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EDITED BY

Qihe Shan,
Dalian Maritime University, China

REVIEWED BY

Jinran Wu,
Queensland University of Technology,
Australia
Zhesen Cui,
Changzhi University, China
Shaotong Zhang,
Ocean University of China, China

*CORRESPONDENCE

Weiguo Zhang,
230209330@seu.edu.cn

SPECIALTY SECTION

This article was submitted to Smart Grids,
a section of the journal Frontiers in Energy
Research

RECEIVED 25 June 2022

ACCEPTED 11 July 2022

PUBLISHED 02 September 2022

CITATION

Zhang W, Gu L, Shi Y, Luo X and Zhou H
(2022), A hybrid SVR with the firefly
algorithm enhanced by a logarithmic spiral
for electric load forecasting.
Front. Energy Res. 10:977854.
doi: 10.3389/fenrg.2022.977854

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A hybrid SVR with the firefly algorithm enhanced by a logarithmic spiral for electric load forecasting

Weiguo Zhang^{1,2*}, Linlin Gu², Yang Shi³, Xiaodong Luo³ and Hu Zhou⁴

¹Southeast University, Nanjing, China, ²Nari Technology Co., Ltd, Nanjing, China, ³State Grid Xiong'an Integrated Energy Service Co, Ltd, Baoding, China, ⁴Nanjing University of Posts and Telecommunications, Nanjing, China

Accurate forecasting of an electric load is vital in the effective management of a power system, especially in flourishing regions. A new hybrid model called logarithmic spiral firefly algorithm-support vector regression (LS-FA-SVR) is proposed to promote the performance of electric load forecasting. The new hybrid model is acquired by combining the support vector regression, firefly algorithm, and logarithmic spiral. Half-hourly electric load from five main regions (NSW, QLD, SA, TAS, and VIC) of Australia are used to train and test the proposed model. By comparing the model results with observed data on the basis of the root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percent error (MAPE), the performance of the proposed hybrid model is the most outstanding among all the considered benchmark models. Hence, the results of this study show that the hybrid model LS-FA-SVR is preferable and can be applied successfully because of its high accuracy.

KEYWORDS

electric load, time series forecasting, firefly algorithm, support vector regression, logarithmic spiral, management of power system

1 Introduction

As an integrated system that can optimize the allocation of energy resources according to the regional energy structure and energy reserves, an integrated energy system has become an important way to accelerate the global sustainable energy transformation. Accurate load forecasting not only plays a decisive role in the comprehensive planning, operation, management and cascade use of energy system but is also a key technology to promote the development of the energy market (Wang et al., 2018; Chen and Wang, 2021; Yang et al., 2022c). Hence, technology for the smart and efficient management of grid uncertainty has attracted research interest. In particular, load forecasting is a core factor of smart grid applications, such as demand response, as it can accurately predict the demand flexibility and potential problems in a grid. In addition, load forecasting can contribute to the efficient integration and wide allocation of distributed energy resources and their

coordination to accommodate supply and demand (Kaur et al., 2016). Therefore, the prediction of the short-term load has become the chief task in power dispatching and power planning (Wu et al., 2021; Yang et al., 2022d).

However, high accuracy in predicting a short-term load is difficult to obtain because the electric load time series is complex and shows vacillating behavior with many variables considered. In order to deal with this problem, regression models, stochastic process models, and exponential smoothing are employed to forecast the electric load in traditional methods (Zhang et al., 2021, 2022b,a). However, the traditional methods scarcely acquire the complexity of the system. Hence, artificial intelligence approaches are extensively used to predict the power load, such as artificial neural networks, support vector machines, and nature-inspired meta-heuristic algorithms.

Among all the data mining techniques based on artificial intelligence, artificial neural networks have become hot techniques in the research of forecasting electric load. Yang et al. (2022a) developed a highly accurate short-term load forecasting method using non-linear auto-regressive artificial neural networks with exogenous multi-variable input. Yang et al. (2022b) presented a novel approach for short-term electrical load forecasting by the radial basis function neural networks, and the result showed that the application of neural networks in short-term load forecasting is encouraging. Wang et al. (2016) proposed an outstanding model based on a wavelet neural network to address the complex nonlinearities and uncertainties in forecasting the electric load, and the accuracy of the proposed model is better than the considered models. Yang et al. (2021b) proposed a new hybrid model to forecast electric load series with outliers, which is based on a robust extreme learning machine and an improved whale optimization algorithm. An et al. (2013) presented a novel approach based on a feed-forward neural network to predict the electricity demand with high accuracy and demonstrated that the proposed model improved the forecasting accuracy noticeably. Yang et al. (2021a) applied the radial basis function neural network (RBFNN) to generate accurate predictions for nonlinear time series. In recent years, with the development of the deep learning theory and hardware equipment, the technology based on deep learning is widely used in power load forecasting. Kong et al. (2017) established a forecasting framework based on LSTM for residential load forecasting. In particular, the recurrent neural network (RNN) and its variants (long short-term memory (LSTM) and gated recurrent unit (GRU)) have been widely used because of their outstanding ability to deal with time series. Feng developed a two-step short-term load forecasting (STLF) model which designed a Q-learning-based dynamic model selection. This model can provide reinforced deterministic and probabilistic load forecasts (DLFs and PLFs) (Feng et al., 2019). Afrasiabi et al. (2020) proposed a model for conditional probability density forecasting of residential

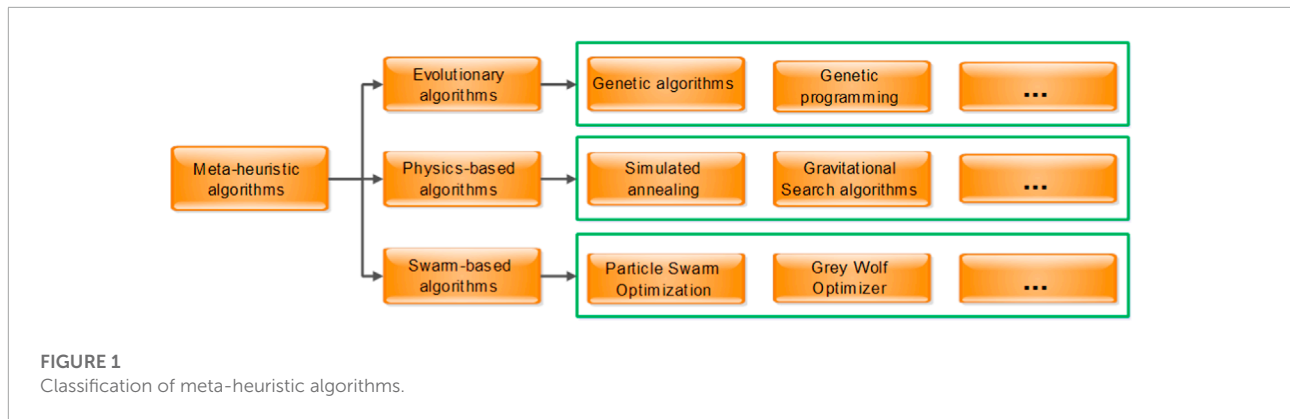
loads based on an end-to-end composite model comprising convolution neural networks (CNNs) and a gated recurrent unit (GRU).

