Research Article

A Hybrid Forecasting Model Based on Empirical Mode Decomposition and the Cuckoo Search Algorithm: A Case Study for Power Load

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Power load forecasting always plays a considerable role in the management of a power system, as accurate forecasting provides a guarantee for the daily operation of the power grid. It has been widely demonstrated in forecasting that hybrid forecasts can improve forecast performance compared with individual forecasts. In this paper, a hybrid forecasting approach, comprising Empirical Mode Decomposition, CSA (Cuckoo Search Algorithm), and WNN (Wavelet Neural Network), is proposed. This approach constructs a more valid forecasting structure and more stable results than traditional ANN (Artificial Neural Network) models such as BPNN (Back Propagation Neural Network), GABPNN (Back Propagation Neural Network Optimized by Genetic Algorithm), and WNN. To evaluate the forecasting performance of the proposed model, a half-hourly power load in New South Wales of Australia is used as a case study in this paper. The experimental results demonstrate that the proposed hybrid model is not only simple but also able to satisfactorily approximate the actual power load and can be an effective tool in planning and dispatch for smart grids.

1. Introduction

In a power system, the short-term power load forecasting is very important for the stable operation of the system. Accurate forecasting is a guarantee in the development of preventive maintenance plans, which include generator safeguards, power system reliability estimation, and scheduling dispatch [1, 2]. High-accuracy power load forecasts improve the economic and social benefits of power grid management, which reduce generation costs, improve the security of power systems, and help administrators develop optimal plans. Moreover, accurate load forecasting is crucial in forecasts of the power price in power markets [3]. Therefore, developing power load forecasting techniques to achieve accurate, simple, and fast load forecasts is necessary. Thus far, many short-term power load forecasting methods have been proposed, and these methods can be mainly divided into three categories: conventional methods, modern forecasting methods, and hybrid forecasting methods. Conventional methods include multiple linear regression analysis [4, 5], time series

[6, 7], state space models [8], general exponential smoothing [9], and knowledge-based methods. However, these methods cannot provide appropriate nonlinear mathematical relationships to express actual power loads. The primary modern forecasting methods are intelligent evolutionary algorithms [10, 11], expert systems [12, 13], neural networks [14–17], and fuzzy inference [18]. Intelligent algorithms and neural networks obtain good performance because of their clear patterns, easy implementation, and strong ability to address the problem. Hybrid forecasting methods, proposed to avoid the shortcomings that exist in individual forecasting methods, have become increasingly prevalent [19, 20]. A detailed introduction of the three categories is given below.

The deduction processes of traditional forecasting methods are rigorous, and most of them are based on traditional mathematics theories such as statistics, calculus, and modeling by subjective data analysis [21]. The main idea of trend extrapolation technology is to look for the trend of data changes, according to the trend equation, to forecast future data. The method is simple, and, especially for smooth power

load changes, it can achieve a good prediction effect. Its deficiency is that its precision is greatly influenced by the random load component [22]. The regression analysis method is often applied to short-term load forecasting [23]. This method has many advantages such as a simple principle and better quality of data which leads to better precision; however, the selection of the main factors affecting power load in the model is difficult as many factors that affect the forecasting accuracy are hard to quantify. This model is lacking any self-study capability, and the input variable and output variable cannot be revised automatically [24]. With years of development, the time series forecasting method has become a mature theory method and has been applied to power load forecasting [25]. The basic time series prediction models mainly include AR, MA, and ARMA [26]. Although the time series forecasting method has advantages such as only requiring a small volume of historical data and a small amount of calculation and the fast speed of its calculation, this method has certain limitations such as its inability to reflect the influence of meteorological factors and how its forecasting accuracy will decrease with the increase of the prediction step [27]. ANN [17] is a type of nonlinear simulation of the human brain information processing system with an intelligent processing process; for an inaccurate variation trend, this method also has a good ability to adapt, is able to grasp information and keep on learning, and has good knowledge reasoning and self-optimization [28]. An expert system is a computer system based on the knowledge of the programming approach, mainly a software system, and the main components of an expert system include the inference engine of the system, the expert knowledge base, the explain interface, and the knowledge acquisition module. An expert system is a program that has decision-making capabilities based on reasoned knowledge; however, this method is limited by whether the expert knowledge is complete [29]. The grey forecasting method is an important technique in grey theory, and it uses approximate differential equations to describe future tendencies for a time series [30]. The limitation of this method is that the greater the dispersion degree of data, the worse the forecasting accuracy. Although traditional forecasting methods and forecasting methods based on intelligent computing have their respective applications, it is difficult to achieve better results when using one of them by itself [31]. In the literature related to forecasting [31–34], the forecasting results are not quite as good with any single forecasting model. The primary reason is that single forecasting models cannot extract the complicated factors encountered in reality.

Due to the limitations of the forecasting capacity of a single model, it cannot always be optimal in all cases. In this paper, a novel hybrid model was developed with the hope of obtaining more accurate power load forecasting results. The proposed hybrid wind speed forecasting model can be grouped into four steps. Firstly, we used the empirical model decomposition technique, which represents a nonstationary data analysis technique, to reconstruct the original wind speed series. Secondly, a WNN model was employed to create the power load forecasting, and the parameters in the WNN

model were tuned by the CSA. The simulation results illustrate that the hybrid model is an effective method in power load forecasting. The main contributions of this paper are summarized as follows:

- (1) The CSA algorithm is applied to choose the optimal initial weight in the WNN model, which always leads to unstable forecasting error.
- (2) In the field of power load forecasting, the proposed hybrid model is manifested as a valid method with efficient computation and satisfactory forecasting accuracy.
- (3) Considering the skewness and kurtosis of the forecasting accuracy distribution, the developed forecasting availability is proposed as an effective evaluation criterion for model selection in the power load forecasting field.

This paper is organized as follows. First, we outline the concept of models used in this paper, including empirical model decomposition, WNN, CSA, BPNN, GABPNN, and EMD-CSAWNN. Second, the modeling processes of the methods mentioned above are introduced. Simulation results are presented and analyzed. Finally, the overall conclusion is included.

2. Methodology

In this section, the required individual tools will be presented concisely, including the empirical model decomposition technique, BPNN, the WNN model, and the CSA and GA algorithms. Moreover, the proposed hybrid approach will be described in detail. In addition, the structure of the feed-forward neural network will be confirmed.

2.1. Empirical Mode Decomposition. Empirical model decomposition was proposed by Karthikeyan and Kumar as an adaptive method for nonstationary time series analysis, and it is now widely used. It can be applied to any type of signal decomposition [35]. Thus, it has obvious advantages in processing nonstationary and nonlinear series. The foundation of this technique is to decompose a time series into a finite set of several IMFs and a residue [36].

Definition 1. All IMFs are defined to satisfy the following conditions: (1) the number of local extreme points and the number of zero crossings must be equal or at least differ by only one; (2) the mean value of the upper envelope and lower envelope is zero.

Definition 2. The stoppage criterion determined is defined as

$$SD_k = \frac{\sum_{t=0}^T |h_{1k-1}(t) - h_{1k}(t)|^2}{\sum_{t=0}^T h_{1k-1}^2(t)}. \quad (1)$$

The sifting process stops when SD_k is smaller than a pre-given value. The process of decomposition is over when the value of SD_k is between 0.2 and 0.3. Additional details of the

FIGURE 1: The construction of empirical model decomposition.

empirical model decomposition technique are illustrated in Figure 1.

2.2. Artificial Neural Network (ANN)

2.2.1. Confirmation of the Structure of the Network. The ANN has received considerable attention as a powerful computational tool for forecasting in many fields since 1980. ANN models always outperform statistical models because of their ability to map the inputs onto outputs via simple computation [37]. We discuss the feed-forward neural network in this paper because of its strong learning ability and simple structure. The determination of the network structure is as follows [38].

Definition 3. Given an arbitrary continuous function $f : [0, 1]^n \rightarrow R^m$, f can be accurately approximated using a three-layer forward neural network realization. The first layer of the network is the input layer, containing n neurons. The middle layer is the hidden layer, containing $2n + 1$ neurons. The third layer is the output layer, which has m neurons.

Definition 4. Let ϕ be bounded continuous monotone in function, let K be the bounded compact subsets, and let $K \subset R^n$, $f(X) = f(x_1, x_2, \dots, x_n)$ be a real continuous function in $f(X) \in K$. $\forall \epsilon > 0$, $\exists$ integer N , real constant C_i , θ_i ($i = 1, 2, \dots, N$) and W_{ij} ($i = 1, 2, \dots, N$), such that $\hat{f}_{ij}(x_1, x_2, \dots, x_n) = \sum_{i=1}^N C_i \phi(\sum_{j=1}^n W_{ij} x_j - \theta_i)$ satisfying $\max |\hat{f}_{ij}(x_1, \dots, x_n) - f(x_1, \dots, x_n)| < \epsilon$. Note that, $\forall \epsilon > 0$, $\exists$ a three-layer network structure, and the output function of the hidden layer is $\phi(x)$, the output function of the input and output layer is linear, and the total relationship of I/O is $f(x_1, \dots, x_n)$, such that $\max |\hat{f}(x_1, \dots, x_n) - f(x_1, \dots, x_n)| < \epsilon$.

Proof. Because $f(X)$ ($X = (x_1, \dots, x_n)$) is a continuous function, $f(X) \in K$, $K \subset R^n$, assume that $f(X)$ is a bounded C^∞ function. Based on the Paley-Wiener Theorem [39], the Fourier transform $F(W)$ ($W = (W_1, \dots, W_n)$) is a real analytic function of $f(X)$, $\forall$ a constant C_N , such that $|F(W)| \leq C_N(1 + |W|)^{-N}$. We define such a function:

$$I_A(x_1, \dots, x_n) = \int_{-A}^A \cdots \int_{-A}^A \phi\left(\sum_{i=1}^n x_i W_i - W_0\right) \frac{1}{(2\pi)^n \phi(1)} F(W_1, \dots, W_n) \exp(iW_0) dW_0 \cdots dW_n,$$

$$I_{\infty,A}(x_1, \dots, x_n) = \int_{-A}^A \cdots \int_{-A}^A \left[\int_{-\infty}^{\infty} \phi \left(\sum_{i=1}^n x_i W_i - W_0 \right) \frac{1}{(2\pi)^n \phi(1)} F(W_1, \dots, W_n) \exp(iW_0) \right] dW_0 \cdots dW_n,$$

$$J_A(x_1, \dots, x_n) = \frac{1}{(2\pi)^n} \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} F(W_1, \dots, W_n) \exp \left(i \sum_{i=1}^n x_i W_i \right) dW_1 \cdots dW_n. \quad (2)$$

