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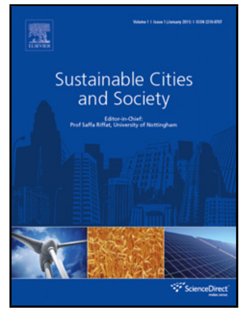

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A novel hybrid forecasting scheme for electricity demand time series

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Highlights

- A comprehensive treatment for the data of electricity demand.
- The advantages of Adaptive Fourier Decomposition are developed.
- The seasonal feature in electricity demand data can be projected.
- A new hybrid scheme proposed for electricity forecasting.

Abstract

Electricity demand/load forecasting always plays a vital role in the management and operation of power systems, since it can help develop an optimal action program for power producers, end-consumers and government entities. Inaccurate prediction may cause an additional production or waste of resources due to high operational costs. This paper investigated the benefit of combining data features to produce short-term electricity demand forecast. The nature of the electricity usually presents the complex characteristic and obvious seasonal tendency. In this paper, the advantage of adaptive Fourier decomposition is firstly used to extract the fluctuation characteristics. Then, the condition of the linear and stationary sequence is satisfied and the sub-series are performed to measure and eliminate the seasonal pattern. In the process of seasonal adjustment, the average periodicity length is identified quantitatively. In addition, to realize the generalization performance on real electricity demand data, the sine cosine optimization algorithm is applied to select the penalty and kernel parameters of support vector machine. The empirical study showed that the superior property of the proposed hybrid method profits from the effect of data pretreatment and the findings prove that this hybrid modeling scheme can yield promising prediction results within acceptable computational complexity.

Keyword: electricity forecasting, hybrid method, adaptive Fourier decomposition, eliminate seasonality, sine cosine algorithm

1. Introduction

It is well known that electricity demand forecasting is an important target for the agents and companies in the electricity market because the production and trading of electricity would be carried out under competitive rules in free markets, as described in Aneiros, Vilar & Raña (2016) and Steinbuks (2019). The goal of electricity demand forecasting is to find the balance between production and consumption through taking advantage of the forecasting models (Chen, Yang & Liu, et al., 2015). Nowadays, a wide range of methodologies and forecasting models have been proposed and developed.

Before developing the electricity demand forecasting, we should state clearly that the rest of this paper uses the term "electricity load forecasting" or "electric load forecast". We will use "electricity demand forecasting" as the term, whose abbreviation is denoted as EDF. Also, we should recognize the similarities between EDF and the forecasting of other utilities, such as wind power, solar radiation and air pollution concentration, in terms of methodologies, strategies, business requirements and even evaluation principles. We hope that the early presentation is beneficial for scholars and practitioners in other forecasting research.

Even though there exists no golden rule for the classification of range of EDF, the forecasting methods can be also grouped roughly into short term demand forecasting (Yang, Chen & Wang, et al., 2016; Ren, Suganthan & Srikanth, et al., 2016; Raza & Nadarajah, , et al., 2017; Ahmad & Chen, 2018) (from 30 min to six hours ahead), medium term demand forecasting (De Felice, Alessandri & Catalano, 2015) (from six hours to one day ahead) and long term demand forecasting (He, Jiao & Chen, et al., 2017; Chen, 2012) (from one day to one week or more ahead). For example, Yang, Chen & Wang, et al. (2016) and Ren, Suganthan & Srikanth, et al. (2016) used half-hour electricity load data of the State of New South Wales in Australia to validate the capability of the proposed method. De Felice, Alessandri & Catalano. (2015) applied the hourly data in the period from the 1990 to 2007 to conduct the research. He, Jiao & Chen, et al. (2017) and Chen (2012) used the practical data of the electricity demand measured in terms of the yearly usage to investigate the proposed new model. This rough classification can provide a refer to things that are specific to these categories (see Hong & Fan, 2016). Among the vast body of literature on EDF, there are many notable works that can be summarized as the state-of-the-art in different methods.

2. Literature review

Many techniques for electricity demand forecasting have been introduced and these techniques can be reviewed based on five subgroups: statistical methods, metaheuristic algorithms, decomposition models, hybrid methods, other methods.

2.1. Statistical methods on EDF

The review of statistical methods of electricity demand forecasting is categorized as time series models, regression models, exponential smoothing models and grey prediction models. Time series models apply time series trend analysis to extrapolate the future electricity demand (Suganthi and Samuel, 2012). Ohtsuka, Oga & Kakamu. (2010) proposed a spatial autoregressive ARMA model to carry out the features of electricity demand in Japan, in which the parameters of the model are estimated by a strategy of Markov chain Monte Carlo (MCMC) methods. Regression models are based on statistical methods for short term electricity demand forecasting. Ramanathan, Engle & Granger, et al. (1997) developed short-term electricity load and peak forecasting through multivariate regression model with the given historical load and weather data and the mean absolute percentage error varies between 4.04% and 5.66% for given data. Exponential smoothing method considering the time series locally stationary with a slowly moving average is also used for electricity forecasting (Deb, Zhang & Yang et al., 2017; Taylor et al., 2006). Bernardi & Petrella (2015) developed an exponential smoothing approach to model the electricity time series from 2004-2014 and the forecasting results show that it performs remarkably well. In the past decade, the grey prediction models have gained popularity due to its simplicity and ability to achieve unknown system with a few data points. The empirical analysis demonstrated that the gray-based cost efficiency model is a good tool to quantify the influences of cost reductions in power generation (Lee and Shih, 2011). An improved grey forecasting model which combines residual modification with genetic programming sign estimation was developed to forecast energy consumption and the model solves the problem of making assumptions such as the normal distribution or on a large sample size (Lee and Tong, 2011). These statistical models are also widely developed for the analysis of other utilities, such as stock price (see Rounaghi, Abbaszadeh & Arashi, 2015), crude oil price (see Yao & Zhang, 2017) and etc.

2.2. Metaheuristic algorithms on EDF

In recent years, heuristics and metaheuristics techniques are being in the field of EDF, in which metaheuristic algorithms are a high-level procedure of heuristic algorithms. Based on the natural characteristics of metaheuristic algorithms, there are three classifications including ecosystem algorithms, swarm intelligence algorithms and evolutionary algorithms. Gupta, Kumar & Barisal (2015) used biogeography-based optimization algorithm for addressing the optimization problem of Small Autonomous Hybrid Power Systems, the results of which demonstrate the performance of the metaheuristic algorithm along with forecasting effects. Many swarm intelligence algorithms have been adapted to electricity forecasting. For example, Azadeh & Taghipour, et al. (2014) presented that the Artificial Immune System algorithm with the Clonal Selection method can obtain satisfactory results for forecasting annual electrical energy consumption. The mean absolute relative error of the proposed method is lower than the forecasting errors of the existing methods at that time. Zhang, Wei & Li, et al. (2018) proposed a new model for forecasting short term electricity load, in which the fruit fly optimization algorithm is applied to optimize the wavelet neural network. It proves that the proposed model outperforms other comparison models. Jiang, Liu & Song (2016) proposed designated fractal interpolation functions (combining winners) based on cuckoo search algorithm for estimating missing values and the superior performance of this method has been confirmed. In metaheuristic algorithms, evolutionary algorithms are a subset of evolutionary computation and a generic population. The Differential Evolution algorithm has been used to tune the weight coefficients of the combined method and it shows that the proposed method have higher accuracy (Jursa & Rohrig, 2008). The improved harmony search algorithm embedding in back propagation neural network were introduced for short term wind power forecasting and the model can generate a more notable result (Jiang, Li & Zhang, 2018). Besides, the ability of metaheuristic algorithms related on EDF has been tested in other papers (see Jiang, Liu & Song, 2017; Jiang & Li, et al., 2019; Ju & Hong, 2013; Moradi & Eskandari, 2014; Wang, Du & Lu, et al., 2018).

