J Electr Eng Technol.2017; 12(6): 2166-2176
http://doi.org/10.5370/JEET.2017.12.6.2166

ISSN(Print) 1975-0102
ISSN(Online) 2093-7423

Forecasting Day-ahead Electricity Price Using a Hybrid Improved Approach

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Abstract – Electricity price prediction plays a crucial part in making the schedule and managing the risk to the competitive electricity market participants. However, it is a difficult and challenging task owing to the characteristics of the nonlinearity, non-stationarity and uncertainty of the price series. This study proposes a hybrid improved strategy which incorporates data preprocessor components and a forecasting engine component to enhance the forecasting accuracy of the electricity price. In the developed forecasting procedure, the Seasonal Adjustment (SA) method and the Ensemble Empirical Mode Decomposition (EEMD) technique are synthesized as the data preprocessing component; the Coupled Simulated Annealing (CSA) optimization method and the Least Square Support Vector Regression (LSSVR) algorithm construct the prediction engine. The proposed hybrid approach is verified with electricity price data sampled from the power market of New South Wales in Australia. The simulation outcome manifests that the proposed hybrid approach obtains the observable improvement in the forecasting accuracy compared with other approaches, which suggests that the proposed combinational approach occupies preferable predication ability and enough precision.

Keywords: Seasonal adjustment, Ensemble empirical mode decomposition, Least square support vector machine, Electricity price; Forecasting

1. Introduction

The electricity price in a deregulated power market has turned into the central issue of all activities to market participants (regulatory agencies, producers and consumers, etc.) [1]; accordingly, the prediction of electricity price has also become a significant operation [2-4]. Accurately estimating electricity price can help power suppliers determine their bidding strategies and manage their risk, and consumers minimize their costs and maximize their utilities. However, the price prediction is a difficult and challenging task because electricity price sequences exhibits the patterns more complex than load series (volatile, non-stationary, and outlier prone in deregulated markets, etc.[5]) owing to the characteristics of the liberalized power market (non-storability of electricity, inelasticity of the short-term demand).

In the last decades, the researchers have made endeavors to seek various approaches for good forecasting performance, such as time series technique and soft computing methods. Time series-based models produce electricity price predictions primarily through mining and extracting intrinsic patterns from historical data. The time series models includes stationary time-series models such as Auto-Regressive Integrated Moving Average (ARIMA) [6, 7] and fractional ARFIMA models [8], and non-stationary time-series models like Generalized Auto-Regressive Conditional Heteroskedastic (GARCH)[9]. The time-sequence approaches can achieve satisfactory predication performance and possess good practicability when the pending data hold the features of linearity and stationarity. However, in most situations, electricity price series vary rapidly, thus depressing the prediction accuracies of the time-series techniques. By contrast, the soft computing approaches possess good extrapolation abilities, particularly in tackling nonlinear problems. Such methods mainly focus on the artificial neural networks (ANN) including back propagation neural network [10, 11], deep neural network [12], fuzzy neural network [13, 14], adaptive wavelet neural network [15], recurrent neural network [16] and dynamic choice artificial neural network [17]. Although artificial neural networks are advantageous over time-series techniques to approximate complex nonlinear functions, weak data dependency, and fault tolerance, their generalization abilities are not guaranteed. A well-trained model may lead to poor prediction performance for new observations. In addition, neural networks occasionally have a problem with local minima or over-fitting. Neural networks are also sensitive to parameter selection and are time-consuming. Support Vector Machine (SVM) [18, 19] is another type of soft computing methods, which is derived on the basis of a statistical learning theory and the structural risk minimization principle.

This study develops a hybrid model for the electricity price forecasting which is composed of data preprocessors and a forecasting engine to enhance the forecast accuracy.

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Received: January 28, 2016; Accepted: August 9, 2017

In this proposed model, the least squares SVM (LSSVM) model is employed as the predictor, which considers equality type constraints instead of inequalities from the classical SVM approach, thereby explaining and solving linear problems in higher speed. Moreover, to obtain better forecasting results with the LSSVM, it is very necessary to optimize the parameters of LSSVM. Heuristic random search algorithms are a fashionable class of stochastic evolutionary algorithms which make use of a large amount of possible solutions in their each iteration to find global or close to global optimum solutions in searching spaces. This study presents a new modified simulated annealing Algorithm technique to handle this problem. Also, to preprocess the input of LSSVM and get better the forecast accuracy, the seasonal adjustment (SA) method and Ensemble Empirical Model Decomposition (EEMD) technique are utilized to denoise the electricity price signal. Thus, the contributions of this study to the electricity price forecasting area can be summarized as follows:

(1) A new forecasting model in which the data preprocessors is composed of seasonal adjustment (SA) method, Ensemble Empirical Model Decomposition (EEMD) and the forecasting engine includes Coupled Simulated Annealing (CSA) and the least square SVM (LSSVM), is proposed to achieve accurate forecast of electricity price. The hybrid approach is put forward not only to remedy the shortcomings of the classical statistical models and artificial intelligence algorithms but also to tackle the characteristic of the electricity price series (high frequency, daily and high volatility, etc.).

(2) The LSSVM with inappropriate parameters may lead to over-fitting or under-fitting in training phase of modeling. Thus, the parameters of LSSVM model should be optimized for the accurate wind speed prediction. The study employs a new modified version of simulated annealing Algorithm technique, namely coupled simulated annealing, to determine the model parameters without much slowing down the convergence speed.

(3) Considering the price series present the periodicity, the season adjustment method, as an effective periodicity removal technique, is adopted to identify and eliminate the characters from the original time series.

(4) Due to the electricity price often affected by some random factors, the EEMD, an intrinsic and adaptive method, is used to remove the stochastic volatility and help extract the meaningful components from the price series.