Using an estimation of $F(\cdot)$, $\lim_{A \rightarrow \infty} J_A(x_1, \dots, x_n) = f(x_1, \dots, x_n)$ can be proved: that is, J_A is uniform convergence. Thus, $\lim_{A \rightarrow \infty} I_{\infty,A}(x_1, \dots, x_n) = f(x_1, \dots, x_n)$. That is, $\forall \varepsilon > 0, \exists A > 0$, such that $\max_{x \in R^n} |I_{\infty,A}(x_1, \dots, x_n) - f(x_1, \dots, x_n)| < \varepsilon/2$. Moreover, for $A' > 0$, let $I_{A',A}(x_1, \dots, x_n) = \int_{-A}^A \cdots \int_{-A}^A \left[\int_{-A'}^{A'} \phi \left(\sum_{i=1}^n x_i W_i - W_0 \right) \cdot (1/(2\pi)^n \phi(1)) F(W_1, \dots, W_n) \cdot \exp(iW_0) \right] dW_0 \cdots dW_n$. For $\varepsilon > 0, A' > 0$ can be found such that $\max_{x \in K} |I_{A',A}(x_1, \dots, x_n) - I_{\infty,A}(x_1, \dots, x_n)| < \varepsilon/2$. That is to say, $f(X)$ is a uniform approximation by the integral $I_{A',A}(X)$, $I_{A',A}(X) \in K$. If $A_i > 0$ ($i = 1, 2, \dots, m$), K is a bounded subset, $K \subset R^n$, and $h_i(x_1, \dots, x_m; t_1, \dots, t_m)$ is a uniformly continuous function of $[-A_1, A_1] \times \cdots \times [-A_m, A_m] \times K$. There are functions:

$$H(t) = \int_{-A_1}^{A_1} \cdots \int_{-A_m}^{A_m} h(x_1, \dots, x_m; t_1, \dots, t_m) dx_1 \cdots dx_m,$$

$$H_N(t) = \frac{2A_1 \cdots 2A_m}{N^m} \times \sum_{k_1, \dots, k_m=0}^{N-1} h \left(-A_1 + \frac{k_1 \cdot 2A_1}{N} \cdots A_m + \frac{k_m \cdot 2A_m}{N} t_1 \cdots t_m \right). \quad (3)$$

$\forall \varepsilon > 0, \exists N_0, N_0$ is a natural number, when $N \geq N_0$, such that

$$\max_{t \in K} |H(t) - H_N(t)| < \varepsilon. \quad (4)$$

Thus, $I_{A',A}(X)$ is a uniform approximate on K ,

$$\phi \left(\sum_{i=0}^n x_i W_i - W_0 \right) = \phi \left(\sum_{i=1}^n \frac{W_i x_i}{\delta} - W_0 + \alpha \right) - \phi \left(\sum_{i=1}^n \frac{W_i x_i}{\delta} - W_0 - \alpha \right). \quad (5)$$

The formula above can be achieved by a three-layer neural network. Thus, $f(X)$ can be approximated by that neural network. $\square$

Definition 5. $\forall \varepsilon > 0$ and $f : [0, 1]^n \rightarrow R^m$, there exists a three-layer structure that can approximate f in any square error precision of ε .

The definition above proves that, $\forall f : [0, 1]^n \rightarrow R^m$, we can use a feed-forward neural network with a three-layer structure $n \times (2n + 1) \times m$ to approximate it accurately.

Thus, this part not only proves the existence of the mapping network but also demonstrates the network structure of the mapping. In summary, this paper adopts the three-layer neural network as the basis neural network.

2.2.2. BPNN. BPNN is a type of multilayer feed-forward neural network with an error back propagation learning process. The structure of BPNN is illustrated in Figure 2. Details of BPNN are introduced in [40].

2.2.3. WNN. WNN, a feed-forward network, is generally multilayer [41]. It is widely applied in signal processing because of its advantages of the localization property and generalization ability [42]. The structure of WNN is shown in Figure 2.

2.3. Neural Network Optimized by an Intelligence Algorithm. The intelligent optimization algorithm provides an efficient and powerful mathematical tool for optimizing the initial weights and thresholds of the ANN [43].

2.3.1. CSA. Cuckoo search is a heuristic swarm intelligence algorithm inspired by the behavior of the obligating brood parasitism of cuckoo species [44]. CSA is utilized in this paper for its stronger capability of global optimization [43].

Definition 6. To simulate the mode of cuckoo breeding, three idealized assumptions are presented, as follows: (1) each cuckoo selects nest randomly and dumps only one egg at a time, (2) the eggs with high quality will be carried over to the next generation, and (3) the available nest number n is fixed, and the probability of the host bird discovering the exotic egg is p_α .

Definition 7. The Lévy flight model simulates the process of the nest-seeking characteristic of cuckoo, and the update formula of the path and location is as follows:

$$X_i^{\text{iter}+1} = X_i^{\text{iter}} + \alpha \oplus L(\lambda). \quad (6)$$

X_i^{iter} represents the location of nest i at generation iter, α is the step length-controlled factor, $\oplus$ is the point-to-point multiplication, and $\text{Levy}(\lambda)$ obeys the Lévy distribution with a random search path of parameter λ :

$$L(\lambda) = 0.01 \frac{u}{|v|} (X_i^{\text{iter}} - X_*^{\text{iter}}). \quad (7)$$

FIGURE 2: The construction of GABPNN and CSAWNN.

Here $u = t^{-\lambda}$, $1 < \lambda < 3$, u and v obey the normal distribution, $u \sim N(0, \sigma_u^2)$, $v \sim N(0, 1)$, $\sigma_u = [\Gamma(\lambda) \sin(0.5\pi(\lambda - 1)) / 2^{(\lambda-2)/2} \Gamma(0.5\lambda)(\lambda - 1)]^{1/(\lambda-1)}$, X_*^{iter} denotes the location of the best nest at generation iter, and Γ is the standard gamma function with unbounded variance and mean of the probability distribution.

2.3.2. GA. GA is a population-based optimization algorithm that simulates natural genetic mechanisms and biological evolutionism. It possesses a capacity for powerful global optimization [45]. The principle of GA relies on a random process, which is constituted by the processes of selection, crossover, and mutation [46]. The implementation process is shown in Figure 2.

2.4. GABPNN. The primary mechanism of GABPNN is composed of three parts: GA optimization, determination of the BPNN structure, and forecasting covered by BPNN [47]. The pseudo-code for GABPNN is as shown in Algorithm 1.

2.5. EMD-CSAWNN. In this paper, the proposed model, which incorporates the empirical model decomposition technique into the WNN model based on CSA, is adopted for short-term power load forecasts. Empirical model decomposition represents a self-adaptive decomposition technique to decompose short-term power load series into several IMFs and one residual item. WNN is adopted as a forecasting engine in the proposed approach because of its powerful approximation and high computation speed. Additionally, to avoid the deficiencies of WNN such as its unstable structure, CSA is used to initialize and determine the weights and thresholds of WNN, thereby imparting an outreach capacity to WNN. Figure 3 illustrates the general structure of the hybrid power load forecasting method. The pseudo-code for

the algorithm of the EMD-CSAWNN model is as shown in Algorithm 2.

3. Experiments and Evaluations

Applications of the proposed hybrid approach and five comparison models are shown in this subsection. All algorithms are operated on the given platform: 3.20 GHz CPU, 8.00 GB RAM, Windows 7, and MATLAB R2012a. Meanwhile, taking into account the randomness factors and to make sure the final results are reliable and independent from the initial weights, we carry out each ANN experiment 50 times and then take the average value.

3.1. Region Description and Data Collection. Australia has plentiful coal and wind resources across its coastline and land. A power load data set from NSW, which is the state with the largest population and highest levels of industrialization and urbanization in Australia, is employed to validate each model. In this paper, power load data are collected randomly from NSW from January 12, 2009, to March 8, 2009, which includes eight weeks of data. Among them, the data from January 12, 2009, to February 1, 2009, is used as a training set to obtain the appropriate model, and data from February 2, 2009, to March 1, 2009, is used as the testing set. The power load data from January 12, 2009, to February 1, 2009, together with their statistical measures, that is, minimum, maximum, mean, and standard deviations, are shown in Figure 4(c); the standard deviations are all above 1800, which implies that the power load series fluctuates significantly with the minimum/maximum of week one, week two, and week three, which are 6049.94/13518.06 (MWh), 6280.27/13326.47, and 6375.84/13096.37, respectively. This can be intuitively observed from the amplitude and frequency of the series fluctuation, which can change from very high to low values and vice versa.


```

(1) GENERATE iter = 0 /* Calculate the fitness of each individual in the population. */
(2) DO WHILE iter ≤ itermax
(3)   iter = iter + 1 /* Record the best fitness values and the average fitness values. */
(4)   FOR EACH 1 ≤ i ≤ P DO /* The process of the select operation. */
(5)     piiter = fiiter(·) / ∑i=1P fiiter(·)
(6)     FOR EACH 1 ≤ j ≤ s DO /* The process of the crossover and mutation operations. */
(7)       wkjiter = wkjiter (1 - b) + wljiter b wljiter = wljiter (1 - b) + wkjiter b
(8)       wijiter = { wijiter + (wijiter - wmaxiter) r2 (1 - iter/Gmax)  r ≥ 0.5
                    wijiter + (wminiter - wijiter) r2 (1 - iter/Gmax)  r < 0.5
(9)   END FOR; END WHILE
(10)  Wbest = [wjk wij aj bk] /* Initial weights and thresholds of BPNN by the obtained best individual. */
(11)  xk = (xk - xmin) / (xmax - xmin), k ∈ [1, q] /* The process of training data normalization. */
(12)  iter = 0 /* Adjust the weights and threshold of BPNN according to the forecast error. */
(13)  DO WHILE iter ≤ itermax
(14)    iter = iter + 1
(15)    FOR EACH 1 ≤ i ≤ n DO
(16)      FOR EACH 1 ≤ j ≤ nHidden DO
(17)        Hj = f(∑i=1n wij xi - a) /* Calculate the outputs of the hidden layer. */
(18)      FOR EACH 1 ≤ k ≤ m DO
(19)        Ok = ∑j=1n Hj wjk - bk /* Calculate the outputs of the output layer. */
(20)        ek = yn(k) - Ok /* Calculate the forecast error in the output layer. */
(21)        wij = wij + η Hj (1 - Hj) x(i) ∑k=1m wjk ek /* Update the connection weights */
(22)        wjk = wjk + η Hj ek
(23)        aj = aj + η Hj (1 - Hj) ∑k=1m wjk ek bk = bk + ek /* Update the threshold. */
(24)    END FOR; END WHILE
(25) RETURN x̂f = (x̂(q + 1), x̂(q + 2), ..., x̂(q + p))

```

ALGORITHM 1: GABPNN.

Figure 4(b) exhibits 1008 power load data points from January 12, 2009, to February 1, 2009, divided into three groups, with 336 data points in every group. Because the power load data of NSW are collected once every half hour, each day includes 48 data points. On different days of the week, daily life and human economic production usually have different behaviors; thus, the characteristics of the load are different on different days. To minimize forecasting error as much as possible, we forecast the load of different days in the week separately. In this paper, the cycles of data division are seven days; the first three weeks of Monday data, January 12, January 19, and January 26, are employed to forecast the next Monday load on February 2, 2009. Accordingly, the data on January 13, January 20, and January 27 are employed to forecast the power load on February 3, 2009. The rest can be conducted in the same manner. The structures of the training and testing sets are illustrated in Figure 3(b).

