MEASUREMENT AND CALCULATION OF CALORIFIC VALUE OF RAW COAL BASED ON ARTIFICIAL NEURAL NETWORK ANALYSIS METHOD

by

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The calorific value of coal is the basic technical basis for calculating parameters such as boiler heat balance, thermal efficiency, and boiler output. The calorific value of coal has different meanings, such as the calorific value of the cartridge, the high calorific value of coal, and the low calorific value of coal to generate heat at a high level of constant humidity and no ash. This paper focuses on the analysis of the structure and algorithm characteristics of artificial neural network and RBF neural network. On this basis, the predictive modelling of the received low-level calorific value is carried out. Through the test summary, the predictiveness of the neural network is better than the empirical formula. For the prediction problem with small sample size, the RBF network has better prediction performance. In addition, the quality of the sample, including its quantity and comprehensiveness, has an important impact on the predictive performance and generalization ability of the model.

Key words: *artificial neural network, RBF neural network, prediction calculation calorific value of raw coal*

Introduction

Power plant boilers and other large boilers are designed to receive a low-level calorific value indicator A for coal. It is the basic technical basis for calculating parameters such as boiler heat balance, thermal efficiency and coal consumption, and boiler output. The boiler is also operated according to the calorific value of the coal to calculate the theoretical air demand, the amount of exhaust gas and flue gas generated, and the theoretical combustion temperature that can be achieved. The calorific value of coal is an important indicator of coal quality analysis. The coal with high calorific value indicates that its ash content is low and the quality is good. When the thermal coal is calculated according to the calorific value, there will be higher economic and social benefits, even if the thermal coal is pressed. Ash is also priced, and coal with high calorific value will also have a high price. In the power coal blending, it is also necessary to guide the reasonable proportion of various calorific value coals in the production according to the calorific value of different coals, so that the calorific value of the coal after the matching meets the needs of various users. In the coal quality research, because the calorific value changes with the degree of coal metamorphism, some coal quality characteristics related to the

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degree of metamorphism, such as cohesiveness and coking property, can be roughly estimated according to the calorific value [1].

Artificial neural network (ANN) is a new intelligent information processing theory. The ANN is a kind of non-linear dynamic system. It is composed of many simple processing units (called neurons). It is gradually developed by many scholars in the process of simulating human brain for analysis and processing problems. The neural network realizes information processing capabilities like human brain functions, such as memory, recognition and learning, by abstracting and simulating human brain associative memory and image thinking [2].

In this paper, the typical neural network structure and algorithms, namely BP neural network and RBF neural network, are systematically studied and studied, and the advantages and limitations of each structure are clarified, and the calorific value and ash melting point of these two structural coals are used for prediction. By analyzing the prediction error, it is determined that the RBF neural network is more advantageous for the prediction problem of small samples [3]. Then, the RBF neural network structure is studied, and the network structure model is improved for specific problems. Experiments show that the ANN algorithm has high accuracy in the measurement and calculation of raw coal calorific value, and it is worthy of application in practice.

The meaning of several different calorific values of coal

The heat of the cartridge

The calorific value of the cartridge, Q_b, is also called the oxygen bomb calorific value, that is, in the oxygen bomb calorimeter, in the measurement environment with excess oxygen, usually the initial pressure of oxygen is below 2.6-3.0 MPa, burning the heat generated by a unit mass of coal is called the calorific value of the coal. At this time, the combustion products generated in the cartridge are mainly the following, namely, nitric acid, sulfuric acid, liquid water, solid ash and CO_2, and the heat generated in the oxygen bomb calorimeter is higher than other types heat.

