Available online at www.sciencedirect.com
ScienceDirect
Neurocomputing 70 (2007) 2659–2667
NEUROCOMPUTING
www.elsevier.com/locate/neucom

Application of bacterial foraging technique trained artificial and wavelet neural networks in load forecasting

M. Ulagammai[a,*], P. Venkatesh[a], P.S. Kannan[a], Narayana Prasad Padhy[b]

[a]*Department of Electrical and Electronics Engineering, Thiagarajar College of Engineering, Madurai 625 015, India*
[b]*Department of Electrical Engineering, IIT Roorkee, Roorkee 247 667, India*

Abstract

A new load forecasting (LF) approach using bacterial foraging technique (BFT) trained wavelet neural network (WNN) is proposed in this paper. Artificial neural network (ANN) is combined with wavelet transform called wavelet neural network is applied for LF. The parameters of translation and dilation in the wavelet nodes and the weighting factors in the weighting nodes are tuned using BFT optimization. With the advantages of global search abilities of BFT as well as the multiresolution and localizing natures of wavelets, the networks are constructed which identifies the inherent non-linear characteristics of power system loads. The proposed approach is validated with Tamil Nadu Electricity Board (TNEB) system, India. The comparison of Delta Rule and BFT-based LF for different periods are depicted with their mean absolute percentage errors (MAPE).

Keywords: Bacterial foraging technique; Load forecasting; Artificial neural network; Wavelet neural network

1. Introduction

Load forecasting (LF) is an integral part of electric power system operations. With the worldwide deregulation of the power system industry, LF is now becoming even more important not only for system operators, but also for market operators, transmission owners, and any other market participants so that adequate energy transactions can be scheduled and appropriate operational plans and bidding strategies can be established [12]. The timeliness and accuracy of LF have significant effects on power system operations and production costs. After the enforcement of Indian Electricity Act 2003, a lot of restructuring process is to be carried out in the State Electricity Boards of India and governed by respective Electricity regulatory commission [13]. Several conventional methods have been used to estimate short-term load forecasting (STLF) [4]. The methods are based on time-series regression, auto regressive moving average (ARMA) and state space models. These models are mostly linear methods and have limited ability to capture non-linearity in the load time-series pattern and fail to estimate STLF in an accurate way. Modern LF techniques such as expert systems, artificial neural networks (ANNs), fuzzy logic, and wavelets have been developed more recently showing good results. The estimation of STLF using ANN is giving a new dimension [3–5,11]. The performance of ANN-based STLF is still facing a drawback because of the non-uniform load fluctuations from hour to hour (or) day to day. An integrated ANN based STLF is proposed by incorporating the effect of temperature to the normal load [10].

ANN can be combined with wavelet transform (WT), having an inherent property of multi scale analysis and wavelet neural network (WNN) is developed to improve the accuracy of the STLF process [1,6,8,14–16]. Evolutionary computation algorithm is used to tune the connection weights and the parameters of dilation and translation in the WNN [2]. A new evolutionary computation technique, called bacterial foraging scheme is proposed [9] and verified for highly epistatic objective functions (i.e., where the optimized parameters are highly correlated) occurring in power system problem [7].

In this paper, the load is predicted for a day, a week, and a month by incorporating bacterial foraging technique (BFT) to ANN and WNN methods of Tamil Nadu

*Corresponding author.
E-mail address: ulagammai_m@yahoo.com (M. Ulagammai).

0925-2312/$ - see front matter © 2007 Elsevier B.V. All rights reserved.
doi:10.1016/j.neucom.2006.05.020

Electricity Board (TNEB) system. The weights and biases of the network are tuned using BFT. The main objective function of this optimization is to train the given network (i.e.) to adapt the given network for the given input and output training set. The comparison and the performance of the delta rule-based ANN and WNN and BFT-based ANN and WNN methods are summarized with their normalized mean absolute percentage errors (MAPE) errors. The validation of BFT with different runs is also carried out for the TNEB 69 bus test system.