3.2. Evaluation Metrics. Forecasting accuracy is an important criterion for evaluating a forecasting model. In this paper, the basic error calculation method is as follows:

$$\text{MAE} = \frac{1}{T} \sum_{t=1}^T |\text{AE}_t| = \frac{1}{T} \sum_{t=1}^T |x_t - \hat{x}_t|. \quad (8)$$

Here, T is the number of data points; the formula AE represents the absolute error between the observed value and the

forecasting value at time t , x is the observed value, and $\hat{x}_t$ is the forecasting value at time t . To avoid a positive or negative offset in forecasting error, solve the problem for which positive and negative forecasting error cannot be added, adding to the absolute value of the error, and take the average in the end. This error belongs to the comprehensive index in error analysis:

$$\text{RMSE} = \sqrt{\frac{1}{T} \sum_{t=1}^T \text{AE}_t^2} = \sqrt{\frac{1}{T} \sum_{t=1}^T (x_t - \hat{x}_t)^2}. \quad (9)$$

RMSE is the square root of the mean square error. It also belongs to the comprehensive index in error analysis. Take the square of the absolute error AE; thus, the role of great values in the error will be strengthened, improving the sensitivity of the indicators, which is the prevailing reason in the error analysis:

$$\text{MAPE} = \frac{1}{T} \sum_{t=1}^T \left| \frac{x_t - \hat{x}_t}{x_t} \right| \times 100\%, \quad (10)$$

