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Neural-Wavelet Based Hybrid Model for Short-Term Load Forecasting

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Abstract
Exactly power load forecasting especially the short term load forecasting is of important significance in the case of energy shortage today. Conventional ANN-based load forecasting methods deal with 24-hour-ahead load forecasting. In this research, the application of neural networks to study the design of Short Term load Forecasting (STLF) Systems for 33 kv Substation of Dayalbagh Educational Institute, Agra was explored. The paper has introduced the neural networks and how we can use it to forecast electric power load. This paper proposes a model developed through neural-Wavelet for prediction of short-term load forecasting.
Keywords: Wavelet transforms, ANN, Load forecast, Short-term load forecast

1. INTRODUCTION

Currently, power utilities are using various load forecasting techniques worldwide. Most of the developed methods can be broadly categorized into three groups, namely parametric, nonparametric, and artificial intelligence based methods. In the parametric methods, a mathematical or statistical relationship is developed between the load and the factors affecting it. Some examples of these models are time functions, polynomial functions, linear regressions, Fourier series and Auto Regressive Moving Average (ARMA) models. In time-series methods, the load is treated as a time series signal with known periodicity such as seasonal, weekly, or daily. Such repetitive cycle gives a rough prediction of the load at the given season, day of the week, and time of the day. The difference between the estimated and actual load can be considered as a stochastic process, which can be then analyzed using Kalman filter methods. Nonparametric methods forecast the load directly from historical data. For example, using nonparametric regression, the load can be forecasted by calculating an average of historical loads and then assign weights to different loads using a multivariate product kernel.

Recently, significant interests and efforts have been directed towards the application of artificial intelligence techniques to load forecasting. This includes the application of expert systems to load forecasting, and comparing its performance to traditional methods. It also includes the use of fuzzy inference and fuzzy-neural models.

However, the models that have received a high share of efforts and focus are the artificial neural networks (ANNs). The main advantage of ANNs is their outstanding performance in data classifications and function approximation. ANN is also capable of detecting dependencies from historical data without the need to develop a specific regression model. First publications on ANN application to the load forecasting problem were made in late 1980's and early 1990's . Since then ANN have been well accepted in practice, and are used by many utilities[11].

Several researchers preferred differential applications. The paper ref. [1] shows the hybrid model based on wavelet support vector machine and modified genetic algorithm penalizing Gaussian noises for power load forecasts, furthermore a short-term load forecasting by using similar day-based wavelet neural network [2]. In ref. [3], the intelligent hybrid wavelet models for prediction. In 2009, the combination of wavelet transform and neuro-evolutionary algorithm approach to demand forecasting [4]. In 2008, the research shows an adaptive wavelet neural network-based energy price forecasting in electricity markets [5] and in the year 2006 the wavelet based nonlinear multi-scale decomposition model [6]. In ref. [7], in the same year, the researcher proposes techniques of applying wavelet transform into combined model for demand forecasting in electricity. In research ref. [8], presents an adaptive neural wavelet model and in ref. [9] proposes a hybrid wavelet-Kalman filter method for load forecasting. Lastly, the wavelets transform and neural networks for short-term electric load forecasting are proposed [10]. All of the researches above were proposed load and price forecasting by using wavelet transform and neural network algorithm but did not present in sub-control center area forecasting.

In this research, proposes the Neural Network-Wavelet (NNW) Short term Load forecasting, implemented by using wavelet transform in preprocessing stage of all areas and neural network for forecasting in the last process. In preprocessing stage, wavelet transform is used to decompose the original signal of demand into one to four levels and after that will take it to find the relationship between factors and demand before choosing the suitable factors for feature input for neural to prediction. Finally, this paper presents the comparison between the different soft computing techniques for STLF based on root mean square error (RMSE).

This article proposes the four major sections. The second section offers an implementation of the research stages.

The third section shows the results and comparison of the research. Finally, conclusion is drawn in the fourth section.

2. Basic theory

2.1 Wavelet decomposition and reconstruction

Electricity load demand is generally complex and consists of multiple frequencies. Furthermore, features of the demand cannot be fully captured by a single neural network. Consequently, wavelet decomposition method in this research is developed and combined with the neural network for increasing the reliable forecast. The research is done by decomposing an original demand into one level, two levels, three levels, and four levels of wavelet. The feature of neural network is selected based on the correlation between affecting factors and demand.

Wavelet theory is an applicable to several subjects. It is a powerful implement which can be used for a wide range of applications, specifically; signal processing, data compression, image de-noising, speech recognition, computer graphics, and many areas of physics and engineering. All of the wavelet transform may be considered forms of time-frequency representation for continuous time (analog) signals and so are related to harmonic investigation. Almost all practically useful discrete wavelet transforms use discrete-time filter banks. These filter banks are called the wavelet and scaling coefficients in wavelet nomenclature.

