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Power Load Forecasting of General Regression Neural Network Based on Particle Swarm Optimization

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To study the power load forecasting optimization of general regression neural network using particle swarm optimization. Refer to the domestic and foreign literature, The paper refers to domestic and foreign literature, by comparing the GRNN with BP, MDE with DE based on particle swarm optimization, it compares the test result and studies the power load forecasting of the general regression neural network. the maximum error rate of the particle swarm optimization is lower than 9%, and the minimum error rate is approximately 0, the forecasting accuracy rate of general regression neural network is high. the optimization method has good convergence and is highly accurate, and could be applied to short-term power load forecasting.

1. Introduction

Power load is a critical factor in the safe operation of power system. As people's living standard improves, there is higher demand for the operation of our power grid. For most power grid companies, power load forecasting plays a positive and critical role in building our power grid and its long-term development. At the current stage, an increasing number of experts and scholars in and out of our country are studying power load forecasting, especially on long-term forecasting and short-term load forecasting. Now, some achievements have been made in short-term power load forecasting. However, particle swarm optimization sees some problems in parameter selection during application, and improper parameter selection will affect the test result and forecasting result. Generally, cross validation method consumes large amount of time and energy, and the accuracy of the power load forecasting result cannot be guaranteed.

The paper refers to domestic and foreign literature, proposes GRNN algorism based on particle swarm optimization, and conducts simulation experiment with this model. Specifically, by comparing the GRNN with BP, MDE with DE based on particle swarm optimization, it compares the test result and studies the power load forecasting of the general regression neural network, to provide reference for related studies.

2. Literature review

In the 21st century, the energy crisis has increasingly become a topic of global concern. As the main form of energy, electric energy undoubtedly occupies an important position in the production and consumption of energy. How to effectively save energy has become a concern for energy production units and every citizen. A very important condition for the electricity market to achieve effective energy-saving and scientific energy use is to accurately predict the power load. The start and stop of generators within the power grid are rationally arranged. The security and stability of the power grid operation are guaranteed. Unnecessary reserve capacity is reduced, which ultimately guarantees normal production and living, reduces the cost of electricity production, and improves economic and social benefits. The power load forecast can be divided into long-term, medium-term and short-term load forecasting. The results of long-term and medium-term load forecasting can determine the future construction of power plants and the installation of equipment, the size, location and time of the unit capacity. It can determine the expansion and reconstruction of the power grid and determine the construction and development of the power grid. Short-term load forecasting generally refers to forecasting the load situation from the next day to one week. The purpose of short-term power load forecasting is to maximize the satisfaction of power system production for demand forecasting. With the

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continuous improvement of the electricity market, accurate short-term power load forecasting will equate to huge economic benefits.

Power system load forecasting refers to the establishment of a corresponding mathematical model based on the historical data of the predicted object to reveal its inherent laws (Keynia and Bahrampour, 2017). The power system load forecast must start from the economic, social, and corresponding needs of the power system, and comprehensively consider political, economic, climate, social, and other factors. Through a large number of comprehensive and accurate system load history data, its precise correlation rules have been explored. At the same time, based on this law model, and combined with future economic and social development, future electricity demand is predicted (Ren et al., 2014). The change of power system load has a certain statistical rule, so it can be predicted. However, there are many factors that affect the load changes, such as emergencies, economic effects, weather factors, date types, and seasonal alternations. All of them can have a certain impact on the power load. At the same time, these factors are characterized by uncertainty and non-linearity without exception. Therefore, in order to make the load forecasting result more reliable and accurate, it is necessary to analyze the factors that affect the load change (Ivankova and Konecna, 2017).

Power load has a strong regularity and randomness. It changes according to certain rules, and its changes are influenced by many factors. Therefore, it is highly random based on its changes. After fully understanding the characteristics of the load itself and the laws of change, a prediction model for solving the actual situation was constructed (Hu et al., 2017). Based on the current and past power load conditions, the power system load forecast will estimate and forecast the amount of electricity load in the future (Jain, 2018). The power load forecast is to be pre-estimated based on the development trend and possible values of the load. Therefore, its research objects are uncertain events and random events (Bhana and Overbye, 2016). According to the development law of the forecasting object, the development trend and situation can be known. This is also the premise and basis for conducting power load forecasting (Oberfoell and Correia, 2016). The development of things often has internal factors. At the same time, there are external factors restricting and promoting it. Based on the current and past power load conditions, the power system load forecast will estimate and forecast the amount of electricity load in the future. The degree and effect of the respective influences are inconsistent. Therefore, the development and changes of things present a variety of possibilities (Xiao et al., 2015).