where the symbolic meaning is as above. The indicator is the average of the absolute error. The index is one of the comprehensive indexes in error analysis that usually occupies a very important position in the analysis and forecasting performance of the model.

```

(1) /* Initialize  $SD_0 = 1, r_0(t) = x(t), h_{k-1}(t) = r_{j-1}(t), k = 1, j = 1$ . */
(2) WHILE  $r_j(t)$  is not a monotonic function DO
(3)     WHILE  $SD_k > 0.3$  DO /* Find all local maxima and minima of  $h_{k-1}(t)$  by cubic spline. */
(4)         /* Produce the upper and lower envelopes expressed as  $e_{\max}(t)$  and  $e_{\min}(t)$ . */
(5)          $m_k(t) = [e_{\max}(t) + e_{\min}(t)]/2, h_k(t) = h_{k-1}(t) - m_{k-1}(t), k = k + 1$ 
(6)     END WHILE
(7)      $IMF_j = h_k(t), r_j(t) = r_{j-1}(t) - IMF_j, j = j + 1$ 
(8) END WHILE
(9)  $x_k = \sum_{i=2}^n IMF_i + r_n, k \in [1, q]$ 
(10) GENERATE iter = 0
(11) DO WHILE iter  $\leq$  itermax
(12)     iter = iter + 1 /* Generate a cuckoo egg  $X_i$  by taking a Lévy flight from a random nest. */
(13)     FOR EACH  $1 \leq i \leq n$  DO /* Calculate the fitness value  $f_i(\cdot)$  and select the candidate. */
(14)          $X_i^{\text{iter}+1} = X_i^{\text{iter}} + \alpha \oplus L(\lambda)$ 
(15)         IF  $f^{\text{iter}}(\cdot) \leq f^{\text{iter}+1}(\cdot)$  DO /* Replace the worse location of the nest by the better one. */
(16)              $X^{\text{iter}+1} = X^{\text{iter}}$ 
(17)         ELSE  $X^{\text{iter}+1} = X^{\text{iter}+1}$ 
(18)         rand = randn()
(19)         IF rand  $> P_\alpha$  DO /* Discard the worst solution by  $P_\alpha$  and produce a new solution. */
(20)              $X_i^{\text{iter}+1} = X_i^{\text{iter}} + r(\chi_j^{\text{iter}} - \chi_k^{\text{iter}})$ 
(21)         ELSE  $X^{\text{iter}+1} = X^{\text{iter}+1}$ 
(22) END IF; END FOR; END WHILE
(23)  $X_{\text{best}} = [\omega_{jk} \ \omega_{ij} \ a_j \ b_j]$  /* Initial weights and thresholds of WNN by obtaining the best individual. */
(24)  $x_k = (x_k - x_{\min})/(x_{\max} - x_{\min}), k \in [1, q]$  /* The process of training data normalization. */
(25) iter = 0 /* Adjust the weights and threshold of WNN according to the forecast error. */
(26) DO WHILE iter  $\leq$  itermax
(27)     iter = iter + 1
(28)     FOR EACH  $1 \leq i \leq n$  DO
(29)         FOR EACH  $1 \leq j \leq n_{\text{Hidden}}$  DO
(30)              $h(j) = h_j((\sum_{i=1}^k \omega_{ij}x_i - b_j)/a_j)$  /* Calculate the outputs of the hidden layer. */
(31)         FOR EACH  $1 \leq k \leq m$  DO
(32)              $y(k) = \sum_{i=1}^{n_H} \omega_{ij}h(i)$  /* Calculate the outputs of the output layer. */
(33)              $e_k = yn(k) - y(k)$  /* Calculate the forecast error in the output layer. */
(34)              $\omega_{i+1,k} = \omega_{i,k} + \Delta\omega_{i+1,k}$  /* Update the connection weights */
(35)              $a_k = a_k + \Delta a_k, b_k = b_k + \Delta b_k$  /* Update the threshold. */
(36)              $\Delta\omega_{i+1,k} = -\eta(\partial e_k / \partial \omega_{i,k}), \Delta a_k = -\eta(\partial e_k / \partial a_k), \Delta b_k = -\eta(\partial e_k / \partial b_k)$ 
(37)         END FOR; END WHILE
(38) RETURN  $\hat{x}_f = (\hat{x}(q+1), \hat{x}(q+2), \dots, \hat{x}(q+p))$ 

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ALGORITHM 2: EMD-CSAWNN.

To determine the degree of correlation between different forecasting model results with observed values, GRA [48] is employed in this paper.

Definition 8 (determining the grey relational coefficient). $\{x_0(i)\}_{i=1}^n$ is the reference sequence, $\{x_j(i)\}_{i=1}^n$ is the comparative sequence, $j = 1, 2, \dots, m$, and the relational coefficient of x_0 and x_j in point k is represented as

$$\xi_j(k) = \frac{\min_j \min_k |x_0(k) - x_j(k)| + \rho \max_j \max_k |x_0(k) - x_j(k)|}{|x_0(k) - x_j(k)| + \rho \max_j \max_k |x_0(k) - x_j(k)|} \quad (11)$$

Here, ρ is the distinguishing coefficient, and $\rho \in [0, 1]$, usually $\rho = 0.5$.

Definition 9 (grey relational degree). By focusing the degree of $\xi_j(k)$ at utter points, the algorithm on the grey relational degree is

$$r_i = \frac{1}{n} \sum_{k=1}^n \xi_i(k). \quad (12)$$

Considering the generation capacity of the proposed hybrid model, four statistical indices are employed as evaluation metrics to measure the forecasting accuracy, MAE, RMSE, MAPE, and GRA. MAPE, MAE, and RMSE measure the mean performance, and GRA illustrates how well the forecasted data points fit the trend.

4. Results and Analysis

The experiments were divided into three parts, Experiment 1, Experiment 2, Experiment 3, Experiment 4, and

FIGURE 3: The construction of EMD-CSAWNN. (a) IMFs and the residual decomposed by empirical model decomposition. (b) The structure of the training and testing sets of the neural network. (c) The procedure of WNN combined with CSA. (d) The procedure of CSA. (e) The structure of WNN. (f) The forecasting sequence and error by using the EMD-CSAWNN model.

FIGURE 4: Description of observations in New South Wales of China. (a) Location of the study site. (b) The original power load series from January 12 to February 1, 2009. (c) The statistical measures for the power load.

Experiment 5. Experiment 1, the primary experiment, aims to compare the performance of different models in one day (February 2, 2009) and, meanwhile, to compare the ARIMA and ANN models. Experiment 2 aims to compare the performance of different models between weekdays and weekends. Experiment 3 aims to compare the performance of different models in 28 days (from February 2, 2009, to March 1, 2009). In order to further validate the hybrid model we proposed Experiments 4 and 5 which are studied in this paper. In addition, ENN (Elman neural network) and RBFNN (radial basis function neural network) are utilized in further comparison. Experiment 4 aims at globally testing the proposed hybrid model by using real power load data on Thursday, April 24, 2008, and Tuesday, April 29, 2008, which is selected from New South Wales of Australia randomly. Experiment 5 aims to prove the general applicability of hybrid model; thus, the power load data on Saturday, June 28, 2008, and Monday, June 30, 2008, from Victoria of Australia are chosen for forecasting.

Experiment 1. According to determination of the network structure, $n \times (2n + 1) \times m$ as the structure of the three-layer neural network will achieve better forecasting results. The network structure of the ANN model is 4-9-1 because of its four nodes in the input layer and one node in the output layer.

The iteration time is set to 100, the learning rate is set to 0.01, and the training requirement accuracy is set to 0.0004. To forecast the power load on Monday, February 2, the historical values from the Mondays of the first three weeks, January 12, January 19, and January 26, are chosen. Test results (MAE, RMSE, MAPE, and GRA) are presented in Tables 1 and 2, Figures 5, 6, and 7. Each individual model exhibits its best performance at a special time. For example, Figure 6 shows that BPNN provides the lowest MAPE value at 3:00 among all of the individual models, and CSAWNN yields the highest accuracy forecasting value from 1:00 to 3:00 among all of the individual models, whereas the maximum error is with the BPNN forecasting model on February 2, with a MAPE value of 10.12%. This result is due to the unstable initialization of the ANN. The result of the original data of empirical model decomposition is shown in Figure 3(a). The noise in the data is eliminated by using the empirical model decomposition technique; in this paper, the IMF1 is a high-frequency sequence with small values, which can be regarded as interference factors. As a result, the rest of the IMFs and the remainder term can be constructed as the training input of the CSAWNN model. Table 1 shows the experimental results for Monday of six types of forecasting models. The average values of MAPE for six models on February 2, 1.6% are 1.54%, 1.97%, 1.37%, 1.02%, and 1.94%, respectively; as shown in Table 2,

TABLE 1: Comparison of power load forecasting result by using different methods in Feb. 2.

Time	Actual value (MWh)	BPNN		GABPNN		WNN		CSAWNN		EMD-CSAWNN		ARIMA	
		Forecasting Value	MAPE (%)	Forecasting Value	MAPE (%)	Forecasting Value	MAPE (%)	Forecasting Value	MAPE (%)	Forecasting Value	MAPE (%)	Forecasting Value	MAPE (%)
0:00	8086.20	7267.78	10.12	7471.59	7.60	7828.93	3.18	7708.89	4.67	8033.14	0.66	8146.33	0.74
2:00	7132.07	7381.04	3.49	7193.94	0.87	7303.83	2.41	7150.74	0.26	7013.90	1.66	7298.17	2.33
4:00	7038.50	7023.50	0.21	7010.09	0.40	6470.25	8.07	6938.94	1.41	6938.97	1.41	6899.89	1.97
6:00	8803.29	8561.04	2.75	8611.39	2.18	8159.83	7.31	8612.24	2.17	8668.60	1.53	8619.45	2.09
8:00	10646.56	10778.68	1.24	10416.06	2.16	10890.92	2.30	10474.09	1.62	10707.41	0.57	10692.11	0.43
10:00	11822.68	11877.37	0.46	11811.56	0.09	11975.11	1.29	11880.45	0.49	11787.15	0.30	12002.49	1.52
12:00	12397.22	12329.59	0.55	12453.22	0.45	12328.77	0.55	12432.34	0.28	12326.00	0.57	12597.51	1.62
14:00	12824.82	12638.87	1.45	12918.86	0.73	12708.23	0.91	12929.78	0.82	12599.61	1.76	13091.61	2.08
16:00	13088.14	12810.33	2.12	13065.94	0.17	12903.89	1.41	13171.34	0.64	12830.13	1.97	12949.91	1.06
18:00	12001.48	11857.34	1.20	12090.61	0.74	12148.48	1.22	11500.36	4.18	11987.11	0.12	11776.37	1.88
20:00	10898.97	10827.46	0.66	10896.10	0.03	10967.20	0.63	10679.01	2.02	10778.06	1.11	10705.75	1.77
22:00	9398.37	9516.59	1.26	9665.37	2.84	9415.90	0.19	9706.03	3.27	9451.51	0.57	9446.46	0.51

FIGURE 5: The forecasting results and actual values for February 2.

the MAPE afforded by the hybrid model decreased by 48.22% compared with the maximum average value of MAPE. In addition, it is shown that the value of MAPE offered by the hybrid model is more stable than that of the other proposed models, and the maximum value of MAPE is 2.54%. By comparing the hybrid model with the other models, it is shown that the hybrid model can provide high and stable forecasting accuracy.

Experiment 2. Figure 8 and Table 3 describe the comparison of six models with values on weekdays and weekends on different evaluation metrics. On weekdays, the best performance model is the hybrid model and the value of MAPE is 0.82%; on the contrary, the worst is the ARIMA model, whose value of MAPE is 1.48%. The MAPE offered by the hybrid model is 44.59% lower than that offered by the ARIMA model. On weekends, the value of MAPE offered by the hybrid model

