Fly Ash Modelling Using Artificial Neural Networks To Predict Unburned Carbon

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Abstract

For the use of the large amount of operational data from power plant, artificial neural network modelling method was proposed to avoid the difficulty of traditional modelling method in power plant unburned carbon in fly ash modelling. Based on the actual operation data of a 200MW unit, statistical model of the unburned carbon in fly ash was constructed by artificial neural network method. The modelling algorithm that are being used are partial least square (PLS), artificial neural network (ANN), and PLS-ANN. A comparison has been made among models respectively obtained by PLS, ANN, PLS-ANN. Results show that with the unburned carbon in fly ash model based on ANN, accurate calculation can be achieved, proving the artificial neural network method to be effective and feasible.

1. Introduction

In the thermal power plant operation, unburned carbon content in the fly ash is a main factor that greatly impacts the boiler efficiency, performance of generator unit and utilization of fly ash. It is difficult to predict and control this parameter because it is affected by many factors and complicated [1-3]. Microwave online measurement system is widely used to provide an intuitive and reliable basis and adjustment information for optimal operation. However, in engineering practice, the problem of the sampling pipeline blocked by ash often leads to the measurement system cannot run. Building a accurate model to predict unburned carbon in fly ash is useful for monitoring the performance of the boilers. Some soft sensing models have been developed with boiler thermal experimental data [3-5]. Thermal experiments spend a lot of time and money, and data can not cover all operating conditions which affect model accuracy. This paper proposed to modelling unburned carbon in fly ash with real operation data saved in power plant Distributed Control System (DCS). Useful knowledge and rules hide in these real operation data, and moreover, these data are obtained in natural conditions. The relationships between data reflect the true information of system structure without any assumptions.

2. Mode of Artificial Intelligence for Modelling

The basic structure of data mining for unburned carbon in fly ash modelling is illustrated as follows:

1. Data preparation: This step is very important to ensure modelling efficiency and accuracy. Data sources come from power plant Distributed Control System (DCS) that saves a large real operation database. An advanced DCS has thousands of measuring parameters. It is no need to use all of these operation data for a given object modelling. Data transformation and selection are to find useful modelling date.
2. Mining model: The goal of the mining model phase is to analyze the modelling data by an appropriate set of algorithms in order to discover meaningful model for given object. Normal modelling methods are partial least-square regression (PLS), association analysis, information gain, artificial neural network (ANN), rough set, time-series analysis, support vector machine and so forth. The obtained model is called primary model.
3. Verification model: This final phase is aimed to verify the accuracy and efficiency of the primary model. If it cannot fulfil certain requirements, the above modelling process can involve iterations and can contain loops between any two steps. Otherwise the primary model can be used as the end model.

3. Modelling based on Artificial Neural Networks

Accuracy of PLS model is not very satisfied because PLS algorithm is linear but the relationship between input and output is non-linear. Artificial neural network (ANN) is a structure of simulated neurons that are connected together somewhat in the same way as natural neurons in the brain. The capability and advantages of ANN are due to their special features including nonlinear, adaptive, and parallel processing [9-10]. Each neuron of ANN receives inputs either from a number of other neurons or from an external stimulus. The weighted sum of these inputs passes through a basis function and the resulted argument is applied to an activation function that finally yields the outputs of the neurons. The manner in which connections are made between these neurons defines the flow of information in the network and is called the architecture of the network. Behaviour of a network depends greatly on the interactions between these building blocks. There are three types of neuron layers: input, hidden, and output layers. The more the layers are used, the greater the power the network possesses will be. On the other hand, an excessive number of layers often appear to be counterproductive. It may cause slower convergence in the back propagation learning. Generally speaking, three layer networks could be adequate as a universal approximation of any nonlinear function.

In this research, a 3-layer BP network was developed for model of unburned carbon in fly ash. Input layer with 14 units, an output layer with 1 unit, and one hidden layer with 14 units which were selected by many times checking, and the Tan- Sigmoid function was used as the activation function for each processing unit in the neural network. The initial weight values were set to 0.5, 0.75, and threshold 0.5,0. The expected error is set to 0.0001. The training was stopped at 1000 iterations to avoid over trained problem.