Because power load forecasting is influenced by a variety of internal and external factors, it is difficult to find a suitable mathematical relationship to express the influence of a single factor on the power load. At the same time, internal and external factors are interrelated, which makes it more difficult to accurately predict the power load. Under such circumstances, the following five principles must be followed to accurately predict the power load. The first is that in forecasting the power load, it is necessary to specify the predicted variables, the level of prediction, and the predicted time. The second is to collect the relevant data and data required for prediction as much as possible, and strive to make predictions based on a large amount of accurate data. The third is to specify the predictability credibility indicator. The fourth is that when forecasting the power load, a suitable model must be constructed under certain conditions. The fifth is to analyze the difference between the predicted results and the actual values at any time and modify the prediction model.

In summary, the above research work mainly tests and analyzes the power load forecasting on neural networks. From the indicators, the influencing factors of power load forecasting were studied. Power load has strong regularity and randomness. It changes according to certain rules, and its changes are influenced by many factors. Therefore, based on the above research status, a comprehensive analysis of the research on power load forecasting based on generalized regression neural network optimized by the particle swarm optimization algorithm is made. From the dual influence of mathematics and physics, the results of the research were found. By building a model, the results of the prediction are modified to arrive at a final conclusion.

3. Method

General regression neural network is a new neural network that is based on mathematical statistics. It could expose the hidden mapping relation of the sample data, even if the sample data is scarce, the output result of the network can still be converged in optimal regression. Currently, this neural network is applied to system identification and forecasting control.

General regression neural network is theoretically based on non-linear regression analysis. Suppose the joint probability density function of the random vector x and the random variable y is f(x, y), in which x value is x0, then the regression value of y is.

As can be seen in Figure 1, GRNN consists of input layer, mode layer, summation layer, and output layer. Mode layer is also called hidden regression layer, with each unit having a corresponding training sample. Take Gaussian function e-d(x0, xi) as the activated kernel function, xi represents the central vector of each kernel function with the total of n units. Summation layer has two units: in unit 1, weighted sum of each unit in the mode layer is calculated, the weight equals the yi value of each training sample, then the numerator of (1) is obtained, called numerator unit; in unit 2, the output sum of each unit in the mode layer is calculated to obtain the denominator of (1) is obtained, called denominator unit (if y is the vector, the dimension is q, the unit number of the summation layer is q+1, or the numerator unit number is q). Divide the output layer unit by the output of the numerator and denominator unit in the summation layer to obtain the estimated y value.

$$\hat{y}(x_0)=\frac{\int_{-\infty}^{\infty} yf(x_0,y)dy}{\int_{-\infty}^{\infty} f(x_0,y)dy} \tag{1}$$

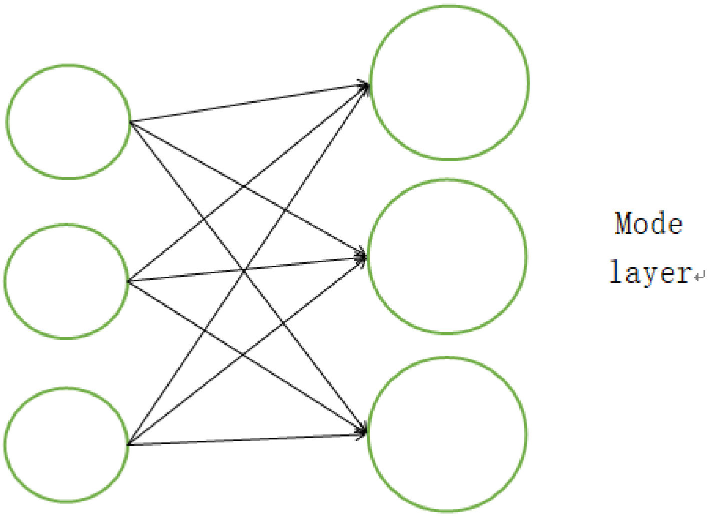

Figure 1: GRNN structure

Apply the GRNN fuzzy neural network to the power load forecasting calculation, data input starts with editing the input variable of input network layer and referring to related literature. This method results in 29*30 normalized vector equation set by processing the history power load. The key step of fuzzy neural network is training and studying the input and output, once a certain mode is secured, the forecasting result could be accessed by processing the power load data. In simulation process, data from day 22th to 27th of a month is collected first as input data, that of 28th as output in the training practice, then data of 23th to 28th is collected as input, to forecast the data on 29th. Whether selecting 29th depends on the lunar calendar of February to facilitate its yearly application.