TABLE 2: Comparison of power load forecasting result by using different methods in Feb. 2.

Model	MAPE (%)		
	Maximum	Minimum	Average
BPNN	10.12	0.05	1.6
GABPNN	7.6	0.03	1.54
WNN	8.07	0.12	1.97
CSAWNN	5.19	0.01	1.37
EMD-CSAWNN	2.54	0.03	1.02
ARIMA	8.67	0.03	1.94

FIGURE 6: The BPNN, GABPNN, WNN, CSAWNN, EMD-CSAWNN, and ARIMA forecasting MAPE (%) for February 2.

is 0.68%, which outperforms all other models and is 49.25% lower than that of the worst model, ARIMA. Figure 8 indicates that, except for the criterion RMSE, the weekdays outperform the weekends when utilizing WNN and the criterion GRA, the weekdays outperform the weekends when utilizing the BPNN, GABPNN, WNN, and CSAWNN models, and the other performances on weekends are all better than those on weekdays when utilizing the six models. The values of MAPE offered by the six models on weekends are 1.23%, 1.05%, 1.27%, 1.13%, 0.68%, and 1.34%, which are 5.38%, 10.25%, 0.78%, 8.13%, 17.07%, and 9.46% lower than the corresponding weekday values, respectively. This illustrates that the forecasting results on weekends outperform those of weekdays.

Experiment 3. Figures 9 and 10 illustrate the forecasting results of Experiment 3. In comparison with the BPNN, WNN, GABPNN, CSAWNN, and ARIMA models, the forecasting results offered by the hybrid model are more accurate. The forecasting results are shown in Figure 10, and detailed prediction results are shown in Table 4. The maximum values of MAPE offered by the six models are 1.28%, 1.14%, 1.27%, 1.2%, 0.78%, and 1.44%, respectively. The maximum value of MAPE offered by the ARIMA model is 4.4% over 28 days. Meanwhile, on all days of the test, the average values of MAE, MAPE, and RMSE offered by the hybrid model are all smaller than those of the other models. The average value of MAPE offered by the hybrid model over four weeks is 0.78%,

and the highest decrease is 39.06% compared with the other ANN models. This indicates that the hybrid model is an effective power load forecasting approach. The GRA result is shown in Table 5. In addition, on March 1, the GRA of GABPNN is higher than that of the hybrid model; on the remaining 27 days, the values of GRA offered by the hybrid model are higher than those of the other five models. According to the average value of GRA over the 28 days, the forecasting effects of all six forecasting models are increasing in the following order: ARIMA, BPNN, which is the WNN, CSAWNN, GABPNN, and EMD-CSAWNN, which concludes that the effect of the hybrid forecasting model is the best model among the six forecasting models.

The higher the power load forecasting accuracy, the lower the economic cost, which has actual economic significance [49]. As is illustrated in this case, the ANN optimized by the intelligence algorithm after denoising provides a better power load forecasting effect.

Experiment 4. The power load on Thursday, April 24, 2008, and Tuesday, April 29, 2008, from New South Wales of Australia is used to globally testing the proposed hybrid model. The results are shown as in Tables 6 and 7. To forecast the power load on Thursday, April 24, 2008, the historical values from the Thursdays of the first three weeks, April 3, April 10, and April 17, are chosen, respectively. To forecast the power load on Tuesday, April 29, 2008, the historical values from the Thursdays of the first three weeks, April 8, April 15, and April 22, are chosen, respectively. Test results (AE, MAE, RMSE, and MAPE) are presented in Tables 6 and 7 and part (a) of Figure 11. Table 6 indicates that EMD-CSAWNN has the highest accuracy forecasting results on Thursday, April 24, 2008; the maximum, minimum, and average MAPE values are 1.2355% at 2:00, 1.1836 at 14:00, and 1.2025%, respectively. The second-highest to sixth-highest accurate models are GABPNN, BPNN, RBFNN, CSAWNN, WNN, ENN, and ARIMA with average MAPE values of 1.6436%, 1.7795%, 1.8314%, 2.3373%, 2.4141%, 3.1381%, and 5.5872%, respectively. Table 7 indicates that EMD-CSAWNN still yields the highest accuracy forecasting value from among all of other models mentioned in this paper when forecasting power load on Tuesday, April 29, 2008; the maximum, minimum, and average MAPE values are 1.9844% at 14:00, 1.6033% at 12:00, and 1.7811%, respectively. According to the average MAPE value, CSANN is the second most accurate model, GABPNN is the third most accurate model, RBFNN is the fourth most accurate model, WNN is the fifth most accurate model, BPNN is the sixth most accurate model, ENN is the fifth most accurate model, and ARIMA is the sixth most accurate model with average MAPE values of 2.5827%, 2.8472%, 2.8473%, 3.1717%, 3.2725%, 3.5151%, and 3.7549%, respectively. As shown in Table 6, the average MAPE afforded by the hybrid model decreased by 78.48% compared with the maximum average MAPE value. In Table 7, the average MAPE afforded by the hybrid model decreased by 52.57% compared with the maximum average MAPE value. In addition, it is shown that the value of MAPE offered by the hybrid model is more stable than that of the other proposed models. By comparing

FIGURE 7: The comprehensive evaluation of forecasting models for February 2. (a) The comparison of GRA by using six different models. (b) The comparison of MAE, RMSE, and MAPE by using six different models. (c) The scatterplot of forecasting versus actual levels by using six different models. (d) The evaluation results of six different models. The value in bold is the best value of each evaluation index.

TABLE 3: Comparison of power load forecasting evaluation by using different methods between weekdays and weekends.

Model	Date	Evaluation criterion			
		MAPE (%)	RMSE	MAE	GRA
BPNN	Weekdays	1.30	164.97	118.03	0.8654
	Weekends	1.23	148.35	101.40	0.8600
GABPNN	Weekdays	1.17	154.94	106.05	0.8781
	Weekends	1.05	137.21	88.33	0.8779
WNN	Weekdays	1.28	162.09	114.33	0.8688
	Weekends	1.27	162.83	108.65	0.8581
CSAWNN	Weekdays	1.23	157.05	109.05	0.8737
	Weekends	1.13	138.86	94.96	0.8689
EMD-CSAWNN	Weekdays	0.82	101.56	72.77	0.9087
	Weekends	0.68	87.00	55.19	0.9148
ARIMA	Weekdays	1.48	184.23	128.98	0.8539
	Weekends	1.34	169.06	109.09	0.8548

GABPNN, BPNN, CSAWNN, WNN, ARIMA, ENN, and RBFNN, it is shown that the hybrid EMD-CSAWNN model is better than that of single models.

Experiment 5. The power load on Saturday, June 28, 2008, and Monday, June 30, 2008, from Victoria of Australia is used to further prove that the proposed hybrid model can improve the performance of power load forecasting in different cases. The historical values from the Saturday of the first three weeks, June 7, June 14, and June 21, are chosen in order to forecast the power load on Saturday, June 28, 2008. Moreover, the historical values from the Monday of the first three weeks, June 9, June 16, and June 23, are chosen in order to forecast the power load on Monday, June 30, 2008. The experimental results are presented in Tables 8 and 9 and part (b) of Figure 11. For Saturday (June 28, 2008) data, the average MAPE values for the BPNN, GABPNN, WNN, CSAWNN, ARIMA, ENN, RBFNN, and EMD-CSAWNN models are 3.3224%, 2.8656%, 3.2301%, 2.5248%, 3.7716%, 3.3890%, 3.1754%, and 1.7699%, respectively. The maximum MAPE values for the six models are 3.5467% at 16:00, 3.3061% at 18:00, 3.5751% at 4:00, 2.9527% at 16:00, 4.2174% at 0:00, 3.7591% at 20:00, 3.3889% at 10:00, and 2.0503% at 14:00, respectively, and the minimum MAPE values are 2.9644% at 20:00, 2.2710% at 12:00, 2.7591% at 20:00, 2.1818% at 20:00, 3.4718% at 4:00, 3.1379% at 18:00, 2.8405% at 22:00, and 1.5798% at 10:00, respectively. The differences between the maximum and minimum MAPE values for the models are 0.5823%, 1.0351%, 0.816%, 0.1936%, 0.7456%, 0.6212%, 0.5484%, and 0.4705%. For Monday (June 30, 2008) data, the average MAPE values for the BPNN, GABPNN, WNN, CSAWNN, ARIMA, ENN, RBFNN, and EMD-CSAWNN model are 3.2747%, 2.8415%, 3.0806%, 2.5422%, 3.7656%, 3.4113%, 3.1982%, and 1.7312%, respectively. The maximum MAPE values for the six models are 3.9915% at 22:00, 3.4117% at 2:00, 3.6561% at 6:00, 2.8144% at 0:00, 4.1783% at 22:00, 3.6738% at 8:00, 3.5262% at 0:00, and 2.0361% at 12:00, respectively, and the minimum MAPE values are 3.0113% at 20:00, 2.3376% at 22:00, 2.4491% at 16:00, 2.1398% at 20:00, 3.2795% at 0:00, 3.2235% at 4:00, 2.9466% at 22:00, and 1.4521% at 10:00, respectively. The differences

between the maximum and minimum MAPE values for the models are 0.9802%, 1.0741%, 1.207%, 0.6746%, 0.8988%, 0.4503%, 0.5796%, and 0.584%. Therefore, the proposed hybrid EMD-CSAWNN model is not only the most accurate but also the most stable of the investigated forecasting models.

5. Discussion

In this section, we discuss two important evaluation metrics, convergence speed and degree of certainty [50], offered by the GABPNN and CSAWNN models to determine a more practical forecasting model by considering reality factors such as forecasting stability and calculation time. The results illustrate that the CSAWNN model is more practical than the GABPNN model in forecasting power load. In addition, we propose forecasting availability to analyze and evaluate the quality of power load forecasting.

5.1. Convergence Speed. The computational complexity of evolutionary algorithms and swarm intelligence still remains a challenging issue; here, we use convergence speed as one of the evaluation metrics to examine the forecasting performance of GABPNN and CSAWNN. We obtain the computation time of the best fitness by analyzing the convergence speed of GA and CSA for use in comparative evaluation of optimization algorithm performance. However, the exploration and development are always two competing goals, and the conflict would exist between the convergence speed and forecasting accuracy. We define performance less than 10^{-5} as the convergence criteria.

We take the data from January 12, January 19, and January 26 as an example to illustrate the convergence speed of GA and CSA; Figure 12 shows the results of the comparison of evolutions among GA and CSA with different population sizes. We observed that the fitness values monotonically decrease as the iterations increase. In addition, when the iterations are less than 100, the larger the population size, the faster the convergence speed. We also observed that CSA has better convergence speed than GA. At iteration 20, the

