Application of ALO-ELM on Electricity Demand Forecasting Under Spot Power Market

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Abstract: The electricity demand of power system and power market change with the development of economy, short-term electricity demand forecasting play a very important role in spot power Market. In this paper, the Ant Lion Optimizer (ALO) is introduced to improve the input weights and hidden-layer Matrix of extreme learning machine (ELM), after the parameters of ELM are optimized by ALO, then input nodes, hidden layer nodes and output nodes are determined, so an electricity demand forecasting model based on ALO-ELM combined algorithm is established. The proposed method is illustrated based on the historical load data of a city in China. The results show that the average absolute error of short-term load demand predicted by ALO-ELM model is 1.41, while that predicted by ELM is 4.34, it has shown than ALO-ELM algorithm is superior to the ELM and meet the requirements of engineering accuracy. Under the spot power market, accurately predicting the electricity demand trend and reducing the deviation of electricity expenditure have become an important means for the market players to make profits.

Keywords: electricity demand forecasting; power market; extreme learning machine (ELM); ant lion optimizer (ALO); parameter optimization; model

1. Introduction

With the development of technology and civilization, human beings are eager to grasp the trend of development and change. Prediction has become the main research field of machine learning. Electricity demand forecasting is to establish the relationship between future load demand and historical load data, impact factors at a specific time [1].Accurate electricity demand forecasting can provide reference for operation, power generation, power distribution, power transmission and system planning and dispatching, power price balance and so on [2]. At the same time, the accurate electricity demand forecasting can provide references for the electricity price adjustment of the power supply enterprise, and promote the reform and development of the electricity market [3].

After many scholars and research unceasing exploration, many valuable research results have been obtained in electricity demand forecasting aspect. A short-term electricity demand forecast method was proposed based on artificial neural network and artificial bee colony algorithms in [4]. A combined method for the short-term load forecasting of electric power systems was presented in [5], which was based on the Fuzzy c-means (FCM) clustering, particle swarm optimization (PSO) and support vector regression (SVR) techniques. A method was proposed to utilize the universal approximation properties of neural and wavelet networks to determine the function relationship between input variables and outputs [6]. A method was propose for short term load forecasting trained by PSO and Core Vector Regression (CVR)[7]. Based on the historical data, the whale algorithm was applied to optimize the parameters of KELM, and the short-term load-forecasting model was established in [8]. Based on fuzzy data processing, bagging algorithm was introduced to sample new samples and trained fuzzy GBDT to establish load-forecasting model[9].To resolve the problem of short-term power load forecasting, a self-adapting particle swarm optimization (PSO) algorithm was proposed to optimize the error back propagation (BP) neural network model[10]. The methods mentioned above have their own characteristics, for example, support vector machine is a small sample learning method, it can deal with

nonlinear problems, and the artificial neural network algorithm has the advantages of strong learning and adaptive ability.

Huang G. B. proposed Extreme Learning Machine (ELM) algorithm in [11]. ELM algorithm has been employed on prediction and large sample learning by randomly giving the hidden layer parameters. However, because the implicit parameters of ELM are generated randomly, a series of non-optimal parameters are generated, which weaken the generalization performance of ELM [12]. At present, the parameter optimization algorithms for ELM include Genetic Algorithm and particle swarm optimization [13]. A hill-climbing method was adopted to optimize the weights and thresholds of extreme learning machines, so as to obtain an optimization model with strong stability and high prediction accuracy, the improved model has faster training speed and more accurate prediction, which is applicable for short-term power load forecasting with a large number of influencing factors and huge data volume[14]. The artificial swarm optimization algorithm was used to select the ELM parameters by Cao J. [15].Particle swarm optimization (PSO) was applied to simulate the behavior of birds, and the optimal solution was obtained by particle iteration. Mutation operator was selected to enhance the diversity of population, and the parallel Algorithm (PIPSO-ELM) was adopt to deal with the big data of power load [16]. Most optimization algorithms obtained by simulating the biological behavior. Mirjalili S. proposed ALO Algorithm in 2015, the results of mathematical experiments show that ALO has better optimization performance [17].

