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User variable load forecasting based on FPA-DELM

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Abstract: Load forecasting is an important hotspot in the field of energy management. Aiming at the problem that user variable load is difficult to predict and the prediction accuracy is low, this paper proposes a deep extreme learning machine model based on the Flower Pollination Algorithm (FPA). When Deep Extreme Learning Machine (DELM) solves the problem, the large number of nodes leads to high resource utilization and slow convergence speed. Combined with the FPA algorithm, it is used to optimize the parameters of the hidden layer, which improves the convergence speed of the algorithm and optimization accuracy. This paper conducts prediction experiments on the load data of household appliances. The experimental results show that FPA-DELM has better prediction accuracy than DELM.

1. Introduction

Electric load forecasting plays a vital role in energy economics and security. On the one hand, accurate power prediction can effectively save energy, reduce energy consumption to a certain extent, and reduce expenses economically. On the other hand, because it can be predicted as much as possible and has an adjustable nature, it can effectively avoid security risks[1].

Short-term load forecasting refers to daily load forecasting and weekly load forecasting, which are used for daily or weekly scheduling respectively. It has a great impact on line exchange power and equipment maintenance. For users, variable load forecasting is very important. At present, there are extensive researches on load forecasting models at home and abroad, which are roughly divided into two categories: classic load forecasting models and modern load forecasting models. Traditional forecasting methods include Trend Extrapolation Method[2], Time Series Method[3] and Regression Analysis Method[4]. The Time Series Method takes advantage of the inertial characteristics and temporal continuity of power load changes; Regression analysis is the use of knowledge in mathematical statistics to analyze and plan variables. In order to improve the accuracy of forecasting, most modern load forecasting models are based on artificial intelligence algorithms for model construction, such as Particle Swarm Algorithm, Genetic Algorithm, Extreme Learning Machine, etc. Which are used to build models, and the learning function of intelligent algorithms is used to allow computers to analyze the mapping in load data relationship, and then use this relationship to predict future loads. For example, reference[5] which using Particle Swarm Algorithm, because of its convergence speed, it can solve the optimal power plans. Reference[6] proposes to use the Gray Wolf Optimization Algorithm to determine the scheduling scheme, minimize the user load value, and achieve the optimum. Reference[7] proposes a hierarchical optimization strategy for household energy management based on Deep Reinforcement Learning, it can propose an optimization for household electricity consumption plans.

Although the above intelligent algorithms can solve the optimal electricity consumption plan and obtain the optimal scheduling plan, the Particle Swarm Algorithm and the Gray Wolf Algorithm are easy to fall into the local optimal solution, and the convergence speed of the Gray Wolf Algorithm is not ideal. In this regard, this paper proposes the FPA-DFLM model. The DELM model uses ELM-AE as the basic unit, performs unsupervised learning greedily, and adjusts it in combination with supervised learning to orthogonalize the hidden layer deviation, which minimizes the error and improves the degree of generalization. Compared with the Particle Swarm Algorithm and the Gray Wolf Algorithm, the FPA algorithm realizes the free conversion of local search and global optimization, and has the characteristics of less parameters and fast convergence speed. The FPA-DELM model improves the solution accuracy and effectively finds the global optimal value and optimal solution[8]. To verify the model validity, a dataset from the System Performance Laboratory of the Energy Systems Integration Facility (ESIF) was selected for testing.

In this paper, the FPA-DELM model is constructed to predict the user's variable load. The advantages, disadvantages and construction of DELM model and FPA model are briefly described. A suitable fitness function is found through the DELM model, and the FPA algorithm is used to optimize its input weights and thresholds, thereby obtaining the optimal FPA-DELM user variable load forecasting model.

2. Model introducing

For the user's variable load, how to accurately know the electricity consumption at a certain moment can effectively alleviate the electricity consumption. Taking a part of the known data as the training set, the DELM model is used to find the fitness function, and the FPA algorithm is used to calculate the fitness function. The input layer and hidden data are optimized, such a predictive model can bring a higher accuracy rate.

