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Prediction of electricity consumption during epidemic period based on improved particle swarm optimization algorithm

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Abstract

A prediction method of electricity consumption is developed in order to address the problems of big change and imbalance in electricity consumption caused by COVID-19. In this method, BP (Back Propagation) neural network and improved particle swarm optimization (IPSO) algorithm are combined and applied. Firstly, Pearson correlation coefficient approach is utilized to conduct data correlation analysis. Then, the BP neural network prediction model is built, and IPSO algorithm is used to optimize the neural network’s initial weights and thresholds. Considering the medical data, public opinion data, policy data and historical data of electricity consumption during epidemic period, the electricity consumption of each industry in the future is predicted. The findings suggest that the proposed model performs well in terms of prediction. The Mean Absolute Percentage Error (MAPE) for each industry’s evaluation index is 1.41\%, 1.70\%, and 1.37\%, respectively. Compared with other models, the prediction accuracy is higher. By exploring the predicted results of electricity consumption during epidemic period, it is hoped that a basis prediction method of electricity consumption for power grid companies in the event of a sudden outbreak will be provided.

Keywords: COVID-19; Prediction of electricity consumption; Modeling; BP neural network; Improved particle swarm optimization; Epidemic

1. Introduction

In 2020, the COVID-19 epidemic broke out across China, which had a serious impact on China’s economy and social development, especially for the electricity market. Social consumption decreased by 16.2\% as a result of the epidemic. Service industries such as catering, entertainment, accommodation and tourism were hit hard, and consumption of housing, automobiles and furniture also dropped significantly [1]. State departments issued a series of policies to reduce the cost of enterprises, relieve the pressure on their production and operation, and

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As the lifeblood of the country, the power industry plays an important and unshakable role. Accurate prediction of electricity consumption can guarantee people’s life and social normal activity, effectively minimize the operation cost of power firms, ensure the economic operation of power grid, and improve social economic benefits. However, due to the uncertainty of demand side and generation side, the balance of operation in power system is full of challenges. At present, the power system’s balance may be maintained via a multi-stage generation scheduling process that includes day-ahead planning, day-ahead scheduling, day-ahead rolling scheduling, and real-time scheduling. These scheduling processes rely heavily on accurate prediction of electricity consumption. Especially in areas where coal is mainly used for power generation, the generating capacity of the generator units must be planned far in advance. Due to sudden outbreak of COVID-19 and rapid changes in epidemic prevention and control policies, load demand will become more unclear, and the difficulty of predicting electricity will also increase. Moreover, the nature of prediction is to discover rules in historical data. In the background of COVID-19, due to the lack of historical data on electricity consumption, the prediction method based on conventional learning is not easy to use. Therefore, it is necessary to propose a novel method to predict the electricity consumption during epidemic period.

Prediction methods are mainly classified into two types: one is the traditional method represented by time series method [3] and regression analysis method [4], the other is the artificial intelligence methods, consisting of artificial neural network (ANN) [5], support vector machine (SVM) [6] and gray model (GM) [7]. Although the traditional prediction method can achieve good prediction effect, it is easy to be affected by a variety of factors and cannot obtain accurate prediction results. Time series method has the benefit of being quick to operate and having a favorable influence on continuous load identification, but its random sequence needs to be stable. If the time series fluctuates greatly or there is bad data, the prediction performance will be reduced. Regression analysis method needs a lot of data to fit when considering uncertain factors, and its matrix involves the solution of the problem. The higher the dimension of the matrix is, the more complex the solution is. The advantage of artificial intelligence method is that it can extract the characteristics of time series without establishing accurate mathematical model. In practice, traditional methods make it difficult to predict the electricity consumption of complex objects. However, the appropriate intelligent algorithm can not only optimize the utilization of computing resources, but also achieve the most efficient prediction of electricity consumption. As described in literature [8–10], a BP neural network can deal with prediction of electricity consumption well in most cases. With the development of artificial intelligence, swarm intelligence optimization algorithm has been widely used in power system. After studying and modeling the swarm behavior in nature, swarm intelligence optimization algorithm is put forward. At present, common swarm intelligence optimization algorithm mainly includes artificial fish swarm algorithm [11], ant colony algorithm [12] and particle swarm optimization (PSO) algorithm [13]. In literature [14], BP neural network with Particle Swarm Optimization (PSO-BP) is used to investigate a short-term load prediction method. The experimental results show that the PSO-optimized method can increase the network’s learning speed and improve prediction precision when compared to the conventional BP method. This method is not only easy to calculate, but it is also useful. In literature [15], the accuracy of load prediction can be improved by considering factors that may lead to load changes, such as temperature and weather, when short-term power load prediction is carried out. In literature [16], a BP network is used to create a short-term forecast model of regional electric load considering the hourly power load data, dry bulb temperature, dew point temperature, humidity, and other meteorological data from a specific area. In literature [17], a PSO-BP model is used to forecast a city’s short-term electric load under conditions similar to [16]. Compared with BP model, the prediction effect of PSO-BP is better and the nonlinear fitting ability is stronger. Although these prediction and optimization methods have been widely used in different scenarios, the impact of the medical data, public opinion data and policy data in these methods has not been considered, and there are no mature prediction cases for emergencies such as epidemic situation. Under normal circumstances, these data have little impact on the electricity consumption of industries. However, when COVID-19 comes, these data play a crucial role in the resumption of production, which has a significant impact on industrial electricity consumption. Therefore, when the electricity consumption of industries is predicted during epidemic period, medical data, public opinion data and policy data must be taken as important input data, and the optimized weights and parameters must be redesigned.