2.3. Decomposition models on EDF

In the past couple of years, decomposition models based on the fluctuation characteristic play an important role in the modelling and forecasting of electricity data. The decomposition models can be grouped into two different types, including component model-based decomposition method and frequency domain analysis-based decomposition methods (Shao, Fu, Yang & Zhou, 2017). Many scholars have investigated that the frequency domain analysis-based decomposition methods can achieve more reliable and accurate results (Theodosiou, 2011). Using the Discrete Fourier transform method with its compact and structured format, wind speed patterns during different times and at different locations could be well characterized (see Jung and Tam, 2013). Wavelet decomposition is also an effective method to analyze the electricity demand signal in both time and frequency domains (Risse, 2019). But there exist shortages of wavelet decomposition, such as the difficulty of making a quantitative presentation of the energy frequency-time distribution, the non-adaptive characteristics, etc, Huang et al. (1998) proposed a new decomposition method, namely empirical mode decomposition (EMD). Nowadays, the EMD method and its improved version have been successfully applied to solve many engineering problems, such as Xiong, Bao & Hu (2014); Cen & Wang (2018); Zhang, Qu & Zhang, et al., (2017). Besides, some other decomposition models, including singular spectrum analysis (see Kumar & Jain, 2010) and filtering analysis (see Takeda, Tamura & Sato, 2016) were also introduced to the applications of power system domain.

2.4. Hybrid methods on EDF

In the literature, many methods have been proposed for the short term electricity demand forecasting. Owing to improvements of hybrid methods in parameter tuning, data mining, different stand-alone models were combined for constructing hybrid methods. There are several categories of hybrid methods in practical applications, such as, combination of different statistical methods, combination of different computational intelligence methods, combination of statistical methods with computational intelligence methods, etc. The hybridization of statistical methods can make used of the characteristics of different methods. Berk, Hoffmann & Muller (2018) used inhomogeneous Markov switching approach for the probabilistic forecasting of electricity load, in which the demand was modeled by autoregressive moving-average process. Liu & Shi (2013) developed autoregressive moving average models with generalized autoregressive conditional heteroskedasticity processes to model and forecast hourly ahead electricity prices. There are many methods based computational intelligence algorithms. For example, Jiang & Li, et al. (2020) introduced a composite framework for electricity demand forecasting, in which the variational mode decomposition method was applied to decompose the historical data and then different salp swarm optimization algorithms were established by the eliminating seasonal factor. Ghanbari, Kazemi & Mehmanpazir, et al. (2013) presented the Cooperative Ant Colony Optimization-Genetic Algorithm to model fluctuations of energy demand, which indicates that this algorithm can provide more accurate-stable results. Some other hybrid computational intelligence methods were utilized to perform the optimization mechanism, such as Liu, Jiang, Zhang & Niu (2019); Yu, Wei and Wang, (2012). Also, ARMA-based-artificial neural network (ANN) and ARIMA-based- support vector machine (SVM) were used for wind speed forecasting and wind power generation (Shi, Guo & Zheng, 2012), in which the linear component of a time series was modeled by ARIMA model and the nonlinear component was by ANN/SVM. In addition, the hybrid methods based decomposition techniques (see Liu & Wu, et al., 2019; Niu & Wang, 2019) are always used to carry out energy forecast.

2.5. Other methods on EDF

Empirical model are developed based on Fuzzy logic to conduct forecast in electricity load/demand (see Kucukali & Baris, 2010; Mamlook, Badran & Abdulhadi, 2009; Song, Baek & Hong, et al., 2005). The results indicate that The EDF of the fuzzy implementation can achieve more accuracy and better outcomes. Neuro fuzzy system has been used for electric load/demand forecasting. For example, Abraham & Nath (2001) performed evolving fuzzy neural network to model electricity demand in Victoria and it proved the neuro-fuzzy system performed well. Zahedi, Azizi & Bahadori, et al. (2013) used adaptive neuro fuzzy inference system to model the electricity demand in Ontario province of Canada from the year 1976–2005 and it found that this model can build electricity demand. And the drivers for increased application of power system forecasting is identified using the computing technology and data mining, such as Weather Research and Forecasting ensemble forecast (see Zhao, Guo & Su, et al., 2016) and Deep Learning Forecasting Model (Mujeeb & Javaid, 2019).

3. Models

In this section, the complete process of the theoretical forecasting methods is illustrated.

3.1. Data pre-processing method

In this sub-section, the detailed presentation for data pre-processing method is provided as follows.

3.1.1. Adaptive Fourier Decomposition

The Adaptive Fourier Decomposition (AFD) technology is to expand processed signals into series mono-components (MCs) that only contain non-negative analytic phase derivatives (Qian, Zhang & Li, 2011). AFD method can produce its basis adaptively based on processed signals to realize fast energy convergence.

Initially, the mean value of the measured noisy signal ***s*(*t*)** is removed, after that ***s*(*t*)** is projected to H^2 space by the Hilbert transform as follow.

$$H\left\{s(t)\right\}=\frac{1}{\pi}\int_{-\infty}^{\infty}s(t)\frac{1}{t-\tau}d\tau \tag{1}$$

The analytic representation of ***s*(*t*)**, which is denoted in *Eq*(2) considering the analytic signal, can be the input of the AFD.

$$\boldsymbol{G}(t)=s(t)+jH\left\{s(t)\right\} \tag{2}$$

Based on the decomposition components of ***G*(*t*)**, the reconstructed signal $\hat{\boldsymbol{h}}(\boldsymbol{t})$ can be calculated by:

$$\hat{\boldsymbol{h}}(\boldsymbol{t})=Re\left\{\sum_{n=1}^{N}\langle G_n,e_{\{a_n\}}\rangle B_n\left(e^{jt}\right)\right\} \tag{3}$$

The problem of determining a suitable maximum decomposition level *N* adaptively can be solved by the estimated signal-to-noise ratio of the noisy signal. The aim of denoising is to make the mean square error (MSE) in *Eq*(4) as small as possible.

$$MSE = L^{-1}E\left\|\hat{h}-h\right\|^2 \tag{4}$$

where *L* is the length of total data. It should be minimized the reconstructed signal at the suitable decomposition level *N* as follows.

$$\frac{\left\|s(t)\right\|^2}{\left\|\hat{h}(t)\right\|^2}-\left(1+\frac{1}{10^{SNR_e/10}}\right) \tag{5}$$

SNR_e is the estimated SNR of the noisy signal, which can be defined as follows.

$$SNR_e = 10log\left(\frac{\left\|h(t)\right\|^2}{\left\|w(t)\right\|^2}\right) \tag{6}$$

The AFD technology decomposes a signal based on its energy distribution. The energy of the reconstructed signal is expressed by:

$$\left\|\hat{h}(t)\right\|^2 = \frac{1}{2}\sum_{n=1}^{N}\left|G_n, e_{\{a_n\}}\right|^2 \tag{7}$$

Then, according to *Eq* (5) and (7), the suitable maximum decomposition level *N* is determined as follows.

$$min\left\{\left|\frac{\left\|\boldsymbol{s}(\boldsymbol{t})\right\|^2}{\frac{1}{2}\sum_{n=1}^{N}\left|\langle G_n, e_{\{a_n\}}\rangle\right|^2}-\left(1+\frac{1}{10^{SNR_e/10}}\right)\right|\right\} \tag{8}$$

Eq (8) can be regarded as the stopping rule of the iterative process of the AFD technology in the denoising process. In each decomposition level, the objective function value in *Eq* (8) should be evaluated. Once the objective function value reaches its minimum point, the decomposition iteration would be stopped. And the filtered results are reconstructed through all extracted mono-components based on *Eq* (3).

The detailed mathematical foundation of the AFD method can be referred to Wang, wan, Wong & Zhang (2016).