High calorific value of coal

The coal sample is placed in an industrial furnace for combustion. The pyrite sulfur and organic sulfur contained in the coal sample can only produce SO_2 during the combustion process, and the nitrogen contained therein becomes a free nitrogen overflow. This process is related to coal. The products burned in the oxygen bomb calorimeter are different. When the coal sample is burned in the oxygen bomb, the sulfur in the flammable state mentioned previously will be converted into dilute sulfuric acid, and the nitrogen in the coal sample due to the high oxygen pressure environment. Combustion in this high pressure oxygen environment produces dilute nitric acid. The process of producing dilute nitric acid and dilute sulfuric acid in the oxygen bomb releases heat, and the heat generated by removing the heat generated in the two dilute acid processes from the calorific value of the cartridge is the high calorific value of the coal, Q_{gr}. Because the calorific value of the cartridge is measured in a constant volume measuring instrument, the high calorific value at this time can be called the constant volume high calorific value, $Q_{\mathrm{gr,v}}$, and there is also a constant pressure high calorific value, $Q_{\mathrm{gr,p}}$. The calorific value is the heat released when the coal is placed in an industrial furnace under a constant pressure (generally atmospheric pressure) environment, and the constant calorific value is generally 8-16 J/g lower than the constant pressure high calorific value. But in general, this deviation is negligible.

Low calorific value of coal

When coal is burned in the industrial furnaces, all of the water in the coal, the coal and the like containing water newly generated self-contained post-combustion, are in the form of water vapor with the exhaust gases produced during combustion is discharged, and in oxygen bomb calorimeter all the water vapor are condensed into liquid water, whereby if the upper portion of the latent heat of vaporization of water to remove heat, is often said coal calorific value, Q_{net}, with the gross calorific value same, if the calorific value of coal is in the environment of constant volume measured is constant-volume calorific value of coal position, $Q_{net,v}$. If a constant voltage is measured at ambient atmospheric pressure, *i. e.*, the position of the coal is a constant voltage hair heat, $Q_{net,p}$. Under the same reference conditions, up to a maximum amount of heat cartridges with one kind of coal, followed by high calorific value, the lowest calorific value.

Coal's constant humidity and ashlars base high calorific value

The high calorific value of coal is converted into high-level calorific value without ash but containing moisture under constant humidity conditions, that is, high temperature calorific value of constant-humidity ash-free base, $Q_{gr,Maf}$, wherein the constant humidity condition generally refers to an ambient temperature of 30 °C, 96%. The relative humidity condition, this calorific value is mainly used to distinguish between long flame coal (*i. e.* young bituminous coal) and lignite.

The industrial analysis of coal has the effect of main components on calorific value

The effect of coal moisture on calorific value

In general, the higher the total moisture of coal, the lower the corresponding calorific value. For example, because the total moisture of lignite is relatively large, the calorific value is relatively low, but the total moisture content of coal is not affected by coalification. In addition the impact, it is also related to the groundwater of the mine. For example, the groundwater volume of an anthracite coal mine in Jiaozuo is relatively large, so that the total moisture of the coal produced is also large.

When dry ash free basis gross calorific value of coal, $Q_{gr,daf}$, is affected by moisture in the air drying group, M_{ad}, is more regular, *i. e.* the higher the M_{ad}, then $Q_{gr,daf}$ will be lower, such as the transition from fat coal, long-flame coal, lignite, then a M_{ad} is gradually decreased with the increase. From lean coal, anthracite, lean coal to the transition, but also exhibits the aforementioned trends. Thus obtained can easily conclude, with water and air dried group, M_{ad}, is increased and decreased to varying degrees of ash-free dry coal of high calorific value, $Q_{gr,daf}$. The closest relationship with the calorific value of coal is the highest inherent moisture of coal, coal dry coal ash-free basis gross calorific $Q_{gr,daf}$ will increase with the highest inherent moisture and gradually reduced.

The effect of coal ash on calorific value

For the coal produced in the same coal seam, the dry base high calorific value, $Q_{gr,d}$, the dry base low calorific value, $Q_{net,a}$, and the dry base cartridge calorific value, $Q_{b,d}$, are inversely proportional to the ash content, A_d, and according to A_d find the value of $Q_{gr,d}$, and the error between the calculated value and the actual value is very small. For commercial coal produced in the same mine and of the same coal type, the dry base high calorific value $Q_{gr,d}$ or the dry base low calorific value $Q_{net,d}$ can be calculated according to the value of ash A_d in general, according to the relevant test results, 95% of the coal sample error is within ±0.3 MJ/kg, and for general coal mines, the equation of this correlation can be used to estimate the calorific value of coal or to check the calorific value of coal [4].