Based on the analysis of the literature, this paper presents a short-term electricity demand forecasting method based on extreme learning machine and ant lion Algorithm. ALO was used to optimize the parameters of ELM, the electricity demand in Chongqing city were selected to verify the effectiveness and feasibility of the proposed prediction algorithm based on ALO-ELM combined method.

2. Prediction Algorithm Based on ALO-ELM

2.1. The Ant Lion Optimizer-ALO

The Ant Lion Optimizer-ALO simulates the predation behavior of ant and ant-lion to obtain the best solution. The main body of the algorithm is ants and ant lions. Firstly, the position and fitness value of the ant are initialized. The factors that affect the ant's migration are the boundary limit and the ant-lion trap. When the ant finds a better position, than the ant-lion immediately preys on the ant and takes the place of the ant, after the iteration, the optimal solution of the ant-lion is the elite ant-lion, finally the global optimal solution is obtained [18-19]. The formula is as follows.

Ant Migration formula is

$$X(t) = [0, cs(2r(t_1 - 1), cs(2r(t_2 - 1), ..., cs(2r(t_n - 1))] \tag{1}$$

In the above equation: cs is the cumulative sum, n is the number of Iterations, and $r(t)$ is

$$r(t) = \begin{cases} 1 & rand > 0.5 \\ 0 & rand \le 0.5 \end{cases} \tag{2}$$

Where t is a random number, and $rand$ is a random number with a range of [0, 1].

In a bounded space, the location of the ant's t-th iteration is

$$X_i^t = \frac{(X_i^t - a_i) \times (d_i - c_i^t)}{(d_i^t - a_i)} \tag{3}$$

When the i variable walk randomly, d_i is the maximum, a_i is the minimum, d_i^t is the maximum value of t-th iteration, c_i^t is the minimum value of the t-th iteration.

The ant moves around the super ball around the ant lion, and affected by the ant-lion trap. The motion formula is

$$c_i^t = Antlion_j^t + c^t \tag{4}$$

$$d_i^t = Antlion_j^t + d^t \tag{5}$$

Where c^t, d^t is the minimum and maximum value of the t-th iteration, $Antlion_j^i$ is the position of the ant-lion j in t-th iteration.

As the travel radius of ant decreases, C and D decrease as the number of iterations increases [18], the formula is as follows:

$$c^t = \frac{c^t}{I}, d^t = \frac{d^t}{I}, I = 10^w \frac{t}{T}, w = \begin{cases} 2 & t > 0.1T \\ 3 & t > 0.5T \\ 4 & t > 0.75T \\ 5 & t > 0.9T \\ 6 & t > 0.95T \end{cases} \tag{6}$$

This can effectively improve the rate of convergence.

When an ant-lion eats an ant, then it updates position to improve chances of catching ant, the formula is as follows:

$$Antlion_j^t = Ant_i^t \qquad f(Ant_i^t) > f(Antlion_j^t) \tag{7}$$

During the iteration, all ants will be affected by the elite ant-lion, and the location of ants will be determined by roulette and random walk in order to reduce the local extremum [18，19]:

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \tag{8}$$

Where R_A^t is the choice of random walk of the roulette wheel in the t-th iteration R_E^t is random walk of the ant around the elite ant lion in the t-th iteration.

2.2. Extreme learning machine

The input weights and hidden layer node offset of the extreme learning machine are selected randomly, and the hidden layer output weights are determined by the algorithm to minimize the training error [11-14].