3.1.2. Fast Fourier Transform

Fast Fourier Transform (FFT) is a simple and effective power spectral analysis technology. It can transform the time series into frequency domain, after that the maximal spectrum power is used to determine the main cyclical pattern in the aspect of mean time-scale estimation (Yu, Wang & Tang, 2015). FFT method is a variant of Discrete Fourier Transform with only difference that FFT is computationally faster (Kumar and Ridder, 2010). Discrete Fourier Transform method is of the order of $O\left(N^2\right)$ while FFT method is of the order of $O\left(N.log_2^N\right)$. Denote a time series as $\left(x_0, x_1, x_2, \cdots, x_{N-1}\right)$, whose discrete fourier transform $\boldsymbol{H_n}$ is calculated as follows.

$$\boldsymbol{H_n} = \sum_{k=0}^{N-1} x_k e^{2\pi ikn/N} \tag{9}$$

$\boldsymbol{H_n}$ can be inverted through inverse Fourier transform by:

$$x_k = \frac{1}{N}\sum_{n=0}^{N-1} \boldsymbol{H_n} e^{-2\pi ikn/N} \tag{10}$$

Eq (1) is periodic in *n* with period *N*. So the frequency range at discrete interval $\frac{n}{N}$ varies from $-\frac{1}{2}$ to $\frac{1}{2}$. Then the periodogram estimates of the power spectrum at different frequencies can be calculated by:

$$P(0) = P\left(f_0\right) = \frac{1}{N^2}\left|H_0\right|^2 \tag{11}$$

$$P\left(f_k\right) = \frac{1}{N^2}\left[\left|H_k\right|^2 + \left|H_{N-k}\right|^2\right] \tag{12}$$

In Eq (12), f_k is calculated only for the zero and positive frequencies. The time series achieved after inverse Fouries transform under selected frequencies has been termed as FFT component of the time series.

3.1.3. Seasonal Patterns Adjustment

It should be noted that cyclic economic activities, seasonal climate and other influences may lead to poor performance of prediction. The seasonal patterns adjustment method should be used to separate the seasonal item from the seasonal electricity demand data and it can help make efficient forecast through estimating the trend.

The addition model and multiplication model are often used to model the cyclic (or seasonal) effects. Since the classical multiplicative decomposition model is suitable for many seasonal time series, it can be applied to help model electricity demand. The details can be presented as follows:

Supposing that the electricity demand at time t is denoted by

$$\boldsymbol{x_t} = f(t)\boldsymbol{I_j} \tag{13}$$

where $f(t)$ and $\boldsymbol{I_j}$ are the trend variable and seasonal variable, respectively. Then, the seasonal variable index $\boldsymbol{I_j}$ can be calculated the inverse operation of *Eq* (13). The average of x_i in each cycle can be regarded as the approximation of the trend component.

Rearrange the dataset $y_1, y_2, \cdots y_T$ to be y_{11}, y_{12}, ..., y_{1s}; y_{21}, y_{22}, ..., y_{2s}; …; y_{m1}, y_{m2}, ..., y_{ms}, where m and s are the number of cycles and data items in each cycle, respectively, and $T = ms$. Then, the average value is derived as follows:

$$\boldsymbol{\bar{y}_k} = (y_{k1} + y_{k2} + \cdots + y_{ks})/s \quad k = 1, 2, \cdots, m \tag{14}$$

Normalizing the data items y_{ms} as follows.

$$I_{ks} = \frac{y_{kl}}{\boldsymbol{\bar{y}_k}} \quad (k = 1, 2, \cdots m; l = 1, 2, \cdots s) \tag{15}$$

Next, the i-th seasonal variable index can be obtained as follows.

$$\boldsymbol{I_i} = \frac{I_{1i} + I_{2i} + \cdots + I_{mi}}{m} \quad (i = 1, 2, \cdots, s) \tag{16}$$

So the series without the seasonal component can be calculated through the value of $\boldsymbol{I_i}$ as follows.

$$y'_{ki} = \frac{y_{ki}}{\boldsymbol{I_i}} \quad k = 1, 2, \cdots m; i = 1, 2, \cdots s \tag{17}$$

Finally, rearrange the data items $y'_{11}, y'_{11}, \cdots y'_{1s}$, $y'_{21}, y'_{22}, \cdots y'_{2s}$,… $y'_{m1}, y'_{m2}, \cdots y'_{ms}$ to y'_1, $y'_2, \cdots, y'_T$ and a new data series without the seasonal component can be achieved.

3.2. Hybrid method

In this sub-section, we describe the sine cosine optimization algorithm and the support vector machine model.

3.2.1. Sine cosine optimization algorithm

Sine Cosine Algorithm (SCA) (Mirjalili, 2016) is a new population-oriented algorithm to address the optimization problems based on sine and cosine operators. The movement of the operators can be updated by the following equations.

$$\boldsymbol{X}_i = \begin{cases} \boldsymbol{X}_i + r_1 \times sin(r_2) \times \left| r_3 P_i - \boldsymbol{X}_i \right| \\ \boldsymbol{X}_i + r_1 \times cos(r_2) \times \left| r_3 P_i - \boldsymbol{X}_i \right| \end{cases} \tag{18}$$

In general, *Eq* (18) can be combined into one function shown in *Eq* (19). In addition, the position can be updated by introducing parameter *w* as follows.

$$\boldsymbol{X}_i^{t+1} = \begin{cases} \boldsymbol{w} \times \boldsymbol{X}_i^t + r_1 \times sin(r_2) \times \left| r_3 P_i^t - \boldsymbol{X}_i^t \right| & r_4 < 0.5 \\ \boldsymbol{w} \times \boldsymbol{X}_i^t + r_1 \times cos(r_2) \times \left| r_3 P_i^t - \boldsymbol{X}_i^t \right| & r_4 \geq 0.5 \end{cases} \tag{19}$$

where $\boldsymbol{X}_i$ and $\boldsymbol{P}_i$ indicate the current solution and the destination solution, respectively. $|\bullet|$ is the absolute value. P_i^t is the position of the destination point in i^{th} dimension. And the values of r_1, r_2, r_3 and r_4 are random parameters. These four random parameters can be updated each iteration to increase the diversity of the solutions. r_1 is used to determine the area of the next solution and the exploration and exploitation can be balance based on r_1 as follows.

$$r_1 = a - \frac{at}{T} \tag{20}$$

where a, t and T are a constant, the current iteration and the maximum number of iterations, respectively. And convenience is given in $[0, 2\pi]$.

r_2 is a random parameter to find the direction of the movement of the next solution. The r_3 gives random weights for $\boldsymbol{P}_i$ to stochastically emphasize ($r_3 > 1$) or deemphasize ($r_3 < 1$) the effect of desalination in defining the distance. And r_4 is a parameter to switch between the two trigonometric functions.

3.2.2. Support vector regression machine

Support vector machine (SVM) or support vector network has a widespread generalization ability, which has been attracted the most attention on regression problems (see Selakov, Cvijetinović & Milović, et al., 2014; Chen & Lee, 2015; Gu, Zhu & Jiang, 2011; Eseye, Zhang & Zheng, 2018).