TABLE 4: Comparison of power load forecasting evaluation by using different methods from Feb. 2 to Mar. 1.

Time	BPNN			GABPNN			WNN			CSAWNN			EMD-CSAWNN			ARIMA		
	MAE	MAPE (%)	RMSE	MAE	MAPE (%)	RMSE	MAE	MAPE (%)	RMSE	MAE	MAPE (%)	RMSE	MAE	MAPE (%)	RMSE	MAE	MAPE (%)	RMSE
Feb. 2	334.27	4.22	211.53	304.59	3.85	196.98	278.96	3.55	233.05	280.07	3.55	186.08	190.32	2.41	130.64	344.95	4.40	225.97
Feb. 3	126.81	1.70	126.63	96.89	1.29	125.59	114.76	1.55	116.64	92.33	1.25	127.49	100.06	1.35	78.43	184.62	2.48	128.64
Feb. 4	115.99	1.67	117.88	106.40	1.53	121.43	121.62	1.75	135.78	89.46	1.30	116.67	100.59	1.46	85.54	97.21	1.40	134.84
Feb. 5	62.90	0.93	209.87	55.75	0.82	177.65	73.07	1.09	141.15	83.43	1.26	142.02	63.85	0.96	115.75	88.74	1.32	169.61
Feb. 6	71.29	1.07	205.84	57.27	0.85	165.60	70.96	1.06	139.43	81.86	1.24	185.20	57.25	0.85	98.40	88.15	1.32	184.44
Feb. 7	84.41	1.21	226.10	60.33	0.86	198.48	86.40	1.24	285.05	82.14	1.19	203.72	75.10	1.07	175.72	121.60	1.75	211.26
Feb. 8	130.54	1.71	123.10	101.31	1.33	145.93	142.19	1.85	123.60	128.98	1.70	120.03	65.08	0.87	67.65	262.37	3.47	124.33
Feb. 9	118.07	1.43	150.69	108.27	1.31	146.03	115.14	1.38	169.23	104.84	1.28	134.63	70.86	0.84	97.30	107.14	1.31	180.04
Feb. 10	107.55	1.21	161.91	96.10	1.06	139.39	128.24	1.48	156.85	123.78	1.39	142.14	61.45	0.69	96.35	145.55	1.70	182.63
Feb. 11	93.31	1.01	192.90	111.84	1.17	177.37	95.98	1.03	172.67	118.18	1.29	219.21	53.49	0.58	83.04	118.46	1.30	221.91
Feb. 12	109.95	1.14	226.38	104.93	1.08	194.03	100.88	1.04	209.32	130.04	1.34	221.86	37.33	0.39	98.76	89.20	0.91	236.75
Feb. 13	81.85	0.82	253.47	58.74	0.59	231.68	92.82	0.94	249.81	79.82	0.79	243.81	43.70	0.44	127.79	61.35	0.62	310.47
Feb. 14	64.30	0.62	141.32	52.72	0.51	124.09	73.70	0.71	152.33	69.55	0.66	124.22	35.49	0.35	66.87	58.42	0.56	176.15
Feb. 15	55.99	0.56	99.81	39.82	0.40	93.03	50.17	0.49	102.20	55.17	0.55	120.02	32.92	0.33	57.69	47.36	0.46	118.80
Feb. 16	79.41	0.77	157.56	66.18	0.63	151.21	71.83	0.66	174.28	61.84	0.60	147.61	40.62	0.39	151.27	63.28	0.60	183.95
Feb. 17	82.06	0.77	116.51	59.34	0.55	147.71	82.63	0.73	128.10	56.92	0.54	131.90	46.33	0.41	97.02	54.36	0.50	142.02
Feb. 18	77.09	0.71	134.92	60.71	0.57	123.87	72.46	0.68	123.32	46.97	0.45	129.04	57.85	0.53	91.79	66.87	0.62	148.78
Feb. 19	96.09	0.89	132.50	87.60	0.82	129.83	99.07	0.92	132.46	83.92	0.79	132.63	58.39	0.52	83.16	71.12	0.68	171.76
Feb. 20	96.07	0.88	146.61	90.49	0.84	140.51	93.47	0.87	132.77	68.44	0.66	104.60	87.30	0.77	93.94	52.59	0.49	148.44
Feb. 21	97.27	0.88	186.13	82.81	0.74	185.30	107.84	0.98	192.47	76.45	0.69	179.31	77.07	0.70	48.00	95.04	0.87	263.72
Feb. 22	131.13	1.28	111.39	109.41	1.11	105.24	128.56	1.26	117.27	93.69	0.95	93.12	61.20	0.61	53.84	138.42	1.38	105.10
Feb. 23	103.86	0.98	132.92	74.92	0.72	150.01	93.02	0.92	168.00	89.48	0.86	173.36	62.09	0.62	93.66	113.45	1.17	163.20
Feb. 24	156.24	1.59	122.25	146.41	1.49	148.16	132.83	1.34	139.12	146.53	1.45	117.79	67.67	0.70	94.62	135.60	1.37	150.05
Feb. 25	152.98	1.59	125.02	146.55	1.51	144.41	162.06	1.67	120.09	146.17	1.50	126.54	99.86	1.05	87.54	174.77	1.82	152.51
Feb. 26	177.81	1.94	128.21	153.29	1.66	118.80	183.35	2.00	157.75	188.12	2.06	141.24	69.22	0.76	82.76	188.15	2.05	192.72
Feb. 27	162.42	1.84	145.73	184.00	2.08	110.68	191.75	2.19	162.54	173.50	1.95	122.48	67.46	0.77	110.58	177.14	2.01	159.88
Feb. 28	100.06	1.18	147.69	120.10	1.41	122.11	106.96	1.25	150.10	96.13	1.12	132.03	55.77	0.64	90.29	121.94	1.43	174.16
Mar. 1	102.17	1.27	104.78	90.90	1.13	74.49	85.07	1.06	92.83	92.96	1.16	101.33	58.62	0.73	62.75	184.40	2.27	111.80
Maximum value	334.27	4.22	253.47	304.59	3.85	231.68	278.96	3.55	285.05	280.07	3.55	243.81	190.32	2.41	175.72	344.95	4.40	310.47
Minimum value	55.99	0.56	99.81	39.82	0.40	74.49	50.17	0.49	92.83	46.97	0.45	93.12	32.92	0.33	48.00	47.36	0.46	105.10
Average value	113.28	1.28	160.39	100.99	1.14	150.09	112.71	1.27	162.30	105.03	1.20	152.07	67.75	0.78	97.62	123.29	1.44	180.03

TABLE 5: Comparison of power load forecasting GRA by using different methods from Feb. 2 to Mar. 1.

Time	BPNN GRA	GABPNN GRA	WNN GRA	CSAWN GRA	EMD-CSAWNN GRA	ARIMA GRA
Feb. 2	0.7962	0.8018	0.7582	0.8186	0.8470	0.7553
Feb. 3	0.7587	0.7532	0.7756	0.7626	0.8121	0.7468
Feb. 4	0.7132	0.7077	0.7216	0.7429	0.7611	0.7076
Feb. 5	0.7225	0.7381	0.7672	0.7717	0.8032	0.7305
Feb. 6	0.7660	0.7991	0.8194	0.7800	0.8598	0.8027
Feb. 7	0.8555	0.8680	0.7952	0.8431	0.8839	0.8381
Feb. 8	0.7507	0.7184	0.7562	0.7504	0.8191	0.7541
Feb. 9	0.7622	0.7682	0.7495	0.7840	0.8352	0.7554
Feb. 10	0.7644	0.8003	0.7750	0.7993	0.8376	0.7573
Feb. 11	0.8297	0.8608	0.8479	0.8035	0.9109	0.8032
Feb. 12	0.7949	0.8509	0.8439	0.8074	0.9018	0.8169
Feb. 13	0.8262	0.8606	0.8396	0.8493	0.9050	0.8156
Feb. 14	0.7628	0.8064	0.7800	0.8067	0.8856	0.8058
Feb. 15	0.7392	0.7565	0.7716	0.7674	0.8262	0.7317
Feb. 16	0.8147	0.8298	0.8093	0.8291	0.8520	0.7859
Feb. 17	0.7927	0.7751	0.7656	0.7755	0.7964	0.7577
Feb. 18	0.7908	0.8114	0.7938	0.8043	0.8400	0.7791
Feb. 19	0.8254	0.8199	0.8227	0.8234	0.8756	0.7884
Feb. 20	0.7249	0.7719	0.7641	0.7901	0.7907	0.7340
Feb. 21	0.8555	0.8756	0.8473	0.8676	0.9334	0.8174
Feb. 22	0.7267	0.7600	0.7412	0.7624	0.8356	0.7547
Feb. 23	0.8258	0.8255	0.7912	0.7951	0.8670	0.7872
Feb. 24	0.7511	0.7630	0.7404	0.7642	0.8316	0.7363
Feb. 25	0.7932	0.7916	0.8259	0.8200	0.8331	0.7758
Feb. 26	0.7628	0.7983	0.7316	0.7402	0.8058	0.7063
Feb. 27	0.7440	0.7870	0.7203	0.7615	0.8257	0.7306
Feb. 28	0.8012	0.8331	0.7970	0.8011	0.8666	0.7607
Mar. 1	0.7681	0.8433	0.7974	0.7667	0.8214	0.7775
Maximum value	0.8555	0.8756	0.8479	0.8676	0.9334	0.8381
Minimum value	0.7132	0.7077	0.7203	0.7402	0.7611	0.7063
Average value	0.8673	0.8811	0.8692	0.8756	0.9127	0.8576

convergence of CSAWNN obtained the best speed in a population of 50, and the convergence of GABPNN at the iteration between 60 and 80, at the iteration 60, obtained the best speed.

5.2. Degree of Certainty. The forecasting results of optimization algorithm-NN are also usually different for each experiment because of the probability mechanism of the optimization algorithm. However, in the actual forecasting field, the future values are not known; thus, we cannot obtain which experiment will obtain the best result. Hence, we use these evaluation metrics to determine the randomness.

We defined the degree of certainty as

$$DC(\sigma) = \frac{\sqrt{\sum_{i=1}^m (\sigma_i - \bar{\sigma})^2}}{m}, \quad (13)$$

where m is the number of experiments, σ_i is the value of i th forecasting experiment on σ , and $\bar{\sigma}$ is the average value of all

n experiments. It is clear that a smaller DC can bring a higher degree of certainty.

The scatterplot in Figure 13 indicates the MAPE and GRA distributions of different results of 100 experiments for February 2 by, respectively, using GABPNN and CSAWNN. Although the minimum value of MAPE of GABPNN is smaller than that of CSAWNN and DC(σ) of CSAWNN, both are smaller than those of GABPNN. DC (MAPE) and DC (GRA) of CSAWNN are 0.0014 and 0.00016, and the DC (MAPE) and DC (GRA) of GABPNN are 0.0016 and 0.00019. Thus, CSAWNN is a better forecasting method than GABPNN in the actual forecasting field.

5.3. Forecasting Availability. Forecasting availability can be measured not only by the square sum of forecasting error but also by the mean and mean squared deviation of the forecasting accuracy. In certain practical circumstances, the skewness and kurtosis of the distribution of forecasting accuracy need

TABLE 6: Comparison of power load forecasting result by using different methods on Thursday, Apr. 24, 2008, from New South Wales.

	Time	0:00	2:00	4:00	6:00	8:00	10:00	12:00	14:00	16:00	18:00	20:00	22:00	Average
BPNN	AE	-83.6894	-49.7095	42.2092	70.1483	-1.1418	81.1176	71.0641	-6.3979	-83.6375	70.2015	-74.2667	68.5518	-10.0773
	MAE	139.0489	107.2347	115.6315	153.4157	181.8889	201.3444	189.9489	186.2829	187.2521	163.6832	160.6981	127.2364	161.7255
	MSE	20126.81	11597.8	13753.41	23870.75	33776.23	41545.23	37131.99	34961.75	35301.52	27696.51	25909.11	16227.94	27452.27
	MAPE	1.7927	1.5953	1.6655	1.7118	1.8221	1.9574	1.8205	1.7860	1.8178	1.7268	1.7671	1.5004	1.7795
GABPNN	AE	-70.5662	-61.4181	14.0903	-5.1011	70.2694	-93.49	62.9971	-5.0262	-175.466	9.4920	87.4908	14.0313	3.7326
	MAE	133.1993	118.7066	120.9694	156.3609	168.3905	175.0163	159.27	175.0882	175.4656	142.1779	169.1021	135.8504	149.0696
	MSE	17861.21	14198.39	14907.39	24782.75	28896.06	30696.38	25765.8	30889.71	31099.72	20391.04	28608.41	18670.9	22988.39
	MAPE	1.7178	1.7651	1.7397	1.7443	1.687962	1.7025	1.5259	1.6792	1.6996	1.4971	1.8594	1.6012	1.6436
WNN	AE	-94.9552	11.0611	86.5661	109.4117	129.0671	-120.256	-133.083	-6.5916	-114.111	-121.37	114.9819	-97.3915	1.46853
	MAE	189.6161	163.6107	182.5346	226.7625	249.978	261.0484	274.6263	247.5517	241.1515	223.7553	230.5013	215.3979	219.2263
	MSE	36049.23	26940.16	33456.37	51459.93	62579.29	68421.2	75544.98	61478.9	58389.42	50583.32	53412.08	46583	49476.49
	MAPE	2.4456	2.4343	2.6249	2.5296	2.5013	2.5395	2.6342	2.3707	2.3368	2.3564	2.5336	2.5407	2.4141
CSAWNN	AE	-21.5793	74.9257	-92.6562	-121.433	-242.688	-4.1947	112.5843	-99.8578	108.9015	-117.485	9.2803	18.8441	0.6051
	MAE	187.2812	162.3261	159.9964	230.9195	242.688	234.3061	254.4321	244.3948	207.1397	244.4175	200.3291	213.4906	212.3467
	MSE	35548.74	26522.19	25927.18	53405.7	60342	55413.93	65290.47	60673.03	43149.33	60030.08	40539.89	45950.18	46910.12
	MAPE	2.4171	2.4145	2.3015	2.5755	2.4308	2.2807	2.4378	2.3433	2.0082	2.5742	2.2039	2.5175	2.3373
ARIMA	AE	-215.208	165.0423	78473	8.6388	-561.165	316.2328	-273.573	24.7401	313.4157	212.8736	210.3343	-0.2804	11.1686
	MAE	482.1711	333.4499	400.0869	495.5127	561.1652	628.2508	580.8741	607.6131	624.4892	463.577	453.6873	432.3235	507.6683
	MSE	234075.7	112032	162067.4	257238.9	322221.9	396897.3	341886.4	369861.6	394541.8	216189.5	206839.9	190582.5	268746.7
	MAPE	6.2181	4.9614	5.7564	5.5391	5.6139	6.1119	5.5704	5.8302	6.0641	4.8836	4.9889	5.0989	5.5872
ENN	AE	-134.3503	-116.9724	26.1762	-9.5096	134.8336	-177.9787	121.4220	-9.2200	-334.7105	17.6777	166.4174	26.0920	7.1333
	MAE	254.0135	226.2179	230.6157	298.0677	321.2936	333.8439	304.7279	334.1142	334.7105	272.1785	321.8414	259.5614	284.6262
	MSE	64935.4893	51544.7643	54128.8887	89996.8881	105084.4741	111677.8252	94240.0696	112436.8781	113110.3356	74693.6074	103626.7463	68117.7863	83742.8823
