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Research on Electric Load Forecasting and User Benefit Maximization Under Demand-Side Response

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ABSTRACT

In this paper, the real-time changes of demand-side response factors are accurately considered. First, CNN is combined with BiLSTM network to extract the spatio-temporal features of load data; then an attention mechanism is introduced to automatically assign the corresponding weights to the hidden layer states of BiLSTM. In the optimization part of the network parameters, the PSO algorithm is combined to obtain better model parameters. Then, considering the average reduction rate of various users under energy efficiency resources and the average load rate under load resources on the original forecast load and the original forecast load, the original load is superimposed with the response load considering demand-side resources to achieve accurate load forecast. Finally, "price-based" time-of-use tariff and "incentive-based" emergency demand response are selected to build a load response model based on the principle of maximizing customer benefits. The results show that demand-side response can reduce the frequency and magnitude of price fluctuations in the wholesale market.

KEYWORDS

Attention Mechanisms, Bidirectional Long-Short Memory Networks, Convolutional Neural Networks, Demand-Side Response, Load Forecasting, Maximum Efficiency

INTRODUCTION

The reform of the electricity market is an inevitable trend of our country's development and the requirements of the times. Electricity supply and demand will maintain a balance of resource utilization through real-time transactions, so as to fulfill the global strategic goal of energy conservation and

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emission reduction. In this context, high-precision short-term load forecasting can formulate efficient and economical power generation plans for power dispatch management departments, rationally arrange unit output, and ensure the safety and stability of the power system(Kong et al., 2017; Lekshmi et al., 2019). At the same time, various facilities such as pumped storage, electric vehicles, and energy storage power stations have been connected to the grid one after another, making the range and amplitude of the load-side response continue to increase, and the range of preferred users for demand-side response has gradually expanded(Hao et al., 2019 ;Mohamed et al., 2018).

The demand-side is an important part of power market planning. By analyzing the characteristics of the demand-side and integrating the supply and use methods of the electric energy system, it can assist the stable operation of the system and improve the market pricing mechanism.Adenso et al. (2002) comprehensively summarized the main problems encountered by OECD countries implementing demand side response projects, introduced the implementation experience of various countries, and clearly pointed out the important role of two demand side response mechanisms in power grid operation. In order to effectively implement demand-side projects,Hopper et al. (2006) conducted a study on the success factors of real-time electricity price project operation, emphasizing convenience, fairness, and information transparency in the implementation of electricity price projects. Based on the implementation of demand response projects under the smart power grid, Fell et al. (2014) considered factors such as time-of-use electricity prices, subsidy policies, accounting and energy storage technology and distributed power generation technology to construct the power distribution income-expense model of demand-side response projects. Under the premise of wind power uncertainty, Qadrdan et al. (2017) established a two-tier planning model for wind power system dispatch with day-ahead hourly electricity price optimization and incentive demand-side response. This model promotes power users to cut peaks and fill valleys, effectively guides the adoption of wind power, reduces the cost of thermal power generation, and improves the benefits of power users.

The purpose of this paper is to study the demand-side response problem under the premise of power load forecasting and power user comprehensive benefit maximization. Firstly, this paper proposes a new ultra-short-term power load forecasting method based on CNN-Bil STM-Attention(AC-BILSTM) for the characteristics of nonlinearity and timing of power load data. Among them, convolutional neural network CNN can effectiely extract the nonlinear local features of power load data. BiLSTM layer is used to extract bidirectional timing features of sequence data. The features generated by the hidden layer of BiLSTM are taken as the input of the Attention mechanism, and the Attention mechanism is used to distinguish the time information extracted from the BiLSTM layer by weighting the importance degree to reduce the influence of redundant information on the load prediction results. Second, in order to improve the prediction accuracy of electric load, an electric load prediction model using particle swarm algorithm (PSO) to optimize the hyperparameters of AC-BILSTM neural network is proposed. The PSO algorithm is used to find the global optimal solution effectively for model hyperparameter search, and the appropriate hyperparameters are found and validated by continuous training.The load level of the system is predicted, the potential of regional demand side response is fully analyzed, and the response load accounting of the original load and demand side resources is superimposed. Perform accurate load forecasting. Finally, a demand-side response model based on demand-side revenue maximization is constructed, and the relationship between electricity price and power demand after the implementation of the two measures is analyzed by examples. By introducing demand-side responses during peak periods of electricity consumption in the electricity market, consumers can adjust their consumption patterns according to price signals in the market. In addition, demand-side response can also reduce electricity consumption during peak load hours, which can generate a certain level of stable revenue in the market.

The contributions of this paper are as follows: 1) A CNN-BilSTM-Attention (AC-BiLSTM) based ultra-short-term power load forecasting method is proposed, which is also combined with PSO algorithm for model hyperparameter finding; 2) Considering the impact of the average consumption reduction rate of each type of users under energy efficiency resources and the average load rate under load resources on the original predicted load, the demand side response potential of this region is fully analyzed, and the original load and the response load are superimposed to make a more accurate load prediction. 3) Two demand-side response measures, “price-based” TOU price and “incentive-based” emergency demand response, are selected to construct a load response model according to the principle of maximizing user benefits, and analyze the changing relationship between electricity price and electricity demand after the implementation of the two measures through examples.

RELATED WORK

Most of the past short-term load forecasting are deterministic forecasts, which can be divided into statistical forecasting methods and intelligent forecasting methods based on machine learning according to different forecasting principles. Statistical prediction methods mainly include linear regression (LR) (Geng et al., 2002), support vector regression (SVR)(Jiang et al., 2018), and Bi-LSTM. These models are mainly constructed for linear relationships, ignoring the influence of factors such as climate and date types on short-term load forecasting, and the forecasting accuracy is low. With the emergence of artificial intelligence, machine learning and deep learning methods have been widely used in short-term load forecasting. Wu et al. (2016) use a support vector machine (SVM) model, which can obtain the optimal solution of the system in the case of limited samples and achieve a relatively ideal prediction accuracy, but when the amount of data increases, its application effect is not as good as neural network models. Su et al. (2017) adopted an error-based back-propagation (BP) model, which has a simple structure and strong applicability, and is widely used in short-term load forecasting. However, the BP model tends to fall into a local minimum and cannot obtain the global optimum solution. Zou et al. (2005) combined the recurrent neural network (RNN) with the ant colony optimization algorithm. This model has both the advantages of ant colony optimization and the timing characteristics of RNN, but RNN is prone to the problem of gradient disappearance when processing long time series.Peng et al. (2019)proposed a network model based on long-term and short-term memory (LSTM), which can take into account the temporal and nonlinear relationship of data and has high prediction accuracy, but it is difficult to mine the deep relationship for data samples with high complexity. Lin et al. (2007) showed that the SVR algorithm can only perform single-step prediction. For the data with a large amount of spurious interference, the prediction error is large and the prediction effect is lagging.