(5) To sum up, the SA method eliminates the obvious periodicity of the electric price series, the EEMD extracts true information from the electric price series, and the LSSVM in which the parameters are optimized by CSA algorithm is used as the predictor to provide the forecasts of electricity price.

The outlines of the rest paper are organized as follows: Section 2 describes the proposed approaches of electricity price. Section 3 provides the numerical results of a real-life case study, the criterions for the forecasting performance and comparisons and analysis on the evaluation of forecast. Finally, the conclusions of this study are made in Section 4.

2. Methodology

This study adopts a methodology for the electricity price forecasting which contains periodicity removal, decomposition, de-noising and final prediction. To serve this purpose, a hybrid method combines the season adjustment method, the EEMD algorithm with the LSSVM optimized by CSA algorithm. This study will reveal the advantages of the aforementioned individual models in forecasting electricity price. Before verifying the effectiveness of the proposed hybrid approach, the SA method, EEMD technique, CSA algorithm and LSSVM model, are briefly introduced; then the proposed approach are illustrated.

2.1 Season Adjustment (SA)

The seasonal component actually exists in the electricity price series. The multiplicative form of Seasonal exponential adjustment is described as follows:

Given a price series $x_1, x_2, \cdots, x_T \left(T = ml\right)$, it can be rewritten as $x_{11}, x_{12}, \cdots, x_{1l}, \cdots, x_{m1}, x_{m2}, \cdots, x_{ml}$ in turn. We can get a matrix $m \times l$, parameter m and parameter l denote the amount of rows and columns, respectively:

$$X = \begin{pmatrix} \boldsymbol{x}_1 \\ \boldsymbol{x}_2 \\ \vdots \\ \boldsymbol{x}_K \end{pmatrix} = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1l} \\ x_{21} & x_{22} & \cdots & x_{2l} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{ml} \end{pmatrix} \tag{1}$$

Then the mean value of each row of this matrix could be computed in terms of the Eq. (2)

$$\bar{x}_k = \left(x_{k1} + x_{k2} + \ldots + x_{kl}\right) / l \qquad \left(k = 1, 2, \ldots, m\right) \tag{2}$$

The mean vector can be expressed as

$$\bar{X} = \left(\bar{x}_1, \bar{x}_2, \cdots, \bar{x}_m\right)^T . \tag{3}$$

The result comes out as follow:

$$I_{ks} = \frac{x_{ks}}{\bar{x}_k} \quad \left(k = 1, 2, \ldots, m; \qquad s = 1, 2, \ldots, l\right). \tag{4}$$

Its matrix can be expressed as

$$I_{ks} = \begin{pmatrix} i_{11} & i_{12} & \cdots & i_{1l} \\ i_{21} & i_{22} & \cdots & i_{2l} \\ \vdots & \vdots & \ddots & \vdots \\ i_{m1} & i_{m2} & \cdots & i_{ml} \end{pmatrix}. \tag{5}$$

Then the average value of I_{ks} at the same time point in each periodicity could be computed according to the Eq. (6),

$$I_j = \frac{I_{1j} + I_{2j} + \ldots + I_{mj}}{m} \quad (j = 1, 2, \ldots, l). \tag{6}$$

The I_j is considered as seasonal index number. Due to

$$\sum_{j=1}^{l} I_j = \frac{1}{m}\sum_{k=1}^{m}\sum_{s=1}^{l} I_{ks} = \frac{1}{m}\sum_{k=1}^{m}\frac{\sum_{s=1}^{l} x_{ks}}{\overline{x}_k} = \frac{1}{m}\sum_{k=1}^{m} l = l, \tag{7}$$

Seasonal index number is fit for normalized condition. Based on the aforementioned calculation, the electricity price series which is been eliminated the seasonality can be obtained

$$y_{ks} = \frac{x_{ks}}{I_s} \quad (k = 1, 2, \ldots, m; \quad s = 1, 2, \ldots, l). \tag{8}$$

2.2 Ensemble Empirical Model Decomposition (EEMD)

In practical application of Empirical Model Decomposition (EMD)[20], the Intrinsic Mode Functions (IMFs) obtained by the EMD algorithm contain oscillations of dramatically disparate scales, or a component of a similar scale residing in different IMFs. In view of the shortcoming of the EMD algorithm, The EEMD algorithm was proposed in Ref.[21] through redefining the IMF as the average value of an ensemble of several trials. The EEMD basically assumes that the observed data are composed of true signal sequence and noise interference. Each trial of the EEMD algorithm works upon the combination of the observed series data and a white noise of finite amplitude. By means of ensemble method, the average of the results from the several trials with different noise levels is closer to the true signal sequence.

Given an price series $X_{orin}(t)(t = 1, 2, \cdots, T)$, its decomposed subseries IMFs can be obtained by the sifting procedure below (also shown in left column of Fig.1).

(1) add Gaussian white noises $\varepsilon_{\mathrm{ne}}$ into the sequences $X_{orin}(t)$, then fuse into the series $X(t)$;

(2) let $r(t) = X(t)$;

(3) if $r(t)$ is a monotonic function or the given threshold is higher than the difference between its amplitude, the algorithm stops; otherwise, go to step(4);

(4) let $h(t) = r(t)$;

(5) if $h(t)$ is an IMF, then go to step (8);

(6) compute the low frequency component of $h(t)$, which is assigned to $m(t)$;

(7) let $h(t) = h(t) - m(t)$, and go to step (5);

(8) let $C(t) = h(t)$;

(9) let $r(t) = r(t) - C(t)$, and go to step (3).