2.1 DELM

The extreme learning machine ELM is a single hidden layer neural network algorithm. Its network parameters do not require complex iterations, and can be directly calculated by the least squares method. In theory, it achieves the smallest error and faster learning speed[9]. It consists of three layers: input layer, hidden layer, and output layer. The weights of the input layer and the threshold of the hidden layer are randomly generated, and then the activation function is determined to calculate the weights of the output layer. An autoencoder (AE) is trained to copy the input to the output, training the data in an unsupervised learning fashion. The ELM-AE structure is to make the output and input of the network as similar as possible, and add orthogonalization to the processing of the parameters of the hidden layer. The ELM-AE network structure is shown in Figure 1.

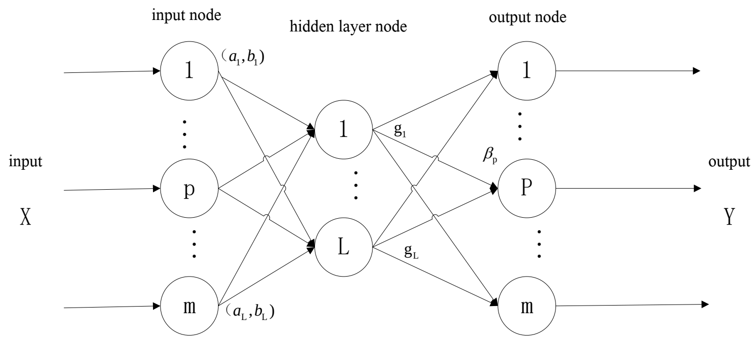

Figure 1. ELM-AE network structure

The Deep Extreme Learning Machine (D-ELM) uses ELM-AE as its basic unit, which is a stack of multiple hidden layers, increasing the number of iterations, and using a step-by-step greedy learning method to train the network. During the initialization process, the hidden layer uses ELM-Hierarchical unsupervised approach in AE architecture. The DELM model improves the prediction accuracy to a certain extent and also enhances the generalization ability. The model of the deep extreme learning machine is shown in Figure 2.

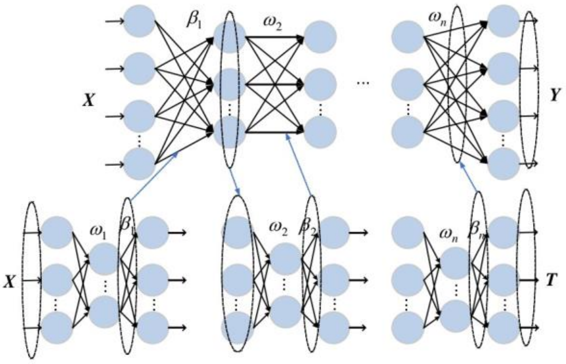

Figure 2. Model of deep extreme learning machine

2.2 FPA

The Flower Pollination Algorithm (FPA) was proposed by Yang, a scholar at the University of Cambridge, UK[10], its basic idea comes from the simulation of natural flower self-pollination and cross-pollination, and it is a new meta-heuristic swarm intelligence stochastic optimization technology.

The flower pollination algorithm is to simulate the process of pollination of flowers of flowering plants in nature. The ideal condition is to simplify the characteristics of plants. Each plant has one flower and only one pollen seed is produced. The assumptions are as follows:

a) Biological cross-pollination is regarded as a global pollination process, in which pollinators with pollen perform Levy flight.

b) Abiotic self-pollination is seen as a local pollination process.

c) The permanence of the flower is considered as the reproduction probability, which is proportional to the similarity of the two flowers involved in pollination.

d) The transition probability $p \in [0,1]$ controls the interaction between global pollination and local pollination, and the transition probability is slightly biased for local pollination due to the influence of some other factors, such as wind, distance, moisture, etc.

Through the above ideas, a model is established to realize the flower pollination algorithm as follows:

a) Initialize various parameters, including the population number n of flowers, and the transition probability p.

b) Calculate the fitness of each solution, and solve the current optimal solution and optimal value.

c) Determine the relationship between the transition probability p and rand, update the solution, and perform out-of-bounds processing.

d) Calculate the fitness value of the new solution obtained in the previous step, compare it with the current solution and the current fitness value, select the optimal one to save, compare it with the recorded optimal value and optimal solution, and select the optimal one to update.