Long short-term memory (LSTM) network has been widely used in the field of power load forecasting because of its special memory ability and gate structure, which can simultaneously take into account the timing and nonlinearity of load data. Ciechulski et al. (2021) used LSTM neural network in the field of power load prediction, and experiments showed that compared with feedforward neural network,LSTM model has higher prediction ability and applicability. Lu et al.(2019) proposed a hybrid neural network model based on CNN and LSTM, and proved that this model has higher prediction accuracy than ARIMA model, random forest model and single structure LSTM model. With the development of deep learning, BiLSTM, a bidirectional long short-term memory network, has been proposed as an extension of the traditional one-way LSTM network. BiLSTM can learn bidirectional timing features and further improve the accuracy of model prediction. Wang et al.(2021) proposed a combination model based on CNN-BIL STM for power load prediction. Compared with the single structure LSTM model and CNN-LSTM combination model, the proposed CNN-BI LSTM model has advantages.

In recent years, as an efficient resource allocation mechanism, attention mechanism has gradually become a research hotspot in the fields of speech recognition, image recognition and machine translation. Some scholars try to apply attention mechanism to power load prediction to improve the accuracy of load prediction. LIN et al.(2020) proposed an LSTM model based on attention mechanism, and tested the effectiveness of the model by using four different types of real load data: housing, large industry, commerce and agriculture. Shao et al.(2021) established VMD-IdbigRU load prediction model based on attention mechanism. Firstly, VMD was used to decompose the original power load data, and then IDBiGRU model based on attention and weight sharing mechanism was used to predict, which improved the accuracy and speed of prediction.Miao et al.(2021) proposeda hybrid model based on convolutional neural networks and bidirectional long short-term memory (CNN-BiLSTM) with Bayesian optimization (BO) and attention mechanism (AM) for short-term load forecasting.CNN is used to capture important features of the input data. BiLSTM is good at time series prediction, while AM can reduce the computational complexity of the model. BO can help to automatically tune hyperparameter gauges.WU et al.(2021) proposed a CNN-LSTM-BIL based on attention mechanism STM is used for load prediction of integrated energy system. In this method, CNN and attention mechanism are combined to extract the effective local features of the model, and LSTM and BiLSTM are used to extract the temporal characteristics of load data. Compared with traditional methods, the proposed model can better predict the power load in the integrated energy system.

METHOD

A combination of CNN-BiLSTM-Attention (AC-BiLSTM) and PSO algorithm is proposed for ultra-short-term power load forecasting method to address the nonlinear and time-series characteristics of power load data. Among them, the convolutional neural network CNN can effectively extract the nonlinear local features of the electric load data; the BiLSTM layer is used to extract the bi-directional temporal features of the serial data; the features generated by the BiLSTM hidden layer are used as the input of the attention mechanism, which distinguishes the importance of the temporal information extracted from the BiLSTM layer by weighting to reduce the influence of redundant information on the load forecasting results. The PSO algorithm is used for model hyperparameter search.

Convolutional Neural Network CNN

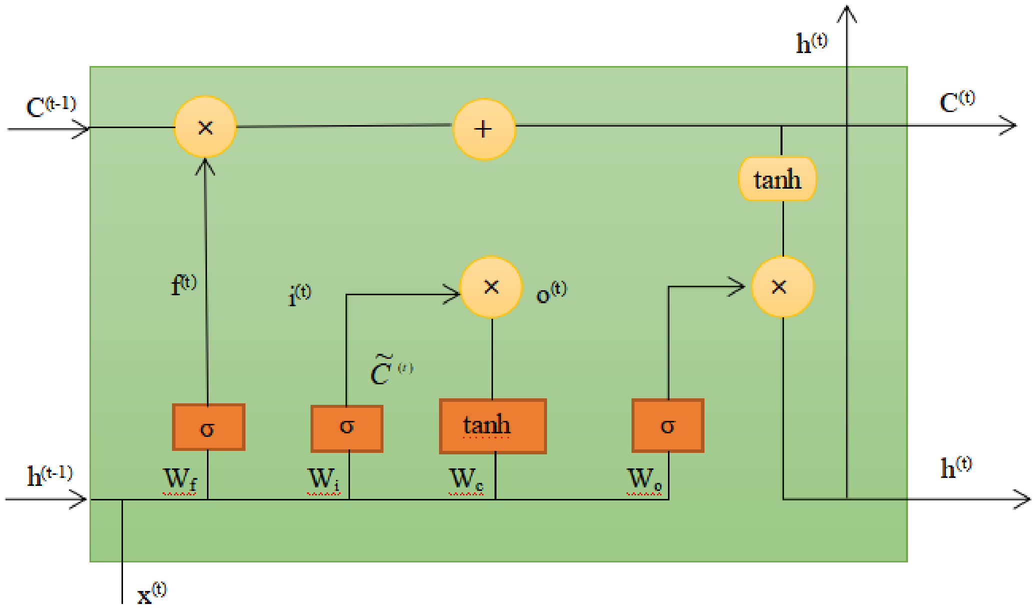
CNNs are mainly composed of these types of layers: input layer, convolutional layer, ReLU layer, pooling (Pooling) layer and fully connected layer (fully connected layer is the same as in a regular neural network). By stacking these layers together, a complete convolutional neural network can be constructed. It is one of the most widely used algorithms in the field of deep learning, and has been used in the field of power system research because of its efficient feature extraction capability.CNN mainly consists of a convolutional layer and a pooling layer, where the convolutional layer uses convolutional kernels for effective nonlinear local feature extraction of power load data, and the pooling layer mainly serves to downsample (downsampling) without corrupting the recognition results, and is used to compress the extracted features and generate more important feature information to improve the generalization ability.