(10) Repeat the aforementioned operation(1-9) with different white noise levels each iteration;

(11) Acquire the average value of the ensemble of all operations as the corresponding IMFs.

In the procedure, the threshold in step (3) should be given prior to the sifting process since the IMF series must retain enough physical sense of amplitude and frequency modulations. The threshold is a standard deviation which is calculated based on the two consecutive sifting results. The standard deviation, S_d is defined as follows

$$S_d = \sum_{t=0}^{T} \frac{\left| h_{1(k-1)}(t) - h_{1k}(t) \right|^2}{h_{1k}^2(t)} \tag{9}$$

The intensity of the additive white noise series is regulated according to the statistical rule shown in Eq. (10):

$$\varepsilon_{\mathrm{ne}} = \frac{\varepsilon}{\sqrt{NE}} \tag{10}$$

where NE denotes the quantity of ensemble members, ε is the amplitude of the additive noise, and $\varepsilon_{\mathrm{ne}}$ is the emendatory deviation of error.

2.3 Coupled Simulated Annealing (CSA)

The CSA algorithm [22] is a random heuristic algorithm for the global or close to global optimum solutions of non-polynomial time problems. As the name describes, the algorithm integrates a series of parallel simulated annealing processes during optimizing a problem. Thus, It can be regarded as an advance version of simulated annealing optimization method. Although the simulated annealing algorithm can be used to handle highly nonlinear problems with many constraints and chaotic and noisy data, etc. yet, the method requires a great many evaluations to cost function before seeking out the global optimum solution. In addition, the simulated annealing method is sensitive to the initial values of parameters, i.e. it lacks robustness when the parameters take different initial values.

Due to the aforementioned disadvantage of the simulated annealing algorithm, the CSA method is proposed to enhance the quality of solutions at the minimal cost of slowing down the convergence speed. In each iterative procedure of the CSA algorithm, each individual solution is separately updated and optimized by performing an individual simulated annealing process. The main difference between simulated annealing and CSA is that the acceptance probability in CSA is generated by coupling several acceptance probabilities from different simulated annealing algorithms, which creates cooperative behavior via information exchange. This coupling design is conductive to provide information on steering the overall optimization process towards the global optimum.

In classical simulated annealing algorithm, the importance sampling technique is adopted rather than random sampling technique to choose sample states of a solution for the cost-function estimation related to an optimization problem. Compared to the random sampling, the importance sampling ensures a more efficient rejection/acceptance mechanism. The main idea of importance sampling used in classical simulated annealing algorithm can be expressed in Eq. (11) according to the master equation of a thermodynamic system,

$$\frac{P(x \to y)}{P(y \to x)} = \frac{\exp(-E(y)/T)}{\exp(-E(x)/T)} \tag{11}$$

where $P(x \to y)$ represents the transition probability from the current state x to a candidate state y, T is a preset temperature parameter and $E(x)$ and $E(y)$ are the energies of the state x and state y, respectively. The transition probability can be decomposed into the product of a generation probability and an acceptance probability, i.e. $P(x \to y) = G(x \to y)A(x \to y)$ When the generation probability takes equal value, i.e., $G = 1/n$, where n is the amount of available states, the formula (11) is simplified as the following formula

$$\frac{A(x \to y)}{A(y \to x)} = \frac{\exp(-E(y)/T)}{\exp(-E(x)/T)} \tag{12}$$

Based on the above Eq. (12), numerous forms of the acceptable probability functions $A(x \to y)$ were proposed. Two commonly used functions are the Metropolis rule

$$A(x \to y) = \exp\left(\frac{E(x) - E(y)}{T_k^{ac}}\right) \tag{13}$$

And the rule

$$A(x \to y) = \frac{1}{1 + \exp\left(\frac{E(x) - E(y)}{T_k^{ac}}\right)} \tag{14}$$

To provide robust solution for multimodal and multidimensional problems without a significant decrease in convergence speed, the CSA algorithm considers many candidate solutions x_i to generate the probing states y_i, and makes the acceptance decision of a probing state y_i in terms of the corresponding candidate solution and the coupling term. The coupling term is designed to share the information of each candidate solution and then to generate cooperative behavior. Thus, this design is conductive to the decision of whether uphill moves are accepted, and the whole optimization process toward the global optimum solution.

The CSA algorithm is presented as follows (also shown in right column of Fig.1)

1) Parameter initialization: Initialize the parameters $T_k = T_0$ and $T_k^{ac} = T_0^{ac}$. Setup the iteration index k=0, σ_D^2=0.99$((m-1)/m^2)$ and $\alpha = 0.05$. Stochastically produce initial solutions Θ . for the problem to be optimized. Calculate the values of cost functions $E(x_i)$, $\forall x_i \in \Theta$, and assess the coupling term γ .

2) Produce a candidate solution y_i for each element in set Θ in terms of the formula $y_i = x_i + \varepsilon_i$, $\forall x_i \in \Theta$, where ε_i denotes a stochastic variable that follows a given probability density distribution $g(\varepsilon_i, T_k)$. And then compute the costs for the newly generated solutions: $E(y_i), i = 1, \cdots, m$

3) Decision of solution. For each $i \in 1 \cdots m$, if cost functions meet the condition $E(y_i) \le E(x_i)$; then accept the newly generated solution y_i; otherwise, with probability $A_\Theta(\gamma, x_i \to y_i)$, i.e., accept the newly generated solution y_i; make $x_i := y_i$ only if $A_\Theta > r$, where r is a variable generated from a uniform distribution [0, 1]. Assess γ and go to Step 2 for N inner iterations (equilibrium criterion).