Although neural networks and deep learning methods have been widely used in load forecasting, it should not be ignored that they usually fall into the local minimum because of the restriction on generalization ability which barely makes full use of information from selecting the sample (Cui et al., 2021). Fortunately, the support vector machine developed by Vapnik (1999), one of the outstanding data mining techniques, can overcome this problem and improve the accuracy of prediction. Because of the excellence of the characteristics, the support vector machine has become one of the popular methods in forecasting the short-term electric load. Stojanović et al. (2013) used least square support vector regression (LSSVR) based on historical daily load demands in combination with the calendar and climate features for forecasting the half-hourly load demand of the next day. Chen et al. (2017) established a new support vector regression (SVR) forecasting model with the ambient temperature of 2 hours before the demand response event as input variables, and the result showed the model offered a higher degree of prediction accuracy and stability in short-term load forecasting.

The SVR has been proved to be an excellent model for load demand forecasting. However, the SVR can be improved in many aspects actually; the parameters of the support vector machine play an important role in the accuracy of prediction and are a core part in improving the SVR (Kisi et al., 2015; Najafzadeh et al., 2016). Various optimization algorithms have been used for the selection of these parameters like the grid search algorithm and gradient descent algorithm (Kisi et al., 2015). Computational complexity seems to be the main disadvantage of the grid method, which restricts its applicability to simple cases. The grid search algorithm is also prone to local minima.

Among the methods of optimizing parameters by using data mining technology, a classic way of optimizing parameters of the SVR is meta-heuristic optimization algorithms. At present, with the development of optimizers, meta-heuristic optimization algorithms are increasingly popular in selecting the optimal parameter value because the algorithms can bypass local optima and are easy to implement (Mirjalili and Lewis, 2016).

The idea of meta-heuristic algorithms comes from the behavior of animal or physical phenomena. In addition, the algorithms can be grouped into three main categories (Figure 1). The process of searching for an optimal parameter can be divided into two phases: exploration and exploitation (Olorunda and Engelbrecht, 2008). More specifically, the exploration phase is targeted to investigate the search space globally, and the exploitation phase is employed to search for the best results by following the exploration phase. Therefore, meta-heuristic optimization algorithms are widely utilized to find the



parameters of support vector regression for short-term electric loads. Peng et al. (2016) presented a support vector regression model hybridized with the quantum particle swarm optimization algorithm for electric load forecasting, and the results showed the proposed model can simultaneously provide forecasting with good accuracy. Hong (2011) proposed an electric load forecasting model which combines the support vector regression model with the chaotic artificial bee colony algorithm to improve the forecasting performance, and the forecasting results indicated the hybrid model was a promising alternative for electric load forecasting. Xiao et al. (2017) employed the multi-objective flower pollination algorithm to optimize the parameters of support vector regression for short-term load forecasting, and the experimental results clearly showed that both the accuracy and stability of the proposed model were superior to those of the single models. Yan et al. (2012) proposed an innovative hybrid model comprising the least square support vector machine and chaos optimization, obtaining the optimal parameters for short-term electric load forecasting. For short-term load forecasting, Zhang and Guo (2019) proposed a hybrid method-based support vector regression (SVR) with meteorological factors and electricity price. This model is optimized by an improved adaptive genetic algorithm (IAGA), which is an improved method of the GA (Najafzadeh et al., 2018).

To prevent the optimization algorithm from falling into the local minimum and make it search parameters over a wide range to expand detection probability in the early period, the current study applies an optimization algorithm which is the firefly algorithm improved by a logarithmic spiral (LS-FA). This algorithm can increase the search efficiency in the late period. Hence, it shows good performance to prevent the operation from falling into local optima and to ensure convergence for searching the parameters of the SVR.

Considering the advantages of the LS-FA and SVR, we combined the LS-FA and SVR and then proposed a novel short-term electric load predictive model for the goal of generating accurate electric load predictions. In this model, better model

parameters are obtained by the FA improved by a logarithmic spiral. We intend to apply the proposed approach in this study to real electric load forecasting tasks to verify the ability of the proposed model. Therefore, the proposed algorithm is compared to existing approaches which use the SVR improved by FA, LR-FA (Yang, 2010a), WOA (Mirjalili and Lewis, 2016), and DA (Mirjalili, 2016) to demonstrate the optimization performance of the LS-FA. The experimental results prove that the LS-FA-SVR can achieve better forecasting performance, which demonstrates that the LS-FA optimization algorithm can optimize better parameters for the SVR.

The main contributions of this study can be summarized as follows:

- 1) From the perspective of parameter optimization, we introduced the Lévy-flight firefly algorithm (LF-FA) and the logarithmic spiral firefly algorithm (LS-FA) to enhance the searching ability of exploring the global space and exploiting the local space. Specifically, the LS-FA can obtain a great trade-off between the exploration and exploitation ability of the FA.
- 2) Since the LS-FA can improve the poor convergence of the LF-FA, we combined the introduced LS-FA and SVR into a novel hybrid model which is denoted as LS-FA-SVR for the tasks of generating accurate electric load tasks. We applied the proposed model to five real electric load time series in Australia, and the experiments proved that the LS-FA can optimize better parameters for the SVR model, and the LS-FA-SVR can generate more accurate electric load predictions.

This study is organized as follows. In Section 2, the support vector regression (SVR), firefly algorithm (FA), Lévy-flight firefly algorithm (LF-FA), logarithmic spiral firefly algorithm (LS-FA), and the establishment of the new model are detailed; Section 3 introduces the dataset of the experiment, the evaluation criteria of the model, the results of the proposed model, and the comparative performance of all the considered models. Section 4 summarizes the proposed model and makes corresponding conclusions. Moreover, future work is also given in this section.

2 Methodology formulation

2.1 Support vector regression

Support vector regression (SVR), one of the greatest data learning tools, is developed by Boser et al. (1992). Compared with other data mining techniques, SVR obtains minimal upper bound generalization error by the principle of the statistical machine learning process and structural risk minimization (Che et al., 2012). According to the theory proposed by Vapnik, given a training dataset $v = \{(x_i, y_i) | i = 1, 2, \dots, l; x_i \in R_n; y_i \in R\}$; here, x_i is the n dimensional input vector, y_i represents the target value, and l stands for the number of samples in the training dataset. SVR can be solved by estimating the linear regression as follows:

$$\begin{aligned} & \text{Minimize } \frac{1}{2} \|w\|^2 + C \sum_{i=1}^l (\xi_i + \xi_i^*) \\ & \text{Subject to } \begin{cases} y_i - \langle w, \phi(x_i) \rangle - b \leq \varepsilon + \xi_i \\ \langle w, \phi(x_i) \rangle + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0, (i = 1, 2, \dots, l), \end{cases} \end{aligned} \quad (1)$$

where w is the weight vector, b is a scale quantity, C represents the regularization constant, and ε is the insensitive loss function. Moreover, the slack variables ξ_i and ξ_i^* represent the upper and lower excess deviation, respectively (Figure 2).

