SHORT-TERM LOAD FORECASTING WITH SPECIFIC MODEL OF FLN USING ARTFICIAL NEURAL NETWORK

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Abstract: Load-forecasting has been tried out using most traditional forecasting models and artificial intelligence techniques and has become one of the major research fields. Artificial Neural Networks have lately received much attention, and a great number of papers have reported successful experiments and practical tests with them. This paper presents a new approach for short-term load forecasting on Artificial Neural Network (ANN). The short-term load forecasting has been done with the help of tensor model of Functional-Link Network (FLN). An attempt has been made for forecasting short-term load pattern of one hour ahead. This paper also helps to concretize the knowledge how Functional-Link Network is applied for forecasting load. The results of the Functional-Link Network show an improved forecast capability

Keywords: **Short-term Load Forecasting, Functional-Link Network (FLN), Artificial Neural Network (ANN).**

I INTRODUCTION

The electricity supply industry requires to forecast electricity demand with lead times that range from the short term (a few minutes, hours, or days ahead) to the long term (up to 20 years ahead). Short-term forecasts, in particular, have become increasingly important since the rise of the competitive energy markets. Short term forecasting of electrical load is important for optimum operation planning of power generation facilities as it affects both system reliability and fuel consumption. Accurate forecasting of electricity and power demand determines the utility to match its generation capabilities to the expected requirements. Electric utility operators for the purpose of scheduling and dispatching generating units need short-term forecasts. A short-term forecast is important for "unit commitment, economic dispatch, hydrothermal co-ordination, load management, etc." Ackerman [12] says that a short-run forecast plays an important role in the day-to-day operations of a utility, and it is typically used for optimizing system operation and scheduling of hydro units and other peaking plants, such as gas turbines. The objective of the operators is to minimize variable costs without jeopardizing the electric system to power failures. The short-term (one to twenty-four hour) load forecast is of importance in the daily operations of the utility**.** With the emergence of Load Management, the short-term load forecast has a broader role in utility operations; it is also required for the co-ordination of Load Management programs with conventional system resources. Since the effectiveness of Load Management programs is sensitive to the system load, this additional function places higher accuracy requirements on the short term forecast, also required for short term maintenance scheduling. Accurate forecasting of power demand is to determine the assessment of the dynamic behavior of the system during disturbances so that the proper preventive action can be taken up. Load forecasting is however a difficult task. First, because the load series is complex and exhibits several levels of seasonality: the load at a given hour is dependent not only on the load at the previous hour, but also on the load at the same hour on the previous day, and on the load at the same hour on the day with the same denomination in the previous week. Secondly, there are many important exogenous variables that must be considered, especially weather-related variables. It is relatively easy to get forecast with

about 10 % mean absolute error; however, the cost of error are so high that research could help to reducing it in a few percent points would be amply justified. Most forecasting models and methods have already been tried out on load forecasting, with varying degrees of success. They may be classified as *time series models*, in which the load is modeled as a function of its past observed values, and *causal models* in which the load is modeled as a function of some exogenous factors, especially weather and social variables. Some models of the first class suggested in recent papers are multiplicative autoregressive models, dynamic liner or nonlinear models, threshold autoregressive models, and methods based on Kalman filtering. Some of the second classes are Box and Jenkins transfer functions, ARMAX models, optimization techniques, nonparametric regression, structural models, and curve-fitting procedures. Despite this large number of alternatives, however, the most popular causal models are still the linear regression ones and the models that decompose the load, usually into basic and weather dependent components [11]. In Functional-Link Network (FLN) model of hybrid neural networks, a non-linear functional transform or expansion of the network inputs is initially performed and the resulting terms are linearly combined. The obtained structure has a good nonlinear approximation capability and the estimation of the network weights is linear [4]. Due to the linear estimation, the training of these networks is rapid, requires low computational effort and its convergence is guaranteed. In the present work a single Artificial Neural Network based on Functional-Link Network [FLN] has been developed to forecast the short-term electrical load.
The accuracy of predicted load results was compared with the actual load data.

II ARTIFICIAL NEURAL NETWORK BASED LOAD FORECASTING

Artificial Neural Networks are relatively crude electronic models based on the neural structure of the brain. The brain basically learns from experience. The biologically inspired methods of computing are thought to be the next major advancement in the computing industry. The fundamental processing element of a neural network is a neuron. The basic units of neural networks, the artificial neurons, simulate the four basic functions of natural neurons. Figure 1 shows a fundamental representation of an artificial neuron. In figure 1, various inputs to the network are represented by the mathematical symbol, x (n). Each of these inputs is multiplied by a connection weight. These weights are represented by w(n). In the simplest case, these products are simply summed, fed through a transfer function to generate a result, and then output. This process lends itself to physical implementation on a large scale in a small package.