In the above algorithm, the iterative formula of the FPA algorithm is:

Mathematical formula for the cross-pollination rule:

$$X_i^{t+1} = X_i^t + L\left(X_i^t - g^*\right) \tag{1}$$

In formula (1): X_i^{t+1}, X_i^t are the solutions of generation t+1 and generation t, respectively; g^* is the global optimal solution in one iteration; L is the step size, and its calculation formula is

$$L \sim \frac{\lambda\Gamma(\lambda)\sin(\pi\lambda/2)}{\pi}\frac{1}{s^{1+\lambda}}, \quad s \gg s_0 > 0 \tag{2}$$

In formula (2): $\Gamma(\lambda)$ is the standard gamma function; s is the step size; s_0 is the minimum step size; λ=1.5.

The mathematical formula for self-pollination is

$$X_i^{t+1} = X_i^t + \varepsilon(X_j^t - X_k^t) \tag{3}$$

Among them, X_j^t, X_k^t is the pollen of different flowers of the same plant; $\varepsilon \in [0,1]$ is reproduction probability[11].

2.3 FPA-DELM

Due to the random generation of parameters in the DELM algorithm, the number of hidden layer nodes may be very large, resulting in low resource utilization. When calculating the output weight, the error mainly comes from the randomness of the input weight and bias, and there may also be some parameters with zero input, which makes some hidden layer nodes invalid. In view of these defects, this paper proposes a Deep Extreme Learning Machine model based on Flower Pollination Algorithm (FPA) optimization -- FPA-DELM.

In the DELM algorithm, the randomly generated parameters will affect the accuracy of the DELM algorithm; while the flower pollination algorithm has the characteristics of simple parameters, fast convergence speed and good robust performance in search, and can effectively find the global optimal solution and the optimal solution. Therefore, this paper introduces FPA into the DELM algorithm, optimizes the input weight w and the hidden layer deviation b, selects the optimal value, and substitutes it into the DELM algorithm training network, which improves the accuracy and saves the operation time.

First, the input layer weights and hidden layer biases in DELM are formed into a vector, that is, the initialization individuals of the FPA population are generated. Using the fitness function of FPA, multiple update iterations are performed to find a set of population position vectors with the smallest fitness value, which is the optimal set of solutions. Then the optimal solution is substituted into the training DELM network, and the output matrix H is calculated by using the reverse fine-tuning feature of DELM, Calculate the output weight according to the calculation formula Hβ=T. The solution obtained by this method is unique and optimal. As long as the optimal input weights and the thresholds of hidden layer nodes are selected, the error can be reduced and the optimal result can be obtained.

The flow of the FPA-DELM algorithm is shown in Figure 3, and its specific steps are as follows:

Step 1: Initialize DELM network model parameters, input training sample data, and set the number N of hidden layer nodes.

Step 2: Define the parameters of the FPA, randomly generate the initial population of the FPA, and the population dimension is d-dimension. Select the fitness function to determine the value of the number of iterations and the number of populations.

Step 3: Calculate the optimal fitness value as the initial fitness value of the optimal fitness of the current population, and calculate the average optimal position of the population.

Step 4: Determine the relationship between the transition probability p and rand of the individual population, perform a local search, and calculate the shrinkage factor. And calculate the fitness value of the individual flower, update the position of the optimal solution.

Step 5: Judges whether the condition of the maximum fitness value is met or the maximum number of iterations is reached: if so, stop the iteration; otherwise, return to step 4.

Step 6: Substitute the input weights and thresholds obtained by FPA optimization into the DELM model, calculate the matrix H, and output weights, and establish a DELM training model.

Step 7: Predict the test samples according to the trained model and evaluate the performance of the network model[12].