Formula 1 can be solved by the Lagrangian multipliers, and the nonlinear regression can be obtained as follows:

$$f(x) = \sum_{i=1}^l (\beta_i^* - \beta_i) \cdot k(x_i, x) + b, \quad (2)$$

where β_i and β_i^* are the Lagrangian multipliers.

It must be noticed that $k(x_i, x)$ is called the kernel function which converts a nonlinear problem in input space to a linear problem in feature space. Moreover, the selection of kernel functions is discussed in Section 3.4.

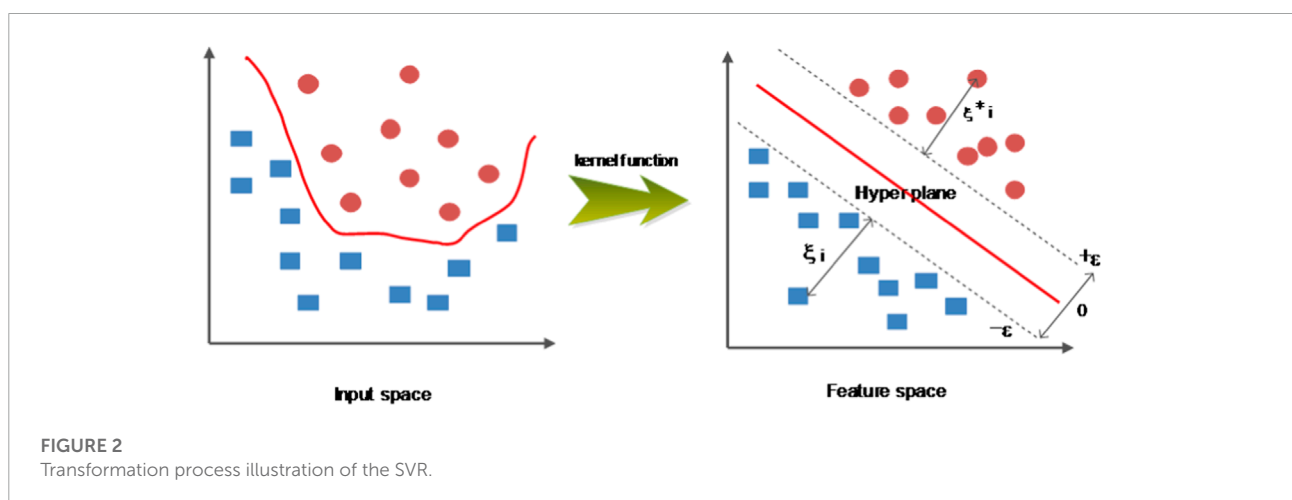
2.2 Firefly algorithm

The firefly algorithm is proposed by Yang in 2008, and it is based on the idealized behavior of the flashing characteristics of fireflies (Yang, 2010b). For simplicity in describing the FA, the following three rules are idealized (Yang, 2009):

- 1) All fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex.
- 2) Attractiveness is proportional to their brightness, so for any two flashing fireflies, the less bright one will move toward the brighter one. The attractiveness is proportional to the brightness, and they both decrease as their distance increases. If there is no brighter one than a particular firefly, it will fly randomly.
- 3) The brightness of a firefly is affected or determined by the landscape of the objective function to be optimized.

In general, the brightness can simply be proportional to the objective function when dealing with the maximum problem. In contrast, when dealing with the minimum problem, some techniques are employed to convert the minimum problem into a maximization problem. Based on what is mentioned previously, the pseudo-code of the FA is shown in Figure 3.

In the FA, there are two issues: the variation of light intensity and the formulation of attractiveness. Generally speaking, the attractiveness of a firefly is determined by its brightness or light intensity which is associated with the objective function. The brightness I of a firefly at location x can be shown as $I(x) \propto f(x)$. But the attractiveness β can be seen in the eyes of the beholder or judged by other fireflies (Kavousi-Fard et al., 2014). Moreover, the light intensity decreases with the distance from its source, and light is absorbed in the media. Hence, attractiveness is allowed to vary with the degree of absorption. Hence, the light intensity $I(r)$ can be obtained on the inverse square law and absorption as



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FA


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Objective function  $f(x)$ ,  $x=(x_1, x_2, \dots, x_d)^T$ 
Initialize a population of fireflies  $x_i$  ( $i=1, 2, \dots, n$ )
Define light absorption coefficient  $\gamma$ 
while ( $t < \text{MaxGeneration}$ )
  for  $i=1:n$  all  $n$  fireflies
    for  $j=1:i$  all  $n$  fireflies
      Light intensity  $I_i$  at  $x_i$  is determined by  $f(x_i)$ 
      if ( $I_j > I_i$ )
        Move firefly  $i$  towards  $j$  in all  $d$  dimensions
      end if
      Attractiveness varies with distance  $r$  via  $\exp[-\gamma r]$ 
      Evaluate new solutions and update light intensity
    end for  $j$ 
  end for  $i$ 
  Rank the fireflies and find the current best
end while
Output results and visualization


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FIGURE 3
Pseudo-code of the FA.

follows:

$$I(r) = I_0 \cdot e^{-\gamma r^2}, \tag{3}$$

where I_0 and γ stand for the original light intensity and light absorption coefficient, respectively. Here, the definition of attractiveness β can be expressed by

$$\beta(r) = \beta_0 \cdot e^{-\gamma r^2}, \tag{4}$$

where β_0 is the attractiveness at $r = 0$.

Then, the Cartesian distance is employed to calculate the distance between any two fireflies i and j at x_i and x_j as follows:

$$r_{ij} = \sqrt{\sum_{p=1}^d (x_{i,p} - x_{j,p})^2}, \tag{5}$$

where $x_{i,p}$ is the p th component of the spatial coordinate x_i of i th firefly.

Finally, the position of firefly i which is attracted to the brighter firefly j at $t + 1$ time can be expressed by

$$x_{i,t+1} = x_{i,t} + \beta_0 \cdot e^{-\gamma r_{ij}^2} (x_j - x_i) + \alpha (rand - 0.5), \tag{6}$$

where $rand$ is a random number in $[0,1]$, and α is the parameter in $[0,1]$.

