Research Article

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Load forecasting of refrigerated display cabinet based on CEEMD–IPSO–LSTM combined model

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Abstract: The load of the showcase is a nonlinear and unstable time series data, and the traditional forecasting method is not applicable. Deep learning algorithms are introduced to predict the load of the showcase. Based on the CEEMD–IPSO–LSTM combination algorithm, this paper builds a refrigerated display cabinet load forecasting model. Compared with the forecast results of other models, it finally proves that the CEEMD–IPSO–LSTM model has the highest load forecasting accuracy, and the model's determination coefficient is 0.9105, which is obviously excellent. Compared with other models, the model constructed in this paper can predict the load of showcases, which can provide a reference for energy saving and consumption reduction of display cabinet.

Keywords: food refrigerated display cabinet, load forecasting, improved particle swarm algorithm, complementary ensemble empirical mode decomposition

Abbreviations

ANN	artificial neural network
AR	auto regressive
ARMA	auto regressive and moving average
ARIMA	auto regressive integrate moving average
BPNN	back propagation neural network
CEEMD	complementary ensemble empirical mode decomposition
CNN	convolutional neural networks
DBN	deep belief network

DNN	deep neural networks
EEMD	ensemble empirical mode decomposition
EMD	empirical mode decomposition
IPSO	improve particle swarm optimization
LSTM	long short-term memory
MA	moving average
MAE	mean absolute error
MAPE	mean absolute percentage error
PSO	particle swarm optimization
RBF	radial basis function
RNN	recurrent neural network
RMSE	root mean square error
R^2	R -square or R^2
SVM	support vector machine
WNN	wavelet neural network

1 Introduction

In recent years, with the deepening of global integration, the cross-border circulation of food has been very common. In particular, the quality of food which is sensitive to temperature mainly depends on the cold chain. The refrigerated display cabinets are the last link of the cold chain transportation, are also an important platform for food preservation and customer-oriented, and an important place for consumers, with better market prospects. For example, the market for refrigerated display cabinets in the UK will reach 8.6 billion pounds in 2020, with an annual growth rate of more than 3% [1]. The open display cabinet is favored by the merchant because of the openness of customers. A strong cold curtain is introduced to isolate the external warm air in order to maintain the refrigerated temperature of the display cabinet. The food temperature in the food refrigerated display cabinet needs to consume a lot of electricity. According to statistics, the electricity consumed by food refrigerated display cabinets accounts for about 50–60% of the total electricity consumption in supermarkets [2]. Therefore, under the condition of ensuring the quality of stored food in display cabinets, the energy saving is an important focus.

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The load data of food refrigerated display cabinet reflect the operating status of the cabinet, which is an important parameter reflecting the energy consumption of refrigerated display cabinet. The study of load can provide an important reference basis for the optimal operation strategy of food refrigerated display cabinets. The current research on refrigerated display cabinets mainly focuses on the optimization of air curtain performance, the influence of environmental temperature and humidity on the performance of display cabinets, food temperature control, the improvement of cabinet structure, the problems of frosting and defrosting, the operation of multiline groups, the introduction Research on application of natural cold source, phase change shelf of display cabinet, improvement of heat exchanger, improvement of refrigerant replacement, etc. [3–5]. The load forecast for food refrigerated display cabinets is estimated based on the percentage of traditional different loads (air curtains, cabinets, food, lights, etc.). It is mainly used for the design of refrigerators, while load forecasting is used to guide operation. No relevant reports have been seen yet. Accurate and scientific prediction of the load of food refrigerated display cabinets, and the development of appropriate operating strategies to achieve the decision to extend the shelf life of food, can enable merchants to grasp the law of load changes and provide reference for merchants to sell goods and reduce costs in advance. It can also provide suggestions for improvement for manufacturers of food refrigerated display cabinets. For food refrigerated display cabinet, load forecast, combined with feedforward control, can achieve its intelligent energy-saving operation. Therefore, it is necessary to make full use of the operation of refrigerated food display cabinets and establish a scientific and accurate prediction model for the load of refrigerated food display cabinets.

The load of food refrigerated display cabinet is a time-related data, and its load forecasting belongs to the forecasting problem of time series. The method of time series prediction has been widely used in the fields of economy, transportation, engineering, natural science, and so on and has achieved fruitful results. The commonly used time series methods include autoregressive integrated moving average model [6], support vector machine (SVM) [7], chaotic time series prediction [8], neural network model [9], etc. The main factors affecting the load of food refrigerated display cabinets are ambient temperature, humidity, flow of people, frosting and defrosting, compressor power consumption, refrigerant types, control strategy, and so on. Some of these factors are necessary, some are unnecessary, some are difficult to quantify, and there are many factors coupling. The factors

are difficult to quantify, and there are also situations where multiple factors work together. Therefore, the previous research work often can only select the main factors for research; there is no deep excavation of the load of the food refrigerated display cabinet. The reason for this reality is mainly related to the lack of in-depth learning research on load forecasting of food refrigerated display cabinets.

