Improvement of the setting method of back pressure setting value of direct air cooling system

Jianyun Bai 1, Qi Ren 1,3, Xinyu Meng 2 and Jiang Yin 1

1 Department of Automation, Shanxi University, Taiyuan 030013, China;
2 School of Mathematical Science, Shanxi University, Taiyuan 030006, China
3 Email: renqi_57@163.com

Abstract. Because the setting method of back pressure of direct air cooling system is not reasonable, the fluctuation range of back pressure and load change are larger when the unit is peak shaving, which reduces the economic efficiency of the unit. In this paper, based on the optimal back pressure of field data calculation, particle swarm optimization (PSO) is used to optimize the modeling of BP neural network. The results show that, compared with the conventional BP model, the back pressure setting value predicted by the optimized model is more accurate, the model precision is higher, and it is more suitable for industrial field application. This method also provides some reference for the modeling of other objects in the process of thermal production.

1. Introduction

In recent years, direct air cooling technology has developed rapidly in the “Three North” region where coal is abundant but water resources are scarce.[1] In the current period of steady development of thermal power plants, how to improve the economic performance of the unit has become the main direction of scholars in the field. The direct air cooling unit axial flow fan group is used as the power consumption of the power plant, and its average power consumption accounts for 10% of the total power consumption of the plant, accounting for 1.3% ~ 1.6% of the total power generation.[2] Therefore, how to reduce the power consumption of the air-cooled fan group without affecting the stable operation of the unit is one of the main research directions of scholars.

The optimal setting of the back pressure set value is one of the means to improve the economics of air-cooled units. [3] At present, the air cooling system of most direct air cooling units adopts manual control. When the direct air cooling system enters the automatic mode, the back pressure value is the unit back pressure value tracked in the manual mode, and the setback pressure value is increased by 3 kPa according to the condensate water temperature of the unit at this time.[4-5] When the load changes little and other factors (such as ambient temperature) play a leading role, the fixed back pressure setting will cause the unit to continuously increase the air volume to reduce the back pressure, and the optimal back pressure will generally be higher than this. At this time, the set value of the back pressure makes the energy consumption of the fan larger than the increase of the power generation, and the economy of the unit is poor.[6] Through the analysis and processing of the field data, the optimal back pressure value under some key unit load conditions is calculated. The BP neural network learning and associated memory functions are used to associate the above data to obtain all back pressure settings at 70% to 100% unit load conditions. Finally, the BP neural network is optimized by PSO algorithm to establish a PSO_BP backpressure setpoint model with higher model accuracy. By
establishing an accurate back pressure setpoint model, the fan energy consumption is reduced and the back pressure is maintained within a certain range of back pressure setpoints, thereby maximizing the economic performance of the unit.

2. PSO_BP neural network algorithm

2.1. Problems with conventional BP algorithms
BP neural network has good robustness, high adaptability and self-learning, which makes it superior to traditional methods in modeling complex process systems. However, the BP algorithm also has some problems that make it difficult to apply to complex process systems.[7]

1) BP algorithm learning process converges slowly;
2) The lack of theoretical guidance for the selection of hidden nodes;
3) Extremely easy to fall into minimum values.

In view of the problems existing in the BP algorithm, scholars generally use an evolutionary algorithm with high stability and global convergence to optimize it. [8] In addition, the evolutionary algorithm does not need to rely on the feature information (such as derivatives) of the problem being solved. Therefore, evolutionary algorithms and BP neural networks are often combined to improve the stability and convergence speed of neural networks. In this paper, the particle swarm optimization algorithm in evolutionary algorithm is used to optimize BP neural network.

2.2. Particle Swarm Optimization (PSO) algorithms
Particle Swarm Optimization (PSO) is an effective global optimization algorithm. The basic principle is to assume all the solutions of the optimized problem as particles in space. Each particle individual has its own fitness value, and relies on the velocity vector and the position vector to continuously adjust its forward direction and distance until the particle population finds the optimal particle.

The algorithm is specifically described as: assuming that there is a group of \( m \) particles in an \( N \)-dimensional target search space. Use \( X_i = (x_{i1}, x_{i2}, \ldots, x_{in}) \), \( i = 1, 2, \ldots, m \) to represent the position vector of the \( i \)th particle in the population; its velocity vector is denoted as \( V_i = (v_{i1}, v_{i2}, \ldots, v_{in}) \). A set of \( X_i \) is randomly generated. As the initial population, the best advantage of the current particle \( X_i \) is recorded as \( X_{\text{best}_i} = (x_{i1}, x_{i2}, \ldots, x_{in}) \), and the current best position of the particle \( i \) can be expressed as:

\[
X_{\text{best}_i}(t + 1) = \begin{cases} 
X_{\text{best}_i}(t) & \text{if } Q[X_i(t + 1)] > QV_{\text{best}_i} \\
X_i(t + 1) & \text{if } Q[X_i(t + 1)] \leq QV_{\text{best}_i}
\end{cases}
\]  