2.3 Lévy-flight firefly algorithm

The Lévy-flight firefly algorithm (LF-FA) is proposed by Yang (2010a) to enhance the ability of exploring the global space and exploiting the local space. Specifically, this algorithm can

obtain a great trade-off between the exploration and exploitation ability of the FA. Hence, the LF-FA is utilized to update the position next time as follows (Yang and Deb, 2009; Kaveh and Khayatizad, 2012):

$$x_{i,t+1} = x_{i,t} + \beta_0 \cdot e^{-\gamma r_{ij}^2} (x_j - x_i) + \alpha \cdot sign[rand - 0.5] \oplus Levy, \tag{7}$$

where α is the randomization parameter, and \oplus is the dot product. $rand$ is a random number in $[0,1]$, and $sign[rand - 0.5]$ provides a random direction while the random step length is drawn from the Lévy flights. It is required to explain formula 7 combining α and $sign[rand - 0.5] \oplus Levy$ which can make a firefly walk more randomly (Mirjalili et al., 2014). In other words, the LF-FA can jump out of the local optimum and enhance the global search capability of the FA.

The LF is one of the random walks, and its steps are decided by the step length. Furthermore, jumps conforming to the Lévy distribution can be shown as follows (Walster et al., 1985):

$$Levy(\eta) \sim \mu = t^{-1-\eta} \quad (0 \leq \eta \leq 2), \tag{8}$$

and the Lévy random number is calculated by

$$Levy(\eta) \sim \frac{\phi \times \mu}{|v|^{1/\eta}}, \tag{9}$$

where v and μ conform to the standard normal distributions. ϕ can be calculated as follows:

$$\phi = \left[\frac{\Gamma(1 + \eta) \times \sin(\pi \times \eta / 2)}{\Gamma((1 + \eta) / 2) \times \eta \times 2^{(\eta-1)/2}} \right]^{1/\eta}, \tag{10}$$

where Γ stands for the standard gamma function and $\eta = 1.5$.

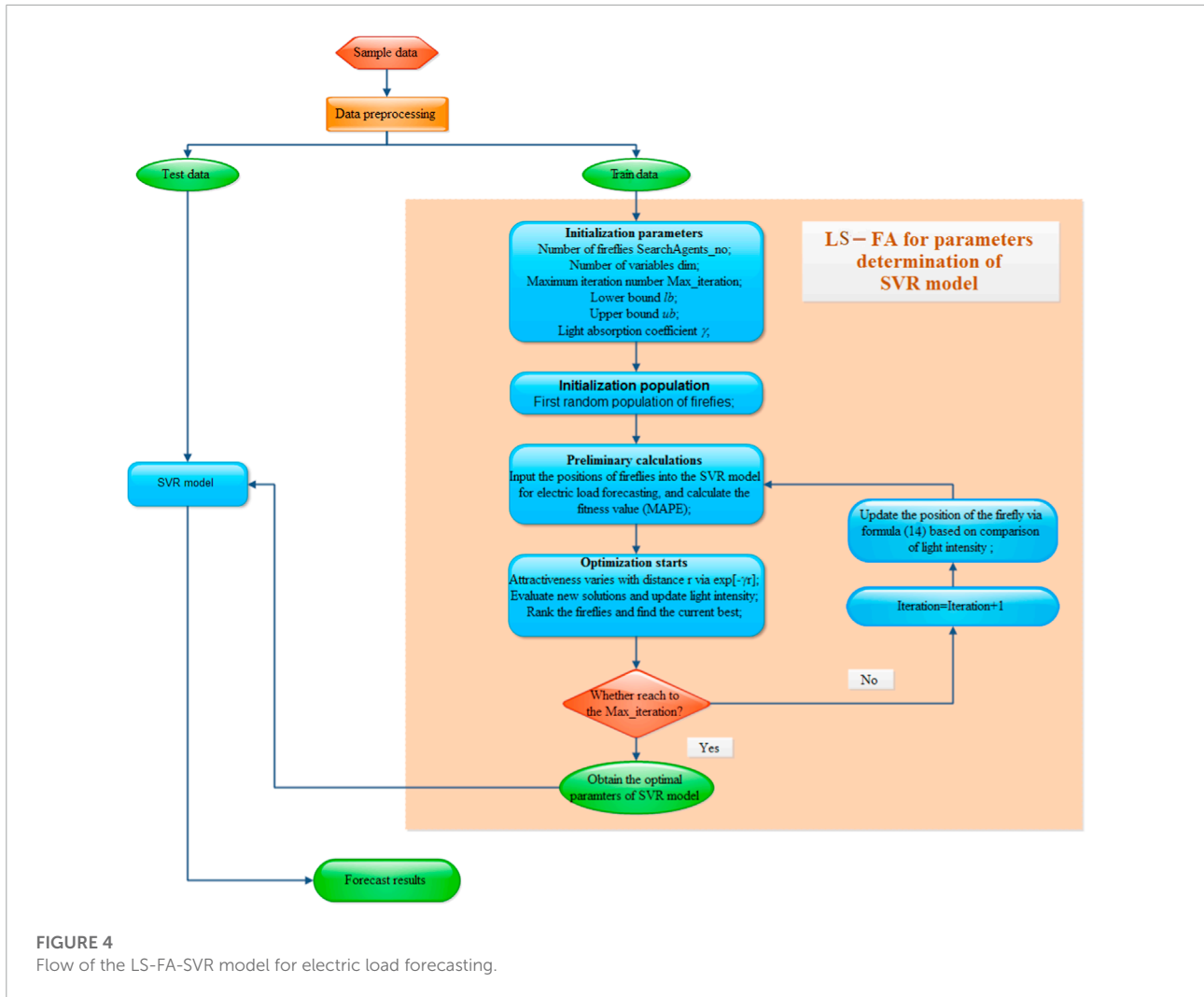


FIGURE 4 Flow of the LS-FA-SVR model for electric load forecasting.

2.4 Logarithmic spiral firefly algorithm

In the section, because of the poor convergence of the LF-FA, the logarithmic spiral is introduced in this study to balance the abilities of exploration and exploitation (Mirjalili and Lewis, 2016). The logarithmic spiral is selected to improve the performance of the FA. Considering formula 6, we propose a modified formula as follows:

$$x_{i,t+1} = x_{i,t} + \beta_0 \cdot e^{-\gamma r_{ij}^2} (x_j - x_i) \cos(2\pi t) + \alpha(rand - 0.5), \quad (11)$$

in which t is a random number from -1 to 1.

In Section 3.1, some experiments would be carried out to assess the performance of the LS-FA by comparing it with some optimizers based on the FA.

2.5 Hybrid model LS-FA-SVR

In this section, the proposed hybrid model LS-FA-SVR will be introduced in detail, and the flow of this proposed model is shown in Figure 4.

- 1) Input train data set;
- 2) initialization parameters;
- 3) initialization population;
- 4) preliminary calculations;
- 5) optimization starts;
- 6) update the position and calculate the fitness;
- 7) optimization stops;
- 8) SVR model obtained; and
- 9) output result of the test dataset.

Above all, the innovative hybrid model LS-FA-SVR can be obtained.