In recent years, the development of computing technology has led to a rapid improvement of computing power; machine learning, especially deep learning, has also been developed by leaps and bounds, but also promoted the further development of time series feature data. The deep learning method is mainly composed of neural networks with multiple hidden layers. Commonly used methods include deep belief networks, convolutional neural networks (CNN), recurrent neural networks (RNN), long short-term memory (LSTM) networks, and other models. Scholars have established a large number of time series prediction models by using deep learning methods. For example, Wang et al. [10] employed LSTM model to predict the energy consumption of the refrigeration system, and the results show that the root mean square error (RMSE) of LSTM load forecasting model was 19.7% lower than BPNN, 54.85% lower than ARMA, and 64.59% lower than ARFIMA. It showed that LSTM model has better prediction accuracy with traditional predictions method. Hasan et al. [11] used the CNN–LSTM hybrid neural network model to predict the short-term power load in Bangladesh. Comparing with the extreme gradient boosting algorithm, the radial basis function, and the LSTM network models proved that the CNN–LSTM hybrid neural network model is a better model to predict short-term power load. Zheng et al. [12] used the BPNN–EMD–LSTM combination model to predict the short-term urban gas load. The average absolute error of the combination model was 3.4%, the single LSTM model was 9.11%, and the BPNN–LSTM model was 7.13%. The predicted results showed that the prediction error of the single prediction model is large, and the combination model can improve the prediction accuracy to a great extent. Usually, time series data contain a lot of noise and have high dimensionality. The deep learning methods cannot deal with the influence of noise when mining data with time series, which will lead to the big errors in learning and prediction results. In order to solve the problem caused by the noise of time series data, the signal processing method is employed to reduce the noise dimension and eliminate part of the noise [13]. In the field of signal processing, researchers have also established a large number of models. Li et al. [14], based on the signal processing of Complementary Ensemble Modal Decomposition (CEEMD) algorithm and SVM machine learning

methods, built a marine surface temperature prediction model. The results show that the model can accurately predict the ocean surface temperature. Li and Wang [15] also decomposed the sunspot time series based on the CEEMD algorithm and used Wavelet Neural Network to predict the different decomposition results and reconstructed to obtain the predicted value of the sunspot. The results show that the model has relatively high performance. The above work proves that the CEEMD algorithm can effectively eliminate noise and improve the prediction accuracy of the model.

The deep learning method can achieve good prediction accuracy and effect on time series data, but the setting of initial parameters mainly depends on experience and human subjectivity has a greater influence on the prediction results. In order to reduce the subjective influence, this work introduces an optimization algorithm for improving the model parameters. For example, Zhang and Liu [16] adopted particle swarm optimization (PSO) to optimize gray neural network (GBP) parameters and built a natural gas long-term load prediction model; the results show that the prediction accuracy and calculation time of the PSO-GBP model are better than the BP model. Qiu et al. [17] used the PSO algorithm to optimize the parameters of the LSTM model to achieve accurate prediction of the railway freight volume. The results show that the PSO-LSTM model can effectively predict the railway freight volume. The above work proves that the PSO algorithm can effectively improve the effects of subjective factors on prediction results.

In this work, the CEEMD algorithm is used to decompose the time series data into different modal components, and then combined with the improved particle swarm optimization (IPSO) to optimize the parameters of the LSTM neural network, the modal components are analyzed and predicted in depth. Finally, the load forecasting model of food refrigerated showcase is compared with the traditional LSTM neural network, BP, and PSO-LSTM load forecasting model.

2 Research methods and principles

This part is based on the CEEMD-IPSO-LSTM algorithm to build a model to predict the load of food refrigerated display cabinets. In order to accurately explain the construction method of the CEEMD-IPSO-LSTM combined model, first, the working principles of CEEMD IPSO and LSTM algorithms are introduced, and then the process of building the model is given.

2.1 Complementary ensemble empirical mode decomposition (CEEMD)

CEEMD is an improved algorithm proposed by Yeh et al. [18] based on the ensemble empirical mode decomposition (EEMD) algorithm [19]. The EEMD algorithm is an improved algorithm based on the Empirical Mode Decomposition (EMD) algorithm. EMD is a method proposed by NE. Huang et al. [20] to decompose a signal into intrinsic mode functions (IMF) and a residual term.