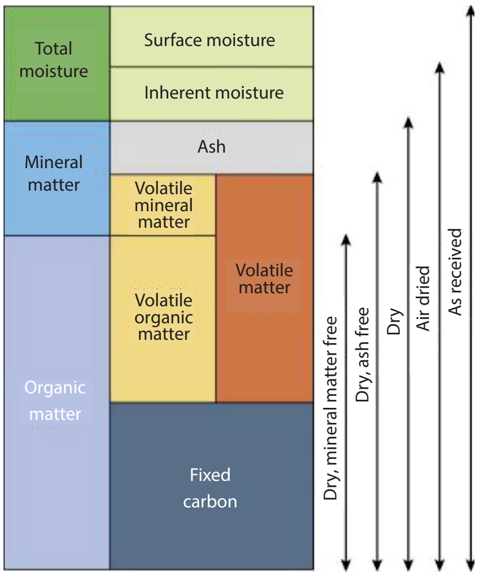

Figure 1. Effect of different factors on calorific value

For coal produced in different mines, although the overall view, but also to meet with the calorific value of coal ash increases continuously reduced, but there is such a phenomenon often made from ash coal production of armor more than the ore produced from B high ash coal, but the former is still higher than the calorific value of the latter heat, mainly due to the different conditions of the coal mine to form different, and depositional environment and the original coal formation of coal plants may also vary, thus resulting in pure coal calorific value thereof, *i. e.* the different mineral-free coal drying heat, and further such that $Q_{gr,d}$ is very different, as shown in fig. 1.

The high ash content but low calorific value is more common among different grades of coal. This is mainly because the difference in the calorific value of the pure coal of different grades of coal is large, so that we can analyze the thermal coal value according to the calorific value. Not just the reason for the ash content of coal, that is, the ash of coal cannot fully reflect the calorific value of coal.

The effect of coal volatiles on calorific value

According to relevant research, the general trend between the volatile matter and calorific value of coal shows an arc-shaped change trend from lignite, bituminous coal, anthracite to various coals. Specifically, the value of volatile ash-free volatile V_{daf} is 8%, 28%, and 40% are the limits. When V_{daf} is around 28% and its coke characteristics are between 7 and 8, the calorific value of coal is the highest. When V_{daf} is higher than 28%, the calorific value is decreased. The trend, and the higher the volatile content of coke slag, the lower the calorific value. When V_{daf} is higher than 40%, the calorific value is significantly reduced. For high cohesive coal the degree of calorific value reduction of the gas-fertilizer coal is not serious, in spite of the fact that volatile matter content between coal is the same, the composition elements and chemical structures of each coal are not the same, resulting in large difference in the calorific value of pure coal.

When the volatile content is less than 28%, the general trend of calorific value is that the calorific value decreases slightly against the volatile matter, and the decrease is not large, but when the volatile matter is less than 8% into the anthracite, the calorific value is significantly decreased as the volatiles decreased. Furthermore, for coals with the same volatile matter content, the calorific value will decrease with the decrease of coke slag characteristics. For example, coking coal with a volatile matter content of 26%, when its coke slag characteristic is 7, its calorific value is 36.5 MJ/kg, and when the coke characteristic is 1, the calorific value is

32 MJ/kg, and the difference between the two is 4.S MJ/kg. In summary, if the volatile matter content of coal is the same, the calorific value will increase as the coke slag characteristics increase, [5, 6].

The BP neural network basic principles

A neural network is a parallel processing of a single set of elements, elements are connected to each other by many simple and complex network formed, highly non-linear, the system can be complex and non-linear relationship between the logical operations implemented. Network functions mainly determined by ganglia, may complete a specific function by changing the connection point of the heavy weights to train the neural network. The actual working process of the neural network after the user enter the required parameters of the input layer, hidden layer network automatically produces a certain output sample data according to its rule and summed up function. The process is neither simple sample data interpolation operation or the fitting operation, which is a highly intelligent operation.

The BP network can learn and store large quantities of input-output relationship mapping mode, without prior disclosed mathematical equation that describes the mapping relationship. Its learning rule steepest descent method is used to continuously adjust the network weights and reverse spread threshold value, the minimum sum of squared error and the network. The BP neural network topology comprises an input layer, a hidden layer and output layer. Basic structure of the ANN shown in fig. 2.