The optimization is used to upgrade the information, search optimal information according to the changing pattern of the fitness function. Simplex method is a high-performing optimization procedure, for it is easy to achieve and doesn't require derivative calculation. Designing simplex optimization operation starts with searching optimization for a single object, then adjusting the variable probability (called optimization rate), lower the optimization rate when the contracting speed is high; and enhance reversely.

Suppose the optimization goal is set as fitness function P(σ), the first 6 steps are similar to that of DE, except the minimum λmin and optimization initial value in step 1 should be set and the cycle range in step 4 should be 5 to 8. From step 7, the simplex optimization operation is as follows: r is randomly picked from [0,1], if r > px, switch to step 8, otherwise: form initial optimization model using σGi and 2 random picked individuals σGj andσGk, obtain the optimal individual σG+1ib by simplex optimization to replace σGi. Designing simplex form in two-dimension sub-space domain could guarantee its convex shape. Step 8: same as step 7 of DE. Step 9: G+1→G. Step 10: calculate the λG value, if λG≤λmin, then repeat the step. If G outnumbers the maximum generation M, or the difference of optimal fitness value between the G generation and G+k generation is smaller than eps, then switch back to step 3.

Particle swarm optimization, PSO for short or called bird flock preying algorism, is a new evolutionary algorism developed in recent years. As one of the evolutionary algorism, it is similar to simulated annealing. Starting from random solutions, it seeks the optimal solution in iteration. It uses fitness to evaluate the solution and has simpler rules than genetic algorism. Without operations of Crossover and Mutation of genetic algorism, it seeks the overall optimal solution by searching the current optimal solutions. This algorism receives academic attention for its easy implementation, high accuracy, and fast collection, and displays its excellence in solving problems. Particle swarm optimization is a parallel algorism, which simulates bird flock preying behavior. Imagine such a scenario: a bird flock are searching food in an area where a piece of food is hidden. The birds have no idea where it is but they know the distance of that food. Then what is the optimal strategy of finding the food? The most effective method is searching the surrounding area of the bird closest to the food. PSO was inspired by this mode to solve problems. In PSO, the optimal method is searching such a bird, or identified as "particle". Each particle has a fitness value determined by the optimal function, with its flying direction and distance determined by speed. Then all the particles follow the most optimal particle in solution seeking. The initial state of the PSO is a pack of random particles (random solutions), before the most optimal solution is obtained through iteration. In each iteration, particles follow two "extreme values" to upgrade themselves. The first is the most optimal solution found by the particle itself, which is called pBest. The other extreme value is found by the whole pack, which is called gBest.

To lower the solution seeking scale, hourly power load forecasting of a day could be established. As the power load is different between workdays and weekend (as well as holidays), multiple samples should be considered. Short-term power load forecasting based on PSO-SVM should follow such steps:

1) Abnormal sample disposal. Consider the before/after power load ratio, when it appears beyond routine, then abnormal data happens, the estimated value within the routine range could be used as the modified value. Checking the power load data every day could help select and modify the abnormal data.

2) Use numbers to record the non-numerical factors, in terms of illumination level, for instance, 4 represents a sunny day, 3 represents a cloudy day, 2 represents overcast, and 1 represents a rainy day. The highest and lowest temperature could use the actual value.

3) Select the sample based on the similar weather and divide them into training and testing samples.

4. Research result and discussion

4.1 Comparison between GRNN and BP

To verify the feasibility and validity of GRNN, we calculate and analyze the short-term power load forecasting of a certain city from Jun. 5 to Jul. 10, 2004, with the sample size of 35, parameter setting of MDE as follows: N=65, C=0.05, F=0.7, k=25, eps=10-8, λmin =0.02, px=0.2. Randomly form initial groups and run 5 times, the fitting squared sum of relative deviation or the most optimal fitting value of the 5 times is 2.6374. By contrast, applying BP method to forecast results in 6.788, approximately 2.57 times of that of GRNN. Thus, the modeling result of GRNN is more accurate.

Table 1 is the forecasting result of Jun. 15,2004, obtained using GRNN, with its error rate within 2%, the accuracy is rather high. Table 2 is the result comparison of two methods for a certain week in June, 2004. From Table 2, GRNN could effectively enhance the accuracy of the short-term power load forecasting.

