Energy xxx (2015) 1–10

Contents lists available at ScienceDirect

Energy

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

A hybrid short-term load forecasting with a new input selection framework

M. Ghofrani [a,*], M. Ghayekhloo [b], A. Arabali [c], A. Ghayekhloo [d]

[a] School of Science, Technology, Engineering and Mathematics (STEM), University of Washington, Bothell, USA
[b] Department of Electrical and Computer Engineering, Science and Research Branch, Islamic Azad University, Qazvin, Iran
[c] Department of Electrical and Biomedical Engineering, University of Nevada, Reno, USA
[d] Department of Electrical and Computer Engineering, Science and Research Branch, Islamic Azad University, Sari, Iran

ARTICLE INFO

Article history:
Received 29 September 2014
Received in revised form
26 November 2014
Accepted 9 January 2015
Available online xxx

Keywords:
Bayesian neural network
Correlation analysis
Input selection
Short-term load forecasting
Wavelet decomposition

ABSTRACT

This paper proposes a hybrid STLF (short-term load forecasting) framework with a new input selection method. BNN (Bayesian neural network) is used to forecast the load. A combination of the correlation analysis and ℓ^2-norm selects the appropriate inputs to the individual BNNs. The correlation analysis calculates the correlation coefficients between the training inputs and output. The Euclidean distance with respect to a desired correlation coefficient is then calculated using the ℓ^2-norm. The input sub-series with the minimum Euclidean norm is selected as the most correlated input and decomposed by a wavelet transform to provide the detailed load characteristics for BNN training. The sub-series whose Euclidean norms are closest to the minimum norm are further selected as the inputs for the individual BNNs. A weighted sum of the BNN outputs is used to forecast the load for a particular day. New England load data are used to evaluate the performance of the proposed input selection method. A comparison of the proposed STLF with the existing state-of-the-art forecasting techniques shows a significant improvement in the forecast accuracy.

1. Introduction

STLF (short-term load forecasting) provides a prediction of the electric load on an hourly or sub-hourly basis for a lead time ranging from one hour to several days ahead. Hybrid WT-NN (Wavelet Transform-Neural Network) methods have been widely used for the load forecasting. This is mainly because of their capability to better characterize the non-linearity and complex features of the load time series [1]. In spite of the recent advances in the hybrid forecasting methods, selecting appropriate input variables is still an open research area as it can significantly enhance the forecast accuracy. The input variable selection for the hybrid methods has been investigated in several studies [1–13]. An intelligent two-stage feature selection was used in Ref. [1] to first select the most relevant input candidates and then remove the redundant candidates. Reference [2] proposed a new method for the input variable selection which is based on the phase-space embedding of the load time-series. Reference [3] classified the days into several different types and used separate neural networks to forecast the load for each day type. Test results demonstrated the efficiency of the proposed classification to improve the forecast accuracy for special days [3]. The partial and standard autocorrelation functions were employed in Ref. [4] to select the basic set of input variables. Different feature-extraction techniques including regression analysis, AIC (Akaike's information criterion) and correlation analysis were examined in Ref. [5] among which the correlation analysis demonstrated the best forecast accuracies. Lagged values of the load subseries for the past 500 h were considered for the proposed feature selection. This limits the correlation analysis to the short-run trends, daily and weekly periodicities and neglects the seasonality of the load patterns as well as their monthly and annual periodicities. Reference [6] selected the similar day's load as the input rather than the yesterday's load used in most NN methods. The selection is based on the similarity of the weather for the historical day and the weather forecast for the day whose load is predicted. However, the load forecast is mainly influenced by the historical load and not the weather. Therefore, the proposed similar-day based input selection is not appropriate for the load forecasting. A wavelet neural network with data pre-filtering was

* Corresponding author. UWBB Room 227, 18807 Beardslee Blvd, Bothell, WA 98011, USA. Tel.: +1 425 352 3224; fax: +1 425 352 3775.
E-mail address: mghofrani@uwb.edu (M. Ghofrani).

http://dx.doi.org/10.1016/j.energy.2015.01.028
0360-5442/

presented in Ref. [7] that effectively detects and filters out the load spikes. The filtered load data was then decomposed into multiple-frequency components using a wavelet transform. The individual components were used as the inputs to separate neural networks and the outputs were combined to provide the forecast. A multi-wavelet transform was used in Ref. [8] to extract the training data from the historical load. Different learning methods were adopted to train a three-layer feed-forward neural network and predict the load. References [9] and [10] used wavelet transforms to decompose the load into the high- and low-frequency components. The high-frequency components were then filtered to reduce the time required for the network training. Although the methods proposed by these references demonstrate comparative results with respect to those of other models, removing the detailed features of the load from the inputs is not appropriate and might significantly reduce the forecast accuracy. Evolutionary algorithms have been used in combination with the hybrid methods to enhance the forecast accuracy [5], [11,12]. Ref. [11] proposed a hybrid wavelet-GA-ANN model that uses genetic algorithm to optimize the RBFNN (radial basis function neural network). A combination of the WT and GM (grey model) was presented for STLF in Ref. [12]. PSO (Particle swarm optimization) algorithm was used to enhance the generation coefficient of GM and improve the forecast accuracy. A similar-shape functional time-series predictor was introduced in Ref. [13] that searches the load time-series history for load curves similar to the expected curve of the day to be predicted. The selected past daily load segments were then weighted and averaged to provide the prediction. The expected curve of the next day was identified based on the expected behavior of the qualitative and quantitative variables associated with the day. However, the quantitative variables such as temperature and wind speed are inherently intermittent with uncertain characteristics. Therefore, the quantitative characteristics cannot be precisely captured and the selection of the so-called reference load segment is prone to errors. Several learning methods have been used for the NN training among which the Bayesian learning demonstrates a more appropriate performance when limited training datasets are available [14–20]. This is particularly true for special days such as public holidays and weekends with less historical data than regular days such as weekdays. Although the references provide valuable insights into the input variable selection and feature extraction techniques as well as the neural network learning methods, they all lack an appropriate mechanism to capture the most relevant information of the load time series for the load forecasting scheme. In addition, absence of an appropriate data selection strategy, which is required filter the uncorrelated data out of the large training datasets, significantly increases the computational time and reduces the forecast accuracy. Table 1 provides a summary of the hybrid STLF methods along with the proposed approaches.