A pair of positive and negative noise signals to the original signal is added to the CEEMD algorithm in order to change the extreme point distribution of the original signal. The reconstruction error can be reduced by canceling each other when the noise signals are averaged. The CEEMD algorithm has the advantages of high signal-to-noise ratio and good time-frequency focusing, can be used to analyze nonlinear and nonstationary signal sequences, and is widely used in the prediction of time series data, such as power load, finance, traffic, passenger flow forecast, etc.

The calculation steps of CEEMD's algorithm are as follows:

- (1) Signal initialization, set the signal to be decomposed as $X(t)$, let $h(t) = X(t)$, $i = 1$;
- (2) Add noise signal, add positive random white noise $\xi_0 n^i(t)$ and negative random white noise $-\xi_0 n^i(t)$ to the signal to be decomposed $X(t)$:

$$h_q^i(t) = h(t) + (-1)^q \xi_0 n^i(t) \quad (1)$$

where $q = 1, 2$, represent positive and negative noises, respectively, and the noise amplitude ξ_0 usually takes 0.1 to 0.2 times the signal standard deviation;

EMD decomposes the combined signal, EMD decomposition of the signal $h_q^i(t)$, and then get $IMF_{q,k}^i$:

$$h(t) + (-1)^q \xi_0 n^i(t) = \sum_{k=1}^K IMF_{q,k}^i(t) + r_q^i(t) \quad (2)$$

where $k = 1, 2, \dots, K$, K is the decomposition order of EMD;

Restrictions, $i = i + 1$, when $i \leq M$, repeat steps (1) and (2), where M is the number of times of adding positive white noise, and the number of times of adding negative white noise is the same as that of positive white noise.

- (3) EMD decomposition is performed on positive and negative white noises, respectively, to obtain two sets of integrated IMF components; IMF_1 and IMF_2 are performed on $IMF_{q,k}^i$ obtained by 2 M EMD decomposition. The integrated average eliminates the added positive and negative pairs of noise, and the decomposition results of CEEMD are as follows:

$$\overline{\text{IMF}}_k(t) = \frac{1}{2M} \sum_{i=1}^M (\text{IMF}_{1,k}^i(t) + \text{IMF}_{2,k}^i(t))(t) \quad (3)$$

The following is the process of EMD decomposing the original data into IMF and residuals as follows:

- (1) First, all the maxima and minima of the original data sequence $y(t)$ are found, and the upper envelope sequence $e_{\max}(t)$ and the lower envelope sequence $e_{\min}(t)$ on the original data sequence are fitted by cubic spline function for the maxima and minima, respectively:

$$m(t) = \frac{e_{\max}(t) + e_{\min}(t)}{2} \quad (4)$$

- (2) A new data sequence $h_1(t)$ is obtained by subtracting the average sequence $m(t)$ from the original data sequence $y(t)$:

$$h_1(t) = y(t) - m(t) \quad (5)$$

- (3) In this case, $h_1(t)$ is the IMF. Generally, the IMF obtained through the first two steps will not meet the two conditions of IMF. Therefore, the first two steps should be repeated until SD (screening threshold value, generally 0.2–0.3) is less than the threshold value. In this way, the first $h(t)$ satisfying the condition is the first IMF. At this time, $h_k(t)$ is recorded as $\text{imf}_1(t)$. The formula of SD is as follows:

$$\text{SD} = \sum_{k=1}^n \frac{[h_k(t) - h_{k-1}(t)]^2}{[h_{k-1}(t)]^2} \quad (6)$$

- (4) The residual sequence $r_1(t)$ is obtained by subtracting $\text{imf}_1(t)$ from $y(t)$, and then the follow-up IMF is obtained by repeating the above process. If there are still more than two extremums, the decomposition is continued, otherwise the decomposition ends and the residual sequence $r_n(t)$ is obtained. In conclusion, the original data series $y(t)$ can be expressed as:

$$y(t) = \sum_{i=1}^n \text{imf}_i(t) + r_n(t) \quad (7)$$

2.2 IPSO calculation

PSO is a biological heuristic method in the field of computational intelligence jointly proposed by Kennedy and Eberhart [21]. It is also a kind of swarm intelligence optimization algorithm. Its basic idea comes from the early research on many birds. Group behavior is inspired by the research results of modeling and simulation. Based on the observation of animal swarm activity behavior, the

particle swarm algorithm uses the information sharing of individuals in the group to make the movement of the entire group produce an evolution process from disorder to order in the problem-solving space, thereby obtaining the optimal solution.