4) Regulate parameter T_k^{ac} in terms of the rules: if $\sigma^2 < \sigma_D^2$, then T_k^{ac}=$T_{k\text{-}1}^{ac}(1-\alpha)$ if $\sigma^2 \ge \sigma_D^2$, then T_k^{ac}=$T_{k\text{-}1}^{ac}(1+\alpha)$;

5) Reduce the values of T_k^{ac}, T_k in terms of the schedule $U(T_k, k)$ and $V(T_k^{ac}, k)$, Increase k.

6) teminate caculation if the criterion is satisfied; otherwise, go to Step 2.

2.4 Least Squares Support Vector Regression (LSSVM)

The SVM model was put forward based on the statistical theory by Vapnik in 1995. And the SVM has shown the practicability and effectiveness in tackling the problems of classification, regression and pattern recognition. But, the main shortage of SVM technique is that the memory of kernel function matrix increases rapidly with the increase of the amount of samples, resulting in time-consuming in model-training when processing huge data. Suykens and co-workers replaced the inequality constraints in the SVM model with a set of linear equations, and then developed the LSSVM model [23].

We briefly review some basic work on the LSSVM method with regard to regression problems. The regression expression of the LSSVM model can be written as below,

$$y = w^T \varphi(x) + b \tag{15}$$

where w is a weight coefficient vector, b is a bias term, and $\varphi(x)$ is the nonlinear mapping of inputs x into a feature space. We can obtain the solution of the coefficient vector w by minimizing the penalized cost function listed as below:

$$C = \frac{1}{2} w^T w + \frac{1}{2} \gamma \sum_{i=1}^{N} e_i^2 \tag{16}$$

Subject to

$$y_i = wx_i + b + e_i \tag{17}$$

where $\{x_i, y_i\}$, $i = 1,2\cdots N$ are training samples, γ is a exogenous parameter usually tuned by cross validation method, e_i is the error variable corresponding to the training data $\{x_i, y_i\}, i = 1,2\cdots N$. Based on the constraints in Eq. (17), we utilize the Lagrange method to construct the following equation:

$$L(w,b,e,\alpha) = \frac{1}{2}\|w\|^2 + \gamma\sum_{i=1}^{N} e_i^2 - \sum_{i=1}^{N}(w^T\varphi(x_i) + b + e_i - y_i) \tag{18}$$

where α_i are Lagrange multipliers. Through determining the partial derivatives with respect to w, b, α_i and e_i, we can obtain the equations below

$$\frac{\partial L}{\partial w} = 0 \to w = \sum_{i=1}^{N}\alpha_i\varphi(x_i) \tag{19}$$

$$\frac{\partial L}{\partial b} = 0 \to \sum_{i=1}^{N}\alpha_i = 0 \tag{20}$$

$$\frac{\partial L}{\partial e_i} = 0 \to \alpha_i = \gamma e_i \tag{21}$$

$$\frac{\partial L}{\partial \alpha_i} = 0 \to w^T\varphi(x_i) + b + e_i - y_i = \gamma e_i, i = 1,2,\cdots N \tag{22}$$

We write Eq. (19)-(22) as a matrix form, and eliminate w, e_i, then we can obtain the following formula

$$A\begin{bmatrix}\alpha \\ b\end{bmatrix} = \begin{bmatrix} y \\ 0\end{bmatrix} \tag{23}$$

Where A is a square matrix given by:

$$A = \begin{bmatrix} K + 1_N/\gamma & 1_N \\ 1_N^T & O \end{bmatrix} \tag{24}$$

Where 1_N denotes the identity matrix, K donates the kernel matrix with ijth element satisfying the Mercer's condition shown in Eq.(25)

$$k(x_i, x_j) = \varphi(x_i)^T\varphi(x_j) \tag{25}$$

Hence, the solution is given by:

$$\begin{bmatrix}\alpha \\ b\end{bmatrix} = A^{-1}\begin{bmatrix} y \\ 0\end{bmatrix} \tag{26}$$

2.5 The proposed SA-EEMD-CSA-LSSVM approach

Section 1 mentioned that the electricity price series present the characteristics of nonlinearity and periodicity.

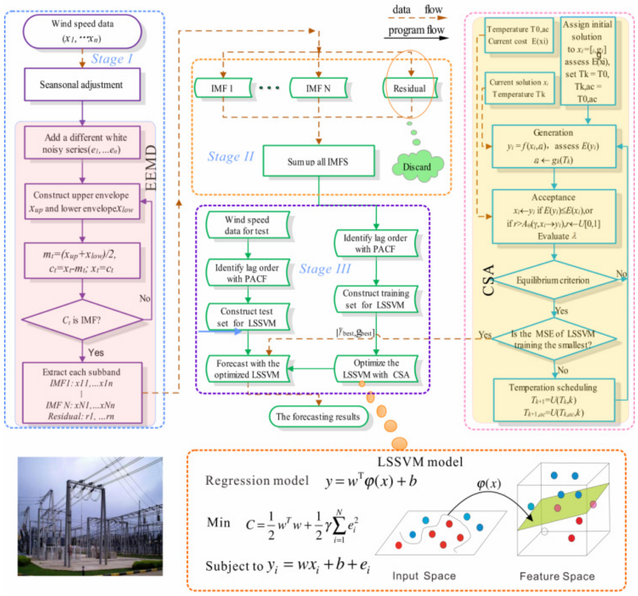

Fig. 1. The outline of the proposed SA-EEMD-CSA-SVR approach

An individual model is difficult to completely capture these characteristics. Thus, a hybrid approach that has the capabilities of de-noising and eliminating periodicity is put forward. Fig. 1 shows the overall framework of the proposed forecasting procedure.