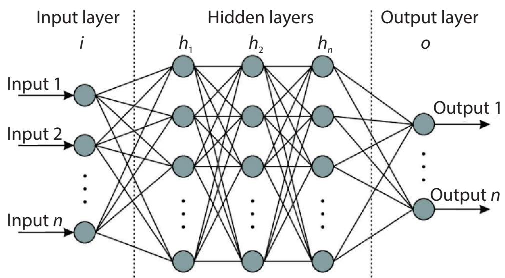

Figure 2. Basic mode of ANN

The ANN to measure and estimate the calorific value of raw coal

Coal calorific value prediction

Data sample

Coal moisture, ash and volatile matter are the main influencing factors of coal calorific value, while coal receiving base low calorific value, $Q_{\mathrm{net,ar}}$, is the main indicator for calculating thermal balance and thermal efficiency of thermal power plant units. Need to receive the base low calorific value. This paper cites a coal-fired test data of a thermal power unit, a total of 148 groups, the sample contains the mass fraction of coal M_{ad}, A_{ad}, V_{ad}, and the corresponding coal receives the base low heat value $Q_{\mathrm{net,ar}}$.

The ANN prediction model

Input layer and output layer. The key influencing factors of raw coal calorific value are coal moisture, ash and volatile matter. These three factors can be used as the input layer nodes to predict the calorific value of raw coal through these three factors. The output layer node is the raw coal calorific value.

Implicit layer structure. First, the hidden layer structure determination comprises determining the number of hidden layers and the number of the hidden layer unit determines two portions. Since the input layer and output layer are relatively simple, the number of hidden layers is taken as one, so that we can achieve the required mapping network will help improve the computing speed and prediction accuracy. Secondly, the number of hidden layer nodes is related to the performance of the entire network. If the number is too small, the network can be used to obtain information solve the problem of too little, too much hidden layer node but also so-called *interim agreement* issues that may arise. Hidden layer determines the general principle is: accurately reflect the input-output relationship based on, should be used fewer hidden nodes, so that the network structure as simple as possible. The hidden layer nodes paper empirical formulas, using the method of multiple trial and error, to output error becomes minimum target trial and error, finally determined considering the number of hidden layers of 10 nodes. The number of nodes in hidden layer empirical formula:

$$n_1 = \sqrt{n+m} + a \tag{1}$$

where n is the number of input layer nodes, m – the number of output layer nodes, and a – the constant, ranging from 1-10. In summary, the blasting strength model structure is set to a three-layer 4-10-1 structure.

The ANN learning algorithm steps

– Sample selection and normalization processing, the data obtained previously are grouped, 1-138 sets of samples are used as the training number sample set of the network model, and the last 10 sets of samples are used as the test sample set of In network to increase the sensitivity of the network weight and threshold to each input value change, it is necessary to normalize the sample data, integrate the sample data into the interval [0, 1], and end the training. The output is then inversely normalized to the original data range.
– Determine the initial value of the network. Overall, the weights are updated with the progress of training, and generally convergent. Between the input layer and hidden layer and between the hidden layer and the output layer weights j^{th} iteration values of w_{ki} and w_{jk}. Between the input layer and the hidden layer, the j^{th} iteration threshold between the hidden layer and the output layer are, respectively, v_{ki} and v_{jk}. The training process, the computer will adjust the four variables. The training model parameter set: The maximum number of training 1500, the learning rate 0.05, 0.001 accuracy requirements.
– Forward calculation of artificial neural network algorithm, *i. e.,* forward propagation process is: the input layer→hidden layer→output layer. Hidden layer transfer function of the forward propagating transfer function f_1, the output layer is f_2. The output of the hidden layer, the threshold value is written in the summation term:

$$z_k = f_1\left(\sum_{i=0}^{n} v_{ki}x_i\right),\ k = 1,2,...,q \tag{2}$$

The output of the output layer node:

