The Load Forecasting Method Based on Adaptive Neural Network and TLBO Algorithm

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Abstract. Load forecasting is of great significance for the arrangement and optimization of the distribution network scheduling. This paper proposes a load forecasting method based on an improved TLBO optimized adaptive neural network. Firstly, the 'teaching' phase in the basic TLBO algorithm is improved, and the average value of all search individuals is changed while adopting adaptive teaching factors, so that the performance of TLBO in the entire search space can be adaptively improved. Then, the 'learning' phase of the TLBO is improved. The Gaussian mutation operator is introduced in the learning phase to maintain the diversity of the population and avoid the TLBO algorithm's premature convergence and local optimization. Finally, using the improved TLBO algorithm to optimize the adaptive neural network forecast model. In the end, the actual load data of Tianjin Power Grid was used to verify the accuracy of the simulation results.

1. Introduction
In recent years, the power data collected by smart electric meters has the scale of big data, and has shown the characteristics of data volume development from TB level to Pb level, many structured types, and fast processing speed. Research based on monthly electricity consumption in the past has now been promoted to research on consumer's daily electricity consumption behavior. It is increasingly important to conduct effective analysis of power big data and provide targeted guidance in practical application scenarios [1-5].

Power load forecasting is the basic work of power grid control optimization and an important part of power system dispatching. At present, there are a variety of forecast methods for long, medium and short-term power load, among which artificial intelligence technology has brought huge economic and social benefits to the marketing, electricity price setting, and user classification of the power industry in the short-to-medium-term load forecasting field [6-10]. References [6-7] compared user power consumption data before and after peak-valley electricity prices, and proposed a user clustering algorithm based on the regulation potential index, which provides a certain reference for screening users who voluntarily participate in demand response regulation. Reference [8] proposes an algorithm for quadratic clustering, which improves the shortcomings of load shape similarity of the clustering algorithm based on Euclidean distance in the load curve of the full-dimensional power system.

In addition, at present, not all forecast methods are suitable for a specific region. Reference [11] compared multiple clustering techniques in the correlation between daily load of substations and population density, and concluded that the K-means algorithm showed the best performance in dividing...
substation loads of dense populations. Reference [12] considers the dynamic demand of users under the current residential tiered electricity pricing mechanism, and introduces the fuzzy C-means (FCM) clustering method based on Euclidean distance, which improves the accuracy of residential users' medium-term power demand forecasting, but the generalization ability of single-core FCM algorithm for regional power big data was not strong. The FCM algorithm has been continuously improved by researchers to optimize the accuracy and stability of power load forecasting, including adaptive fuzzy C-means clustering method [13], genetic-simulated annealing optimization FCM algorithm [14], particle swarm optimization FCM algorithm [15], artificial bee colony optimization FCM algorithm [16], etc. At the same time, the complexity and calculation time of these improved FCM algorithms increase accordingly.

In practical applications, the non-linear relationship between environmental factors and load changes described by the improved optimization algorithm [12-16] and artificial neural network [17] can effectively reduce the deviation between forecast results and actual results. However, the essence of the FCM algorithm based on the single-core Euclidean distance is the similarity of the geometric mean distance, and the learning of multiple features of power big data in different regions is insufficient [8], so that it is not possible fully reveal the differences in user power consumption patterns, and the artificial neural network also has the disadvantages of complex topological structure and long training time [17].

In view of this problem, a short-term load forecasting method based on the improved TLBO optimized ANFIS (Adaptive Network-based Fuzzy Inference System) is proposed to improve the forecast accuracy. Firstly, the 'teaching' phase in the basic TLBO algorithm is improved, and the average value of all search individuals is changed while adopting adaptive teaching factors, so that the performance of TLBO in the entire search space can be adaptively improved. Then, the 'learning' phase of the TLBO is improved. The Gaussian mutation operator is introduced in the learning phase to maintain the diversity of the population and avoid the TLBO algorithm's premature convergence and local optimization. Finally, the improved TLBO algorithm is used to optimize the ANFIS forecasting model, the simulation results show that the improved TLBO optimized ANFIS method has better stability and higher accuracy for short-term load forecast than PSO optimized ANFIS method.