Assume that a training data $\{x_i y_i\}_i^n$, where x_i and y_i are the observations of inputs and outputs, respectively. In support vector regression (SVR), the objective is to find a $f(\boldsymbol{x})$ that is as flat as possible while has most ε deviation from the observations for all the training data (see Papadimitriou, Gogas & Stathakis, 2014). In order to accomplish the objective, the SVR optimization problem can be provided in the following quadratic programming problem:

$$\boldsymbol{Min} \quad 0.5\|\boldsymbol{w}\|^2 + C\sum_{k=1}^{N}\xi_k + \xi_k^* \tag{21}$$

$$\begin{aligned} \boldsymbol{Sb.} \quad & y_k - \boldsymbol{w}\boldsymbol{x}_k^T - b \le \varepsilon + \xi_k \\ & \boldsymbol{w}\boldsymbol{x}_k^T + b - y_k \le \varepsilon + \xi_k^* \\ & \xi_k, \xi_k^* \ge 0, i = 1, 2, \cdots, l \end{aligned} \tag{22}$$

where $\|\boldsymbol{w}\|$ is the confidence range reflecting the generalization ability. C is the error penalty of estimating the outputs. ξ_k and ξ_k^* represent the slack variables. $\sum_{k=1}^{N}\xi_k + \xi_k^*$ is the experimental risk showing the learning capacity of function. And ε is the regularization factor that weights the balance between the estimated value and the target value (Lahmiri, 2018). The above equation set is a convex optimization problem.

In the implementation of SVR, the dual problem of this equation is often derived through the Lagrange multiplier method (Fan, Pan & Li, 2016) and a linear regression function is formulated as follows.

$$f(x) = \boldsymbol{w}^T x + \boldsymbol{b} = \sum_{i=1}^{N}(\hat{\alpha}_i - \alpha_i)K(x_i, x) + b \tag{23}$$

where $\hat{\alpha}_i$ and α are the Lagrange multipliers.

Then, the kernel function should be determined to construct a satisfactory SVR model. Kernel function is applied to transform the input space into high-dimensional feature space. Kernel function on the vectors $\boldsymbol{v}$ and $\boldsymbol{z}$ is the function K.

$$K(\boldsymbol{v}, \boldsymbol{z}) = \Phi(\boldsymbol{v}), \Phi(\boldsymbol{z}) \tag{24}$$

Radial basis function is selected in this paper:

$$\begin{aligned} K(\mathbf{v}, \mathbf{z}) &= exp\left(-\gamma \mathbf{v} - \mathbf{z}^2\right) \\ &= exp\left(-\gamma\left(\mathbf{v}, \mathbf{v} + \mathbf{z}, \mathbf{z} - 2\mathbf{v}, \mathbf{z}\right)\right), \ for \quad \gamma > 0 \end{aligned} \tag{25}$$

In this paper, the LIBSVM Matlab toolbox is added in the platform to implement the SVR. And the most critical two parameters including the regularization parameter C and the width of the ε-tube would be optimized by the abovementioned sine cosine optimization algorithm.

3.3. The whole scheme of the proposed hybrid method

In this section, the proposed hybrid modelling method for electricity demand forecasting is described. To make the hybrid method realistic and useful, the construction procedure of the hybrid method is demonstrated in **Fig. 1**, which represents that how we used the hybrid method to model the electricity demand data in a novel way.

To avoid the noise factors and improve the forecast accuracy efficiently, data noise filtering was firstly introduced to extract the noise from the raw electricity demand data. Considerable studies in recent years have confirmed that the efficiency of data decomposition technique. Adaptive Fourier Decomposition technique, which decomposes and reconstructs the signal based on the conventional exhaustive, can provide a favorable strategy to fully address the fluctuation and non-stationary issues. Meantime, the Fast Fourier Transform method was used to identify the cycle of decomposed series, after which the seasonal adjustment method can be applied to eliminate the seasonal components. It plays an essential role in the hybrid method for data-preprocessing technique.

In the proposed hybrid method, the penalty factor c and *RBF* kernel parameter σ of support vector regression machine were trained and tuned by sine cosine optimization algorithm training, thus it can achieve better generalization ability. At the beginning, data normalization ('*mapminmax*' function in MATLAB) should be performed to scale features to the range $[-1, 1]$. Moreover, the parameter pair (c, σ) can be obtained through the process of loop iteration. Finally, the trained model was applied to implement forecast and the forecasting value should multiply the seasonal index to get the final value of the trend component.

4. Experimental design and results

The detailed description of the data and the performance criterion are presented in this section. Further, the results and comparisons are conducted below.

4.1. Data description

As regards data sources, this paper collected the electricity demand data of New South Wales (NSW) and Singapore (SG) electric markets. For residents and social community, summer and winter are the peak seasons of electricity consumption, so the electricity demand data presents obvious characteristics of regular fluctuation. The analysis is based on the electricity demand data each market recorded by 30-min interval in megawatts (MW). For electricity demand data, the data is range from 1st May to 31st May 2014 and 1st November to 30th November 2014. The sample data are split into the training datasets and the testing datasets, with the former 24-day/23-day data points are selected as the training datasets and the later 7-day data points are selected as the testing datasets. **Fig. 2** shows the trends of the electric data series. The predictions the proposal are contained and compared in the testing set and the study aims to investigate the performance of the proposal through forecasting analysis.

4.2. Data analysis and pre-processing

For the abovementioned datasets, a key procedure is to address the noise information and seasonality process and we would choose the pre-processed off-line. From **Fig. 2**, it is obvious that the raw data series contain the noise component and seasonal component. First of all, the Adaptive Fourier Decomposition technology is employed to eliminate the noises. In the de-noising mechanism, the original electric signal was decomposed to series mono-components in view of the energy distribution. Thus the desired signal and the noise factors are separated.

For the electricity demand, each month has its periodic status; therefore, the seasonal length should be measured by the Fast Fourier Transform method. After measuring the average periodicity length of de-noised series, the seasonal adjustment method was used to conduct the process of eliminating seasonal factor. **Table 1** presents the seasonal indexes for May and November of NSW and SG markets. It should be noticed that the final forecasting value can be obtained through multiplying the seasonal indexes in **Table 1** to the forecasting results, respectively.

4.3. Performance measures and validation criteria

In this sub-section, the performance measures and validation criteria are presented below.

4.3.1. Error evaluation

Six classical error evaluation criteria are used to compare the effectiveness of the involved models, consisting of Standard Deviation of Error (**SDE**), Pearson's correlation coefficient (***ρ***), the symmetric mean absolute percent error (**sMAPE**), the mean absolute scaled error (**MASE**) and . And the evaluation criteria can be defined as follows.

$$\boldsymbol{SDE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(y_t^{pred} - y_t^{obs} - \frac{1}{N}\sum_{t=1}^{N}\left(y_t^{pred} - y_t^{obs}\right)\right)^2} \tag{27}$$

$$\boldsymbol{sMAPE} = \frac{2}{N}\sum_{t=1}^{N}\frac{\left|y_t^{obs} - y_t^{pred}\right|}{\left|y_t^{obs}\right| + \left|y_t^{pred}\right|} \times 100\% \tag{28}$$

$$\boldsymbol{MASE} = \frac{1}{N}\frac{\sum_{t=1}^{N}\left|y_t^{obs} - y_t^{pred}\right|}{\frac{1}{N-1}\sum_{t=2}^{n}\left|y_t^{obs} - y_{t-1}^{obs}\right|} \tag{29}$$

where N is the number of the sample. y^{pred} and y^{obs} are the predicted output and the observed output, respectively.

4.3.2. Pearson's test

In this sub-section, Pearson's test is used to validate the strength of association between the observed output and predicted output of electricity demand. If the value of Pearson's test is equal to 0, then there is no relationship of these two series. And if the value of Pearson's test is equal to 1, then there exists a linear relationship of these two series. The definition of Pearson's test can be described as follows.

$$\boldsymbol{Pear} = \frac{\sum_{t=1}^{N}(y_t^{obs} - y_t^{mean})(y_t^{pred} - y_t^{pred\_mean})}{\sqrt{\sum_{t=1}^{N}\left(y_t^{obs} - y_t^{mean}\right)^2 \cdot \sum_{t=1}^{N}\left(y_t^{pred} - y_t^{pred\_mean}\right)^2}} \tag{32}$$

where y_t^{mean} and $y_t^{pred\_mean}$ are the means of the observed output y_t^{obs} and the predicted output

$y_t^{pred\_mean}$, respectively.