	MAPE	3.2760	3.3639	3.3167	3.3253	3.2205	3.2476	2.9197	3.2042	3.2422	2.8661	3.5391	3.0595	3.1381
RBFNN	AE	-73.9591	-57.3006	1.4359	-115.7463	-11.4324	-103.9494	-69.3536	80.0282	145.0666	-90.0793	-80.4687	-4.8787	-31.7198
	MAE	122.8559	107.0627	125.1804	199.8651	161.9459	204.8784	190.0733	161.0021	145.0666	178.5049	152.1063	180.7679	160.7758
	MSE	15669.7874	11588.6074	15777.1354	40494.5143	26595.7994	43189.1618	37331.3576	26588.7852	21332.3809	31894.7300	23497.2824	33025.1939	27248.7280
	MAPE	1.7706	1.5996	1.4716	2.0627	1.5745	1.9708	1.8099	1.6528	1.5475	2.0890	2.0250	2.4029	1.8314
EMD-CSAWNN	AE	-5.8199	-40.1789	3.2302	-53.9029	0.3157	56.8411	-1.4835	-2.3791	-58.6926	-55.7161	-59.25	55.1392	-9.7616
	MAE	92.57402	83.04634	83.72504	106.387	120.3944	124.3859	128.0547	123.5589	124.0705	116.6259	111.4998	102.3642	109.1557
	MSE	8608.774	6911.941	7025.682	11341.53	14539.97	15513.36	16423.82	15278.06	15453.49	13635.16	12451.61	10503	12183.36
	MAPE	1.1938	1.2355	1.2045	1.1866	1.2037	1.2096	1.2272	1.1836	1.2016	1.2293	1.2265	1.2071	1.2025

TABLE 7: Comparison of power load forecasting result by using different methods on Tuesday, Apr. 29, 2008, from New South Wales.

	Time	0:00	2:00	4:00	6:00	8:00	10:00	12:00	14:00	16:00	18:00	20:00	22:00	Average
BPNN	AE	4.3235	104.427	1.9326	-169.582	7.9721	-163.878	-189.155	-9.9777	-133.868	-23.2861	22.6951	-8.1229	-9.6227
	MAE	217.8733	215.1561	232.6085	296.2496	297.4614	329.2282	349.862	321.6289	310.8799	328.0564	307.5204	253.7871	293.1005
	MSE	47552.31	46537.35	54319.34	88796.61	89366.89	109897.5	122842.7	104957.9	98292.89	108873.5	96080.46	64784.3	88590.6
	MAPE	2.8131	3.2020	3.3602	3.3071	3.0174	3.2299	3.4431	3.2158	3.1271	3.4705	3.4071	3.0137	3.2725
GABPNN	AE	-128.819	116.37	-93.8387	5.9302	-25.0426	-157.356	2.0908	145.7456	-282.984	11.7947	129.7324	-11.5832	-16.1558
	MAE	260.8535	181.5997	191.8484	262.899	271.7663	306.0667	293.922	285.5415	282.9845	279.7753	244.2308	206.0163	254.9086
	MSE	68557.96	35322.65	39010.9	71358.5	76860.8	96621.05	91438.31	82785.86	81937.17	80203.93	60197.01	43169.73	68551.07
	MAPE	3.3665	2.7102	2.7624	2.9323	2.7553	3.0142	2.8718	2.8589	2.8581	2.9660	2.7122	2.4488	2.8472
WNN	AE	-102.792	-89.2578	95.7712	-95.0562	15.7301	-8.0755	-132.3	110.6793	127.7917	-302.974	17.0601	33.8715	23.1926
	MAE	237.6748	198.5173	194.0934	276.8971	362.0218	334.4987	301.0269	303.3078	290.4403	302.9738	315.3741	285.342	284.0601
	MSE	57399.3	40265.36	39263.54	79362.39	131879.1	114268.9	91690.29	94464.47	85736.09	95667.19	101536.4	83146.33	85230.43
	MAPE	3.0684	2.9532	2.8117	3.0867	3.6747	3.2822	2.9631	3.0161	2.9222	3.2051	3.4881	3.3871	3.1717
CSAWNN	AE	2.7198	2.9868	-88.3877	122.0205	-143.045	-12.6708	-13.6472	4.8180	110.5905	-114.276	1.9674	-127.205	0.9651
	MAE	205.4517	170.8708	173.308	216.7274	244.0602	287.2786	252.2365	266.4932	268.5673	259.4214	244.6435	229.1077	231.6409
	MSE	42279.49	29713.52	30554.35	47370.17	60689.6	82774.86	63979.43	72549.97	72983.45	67791.63	60267.6	52777.79	55535.78
	MAPE	2.6528	2.5465	2.4986	2.4191	2.4748	2.8256	2.4824	2.6584	2.6966	2.7463	2.7141	2.7266	2.5827
ARIMA	AE	22.0044	278.4617	-1.9584	-222.701	-204.82	-201.995	-411.791	-53.4355	193.9193	-232.404	-15.6347	3.8278	-48.5181
	MAE	276.2362	278.4617	255.0419	411.837	374.2884	384.3065	411.7913	355.8697	329.2014	404.3898	374.5698	299.1434	336.7285
	MSE	78244.45	78470.78	65671.56	170074.2	144274.5	151190.6	173159.5	133331.2	112870.9	165704.4	141249.1	90175.37	118788.7
	MAPE	3.5681	4.1448	3.6876	4.5914	3.8021	3.7762	4.0691	3.5361	3.2986	4.2747	4.1591	3.5501	3.7549
ENN	AE	-122.3804	-106.1050	112.1774	-124.5511	11.2302	-5.7063	-154.8530	138.7430	150.4820	-334.3572	13.6915	25.3581	23.7370
	MAE	266.7030	226.0328	225.6456	309.9669	380.8511	365.7942	342.4249	342.0588	332.0910	334.3572	337.4444	308.6425	314.8147
	MSE	71574.4601	51519.8987	51615.5316	97406.4037	145424.6816	135137.5738	117847.8733	118529.0844	111042.3847	113745.3418	115039.8651	96156.4770	102413.9259
	MAPE	3.4432	3.3631	3.2647	3.4560	3.8651	3.5920	3.3700	3.4068	3.3416	3.5383	3.7352	3.6650	3.5151
RBFNN	AE	-128.8194	116.3700	-93.8387	5.9302	-25.0426	-157.3556	2.0909	145.7456	-282.9845	11.7948	129.7324	-11.5832	-16.1558
	MAE	260.8535	181.5997	191.8484	262.8990	271.7663	306.0667	293.9220	285.5415	282.9845	279.7753	244.2308	206.0163	254.9086
	MSE	68557.9649	35322.6478	39010.8992	71358.4965	76860.7961	96621.0544	91438.3143	82785.8632	81937.1664	80203.9338	60197.0099	43169.7279	68551.0659
	MAPE	3.3665	2.7103	2.7625	2.9324	2.7553	3.0142	2.8718	2.8589	2.8582	2.9660	2.7123	2.4489	2.8473
EMD-CSAWNN	AE	71.8585	19.0263	119.4944	-0.2347	-85.8361	21.7152	162.9778	198.7374	12.5729	0.7221	7.0831	11.6529	13.8229
	MAE	135.0333	124.2513	119.4944	159.9286	166.286	188.3798	162.9778	198.7374	191.4925	164.075	155.0245	145.8072	159.2127
	MSE	18544.32	15861.56	14935.85	25684.91	28077.06	36387.53	26760.25	39816.23	38064.54	28373.25	24954.2	21683.46	26609.38
	MAPE	1.7439	1.8477	1.7241	1.7831	1.6889	1.8577	1.6033	1.9844	1.9379	1.7341	1.7161	1.7319	1.7811

TABLE 8: Comparison of power load forecasting result by using different methods on Saturday, Jun. 28, 2008, from Victoria.

	Time	0:00	2:00	4:00	6:00	8:00	10:00	12:00	14:00	16:00	18:00	20:00	22:00	Average
BPNN	AE	-74.2069	88.5026	164.3428	-94.2384	-108.445	99.3887	-131.822	-97.1293	132.6263	-9.9181	-199.556	95.9906	-25.4772
	MAE	161.8614	176.3894	164.3428	175.3241	219.8255	225.0625	233.3815	229.9635	234.7046	233.2327	199.5555	182.4864	206.2306
	MSE	26380.04	31503.46	27247.69	31227.59	48517.87	51693.03	54905.29	54093.61	55631.95	54814.4	39922.9	33457.23	43708.18
	MAPE	2.9997	3.3342	3.4049	3.1834	3.3696	3.3340	3.5174	3.4406	3.5467	3.1652	2.9644	3.0498	3.3224
GABPNN	AE	95.3661	152.9973	70.1585	95.8643	21.4256	-10.3011	65.8767	6.8887	-16.0091	-14.2224	97.4645	19.2111	3.9264
	MAE	163.6398	152.9973	142.3091	180.6853	192.6446	181.9683	151.09	198.873	168.6475	242.7444	202.9146	183.0895	178.1422
	MSE	27233.94	23592.27	20427.45	33187.61	37879.35	34166.35	23242.55	40431.09	28919.45	60044.79	41793.54	34130.68	33502.97
	MAPE	3.0324	2.8936	2.9494	3.2736	2.9262	2.7029	2.2710	3.0080	2.5461	3.3061	3.0207	3.0576	2.8656
WNN	AE	175.8896	27.8588	-7.9285	86.3077	139.9775	201.231	90.7231	39.9104	18.8402	-108.905	-114.363	193.1549	4.4674
	MAE	175.8896	156.0152	172.6755	164.069	207.6373	201.231	193.4483	205.2855	183.8711	259.0394	186.1753	193.1549	200.6168
	MSE	31845.68	25360.07	30586.03	27917.8	45875.7	42312.96	38650.67	43776.7	34700.63	69347.15	35949.54	38952.51	42677.08
	MAPE	3.2604	2.9507	3.5751	2.9766	3.1492	2.9988	2.9427	3.1425	2.7626	3.5188	2.7591	3.2385	3.2301
CSAWNN	AE	-44.652	-131.152	-63.0165	11.4112	-9.5339	-0.7664	171.5844	193.7814	79337	106.7022	3.6645	-69.7819	12.6984
	MAE	124.0692	131.1523	114.0833	146.3165	167.5085	165.3564	171.5844	193.7814	195.2323	191.7276	146.8918	141.5059	156.8164
	MSE	15804.77	17589.3	13292.63	21642.06	29014.79	27346.81	30261.31	37723.03	38246.53	36979.81	21623.75	20248.95	25425.16
	MAPE	2.2995	2.4781	2.3604	2.6579	2.5319	2.4803	2.5786	2.9203	2.9527	2.6113	2.1818	2.3631	2.5248
ARIMA	AE	18.5613	124.0827	-14.7831	111.8472	-20.6124	-19.7243	120.3048	26.1011	-146.313	-172.198	23.3302	145.1471	18.9775
	MAE	227.3289	204.722	167.4229	212.6136	230.4365	247.6076	230.858	253.9037	267.5722	296.6621	255.3748	241.6215	233.6259
	MSE	52394.21	43176.64	28355.68	45620.29	53698.66	62570.82	54191.74	65290.6	72666.23	90860.47	67238.24	59345.33	56855.39
	MAPE	4.2174	3.8741	3.4718	3.8504	3.5598	3.7094	3.4799	3.8433	4.0557	4.0217	3.7627	4.0433	3.7716
ENN	AE	-98.995	-95.8081	171.172	6.0116	90.0902	-141.101	100.5493	4.7625	-229.624	18.1665	126.2839	11.7423	6.5262
	MAE	189.6312	190.0733	171.6852	196.7854	231.2569	235.0732	210.1064	229.5182	229.6243	230.8097	254.2102	198.2688	210.274
	MSE	36109.8	36258.98	29924.18	39256.18	56148.35	56021.74	44222.47	53380.62	52793.31	53676.67	64753.52	39571.84	45444.62
	MAPE	3.5163	3.5974	3.5538	3.5618	3.4650	3.4901	3.1873	3.4500	3.4851	3.1379	3.7591	3.3164	3.3890
RBFNN	AE	-98.2027	-73.2415	57.3594	77.1316	9.4619	96.7952	101.7499	-14.9842	-97.2306	97.9996	-110.216	86.7962	-11.4032
	MAE	172.1148	156.3662	146.8716	171.0673	214.0821	228.8974	212.5963	212.2372	213.3772	228.0278	213.4688	169.8724	196.9359
	MSE	30159.71	24592.22	21954	29579.24	47567.12	53850.57	45459.14	45699.94	45988.64	52566.64	45607.02	28877.88	39869.92
	MAPE	3.1912	2.9543	3.0386	3.0942	3.2266	3.3889	3.2246	3.1832	3.2214	3.1122	3.1605	2.8405	3.1754
EMD-CSAWNN	AE	35.0621	51.5938	41.9313	-56.3883	-10.8655	51.1997	-42.3959	84.1310	70.1839	82.8233	46.4874	-55.1894	6.6501
	MAE	91.3676	100.3773	81.2863	92.1573	108.8744	104.7747	119.9606	137.012	110.6269	141.76	109.7464	115.5855	109.712
	MSE	8629.51	10214.74	6858.997	8885.95	12543.16	11063.31	14958.06	19196.88	12798.02	20368.17	12301.46	13873.76	12612.17
	MAPE	1.6951	1.8968	1.6898	1.6576	1.6298	1.5798	1.8118	2.0503	1.6639	1.9325	1.6329	1.9192	1.7699

TABLE 9: Comparison of power load forecasting result by using different methods on Monday, Jun. 30, 2008, from Victoria.

	Time	0:00	2:00	4:00	6:00	8:00	10:00	12:00	14:00	16:00	18:00	20:00	22:00	Average
BPNN	AE	-97.1358	-5.79918	-77.632	-69.5865	-5.12235	181.7938	-108.862	172.1967	-11.7116	-112.91	-1.05112	-5.29961	7.270652
	MAE	180.8076	174.7874	160.6262	161.5628	166.0493	181.7938	187.9272	172.1967	176.0733	215.9977	187.979	197.6079	181.9883
	MSE	32946.72	30612.98	26035.71	26290.49	27633.14	33390.49	35789.18	29752.65	31224.95	46849.69	35447.84	39567.68	33681.6
	MAPE	3.2431	3.2773	3.3784	3.3739	3.1979	3.2166	3.3433	3.0728	3.0901	3.2467	3.0113	3.9915	3.2747
GABPNN	AE	87.0447	182.023	62.5079	-12.5589	-92.6525	-84.4608	-25.4557	19.48	-22.7953	76.9831	78.4895	-6.6962	4.1017
	MAE	148.3886	182.023	116.5217	112.0699	155.8314	181.3435	153.1462	162.2208	182.3206	182.7003	175.2353	132.1649	158.2286
	MSE	23338.89	33529.04	14089.3	12900.14	24927.85	33303.2	24526.58	26867.37	34101.29	35242.19	31203.34	17935.79	26253.68
	MAPE	2.6633	3.4117	2.4520	2.3381	3.005	3.2113	2.7189	2.8955	3.1883	2.7492	2.8096	2.3376	2.8415
WNN	AE	-3.4921	-74.9511	-134.269	-80.2326	-142.363	64.7736	-111.042	-89.0593	139.566	14.1565	-82.5293	66.4498	-4.1007
	MAE	153.3954	185.6073	134.2689	174.9947	142.3635	174.6803	186.5582	193.4015	139.566	212.2396	156.4929	167.1148	171.6629
	MSE	23561.14	35229.8	18364.93	31218.27	21459.47	33650.21	37245.82	38184.73	19503.57	47310.2	24810.93	28778.48	31298.91
