USING WAVELET TRANSFORM AND NEURAL NETWORK ALGORITHM FOR POWER DEMAND PREDICTION

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ABSTRACT
This paper presents a method for prediction short-term power demand of a vehicular power system. The forecasting of power demand is presented using wavelet decomposition and artificial neural network, a hybrid model which absorbs some merits of wavelet transform and neural network. The power demand time series is first decomposed into a certain number of levels with discrete wavelet transform and for each individual wavelet sub-series are created neural networks to predict future values. To form the aggregate prediction the individual wavelet sub-series forecasts are recombined utilizing the reconstruction property of wavelet transform. The results are conducted in Matlab software and the performance of this procedure is investigated.

INTRODUCTION
The aim of this work is to realize a short-term prediction model for the power demand of a vehicular system using wavelet analysis and neural-networks. Wavelet analysis has become a research hot point; it has good time and frequency multi-resolution and can effectively diagnose signal’s main frequency component and abstract local information of the time series. It has huge advances in signal processing, image compress, mode identification and nonlinear science fields (Wang et al. 2003).

Wavelet technology has been successfully employed in electrical power systems for transient process analysis. Wavelets were first applied precisely to analyze transients under the assumption that they could help detect the transient wave structure. By using discrete wavelet transform, Robertson studied the propagation of transients through switch capacitors (Zhang et al. 2011).

As it concern time series prediction, it means to predict value \( y(t+k) \) of future time \( t+k \) \((t>0)\) on the basis of real history data of time series \( \{y(t), y(t-1), \ldots, y(t-m+1)\} \) and corresponding variance which influence the time series, that is to find, the relationship between future value \( y(t+k) \) and history data \( \{y(t), y(t-1), \ldots, y(t-m+1)\} \).

As we told at the beginning we propose here the forecasting model based on neural networks and the wavelet decomposition of the power demand of a vehicular system. The measured signal is decomposed into wavelets and the prediction is performed for the wavelet coefficients (the detailed coefficients up to some level and the approximated coarse signal corresponding to the last level) in the original resolution. On the basis of these predicted values the reconstruction of the real value of the forecasted power demand is performed by simply summing up the predicted decomposition signals.

WAVELET ANALYSIS

The wavelet transform has been used for time series analysis in many papers in recent years. Much of this work has focused on periodogram or scalogram analysis of periodicities and cycles. Wavelet would appear to be very appropriate for analyzing non-stationary signals. In this paper we used the undecimated Haar transform and the choice of it can be motivated by the fact that the wavelet coefficients are calculated only from data obtained previously in time and the aliasing problems are avoided (Renaud et al. 2003).

Wavelet Transform

Wavelet analysis is a multi-resolution analysis in time and frequency domain which projects a time series onto a collection of wavelets to produce a set of wavelet coefficients. Wavelet faction \( \psi(t) \) is called mother wavelet and it can be defined as:

\[
\int_{-\infty}^{\infty} \psi(t) \, dt = 0 \tag{1}
\]

The discreet wavelet transform (DWT) involves choosing scales and positions based on powers of two—so called dyadic scales and translation. 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 (Hwa Loh R. 2003). The DWT with respect to a mother wavelet, \( \Psi(t) \), is defined as:

\[
F(\tau) = \sum_{k} c_{j0,k} \Phi_{j0,k}(\tau) + \sum_{j \geq 0} \sum_{k} w_{j,k} 2^{j/2} \Psi(2^{j} \tau - k) \tag{2}
\]

where \( j \) is the dilatation or level index, \( k \) is the translation or scaling index, \( \Phi_{j0,k} \) is a scaling function or coarse scale coefficients and the functions \( \Psi(2^{j} t - k) \) are all orthogonal to one another. \( c_{j0,k} \) and \( w_{j,k} \) are the scaling function of detail coefficients. The coefficients \( w_{j,k} \) conveys information about the behavior of the function \( F \) concentrating on effects of scale around \( 2^{-j} \) near time \( kx2^{-j} \).