4.4. Results and comparisons

Based on the abovementioned subsections, the performance of the proposed modelling scheme and the benchmark models have been involved in the comparison.

4.4.1. Results of electricity demand forecasting

Evaluation of the involved models to forecast the electricity demand for NSW and SG electric markets is shown in this subsection through the abovementioned error evaluation criteria. I choose the random walk model (NAIVE) as normal benchmark. The involved models includes extreme learning machine (ELM), ARMA model, back propagation neural network (BPNN), support vector machine (SVM), the support vector machine-based-data pre-processing method and the proposed hybrid model. And the forecasting error evaluation results of the models are presented in **Tables 2-3**.

Tables 2 and **3** depict the error evaluation of different models. The models with lowest error evaluation criteria are the best. Based on the competitive error measures, the involved models are better than the benchmark method (e.g. highest sMAPE or MASE). The vivid comparison can be easily found in **Fig. 3**, which presents the scatter plots of forecasted electricity demand data and observed electricity demand data in May at NSW market. From the scatter plot, the NAIVE method has original correlation coefficient **Fig. 3** (***a***). As seen in **Fig. 3** (***b***, ***d***, ***d***), there is a linear relationship between the forecasted data and the observed data, indicating that the extreme learning machine, ARMA model and back propagation neural network have the ability of forecast electricity demand. **Fig. 3** (***e***: support vector machine), **Fig. 3** (***f***: support vector machine optimized by sine cosine algorithm/SCASVM) and **Fig. 3** (***g***: SCASVM based on seasonal adjustment/FSSCASVM) show a positive linear trend, which indicates that these three model can achieve a good forecast. **Fig . 3** (***h***: SCASVM based on the Adaptive Fourier Decomposition/AFDSCASVM) and **Fig. 3** (***p***: the proposed model) also show positive linear trend and the Pearson correlation coefficient of the proposed model (r = 0.9979) is larger than that of the AFDSCASVM model (r = 0.9976).

Besides, the SCASVM model yield better electricity demand forecasting results ($s\boldsymbol{MAPE}_{\text{May}}$ = 0.646 and $s\boldsymbol{MAPE}_{\text{November}}$ = 0.800 in NSW market, and $s\boldsymbol{MAPE}_{\text{May}}$ = 0.430 and $s\boldsymbol{MAPE}_{\text{November}}$ = 0.347 in SG market) between the SVM and ARMA model. The optimization of sine cosine algorithm can improve the forecasting performance. The analogous analysis based on **Tables 2-3** confirmed that the data pre-processing technique was pretty responsive in improving the electricity demand forecasting.

In addition, **Fig. 4** provides the bar graph of forecasting residual errors in November at SG market for the involved models, respectively. From **Fig. 4**, the proposed model shows apparently a better curve fitting of the actual electricity demand data and smaller residual errors when compared with other forecasting models. Boxplots with respect to the forecasting performance of the models in May and November at SG market have also been illustrated in **Fig. 5**. From the boxplots given in **Fig. 5**, it can be seen that the forecasting error values of extreme learning machine model ($\mathbf{M_7}$) is the maximum. Overall, based on the information provided in **Fig. 5**, it can be seen that there are slight differences among the performance of the models $\mathbf{M_1}$, $\mathbf{M_2}$, $\mathbf{M_3}$, $\mathbf{M_4}$, $\mathbf{M_5}$, $\mathbf{M_6}$, and $\mathbf{M_8}$**.** Furthermore, the minimum forecasting error value was achieved by the proposed model ($\mathbf{M_8}$).

Based on provided results, it can be conducted that: a) the proposed model has superior forecasting performance, which indicates the efficiency of the data pre-processing technique and the optimization algorithm; b)the Adaptive Fourier Decomposition technology and the seasonal adjustment method can help the hybrid method improve the overall performance.

4.4.2. Contrast analysis

The results of the Pearson's test are also presented in **Table 4**. From **Table 4**, it can be found that the proposed model outperforms than other models in May and November at both electric markets.

From the above presentation, it can be found that the performance of the proposed model is superior to the benchmark model and other involved models. The advantage of the high-precision forecasting depends on the data pre-processing technique and the parameter optimization stage. Further error evaluation results of the obtained forecasting results from **Section 4.4.1** are shown in **Fig. 6**. **Fig. 6** shows the improving performance of MAE(mean absolute error), RMSE(root mean square error) and MAPE(mean absolute percentage error) indexes for the comparison and reference models, including SCASVM *vs*. SVM, AFDSCASVM *vs*. SCASVM, FSSCASVM *vs*. SCASVM and the proposed model *vs*. AFDSCASVM. Based on the values, a general conclusion can be conducted that: a) the optimization algorithm is positive to improve the forecasting performance; b) the adaptive fourier decomposition technology and the seasonal adjustment method are significantly superior than the individual model and the proposed model finally won the rivalry.

5. Conclusions and future research

Demand/load forecasting in electricity network operation is a crucial problem which requires supportive and efficient tools, especially in the case of that the predictions are performed for reaching the generation economically and more benefit in operating the system. The electric system is affected by various unstable factors, such as weather, holiday, plants and population, leading to make it not easy for the electricity industry department to estimate their output. More innovative and efficient forecasting tools can help traders to determine, in a more appropriate manner, the quantity of electricity production that maintain the balance between the workload and generation, contributing positively to planning the expansion of power grids. This process will ultimately be presented in purchasing electricity for resale to elaborate profitable bidding strategies. A close requirement in equilibrium output at low operational costs can also act as a significant in reliability and quality of the power supply.

This paper undertook the development of a hybrid method to estimate the future electricity demand/load with high accuracy and effectiveness. The potential of using a data pre-processing technique and metaheuristic optimization algorithm to achieve this purpose was explored. The electricity demand data provided by a company operating in the electric markets was adopted. Due to high volatility and randomness, the dataset exists noise information, but it can be mined the predictive variables through the Adaptive Fourier Decomposition technique. Then, we applied Fast Fourier Transform strategy to capture and measure the seasonal cycles in electricity demand data so as to the seasonal component can be eliminated. Another advantage is that the metaheuristics algorithm was applied to tune the parameters. And the hybrid method generally presents superior forecast performance.

The results demonstrate that the use of hybrid method technique for performing electricity demand forecasting when there exist noise filter and seasonal cycles in the data. This hybrid method may constitute a potential tool to help managers to make the design and analysis of energy planning. In particular, the data pre-processing technique proposed is effective and easy to implement, each modular of which plays a valid role in the entirety. Given the individual forecasts, the metaheuristic optimization algorithm can be considered for combination to improve the instability. Therefore, although the computational complexity of the proposed hybrid method get becoming incremental as the improvement process is more complex, it is significant that the proposed hybrid method exhibit satisfactory predictive capability when comparing with other simpler models.

As for future work, the authors believe that the forecasting performance can be improved if other predictive strategies and variables are integrated. For this purpose, more innovative and complex techniques would be employed, enhancing the computational complexity of the hybrid method. It can balance the forecasting accuracy and the computational complexity so that the hybrid method performs well in performance under acceptable cost.

Conflict of interest

The authors must claim that there is no possible conflict of interests with the publication of this work.