(1)

\( QV_{\text{best}_i} \) is the fitness value calculated by the particle through the objective function \( Q(X_i) \), and it is judged whether the particle is the optimal particle according to the value of the value. In the process of optimization, the optimal position of the particle swarm is recorded as \( X_{\text{best}_g} = (x_{g1}, x_{g2}, \ldots, x_{gN}) \), then the particle updates its own speed according to formula (2). When the speed is updated, it should not exceed the given speed range, that is, the speed is required to meet \( V_i \in [-V_{\text{max}}, V_{\text{max}}] \).

\[
v_{in}(t + 1) = v_{in}(t) + c_1 r_1 [X_{\text{best}_i} - x_{in}(t)] + c_2 r_2 [X_{\text{best}_g} - x_{in}(t)]
\]  

(2)

In the above formula, \( c_1 \)—cognitive factor; \( c_2 \)—social factor; \( i = 1, 2, \ldots, m, n = 1, 2, \ldots, N, t \)——t-th iteration.

According to formula (3) to update the position vector particles \( X_i \), as follows:

\[
x_{in}(t + 1) = x_{in}(t) + v_{in}(t + 1)
\]  

(3)

In this paper, the BP neural network is optimized by the standard particle swarm optimization algorithm. The standard particle swarm optimization algorithm refers to the PSO with inertia weight, mainly introducing the inertia weight \( w \) in equation (2), namely:
In the iterative process, in order to optimize the speed and accuracy of the population, the inertia weight decrement method is usually adopted, as follows:

\[
\omega = \omega_{\text{max}} - \frac{\omega_{\text{max}} - \omega_{\text{min}}}{T_{\text{max}}} t
\]  

(5)

In the above formula: \(\omega_{\text{max}}\) and \(\omega_{\text{min}}\) are the maximum and minimum values of \(\omega\), respectively. \(T_{\text{max}}\) and \(t\) are the maximum number of iterations and the current number of iterations, respectively.

2.3. Particle Swarm Optimization BP neural network method

In this paper, particle swarm optimization (PSO) algorithm is used to optimize the connection weights and thresholds between BP neural network nodes, and give full play to the global optimization ability of PSO algorithm and the local search advantage of BP algorithm. The specific optimization algorithm steps are as follows:

**Step 1:** Determine the BP network structure and particle dimensions
Defining the particle dimension is also mapping the connection weights and thresholds in a well-defined BP neural network to the particle dimensions in the particle swarm. Assuming that the number of optimized weights and thresholds in the network is \(D\), each individual can be represented by a \(D\)-dimensional vector. Specifically as formula (6):

\[
D = (\text{indim} + 1) \times \text{hiddennum} + (\text{hiddennum} + 1) \times \text{outdim}
\]  

(6)

In the above formula, \(D\) - the dimension of each particle; \(\text{indim}\) - the number of input nodes of the neural network; \(\text{hiddennum}\) - the number of hidden layer nodes; \(\text{outdim}\) - the number of output nodes.

**Step 2:** Initialize the particle swarm
The particle swarm size \(N\), the iteration number \(\text{itmax}\), the cognition factor \(c_1\), the social factor \(c_2\), the particle dimension \(D\), the inertia weight \(\omega\), the particle initial position and velocity, the particle's position range, and the velocity upper limit are selected.

**Step 3:** Select the fitness function
Each particle in the particle swarm is mapped to a connection weight and a threshold in the BP network to form a neural network. The training sample is used to train the network, and the mean square error generated by the neural network on the training set is calculated and used as the objective function. Through the PSO algorithm, the optimization is continuously performed in the global space, so that the obtained objective function value is minimized. The fitness function is given by equation (7) to calculate the fitness of the individual:

\[
F = \frac{1}{n} \sum_{p=1}^{n} \sum_{s=1}^{m} (y_{j,i} - y'_{j,i})^2
\]  

(7)

In the above formula: \(m\)—the number of output neurons; \(n\)—the number of training samples; \(y_{j,i}\)—the expected output of the first output neuron of the first sample; \(y'_{j,i}\)—the predicted output of the \(j\)-th output neuron of the \(i\)-th sample.

**Step 4:** Update the resulting optimal solutions \(X_{\text{best}_i}\) and \(X_{\text{best}_g}\)
According to the fitness function formula (7), the optimal solutions \(X_{\text{best}_i}\) and \(X_{\text{best}_g}\) are obtained, and the position and velocity of the particles are updated according to formulas (3) and (4), respectively, to generate new individuals. The two values \(X_{\text{best}_i}\) and \(X_{\text{best}_g}\) are constantly updated by calculating the fitness value of the new individual.