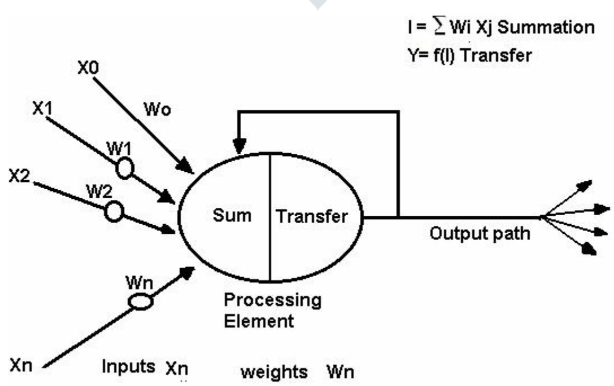

Fig.1. A Basic Artificial Neuron

Artificial Neural Networks have been developed and extensively applied since the mid-1980. There are many reports of successful applications, particularly in pattern recognition and classification, and in nonlinear control problems. Since quantitative forecasting is based on extracting patterns from observed past events and extrapolating them into the future, the ANNs are very well suited for it for at least two reasons. First, it has been formally demonstrated that ANNs are able to approximate numerically any continuous function to the desired accuracy. In this sense, Neural Network may be seen as multivariate, nonlinear and nonparametric methods. Secondly, ANNs are date-driven methods, in the sense that it is not necessary for the researcher to postulate tentative models and then estimate their parameters. Given a sample of input and output vectors, the ANNs are able to automatically map the relationship between them; they "learn" this relationship, and store this learning into their parameters. As these two characteristics suggest, Neural Networks should prove to be particular useful when there is a large number of data. But had little a priori knowledge about the laws that govern the system that generated data. [11]. with power systems growth and the increase in their complexity, many factors have come influential to the electric power generation and consumption. Therefore, the forecasting process has become even more complex, and more accurate forecasts are needed. The relationship between the load and its exogenous factors is complex and nonlinear, making it quite difficult to model through conventional techniques, such as time series and linear regression analysis [8]. Artificial Neural Network (ANN) models provide new approach to problem solving. Neural Networks (NNs) have succeeded in several power system problems, such as planning, control, analysis, protection, design, load forecasting, security analysis, and fault diagnosis. The last three are the most popular [9]. The NN ability in mapping complex nonlinear relationships is responsible for the growing number of its application to the short-term load forecasting (STLF) [10]. ANNs can achieve high computational speed by employing a massive number of simple processing elements arranged in a parallel with high degree of connectivity between the elements. Neural Networks have been applied to various fields of complex, non-liner and large-scale power systems [6]. During the course of this study several attempts were made to enhance the accuracy of forecast by selected structure of neural network. Neural networks are such flexible models that the task of designing a NN-based forecasting system for a particular application is far from easy. Neural networks might be classified into two groups, according to the number of output nodes. In the first group, that have only one output node, used to forecast next hour's load, next day's peak load or next day's total load. In the second group, that has several output nodes to forecast a sequence of hourly loads. The NNs with only one output neuron are used to forecast profiles, in either of two ways. The first way is by repeatedly forecasting one hourly load at a time. The second way is by using a system with 24 NNs in parallel, one for each hour of the day. Estimating a model that fits the data so well that it ends by including some of In Multi-Layer Perceptron (MLP) structure of neural network, the most commonly training algorithm use is the back propagation algorithm, based on a steepest-descent method that performs stochastic gradient decent on the error surface Since these algorithms are iterative, some criteria must be defined to stop the iterations. For this either training is stopped after a fixed number of iterations or after the error decreased below some specified tolerance. This criterion is not adequate, as they insure that the model fits closely to the training data, but does not guarantee good out-of-sample performance; they may lead to over-fitting of the model. "Overfitting" usually means the error randomness in its structure, and then produces poor forecasts. Adya and Collophy [13] remark that the usual MLPs trained by back-propagation "are known to be seriously prone to over-fitting" and by avoiding excessive training could prevent this. On the other hand, Gorr, Zhang, Patuwo and Hu [14], [15] had remark that MLPs are prone to over-fit sample data because of the large number of parameters that must be estimated. In MLPs, as the remarks above imply, this may come about for two reasons: because the model was over-trained or because it was too complex. One way to avoid overtraining is by using cross-validation. The sample set is split into a training set and a validation set. The neural network parameters are estimated on the training set, and the performance of the model is tested, every few iterations, on the validation set. When this performance starts to deteriorate (which means the neural network is over-fitting the training data), the iterations are stopped, and the last set of parameters to be computed is used to produce the forecasts. Another way is by using regularization techniques. This involves modifying the cost function to be minimized, by adding to it a term that penalizes for the complexity of the model. This term might, for example, penalize for the excessive curvature in the model by considering the second derivatives of the output with respect to the inputs. Relatively simple and smooth models usually forecast batter than complex ones. Over-fitted neural networks may assume very complex forms, with pronounced curvature, since they attempt to "track down" every single data point in the training sets; their second derivatives are therefore very large and the regularization term grows with respect to the error term. Over-fitting however may also be a consequence of over-parameterization, that is, of the excessive complexity of the model. The problem is very common in MLP-based models; since they are often (and improperly) used as "black-box" devices, the users are sometimes tempted to add to them a large number of variables and neurons, without taking into account the number of parameters to be estimated. Many methods have been suggested to "prune" the neural network, i.e., to reduce the number of its weights, either by shedding some of the hidden neurons, or by eliminating some of the connections. However, the adequate rate between the number of sample points required for training and the number of weights in the network has not yet been clearly defined; it is difficult to establish, theoretically, how many parameters are too many, for given sample size. In present work, to avoid the problems of over fitting and over-parameterization, the ANNs architectures used for prediction of electrical load is Functional Link Network (FLN) model, other than the MLP, which is briefly described below.

