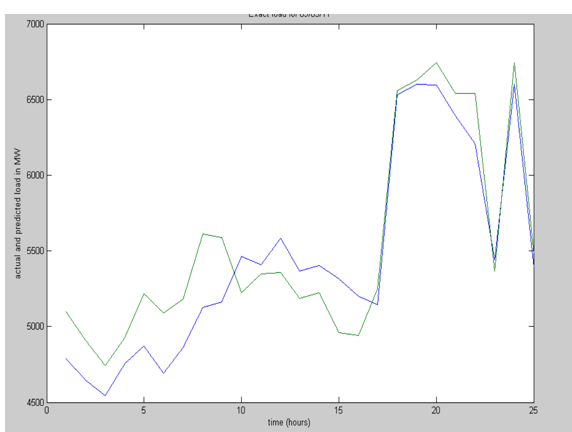
A two-layer feed-forward neural network

The estimation of the parameters is called the training of the network. The most used training algorithm in load Forecasting is back-propagationone, There are many variations of the back-propagation algorithm [8].The simplest implementation of back-propagation learning updates the network weights and biases in the direction in which thePerformance function decreases most rapidly, the negative of the gradient. An iteration of this algorithm can be written in (3).

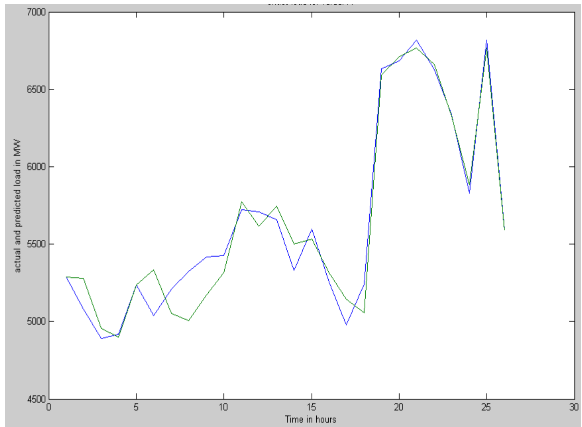
$$x\ (k+L) = xk - \alpha kgk \qquad \text{……..(3)}$$

Where xk is a vector of current weights and biases gk is the current gradient, and αk is the learning rate. In load forecasting applications, this basic form of Multilayer feed-forward architecture is still the most popular. Nevertheless, there are a large number of other designs, which might be suitable for other applications. ANN should prove to be particularly useful when one has a large amount of data, but little a prior knowledge about the laws that manage the system that generated the data.

Solution Methodology: There is trade-off in amount of data that can be input to ANN. The more data inputs and the more training patterns to the network the longer the training time which depending on the hardware available can take several hours. On the other hand, if not enough data and training patterns are presented to the network then the output will not be representative to the true input. There is also the possibility of confusing the network by showing it data in which the relationships are very weak or even misguiding. The proposed architecture is trained by using back propagation algorithm [11] with Matlab SIMULINK NN Toolbox. The performance of the proposed neural network based STLF model was tested using hourly load data. Comparison of 24 hours ahead load forecasting and exact load is shown below:



Load forecasting using ANN for date 09/04/12



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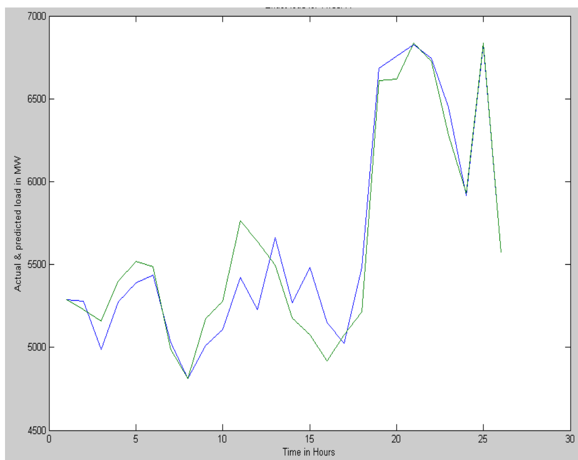
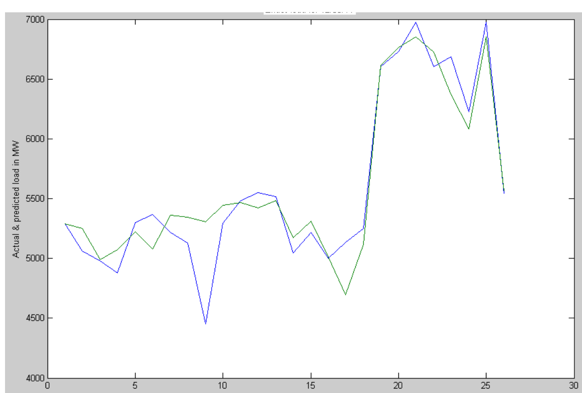
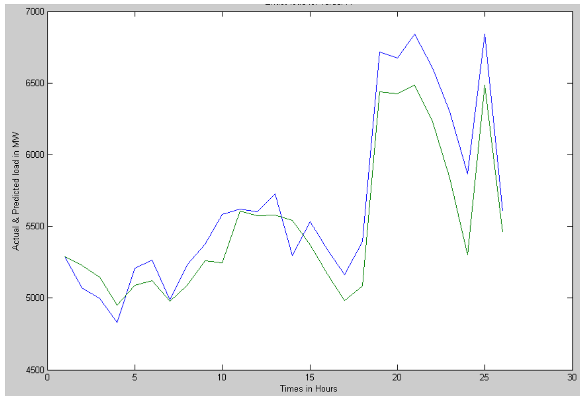


Load forecasting using ANN for date 11/04/12



Load forecasting using ANN for date 12/04/12



Load forecasting using ANN for date 13/04/12

Conclusion: Short-term load forecasting is given new significance as well as complexity due to the emergence of the new competitive electricity market environment. In this paper, first we introduce the system model of the short-term load forecasting and explain every section particularly. Then we present a short-term load forecasting method. Which obtains input sets belong to multi-layered fed-forward neural network, and artificial neural network in which BP learning algorithm is used to train samples. That the patterns considered for training the ANNs also have an impact on forecasting accuracy.

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