Let N sample sets are $\{(x_j, t_j), j = 1,2,\ldots, N \}$,where $x_j=[x_{j1}, x_{j2},\ldots x_{jn}]^T \in R^n$, $t_j=[t_{j1}, t_{j2},\ldots t_{jn}]^T \in R^m$,then ELM with L hidden nodes can be expressed as:

$$f_L(x_j) = \sum_{i-1}^{L} \beta_i g_i(\omega_j + b_i) \qquad j = 1,2,\ldots N \tag{9}$$

where ω_i is the input weight of the i hidden layer node, β_i is the connection weight between the hidden layer node and the output node, b_i is the bias vector of the hidden layer node, and L is the number of hidden layer nodes[11，12].A Matrix represents the output of the network is:

$$H\beta = T \tag{10}$$

$$H = \begin{bmatrix} g(\omega_1 x_1 + b_1) & g(\omega_2 x_1 + b_1) & \ldots & g(\omega_L x_1 + b_1) \\ g(\omega_1 x_2 + b_1) & g(\omega_2 x_1 + b_1) & \ldots & g(\omega_L x_1 + b_1) \\ \ldots & \ldots & & \\ g(\omega_1 x_N + b_1) & g(\omega_2 x_1 + b_1) & \ldots & g(\omega_L x_1 + b_1) \end{bmatrix} \tag{11}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \beta_2^T \\ \vdots \\ \beta_L^T \end{bmatrix} \qquad T = \begin{bmatrix} T_1^T \\ T_2^T \\ \vdots \\ T_N^T \end{bmatrix} \tag{12}$$

Where H is the hidden layer output matrix, β is the output weight matrix, T is the expected output Matrix. The minimum error of $\|H\beta - T\|$ is calculated first, then the least square algorithm is used to obtain the minimum output weight $\hat{\beta} = H^{-1}T$.

2.3. The ALO-ELM Algorithm on Electricity Demand Forecasting

The disadvantage of the extreme learning machine is that the input weights and the hidden layer deviation matrix are random, which affects the stability of the prediction results [14]. Ant-lion Algorithm was utilized to optimize the parameters of the extreme learning machine, to avoid the influence by random selection of parameters. The optimization function of the ALO-ELM Algorithm is described as:

$$\begin{cases} \min F(\omega, b) \\ s.t. \qquad \omega \in (-1,1), b \in (-1,1) \end{cases} \tag{13}$$

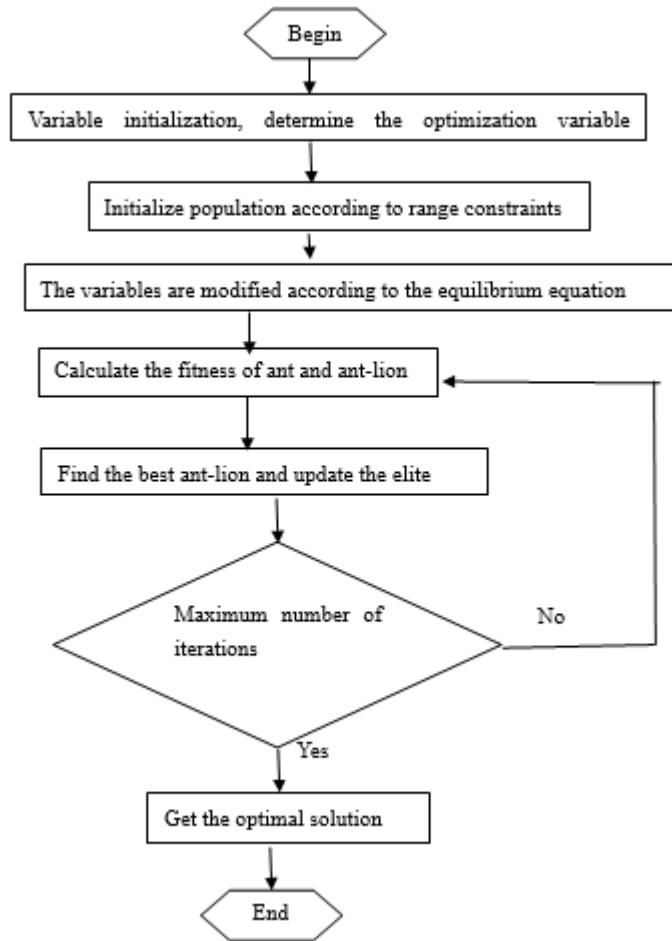The flow diagram of the ALO-ELM prediction model is as follows：

Figure 1. Flow chart of ALO-ELM algorithm

The daily maximum electricity demand is not only related to historical data, but also influenced by temperature, day type (working day or holiday) and weather humidity. Based on the above factors and the historical daily maximum electricity demand of a city in China from August 2019 to July 2020, a daily maximum electricity demand -forecasting model is established. The 10-day electricity demand data in August 2020 were selected as the test sets.