3 Empirical study

3.1 Performance of the LS-FA

This section aims to test the performance of the optimization by the proposed modified algorithm LS-FA through some classical unimodal benchmark functions. The structure of the four benchmarks considered in this experiment is as follows (Mirjalili and Lewis, 2016):

$$F1 : f_1 = \sum_{i=1}^l x_i^2, \tag{12}$$

$$F2 : f_2 = \max \{ |x_i|, 1 \leq i \leq l \}, \tag{13}$$

$$F3 : f_3 = \sum_{i=1}^l |x_i| + \prod_{i=1}^l |x_i|, \tag{14}$$

$$F4 : f_4 = \sum_{i=1}^l i \cdot x_i^4 + random [0, 1), \tag{15}$$

where the value of the dimension in this experiment is 20. To compare the LS-FA with the FA and LF-FA, all the numbers of

fireflies are set at the same value (10), and the values of alpha and gamma are 0.25 and 1, respectively.

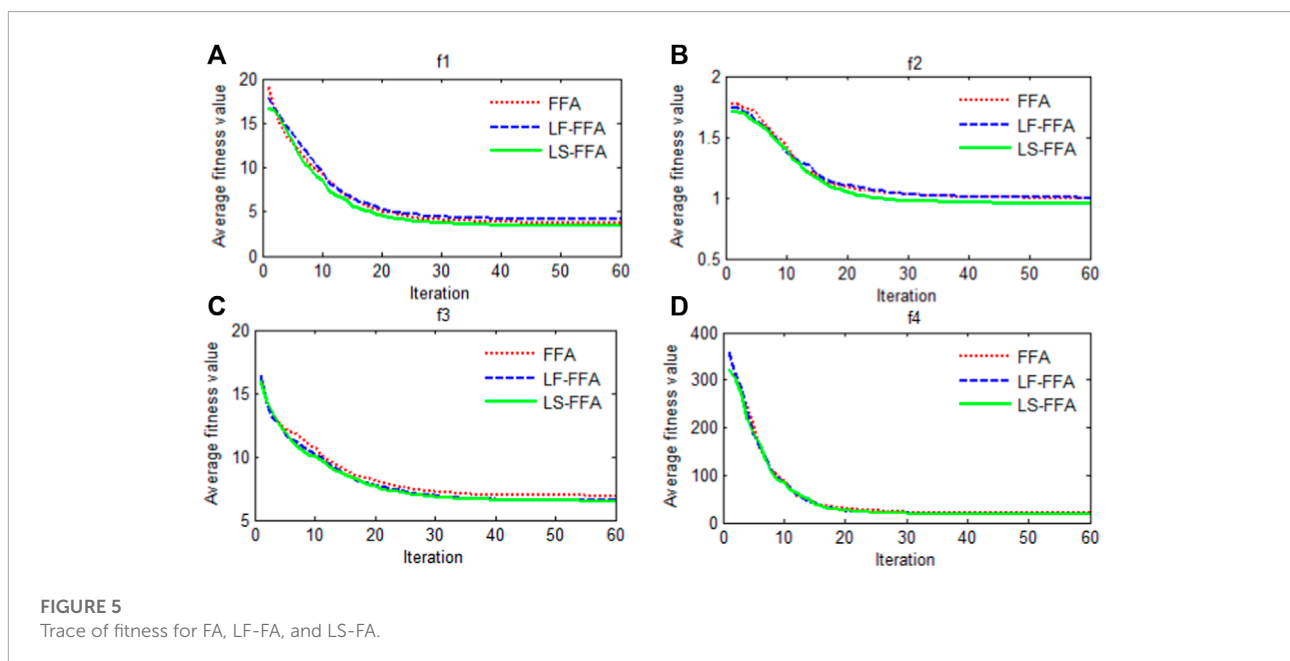
To perform the result of the proposed method LS-FA, minimum (Min), maximum (Max), and standard deviation (Std) are selected to measure the errors of the optimizer. After implementing the FA, LF-FA, and LS-FA using Matlab 2014(b), every algorithm has been run 30 times to get the average error for each method. Table 1 shows the results with the optimization.

Multiple studies have shown that the modified algorithm LS-FA has the best predictive results among the other two algorithms (FA and LF-FA) by searching the minimum of four benchmark functions. To be specific, the maximum of the LS-FA is smaller than that of the FA and LF-FA. The minimum of the LS-FA is relatively small among all the three methods. Moreover, the LS-FA has the smallest standard deviation, and it means the performance has the best stabilization. In addition, Figure 5 presents the trace of optimization by calculating the mean of errors for the four benchmark functions. The LS-FA has outstanding performance for searching the minimum of the

TABLE 1 Performance of FA, LF-FA, and LS-FA.

Criterion	F1			F2			F3			F4		
	FA	LF-FA	LS-FA	FA	LF-FA	LS-FA	FA	LF-FA	LS-FA	FA	LF-FA	LS-FA
Max ^a	5.34	6.65	4.87	1.24	1.26	1.10	8.82	8.52	8.05	59.87	41.35	35.41
Min ^b	1.50	2.16	1.68	0.80	0.70	0.68	4.58	4.66	3.69	4.73	5.90	3.49
Std ^c	1.10	1.17	0.72	0.12	0.16	0.10	1.32	0.99	0.81	13.91	9.75	8.40

^aMin is the minimum.
^bMax is the maximum.
^cStd is the standard deviation.



four functions. Specifically, the speed of the LS-FA is faster than that of the FA and LF-FA. Moreover, the average error for all four models by the LS-FA is significantly smaller than that by other algorithms. In short, through these studies, it can be proved that the proposed algorithm LS-FA has a better performance of optimization. In other words, the logarithmic spiral can improve the performance of the FA by boosting the ability to balance exploration and exploitation. Hence, this modified optimizer is chosen to search for suitable parameters of SVR in the study.

3.2 Data description

To verify the effectiveness of the proposed model, the datasets of electric load from 1 January 2018 to 1 February 2018 in NSW, QLD, SA, TAS, and VIC are used as the experimental data (Table 2 and Figure 6). The datasets of the electric load (MW) are retrieved from the website of energy security for all Australians (<http://www.aemo.com.au/>). The sample data used in this study are half-hourly electric load, and the total number of these five regions is 1,488. In this study, each dataset was divided into two sets: the training dataset including 960 data points (from 2018/1/1 0:30 to 2018/1/21 0:00) and the remaining as the test dataset (from 2018/1/21 0:30 to 2018/2/1 0:00).

3.3 Evaluation criteria

Because there is no confirmed universal standard method, this study adapts multiple error criteria to evaluate the effectiveness of the proposed hybrid model: the mean absolute error (MAE), root mean square error (RMSE), and mean absolute percent error (MAPE). The MAE, RMSE, and MAPE are applied to quantify the forecast error, and the performance of the model is reliable when their value is close to zero.

These three criteria are calculated as follows:

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i|, \tag{16}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}, \tag{17}$$

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left| \frac{\hat{y}_i - y_i}{y_i} \right| \times 100\%, \tag{18}$$

where y_i is the observed value, \hat{y}_i is the predicted value to y_i , and N is the number of samples.