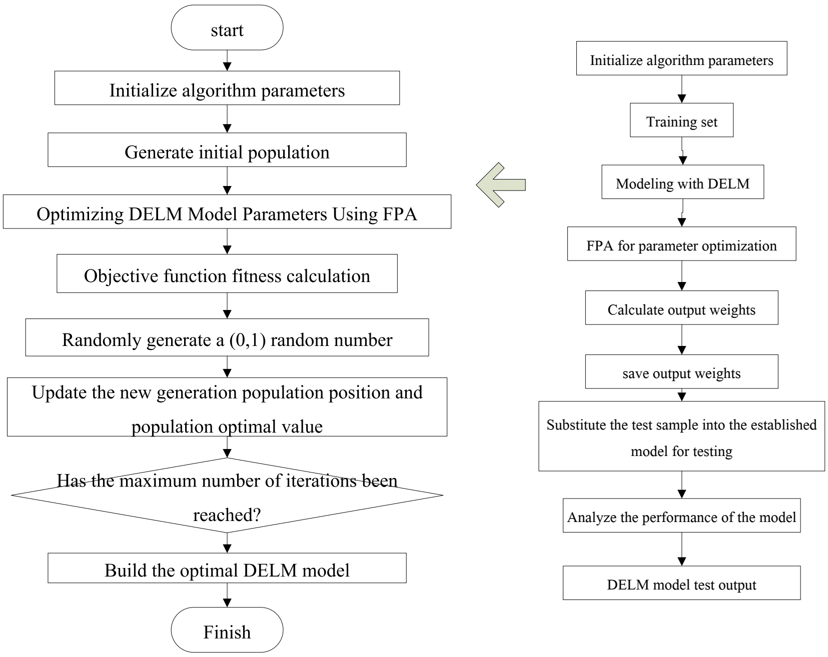

Figure 3 Flow of FPA-DELM

3. Example measurement

3.1 Sample selection and data sources

The data set used in this article is from the System Performance Laboratory (SPL) of the Energy Systems Integration Facility (ESIF), and a household was selected at 8:33:53.56 AM on May 2, 2016 - May 2, 2016 1:59: Power data of 6 residential appliances (refrigerator, washer, dryer, dishwasher, waterheater, lights) used at 18.36 PM, the time interval is 1 second, 18,208 pieces of data are collected for each appliance, and 109,248 pieces of data are collected in total valid data[13].

3.2 Data processing

In this paper, the user variable load data is normalized by formula (4) [14], that is, the size of the original load data is normalized to the interval [1, 2]. The normalization process is beneficial to the solution of the prediction model.

$$x_i^* = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{4}$$

In the formula : x_i^* is the normalized load data at time i; x_i is the original load data at time i; x_{min} is the minimum load data in the sample data; x_{max} is the maximum load data in the sample data.

3.3 Error evaluation index

To evaluate the performance of the prediction model, this paper adopts the following four commonly used error evaluation indicators: Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Coefficient of Determination (R^2). The relevant calculation formula is as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \times 100\% \quad (5)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2} \quad (6)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right| \quad (7)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2}{\sum_{i=1}^{n}\left(\bar{y}_i - y_i\right)^2} \quad (8)$$

In the above formula, is the total number of prediction samples, y_i and $\hat{y}_i$ are the actual load value and the predicted load value at the forecast time, respectively. Among them, the smaller the values of MAPE, RMSE and MAE, the smaller the error and the better the model prediction effect. The larger the value of R^2, the smaller the error and the better the prediction effect of the model.

3.4 FPA-DELM model prediction

Use FPA-DELM to train 18,000 pieces of data, test with 70 pieces of data, and normalize the original data to the interval [1, 2], as shown in Figure 4. It is the power prediction chart of six household appliances, such as refrigerator, washer, dryer, dishwasher, waterheater, and lights. The DELM model is compared with the FPA-DELM model.

3.5 Predictive Model Comparative Analysis

Comparative analysis of prediction models from Table 1, it can be seen that compared with DELM, the accuracy of FAP-DELM algorithm is high. This is because FAP-DELM increases the parameter optimization and increases the computational complexity, but at the same time selects a suitable parameter.In addition, FPA has high optimization accuracy and fast convergence speed; according to Table 1, it is not difficult to see that the accuracy of FPA-DELM model is about 82.6087%. Based on the above experiments, the feasibility of the FPA-DELM model can be seen.