The following is the basic principle of the algorithm:

- (1) The particle in PSO is the basic unit, which represents a candidate solution in the solution space. Suppose the solution vector is D -dimensional, when the number of iterations of the algorithm is t , the i -th particle can be expressed as $x_i = [x_{i1}, x_{i2}, \dots, x_{iD}]$, $i = 1, 2, \dots, N$, where $x_{ik}(t)$ represents the position of the i -th particle in the k -th dimensional solution space, that is, the k -th variable to be optimized in the i -th candidate solution.
- (2) Assuming that the velocity change rate of the i -th particle is $v_i = [v_{i1}, v_{i2}, \dots, v_{iD}]$, $i = 1, 2, \dots, N$, the best position of the i -th particle searched so far is the individual pole. The value is $p_{\text{best}} = [p_{i1}, p_{i2}, \dots, p_{iD}]$, $i = 1, 2, \dots, N$, the best position of the entire particle swarm so far searched, that is, the global extremum is $p_{\text{best}} = [p_{g1}, p_{g2}, \dots, p_{gD}]$, $i = 1, 2, \dots, N$.
- (3) Update its own speed and position through the optimal value of a single particle and the optimal value of a particle swarm. The expression of the movement of the i -th particle in the D -dimension is:

$$v_{ij}(t+1) = v_{ij}(t) + c_1 r_1 [p_{ij}(t) - x_{ij}(t)] + c_2 r_2 [p_{gj}(t) - x_{ij}(t)] \quad (8)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \quad (9)$$

$$1 \leq i \leq N, 1 \leq j \leq D \quad (10)$$

Among them, c_1 , c_2 are acceleration constants, called learning factors, generally constant 2. The former is the individual learning factor of each particle, and the latter is the social learning factor of each particle; r_1 and r_2 are between 0 and 1 Uniform random number; ω is called the inertia weight, which adjusts the search range of the solution space.

The basic PSO is easy to fall into the local optimum, resulting in large error in the result, easy to fall into the local extremum, and low search accuracy. Basic PSO has poor ability to find the optimal value locally in the early stage of operation and poor ability to find the optimal value globally at the end of operation. In order to avoid the problems of basic PSO, this paper chooses IPSO. The improved algorithm improves the inertia weight. When ω is large, the global optimization ability is strong, and the local optimization ability is weak; ω is relatively large. Hourly global optimization ability is weak; local optimization ability is strong. The evolution process of the improved algorithm is as follows:

$$v_{ij}(t+1) = \omega * v_{ij}(t) + c_1 r_1(t) [p_{ij}(t) - x_{ij}(t)] + c_2 r_2(t) [p_{gj}(t) - x_{ij}(t)] \quad (11)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \quad (12)$$

$$\omega = \omega_{\max} - \frac{(\omega_{\max} - \omega_{\min}) \times t}{T_{\max}} \quad (13)$$

In the formula: $T_{\max}$ represents the maximum number of evolutionary iterations; $\omega_{\max}$ and $\omega_{\min}$ are the maximum and minimum values of the inertia weight, respectively; t represents the current number of iterations. (Generally, $\omega_{\max} = 0.9$, $\omega_{\min} = 0.4$).

2.3 LSTM

LSTM is a special RNN proposed by Hochreiter and Schmidhuber [22]. It is actually a variant of RNN, which is mainly to solve the problem of gradient disappearance and gradient explosion in the process of long sequence data training. The LSTM network is an improved algorithm of the RNN. The three gates (input gate, output gate, and forget gate) added to the model make the model to have a memory function and improve the approximation ability of time series data. Different from RNN, LSTM has a unique memory unit and three gate structures. The structure of LSTM memory unit and gate is shown in Figure 1:

The calculation formula of LSTM memory unit [23] is as follows:

$$f_t = \sigma(W_f * [h_{t-1}, x_t] + b_f) \quad (14)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (15)$$

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \quad (16)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (17)$$

Figure 1: LSTM memory cell and gate structure.

$$o_t = \sigma(W_o * [h_{t-1}, x_t] + b_o) \quad (18)$$

$$h_t = o_t * \tanh(C_t) \quad (19)$$

$$\sigma = \frac{1}{1 + e^{-x}} \quad (20)$$

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (21)$$

In the formula: $f_t, i_t, \tilde{C}_t, o_t, h_t, x_t, C_t$ are stand for forget gate, input gate, intermediate value, output gate, output value, input value, and network unit state, respectively; W_f, W_i, W_c, W_o are stand for the weight between the gate and the next calculation, respectively; b_f, b_i, b_c, b_o are stand for the partial vectors of the corresponding gate; σ is stand for the sigmoid function; and $\tanh$ functions is stand for the hyperbolic tangent function.