This paper proposes a hybrid WT-BNN load forecasting framework. A new input selection method is developed to determine the input sub-series of the BNNs which are most correlated to the output series. These sub-series provide an appropriate training of the BNNs and result in a more accurate forecast compared to the existing input selection techniques. The proposed input selection method uses a combination of the correlation analysis and ℓ^2-norm to first calculate the correlation coefficients between the individual training inputs and output and then obtain the Euclidean distance with respect to the desired correlation coefficient. The sub-series with the minimum Euclidean norm is decomposed by a wavelet transform to provide different frequency components for the BNN training. The sub-series whose norms are so close to the minimum norm are further selected as the inputs to the individual BNNs. A weighted sum of different forecast components is used to provide the final forecast for a particular day. The weighting coefficient for each forecast component is defined as the ratio of the calculated norm for the associated sub-series to the sum of the norms for the selected sub-series. This significantly improves the forecast accuracy compared to the existing forecasting methods where the individual forecasts are added up or simply combined without assigning any weighting coefficients.

Section 2 explains the DWT (discrete wavelet transform) and BNN (Bayesian Neural Network). The developed input selection method and the proposed STLF framework are also described in this section. Section 3 provides the case studies where the performance

Table 1
STLF methods and their proposed approaches.

Paper	Method	Time horizon
[1]	WT + Two-stage feature selection + CNN	1 HA
[2]	Phase-space embedding + ANN	1 DA
[3]	ANN + Fuzzy inference	1 DA
[4]	DWT + NN	1 HA
[5]	WT + NN + EA	1–24 HA
[6]	Similar-day based input selection + WT + NN	1 HA
[7]	Spike filtering + Wavelet decomposition + NN	5-min ahead
[8]	Multiwavelet transform + Multiple NNs	1 HA
[9]	Wavelet decomposition + Smoothening of the decomposed data + Reconstruction + RBFNN	1–7 DA
[10]	WT + Combined forecasting model	1 DA
[11]	WT + FPGA + ANN	1-7 HA
[12]	WT + GM + PSO	1 DA
[13]	Functional similar shape time series	1 HA
[14]	SOM neural network	1–24 HA
[15]	Bayesian regularization/Resilient/Adaptive backpropagation learning based ANNs	1–7 DA
[16]	Bayesian learning based ANN	1 HA
[17]	BNN + HMC	1 HA
[18]	SVR + RBFNN + DEKF	1–3 DA
[19]	SOM + *k*-means + MLPNN	1 HA

CNN, cascaded neural network; HA, hour ahead; DA, day ahead; EA, evolutionary algorithm; RBFNN, radial basis function neural network; FPGA, floating point genetic algorithm; GM, grey model; SOM, self-organizing map; HMC, hybrid Monte Carlo; SVR, support vector regression; DEKF, dual extended Kalman filter; MLPNN, multilayer perceptron neural network.

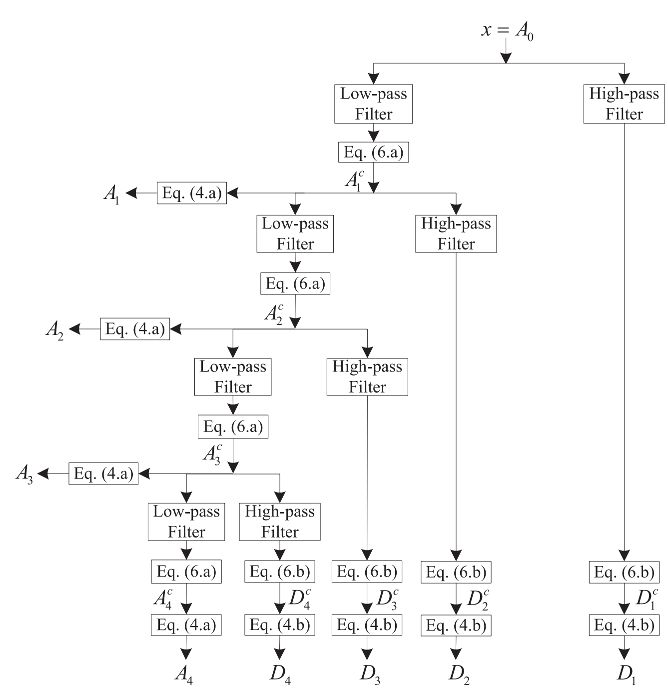

Fig. 1. Multi-resolution decomposition for a four-level DWT.