The output of a discreet wavelet transform can take various forms. Usually, a triangle is used to represent all that we have to consider in the sequence of resolution scales. Such a triangle comes about as a result of “decimation” or the retaining of one sample out of every two. Although it has a major advantage of keeping enough information which allow exact reconstruction of the input data, the decimated form of output not allow having shift invariance. This means that if we had deleted the first few values of our input time series then the output wavelet transformed, and decimated, data would not be the same as all these. This problem can be solved by using a redundant or non-decimated wavelet transform.

**The Algorithm of Wavelet Transform**

A redundant transform based on an N-length input time series has an N length resolution scale for each of the resolution levels that we consider. In these conditions it is easy to relate information at each resolution scale for the same time point and we do have shift invariance. The à trous wavelet transform decomposes a signal \( F=(F_1, F_2, \ldots, F_N) \) as a superposition of the form:

\[
F_{\tau} = c_{j0,\tau} + \sum_{j=1}^{J} w_{j,\tau} \tag{3}
\]

where, \( c_{j0} \) is the smooth version of the original signal \( F \) and \( w_{j} \) represents the details of \( F \) at scale \( 2^{j} \).

In this paper we used for the decomposition the non-decimated Haar algorithm which is the same with à trous wavelet transform with the difference that Haar algorithm uses a simple filter \( h=(1/2, 1/2) \).

Considering the first wavelet resolution level, we derive it from the input data by convolving the latter with \( h \). Then:

\[
c_{j+1,t} = \frac{1}{2} (c_{j,t-2} + c_{j,t}) \tag{4}
\]

and

\[
w_{j+1,t} = c_{j,t} - c_{j-1,t} \tag{5}
\]

This algorithm has the following advantages:

- It is easy to implement;
- The wavelet coefficients at any scale \( j \) of the signal \( (F_1, \ldots, F_N) \) are strictly equal to the first \( t \) wavelet coefficients at scale \( j \) of the signal \( (F_1, \ldots, F_N) \), \( N>t \).

In figure 1 is shown the level-2 decomposition using this algorithm:

\[
\begin{array}{c}
\text{à trous filtering} \\
\text{data segments} \\
\hline
1 & 2 & \ldots & k \\
\hline
1 & 2 & \ldots & k-1 \\
1 & 2 & \ldots & k-2 \\
1 & 2 & \ldots & k-3 \\
\end{array}
\]

Figure 1: Procedure for Preparing Data for Prediction Using a Hybrid Method with Wavelet Transform and Neural Network (Ahmad et al. 2005)

The wavelet coefficients and scale coefficients of the power demand time series derived from wavelet decomposition algorithm are shown in figure 2. In this figure \( w1(t) \) and \( w2(t) \) denote wavelet coefficients at the resolution level 1 and 2 respectively and \( c2(t) \) denotes scale coefficients at resolution level 2.

![Wavelet Decomposition for Power Demand Time Series](image-url)
ARTIFICIAL NEURAL NETWORK

Artificial neural networks have a large numbers of computational units neurons algorithms are based and do not require an explicit formulation of the mathematical or physical relationships of the handled problem (Ting et al. 2009). Figure 3 is a typical neural network.

Feedforward neural networks are composed of layers of neurons in which the input layer of neurons is connected to the output layer of neurons through one or more layers of intermediate neurons. The training process of the neural network involves adjusting the weights till a desired input/output relationship is obtained. The majority of adaptation learning algorithms are based on the back-propagation algorithm.

Suppose we have the signal \( F = (F_1, F_2, ..., F_N) \) and assume that \( F_{N+1} \) will be predicted. The main idea of neural network model is that, using coefficients that are found by the decomposition will predict \( F_{N+1} \) value with certain neural network architecture.