II a) FUNCTIONAL-LINK NETWORK

The functional-Link Network [7] has been developed by Y. H. Pao for enhancing 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: (1) the net structure becomes very complex and learning of weights becomes a very complex process, as the required output of the middle layer is not known. (2) There are two sets of weights to be learnt and this stresses the memory of computer. To solve these two problems Pao suggested a method. The idea was to remove the middle layer. Adding a link, which enhances the inputs depending upon the type of? output to be approximated, solved problem of a linear combination of inputs. 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. The idea of a functional link is the functional transform along a nonlinear link. By functional transformation; an input pattern (vector) is enhanced in its representation. In the Functional-Link Network, 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. The first method is called the functional-expansion model and the second is called the tensor model, or outer product model.

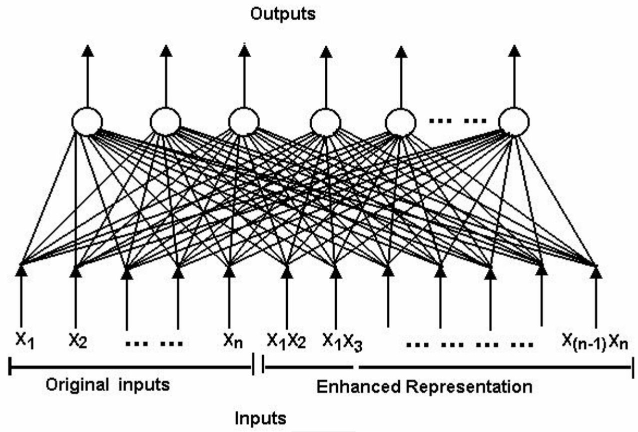

Fig.2. Tensor model of functional link network

In the present work, supervised tensor model of Functional-Link Network has been used. Figure 2, illustrates the tensor model of Functional-Link Network schematically. In the tensor model, each component of input patterns multiplies the entire input pattern vector. The functional link in this case generates an entire vector from each of the individual components. In this model the pattern might undergo a sequence of transformations such as

{ xi } ⇒{xi , xixj } j≥i ⇒{ xi , xixj , xixjxk} k≥j≥i ⇒ . . .

Assume that J-tuple vectors represent the original data. In the so-called tensor model, suitable for handling input patterns in the form of vectors, the additional input terms are obtained for each Jdimensional input pattern as the products xixj for all 1 ≤ i and j ≤ J such that I < j ≤ J (case A). A number of product terms generated are shown in table1 below. Alternatively the product can be computed as in case A and augmented with xixjxk terms for all 1≤ i, j, k ≤ J such that i< j< k ≤ J (case B). This discussion shows that the number of additional inputs required for functional link method grows very quickly. In the present work tensor (outer product) mode only up to the second order product of the inputs, has been used which was found to provide desire accuracy for load prediction problem. Thus, if xj,….xn are the original inputs, the enhanced inputs contain (x1x2, ……,x(n-1) xn) terms, which have been used as additional input vector to Functional- Link Network.