$$y_j = f_2\left(\sum_{k=0}^{q} w_{jk}z_k\right),\ j = 1,2,...,n \tag{3}$$

Among them are $f_1 = f_2 = \tan sig(x)$ and $\tan sig(x) \in [-1, 1]$. The transfer functions f_1 and f_2 are continuously differentiable and monotonically increasing. At this point, the BP network completes the approximate mapping of the m-D space vector to the n-D space.
– Backpropagation. That is, the error calculation, when the output value obtained by the forward propagation cannot meet the error requirement of the objective function, the data is transmitted in the opposite direction of the original route, and the weight and threshold between the layers

are corrected, and finally a minimum error is obtained [7]. The mean square error is calculated from the output value and the actual value, and the global error of the sample:

$$E = \frac{1}{q}\sum_{p=1}^{q}\sum_{j=1}^{n}\left(t_j^p - y_j^p\right)^2 \tag{4}$$

At this point, the structure and calculation process of the network are basically determined, and the aforementioned calculation steps are all realized by MATLAB software.

The RBF prediction model

The RBF network model with three input nodes and one output node is established. The three inputs correspond to the air drying base moisture M_{ad}, the air drying base ash A_{ad}, and the air drying base volatiles V_{ad}. One output corresponds to the received base low calorific value, $Q_{\mathrm{net,ar}}$. Training the RBF network with the training sample set, and then testing with the test sample set 3 is a normalized relative error preprocessed training data after the end of the RBF network training obtained can be seen, the maximum relative error of the measured value and the predicted result of the calorific value of coal which training data set 1384.05%, the minimum relative error is zero, fig. 3.

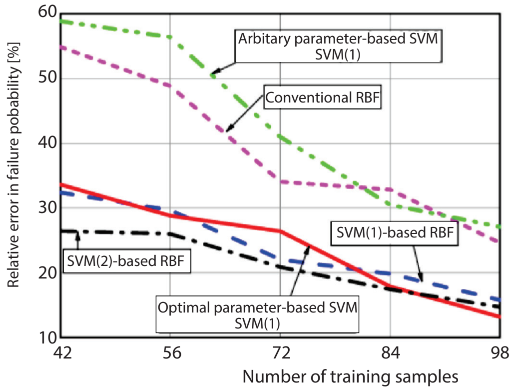

Figure 3. Training relative error of RBF network

Figure 4 is a normalized relative error test preprocessed data via prediction result of the RBF network can be seen, the maximum relative error between the measured and predicted values in the set of test data 10 is 4.74, the minimum relative error is 0.49%, the average relative error is 2.46%.

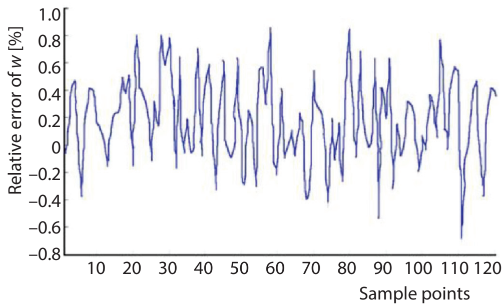

Figure 4. Test relative error of RBF model

The BP neural network prediction model

Previous section content, BP model. This section also taken to establish a three-input single-output structure, namely input M_{ad}, A_{ad}, and V_{ad} is the mass fraction of the output of $Q_{\mathrm{net,ar}}$. Training sample set using BP network training, the test set and then the test sample, fig. 5 is a normalized relative error test preprocessed data via network prediction result of BP can be seen, ten groups of test data maximum relative error between the measured value and the predicted value is 6.09, the minimum relative error is 0.01, the average relative error was 3.29% [8].

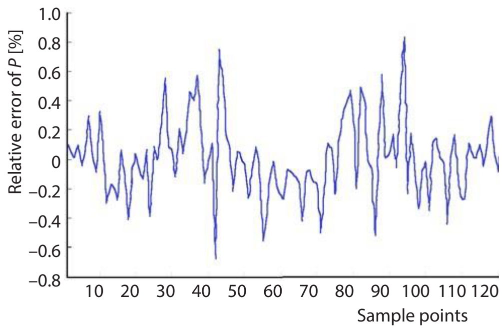

Figure 5. Test relative error of BP model

The ANN prediction model based on particle swarm optimization

Basic principles of particle swarms

The PSO algorithm is like the genetic algorithm. It is an optimization method based on iterative calculation. At the beginning, the system will initialize a set of random solutions, and finally obtain the optimal solution of the system through some iteration. However, the PSO algorithm is better than the genetic algorithm. The algorithm is simple and easy to understand, mainly because the algorithm has no choice, crossover, and mutation process. Therefore, the PSO algorithm has been rapidly developed, which has been successfully applied to many areas such as optimizing control performance and training neural networks.