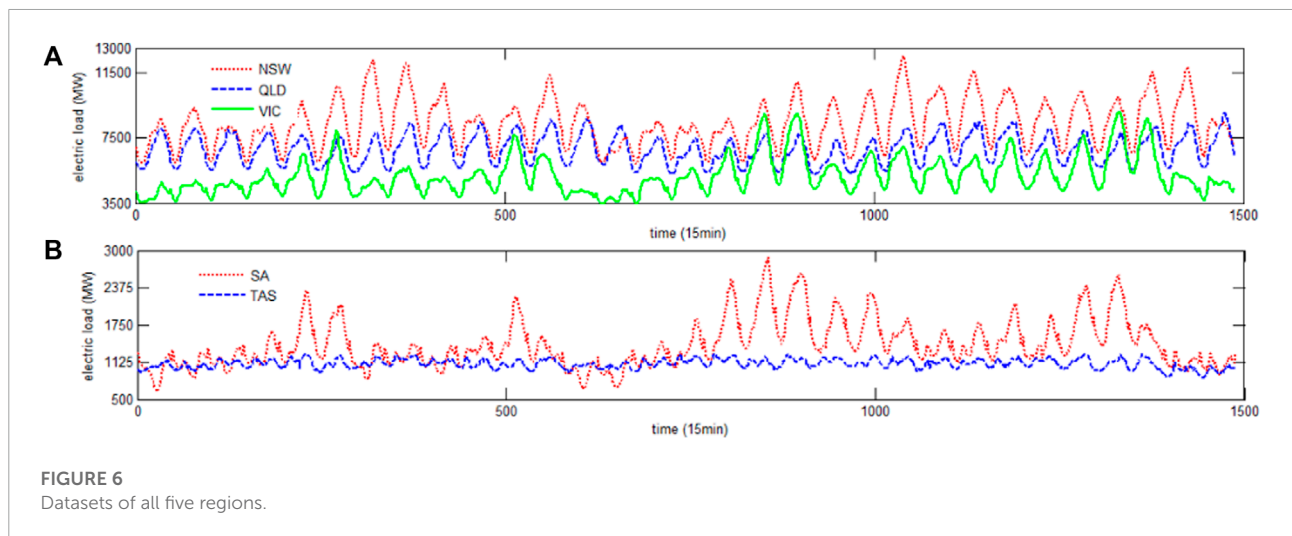


TABLE 2 Statistical properties for each dataset.

Region	Training set					Test set				
	NSW	QLD	SA	TAS	VIC	NSW	QLD	SA	TAS	VIC
N	960	960	960	960	960	528	528	528	528	528
Mean	8115.3	6720.3	1375.8	1102.9	4987.3	8818.6	6937.8	1503.0	1085.7	5578.9
Std	1350.0	873.1	417.8	70.3	1095.6	1493.2	905.8	357.5	86.3	1156.5
Min	5910.1	5258.4	653.2	950.8	3449.8	6197.6	5359.5	894.2	865.2	3683.1
Max	12230.6	8670.0	2879.9	1263.8	8999.2	12494.6	9020.4	2609.9	1256.5	9085.2

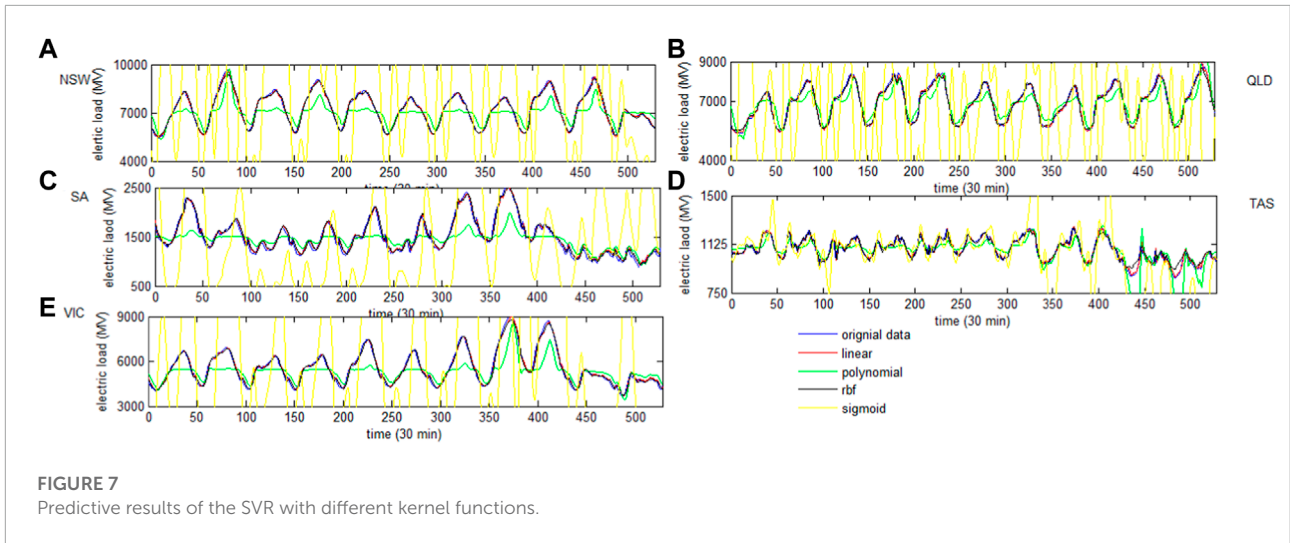


FIGURE 7
Predictive results of the SVR with different kernel functions.

TABLE 3 Performance of the SVR with different kernel functions based on MAPE, MAE, and RMSE.

Criterion	Linear			Polynomial			rbf			Sigmoid		
	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE
NSW	1.13	99.08	123.22	8.58	786.68	964.58	1.38	122.32	155.59	61.88	5462.42	6533.04
QLD	1.04	73.10	91.57	4.41	312.24	401.27	1.27	88.97	113.14	38.79	2638.53	3916.17
SA	3.38	48.78	59.70	11.00	182.03	256.63	3.75	54.11	64.30	62.73	941.26	1154.82
TAS	1.38	14.85	20.99	5.04	51.30	99.96	1.70	17.78	25.19	24.34	242.74	612.28
VIC	2.07	112.63	137.15	9.28	565.44	763.20	2.28	124.07	151.53	91.87	5327.46	7083.36

3.4 Selection of the kernel function

In this section, the selection of the kernel function in the SVR for electric load forecasting is discussed, and the data of five regions in Australia are applied to search for the fittest choice of the kernel function. First, four main kernel functions are provided when the model is established by SVR, and they are shown as follows:

$$\begin{aligned}
 \text{Linear: } & K(x, x_i) = x^T x_i, \\
 \text{Polynomial: } & K(x, x_i) = (\gamma x^T x_i + r)^p, \quad \gamma > 0 \\
 \text{Rbf: } & K(x, x_i) = \exp(-\gamma \|x - x_i\|^2), \quad \gamma > 0 \\
 \text{Sigmoid: } & K(x, x_i) = \tanh(\gamma x^T x_i + r).
 \end{aligned} \tag{19}$$

Second, in order to find the best kernel function for forecasting electric load, we selected the last twelve half-hour load data $(x_{n-12}, x_{n-11}, x_{n-10}, \dots, x_{n-2}, x_{n-1})$ as the input variables of SVR with different kernel functions, and the output variable is x_n . At last, the best kernel function can be selected from the four kernel functions based on the performance of prediction. The experiment is performed, and the results of forecasting electric load based on different kernel functions are shown in **Figure 7**. It is obvious that the sigmoid kernel

function has the worst performance, and the accuracy of the polynomial is just higher than it. In addition, the SVR based on the rbf kernel function and linear kernel function has better predictive results since it approaches the original data.

