Electrical Power and Energy Systems 64 (2015) 340–346

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Short term load forecasting using wavelet transform combined with Holt–Winters and weighted nearest neighbor models

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ARTICLE INFO

Article history:
Received 5 August 2013
Received in revised form 26 June 2014
Accepted 7 July 2014

Keywords:
Holt-Winters
Weighted nearest neighbor
Haar wavelet
Load forecasting
Hybrid model

ABSTRACT

Short term load forecasting (STLF) is an integral part of power system operations as it is essential for ensuring supply of electrical energy with minimum expenses. This paper proposes a hybrid method based on wavelet transform, Triple Exponential Smoothing (TES) model and weighted nearest neighbor (WNN) model for STLF. The original demand series is decomposed, thresholded and reconstructed into deterministic and fluctuation series using Haar wavelet filters. The deterministic series that reflects the slow dynamics of load data is modeled using TES model while the fluctuation series that reflects the faster dynamics is fitted by WNN model. The forecasts of two subseries are composed to obtain the 24 h ahead load forecast. The performance of the proposed model is evaluated by applying it to forecast the day ahead load in the electricity markets of California and Spain. The results obtained demonstrate the forecast accuracy of the proposed technique.

Introduction

The accurate forecast of electricity demand (load) for a range of lead times is important for the effective management of power systems [1]. Short term load forecast (STLF) of power system loads with lead times ranging from an hour to several days ahead has a significant impact on the operational efficiency of electrical utilities [2]. The forecasts are needed for a variety of utility attributes such as generation scheduling, the scheduling of fuel purchase, maintenance scheduling, security analysis and energy transactions [3]. This importance of load forecasts on decision making in energy sector, calls for the development of accurate, fast and simple prediction algorithms. Unfortunately, the load demand is a non-stationary process influenced by a multitude of factors ranging from weather conditions over seasonal effects to socio-economic factors and random effects, which makes load forecasts difficult [4,5].

The existing models for load forecasting can be broadly classified into conventional (statistical) approaches, artificial intelligence based models and hybrid/combination models. The survey papers [4,6–9] give an account of different techniques devoted to electrical load analysis and forecasting. The conventional models are linear and make certain assumptions regarding the characteristics of the load series. Among these models, the autoregressive integrated moving average (ARIMA) model has excellent natural statistical characteristics and is the most popular [10]. However, these models are known to show some weakness in the presence of special events and nonlinearities [11,12]. The low adaptability of the statistical techniques to deal with nonlinear series has generated an increasing interest in using Artificial intelligence based techniques [13,14]. Among the AI based techniques, artificial neural networks (ANN) have been successful applied to STLF [8]. However, a certain regularity of the data is an important precondition for the successful application of Neural Networks (NN) [15] and in addition they suffer from a number of weaknesses such as network construction problem, over fitting issue, connection weight estimation and the need for a large number of data for training [16]. Moreover, these methods cannot capture well the rapid changes in load [17]. Currently the emphasis is on hybrid models that blend different technique to enhance the performance and eliminate the limitations of existing individual models [18,19]. Both theoretical and empirical findings in the literature show that combining different methods can be an effective and efficient way to capture the different patterns in the data and improve the forecasting performance [3,20].

Recently, hybrid models that integrate wavelet transforms with other techniques [2,15,16,21–25] have been extensively used for short term load forecasting. In these studies, wavelet transforms have been effectively employed to extract/analyze the characteristic

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http://dx.doi.org/10.1016/j.ijepes.2014.07.043
0142-0615/

features embedded in the load time series at different frequencies. In [15], two strategies for embedding the DWT into NN based STLF model is proposed. The first strategy consists of creating a model using information from the original series and the wavelet domain subseries. The second strategy involves predicting the load's future behavior by independently forecasting each subseries in the wavelet domain. In [22], a hybrid forecasting method composed of wavelet transform, a two step correlation analysis, NN, evolutionary algorithm and cross validation is proposed for hourly load forecasting. In [2], the hourly load was predicted via an adaptive NN structure with the NN weights adjusted by the particle swarm optimization algorithm. The wavelet processed data was fed as input for the adaptive NN structure. Some intelligent hybrid models utilizing only low frequency components of load data is proposed in [23]. The proposed models include wavelet decomposition based radial basis function model, wavelet decomposition based time series model and wavelet decomposition based fuzzy inference NN model. These studies bring out the importance of wavelet transform as a multiscale decomposition tool that can be used to capture/differentiate the different characteristics of load data for easy integration with other forecasting techniques.