In the above summary and analysis, a BP neural network of prediction of electricity consumption optimized by Improved Particle Swarm Optimization (IPSO) algorithm is proposed, which is called IPSO-BP neural network. This
The paper’s major contributions are as follows: ① During the epidemic period, a novel prediction model is developed using data from multiple sources. ② The parameters of an electricity consumption prediction model are designed. ③ The predictions of electricity consumption under the influence of epidemic situation are examined. The rest of this paper is structured as follows. Section 2 explains the modeling process and predicting steps for electricity consumption using the IPSO-BP neural network. Section 3 firstly designs the parameters of the prediction model and then analyzes prediction results for electricity consumption of several case studies. Section 4 brings the paper to a close.

2. Modeling based on IPSO algorithm

2.1. Data analysis

The main idea of prediction of electricity consumption is to find out the relationship between the historical data of electricity consumption and the data of influencing factors, and then establish a model based on this relationship to simulate the evolution of electricity consumption. As a result, prior to modeling, data must be analyzed and processed. The collected medical data include multiple items. To improve the prediction’s accuracy, some items highly related to electricity consumption must be chosen from among these medical data items. Pearson correlation coefficient approach is utilized to examine data correlation in this paper, it is as follows:

$$\rho_{X,Y} = \frac{N \sum XY - \sum X \sum Y}{\sqrt{N \sum X^2 - (\sum X)^2} \sqrt{N \sum Y^2 - (\sum Y)^2}}$$  (1)

where, $X$ represents the electricity consumption data, $Y$ represents the medical data for an item in newly confirmed cases, newly severe cases, newly dead cases, newly suspected cases, newly cured cases, cumulative confirmed cases, cumulative cured cases, cumulative death cases or cumulative severe cases. $N$ is the total number of data. Partial data are shown in Table 1. The corresponding relationship between correlation coefficient and correlation strength is shown in Table 1. The higher the connection between the two variables is, the closer the coefficient value is to $-1$ and $1$. The weaker the association is, the closer the coefficient value is to $0$.

| The correlation coefficient | Correlation strength         |
|-----------------------------|------------------------------|
| 0.8–1.0                     | Significantly important      |
| 0.6–0.8                     | Important                    |
| 0.4–0.6                     | General important           |
| 0.2–0.4                     | Weak correlation             |
| 0.0–0.2                     | Weakly correlated or irrelevant |

The three data items in Table 2 have the strongest correlation with the electricity consumption data.

| Table 2. Correlation results. | Cumulative confirmed cases | Cumulative cured cases | Cumulative deaths |
|-------------------------------|-----------------------------|------------------------|-------------------|
|                               | 0.7568                      | 0.7982                 | 0.7852            |