LSTM Neural Network

In traditional neural networks, the model does not pay attention to what information will be available in the previous moment of processing for the next moment, and only focuses on the current moment of processing each time. the proposed LSTM neural network is a good solution to this problem. Hochreiter et al. first proposed a novel recurrent network architecture LSTM neural network.LSTM strengthens the long-term memory capability by introducing logical control units of three kinds of gates: forgetting gate, input gate and output gate to maintain and update the cell state.LSTM is an excellent variant model of RNN, which inherits most of the characteristics of RNN model and solves the gradient backpropagation process due to gradual reduction and Vanishing Gradient problem, which can well solve the problem of gradient disappearance and gradient explosion of RNN.The LSTM helps to improve the accuracy of ultra-short-term power load forecasting by learning the long time correlation of time-series data so that the network can converge better and faster.The LSTM structural unit is shown in Figure 1.

The forgetting gate determines the information to be forgotten from the cell state $C^{(t-1)}$ at moment t-1, as shown in equation (1). The forgetting gate reads the hidden state $h^{(t-1)}$ at moment t-1 and the input sequence $x^{(t)}$ at moment t,and outputs a value between 0 and 1, with 1 indicating that the complete information is retained and 0 indicating that the information is completely discarded.

Figure 1. Structure of LSTM



$$f^{(t)} = \sigma(W_f \bullet [h^{(t-1)}, x^{(t)}] + b_f) \tag{1}$$

where: $f^{(t)}$ is the forgetting gate state at moment t; W_f and b_f are the weights and biases of the forgetting gate, respectively;σis the bipolar sigmoid activation function.

The input gate reads the input $x^{(t)}$ at moment t and determines the information stored in the neuron. Then the temporary state $C^{(t)}$ of the memory cell at moment t is generated by the tanh layer. Finally, the cell state is updated again to get the new cell state $C^{(t)}$, and the update process of the input gate is shown in equation (2)-equation (4).

$$i^{(t)} = \sigma\left(Wi \bullet \left[h^{(t-1)}, x^{(t)}\right] + bi\right) \tag{2}$$

$$\tilde{C}\left(t\right) = \tan h(Wc \bullet \left[h^{(t-1)}, x^{(t)}\right] + bc) \tag{3}$$

$$C^{(t)} = f^{(t)} \otimes C^{(t-1)} + i^{(t)} \otimes \tilde{C}^{(t)} \tag{4}$$

where: $i^{(t)}$ is the input gate state at time t, and the amount of information passed from control $x^{(t)}$ to $C^{(t)}$: W_i, b_i, are the weight and bias of the input gate, respectively: W_c, b_c are the weight matrix and bias term of the cell state, respectively; tanh is the hyperbolic tangent activation function: $\otimes$ is the Hadamard product.

The output gate selects the important information from the current state. The sigmoid layer first decides which part of the neuron state needs to be output, and then the neuron state to be output goes through the tanh layer and multiplies with the output of the sigmoid layer to get the output value $h^{(t)}$, which is also the input value of the next hidden layer. The output gate is calculated as shown in Eq. (5) and Eq. (6)

$$O^{(t)} = \sigma\left(Wo \bullet \left[h^{(t-1)}, x^{(t)}\right] + bo\right) \tag{5}$$

$$h\left(t\right) = o^{(t)} \otimes tahnC^{(t)} \tag{6}$$

where: $O^{(t)}$ is the output gate state at time t; W_O and bo are the weight matrix and bias term of the output gate, respectively.

BiLSTM Neural Network

LSTM is a one-way recurrent neural network, and the model actually only receives the information from “above” without considering the information from “below”. In a practical application scenario, the output result may need to be determined by several inputs before and several inputs after, and the information of the whole input sequence is obtained.

A complete BILSTM network contains an input layer, a forward LSTM layer, an inverse LSTM layer and an output layer.The bi-directional long short-term memory neural network BiLSTM is an optimized improvement of the traditional one-way LSTM, which combines a forward LSTM layer and a backward LSTM layer, both of which affect the output.The unidirectional LSTM can make full use of the load data history information to avoid long-distance dependence, while the BiLSTM facilitates both forward and backward sequence information input, fully considering both past and future information, which is conducive to further improving the accuracy of model prediction.The structure of BiLSTM is shown in Figure 2.

Attention Mechanism

Attention originated from the simulation of the attentional features of the human brain, and the method was first applied to the field of image processing. In the field of deep learning, the Attention mechanism considers that the importance of different features in each layer of the network is different, and the later layers should focus more on the important information and suppress the unimportant information. The structure of the Attention unit is shown in Figure 3.

Figure 2. Structure of BiLSTM memory neural network

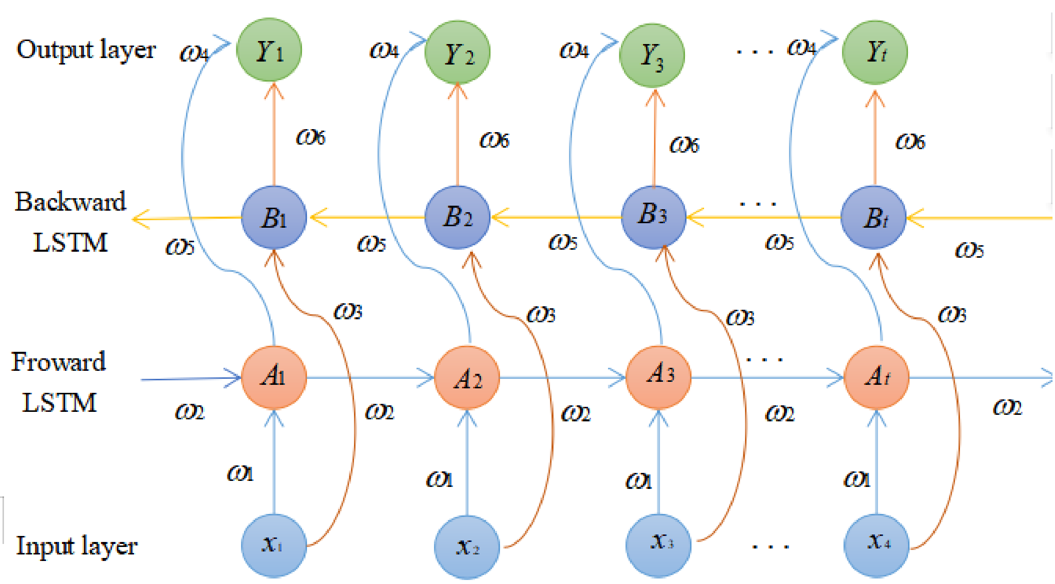
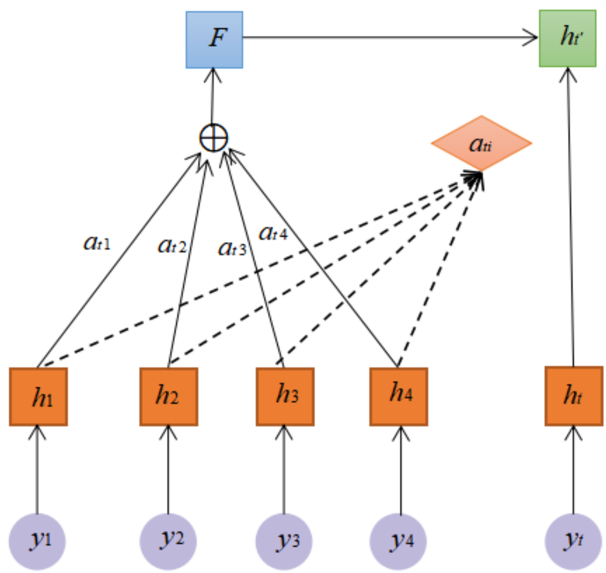