**Step 5:** Determine if the algorithm is terminated
Determine the number of iterations and the size of the fitness value. If the condition is met, the iteration is terminated. Otherwise, return to step 4.

**Step 6:** Train the BP network with the weights and thresholds obtained by the optimization
The last optimal particle is mapped to BP network weight and threshold, and used as the initial weight and threshold training network of BP neural network to obtain the final neural network prediction result.

2.4. BP model quality evaluation

The functions that evaluate the quality of the model in the neural network are mainly the mean square error function $MSE$ and the root mean square error function $RMSE$. Its expression is as follows:

$$MSE = \frac{1}{n} \sum_{p=1}^{n} \sum_{j=1}^{m} (y_{j,i} - y'_{j,i})^2$$

$$RMSE = \sqrt{MSE}$$

To further determine the accuracy of the model, a deterministic coefficient is introduced to quantify the similarity between the predicted value and the expected value, as in equation (10).

$$r^2 = 1 - \frac{\sum_{p=1}^{n} (y - y')^2}{\sum_{p=1}^{n} (y - \bar{y})}$$

In the above formula: represents the average value of the expected value. The closer the deterministic coefficient $r^2$ is to 1, the closer the predicted value is to the expected value, and the system performance is better.

3. Modeling and analysis of the set-point of the direct air-cooled back-pressure

3.1. Selection of auxiliary variables and parameter setting of PSO_BP model

There are many factors affecting the back pressure, including unit load, ambient temperature, fan speed, tightness of the vacuum system, and cleanliness of the air condenser.[9] In order to establish the back pressure set value model, this paper selects the three main factors (fan frequency, unit load and ambient temperature) which have the greatest influence as the input of the PSO_BP model.[10]

The BP neural network structure uses three layers, which are the input layer, the hidden layer and the output layer. The specific structure is 3-7-1: Since three main influencing factors are selected as inputs and the back pressure set value is used as the output, there are 3 input nodes and 1 output node, and the hidden layer nodes are set to 7 according to experience. The number of network training is 500, the training target is 0.001, the learning rate $\eta$ is 0.1, the training function selects the BP algorithm training function trainm of Levenberg-Marquardt, and the other adopts the system default parameters.

Set the number of PSO iterations $itmax=100$, particle swarm size $N=20$, particle maximum velocity $v_{max}=1$, minimum velocity $v_{min}=-1$, inertia weight $w_{max}=0.9$, inertia weight $w_{min}=0.4$, the cognitive factor $c_1$ and the social factor $c_2$ equal to 2, particle dimension $D = 36$ dimensions.

3.2. Modeling data

This study collected the data of the normal operation of a 300MW 4# unit of a meteorite power plant in Shanxi for one month as a data source, covering the state of the different influencing factors under the normal operating conditions of the unit during 70%~100% of the working conditions, fully considering the different loads of the unit. The effect of different fan speeds and ambient temperature changes on back pressure.

Firstly, according to the principle of the optimal back pressure value and the field data corresponding to the maximum value of the difference between the power generation increment of the unit and the energy consumption of the fan, 70%~75%, 75%~80%, 80%~85%, 85%~90%, 90%~95% and 95%~100% of the optimal back pressure values for 6 load intervals, as shown in Table 1.
Table 1. The optimal backpressure value of six typical working conditions.

| Typical working condition interval | Optimal back pressure value / kPa |
|-----------------------------------|----------------------------------|
| 70%~75% Unit load                | 15.444                           |
| 75%~80% Unit load                | 16.605                           |
| 80%~85% Unit load                | 19.984                           |
| 85%~90% Unit load                | 21.757                           |
| 90%~95% Unit load                | 22.712                           |
| 95%~100% Unit load               | 24.150                           |

Since the data selection time is in summer, 95% ~ 100% unit load is distributed around 5 pm, and the average temperature is 25 °C. Therefore, the optimal back pressure value is based on 26.150 kPa of the power plant data. After obtaining the optimal back pressure value of the six working conditions, the back pressure setting values of the six working conditions are appropriately adjusted according to the influence degree of different influencing factors in the original data, so that they are in different working conditions and different environments. The fluctuation is within a certain range, that is, according to the load size, the ambient temperature and the fan speed, and the back pressure setting value is appropriately increased or decreased according to the collected field data. After adjustment, some key operating point data were obtained in 2000 groups, and some of the back pressure setting values are shown in Table 2.