The proposed forecasting procedure primarily contains three stages; the main task of each stage is presented as below:

Step 1: employ the SA method to detach the periodicity of original electricity price series, thereby obtaining the adjusted data series.

Step 2: utilize the EEMD method to break down the adjusted data sequences into several independent subseries plus a residual sequence. Discard the residuals and the IMF in the highest frequency to provide a denoising and smoothing effect on the original electricity price data and then reconstruct the rest IMFs subseries into a modified electricity price series to prepare for the follow-up operation.

Step 3: use the CSA algorithm to search for the optimum parameters of LSSVM, and then utilize the well-trained LSSVM model to forecast the day-ahead electricity price.

The adjusted electricity prices series obtained in step 1 have no obvious periodicity. The instantaneous frequency of each IMF obtained in step 2 is meaningful at any point and different IMFs take on different meanings. Before the model building for the electricity price prediction in step 3, selecting the input for a model is an essential process since the most appropriate inputs are conducive to the improvement of forecasting accuracy. It is of particular importance to soft computing models that are powerful, non-linear predictors, because the model complexity and the calculated quantity increase with the input dimension growth, resulting in slowing down the convergence speed.

Conversely, the model may lead to poor performance due to the poor information of small quantities of the considered relevant inputs. Hence, prior to applying the LSSVM model for the electricity price forecasting, the appropriate input should be obtained by appropriate methods. The paper employs the Partial Autocorrelation Function (PACF)[24] to select the appropriate features for the proposed models. The PACF identifies the partial autocorrelation after the elimination of internal correlation in time series, thereby obtaining the suitable relationship between covariant and response variables of the approach. To provide consistent inputs and refrain from the saturation phenomenon in the training process of the LSSVM model, the training samples are normalized by the method of maximum and minimum normalization. Once the forecasts obtained by the optimized LSSVM, the corresponding predictions are re-scaled through the inverse maximum and minimum normalization process.

3. Case Study

This section is to empirically demonstrate the validity and practicability of the proposed forecasting procedure though a case study. The case study includes the description of the data which is used for the simulation, the implementation of the proposed model which is illustrated in detail and the comparisons and analysis of the simulation results which are performed between the developed approach and other models.

3.1 Collections of data

Electricity price is affected by external factors such as weather conditions, load requirement, electricity supply, trading strategy and production cost, etc. An ideal model for the electricity price forecasting should contain all the possible elements affecting the electricity price. Nevertheless, in reality, it is impossible for the forecasting system to incorporate all those elements since it is quite difficult for the ideal forecasting system to acquire prompt information from other systems such as weather system, business system, etc. the affected factors such as business strategy and unethical competition behaviors are not easy to precisely measure. And other elements like generator status are confidential information for the sake of safety. Thus, this paper only analyzes univariate electricity price time series, and excludes other factors from the proposed hybrid model. The data of electricity price are collected from the NEM electricity market [25] for the test of the proposed approaches. As the LSSVM does not require a great many samples to forecast the day-ahead electricity price, the 336 electricity price data in seven days (shown in Fig. 2) are selected as training set and the following 48 data in the next day are used as testing data.

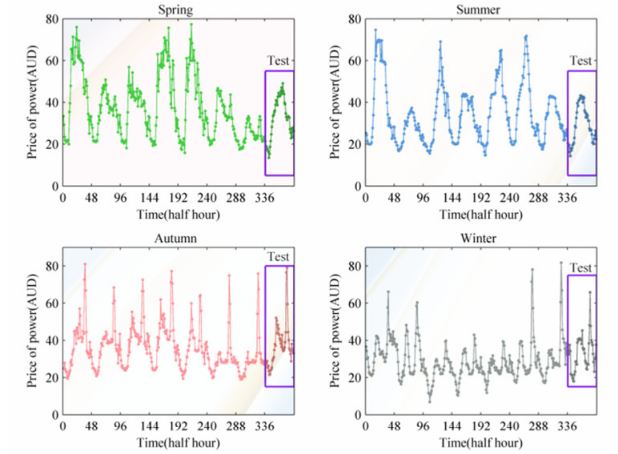

Fig. 2. The original half-hour electricity price series for four seasons

3.2 Evaluation of forecast performance

To make assessment to the feasibility and predictive ability of the models used in the case study, three evaluation metrics are employed to evaluate forecasting accuracy. The indices are mean absolute error (MAE), root mean square error (RMSE) and mean absolute percent error (MAPE). The low values of these indices mean the good forecast performances of the models. The metrics are listed as below:

$$\mathrm{MAE} = \frac{1}{T}\sum_{t=1}^{T}\left|p_t^{ture} - p_t^{forecast}\right| \tag{27}$$

$$\mathrm{MAPE} = \frac{1}{T}\sum_{t=1}^{T}\frac{\left|p_t^{ture} - p_t^{forecast}\right|}{p_t^{ture}} \times 100\% \tag{28}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{T}\sum_{i=1}^{T}\left|p_i^{ture} - p_i^{forecast}\right|^2} \tag{29}$$

where p^{ture} is the observed value for the time period t and $p^{forecast}$ is the predicted value for the corresponding period. The MAE reveals how similar the predicted values are to the observed values, while the RMSE measures the overall deviation between the predicted values and the observed values. The MAPE is a unit-free measure of accuracy for the predicted electricity price series and is sensitive to small changes in the data.