According to the output value of the previous time and the current input value, the forgetting gate generates a 0–1 f_t value through the sigmoid layer to determine whether the historical information is retained. The input gate uses the sigmoid layer to determine which information needs to be updated, and the $\tanh$ layer generates a vector, which is the alternative content C_t to be updated. Then the two parts are combined to update the state of the memory unit. The output gate gets an initial output through the sigmoid layer, and then uses $\tanh$ to scale C_t to between -1 and 1 , and then multiplies the sigmoid output pair by pair to get the output of the model and the information that continues to the next time.

2.4 Prediction model based on CEEMD-IPSO-LSTM

The load number of foods refrigerated display cabinets is affected by many factors and is complex. If the load data are predicted and analyzed directly, it will undoubtedly cause the difficulty of establishing the model and reduce the accuracy of the model prediction. The CEEMD algorithm does not use any defined function as a base, but adaptively generates modal components according to the analyzed signal, avoiding unnecessary errors caused by human subjectivity. The load data of food refrigerated display cabinets is a nonlinear time series, which is related to many factors such as ambient temperature, humidity, flow of people, frosting and defrosting, compressor power consumption, refrigerant, and so on. Because LSTM neural network has the ability to process long sequence of time series data and avoids the phenomenon of gradient disappearance and gradient explosion, it has good applicability for nonlinear time series data

prediction. This work uses the advantages of the CEEMD and IPSO algorithms to improve the prediction accuracy of the LSTM neural network, combines the two to predict the load of the food refrigerated display cabinet, and proposes a combined prediction model based on the CEEMD–IPSO–LSTM.

Based on the CEEMD–IPSO–LSTM combined model to predict the load of food refrigerated display cabinets, the steps are as follows:

- (1) Use CEEMD to decompose the original data of food refrigerated display cabinets to obtain multiple specific eigenmode function components and residuals.
- (2) Initialize the parameters of the IPSO model. Set the value range of the population size, particle position, and particle velocity in the IPSO algorithm, and set the initial hyperparameters of the LSTM neural network;
- (3) Train the LSTM neural network and get the initial prediction value, determine the fitness function, and select the optimal particle fitness value by calculating and comparing the fitness value of each particle. According to formula (11) and (12), individual extremum

and global extremum to update the speed and position of the new particle itself;

- (4) After reaching the maximum number of iterations and model accuracy selected by the model, output the optimal particle population position, assign the obtained parameters to the network hyperparameters of the LSTM, and use the trained optimization model to predict the modal components and residual items, respectively, and then Reconstruction to obtain the load forecast result.

The implementation logic block diagram of the above-mentioned CEEMD–IPSO–LSTM combined model is shown in Figure 2. In the figure, IMF-a and IMF-b are data signals in which a positive and negative noise signal is added to the original signal.

In order to demonstrate the advantages of the combined model built in this work in predicting the load of food refrigerated display cabinets, the CEEMD–IPSO–LSTM and CEEMD–BP, CEEMD–LSTM, and CEEMD–PSO–LSTM three prediction models are used to predict the load of the

Figure 2: CEEMD–IPSO–LSTM combined model for food refrigerated display cabinet load prediction process.

display cabinets. The prediction results are compared and studied.

2.5 Model evaluation index

In order to compare the prediction effects of different models, this paper uses three indicators: Mean Absolute Error (MAE), RMSE, and Mean Absolute Percentage Errors (MAPE). The reason for using three parameters is that literature [24] also uses the same method to evaluate the prediction effect of the model. This paper introduces the coefficient of determination (R^2) to evaluate the quality of the model and selects RMSE as the fitness function of the IPSO algorithm. The definitions of different evaluation criteria are as follows:

$$MAE = \frac{1}{n} \sum_{i=1}^n |\hat{y}_i - y_i| \quad (22)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2} \quad (23)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{\hat{y}_i - y_i}{y_i} \right| \times 100\% \quad (24)$$

$$f = \frac{1}{N} \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (25)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (26)$$

Where n is the number of sample points, $\hat{y}_i$ and y_i are the predicted value of the model and the actual value of the load, respectively, and N represents the population size.