Electricity consumption during epidemic period is particularly affected by medical data. Normalizing the medical data and electricity consumption data is required to improve the prediction model’s accuracy. The min–max standardization method is used in this paper for data normalization, which is shown as follows:

$$x_n = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$  (2)

where, $x_n$ is the normalized data. The original data is represented by $x$. $x_{\min}$ is the original data’s minimum value. The maximum value of the original data is represented by $x_{\max}$. 
2.2. Modeling of electricity consumption prediction

At present, there are many prediction methods of electricity consumption, among which neural network prediction is very suitable during epidemic period. Therefore, BP neural network is used to established the prediction model of electricity consumption in this paper. BP neural network is a type of multilayer feedforward neural network that is trained using the error back propagation technique, so its model has obvious advantages in predicting electricity consumption. It is made up of three layers: the input layer, the hidden layer and the output layer. Fig. 1 depicts the structure of a BP neural network for prediction of electricity consumption.

The forward propagation and reverse optimization processes of the learning algorithm are depicted in Fig. 1. Forward propagation is the process of calculating each neuron’s output value and error term. Reverse optimization is to optimize the weight and threshold of neural network by using error back propagation. When forward propagation process, \(x_1, x_2, \ldots, x_j, \ldots, x_m\) are the neural network input in Fig. 1. The \(i\)th neuron’s input in the hidden layer is

\[
net_i = \sum_{j=1}^{m} w_{ij} x_j + b_i
\]

where, \(w_{ij}\) is the weight between the \(j\)th neuron in the input layer and the \(i\)th neuron in the hidden layer \((j = 1, 2 \ldots m)\). \(b_i\) is the threshold of the \(i\)th neuron in the hidden layer. Under the action of activation function \(\varphi(\cdot)\), the output of neurons in the output layer can be written here:

\[
Net_k = \sum_{i=1}^{n} w_{ki} h_j + a_k = \sum_{i=1}^{n} w_{ki} \varphi \left( \sum_{j=1}^{m} w_{ij} x_j + b_i \right) + a_k
\]

where, \(w_{ki}\) is the weight between the \(i\)th neuron in the hidden layer and the \(k\)th neuron in the output layer. The threshold of the \(k\)th neuron in the output layer is denoted by \(a_k\). According to the activation function \(\psi(\cdot)\), the output of the \(k\)th neuron in the output layer is

\[
o_k = \psi (Net_k) = \psi \left[ \sum_{i=1}^{n} w_{ki} \varphi \left( \sum_{j=1}^{m} w_{ij} x_j + b_i \right) + a_k \right]
\]

When reverse optimization, the error between the neural network’s output value and its target value is

\[
e = \frac{1}{2} \sum_{k=1}^{r} (t_k - o_k)^2
\]
The error of \( s \) training samples is

\[
e_s = \frac{1}{2} \sum_{q=1}^{s} \sum_{k=1}^{r} (t_k^q - o_k^q)^2
\]  

(7)

where, \( t_k \) is the target value, \( t_k^q \) is the target value of the \( q \) sample.

The threshold correction of output layer and hidden layer is as follows:

\[
\begin{align*}
\Delta w_{ki} &= \eta \sum_{q=1}^{s} \sum_{k=1}^{r} (t_k^q - o_k^q) \psi'(Net_k) h_i \\
\Delta a_k &= \eta \sum_{q=1}^{s} \sum_{k=1}^{r} (t_k^q - o_k^q) \psi'(Net_k) \\
\Delta w_{ij} &= \eta \sum_{q=1}^{s} \sum_{k=1}^{r} (t_k^q - o_k^q) \psi'(Net_k) w_{ki} \psi'(net_i) x_j \\
\Delta b_i &= \eta \sum_{q=1}^{s} \sum_{k=1}^{r} (t_k^q - o_k^q) \psi'(Net_k) w_{ki} \psi'(net_i)
\end{align*}
\]

(8)

where, \( \eta \) is the learning rate between 0.01 and 0.8. \( \varphi(\cdot) \) is the hidden layer’s activation function, while \( \psi(\cdot) \) is the output layer’s activation function.

The complex nonlinear mapping from input to output is realized by BP neural network. The BP neural network algorithm, on the other hand, is a local search optimization algorithm that is easily influenced by the local optimal solution. Therefore, the random initial weight and threshold may lead to a large difference in each training result of the algorithm, so it is necessary to use the algorithm to optimize the weight and threshold.