Declaration of interests

None

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Figure captions

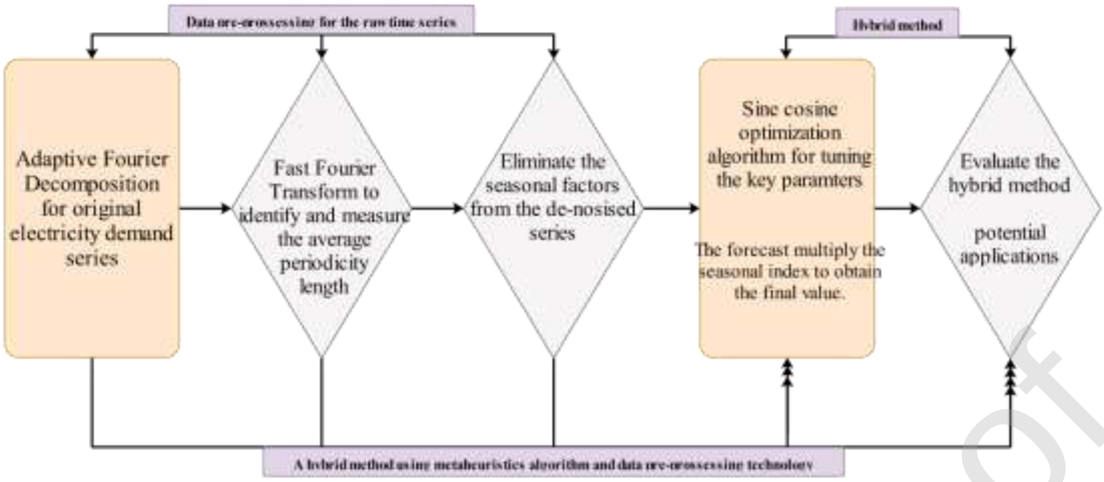


Fig. 1. The general scheme of proposed hybrid method.

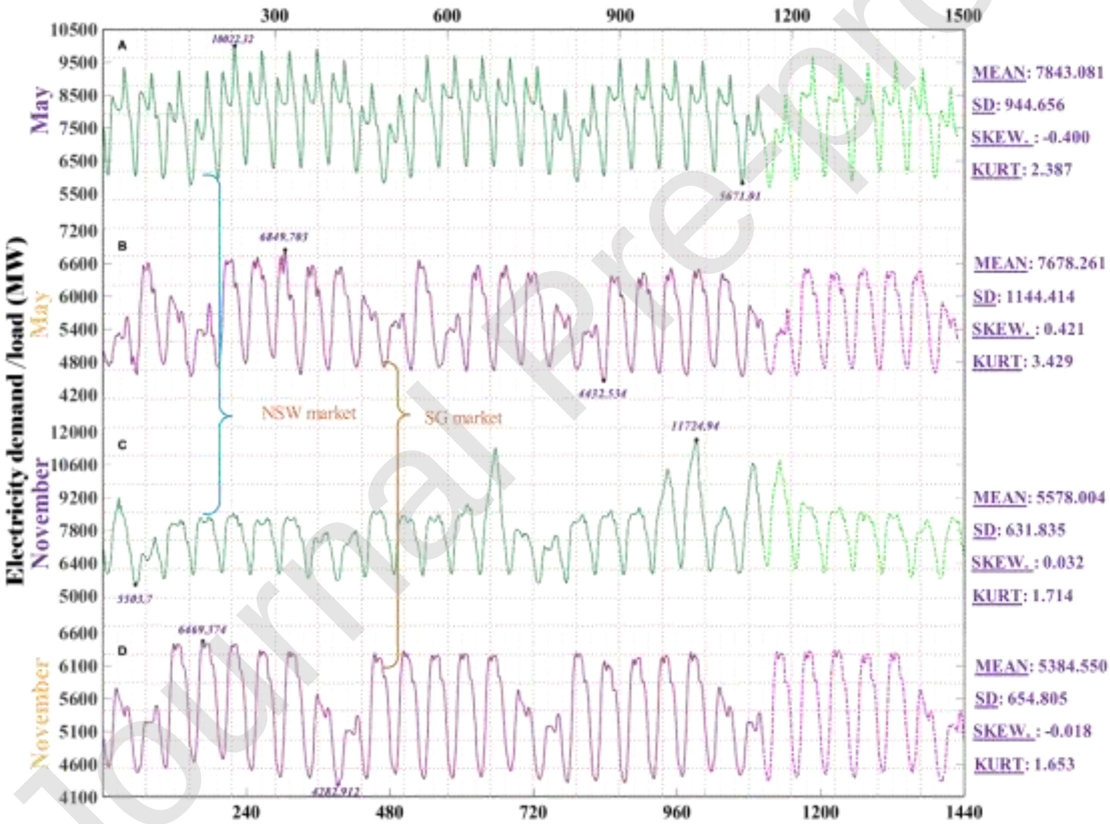


Fig. 2. The trend of four electric data series

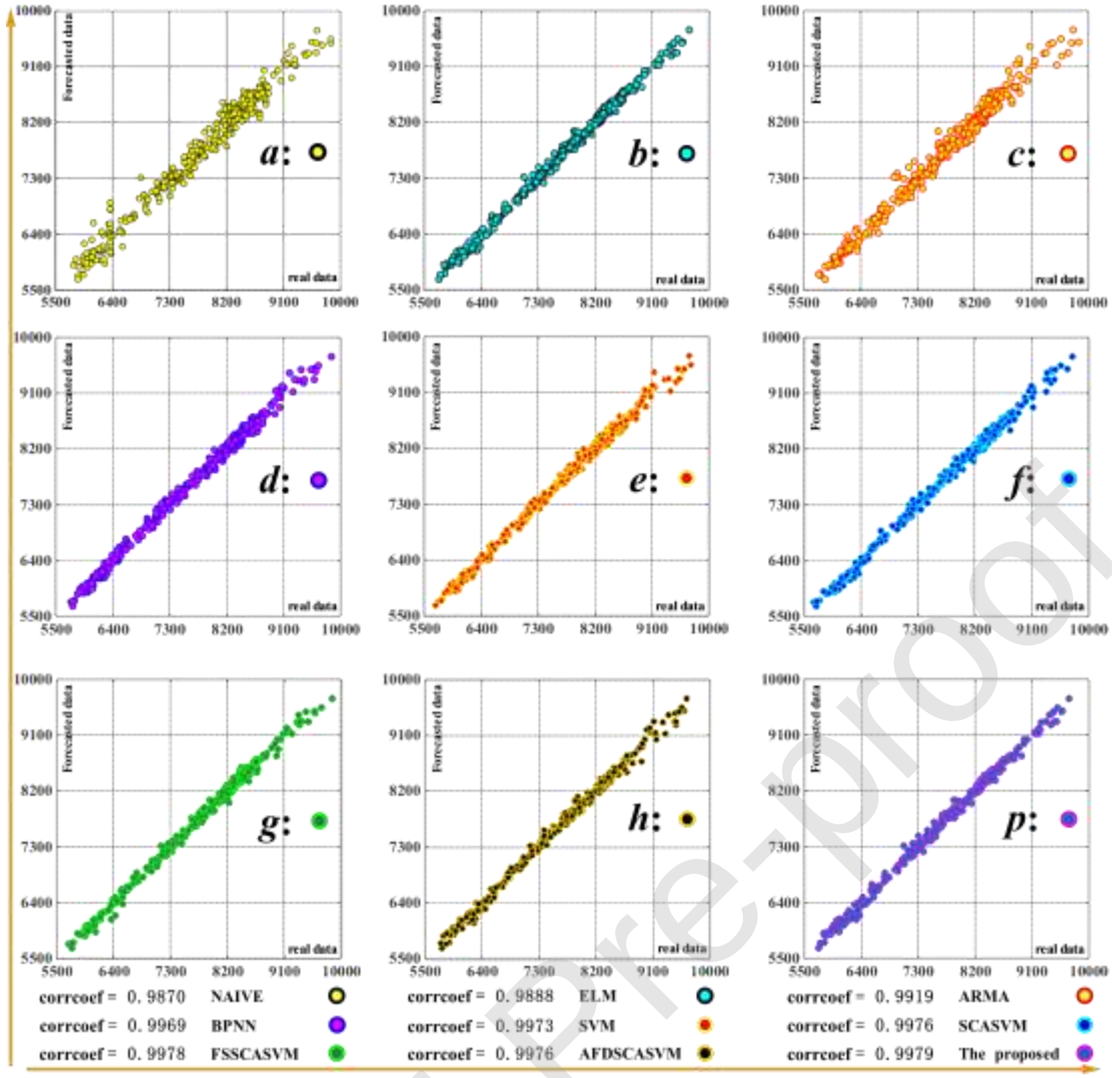


Fig. 3. Scatterplot of the forecasted data vs. the observed data of NSW market in May.