3.3 Simulation

As can be seen from Figs. 2, the electricity price data has obvious periodicity and presents the feature of small serrations in time domains. According to the process of the proposed approach, the season adjustment method is firstly used to the eliminated the seasonal periodicity in electric price series, with the result shown in Fig. 3. The adjusted electricity prices series shows the following features in comparison with the original ones: (i) The range of the adjusted series data is much narrower than the ones of the original ones. For example, the range of the original price series in winter (shown in Fig. 2) is adjusted from the intervals between 6.91 and 81.84 to the intervals between 13.06 and 41.06(shown in Fig. 3), (ii) Compared with the original price series, the adjusted price series has no obvious periodicity, which demonstrates the seasonal adjustment method has the ability to capture the character of periodicity. Secondly, using EEMD decomposition algorithm, the adjusted price series breaks down into several uncorrelated modes and one residual and these decomposed subseries are shown in Fig. 4-7. The instantaneous frequency of each mode is meaningful at any point and different modes possess different meanings, e.g. mode 1 is the lowest frequency band represents the central tendency of data. To improve the forecasting precision of the disordered electricity price series, the residual is neglected because of quite small value and the IMF8 in highest frequency is discarded because of rich noisy information, which de-noises the adjusted electricity price sequences. After that, all of the rest IMFs are

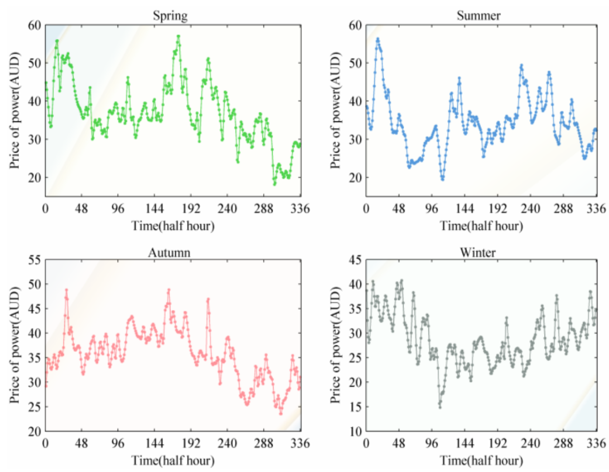

Fig. 3. The adjusted half-hour electricity price series by the season adjustment method for four seasons

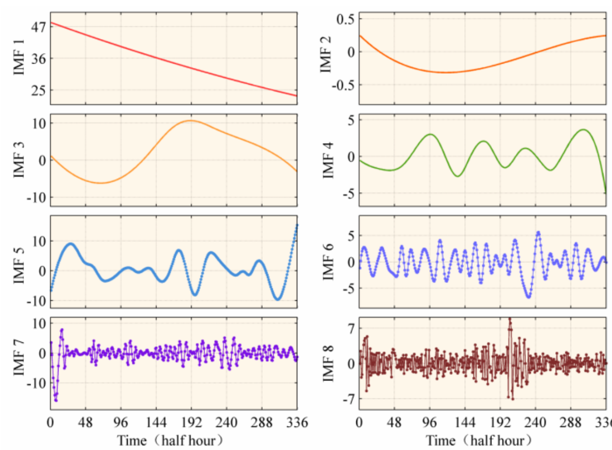

Fig. 4. The subsequences generated by EEMD from the half-hour electricity price series (Spring)

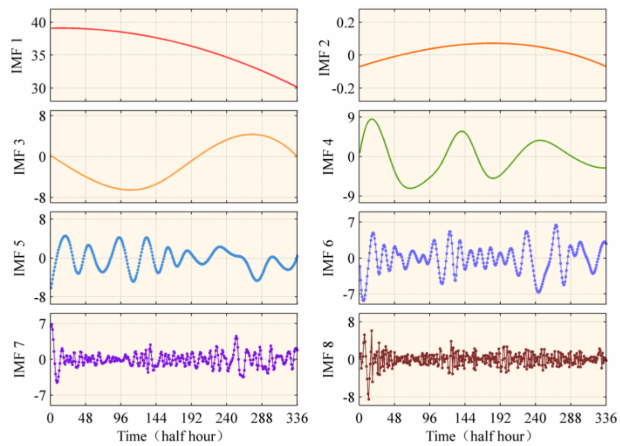

Fig. 5. The subsequences generated by EEMD from the half-hour electricity price series (Summer)

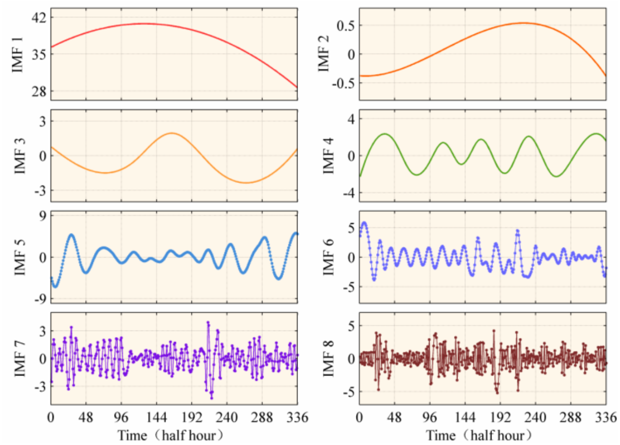

Fig. 6. The subsequences generated by EEMD from the half-hour electricity price series (Autumn)

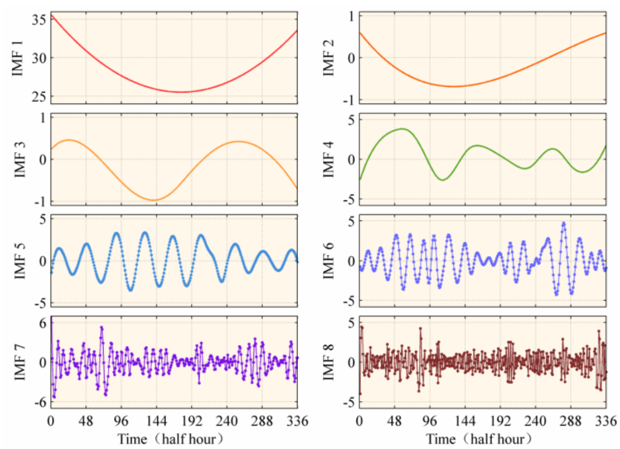

Fig. 7. The subsequences generated by EEMD from the half-hour electricity price series (Winter)

assembled back into a new sequence for the following procedure.