3 Results and analysis

3.1 Data sources and characteristics analysis

The experimental data used in the work came from the test data of the real vertical refrigerated display cabinet provided by Shandong Xiaoya Cold Chain Equipment Co., Ltd. The test time is from July 1, 2019 to July 7, 2019. The sample sampling interval is 10 min, a total of 1,008 sets of sample points, the sample points collected include refrigeration load, refrigerant mass flow rate, expansion valve power, refrigerant evaporation pressure, evaporator inlet and outlet temperature, and refrigerant condensation pressure. The solution uses open-source Spyder and jupyter notebook software, writes a program, and builds the model by calling the python language integrated NumPy, matplotlib, tensorflow 2.0, pandas, stats, and other modules. The load data of the refrigerated showcase are shown in Figures 3 and 4:

It can be seen from Figure 2 that the load curve of the refrigerated display cabinet will have a valley at an interval of about 25 sample points, followed by the peak

Figure 3: Day load data of refrigerated display cabinet.

Figure 4: One week's load data of refrigerated display cabinet.

value, and the waist value will maintain frequent fluctuations between the peak and the valley. It can be found from Figure 3 that in the load curve of the refrigerated display cabinet for a week, the daily load presents a cyclical fluctuation. The reason for the periodic valleys and peaks in the load curves in Figures 3 and 4 is that in order to maintain the temperature in the cabinet, the refrigerated display cabinet must rely on an air curtain lower than the ambient temperature to isolate the outside world from the display cabinet storage area. This causes the evaporator of the refrigerated display cabinet to be prone to periodic frost. The refrigeration system of the display cabinet is equipped with a regular defrosting mechanism. When the cabinet is defrosted, the compressor of the unit stops working, resulting in reduced heat exchange. The electric heating wire starts to defrost to increase the temperature in the cabinet, and then triggers the start of the showcase Conditions; the heat exchanged in the cabinet at this moment is the largest. The valley value of the frequent fluctuation of the load curve is that the temperature of the cabinet after defrosting reaches the lowest temperature limit, and the compressor frequently starts and stops to adjust the stability of the temperature in the cabinet.

Figure 5 is based on the linear analysis of the collected sample data in python language, and then draws the heat map, which mainly showed the linear relationship between the various data. The colder the color in the picture, the higher the linear correlation between each

other. It can be seen that the refrigerant mass flow rate and refrigerant liquid pressure have a higher linear correlation with the display cabinet load, and the lower correlation is the evaporator inlet and outlet temperature and refrigerant gas pressure. The heat map reflects the linear correlation between the operating data, does not reflect the nonlinear characteristics of the load of the refrigerated display cabinet, and can provide a reference for studying the influencing factors of the load.

3.2 Comparison of predictions of CEEMD decomposition results by multiple models

The CEEMD algorithm decomposes the load data of the refrigerated showcase into six IMF and RES. Calculate the correlation coefficient between the above data and the load data to get Table 1. The formula of the correlation coefficient is as follows:

$$\rho_{X,Y} = \frac{\text{cov}(\text{IMF}_i, h(t))}{\sigma_{\text{IMF}_i} \sigma_{h(t)}} \quad (27)$$

Where $\text{cov}(\text{IMF}_i, h(t))$ is the covariance of the calculated IMF component and load data $h(t)$, σ_{IMF_i} and $\sigma_{h(t)}$ are the IMF component and load, respectively, the standard deviation of the data $h(t)$.

Figure 5: Correlation analysis of sample data (Q: showcase load; Qm: refrigerant mass flow; T1: evaporator inlet temperature; T2: evaporator outlet temperature; P1: refrigerant liquid pressure; P2: refrigerant gas pressure).

Table 1: Correlation coefficients between each modal function and the original data

IMF component	Correlation coefficient
IMF1	0.7709
IMF2	0.5941
IMF3	0.2868
IMF4	0.1335
IMF5	0.1033
IMF6	0.0479
RES	0.0103

The correlation coefficient is the linear relationship between the two sets of data. It can be found from Table 1 that the relationship between IMF1 to IMF3 and load data is relatively close, so accurate prediction of this IMF is helpful to the prediction of load data. The IMF and RES decomposed by CEEMD help reduce the difficulty of model prediction and remove noise in the data.

Six IMF components were obtained from load data sequences by CEEMD decomposition, and select BP,

LSTM, PSO–LSTM, IPSO–LSTM models to predict each IMF component and residual, respectively; finally, reconstruct the prediction results of modal components and residual to obtain the final load forecast value. The noise signal of the CEEMD algorithm in this section is a pair of positive and negative Gaussian random numbers; the parameters of the LSTM algorithm are set as follows: the number of nodes in the input layer is 8, the number of nodes in the output layer is 1, the number of neurons is set to 50, and the number of fully connected layers is set to 20. The number of neurons is 20, the learning rate is set to 0.001, the number of iterations is 500, the activation function is set to “relu,” and the sample size read in each batch is 128; the parameters of the PSO and IPSO algorithms are set as follows: the number of particles is 10, the maximum number of iterations is 500, the inertia weight ω is 0.8, the learning factors c_1 and c_2 are both 1.5, and the maximum particle velocity $v_{\max}$ is 4.