This section provides a brief summary of wavelet transform method which can be divided into two categories: continuous wavelets transform (CWT) and discrete wavelet transforms (DWT). In this research, discrete wavelet transform is used. The DWT algorithm is capable of producing coefficients of fine scales for capturing high frequency information, and coefficients of coarse scales for capturing low frequency information. For a mother wavelet function ψ and for a given signal f (t) , a DWT can be expressed as follows [12]:

$$f(t) = \sum c_{j0,k}\phi_{j0,k}(t) + \sum_{j>j0}\sum_{k}\omega_{j,k}2^{\frac{j}{2}}\varphi(2^{j}t-k)$$

where j is the dilation or level index, k is a translation or scaling index, Φj 0,k is a scaling function of coarse scale coefficients, c j 0,k ,ωj ,k are the scaling function of detail coefficients, and all function of ψ (2 j t - k) are orthonormal.

Wavelet processing has two stages: decomposition and reconstruction. The decomposition computes the convolution between the load demand and high pass/ low pass filter, while the reconstruction calculates the convolution between the load and inverse filter. A mother wavelet based on

Daubechie8 (Db8) is used for the filter's coefficients. It used to decompose an input load demand into low frequency and high frequency components. The decomposition is implemented by using multichannel filter bank: one, two, three, and four channels. The reconstructed details and approximations are true parameters of the original signal as follow [12]:

S = A1 + D1 (Level1)
= A2 + D2 + D1 (Level2)
= A3 + D3 + D2 + D1 (Level3)
= A4 + D4 + D3 + D2 + D1 (Level4)

For example, in Level 1, the coefficient vectors A1 and D1 are produced by down sampling and only half a length of the original signal. Thus, they cannot directly combine to reproduce the signal. It is necessary to reconstruct the approximations and details before combining with each other. Wavelet reconstruction provides the components to assemble back into the original signal without loss of information. This process is called reconstruction.

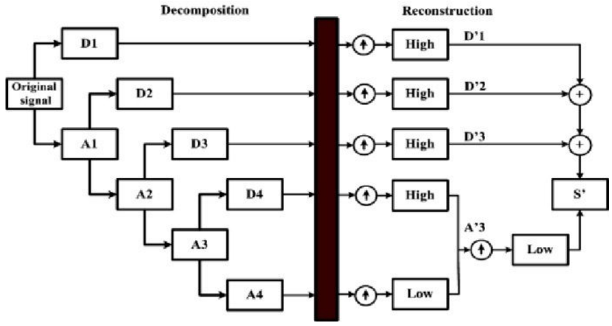

Fig.1 Wavelet decomposition and reconstruction.

2.2 Neural Network Model for Load Forecasting.

Most input signals are time series in their raw format. Most signals are measured as functions of time. The forecast model for electricity load is shown in figure. In this figure the raw data input is a time series pattern, which can affect the accuracy of the forecast model's prediction. To produce the best quality of the raw input signal for time series forecast, the neural network model is used.

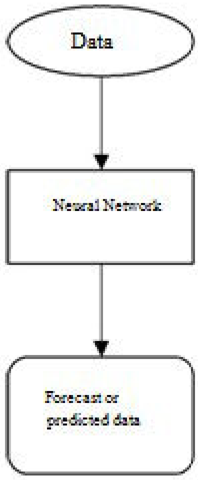

Fig. 2 Neural model for forecasting

This multiple resolution is based on wavelet transform. The wavelet transform can be divided into three steps. In the first step, the input time series raw data is pre-processed using wavelet decomposition. Then each decomposed scale put into one neural network as its input and the respective neural network take in their allocated scale for training or for prediction in the second step. In the third step the decomposed scales at the output of the neural network are recombined to obtain the required prediction [13].

3. SIMULATION and RESULTS

The results are as shown in Fig. 3,4. In Fig. 3,4, we can observe that the neural wavelet is better then the artificial neural network[14-16].

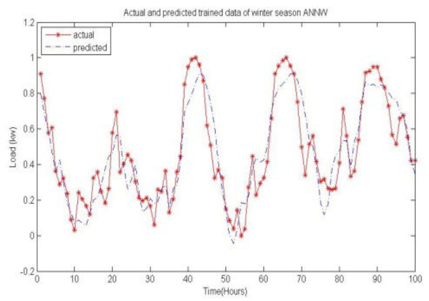

Figure 3. Actual and predicted training output using artificial neuron wavelet model (ANNW).

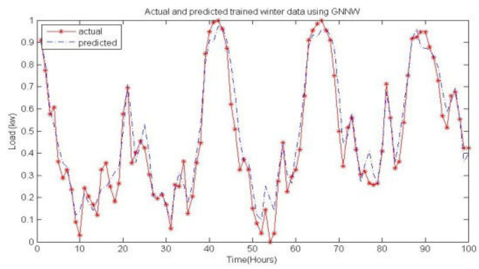

Figure 4. Actual and predicted training output using neuron wavelet model (NNW).

5. CONCLUSION

This paper proposed a STLF model with a high forecasting accuracy. The NN-WT has been successfully implemented in the model. The implementation of N-WT has reasonably enhanced the learning capability of the NN in the model, thus minimizing their training frequencies as shown in the simulations. In summary, the inclusion of load data (as input variable) and the use of NN-WT (as the data processing tool) for the proposed STLF model have been a success.

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