The particle swarm algorithm is made up of \( m \) particles, and the problem is solved by searching in \( D \)-dimensional space. If \( x_1^{(k)}, x_2^{(k)}, \ldots, x_m^{(k)} \) are particles and \( k \) is the current iteration number, the vectors of position \( x \) and velocity \( v \) of the \( i \)th particle in the \( D \)-dimensional space are

\[
\begin{align*}
x_i^{(k)} &= (x_{i1}^{(k)}, x_{i2}^{(k)}, \ldots, x_{im}^{(k)}) \quad (i = 1, 2, \ldots, m) \\
v_i^{(k)} &= (v_{i1}^{(k)}, v_{i2}^{(k)}, \ldots, v_{im}^{(k)}) \quad (i = 1, 2, \ldots, m)
\end{align*}
\]

(9)

Then, the updated equation of velocity and position are

\[
\begin{align*}
v_{id}^{(k+1)} &= v_{id}^{(k)} + c_1 \cdot r_1 \cdot (p_{id}^{(k)} - x_{id}^{(k)}) + c_2 \cdot r_2 \cdot (p_{id}^{(k)} - x_{id}^{(k)}) \\
x_{id}^{(k+1)} &= x_{id}^{(k)} + v_{id}^{(k+1)}
\end{align*}
\]

(10) \hspace{1cm} (11)

where, \( c_1 \) and \( c_2 \) are acceleration factors. \( r_1 \) and \( r_2 \) are random numbers between (0,1). \( x_{id}^{(k)} \) is position vectors. \( p_{id}^{(k)} \) is the optimal value for each individual position. Inertial weight factor, velocity coefficient and adaptive variation coefficient are introduced into the IPSO algorithm. The updated equation of velocity and position are

\[
\begin{align*}
v_{id}^{(k+1)} &= w \cdot v_{id}^{(k)} + c_1 \cdot r_1 \cdot (p_{id}^{(k)} - x_{id}^{(k)}) + c_2 \cdot r_2 \cdot (p_{id}^{(k)} - x_{id}^{(k)}) \\
x_{id}^{(k+1)} &= x_{id}^{(k)} + \gamma v_{id}^{(k+1)}
\end{align*}
\]

(12) \hspace{1cm} (13)

In (12), inertia weight factor is

\[
w(k) = w_{\text{min}} \left( \frac{w_{\text{max}}}{w_{\text{min}}} \right)^{-\frac{1}{1+\sqrt{\gamma}}}
\]

(14)

Let the velocity coefficient \( \gamma \) be 0.5, the adaptive variation condition is: If \( \max(r_1, r_2) > 0.95 \), select a random location in this iteration to initialize.

Based on the above analysis, in order to solve the problems of BP model, the IPSO method is employed to solve these problems. The predicting steps for electricity consumption are described as follows:
1. The parameters of BP neural network are initialized and the number of neurons is determined in input layer, output layer and hidden layer.

2. The parameters of the IPSO algorithm are initialized. The dimension \( D \) of the particle is determined according to the weight and threshold of the network. Some coefficients are set, including the number of particles \( n \), maximum position \( x_{\text{max}} \), minimum position \( x_{\text{min}} \), maximum speed \( v_{\text{max}} \), minimum speed \( v_{\text{min}} \), acceleration factor \( c_1 \) and \( c_2 \), maximum number of iterations \( \text{iter}_{\text{max}} \), weight factor \( w_{\text{max}} \) and \( w_{\text{min}} \), parameter \( c \) and minimum error \( E_r \) of the network. Then the particle's velocity and position are initialized.

3. Taking the mean square error function of neural network as the fitness function of particles, optimization is carried out by IPSO algorithm. When the maximum number of iterations is reached or the error requirement of the network is met, the optimal particle position is taken as the initial weight and threshold value of BP model.