In order to show the performances clearly, the three criteria (MAPE, MAE, and RMSE) of errors are calculated, and the results are shown in **Table 3**. The MAPE, MAE, and RMSE of the liner kernel function have the smallest values in all five regions. It must be noted that the rbf kernel function is just slightly poorer than the linear one. Moreover, it can be found that the polynomial and sigmoid functions are not suitable for electric load forecasting with larger errors. Based on this research, the linear is chosen as the kernel function of SVR in the study.

3.5 Process of LS-FA-SVR

In **Section 2.5**, the hybrid model LS-FA-SVR is established for short-term load forecasting. Here, the bandwidth of liner

TABLE 4 Performance of the LS-FA-SVR in NSW, QLD, SA, TAS, and VIC.

Run No.	NSW			QLD			SA			TAS			VIC		
	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE
1	0.866	91.237	112.178	0.819	59.613	75.405	2.777	42.653	51.459	1.116	11.390	10.356	1.363	89.422	109.661
2	0.933	91.397	112.035	0.753	59.866	75.402	2.689	42.857	51.378	1.131	11.338	10.424	1.346	89.354	109.649
3	1.048	91.211	112.124	0.582	59.756	75.571	2.832	42.701	51.371	1.138	11.487	10.402	1.438	89.289	109.463
4	0.892	91.307	112.078	0.673	59.861	75.288	2.718	42.624	51.360	1.043	11.440	10.318	1.243	89.362	109.710
5	0.804	91.467	112.038	0.793	59.838	75.523	2.716	42.704	51.385	1.048	11.424	10.430	1.281	89.365	109.837
6	0.951	91.380	112.071	0.699	59.726	75.462	2.693	42.554	51.402	1.061	11.424	10.408	1.367	89.426	109.517
7	0.830	91.363	112.133	0.666	59.853	75.420	2.767	42.724	51.458	1.218	11.381	10.263	1.390	89.280	109.722
8	0.905	91.442	112.044	0.652	59.831	75.308	2.811	42.737	51.387	1.069	11.567	10.371	1.294	89.279	109.558
9	0.905	91.460	112.077	0.686	59.718	75.474	2.652	42.752	51.291	1.086	11.256	10.444	1.364	89.299	109.648
10	0.965	91.416	112.118	0.824	59.745	75.365	2.754	42.686	51.469	1.092	11.335	10.389	1.404	89.321	109.570
11	1.031	91.331	112.079	0.682	59.636	75.429	2.732	42.728	51.281	1.202	11.441	10.276	1.394	89.307	109.647
12	0.970	91.253	111.879	0.784	59.727	75.369	2.791	42.647	51.452	1.108	11.323	10.468	1.347	89.454	109.552
13	0.880	91.348	112.161	0.807	59.755	75.398	2.809	42.859	51.469	1.103	11.356	10.441	1.270	89.373	109.685
14	1.026	91.370	112.218	0.889	59.602	75.275	2.683	42.542	51.369	1.069	11.422	10.424	1.254	89.289	109.686
15	0.921	91.213	112.109	0.757	59.721	75.470	2.775	42.685	51.394	1.133	11.367	10.317	1.297	89.364	109.664
16	0.950	91.286	112.156	0.732	59.819	75.440	2.756	42.695	51.324	1.022	11.325	10.544	1.293	89.429	109.651
17	1.101	91.397	112.010	0.715	59.825	75.440	2.938	42.698	51.274	1.132	11.329	10.405	1.395	89.379	109.647
18	0.936	91.311	112.100	0.517	59.785	75.496	2.653	42.580	51.448	0.975	11.268	10.464	1.257	89.454	109.520
19	0.903	91.342	112.152	0.778	59.769	75.399	2.711	42.740	51.367	1.130	11.489	10.221	1.453	89.303	109.728
20	1.076	91.205	112.122	1.018	59.737	75.456	2.783	42.803	51.485	1.020	11.367	10.428	1.304	89.557	109.658
21	0.987	91.256	112.003	0.805	59.738	75.469	2.690	42.774	51.253	1.221	11.470	10.410	1.216	89.322	109.643
22	1.049	91.240	112.212	0.962	59.714	75.455	2.704	42.565	51.516	1.152	11.361	10.410	1.291	89.237	109.392
23	0.948	91.286	112.062	0.673	59.609	75.375	2.770	42.617	51.434	1.074	11.394	10.287	1.248	89.387	109.560
24	0.965	91.481	112.172	0.824	59.943	75.511	2.789	42.858	51.326	1.041	11.563	10.437	1.306	89.391	109.602
25	0.929	91.292	112.064	0.666	59.749	75.371	2.872	42.721	51.480	1.085	11.395	10.502	1.426	89.357	109.758
26	0.990	91.352	112.283	0.864	59.827	75.449	2.714	42.693	51.544	0.934	11.351	10.386	1.321	89.211	109.665
27	1.010	91.248	112.087	0.644	59.884	75.447	2.737	42.628	51.406	1.231	11.424	10.429	1.213	89.367	109.685
28	0.841	91.413	112.305	0.616	59.589	75.411	2.818	42.695	51.385	1.097	11.317	10.269	1.436	89.377	109.528
29	1.038	91.219	112.098	0.800	59.687	75.389	2.759	42.858	51.435	1.064	11.384	10.379	1.414	89.331	109.560
30	0.971	91.315	112.171	0.818	59.841	75.469	2.808	42.854	51.305	1.068	11.266	10.475	1.311	89.330	109.485
MEAN	0.954	91.328	112.111	0.750	59.759	75.423	2.757	42.708	51.397	1.095	11.389	10.393	1.330	89.354	109.622