2. Analysis of forecast model and algorithm mechanism

2.1. Adaptive Network-based Fuzzy Inference Algorithm

ANFIS [18] can organically combine fuzzy logic units and neural networks to form a new fuzzy inference system. The premise parameters and conclusion parameters in the model are obtained by back propagation algorithm and least squares method learning. Therefore, ANFIS can give full play to the advantages of both and obtain better learning results.

Figure 1. Model architecture of Adaptive Network-based Fuzzy Inference System

The structure of the ANFIS model is shown in Figure 1. Generally, it consists of five layers. The first layer is a fuzzification layer. The input fuzzy membership expression corresponding to each node in the first layer is:
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Where: $x$ and $y$ represent the input of the $i$-th node respectively. $O_{ij}$ represents the fuzzy membership. $\mu A_i$ and $\mu B_i$ are bell functions with a maximum equal to 1 and a minimum equal to 0. The expression for $\mu A_i$ is:

$$\mu A_i(x) = \frac{1}{1 + \left| \frac{x - r_i}{p_i} \right|^{2q_i}}$$

Where: $\{p_i, q_i, r_i\}$ represents the corresponding parameters of the membership function, and the parameters in the membership function will be determined through training.

The second layer is the Rule Layer. This layer needs to calculate the incentive intensity of each rule. The expression of the incentive intensity is:

$$O_{2,i} = w_i = \mu A_i(x) \mu B_i(y), \quad i = 1, 2$$

Where: $w_i$ represents the weight of the corresponding fuzzy rule.

The third layer is the Normalization layer. This layer’s main function is to normalize the incentive intensity of each rule. The output expression of the normalization layer is:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2$$

Where: $\overline{w}_i$ is the normalized incentive intensity of the $i$-th rule, and represents the contribution of the $i$-th rule to the final result.

The fourth layer is the Defuzzification layer. This layer calculates the output of each rule. The weighted result value of each rule reflects the contribution of each rule to the overall output. The output expression is:

$$O_{3,i} = \overline{w}_i \overline{z}_i = \overline{w}_i (a_i x + b_i y + c_i), \quad i = 1, 2$$

Where: $\{a_i, b_i, c_i\}$ is the conclusion parameter set.

The last layer is the Summation layer. The Summation layer needs to calculate the sum of all nodes. The model output expression is:

$$O_{5,i} = \sum_{i} \overline{w}_i = \frac{\sum_i w_i z_i}{\sum_i w_i}, \quad i = 1, 2$$
During the model learning process, the ANFIS network can adaptively calculate and adjust related parameters, so that the mapping relationship between input data and output labels can be more accurately expressed.

2.2. TLBO algorithm

TLBO algorithm is a new intelligent optimization algorithm based on teaching process proposed by Rao et al in 2010. The solution process of TLBO is divided into two stages: ‘teaching’ and ‘learning’. The teacher imparts his knowledge to the students in the ‘teaching’ stage, reducing the gap between the students and their own knowledge level; And then, in the ‘learning’ stage, the students learn from students who are better than themselves to improve their learning level.

2.2.1. ‘teaching’ stage. The optimal individual is selected as the “teacher” by comparing all fitness function values of the entire population in each iteration. The teacher imparts his knowledge to the students as much as possible to improve the knowledge level of the entire class. The mathematical expression is:

\[ X_{\text{new}} = X_{\text{old}} + \text{rand}(X_{\text{teacher}} - T_F \times \text{Mean}) \]  

(8)

Where: \( X_{\text{teacher}} \) represents the teacher, \( T_F \) is the teaching factor, and the value is 1 or 2, \( T_F = \text{round}(1 + \text{rand}) \). \( \text{Mean} \) is the average score of all individuals in the class, which reflects the average level of the students. And rand is a random value, which reflects the general learning ability of the classroom.