Figure 3. Structure of Attention



$$Sti = V \tan h(Wht + Uhi + b) \tag{7}$$

$$ati = \frac{\exp(Sti)}{\sum_{i=1}^{t} \exp(Stk)}, i = 1,2,3,\ldots,t-1 \tag{8}$$

$$F = \sum_{i=1}^{t} ati \times hi, i = 1,2,3,\ldots,t-1 \tag{9}$$

$$h't = f\left(F, ht, yt\right) \tag{10}$$

where: a_{ti} is the attention layer output value weight value of BiLSTM hidden h_i on the current input; y_2,y_3,..., y_t are the input sequences; h_1,h_2,h_3,..., ht are the hidden layer state values corresponding to the input sequences y_1,y_2,y_3,..., y_t are the hidden layer state values, i.e., ht is the hidden layer state value corresponding to the input y_t; $h't$ is the final feature vector; V, W, U, B are the learning parameters of the model, which are continuously updated with the model training process.

PSO Algorithm

Since the historical data of electric load is a time series data, the AC-BiLSTM model performs well in the analysis of time series. And the hyperparameters in the algorithm have a great impact on the accuracy of load forecasting. In this paper, we use PSO to find the optimal hyperparameters of AC-BiLSTM and update their corresponding values in load forecasting.The PSO algorithm is a global optimization algorithm derived from simulating the foraging behavior of a flock of birds in nature. Each possible particle in the global flock is considered as a particle, and each particle has a different direction and speed of motion toward the optimal position. By updating the individual optimal position and the global optimal position, the optimal solution of the objective function is obtained, and thus the global optimization search is realized. In this paper, PSO is combined with AC-BiLSTM algorithm to construct a power load forecasting model.

AC-BiLSTM prediction model structure

In this paper, we propose a combination of AC-BiLSTM model and PSO algorithm for ultra-short-term power load forecasting, as shown in Figure 4. First, the collected load data are preprocessed and divided into training and test sets. Secondly, the AC-BiLSTM model is constructed. In this paper, a CNN framework consisting of a one-dimensional convolutional layer and a pooling layer is used to automatically extract the internal features of the load data.BiLSTM hidden layer modeling learns the internal dynamics of the local features extracted by CNN and iteratively extracts more complex global features from the local features. The features generated by the BiLSTM hidden layer are used as the input of the Attention mechanism, and the attention mechanism is used to automatically differentiate the importance of the temporal information extracted by the BiLSTM hidden layer by weighting, so that the time series properties of the load data itself can be used more effectively to explore the deep temporal correlation.The attention mechanism is effective in reducing the loss of historical information and highlighting key historical time points to weaken the impact of load forecasting results. The attention mechanism can effectively reduce the loss of historical information and highlight information at key historical points in time to weaken the impact of redundant information on load prediction results.Then the output of the Attention layer is used as the input of the fully connected layer, and the final load prediction result is output through the fully connected layer. In addition, a Dropout technique is introduced to prevent overfitting, i.e., a Dropout layer is added after each BiLSTM hidden layer, which can improve the generalization of the model and reduce the training time of the model while preventing the overfitting. In the network parameter optimization part of this paper,In this paper, we combine PSO with AC-BiLSTM neural network by using three key hyperparameters of the algorithm (number of neurons $L1$, learning rate $å$, and number of training iterations k) as optimization variables for PSO particles, and by updating the velocity and position of the particles to minimize the adaptation initialization population value for load prediction and to obtain better model parameters.Finally, the trained AC-BiLSTM model is saved and the validity of the model is verified using a test set, and the load prediction results are analyzed to identify deficiencies and to continuously optimize the prediction model.

Load forecasting method that takes into account the response resources on the demand-side

With the development of active power distribution systems and user-side demand response, diversified response resources continue to be added, and more power grid entities participate in market competition. On the one hand, power users with different power consumption behaviors exhibit different response methods in the operation of active distribution networks. On the other hand, in an environment where the electricity sales market is gradually liberalized, in order to avoid the waste of investment caused by extensive expansion plans, it is necessary to consider the response potential of demand-side resources and take the impact of demand-side resources on the load into account to achieve a more accurate load forecasting. Therefore, the load forecasting is divided into the following three steps:

1) Calculate the impact of energy efficiency resources on the load of power users

Considering the change in power consumption of users under the action of various energy efficiency resources. Energy efficiency resources can reduce the power consumption of power users throughout the forecast period.