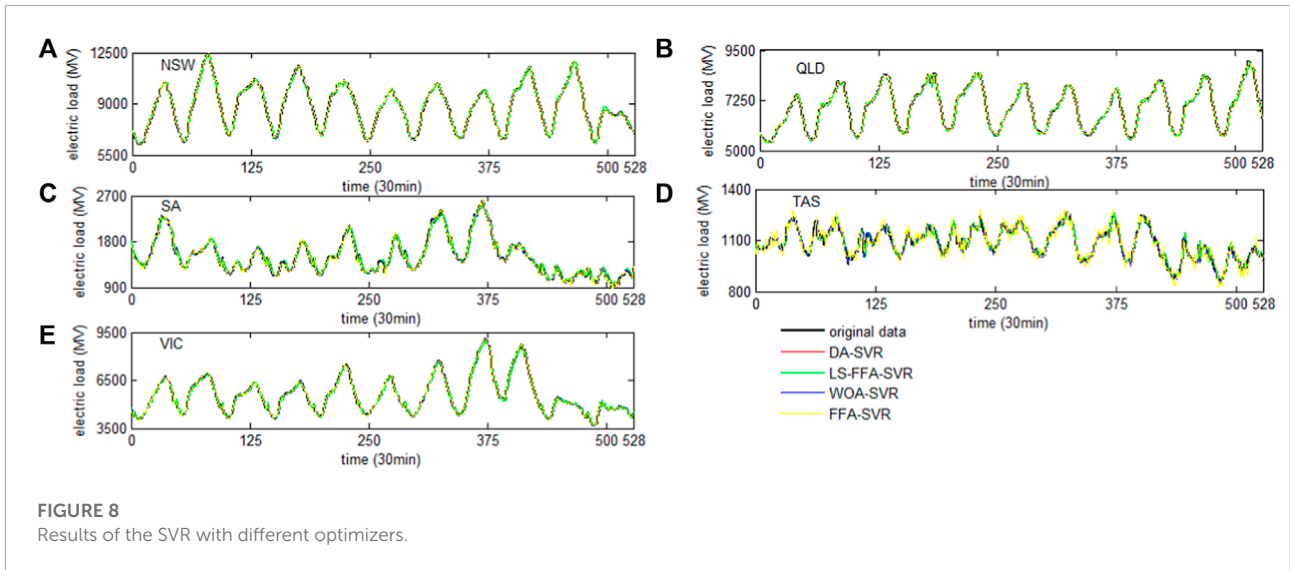


FIGURE 8 Results of the SVR with different optimizers.

TABLE 5 Performance of the LS-FA-SVR based on MAE, MAPE, and RMSE compared to other models.

Region	DA-SVR			WOA-SVR			LS-FA-SVR			FA-SVR		
	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE
NSW	1.089	95.816	119.326	1.089	95.786	119.294	0.954	91.328	112.111	1.11	96.88	119.92
QLD	0.920	63.994	80.608	0.921	64.020	80.597	0.750	59.759	75.423	0.92	64.15	80.72
SA	3.379	48.791	59.686	3.376	48.763	59.656	2.757	42.708	51.397	3.41	49.12	60.13
TAS	1.376	20.961	14.797	1.376	14.796	20.964	1.095	11.389	10.393	1.38	13.93	14.49
VIC	1.702	116.478	94.186	1.701	94.169	116.498	1.330	89.354	109.622	1.70	94.26	116.60

To verify the proposed model LS-FA-SVR, we conducted a forecasting experiment with the same electric load in NSW, QLD, SA, TAS and VIC. The comparisons of electric load values forecast using WOA-SVR, DA-SVR; FA-SVR, and the new proposed LS-FA-SVR are shown in Table 5 (Mirjalili and Lewis,2016; Mirjalili, 2016). It is clear that the new model LS-FA-SVR has the lowest MAE, MAPE, and RMSE, among all four models.

kernel and the regularization parameter of SVR can be optimized by the LS-FA. In this study, the numbers of fireflies, absorption coefficient, and iteration of LS-FA are 15, 1, and 20, respectively. Based on these, the prediction of short-term load in NSW, QLD, VIC, SA and TAS can be obtained.

3.6 Empirical analysis

To avoid some accidental situations which would cause unreliable conclusions, we conducted 30 runs for experiments in five regions, and three error indicators are recorded in Table 4 in each run.

Comparing the LS-FA-SVR with FA-SVR, the difference between them is whether the logarithmic spiral has been improved. It can be found that after introducing the logarithmic spiral into the model, the MAE, MAPE, and RMSE in five regions all decrease, which indicates that the LS is necessary

for forecasting the electric load. Moreover, this study compared LS-FA-SVR with two new optimizers which were developed in 2016. The two benchmark models are DA-SVR and WOA-SVR. Through the comparisons, the three error indicators have decreased significantly. For example, the RMSE of THE LS-FA-SVR in NSW is 112.111, yet the values of DA-SVR and WOA-SVR are 119.326 and 119.294, respectively. The smaller the values of MAE, MAPE, and RMSE, the better the model will be. According to the aforementioned results, it is clear that the proposed model LS-FA-SVR outperforms the three benchmark models for five regions, and they are shown in Figure 8.

We applied the LS-FA-SVR model to the forecasting experiments for the five experimental datasets and stated the results in Table 5. As the last row of this table shows, the mean values of MAE, MAPE, and RMSE in NSW are 91.328, 0.954, and 112.111, respectively. Meanwhile, the mean values of MAE, MAPE, and RMSE in QLD are 59.759, 0.750, and 75.423,

respectively. Moreover, **Figure 8** clearly shows that the model LS-FA-SVR interprets the curves of the original electric load in NSW, QLD, SA, SAT, and VIC, which indicates that the new model gets a satisfactory performance and a high forecasting accuracy. Comprehensively considering the results of MAE, MAPE, and RMSE in NSW, QLD, SA, TAS, and VIC, it can be concluded that the LS-FA-SVR model is the best overall, and its prediction is the best.

4 Conclusion and future work

Accurate forecasting of the electric load can provide valuable references for economic managers and electric power system operators. The study proposed a hybrid model LS-FA-SVR for improving the forecasting accuracy, where the parameters of SVR are optimally determined by the optimization algorithm LS-FA. This hybrid approach can search over a wide range to expand the detection probability in the early period. It can increase the search efficiency in the late period. Hence, the LS-FA has a good performance to prevent the operation from falling into local optima and to ensure the convergence for searching the parameters of SVR. In addition, the empirical results show that the MAE, MAPE, and RMSE values of LS-FA-SVR are all modestly smaller than those of WOA-SVR, DA-SVR, and FA-SVR. Compared with these other methods, the new method has a strong ability to find the optimal solution, and the run time is shorter. In other words, LS-FA-SVR is an attractive and effective model which combines a novel optimization algorithm to determine the parameters of SVR. In future work, several research directions can be tried. More related variables can be taken into consideration. One possibility is to apply other factors which may influence electrical demand, such as the population and GDP, to obtain more comprehensive results (Li et al., 2017).

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Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

Author contributions

WZ: formal analysis and writing—original draft; LG: writing—review and editing; YS: writing—review and editing; XL: writing—review and editing; and HZ: supervision, investigation, and project administration.

Conflict of interest

WZ and LG were employed by Nari Technology Co., Ltd, and YS was employed by State Grid Xiong'an Integrated Energy Service Co, Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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