It is set to have a population in a solution space of a D-dimension, including n particles. Taking particle i as an example, its position information can be represented by $X_i = (x_{i1}, x_{i2},...,x_{id})$. Similarly, its speed can be represented by $V_i = (v_{i1}, v_{i2},...v_{id})$, where t is the time, particle i searches for an individual extreme value of $P_{\text{best}}(t) = (p_{i1}, p_{i2},...,p_{id})$, and a global extreme value of $P_{\text{gbest}}(t) = (p_{gi1}, p_{gi2},...p_{gid})$, so that t can also be regarded as current. The number of iterations. After determining the two optimal solutions, the particles can correct their position and velocity:

$$V_i^{t+1} = \omega V_i^t + c_1\text{rand}_I(*)\left(P_i - X_i^t\right) + c_2\text{rand}_2(*)\left(P_{gi} - X_i^t\right) \tag{5}$$

$$X_i^{t+1} = X_i^t + V_i^t, \qquad 1 \le i \le n \tag{6}$$

where V_i^t is the velocity vector of particle i after t iterations, X_i^t – the position vector of particle i, which has undergone t iterations, P_i is the $P_{\text{best}i}$ of the previous particle i, P_{gi} is the $P_{\text{gbest}i}$, c_1 of the previous particle i, and c_2 – the acceleration factor, where c_1 is used to correct the coefficient of its optimal solution, and c_2 is used to correct the coefficient of the optimal solution the whole population. Generally, both values are 2, ω – the inertia coefficient, $\text{rand}_1(*)$ and $\text{rand}_2(*)$ is a random number evenly distributed, Here this article can use * to represent arbitrary functions and numbers between [0,1].

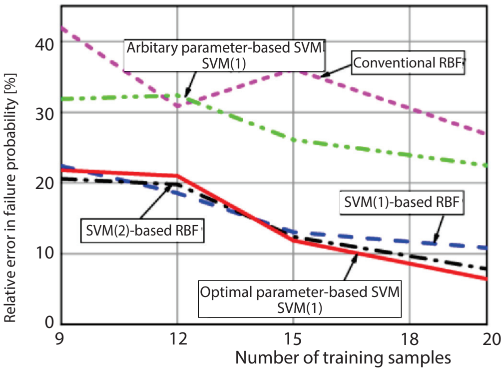

Figure 6. Test relative error of improved RBF network

Improved RBF model to predict the calorific value of coal

The optimization weight is an iterative process. Firstly, each particle should be evaluated for fitness. In this paper, the average relative error is selected as the fitness of the particle group to evaluate each particle, and then the extremum is based on the eqs. (5) and (6). Point and population extreme points are corrected. When the end condition is satisfied, that is, the error is within the allowable range or the specified maximum number of trainings is reached, the operation is ended.

After improved RBF network trained with training sample set, then the set of test samples were tested, as shown in fig. 6 to be trained relative error curve. Can be obtained, the maximum value of the test data set 10 relative error is 3.80, the minimum relative error is 0.37%, the average relative error is 1.24. Compared with a conventional RBF network test results are shown in tab. 1, you can see whether the improved RBF is the maximum relative error, or are better than the average conventional RBF network, the prediction for optimized performance.

Table 1. Comparison of heat error between improved RBF and conventional RBF networks

	Maximum relative error [%]	Relative error mean [%]
Conventional RBF	4.74	2.46
Improve RBF	3.80	1.24

Conclusion

Neural networks for complex relationships among the components of coal has good processing power, theory and practice has shown that ANN can be applied to work quickly estimate the power of coal and coal calorific value of online testing, to collect a large number of a representative sample of coal, artificial neural network used in the practice of great significance.

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