Use ΔQ_t to represent the power savings of users at time t, and use ΔQ_{it} to represent the power savings of power users under the action of the i_{th} energy efficiency resource at time t. $\Delta Q_{it,0}$ represents the initial power consumption of power users before the i_{th} energy-efficiency resource takes effect at time t, $_{öer,i}$ is the total consumption reduction rate of the i_{th} energy-efficiency resource, and G is equal to the product of the load penetration rate and the natural power saving rate; h_i is the state Coefficient, used to describe whether the i_{th} energy efficiency resource exists, its value is 0 means it exists, and 1 means it does not exist. Therefore, under the action of energy efficiency resources, the power saving of the user at time t.

$$\Delta Q_{it} = Q_{it,0} h_i \varphi_{er,i} \tag{11}$$

It can be concluded that under the action of multiple energy efficiency resources, the total amount of electricity saved by users at time i is:

$$\Delta Q_t = \Delta Q_{1t} + \Delta Q_{2t} + ... + \Delta Q_{mt} \tag{12}$$

Among them, m is the total number of types of energy efficiency resources. Therefore, by superimposing the change in electricity consumption with the original electricity consumption, the electricity consumption at time t after the user responds to the energy efficiency resources can be obtained:

$$Q_{er,t} = Q_{t,0} - \Delta Q_t \tag{13}$$

2) Consider the impact of load resources on the user load

Load resources include various administrative measures or economic means. These measures are mainly used by demand response users to transfer electricity time or reduce their own electricity consumption through voluntary selection in order to achieve the purpose of changing electricity load. Among them, administrative measures mainly include direct load control and orderly power management. Economic measures mainly include electricity price policies such as tiered electricity prices, peak-to-valley electricity prices, interruptible electricity prices, and seasonal electricity prices. Under the influence of administrative measures, the load curve mainly shows a downward trend, and the load reduction model is:

$$\Delta P_{i,t} = P_{t,er,0} - Q_{er,t} \mu_i \frac{1}{\eta_{lo,i} t} \tag{14}$$

In the formula, $\Delta P_{i,t}$ represents the load reduction under the influence of the i_{th} load resource at time t; $P_{t,er,0}$ is the load after the response of the energy efficiency resource at time t; $_{ii}$ is the state coefficient, which describes whether the i_{th} load resource exists, which is 1 means it exists, and 0 means it does not exist. $_{çlo,i}$ represents the load rate of the electric power user under the influence of the i_{th} load resource at the time t. The load rate is equal to the product of the average load rate and the load penetration rate. Therefore, under the influence of administrative measures, the amount of load reduction in response to multiple load resources is:

$$\Delta P_t = \left(\Delta P_{t,1} + \Delta P_{t,2} + ... + \Delta P_{t,n}\right) \sigma_t \tag{15}$$

In the formula, $_{6t}$ is the simultaneous rate of load resources acting together; n is the total number of load resources owned by power users. Therefore, the load at time t under the combined action of energy-efficient resources and load resources under administrative measures is:

$$P_t = P_{t,0} - \Delta P_t \tag{16}$$

Among them, $P_{t,0}$ is the original load of the power user without the response resource on the demand-side.

3) Load stacking

On the basis of measuring and calculating the impact value of demand-side response resources on user load in the first two steps, it is superimposed with the original load to obtain the load forecast value and calculate the forecast error.

Demand-side Response Load Model

The common forms of demand-side response in my country's power system at this stage are time-of-use price and emergency demand response. In order to avoid the large difference between the peaks and valleys of the load, the policy of time-of-use electricity prices is usually adopted to guide users to reduce electricity consumption during the peak period and adjust the electricity consumption behavior to the valley period. However, the implementation method of emergency demand response is that the power system operator formulates the incentive payment price in advance. When the security and stability of the power grid are threatened, the power user can reduce the load usage to deal with this emergency that threatens the reliability of the power grid. The following will analyze the load adjustment methods of power users and the impact of electricity price changes and incentive payments on user demand through the construction of the response model.

Avoidable Load Model

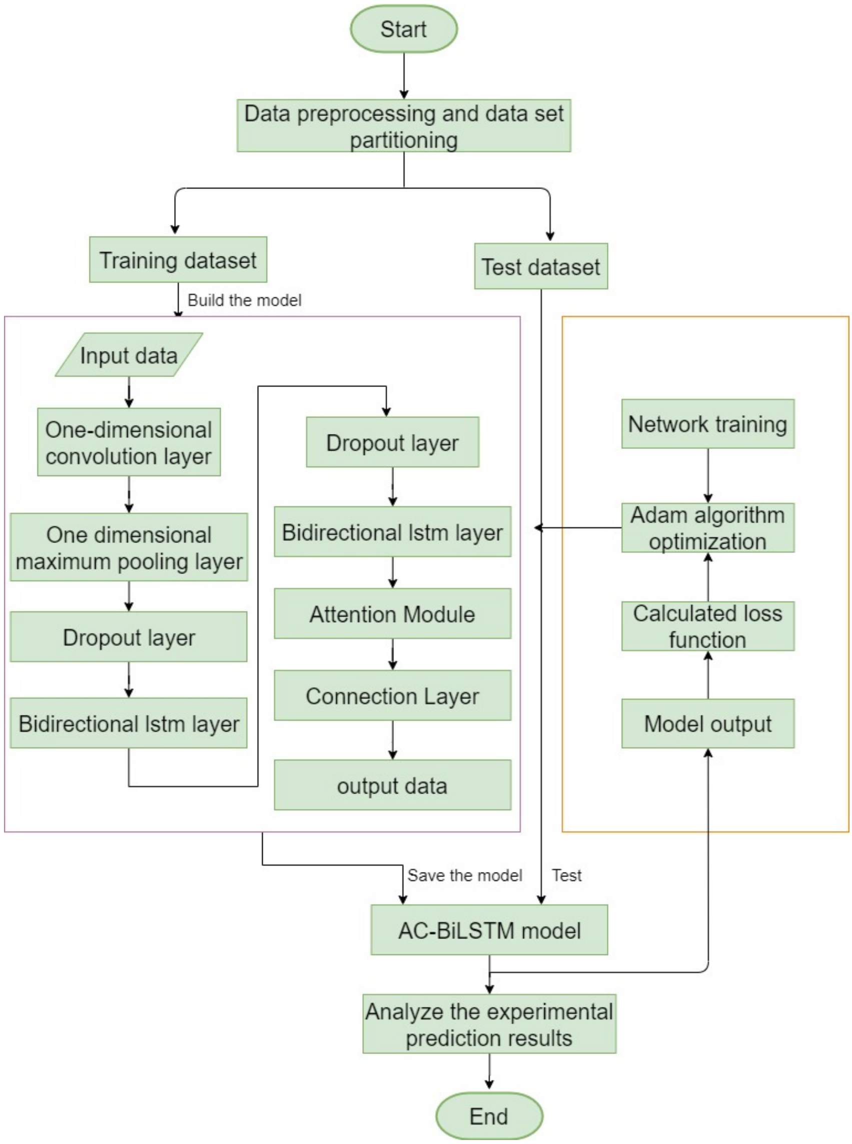
The avoidable load model is related to the self-elasticity coefficient of the price elasticity of demand, and users can reduce electricity demand by focusing on moderation or improving management. Usually this type of electricity consumption is small, and it has not attracted enough attention from users. But when the stimulus of the electricity price policy is large enough, users will take measures to reduce the additional electricity consumption. Therefore, the policy formulation mainly focuses on the ratio of basic user needs and general demand, sensitivity to electricity prices, electricity price grading and incentive policies. The model construction process is as follows.