Table 1: Forecasting result of June 15, 2004

time	Actual value	Predictive value	Relative error（%）
3:00	5839	5860.5	0.37
7:00	6004	6128.3	2.07
11:00	5908	5937.8	0.50
15:00	6332	6436.5	1.65
19:00	5839	5926.8	1.54
24:00	5929	6121.1	3.24

Table 2: Comparison of BP and GRNN Methods

time	BP	GRNN
3:00	2.32	1.61
7:00	2.63	2.04
11:00	2.15	1.44
15:00	2.39	1.69
19:00	2.47	1.72
24:00	2.53	1.97

In order to directly compare the difference between estimated value and actual value, a comparison graph between predicted and actual values and error curve of the predicted value is drawn, as can be seen in Figure 2 and Figure 3.

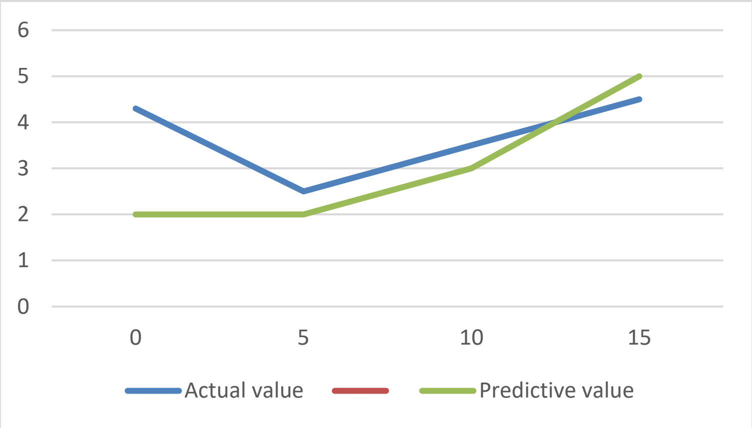

Figure 2: Comparison between predicted and actual values

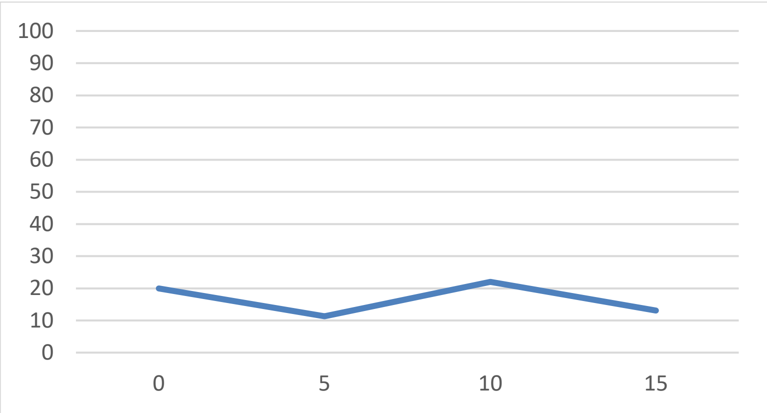

Figure 3: error curve of the predicted value

4.2 Comparison between MDE and DE

Power load data between Jun. 5 and Jul. 10, 2004 is used, with the sample size of 35, then apply the methods of MDE and DE to process the 35 initial groups. The group size, weighted coefficient, hybrid rate, maximum evolutional generation number, k, and eps parameter are 65, 0.7, 510, 0.05, 25, and 10-8, respectively. Besides, for MDE, px=0.2, λmin =0.02. It is operated 35 times to reduce incidences and the initial groups are the same for both methods. The result from the 35 operations can be seen in Table 3. Apparently, MDE is faster and easier to search the most optimal solution than DE.

Table 3: Comparison of MDE and DE results

method	Optimal number of solutions	Minimum algebra	Average algebra	Average optimal fitness value
MDE	26	88	572	$4.33*10^{-9}$
DE	11	1136	1567	$7.86*10^{-9}$

5. Conclusion

The paper refers to domestic and foreign literature, by comparing the GRNN with BP, MDE with DE based on particle swarm optimization, it compares the test result and studies the power load forecasting of the general regression neural network. As it turns out, the maximum error rate of optimal calculation based on particle

swarm optimization is lower than 9% and the minimum error rate is close to 0, with high forecasting accuracy of general regression neural network. From the test result, the optimal method used by the paper not only has good convergence, but also high accuracy, and could be applied to short-term power load forecasting.
Due to limited knowledge, the paper has some weaknesses. First, in the simulation experiment of a certain city, the paper didn't fully consider whether the data could be entered the experiment, thus, the objectivity of the data is in question and it is hard to search the most optimal solution during calculation, which should be addressed in the future studies. Second, in introducing the related data to search the most optimal solution, other disturbing factors might affect the accuracy of the test result, which should also be solved.

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