4. Finally, the network optimized by initial weight and threshold is used for training and predicting.

5. The flow chart of optimization based on IPSO algorithm is shown in Fig. 2.

3. Predicting cases of electricity consumption

3.1. Design of prediction model for electricity consumption

Due to the impact of the epidemic, the average daily electricity consumption after the Spring Festival in 2019–2020 only recovered to 67.31% before the Spring Festival, down 23.51% compared with the same period of the previous year. Therefore, considering the medical data, public opinion data and policy data during the epidemic, a BP neural network model optimized by IPSO algorithm is established to predict the electricity consumption of various industrial chains under the impact of the epidemic. The electricity consumption data in the forecasting cases come from Electric Power Acquisition System (EPAS), which is applied to collect electric data by State Grid Liaoning Electric Power Co. LTD. We selected the electricity consumption data of automobile sales, automobile manufacturing and automobile raw material processing industry in Fuxin City of Liaoning Province from January 1 to July 17, 2020. The medical data come from reports of Liaoning Center for Disease Control and Prevention. Public opinion data come from WEIBO and policy data come from official media news. The parameters of the prediction model in Fig. 1 are designed as follows:

There are 12 nodes in the input layer, including the public opinion data, policy data, historical electricity consumption data and the cumulative number of confirmed cases, cured cases and deaths. The output layer has one node, which represents the day’s electricity consumption. The number of nodes in the hidden layer is 8. The
neural network’s learning rate is set to 0.1. The maximum number of learning times is set to 100. The target error accuracy is set as 0.001. 113 weights and thresholds are defined in the neural network in Fig. 1, so $D$ is set as $113$. $n$ is set as 30. $x_{\text{max}}$ and $x_{\text{min}}$ are set as 5 and $-5$, respectively. The values for $v_{\text{max}}$ and $v_{\text{min}}$ are 1 and $-1$, respectively. $c_1$ and $c_2$ are set as 1.5. $\text{iter}_{\text{max}}$ is set as 100. The values for $w_{\text{max}}$ and $w_{\text{min}}$ are set to 0.9 and 0.4, respectively. $c$ is set as 0.9. $E_r$ is set as 0.001. The number of nodes in the hidden layer is calculated using Eq. (15).

$$l = \sqrt{a + b + c}$$  \tag{15}$$

where, $a$ is the number of nodes in the input layer. The number of output layer nodes is denoted by $b$. The number of hidden layer nodes is given by $l$. $c$ is a number ranging from 1 to 10.

### 3.2. Evaluation of electricity consumption prediction model

Several evaluation indices are used to assess the accuracy of the prediction model for electricity consumption. The evaluation indexes selected in this paper are Mean Absolute Percentage Error ($\text{MAPE}$) and Root Mean Square Error ($\text{RMSE}$).

The $\text{MAPE}$ is described in (16).

$$\text{MAPE} = \left( \frac{1}{n} \right) \times \sum_{i=1}^{n} \left( \frac{|p_i - y_i|}{y_i} \right) \times 100\%$$  \tag{16}$$

The $\text{RMSE}$ is described in (17).

$$\text{RMSE} = \left( \frac{1}{n} \right) \cdot \sum_{i=1}^{n} (p_i - y_i)^2$$  \tag{17}$$

where, $p_i$ is the predicted value. $y_i$ is the true value. The sample size is denoted by $n$.

### 3.3. Results analysis of prediction cases for electricity consumption

According to the investigation, the automobile industry in a city stopped production from February 10, 2020 to February 14, 2020 in response to the policy issued due to the epidemic by the government. The local government assessed the situation and ordered the resumption of production on February 15. However, the data shows that from February 15 to 18, the electricity consumption for car sales increased very little, indicating that the epidemic was still serious at that time, and the resumption of production was not reasonable. On February 18, the local government issued another order to resume production. From February 20 to 25, the electricity consumption for car sales increased slightly. After February 29, the epidemic eased and the electricity consumption for car sales increased significantly. The city’s automobile industry almost recovered to the same level as in previous years after March 30. In prediction cases, three different models such as BP, PSO-BP and IPSO-BP are used to predict the electricity consumption of the city’s automobile industry from January 28 to March 6, 2020 [16,17]. Among them, IPSO-BP model is proposed in this paper. Electricity consumption is predicted from automobile selling, automobile manufacturing and automobile raw materials machining. Results of prediction cases are as follows.

The mean square error function of a neural network was chosen as the fitness function in this paper. The smaller the fitness function value is, the closer the predicted value is to the target value. In the iterative process of predicting the electricity consumption in automobile sales industry by using IPSO-BP neural network, the variation trend of fitness function is shown in Fig. 3(a). As can be seen, the fitness function value is relatively large at the beginning of iteration, and then gradually decreases and stabilizes below 0.01. It is indicated that the algorithm proposed can be used to optimize the weight and threshold value of BP neural network.