Assuming that the power user's power demand at time t is $D(t)$, the incentive compensation payment is $I(t)$, and the electricity price is $P(t)$. When the user participates in the emergency demand project, the change in electricity demand is:

$$\Delta D(t) = D_0(t) - D(t) \tag{17}$$

Among them, $D(t)$ is the initial power demand, that is, the power demand that does not participate in the response of the demand-side. The total incentive compensation TI and total revenue B that the user gets at time t are:

Figure 4. Flow chart of power load forecasting under demand side response



$$TI\left(\Delta D\left(t\right)\right) = I\left(t\right) \times \Delta D\left(t\right) \tag{18}$$

$$B\left(t\right) - \underline{B}\left(D\left(t\right)\right) - D\left(t\right) \times P\left(t\right) + TI\left(\Delta D\left(t\right)\right) \tag{19}$$

Among them, $\underline{B}\left(t\right)$ represents the income when the user's electricity demand is $D\left(t\right)$ before the compensation is paid at time t. The income function is expressed as:

$$B\left(D\left(t\right)\right) = B_0\left(t\right) + P_0\left(t\right) \times \Delta D\left(t\right) \times \left[1 + \frac{\Delta D\left(t\right)}{2E\left(t\right) \times D_0\left(t\right)}\right] \tag{20}$$

Where $B_0(t)$ represents the income when the user's initial demand is $D_0(t)$; $E(t)$ is the response elasticity coefficient at the time t. According to formula (12) and formula (15):

$$P(t)+I(t)=P_0(t)\times\left[\frac{D(t)-D_0(t)}{E(t)\times D_0(t)}+1\right] \tag{21}$$

Among them, $P_0(t)$ is the initial electricity price. It can be seen from the above formula that if $I(t)=0$, then $D(t)=D_0(t)$. It shows that when there is no incentive to pay, the electricity price remains unchanged and $E(t)$ is zero.

Transferable Load Model

The transferable load is related to the cross-elasticity coefficient of the price elasticity of demand. The transferable load often changes with the development of the entire industry. The greater the user's power consumption, the stronger the sensitivity to the time-of-use electricity price. The load transfer period is a common cost control method. In addition to shifting the load during different periods of electricity use, other forms of energy will be used to replace the electricity load, such as direct purchase of hot water or gas boilers instead of electric heating boilers. The policy formulation mainly focuses on basic electricity demand, transfer potential, electricity price grading and incentive policies.

The cross-elasticity coefficients of power users at time t and time j are expressed as follows:

$$E(t,j)=\frac{P_0(t)}{D_0(t)}\times\frac{\partial D(t)}{\partial P(t)} \tag{22}$$

The demand under the time-of-use price response can be expressed as:

$$D(t)=D_0(t)+\sum_{t=0}^{23}E(t,j)\times\left(P(j)-P_0(j)\right)\times\frac{D_0(t)}{P_0(j)} \tag{23}$$

Assuming that the emergency demand measures are implemented at the same time at the time j, the incentive compensation $I(j)$ at this time needs to be considered together with the electricity price, that is:

$$\Delta P(j)=P(j)-P_0(j)+I(j) \tag{24}$$

After comprehensively considering the time-of-use electricity price and incentive compensation, the demand of power users at time t can be expressed as:

$$D(t)=D_0(t)+\frac{D_0(t)}{P_0(j)}\times\sum_{t=0}^{23}E(t,j)\times\Delta P(j) \tag{25}$$

Finally, we combined the avoidable load and the transferable load model to obtain the power consumption form of the power user at each time of the day, as in equation (26).

$$D\left(t\right)=\left[D_0\left(t\right)+\frac{D_0\left(t\right)}{P_0\left(j\right)}\times\sum\nolimits_{t=0}^{23}E\left(t,j\right)\times\Delta P\left(j\right)\right]\times\left[1+\frac{E\left(t\right)\times\Delta P\left(t\right)}{P_0\left(t\right)}\right] \tag{26}$$

EXPERIMENTAL ANALYSIS AND RESULTS

Experimental Environment

This paper uses Intel (R) core (TM) i5-5200 cup2.20-ghz processor and 8GB memory. In terms of data sets, the historical load of one year after asynchronous operation of power grid in a certain region is taken as the training set database of load model (the sampling period is 15 minutes), the load data of the last week of a year is taken as the prediction data set, and the historical load data of the rest of the time is taken as the training set. Features related to date and time (load difference from the previous 24 hours, the hour of the day, the load value before 48 hours, the load value before 24 hours, whether it is a working day, the day of a week, and the month of the year) are extracted, and the output of the model is the load data of the prediction point. In addition, outliers and missing values in the data were treated as missing values, and the average method was used to fill in the missing values (Li Al., 2015).

Power Load Forecast Results

Analysis of Short-Term Load Prediction Results of AC-BiLSTM Model

The short-term load forecasting results and the absolute error (the absolute value of the difference between the predicted and actual values) for the dataset using the AC-BiLSTM forecasting model are shown in Figure 5.

The forecast results in Fig. 5 show that although the load forecasting model can avoid falling into the local optimal, expand the search space, and increase the probability of obtaining the global optimal value, which improves the accuracy of load forecasting, there are still some errors in a certain period of time. This may be caused by outliers and missing values in the data set.

Results of load forecasting taking into account the demand side response

In order to grasp the historical data pattern and further improve the prediction accuracy. We refine the main electricity consumption facilities of various types of users, consider the role of energy efficiency class resources and load class resources policies (Table 1), measure the electricity saving behaviors occurring in users, and superimpose them to the load forecast values of each moment of the AC-BiLSTM forecasting model, and finally calculate the electricity load forecasting results. The load forecasting results and absolute errors are shown in Figure 6.