The parameters of ELM structure, input node parameters, hidden layer node parameters and output node parameters are optimized by ALO. Other parameters: maximum iteration times are 320, population sizes are 75, and excitation function is sigmoid type.

3. Simulation Results and Discussion

In order to verify the superiority of the ALO-ELM prediction model, the original ELM model was applied to forecast the maximum load demand of the same day, and then the comparison was made. Figure 2 is a comparison of the daily maximum load forecasting results of the two forecasting models in the validation data set. It can be seen that the predicted results of the two models are close to the actual load, but the ALO-ELM model has a better agreement with the actual load. Figure 3 shows the prediction error curve. As can be seen in Figure 3, the prediction error of ALO-ELM is less than that of ELM. Compared with the forecast results and forecast errors in Figure 2,Figute 3 and Table1, it is obvious that the daily maximum load demand predicted by the ALO-ELM model can match the actual demand very well, while the ELM forecast results have relatively large deviation, therefore, the ALO-ELM prediction model has higher prediction accuracy.

The forecast of daily maximum electricity demand is affected by many factors, and the variability of the forecast will lead to the forecast error between the forecast value and the actual value. The error evaluation index can evaluate the error level between the predicted value and the true value, and the average absolute error MAPE is selected as the evaluation index. MAPE is expressed as:

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{F_i - R_i}{R_i} \right| \times 100\% \qquad (14)$$

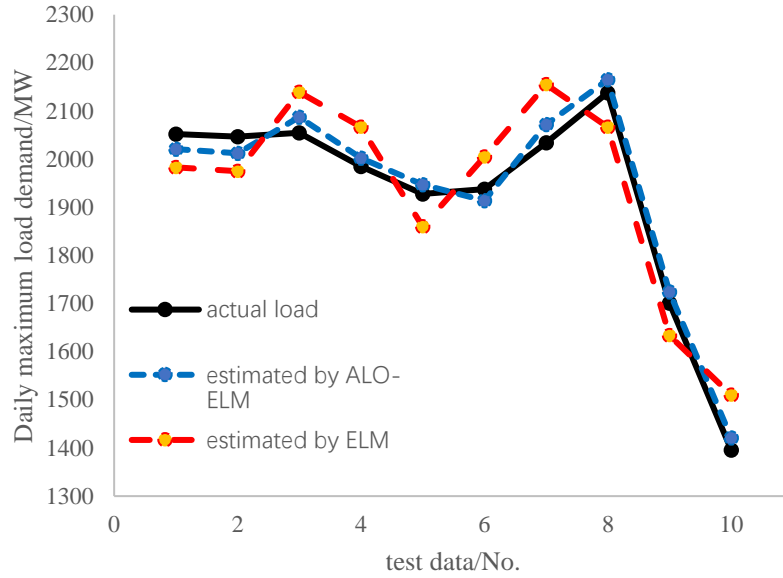Where N is the number of samples, R_i is the actual value, F_i is the predicted value.