II b) TRAINING OF FUNCTIONAL LINK NETWORK

The Functional link network consists of only two layers, the input layer and output layer. It does not have any hidden layer. Hence, simple Delta rule can be used for training of the functional link network. The training algorithm is described below: (i) Input pattern is enhanced by multiplying each of its components by the entire input pattern vector. (ii) Output of node j, Oj is function of (netj) i.e., Oj = f(netj) (1)

Where,

netj =Σ=

N

i

i ij x w

1
j = 1;……….,m
xi = inputs including enhanced terms
wij = weight between neuron i and neuron j
m = number of output nodes
N = number of enhanced inputs

(iii) Compare the actual output with the desired output and determine the measure of error δj at each output node. Where, δj = {(desired output - actual output) at node j

(iv) Change in weight is determined by

dwij(t) = ηδjf(netj) + 1δwij(t-1) (2)

Where,

η is the learning rate and 1 is the momentum

(v) Weights are adjusted by wijnew = wijold + dwij (3)
(vi) Steps (ii) to (v) are repeated till the error reduces to a prespecified tolerance.

III NETWORK TRAINING

In the present work, one-output FLN is used to produce one-step ahead forecasts: forecasts for next day's peak load or total load, or forecasts for hourly loads (i.e. given the load series up to hour h, forecasts for the load at hour h +1). The forecasting profiles used is iterative forecasting; Iterative Forecasting is done by forecasting one hourly load at a time and then aggregating this load to the series, so that the forecasts for the later hours will be based on the forecasts for the earlier ones. Common hours of industrial sector as well as agricultural sector some strong statistical pattern of load has been found. Of course some gradual change will be there due to weather variation and some other reasons. During the supervised training, the pair of training vector is composed of 24 hour past load at hour (t) as input vector and one-hour load at hour (t+1) as output vector. The inputs to the functionallink network are normalized by using their maximum and minimum values. To illustrate the learning procedure of one-hour ahead forecasting, the following procedure is repeated until a prespecified tolerance is achieved. To predict the load on required day at hour‘t’, the previous 24- hour data is used for training and producing load forecast of ‘t’ hour at required day.

IV RESULTS AND DISCUSSION

After the functional-link network is trained on the pattern association of input and output data, it generates output patterns. In this way, the trained functional –link network predicts future hourly load based on new sets of input vector. The results of simulation of functional link network (with learning rate = 0.6 and momentum = 0.3) of a period of one day are given in the Table I. The actual peak loads are compared with the load forecast by functional link network. The percent error illustrates the forecast accuracy of the functional-link network. The percent errors vary between -1.1630 to 1.2766. Figure 3, shows the plot of peak loads v/s hours of the day, where the actual peak loads are plotted along with load predicted by functional link network, one hour ahead.

V CONCLUSION

It is shown that the approach proposed in this work, based on the Functional Link Networks, enables the development of hybrid neural models with significant advantage when compared to conventional artificial neural networks. The hybrid model using the Functional Link Networks presents a good performance and is much simpler than the one using the ANNs. As the estimation of the network weights in the Functional Link Networks is linear, their use in the hybrid model enables a simple implementation of an adaptive scheme in which weights are re-estimated. The present work has not kept any threshold or ramping function that helps in mirroring the input within a given range and therefore can act as a hard limiter outside the range. However by incorporating a suitable threshold value, we can increase the potential of obtaining the better results. Moreover, in this work, learning rate is kept as a constant but if the learning rate changes in smaller steps, it may lead to better results with increased iterations.

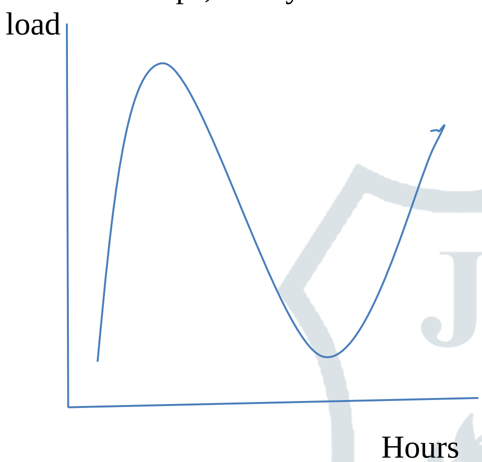

Fig.3. Comparison of actual load and predicted by Functional-link Network

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