2. Problem formulation

The prediction of loads ($X_{f,t}$) at ith day at time t, depends on the previous 2 h loads ($t-1$, $t-2$) of the same day, previous week loads, and previous year same day, same hour load since the distribution of load will be similar. For example, if the load is to be forecasted on third week Monday of March 2004 the inputs considered are the load on previous 2 h of the same day, previous week (i.e.) second week Monday of March 2004, and previous year load (i.e.) third week Monday of March 2003 and is shown in Fig 1. It is mathematically represented as

$X_{f,t}(i) = F(W, Y_t)$,

where $X_{f,t}(i)$ is the forecasted load at day i, time t

$$Y_t = \begin{Bmatrix} y(i,t-1),\ y(i,t-2),\ y(i-7,t),\ y(i-7,t-1), \\ y(i-7,t-2),\ y(i-365,t) \end{Bmatrix}^t \quad (1)$$

where Y is the load to be forecasted at tth hour, y is the input load values, W is the weight vector, and F is the activation function.

For training the networks (both ANN and WNN), the inputs provided are the variables related to historical load data and calendar variables as per the above mathematical representation.

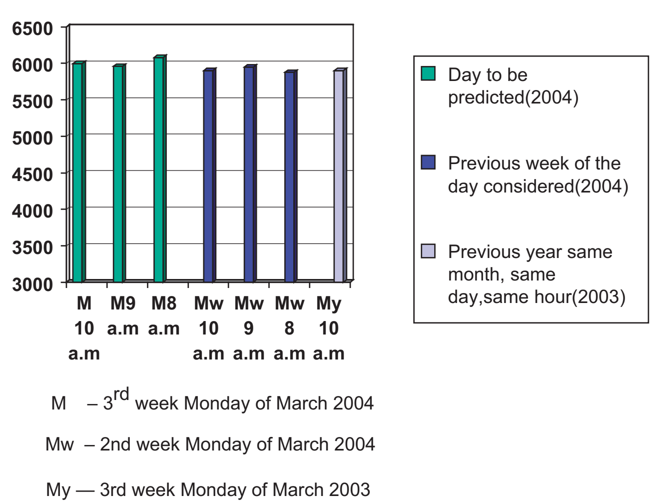

Fig. 1. Input variable selection.

3. Forecasting methods

In last few decades, several methods for STLF such as ANN, WNN, etc. have been proposed. In general, the feed forward ANNs are commonly trained in supervised fashion with the error back propagation (BP) algorithm. The BP algorithm is applied by first passing an input signal forward through the network in the direction towards the output until a set of the actual response is obtained from the network. The error signal is then generated based on the difference between the actual and the target response. Finally, the generated error signal is passed backwards through the hidden layers, in the direction towards the inputs. During the forward pass, the synaptic weights of the network are fixed. During the backward pass, the synaptic weights are adjusted to adapt the network in producing desired outputs. The basic BP algorithm is a gradient descent algorithm, which adjusts the network weights along the steepest descent direction of the error function (i.e., the direction in which the error function decreases most rapidly).

The BP algorithm adjusts the weights of the network (including bias weights) in proportion with the difference between the desired and computed values.

The weight adjustment for the BP algorithm called as delta rule is given by

$$W_k^p(t+1) = W_k^p(t) + \alpha\delta_k^p x_t^p + m\Delta W_k^p(t), \quad (2)$$

where x is the input vector, α is the learning rate parameter, m is the momentum bias coefficient term used for faster convergence which ranges from 0 to 1 and δ is the negative derivative of the total squared error in respect to the neuron's output, k and p are iteration count and pattern count, respectively. But ANN suffers from the problem of obtaining monolithic global models for a time series. To enhance the ANNs ability in learning the signals, the hidden patterns from the load data should be extracted. Hence, to perform this, a multiresolution decomposition technique such as WT approach is introduced.

For the analysis of highly non-linear and random load signal, WT approach is introduced. WT is a scalable windowing technique. The adjustable window size allows the use of long time intervals when more precise low-frequency information is desired and short time intervals when desiring high-frequency information. Wavelet analysis adopts the concept of scale and link between scale and frequency. It breaks the signals into shifted scaled versions of the original wavelet as compared to Fourier analysis, where signals are broken into sinusoids of different frequencies instead. In addition to that, the technique uses a time-scale region instead of a time–frequency region.

3.1. Wavelet neural network

In order to improve the accuracy and the stability of the ANNs, they are combined with wavelet to set a hybrid model. The load serial is first decomposed to several