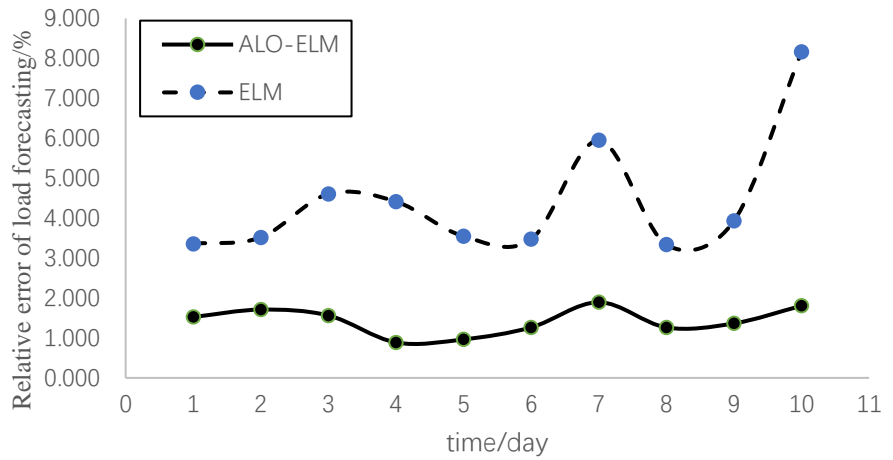**Figure 2.** Forecasting results of daily maximum electricity demand

Figure 3. The electricity demand prediction error

Table 1. Comparison of electricity demand forecasting by two methods

Data （2020）	Actual electricity demand / MW	ALO-ELM		ELM	
		/ MW	Relative error/%	/ MW	Relative error/%
August 1st	2052.5	2021.2	1.525	1983.6	3.357
August 2nd	2047.4	2012.4	1.709	1975.5	3.512

August 3rd	2055.6	2087.7	1.562	2139.2	4.067
August 4th	1985.2	2002.8	0.887	2067.4	4.141
August 5th	1928.7	1947.3	0.964	1860.3	3.546
August 6th	1938.6	1914.1	1.264	2005.9	3.472
August 7th	2034.1	2072.6	1.893	2155.1	5.949
August 8th	2138.8	2165.8	1.262	2067.4	3.338
August 9th	1701.4	1724.6	1.364	1634.5	3.932
August 10th	1396.3	1421.5	1.805	1510.3	8.164

Table 2. Prediction error analysis of two prediction models

Algorithm	MAPE / %
ALO-ELM	1.41
ELM	4.34

From the error analysis of Table 1 and Table 2, it can be seen that MAPE values of both forecasting models are small. The average absolute error of short-term electricity demand predicted by ALO-ELM model is 1.41, while that predicted by ELM is 4.34, obviously the mean absolute error of ALO-ELM model is lower. The prediction accuracy of the improved ELM is higher as shown in Table 2 and Figure 2, which shows the validity of the proposed ALO-ELM prediction method.

The electricity market covers a wide range, such as the wholesale and retail markets and the electricity spot market. Market participants need to have a keen sense of market smell, especially power generation enterprises and power sales companies. They need to accurately predict the power supply and transaction prices, reduce the deviation of electricity charges and ultimately make profits. All these must rely on accurate short-term load forecasting data. The ALE-ELM prediction model can reduce the short-term load forecasting error and control the error to less than 1.9%.Based on the forecasted results, combined with historical transaction data (including electricity and electricity prices) and future market fluctuations, the trend of electricity and electricity prices can be predicted, so as to guide market players to conduct market-oriented transactions and make the maximum benefit.

4. Conclusion

The Ant-lion Optimizer was applied to optimize the input weights and hidden-layer node offset of Extreme Learning Machine, and short-term electricity demand forecasting model based on ALO-ELM combined method was established in this paper. To train and verify the superiority and validity of the ALO-ELM forecast model, the practical daily maximum electricity demand of a city in one-year are illustrated it. Compared with those predicted by the basic extra learning machine model, the results show that:

1）The daily maximum electricity demand predicted by the ALO-ELM model is in good agreement with the actual demand, while the ELM prediction results have a relatively deviation;

2）Both models have small MAPE values. The mean absolute error of short-term electricity demand predicted by ALO-ELM is 1.41, while that predicted by ELM is 4.34, obviously, the ALO-ELM model has a lower mean absolute error.

3）It can control the short-term electricity demand forecasting error of the power market within 1.9%, provide reference for the market players, and help to avoid market risks.

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