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Hybrid Improved Differential Evolution and Wavelet Neural Network with load forecasting problem of air conditioning

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ABSTRACT

Air-conditioning load forecasting accuracy precludes high efficacy air-conditioning operation, and is also a key advantage in developing Smart Microgrid (SMG) power generating system control. The Wavelet Neural Network (WNN) was adopted as a principle element in air-conditioning load forecasting with Improved Differential Evolution Algorithm (IDEA) as an optimizing method for adjusting WNN parameters. This approach has replaced the formal feedback method used in solving network parameters. IDEA is an optimizing technique with simple calculation and fewer adjustable parameters, allowing the optimum solution for the entire system to be acquired more accurately and rapidly. After solving the optimum parameters WNN is further applied to accomplish air-conditioning load forecasting. A Fuzzy Expert System is adopted as an adjustment measure for special conditions, allowing ideal forecasting results to be reached. This study made practical comparisons among the generally applied methods for optimizing air-conditioning forecasting, such as the Artificial Neural Network (ANN), Evolutionary Programming-Artificial Neural Network (EP-ANN), Genetic Algorithm-Artificial Neural Network (GA-ANN), Ant Colony Optimization-Artificial Neural Network (ACO-ANN) and Particle Swarm Optimization-Artificial Neural Network (PSO-ANN), to prove the advantages and applicability of the proposed method.

Introduction

In conventional air-conditioning load forecasting methods, adjustments are usually made using a few major factors that affect the air-conditioning load. The advantages of conventional methods are forecasting model simplicity for air-conditioning load forecasting. However, non-linear relations exist among air-conditioning load factors and such non-linear relations are difficult to solve using conventional methods. In recent years several methods have been adopted for air-conditioning load forecasting, such as the Time Series Method [1], Gray Theory [2], Least Square Method [3] and Neural Networks (NN) [4–11]. Owing to multiple-dimension, non-linear air-conditioning load characteristics, some limitations exist for applying conventional methods. Several improved methods have been adopted that apply NN [12–24] for air-conditioning load forecasting. NN is quite suitable to air-conditioning load forecasting because it is capable of dealing with non-linear mapping and generalization. However, some limitations still exist, such as a poor fit for air-conditioning load forecasting on certain special load days. NN requires mass data such as weather data, air-conditioning load variations and air-conditioning load cycles. There are also shortcomings in conventional NN, such as the slow training pace and weaker integrated optimum solution probing. There are many methods being used to solve this problem such as the Autoregressive Integrated Moving Average-ARIMA [25], Genetic Algorithm Combined Artificial Neural Network-GA-ANN [26], Particle Swarm Optimization-PSO [27–30], Ant Colony Optimization-ACO [31–32], Support Vector Machine-SVM [33–35]. All of these methods have some calculation bottleneck problems that need to be improved. To improve the available air-conditioning load forecasting method shortcomings this study proposes the Improvement Differential Evolution Algorithm (IDEA) [36–40] to amend the conventional NN shortcomings. This study introduces a concept and Wavelet Neural Network algorithm (WNN) [41–45]. The concept is to replace neural variables with Wavelet variables, that is, replace the sigmoid function with the Wavelet function as a trigger function by applying the affine transformation to establish connections among the Wavelet transformation and network parameters. The WNN advantages are strong approximation, faster convergence and theoretical network parameters (quantities in hidden layer nodes and weighting value) selection which are effective in avoiding the local optimum value. The IDEA is applied to find the optimum solution parameters for the of threshold and weighting

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values using relevant affecting factors (such as temperature, humidity, rain fall, and sun radiation) with the Fuzzy Expert System calculating final amendments for using this special data. The optimum solution for the entire system is then output.

Basic structure of IDEA–WNN with Fuzzy Expert System

The IDEA–WNN and Fuzzy Expert System flow charts are illustrated as shown in Fig. 1. The basic principle is to search for the optimum values for various parameters in the WNN by applying the IDEA. The acquired parameter values are input into WNN which performs practical air-conditioning load forecasting. Final amendments are performed with the Fuzzy Expert System, with the optimum air-conditioning load forecasting solution output at the end.

The WNN model

Wavelet analysis

In the function space $L^2(R)$ (or more extensive Hilbert space), select a Wavelet function (also known as a basic Wavelet function) $\psi(x)$, such that the constraint criteria are satisfied:

$$C_\psi = \int_{-\infty}^{+\infty} \frac{|\hat{\psi}(w)|^2}{|w|} dw < \infty \tag{1}$$

In Eq. (1), $\hat{\psi}(w)$ is a Fourier transformation from $\psi(x)$. By performing the stretch and translation transformation to $\psi(x)$, acquire the Wavelet based function series $\{\psi_{a,b}(x)\}$.

$$\psi_{a,b}(x) = \frac{1}{\sqrt{a}}\psi\left(\frac{x-b}{a}\right) \tag{2}$$

where a is stretch coefficient, b is translation coefficient.