Prior to applying the combined series to the forecasting, the feature detector PACF is utilized to obtain the autocorrelation among the assembled sequential data. The lags of electricity price for four seasons are five, nine, seven and five, respectively. Thus the corresponding lagged electricity price data are considered as the input features of the proposed model. In addition, refrain from the saturation phenomenon in the training process of the LSSVM model, to avoid saturation phenomenon during the model training process, the input variable and response variable of the LSSVM model are linearly normalized to be within the range [-1, 1]. And then the parameters of LSSVM model is determined by CSA optimization algorithm in training process, in which the cross validation method is employed in training model to avoid collecting the validation data. After that, the predictions of the assembled sequence are produced by the developed LSSVM model. Finally, the final forecasts of the next electricity price are obtained through the inverse seasonal adjustment method.

To make comparisons with the developed hybrid approach, some of popular forecasting models are also established as the benchmark, which are time series-based models and statistical learning algorithms. The established time series-based models are the ARIMA model and the SARIMA model. The established statistical learning tools are CSA-LSSVM and SA-CSA-LSSVM.

Table 1. The prediction assessment to the model performance in four seasons.

Season	indicators	Models				
		M1	M2	M3	M4	M5
Spring	MAE	9.22	3.79	8.98	4.27	2.61
	MAPE(%)	31.22	11.88	31.39	13.03	7.91
	RMSE	10.61	4.86	10.96	5.26	3.57
Summer	MAE	8.78	3.63	5.27	4.31	2.51
	MAPE(%)	27.09	12.31	23.51	14.64	8.61
	RMSE	10.98	5.02	6.59	5.96	3.22
Autumn	MAE	10.29	7.98	8.16	3.97	3.71
	MAPE(%)	23.67	21.89	24.25	10.67	10.08
	RMSE	14.71	8.81	11.69	5.15	4.56
Winter	MAE	7.53	4.31	7.64	3.91	3.11
	MAPE(%)	23.42	12.35	25.49	11.35	9.07
	RMSE	9.52	6.11	9.45	5.01	4.16

M1: ARIMA; M 2: SARIMA; M 3: CSA-LSSVM; M 4: SA-CSA-LSSVM; M 5: SA-EEMD-CSA-LSSVM

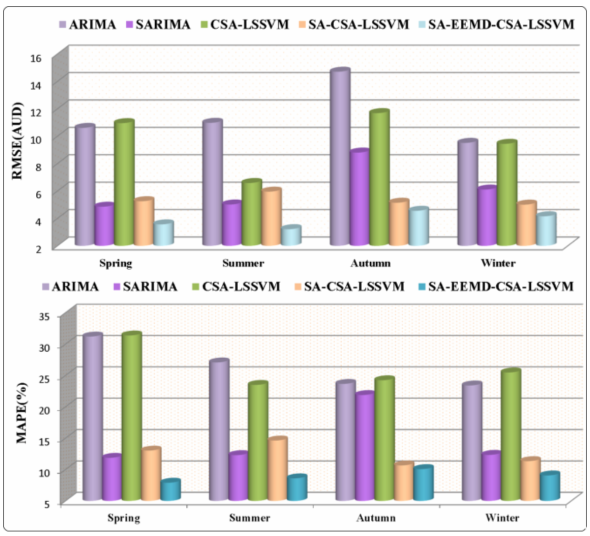

Fig. 8. The comparison of RMSE and MAPE obtained by models in four seasons

3.4 The comparisons and analysis

In this section, the developed approach is investigated for the deregulated power market of New South Wales in Australia. The proposed approach is compared with four other electricity price forecasting models. The model comparisons and discussions are made among the ARIMA, SARIMA, CSA-LSSVM, hybrid SA-CSA-LSSVM and hybrid SA-EEMD-CSA-LSSVM models. The forecasts obtained by these different models are revealed in Fig. 8 and in Table 1.

We can see from Fig. 9 that the day-ahead electricity price predictions of the developed hybrid approach match the test data of electricity price sequences well, while the price forecasts generated by the ARIMA method are the worst. As is shown in Table 1, it is clear that three evaluation metrics of estimated performance (MAE, RMSE and MAPE) generated by the proposed combinational approach are lower than the ones produced by other models. The comparisons between the predicting outcomes manifest that the composition of the SA method, EEMD technique and the LSSVM algorithm is an effective attempt for the day-ahead electricity price estimation, and the proposed hybrid approach can generate good day-ahead electricity price predictions since the method used in the proposed procedure can adaptively work in terms of the properties of the electricity price series.