The results of Figures 6–9 showed that the overall fitting effect of the four models of BP, LSTM, PSO–LSTM,

Figure 6: BP model predicts the results of CEEMD decomposition.

and IPSO–LSTM in IMF1 is gradually improving. Among them, the BP algorithm has the worst fitting effect, and the predicted value deviation from most actual values; in IMF2, the fitting effect of the BP model has been partially improved but it is still the worst. The fitting effects of the other three algorithms are better. The LSTM model

cannot fit perfectly in some trough areas. PSO–LSTM and IPSO–The LSTM model can fully fit the peaks and troughs. Among IMF3, IMF4, and IMF5, the worst performance of the four models is still the BP model, which cannot accurately fit the peaks, troughs, and curves. The LSTM model does not fit well in some areas of the

Figure 7: LSTM model predicts the results of CEEMD decomposition.

Figure 8: PSO-LSTM model predicts the results of CEEMD decomposition.

peaks and troughs. The fitting accuracy of the PSO-LSTM and IPSO-LSTM models in the peaks and troughs is obtained. The improvement reflects the superiority of these two algorithms, especially the high degree of fit between the regional prediction curve of the first 120 sample points and the actual curve, reflecting the excellent prediction performance of these two algorithms; in IMF6 and RES,

among the four models, BP performed the worst, LSTM performed better, and PSO-LSTM and IPSO-LSTM performed the best. The PSO-LSTM model showed large errors in the peak area, and IPSO-LSTM avoided this phenomenon. Based on the above analysis, it can be concluded that the prediction effect of the IPSO-LSTM model is the best; whether it is a curve or a peak and trough, it can achieve a

Figure 9: The IPSO-LSTM model predicts the results of CEEMD decomposition.

Table 2: BP, LSTM, PSO–LSTM, and IPSO–LSTM model to predict the evaluation parameters of each modal component

CEEMD decomposition	Evaluation parameters	BP	LSTM	PSO–LSTM	IPSO–LSTM
IMF1	R^2	0.2148	0.3193	0.4960	0.6780
	MAE	0.6519	0.4848	0.4798	0.4617
	RMSE	0.8670	0.6589	0.6247	0.6051
IMF2	R^2	0.2808	0.9405	0.9531	0.9730
	MAE	0.3874	0.1136	0.0982	0.0944
	RMSE	0.4846	0.1504	0.1240	0.1232
IMF3	R^2	0.4622	0.9539	0.9780	0.9876
	MAE	0.1570	0.0295	0.0297	0.0277
	RMSE	0.1950	0.0392	0.0376	0.0345
IMF4	R^2	0.5608	0.9710	0.9852	0.9950
	MAE	0.0554	0.0091	0.0088	0.0068
	RMSE	0.0662	0.0119	0.0095	0.0091
IMF5	R^2	0.5967	0.9811	0.9814	0.9982
	MAE	0.0641	0.0099	0.0049	0.0044
	RMSE	0.0801	0.0152	0.0083	0.0069
IMF6	R^2	0.3947	0.9859	0.9862	0.9915
	MAE	0.1960	0.0266	0.0260	0.0241
	RMSE	0.2394	0.0394	0.0375	0.0300
RES	R^2	0.8240	0.9643	0.9782	0.9975
	MAE	0.1275	0.0387	0.0296	0.0124
	RMSE	0.1586	0.0546	0.0427	0.0033

good fitting effect, demonstrating the superior prediction performance of the algorithm.

Table 2 shows that the three evaluation parameters of R^2 , MAE, and RMSE reflect the prediction effects of the four models on the decomposition results.

The load data are decomposed by CEEMD to obtain the modal components. The BP, LSTM, PSO–LSTM, and

IPSO–LSTM models are used to predict each modal component, and the prediction results are reconstructed to obtain the load forecast curve. The load forecast curve of each model is shown in Figure 10. It can be seen that the prediction accuracy of the four models' load prediction value and the true value is arranged from high to low. This is CEEMD–IPSO–LSTM, CEEMD–PSO–LSTM, CEEMD–LSTM,

Figure 10: Load forecast curve after reconstruction of the four model modal components.