2.2.2. ‘learning’ stage. After teaching, mutual learning between students has an important impact on improving students’ learning level. Randomly select two classmates from the class. The poorer one learns from the better one and updates himself accordingly. The learning phase can be expressed as:

\[ X_{\text{new}} = \begin{cases} 
\text{if } f(X_{r1}) < f(X_{r2}) \\
X_{\text{old}} + \text{rand}(X_{r1} - X_{\text{old}}) \\
\text{otherwise } X_{\text{old}} + \text{rand}(X_{r2} - X_{\text{old}})
\end{cases} \]  

(9)

Where, \( X_{r1} \) and \( X_{r2} \) are two random classmates different from \( X_{\text{old}} \) in the class.

2.2.3. Improved TLBO algorithm. There are two problems in the basic TLBO algorithm: (1) The value of the teaching factor \( T_F \) is 1 or 2, which means that the students may accept or reject all the knowledge taught by the teacher, which does not reflect the learning ability of the students well. (1) The value of the teaching factor is 1 or 2, which means that the students may accept or reject all the knowledge taught by the teacher, which does not reflect the learning ability of the students well. Moreover, in each iteration, the position change of each student guided by the best teacher is blind, and the differences between students will cause the search to stagnate. (2) In the ‘learning’ stage, individuals only improve their knowledge level by learning from neighboring better individuals, which will reduce the diversity of algorithms and fall into a local optimum. This paper proposes to solve the problem (1) by adopting adaptive teaching factors while changing the average value of all individuals to improve the search performance of the algorithm. According to the problem (2), the Cauchy mutation operator is introduced in the ‘learning’ stage to maintain the diversity of the population. Specific improvement strategies are as follows.

2.2.4. Improved ‘teaching’ stage. In the basic TLBO algorithm, the teaching factor \( T_F = \text{round}(1 + \text{rand}) \) has a value of 1 or 2, which is not conducive to students' learning. Therefore, an adaptive teaching factor is used, and the expression is as follows:
\[ T_{Fi} = \frac{M_i}{M_{newi}} \quad (i = 1,2,3,\ldots,d) \] (10)

Where: \( M_i \) represents the students’ average score in subject \( i \), and \( M_{newi} \) represents the teacher’s teaching level in subject \( i \). The adaptive teaching factor will be adjusted according to the learning ability of the students during the search process, so that the performance of the TLBO in the entire search space can be adaptively improved.

In addition, according to the equation (8), the students’ position change guided by \( X^{teacher} \) is blind, and individual differences in students will cause the search to stagnate. Therefore, changing \( Mean \) to improve individual differences and the search performance of the algorithm. The improved expression for the ‘teaching’ stage is:

\[ X_{i}^{new} = X_{i}^{old} + \text{rand} \left( X^{teacher} - T_{Fi} \times \frac{\text{Mean} - X_{i}^{old}}{2} \right) \] (11)

2.2.5. Improved ‘learning’ stage. In order to avoid the TLBO algorithm from falling into the local optimum and maintaining the diversity of the population, a Gaussian mutation operator is introduced during the learning phase. The mutation formula is:

\[ X_{best}(i+1) = X(i)[1 + N(0,1)] \] (12)

Where \( X(i) \) and \( X_{best}(i+1) \) are the individual's current best performance and the results after introducing Gaussian mutation, respectively. Taking the best individual by compare the fitness values before and after individual mutation to participate in the next iteration process.

3. Load forecasting model based on data cleaning and combined learning

The parameters of the ANFIS model have weights and offsets. In this paper, an improved TLBO algorithm is used for global optimization to determine ANFIS parameters, which can improve the accuracy of the ANFIS forecast model. The steps of the improved TLBO algorithm to optimize the parameters of ANFIS are as follows:

(1) Step1: Data pre-processing. The input of the ANFIS model is wind speed, temperature, humidity, and power. Because their dimensions are different which will affect the forecast result, the min-max normalization processing is performed on the original data, and the expression is:

\[ \bar{x}_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (i = 1,2,\ldots,N) \] (13)

Where: \( \bar{x}_i \) is the normalized value, \( x_{\min} = \min(x_i), x_{\max} = \max(x_i) \). Assuming that the forecast result after data preprocessing is \( y' \), the actual forecast value is \( y(x) = y'(x_{\max} - x_{\min}) + x_{\min} \).