Table 2. Partial back pressure setting value under different working conditions.

| Unit load /MW | Air cooling fan motor speed feedback /rpm | Ambient temperature / °C | Back pressure set value / kPa | Unit load /MW | Air cooling fan motor speed feedback /rpm | Ambient temperature / °C | Back pressure set value / kPa |
|---------------|------------------------------------------|--------------------------|-------------------------------|---------------|------------------------------------------|--------------------------|-------------------------------|
| 216.48        | 1036.06                                  | 23.2                     | 14.37                         | 250.93        | 1041.13                                  | 27.15                    | 20.42                         |
| 219.45        | 1038.54                                  | 20.55                    | 14.63                         | 254.17        | 1041.24                                  | 27.4                     | 22.21                         |
| 223.06        | 1039.09                                  | 25.6                     | 17.83                         | 259.06        | 1040.54                                  | 27                        | 22.46                         |
| 225.99        | 1036.34                                  | 22.8                     | 15.26                         | 261.47        | 1041.24                                  | 27.4                     | 22.21                         |
| 227.09        | 1039.01                                  | 25.4                     | 18.04                         | 265.15        | 1041.48                                  | 27.6                     | 23.97                         |
| 230.58        | 1036.61                                  | 22.9                     | 15.65                         | 272.98        | 1039.6                                   | 21.7                     | 20.41                         |
| 234.46        | 1036.73                                  | 22.9                     | 16.56                         | 277           | 1039.75                                  | 21.9                     | 20.91                         |
| 238.6         | 1037.01                                  | 23                       | 17.78                         | 284.86        | 1041.56                                  | 27.7                     | 24.51                         |
| 242.47        | 1034.89                                  | 19.9                     | 15.5                          | 288.96        | 1041.56                                  | 27.9                     | 23.71                         |
| 246.95        | 1040.93                                  | 27                       | 20.31                         | 299.53        | 1041.64                                  | 28                       | 24.73                         |

3.3. Analysis of PSO_BP model simulation results

A three-input, single-output PSO_BP model was established by MATLAB simulation software using the calculated 2000 sets of data, and 200 sets of data were selected as the test array. After simulation, the results shown in Figure 1 and Figure 2 are obtained.

It can be seen from Figure 1 that the predicted value and the expected value are basically close, and the absolute error of the sample points around 70% is within ± 0.5 kPa, and both are distributed within ± 0.9 kPa, and the relative value can be seen from Figure 2. The error concentration is distributed within ± 2%, and only a small portion is located at ± 2% ~ ± 4%. From the above data analysis, the model has high performance and accuracy. In order to further understand the performance of the model, the following comparative analysis is carried out, as shown in Table 3.
Figure 1. Comparison of predicted value and expected value of back pressure setpoint model.

Figure 2. The relative error between the predicted value and the expected value of the back pressure setpoint model.

Table 3. Performance analysis of PSO_BP model.

| Predictive model     | Maximum error / kPa | Mean square error | Deterministic coefficient |
|----------------------|---------------------|-------------------|---------------------------|
| BP network model     | 2.23                | 0.0931            | 0.0019                    |
| PSO_BP model         | 0.92                | 0.1144            | 0.8968                    |

It can be seen from the table that the maximum error and mean square error MSE (whether the training set or the test set) of the BP neural network model after PSO optimization are much smaller than the BP network model, and the deterministic coefficient $r^2$ is 0.9932, which proves the optimization. The latter model is more accurate and has more accurate prediction capabilities, making it more suitable for industrial use.

4. Conclusions

Through the analysis and calculation of the field data, the back pressure set value data of the test unit under some key operating conditions of 70%–100% load is obtained. These data are modeled by the BP neural network to approximate the back pressure setpoints of all operating points under the load segment. The model is optimized by the PSO algorithm to improve the generalization ability and model accuracy of the BP neural network model. The simulation results show that the BP network model optimized by PSO is more accurate in predicting back pressure, and the model has higher precision and is more suitable for field use. It provides method guidance for the establishment of complex control object model for on-site thermal process, and has certain reference significance for future back pressure online modeling.
References

[1] Zhang W, Jiang Y 2016 J. Thermal Power Generation 45(12) 84-88
[2] Ni W M, Du X Z, Yang L J, et al. 2019 J. Proceedings of the Chinese Society of Electrical Engineering 1-13
[3] Liu L H, Wei X, et al. 2018 J. Thermal Power Generation 47(12) 87-92
[4] Lü S L, Zhang W D, et al. 2018 J. Power System Engineering 34(06) 5-8
[5] Bai J Y, Shao J X, Hou P F. 2011 J. Power System Engineering 27(02) 39-42
[6] Liang W P, ZHANG J S 2018 J. Thermal Power Generation 47(10) 96-102
[7] Zhao H, Song T, Hou W, et al. 2016 J. Journal of Engineering Thermophysics 37(12) 2502-2506
[8] Zhang B, Ma H, et al. 2018 J. Proceedings of the CSEE 1-8
[9] Gao J Q, Wang Y. 2013 J. Journal of Power Engineering 33(06) 443-447
[10] Yang L J, Du Xi Z, Yang Y P. 2008 J. Proceedings of the CSEE 08 24-28