Feed Forward Neural Network architecture used to process the wavelet coefficients consists of one hidden layer with \( P \) neurons, which is mathematically written as (Hwa Loh R. 2003):

\[
\hat{F}_{N+1} = \sum_{p=1}^{2} \sum_{k=1}^{A_j} \sum_{j=1}^{d_j} \sum_{k_p}^{G} w_{j,N-2(j-1)} + w_{j,N-2(j-1)} + \sum_{k=1}^{A_j} \sum_{j=1}^{d_j} \sum_{k_p}^{G} w_{j,N-2(j-1)} \]

(6)

where, \( j \) is the number of levels \( j=1,2,3, ..., d_j \), \( A_j \) orders of model \( k=1,2,3, ..., A_j \), \( w_{j,N-2(j-1)} \) is the wavelet coefficient value, \( v_{j,N-2(j-1)} \) is the scale coefficient value.

\( G \) is an activation function in hidden layer, which is usually sigmoid logistic, but in this architecture of neural network the activation function in output layer is linear.

RESULTS

Figure 4 illustrates the hybrid neuro-wavelet scheme for power demand prediction.

The method basically involves three stages described as follows:

Stage 1: Data Pre-processing
Stage 2: Data Prediction
Stage 3: Data Post-processing

Stage 1: Data Pre-processing. The data used in this article is the power demand time-series for a vehicular system. Non-decimated Wavelet Transform is used as the data pre processor. The resolution level is defined as 2 and after decomposing the wavelet coefficients signals at the output of the pre-processor. In this case we have 3 neural networks because for each wavelet coefficient signal one neural network is required to perform the corresponding prediction.

Stage 2: Data prediction. Neural networks are used for data prediction in the forecasted model. The number of neural networks needed for the model is determined by the number of wavelet coefficients signals at the output of the pre-processor. In this case we have 3 neural networks.

Stage 3: Data Post-processing. In this stage we used the same wavelet technique and resolution level as data pre-processing. The output from the neural networks is recombined to form the final predicted output.

We considered the power demand time series with 11962 data samples, on which we wish to carry out level 2 based a trous transform. We can do this by implementing the scheme described in Fig. 1 by starting off with 11953 samples (\( k=11953 \)). That is we simply carry out a level 2 wavelet transform on values \( F(1) \) to \( F(11954) \). The last values of the wavelet coefficients at time-point \( t=11953 \) are kept because they are the most useful ones for prediction. Then we repeated the same procedure at time point \( t=11954 \) (carry out level 2 wavelet transform on values \( F(1) \) to \( F(11954) \) and keep coefficients at \( t=11954 \)) and so on until we reached 11962, the total number of samples in the original data. In this way, we had wavelet decompositions for the time-series from \( t=11953 \) to \( t=11962 \).

In figure 5 is illustrated the power demand from \( t=11953 \) to \( t=11962 \), a total of 10 samples and the corresponding wavelet transform computed by the above method. From top to bottom the power demand, the wavelet “smooth”, \( w_1(D_1) \) and \( w_2(D_2) \).
In the second stage, separate neural networks models are created for each of the wavelet coefficients, approximation and details at level 1 and 2. For the approximation time series we created a Feed forward neural network with three layers: input layer, hidden layer and output layer. The number of nodes in hidden layer is equal to 3 and the number of training is 1000. The results are shown in the figure 6.

For the detail at level 1 we used also a Feed forward neural network with three layers and the number of nodes in hidden layer was 5. The results are shown in figure 7.

In figure 8 are shown the results for the detail coefficients at level 2. The red color is for the actual detail signal at level 2 and the blue color is for the predicted one.

Figure 9 illustrates the aggregate prediction (sum of the individual wavelet predictions) for the power demand series over a test set of 10 samples.
CONCLUSION
This paper presented a method that combines a trous wavelet transform pre-processing with neural networks for short-term power demand prediction. The results show advantages of wavelet pre-processing for time series analysis and prediction. Also from results we can see that the model was capable of producing a reasonable accuracy in short-term prediction.

REFERENCES

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