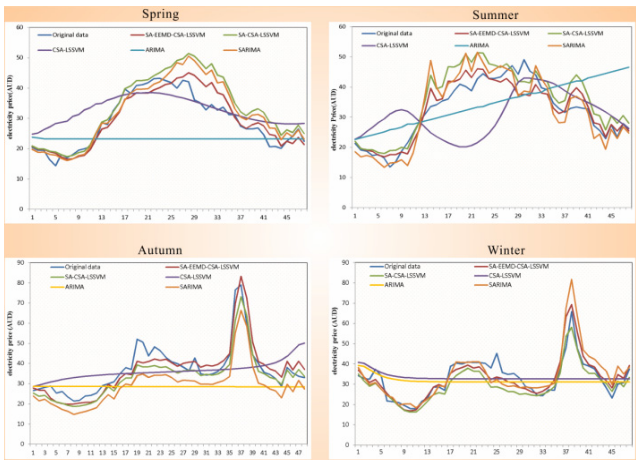

Fig. 9. The forecast comparison among the established models

Table 2. The reduction rate of models for four seasons

Season	Indices reduction	Reduction rate					
		M1/ M5	M2/ M5	M3/ M5	M4/ M5	M1/ M2	M3/ M4
Spring	MAE	54%	32%	71%	39%	59%	52%
	MAPE	58%	33%	75%	39%	62%	58%
	RMSE	50%	27%	67%	32%	54%	52%
Summer	MAE	51%	31%	53%	42%	59%	18%
	MAPE	46%	30%	63%	41%	55%	38%
	RMSE	45%	36%	51%	46%	54%	9%
Autumn	MAE	61%	54%	55%	8%	22%	51%
	MAPE	55%	54%	58%	6%	8%	56%
	RMSE	65%	48%	61%	11%	40%	56%
Winter	MAE	48%	28%	59%	20%	43%	49%
	MAPE	52%	27%	64%	20%	47%	55%
	RMSE	47%	32%	56%	17%	36%	47%

M1: ARIMA; M2: SARIMA; M3: CSA-LSSVM; M4: SA-CSA-LSSVM; M 5: SA-EEMD-CSA-LSSVM

To compare models more clearly and better evaluate the models, the decreased relative error (RE) can be calculated according to the following functions.

$$RE_{MAEi} = \frac{MAE_{propsed\ \mathrm{mod}\,el} - MAE_{\mathrm{mod}\,el\ i}}{MAE_{\mathrm{mod}\,el\ i}} \tag{33}$$

$$RE_{MAPEi} = \frac{MAPE_{propsed\ \mathrm{mod}\,el} - MAPE_{\mathrm{mod}\,el\ i}}{MAPE_{\mathrm{mod}\,el\ i}} \tag{34}$$

The model comparisons witness a good predictive performance provided by the proposed SA-EEMD-CSA-LSSVM model through analyzing the forecasts from these models.

And the analyses of the models are performed from three aspects to clearly illustrate that the proposed approach possesses good abilities of prediction and generalization. The analyses in aspect (1) and (2) are obtained from the forecasts in the season of Spring and the analysis in aspect (3) is obtained from the forecasts in four seasons. (1) Comparisons between individual and hybrid models. As seen from Table 2, in comparison with the ARIMA, SARIMA, CSA-LSSVM and SA-CSA-LSSVM, the developed combination approach results in reductions of 54%, 32%, 71%, 39% in total MAE, reductions of 58%, 33%, 75% and 39% in MAPE and reductions of 50%, 27%, 67% and 32% in total RMSE, respectively. The ARIMA performs worse than CSA-LSSVM in prediction accuracy as the ARIMA model was initially proposed for mining the internal knowledge and linear patterns of the time series data, which demonstrate that the electricity price series show more nonlinearity than linearity. (2) Data characteristic acquisition. Compared to the ARIMA method, the SARIMA leads to reductions of 59%, 59%, 22% and 43% in total MAE, and reductions of 62%, 55%, 8% and 47% in total MAPE, respectively. The reductions in statistical indices lies in the seasonal elimination, which indicates the periodicity exists in the electricity price series. The SARIMA model effectively removes the season factor in price series though the difference method, thereby obtaining more precise prediction. The comparisons between SA-CSA-LSSVM and CSA-LSSVM can also verify the above conclusion. For example, the comparison between the forecasts obtained by SA-CSA-LSSVM model and CSA-LSSVM model for spring reveals that the SA-CSA-LSSVM leads to reductions of 58% in MAPE, and reductions of 52% in MAE, respectively. The two aforementioned comparisons indicate that the SA method and difference method is efficient to eliminate the periodicity in electricity price series. (3) The effect of data preprocessor. Overall, the hybrid models with data preprocessors perform better than the hybrid approaches without data preprocessors. To be specified, the hybrid SA-CSA-LSSVM model outperforms the CSA-LSSVM approach. And the developed SA-EEMD-CSA-LSSVM approach leads to reductions of 39%, 42%, 8% and 20% in total MAE, and reductions of 39%, 41%, 6% and 20% in total MAPE for four seasons from the comparisons between SA-CSA-LSSVM model and SA-EEMD-CSA-LSSVM model, respectively. The comparisons demonstrate that the data preprocessing techniques are conducive to the enhancement of the precision of prediction, as the hybrid models take full advantage of the data preprocessing techniques and LSSVM model and play to their strengths.

4. Conclusion

Accurately estimating electricity price is conducive to the electricity energy systems operation including market participants and consumers. Due to the nonlinearity, nonstationarity and uncertainty of the electricity price series, this study puts forward an improved hybrid procedure which consists of SA method, EEMD technique, CSA algorithm and the LSSVM model to handle these characteristics for the electricity price forecasting. The proposed SA-EEMD-CSA-LSSVM model achieves considerable improvements in forecasting accuracy that is relatively satisfactory for current research. The developed approach in this study can efficiently deal with the characteristics of periodicity presented in the electricity. Regarding to removing the random disturbance, the IMF in the highest frequency obtained by EEMD technique is discarded to smooth the nonlinear electricity price series. And then the forecasting engine of the optimized LSSVM model makes a prediction to the electricity price series. The simulation results suggested that the SA-EEMD-CSA-LSSVM model be taken to tackle the forecasting problem with periodicity and uncertainty. Meanwhile, the paper provides comparisons among different models and comparisons of forecast performance using original price data.

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