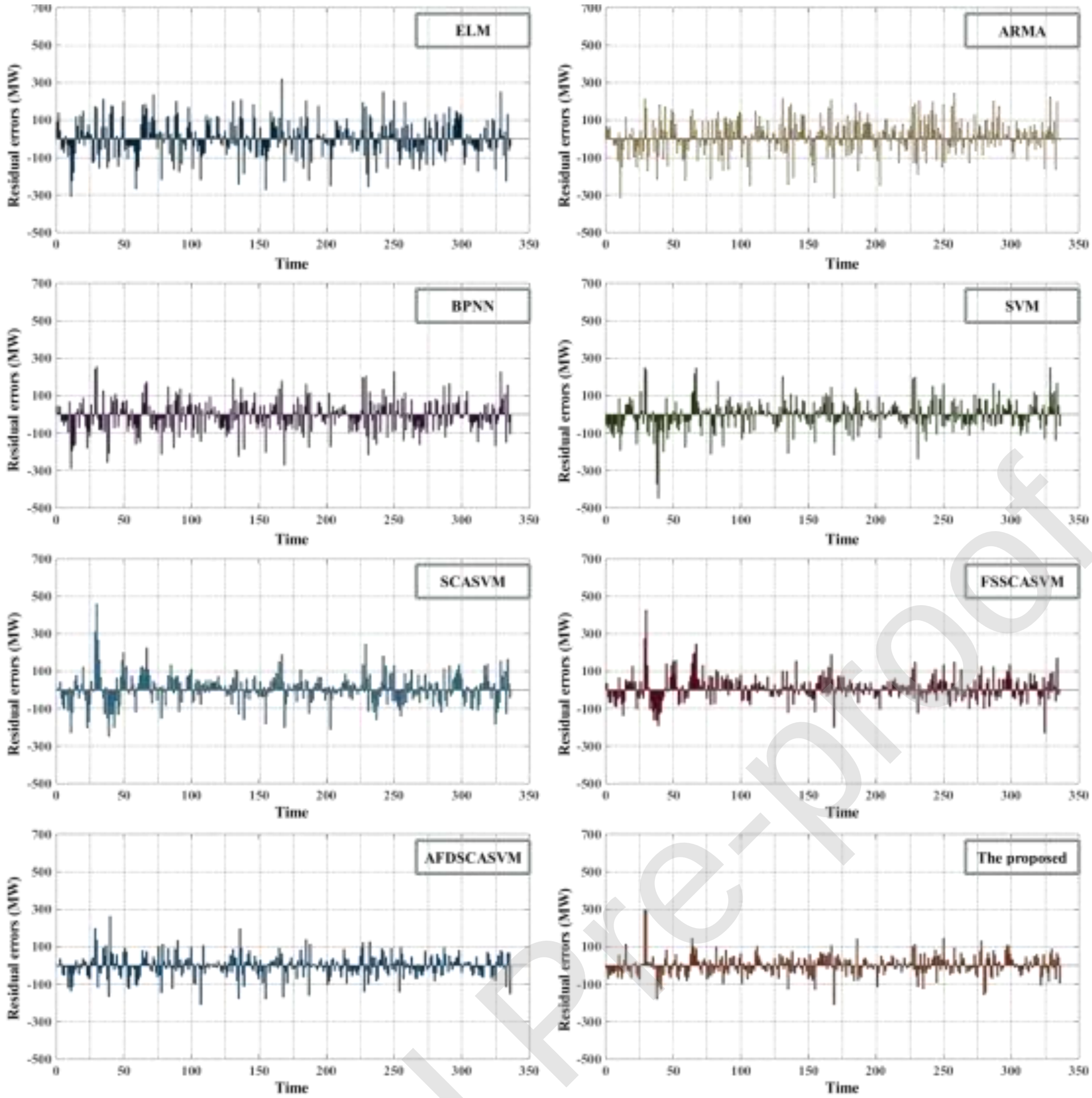
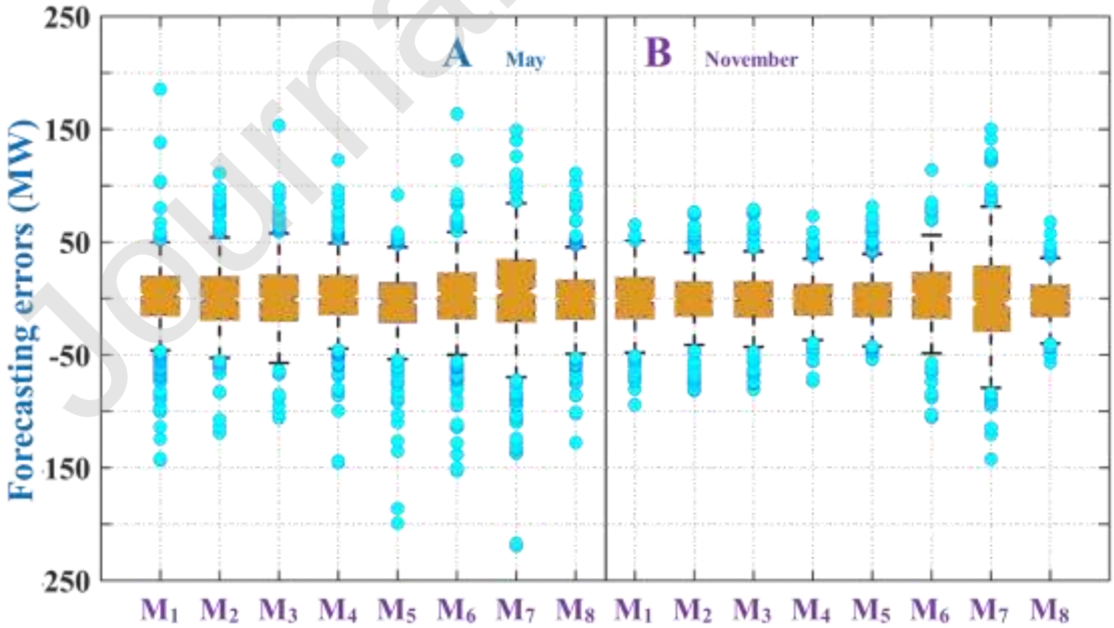


Fig. 4. The forecasting residual errors of NSW market in November for different methods.



*where M_1, M_2, M_3, M_4, M_5, M_6, M_7, M_8 mean the ARMA model, SVM model, SCASVM model, AFDSCASVM model, FSSCASVM model, BPNN model, ELM model and the proposed model, respectively.

Fig. 5. Error box plot of the involved model for forecasting electricity demand at SG market.