It can be clearly seen that the node effect is significantly improved after the introduction of demand-side resources. The forecast deviation is smaller and closer to the actual situation. In addition, in order to verify the effectiveness of the prediction model proposed in this paper, several common short-term load prediction algorithms in the literature are selected: LSTM network, bidirectional long and short-term memory network (Bi-LSTM), and Genetic algorithm improved BP neural network (GA-BP-Optimization) as comparative experiments. Figure 7 shows the daily load forecasting effect of the selected algorithm randomly selected on the test set and the forecast error calculated by the evaluation index selected in this paper, as shown in Table 2.

To further illustrate the power saving effect of demand-side response, we compare and analyze the data of annual electricity consumption and maximum load of various users before and after the

Figure 5. AC-BiLSTM models to compare short-term load prediction with actual value

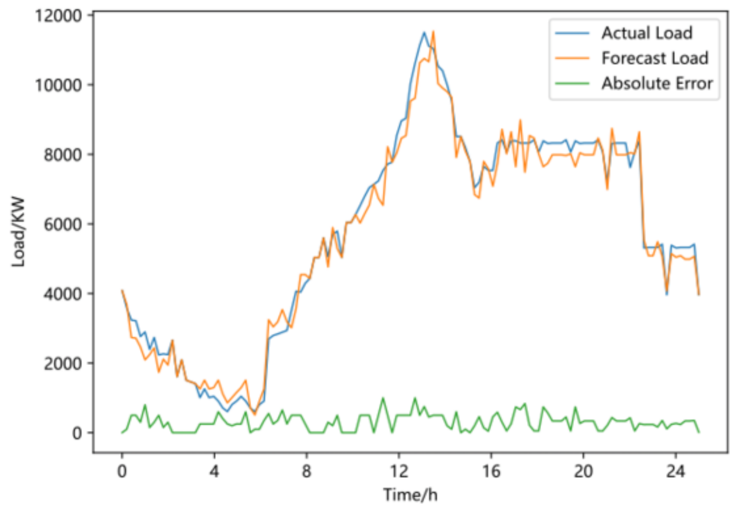
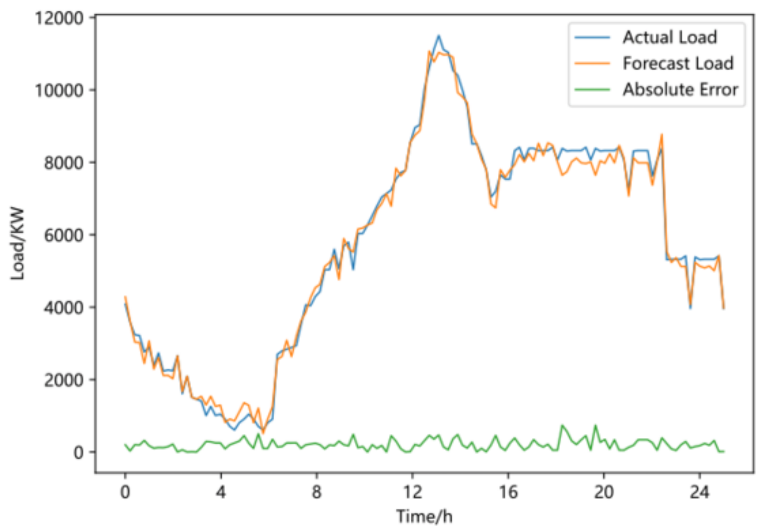


Figure 6. Consider the demand side response load forecast and actual value comparison



introduction of demand-side resources, as shown in Table 3 and Table 4. With the effect of demand-side resources, the electricity consumption of each power user is reduced by more than 10% and the maximum load is reduced by more than 20%, both of which show an obvious downward trend, achieving the expected effect of demand-side response and reducing the expansion demand of substations and lines, with considerable investment saving benefits.

The Impact of Time-of-Use Electricity Prices and Emergency Demand Response on the Load Curve

The data set comes from the historical load data of one month after the asynchronous operation of the power grid in a certain area. According to the model proposed in this paper, based on the principle of

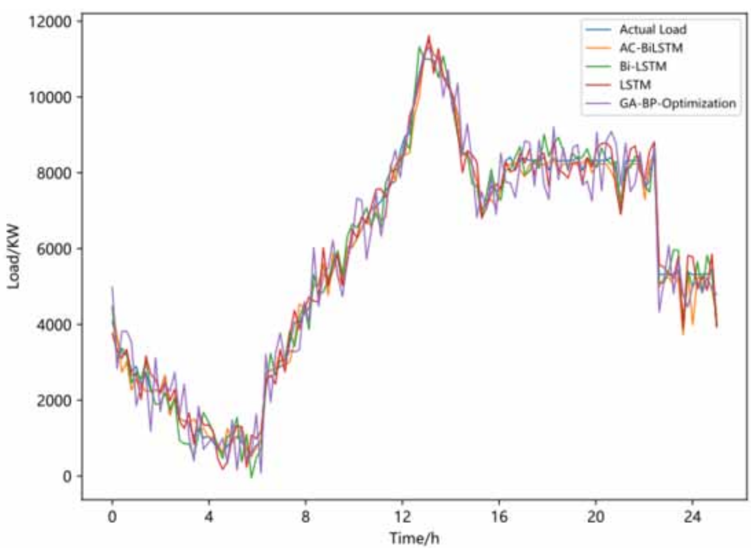
Table 1. The base data of load forecasting as considering

User Type	Energy efficiency resources avg	Load resources avg
Industry	0. 0243	0.6220
Construction	0. 0325	0.6691
Transport	0. 0365	0.3358
IT	0. 1235	0.9025
Business	0. 1349	0.5236
Accommodation and meals	0. 1267	0.6326
Finance	0. 0885	0.6911
Agency	0. 1475	0.5433
Resident	0. 1565	0.3366

Table 2. Algorithm error comparison

Study	Algorithm	E_{MAE}/(kW·h)	ER_{MSE}/(kW·h)
Wenna et al.(2022)	AC-BiLSTM	485.82	713.66
Yixiu et al.(2022)	Bi-LSTM	553.35	905.22
Cui et al.(2022)	LSTM	842.02	1358.35
Xiao et al.(2020)	GA-BP-Optimization	1056.72	1659.65