A novel technique proposed recently [16] utilizes the wavelet transform, ANN and ARIMA model to propose a hybrid method for STLF. The technique is based on the idea that a time series can be considered to be made up of two parts: a linear component and a nonlinear component. The linear component is modeled using the ARIMA model and the residuals of ARIMA model consisting of nonlinear components is decomposed via the wavelet transform into their details and approximation parts so that each of them could be modeled by the approximate ANN. The forecast values of the linear and nonlinear components were composed to obtain the forecast value of the load. A slightly similar approach is presented in [3] where in the seasonal ARIMA (SARIMA) is used to address the linear relationship while the back propagation neural network (BPNN) model is used to handle the nonlinear patterns in the wavelet denoised load series. A variance–covariance approach is then used in the model to combine the predicted values of SARIMA and BPNN.

In this work, a hybrid method is proposed for STLF by integrating Haar wavelet transform with Triple Exponential Smoothing (TES) and weighted nearest neighbor (WNN) techniques. The basic idea of the proposed hybrid method consists in assuming that the load series can be considered to be made up of two parts: a deterministic component and a stochastic component. The deterministic component that represents the general pattern of the load signal is modeled using TES model while the WNN technique is used to find and weight similar data in the stochastic/fluctuation component. The TES model accounts for the trend and the seasonality of the data and is optimal for a seasonal ARIMA model. The WNN model is capable of accounting for both the nonlinearity and nonstationarity in the given data [26]. The Haar wavelet transform is used to separate the faster dynamics (fluctuation component) of load data from the slowly varying characteristics (deterministic components) of data using suitable wavelet coefficient thresholds. During thresholding, the wavelet transform will separate the faster changing data in the wavelet domain and inverse wavelet transform will then retrieve the slowly varying characteristics of data with little loss of detail. The maximum time scale level and threshold is obtained by testing on the load series data. The feasibility of the proposed hybrid method is evaluated using historical load data from the California and Spain energy markets. The results evaluate day ahead prediction.

The paper is organized as follows: section 'Theory' deals with some basic theoretical aspects of the wavelet transform, triple exponential smoothing method and weighted nearest neighbor approach. In section 'Proposed methodology', the proposed forecasting model is described. Numerical results concerning the application of the proposed approach to the two electricity markets are shown in section 'Results and discussion'. Finally, section 'conclusion' presents the main conclusions of this work.

Theory

Discrete wavelet transform

The Discrete Wavelet Transform (DWT) whose main idea is the process of multi-resolution analysis is one of the most appropriate techniques to make a joint time–frequency analysis of discrete signals. The DWT [27] utilizes two set of functions $\phi(t)$ and $\psi(t)$, each associated with the low pass and high pass filters respectively to decompose the signal in terms of approximations and details. The scaling function $\phi(t)$ is associated with the low pass filters with filter coefficients $\{h(n), n \in Z\}$ and the wavelet function $\psi(t)$ is associated with the high-pass filters with filter coefficients $\{g(n), n \in Z\}$. The DWT is usually computed using the pyramid algorithm [28] and is realized by means of the filters $h[k]$, $g[k]$ that are related to each other through

$$g[k] = (-1)^{k+1}\ h[N-k-1] \quad \text{for } k = 0, 1, \ldots, N-1 \tag{1}$$

where N is the length of the filter. These filters are constructed from the wavelet kernel $\psi(t)$ and the companion scaling function $\phi(t)$ through the relations

$$\phi(t) = \sqrt{2}\sum_k h[k]\phi(2t-k) \tag{2}$$

$$\psi(t) = \sqrt{2}\sum_k g[k]\phi(2t-k) \tag{3}$$

Using the wavelet filters, the data can be decomposed into a set of low and high frequency components named approximations $a_j[k]$ and details $d_j[k]$ respectively. They are given by

$$d_{j+1}(k) = \sum_n a_j[n]g(2k-n) \tag{4}$$

$$a_{j+1}(k) = \sum_n a_j[n]h(2k-n) \tag{5}$$

If $x_k = a_{0,k}(k = 1, 2, \ldots, l)$ is the original series and if $a_{j,k}, d_{j,k}; j = 1, 2, \ldots, J, k = 1, 2, \ldots, l$ are respectively the approximations and detail series obtained after J levels of decomposition

$$\text{then } x_k = a_{J,k} + \sum_{j=1}^{J} d_{j,k}(k = 1, 2, \ldots, l) \tag{6}$$

Here $a_{J,k}(k = 1, 2, \ldots, l)$ presents the tendency of the series and is characterized by slow dynamics, while the details $d_{j,k}$ presents the local details of time series and has fast dynamics [29,30]. The Haar wavelet filter, which is a filter of length $N = 2$, $g_0 = g_1 = \frac{1}{\sqrt{2}}$ is used in the present work to decompose the load signal into its deterministic and fluctuation components. The Haar wavelet coefficients within each time scale are statistically independent and they can be directly understood and described in simple terms of up and down variations from one region to the next [31]. Moreover, Haar wavelet is the only symmetric compactly supported orthonormal wavelet [32].

Triple exponential smoothing

There are many forms of exponential smoothing methods of which the Holt–Winters family of exponential smoothing methods is the one most commonly used [33]. Exponential smoothing is a pragmatic approach to forecasting whereby the prediction is