(2) Step2: Initialize the main parameters of the improved TLBO algorithm. It mainly includes the population size, the maximum number of iterations, and the Gaussian mutation operator. Based on the initialization population, the fitness value of the function is calculated, and the individual with the best fitness value is used as the teacher.

(3) Step3: Perform the teaching process according to formula (11). Students learn from the teacher to improve their scores in various subjects, thereby improving the knowledge level of the entire class. Simultaneously update the population individuals, and then use Equation (9) for interactive learning between students.

(4) Step4: Perform mutation operation on the interacted individuals according to formula (12), and update the population individuals.

(5) Step5: Determine whether the loop is over. If the maximum number of iterations has been reached, the optimal score obtained by the individual at this time is assigned to the penalty factor \( c \) and the kernel parameter \( \sigma \) in the ANFIS model. Otherwise, steps 2 to 4 are looped.
The flowchart of short-term load forecast based on improved TLBO to optimize ANFIS is shown in Figure 2.

![Flowchart](image)

**Figure 2.** The flowchart of forecast based on improved TLBO to optimize ANFIS

### 4. Example analysis

The calculation example is selected from the actual operation data of Tianjin Power Grid for verification. In order to better analyze the application scenarios of this algorithm, the weather information comes from Numerical Weather Forecast (NWP). The forecast goal is the load result for the next hour. Among them, the data for 2017 is training data, and the data for 2016 is test data. The test machine uses Win 10 system and Core i5 processor, and completes the relevant program compilation in Matlab 12a.

The precision indicators used in this paper include root mean square error (RMS) and mean absolute error (MAE).

\[
\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} |P_i - \bar{P}_i| \tag{14}
\]

\[
\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (P_i - \bar{P}_i)^2} \tag{15}
\]

Where: \( N \) is the number of predicted samples, and \( P_i \) and \( \bar{P}_i \) are the actual and predicted values at the time \( i \), respectively.
Figure 3. Winter (January 4, 2016) Forecast Results

Figure 4. Spring (April 13, 2016) Forecast Results

Figure 5. Summer (July 22, 2016) Forecast Results
Figure 6. Autumn (October 15, 2016) Forecast Results

In order to further analyze the effectiveness of the algorithm in this paper, representative dates of spring, summer, autumn, and winter are selected for analysis. The load curves of predicted power and actual power are shown on different dates. According to the Figure 3-6, the power load shows different patterns in each season, the double-peak shape of the winter load is not obvious, and the peak-to-valley difference of the spring and autumn load is more obvious. For different forecast scenarios, the algorithm in this paper has obtained good forecast accuracy, and the error from the actual load is small.

Table 1. Comparison of forecast results of several load forecast models

| Load forecast models   | MAE    | RMSE   |
|-----------------------|--------|--------|
| PSO-ANFIS             | 22.258 3 | 29.345 0 |
| TLBO- ANFIS           | 14.263 4 | 18.558 9 |
| Improved TLBO-ANFIS   | 6.664 7  | 8.161 1  |

In addition, the algorithm in this paper is compared with other algorithms to reflect the optimization effect of the improved TLBO algorithm. The compared algorithms include Particle Swarm Optimization (PSO) and conventional TLBO algorithm. It can be seen from Table 1 that the values of the average absolute error and the root mean square error of the short-term load model optimized by the improved TLBO algorithm for the ANFIS forecast are smaller than those of the PSO-ANFIS and TLBO-ANFIS load forecast models. The algorithm has higher forecast accuracy, stronger generalization ability, and better forecast effect that the forecast result is closer to the actual value.

5. Conclusion

In order to solve the problems such as premature convergence and local trapping in load forecasting based on the conventional algorithm to optimize ANFIS, the improved TLBO algorithm is used to optimize the ANFIS forecasting model. By improving the 'teaching' and 'learning' phases in the basic TLBO algorithm, the performance of the TLBO algorithm in the entire search space is improved, and problems of premature convergence and local optimization are avoided. Finally, using the measured data from Tianjin Power Grid as an example, the simulation results show that the improved TLBO optimized ANFIS method has better stability and higher accuracy for short-term load forecast than PSO optimized ANFIS method.
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