Figure 7. Comparison of daily load forecast results



maximizing user benefits, calculate the user's load demand at each moment. After implementing the time-of-use electricity price and emergency demand response, according to the current peak-valley price mechanism in the region, the peak electricity price (1.26 RMB/KW·h) and the low electricity price (0.42 RMB/KW·h) are respectively at the equilibrium price (0.84 RMB/KW·h), which rises and

Table 3. Comparison of annual electricity results before and after considering demand-side resources

User Type	Unconsider demand side resources (MW·h)	Consider demand side resources (MW·h)
Industry	9133. 262	8766. 565
Construction	547. 355	516. 266
Transport	5698. 561	5986. 365
IT	310. 256	298. 362
Business	16523. 154	13950. 845
Accommodation and meals	705. 264	703. 265
Finance	129. 656	126. 325
Agency	225. 365	300.562
Resident	1221. 689	1119. 986

Table 4. Comparison of maximum load results before and after considering

User Type	Unconsider demand side resources (MW·h)	Consider demand side resources (MW·h)
Industry	4401.562	4090.326
Construction	213. 325	200. 236
Transport	1595. 564	1501. 369
IT	99. 265	88. 639
Business	3684. 856	3416. 691
Accommodation and meals	88. 336	90. 226
Finance	12. 302	9. 365
Agency	3. 396	3. 698
Resident	345. 264	309. 566

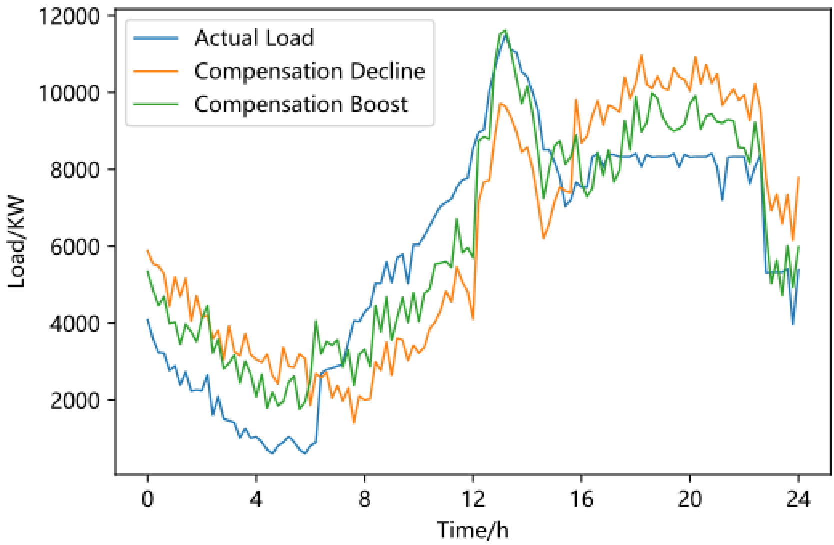
falls by 50%. Assume that the compensation received by power users participating in the response is 1.3 RMB/KW·h. When the incentive compensation is reduced, for example, 0. 4 RMB/KW·h, the comparison of the load curve results is shown in Figure 8.

It is not difficult to understand that when the incentive compensation decreases, the user response level decreases. In addition, in order to obtain high compensation payments, some users will inevitably use improper means to reduce the load. In order to prevent this phenomenon from happening, the power system operating agencies usually set the lower limit of load usage for users, which is used to stipulate the minimum power consumption of power users under normal power consumption conditions. Therefore, the introduction of demand-side response during the peak electricity consumption period of the electricity market can enable consumers to adjust their own electricity consumption patterns according to the price signals in the market. However, in the medium and long term, demand-side response can reduce the frequency and amplitude of electricity price fluctuations in the wholesale market, realize the linkage between the retail market and the wholesale market, and play a positive role in the reliable operation of the system throughout the power supply cycle.

LIMITATIONS AND FUTURE WORK

Although the AC-BiLSTM model and PSO algorithm considering energy efficiency resources are beneficial for improving the accuracy of electric load forecasting, since the adopted dataset is a one-

Figure 8. Comparison of load curve results after implementing time-of-use electricity prices and emergency demand response measures



year dataset, future research will use more data to make full use of the advantage of big data to dig deeper into the load change pattern and further improve the ultra-short-term electric load forecasting accuracy. Secondly, future research will consider the problem of electricity load forecasting in a more complex environment with factors such as holiday effects, electricity prices, and rainfall. In addition, future research will consider the response potential of more demand-side resources and take into account the impact of more demand-side resources on load to achieve more accurate load forecasting.

CONCLUSION

Based on the development background and research status of demand side response in China, this paper studies the problem of demand side response under the premise of load forecasting and maximizing the comprehensive benefit of power users:

1) In load prediction, AC-BILSTM model is adopted to predict the system load level, give full play to the advantages of CNN and effectively extract spatial features. Combined with BiLSTM network's ability to extract bidirectional temporal features of sequence data, and the Attention mechanism can selectively pay Attention to the hidden layer state. Thus fully excavate the time series attribute of load data itself and obtain the deep time correlation. The attention mechanism can also effectively reduce the loss of historical information and highlight the information of key historical time points to reduce the influence of miscellaneous information on load prediction results.In the network hyperparameter optimization part of this paper, the PSO algorithm is used to efficiently find the global optimal solution of hyperparameters for AC-BiLSTM network optimization, which can avoid the problem of suboptimal model parameters caused by artificial parameter selection and reduce the influence of human factors on the model accuracy.
2) Fully analyze the demand-side response potential of the region, and superimpose the original load with the response load considering demand-side resources to achieve accurate load prediction.
3) In terms of customer benefits, two demand-side response measures, namely "price-based" TOU price and "incentive-based" emergency demand response, are selected, and a load response model

is constructed based on the principle of maximizing customer benefits. The relationship between electricity price and power demand after the two measures are analyzed. The EXPERIMENT SHOWS THAT THE INTRODUCTION OF demanD-SIDE RESPONSE in the peak HOURS of the electricity market can make consumers adjust their electricity consumption according to the market price signal and reduce the electricity cost. In addition, demand-side response can also reduce the power consumption during peak hours, reduce the balance adjustment cost of the power system, and save the power related resources for the whole society. In the medium and long term, demand-side response can reduce the frequency and amplitude of price fluctuation in the wholesale market, realize the linkage between the retail and wholesale markets, and play a positive role in the reliable operation of the system in the whole power supply cycle.

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COMPETING INTERESTS

All authors of this article declare there are no competing interest.

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