	MAPE	2.7532	3.4749	2.8191	3.6561	2.7458	3.0828	3.3176	3.4628	2.4491	3.1823	2.5057	2.9566	3.0806
CSAWNN	AE	-5.0573	-3.8213	1.3263	41.3898	54.9301	-66.0719	14.6333	-3.6448	149.7019	80.7116	3.7387	-73.6169	8.0382
	MAE	156.8892	136.6022	125.5879	113.7244	116.9543	143.8786	140.1588	139.9815	149.7019	159.8907	133.4934	137.4735	141.3812
	MSE	24786.49	18999.83	15803.74	13261.64	13725.91	20966.75	20021.99	19790.28	22684.1	25822.94	17849.43	18934.4	20481.5
	MAPE	2.8144	2.5621	2.6401	2.3753	2.2519	2.5478	2.5001	2.5018	2.6261	2.4020	2.1398	2.4302	2.5422
ARIMA	AE	14.7023	24.8103	26.0758	96.5552	-103.598	67.3243	1.5328	-12.8999	229.6626	254.5464	-133.048	125.5915	-0.7485
	MAE	183.057	217.205	158.1086	187.75	186.6591	198.3604	205.3784	213.5527	229.6626	254.5464	240.3672	236.3162	209.7854
	MSE	34965.65	47841.28	26107.02	35347.8	35329.16	41301.58	42893.69	46719.97	54654.13	65818.94	58199.06	55984.16	45718.98
	MAPE	3.2795	4.0777	3.3209	3.9201	3.5982	3.5138	3.6743	3.8162	4.0242	3.8204	3.8526	4.1783	3.7656
ENN	AE	-88.6146	-85.0312	75.6176	-69.7223	4.5320	-0.8129	-87.546	82.3113	88.4143	-227.985	3.5052	12.0972	8.3585
	MAE	186.9891	175.8838	153.515	161.1809	190.7898	196.0601	185.4341	186.5996	187.2131	227.9848	223.304	199.3213	189.5443
	MSE	35060.02	31090.34	23853.32	26154.44	36507.3	38584.26	34554.06	35020.38	35263.23	52336.47	50161.92	39941.99	36505.16
	MAPE	3.3574	3.2973	3.2235	3.3669	3.6738	3.4690	3.3024	3.3301	3.2811	3.4287	3.5763	3.5237	3.4113
RBFNN	AE	-98.586	97.2085	-72.7937	0.0161	-10.8099	-94.714	-1.0184	92.2613	-182.302	5.0740	100.423	-5.2195	-12.4652
	MAE	196.4346	166.1881	149.5233	155.7541	163.1654	186.8753	180.256	179.795	182.3024	217.8852	194.234	166.6086	177.8178
	MSE	38661.36	28328.97	22697.24	24518.37	27001.22	35355.86	32968.16	32671.75	33413.99	47850.86	37890.5	27884.44	32243.32
	MAPE	3.5262	3.1117	3.1447	3.2520	3.1402	3.3037	3.2137	3.2056	3.2051	3.2732	3.1130	2.9466	3.1982
EMD-CSAWNN	AE	-4.1652	-40.9803	-54.073	-28.5539	-49.4364	-46.9202	-1.3708	-51.2203	-61.0243	58.5634	44.2871	55.8282	6.1509
	MAE	99.0617	81.542	83.7323	70.3801	80.9749	82.0208	114.0354	111.8617	115.3834	129.6408	110.32	105.1976	96.6039
	MSE	10306.84	6696.25	7299.67	5046.59	6865.14	6815.57	13126.18	12711.91	13468.79	17077.42	12871.21	11278.86	9834.31
	MAPE	1.7771	1.5295	1.7617	1.4701	1.5594	1.4521	2.0361	2.0032	2.0227	1.9479	1.7703	1.8607	1.7312

FIGURE 8: The BPNN, GABPNN, WNN, CSAWNN, EMD-CSAWNN, and ARIMA forecasting results between weekdays and weekends.

further consideration; on that basis, this section will give a general discrete form of forecasting availability [51].

Definition 10. Let

$$e_{it} = \begin{cases} -1, & \frac{(x_t - x_{it})}{x_t} > 1 \\ \frac{(x_t - x_{it})}{x_t}, & -1 \leq \frac{(x_t - x_{it})}{x_t} < 1 \\ 1, & \frac{(x_t - x_{it})}{x_t} > 1. \end{cases} \quad (14)$$

e_{it} denotes the relative forecasting error of i th forecasting method at time t , $i = 1, 2, \dots, m$, $t = 1, 2, \dots, N$. The matrix $E = (e_{it})_{m \times N}$ is called the relative error matrix of the forecasting model.

Definition 11. $A_{it} = 1 - |e_{it}|$ is called the forecasting accuracy of i th forecasting method at time t , $i = 1, 2, \dots, m$, and $t = 1, 2, \dots, N$.

Definition 12. $m_i^k = \sum_{t=1}^N Q_t A_{it}^k$ is called k th-order forecasting availability unit of i th forecasting method, k is a positive integer, $i = 1, 2, \dots, m$, $\{Q_t, t = 1, 2, \dots, N\}$ is the discrete

FIGURE 9: The forecasting results and actual values from February 2 to March 1.

FIGURE 10: The comprehensive evaluation of forecasting models from February 2 to March 1. (a) The radar diagram of MAPE by using six different models. (b) Comparison of forecasting MAPE by using the EMD-CSAWNN and ARIMA models. The red line is the polynomial regression line. (c) The comparison of GRA and MAPE by using six different models. (d) The comparison of MAE and RMSE by using six different models. (e) The scatterplot of forecasting versus actual levels by using six different models. The solid line represents the perfect fit: that is, $y = x$. (f) Evaluation results of six different models. The red font is the best value of every evaluation index; the green font is the worst. (g) The comparison of the box plot by using six different models. The whiskers in the box plot indicate the primary range for the data, in which the lowest data are 1.5 times the interquartile range of the lower quartile and the highest data are 1.5 times the interquartile range of the upper quartile. The outliers, which are not included between the whiskers, are represented by the red crosshair.

FIGURE 11: The comprehensive evaluation of forecasting models in Experiments 4 and 5. (a) Comparison of forecasting results by eight models on Thursday, April 24, 2008, and Tuesday, April 29, 2008, from New South Wales of Australia. (b) Comparison of forecasting results by eight models on Saturday, June 28, 2008, and Monday, June 30, 2008, from Victoria of Australia.

FIGURE 12: A convergence speed comparison of the fitness values between GA and CSA with different population sizes.

FIGURE 13: The DC (MAPE) and DC (GRA) of 100 experiments by comparison of GABPNN and CSAWNN.

probability distribution of m types of methods at time t , and $\sum_{t=1}^N Q_t = 1$, $Q_t > 0$.

Especially if the priori information of the discrete probability distribution of m types of methods is unknown, we define $Q_t = 1/N$, $t = 1, 2, \dots, N$.

Definition 13. m_i^k is called the k -order forecasting availability unit of i th forecasting method, and H is a continuous function of a certain k unit. $H(m_i^1, m_i^2, \dots, m_i^k)$ is called the k -order forecasting availability of i th forecasting method.

Definition 14. When $H(x) = x$ is a continuous function of one variable, $H(m_i^1) = m_i^1$ is the 1-order forecasting availability of i th forecasting method. When $H(x, y) = x(1 - \sqrt{y - x^2})$

is a continuous function of two variables, $H(m_i^1, m_i^2) = m_i^1(1 - \sqrt{m_i^2 - (m_i^1)^2})$ is the 2-order forecasting availability of i th forecasting method.

Especially if the first decimal of $H(m_i^1, m_i^2, \dots, m_i^k)$ is the same, we define $H(m_i^1, m_i^2, \dots, m_i^k) = \{10H(m_i^1, m_i^2, \dots, m_i^k)\}$, where $\{\cdot\}$ denotes the fractional part.

Definition 14 illustrates that the 1st-order forecasting availability is the expectation forecasting accuracy sequence. The 2nd-order forecasting availability is the difference between the expectation and standard deviation of the forecasting accuracy sequence. We use the forecasting availability to evaluate the power load forecasting results in this paper. Through Figure 14, we obtain that the 1st-order and 2nd-order

FIGURE 14: The forecasting availability of BPNN, GABPNN, WNN, CSAWNN, EMD-CSAWNN, and ARIMA.

forecasting availability offered by the hybrid model are 0.9222 and 0.8366, respectively, which outperform those of the others; this evaluation result corresponds to the previous evaluation criterion. Thus, the hybrid model is a more valid model than the others.

6. Conclusion

The one-day-ahead power load forecasting is an extremely important problem in power load planning, secure operation, and energy expenditure economy. Assessment of the power load as accurately and quickly as possible is the primary objective in power load forecasting. However, power load is affected by various uncertain factors such as climate change and the social environment, which may lead to difficulty in obtaining accurate power load forecasts. The accuracy of traditional individual forecasting methods, which lack denoising, is not satisfactory for power load forecasting. Herein, a hybrid EMD-CSAWNN model for short-term power load forecasting is developed. The empirical model decomposition technique is applied to reduce the high-frequency items. On the basis that WNN can handle the data with nonlinear features, the ensemble forecasting method is adopted to overcome the uncertainty of the outcomes that can be attributed to the randomness of the initialization of the single WNN. Moreover, we use the CSA to optimize the parameter in the ensemble forecasting model. Experimental studies of power load forecasting in NSW demonstrate that the hybrid model has higher precision than conventional forecasting models. The proposed EMD-CSAWNN model can provide efficient

computation and satisfactory forecasting accuracy for this type of data. Therefore, the developed hybrid approach is suggested for broad application in power load forecasts or even other fields such as wind speed and traffic flow forecasts.

Abbreviations

BPNN:	Back Propagation Neural Network
WNN:	Wavelet Neural Network
GA:	Genetic Algorithm
CSA:	Cuckoo Search Algorithm Back Propagation Neural
GABPNN:	Network Optimized by Genetic Algorithm
CSAWNN:	Wavelet Neural Network Optimized by Cuckoo Search Algorithm
AR:	Autoregressive model
MA:	Moving average model
ARIMA:	Autoregressive integrated moving average model
IMF:	Intrinsic mode function
ANN:	Artificial Neural Network
PSO:	Particle swarm optimization algorithm
ACO:	Ant colony optimization algorithm
SAO:	Simulated annealing optimization algorithm
MAE:	Mean absolute error
RMSE:	Root mean square error
MAPE:	Mean absolute percentage error
GRA:	Grey relational analysis
q :	The number of sample data points used to build the NN model

p :	The number of data points to be forecasted in the NN model
ω :	The connection weights between the neurons of the input layer, hidden layer, and output layer, with values belonging to $[-1, 1]$
$f(\cdot)$:	The excitation function of the hidden layer
η :	The learning rate of the NN, which is used to adjust the weights and thresholds of the NN
$\text{iter}_{\max}$:	The maximum number of iterations
P :	The population size of the initial population space
b :	A random number belonging to $[0, 1]$
r :	A random number belonging to $[0, 1]$
$w_{\max}^{\text{iter}}, w_{\min}^{\text{iter}}$:	The higher and lower bounds of the value of the gene w_{ij}^{iter}
$G_{\max}$:	The maximum number of generations
P_{α} :	The possibility of finding an exotic egg by the nest master
X_{*}^{iter} :	The location of the optimum nest in generation iter
$\chi_j^{\text{iter}}, \chi_k^{\text{iter}}$:	Two random numbers in generation iter.

Competing Interests

The authors declare that they have no competing interests.

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