Figure 11: The load forecast curves of the four models are enlarged at sample points 123–129.

and CEEMD–BP. Before 30 sample points, the prediction effect of the BP model is the worst and cannot accurately predict the peak load. The IPSO–LSTM model can accurately identify the peak load, and the LSTM model judges that the peak load is too high. The prediction effect of the PSO–LSTM model is higher than LSTM model. The LSTM algorithm is weaker than the IPSO–LSTM model. At sample points 22–30, the IPSO–LSTM model performs best. The other three models have poor load forecasting effects and cannot accurately predict load curve changes. At sample points 30–52, the prediction effects of the four algorithms are slightly improved compared to the previous ones. At sample points 52–67, IPSO–LSTM can reflect the trend of the load curve, but there is a slight delay in forecasting in some areas. At sample points 67–120, the prediction accuracy of PSO–LSTM and IPSO–LSTM algorithms has improved greatly, which can accurately reflect the changes and peaks of load forecasting; at sample points 120–144,

IPSO–LSTM can accurately reflect the trend of the load curve. Only near the sample point 130, the actual value of the load cannot be accurately predicted, but the change trend of the load during this time period is predicted. Combining Figure 11, it can be found that at sample points 123–129, IPSO–LSTM has the best predictive effect among the four models. The load predicted by the PSO–LSTM model has an overfitting phenomenon, and the predicted value cannot meet the actual meaning. Comparing the LSTM and BP models in Figure 10, it can be found that the LSTM model has a great improvement in the prediction of the load curve trend compared with the BP model, but it cannot accurately reflect the load value, especially some change points cannot be accurately predicted. PSO is introduced. With the IPSO algorithm, the LSTM model improves the prediction accuracy of the load value and can accurately predict the load change point. The improvement of the LSTM model through the PSO and IPSO algorithms is effective and can improve the prediction accuracy of the LSTM algorithm.

Table 3: Prediction and evaluation parameters for reconstruction of modal components of each model

Predictive model	MAPE	RMSE	MAE	R^2
CEEMD–BP	2.2707	1.1151	0.8189	0.3009
CEEMD–LSTM	0.4347	0.6398	0.4819	0.7698
CEEMD–PSO–LSTM	0.2053	0.4752	0.4508	0.8539
CEEMD–IPSO–LSTM	0.1361	0.2468	0.2814	0.9105

Table 3 shows the load prediction evaluation parameters of the four models. The prediction accuracy of the CEEMD–BP model is the worst. The prediction accuracy of the CEEMD–LSTM model is greatly improved, and all evaluation parameters are significantly better than the BP model. Compared with the traditional LSTM model, the PSO–LSTM model reduces the MAE, MAPE, RMSE, and R^2 by 77.21, 36.64, 6.90, and 10.92%, respectively. The MAE, MAPE, RMSE, and R^2 of the IPSO–LSTM model

are 0.2814, 0.1361, 0.2468, and 0.9105, respectively; compared with PSO–LSTM model, the MAE, MAPE, and RMSE are reduced by 80.23, 92.54, and 60.20%, respectively, and the R^2 is increased by 6.63%. It can be found that the prediction effect of the CEEMD–IPSO–LSTM model is the best. The accuracy is the best, and it can accurately reflect changes in load.

4 Conclusion

This paper mainly adopts the LSTM network model to study the load forecasting of refrigerated display cabinets and introduces the CEEMD and the IPSO algorithm to improve the load forecasting accuracy of the LSTM model. Draw the following conclusions:

- (1) The load of the refrigerated display cabinet is a non-linear and unstable time series data. There will be periodic valleys and adjacent peaks every 4.16 h. The load curve fluctuates greatly, which will affect the forecasting effect. Certain interferences: The higher linear correlation with the display cabinet load is the refrigerant mass flow and the refrigerant liquid pressure, and the lower correlation is the evaporator inlet and outlet temperature and refrigerant gas pressure.
- (2) The introduced CEEMD algorithm can smoothly process load data, and the IPSO algorithm optimizes the parameters of the LSTM model. The example analysis proves that these two methods can improve the accuracy of load forecasting.
- (3) The load forecast comparison of multiple models shows that the CEEMD–IPSO–LSTM model has the highest forecast accuracy, and the model's determination coefficient is 0.9105. Compared with the CEEMD–IPSO–LSTM model in MAPE, RMSE, MAE, and CEEMD–PSO–LSTM model, the CEEMD–IPSO–LSTM model reduces 80.23, 92.54, and 60.20%, respectively, and improves the R^2 by 6.63%, which can accurately predict load changes.

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