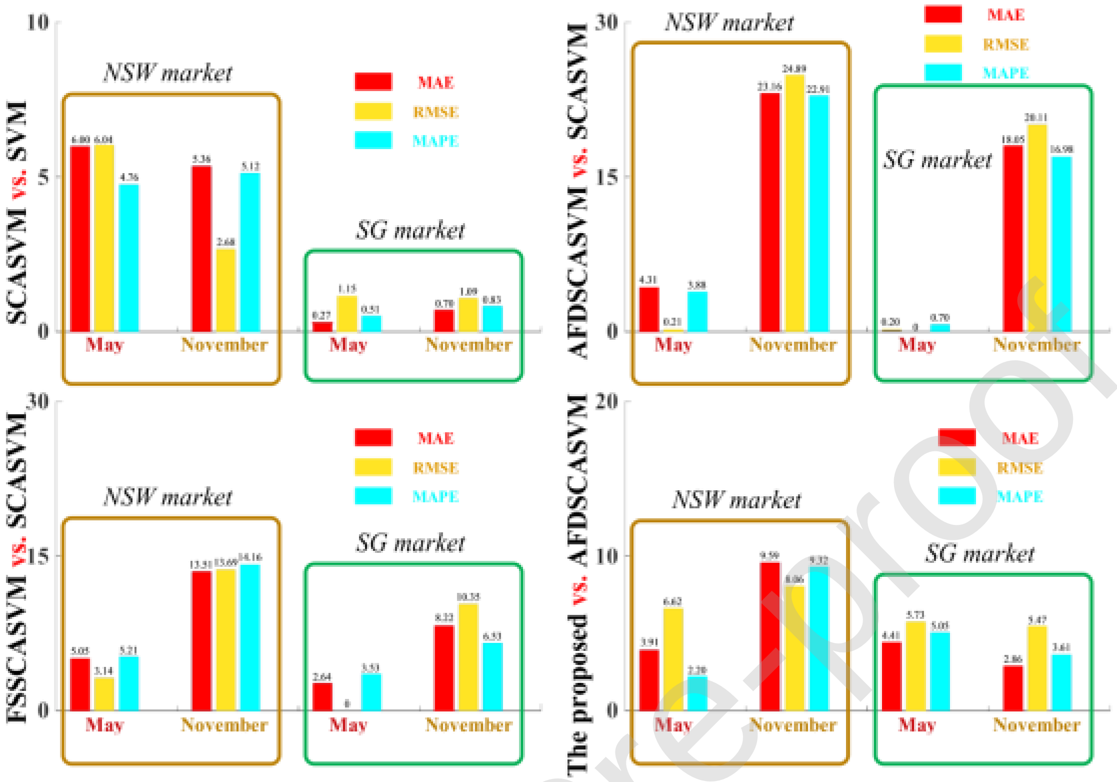


Fig. 5. The improving percentages error of the involved forecasting methods.

Table

Table 1. The seasonal factors for each month of NSW and SG markets.

Time	NSW		SG		Time	NSW		SG	
	May	*November*	*May*	*November*		*May*	*November*	*May*	*November*
0:00	0.954448	0.891768	0.91107	0.896548	12:00	1.031091	1.096868	1.087741	1.102856
0:30	0.93078	0.865437	0.893094	0.878238	12:30	1.024463	1.101685	1.089476	1.101273
1:00	0.906031	0.82901	0.880621	0.865437	13:00	1.022223	1.105652	1.0976	1.105475
1:30	0.877579	0.79941	0.869523	0.853995	13:30	1.020809	1.106184	1.104534	1.109905
2:00	0.837656	0.780315	0.859691	0.844468	14:00	1.019046	1.108435	1.106483	1.110864
2:30	0.808453	0.770555	0.850433	0.836221	14:30	1.018333	1.11773	1.103825	1.107222
3:00	0.788858	0.770126	0.842913	0.83	15:00	1.01969	1.123081	1.099522	1.104559
3:30	0.77855	0.777442	0.837793	0.825975	15:30	1.031624	1.12995	1.095684	1.103213
4:00	0.777481	0.79872	0.835357	0.824777	16:00	1.049379	1.126055	1.089503	1.100022
4:30	0.786733	0.819763	0.838078	0.827493	16:30	1.080262	1.127111	1.080315	1.093233
5:00	0.815201	0.866711	0.847205	0.837391	17:00	1.136033	1.109707	1.068901	1.082131
5:30	0.850643	0.916267	0.86618	0.856374	17:30	1.192199	1.101245	1.054011	1.065282
6:00	0.923552	0.958705	0.889164	0.879779	18:00	1.182603	1.083393	1.045341	1.05538
6:30	0.983995	0.999541	0.905526	0.899965	18:30	1.163297	1.083715	1.053699	1.061768
7:00	1.023616	1.023049	0.926229	0.927185	19:00	1.126615	1.086085	1.062496	1.067426
7:30	1.062376	1.039591	0.967659	0.972116	19:30	1.100693	1.068128	1.063093	1.065817
8:00	1.076345	1.060968	1.013332	1.01893	20:00	1.081058	1.038113	1.06001	1.060195
8:30	1.072876	1.071777	1.045684	1.053408	20:30	1.062864	1.005538	1.054277	1.051673
9:00	1.075583	1.079568	1.067017	1.076639	21:00	1.039002	0.996507	1.04399	1.039657
9:30	1.070935	1.084535	1.084201	1.093655	21:30	1.012802	0.973258	1.024938	1.020017
10:00	1.065176	1.085637	1.097815	1.10755	22:00	1.018157	0.967431	1.002327	0.995324
10:30	1.055048	1.088998	1.105883	1.116543	22:30	0.995423	0.948694	0.981798	0.972077
11:00	1.04347	1.088588	1.103727	1.118307	23:00	0.990161	0.92623	0.961408	0.950205
11:30	1.036183	1.091967	1.095309	1.111339	23:30	0.980607	0.910753	0.935526	0.922095

Table 2. The forecasting error measures of electricity demand in NSW market generated by the involved models.

Month	Index	NAIVE	ARMA	SVM	SCASVM	AFDSCASVM	FSSCASVM	BPNN	ELM	The proposed
	SDE	***153.5941***	119.5697	69.0349	64.6726	64.6902	62.8310	74.0165	140.3847	***60.4526***
May	**sMAPE**	***1.629***	1.133	0.679	0.646	0.621	0.612	0.758	1.427	**0.608**
	MASE	***0.773***	0.547	0.329	0.309	0.296	0.294	0.365	0.690	**0.284**
	SDE	***222.4934***	98.7286	86.5819	84.2486	63.3020	72.2233	90.4839	106.3011	***58.2931***
Nov	**sMAPE**	***2.052***	1.016	0.844	0.800	0.617	0.686	0.942	1.108	**0.559**
	MASE	***1.211***	0.583	0.487	0.461	0.354	0.399	0.542	0.634	**0.320**

Table 3. The forecasting error measures of electricity demand in SG market generated by the involved models.

Month	Index	NAIVE	ARMA	SVM	SCASVM	AFDSCASVM	FSSCASVM	BPNN	ELM	The proposed
	SDE	***80.889***	35.9417	32.2631	31.8670	33.0041	33.0070	38.6545	49.3780	**31.1396**
May	**sMAPE**	***1.088***	0.441	0.432	0.430	0.427	0.416	0.489	0.653	**0.406**
	MASE	***0.797***	0.327	0.316	0.315	0.314	0.306	0.364	0.482	**0.300**
	SDE	***135.191***	26.0254	25.5578	25.2881	20.1933	22.6786	30.3405	45.7401	**19.0064**
Nov	**sMAPE**	***1.580***	0.384	0.350	0.347	0.288	0.325	0.436	0.655	**0.278**
	MASE	***1.013***	0.272	0.249	0.248	0.203	0.227	0.311	0.468	**0.197**

Table 4. The results of the Pearson's test.

Market	Month	NAIVE	ARMA	SVM	SCASVM	AFDSCASVM	FSSCASVM	BPNN	ENN	ELM	The proposed
NSW	**May**	0.9870	0.9919	0.9973	0.9976	0.9976	0.9978	0.9969	0.9889	0.9888	**0.9979**
	November	0.9791	0.9957	0.9967	0.9969	0.9983	0.9977	0.9964	0.9899	0.9952	**0.9985**
SG	**May**	0.9920	0.9984	0.9987	0.9988	0.9987	0.9987	0.9982	0.9975	0.9970	**0.9988**

November	0.9798	0.9992	0.9993	0.9993	0.9996	0.9994	0.9990	0.9991	0.9976	**0.9996**