For arbitrary $f(x) \in L^2(R)$, its continuous Wavelet transformation is defined as:

$$W_f(a,b) = \int_{-\infty}^{+\infty} f(x)\psi_{a,b}(x)dx \tag{3}$$

Similar to Fourier analysis Wavelet analysis based on Wavelet transformation decomposes the signal function into an orthogonal Wavelet standard and constructs a progression to approximate the signal localization feature, achieving the optimum approximation function capability based on the Wavelet theory.

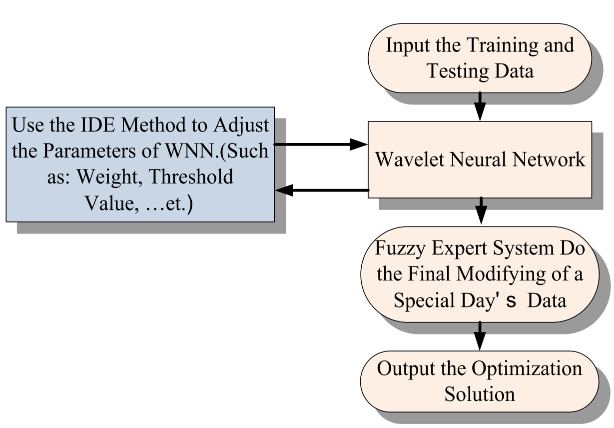

Fig. 1. The flowchart of combined improved Differential Evolution–Wavelet Neural Network and Fuzzy Expert System model do the load forecasting of air-conditioning.

The structure of WNN

WNN is an Artificial Neural Network model constructed basis on Wavelet analysis, that is, replacing the conventional sigmoid function with a mother Wavelet, wherein, the function description is obtained by selecting a cluster of overlapping mother Wavelets. Function $f(x)$ can perform the approximation with a cluster of mother Wavelets:

$$\hat{f}(x) = \sum_{l=0}^{N} w_l \cdot \psi_l\left(\frac{x-b_l}{a_l}\right) \tag{4}$$

In this equation, $\hat{f}(x)$ is a fitting function; w_l is a weighting coefficient; N is the quantity of mother Wavelets.

It has been theoretically proven that a three layer feed-forward network with a hidden layer can perform non-linear mapping approximation with arbitrary precision. The Neural variables in the network hidden layer adopt the Wavelet function as the trigger function. The Neural variables in the output layer adopt the sigmoid function as the trigger function. A structure schematic diagram of the network structure is shown in Fig. 2.

Assume x_i as the number i Wavelet Neural variable, y as the output layer output value, w_{ij} as the connection weighting value that connects the input layer and hidden layer nodes, θ_j as the hidden layer threshold value, w_{jk} as the connection weighting value between the hidden layer j and output layer (there is only one node in the output layer), θ_k as the output layer threshold value, a_j, b_j as the stretch and translation coefficients of the hidden layer. p is the quantity of input layer nodes, q is the quantity of hidden layer nodes, and the output from the above model is presented as:

$$\overline{y_z} = \sigma\left(\sum_{j=1}^{q} w_{jk} \cdot \psi_{a,b}\left(\sum_{i=1}^{p} w_{ij} \cdot x_i - \theta_j\right) - \theta_k\right) \tag{5}$$

$$\sigma(x) = 1/[1+\exp(-x)] \tag{6}$$

$\psi_{a,b}(x)$ adopts the Morlet function as the mother Wavelet, then

$$\psi(x) = \cos(1.75x)\exp(-x^2/2) \tag{7}$$

To calculate the disparity value

(1) Calculate the output layer disparity value

$$\delta_k = (\bar{y}_z - y_z) \cdot y_z \cdot (1 - y_z) \tag{8}$$

(2) Calculate the hidden layer disparity quantity

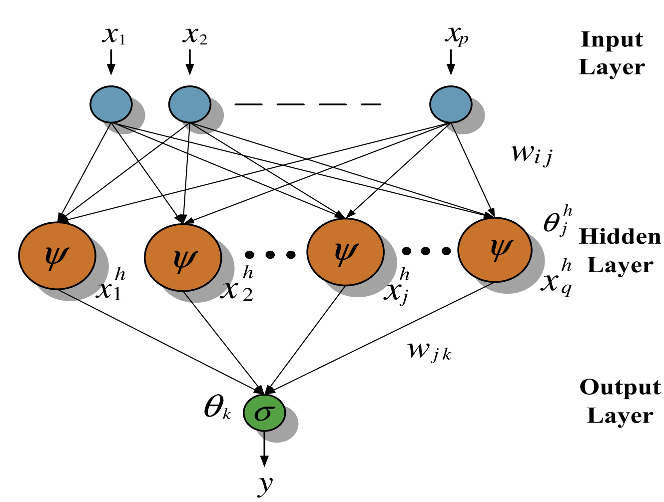

Fig. 2. The construction figure of Wavelet Neural Network.