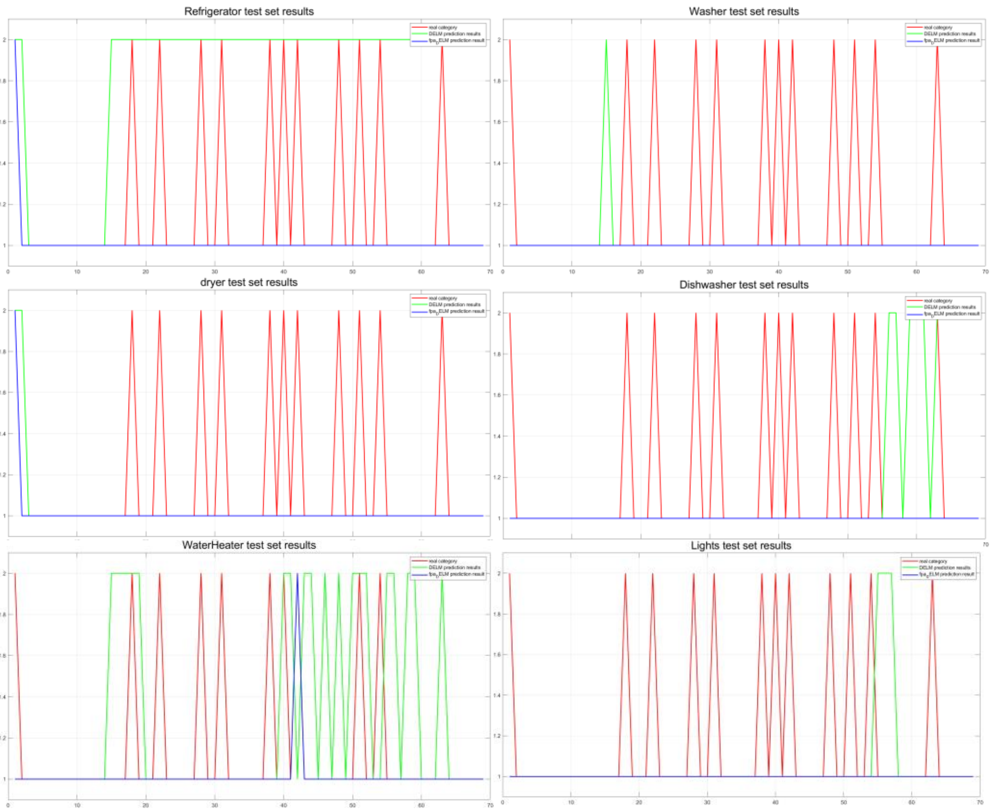

Figure 4. FPA-DELM model prediction results

Table 1. Accuracy comparison

Name of electrical appliance	Algorithm	Accuracy
Refrigerator	DELM	34.7826%
	FPA-DELM	84.058%
Washer	DELM	81.1594%
	FPA-DELM	82.6087%
Dryer	DELM	82.6087%
	FPA-DELM	84.058%
Dishwasher	DELM	68.1159%
	FPA-DELM	82.6087%
Waterheater	DELM	69.5652%
	FPA-DELM	85.5072%
Lights	DELM	78.2609%
	FPA-DELM	82.6087%

4. Conclusion

DELM is a model with ELM-AE as the basic unit for optimization based on ELM, but it has a large number of nodes and high resource utilization when solving problems; FPA is an intelligent optimization algorithm that imitates the process of plant flowering and pollination. It has the advantages of high search accuracy and fast convergence speed. Aiming at the problem of DELM, using the FPA model, this paper proposes a DELM algorithm based on flower pollination (FPA-DELM). The parameters of the hidden layer are optimized, which improves the convergence speed and optimization accuracy of the algorithm. The experimental results show that the flower pollination Algorithm-based DELM algorithm (FPA-DELM) proposed in this paper has higher prediction accuracy than other algorithms, which proves that the improved strategy in this paper can improve the optimization performance of DELM. In future research, the FPA-DELM model will be further applied to complex engineering optimization problems in different fields.

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