The predicted results of IPSO-BP neural network prediction model, BP neural network model and PSO-BP neural network model are drawn in Fig. 3(b). It can be seen that the predicted electricity consumption of automobile sales continued to decline from January 30 to February 7, then remained at a low level until February 20 and gradually recovered. Table 3 also shows that the $\text{MAPE}$ of IPSO-BP neural network prediction model is 1.41% and $\text{RMSE}$ is 754 936.89. Compared with the other methods, the prediction accuracy is significantly improved, and the prediction result is higher precision and better effect.
Table 3. Evaluation indexes of different models.

| Model   | The evaluation index |
|---------|----------------------|
|         | MAPE (%) | RMSE     |
| BP      | 2.33      | 1 259 861.29 |
| PSO-BP  | 1.89      | 1 027 971.53 |
| IPSO-BP | 1.41      | 754 936.89  |

Fig. 3. Prediction results of electricity consumption in automobile sales industry.

Fig. 4. Prediction results of electricity consumption in automobile manufacturing.

In the iterative process of predicting the electricity consumption in automobile manufacturing by using IPSO-BP neural network, the variation trend of fitness function is shown in Fig. 4(a). The predicted results are drawn in Fig. 4(b). According to the prediction results, the government issued two orders to resume production on February 15 and 18, the electricity consumption of automobile production increased. But the sales did not recover due to the epidemic, and the electricity consumption of automobile production continued to decline again. In Fig. 4(b), the prediction results of IPSO-BP neural network model are closer to the real value, with the maximum relative error of 2.89% and the minimum relative error of 0.61%. Table 4 also shows that the MAPE of this model is 1.70%.
Table 4. Evaluation indexes of different models.

| Model   | The evaluation index |
|---------|----------------------|
|         | MAPE (%) | RMSE       |
| BP      | 2.57      | 53 980.16  |
| PSO-BP  | 2.03      | 45 865.93  |
| IPSO-BP | 1.70      | 36 331.74  |

In the iterative process of predicting the electricity consumption in automobile raw materials machining by using IPSO-BP neural network, the variation trend of fitness function is shown in Fig. 5(a). The predicted results are drawn in Fig. 5(b). As shown by the prediction results, the variation trend of the electricity consumption of automobile raw materials machining is roughly the same as that of automobile manufacturing. It can also be seen from Table 5 that the MAPE of this model is 1.37% and the RMSE is 4207.52. Although the government ordered resumption of production, it was not able to reproduce well due to the continued decline in sales as the epidemic did not improve. It is clear that the timing of the government’s order to resumption of production was unreasonable.

Table 5. Evaluation indexes of different models.

| Model   | The evaluation index |
|---------|----------------------|
|         | MAPE (%) | RMSE       |
| BP      | 2.05      | 6191.77    |
| PSO-BP  | 1.76      | 5711.67    |
| IPSO-BP | 1.37      | 4207.52    |

Based on the above results of prediction cases, it is not difficult to find that the prediction made by IPSO-BP model is essentially consistent with the actual condition of the resumption of production in the automobile industry. If the government can refer to the prediction results of electricity consumption in the automobile industry during the epidemic, it can predict the date when the impact of the epidemic will decrease and order the resumption of production at a more appropriate time. Similarly, when enterprises resume production, they look at the prediction results rather than no more informed decisions, reducing the losses generated by unsold products. According to an investigation of the prediction results of different models, it is also found that the prediction accuracy of IPSO-BP model is higher in predicting industrial effectively consumption under epidemic situation.
4. Conclusion

In order to prediction for electricity consumption during epidemic period, a BP neural network model optimized by IPSO algorithm is established, so the problem of unpredictable electricity consumption is solved during epidemic period. In the process of electricity consumption predicted by IPSO-BP model, compared with other prediction methods, not only the historical data of electricity consumption are used, but also the medical data, public opinion data and policy data during epidemic period are especially considered. Therefore, the prediction results have high accuracy and good effect. IPSO-BP model developed in this research is both practicable and superior in predicting electricity consumption during epidemic period. In this way, when an epidemic suddenly breaks out in a certain area in the future, the prediction results of electricity consumption will be immediately provided to the local power grid company.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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