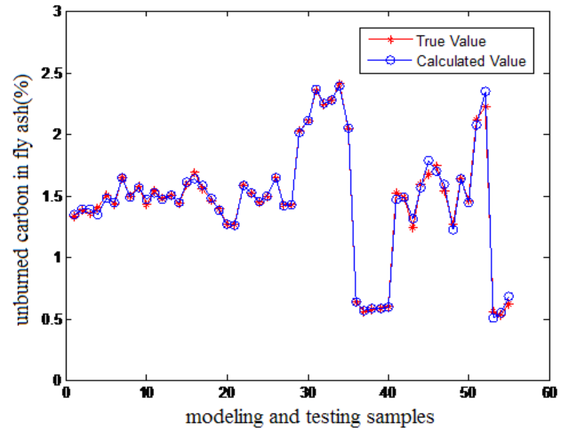

Fig1: ANN Model Results

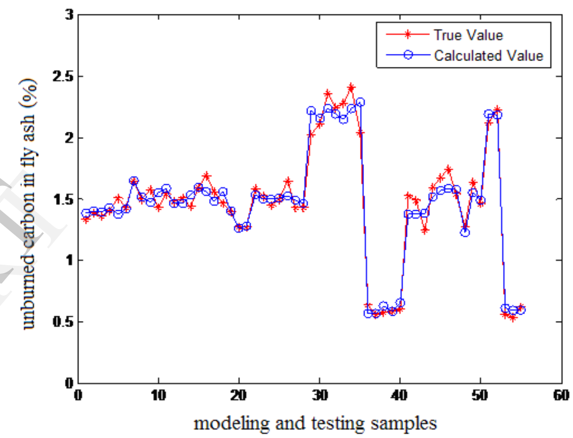

Fig2: PLS Model Results

Fig. 1 and fig. 2 separately showed the ANN modeling and testing samples results and PLS model results. Like PLS, 1-40 are modelling samples and 41-55 are testing samples.

The vast majority of test data relative error was within ±10%, the maximum value is 11.6%. Although this PLS model can be used to forecast unburned carbon in fly ash, accuracy is not very satisfied.

The vast majority of test data relative error was within ±5%, the maximum value is 7.1 %. So ANN model is more accurate than PLS model.

4. Modelling based on ANN-PLS

The advantage of PLS method is simple and fast while ANN is non-linear and precision. But training ANN spends a lot of time. Combined the advantages of two algorithms, PLSANN model was proposed and the structure was showed in Fig. 3. In order to reduce ANN input layer units, PLS algorithm is used to extract principal components from input variables as ANN input layer units. The less the input layer units are used, the faster the network training will be.

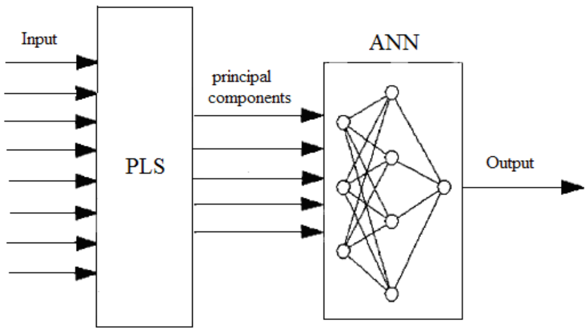

Fig3. PLS-ANN model structure

By calculation, PLS extracted 7 principal components as ANN input layer units. Thus ANN input layer units reduced from 14 to 7. One hidden layer with 14 units which were selected by many times checking, an output layer with 1 unit, and the Tan-Sigmoid function was used as the activation function for each processing unit in the neural network. The initial weight values were set to 0.2, 0.3, and threshold 0.2, 0.3.

The expected error is set to 0.0001. The training was stopped at 1000 iterations to avoid over trained problem.

5. Comparison of Three Models

Three models performance are as follows:

MaxRE =Maximum relative error

ARE=the average relative error

Table 1 showed the comparison results of three models.

Table 1: Comparison of three models

Algorithm	MaxRE	ARE
PLS	0.116	0.062
ANN	0.071	0.035
PLS-ANN	0.074	0.052

As can be seen from Table 1, the linear PLS model is predictive worst, and this algorithm is not suitable for nonlinear problem, but can extract principal components in data mining to reduce input variables to improve computing speed. ANN model is the highest accuracy but training time is longer than PLS-ANN. Considering the need of the operation and monitoring, ANN model was selected as the final model. The final model could be used as on-line prediction model of unburned carbon in fly ash in different conditions

6. Conclusion

To solve the modeling problem of power plant unburned carbon in fly ash which is difficult to predict and control because it is affected by many factors and complicated, A new modeling thought - data mining modelling method was proposed which use real-time operation data saved in the DCS system instead of boiler thermal experimental data. Based on the actual operation data of a 300MW unit, mathematic model of the unburned carbon in fly ash was constructed by data mining method. The modelling algorithm were partial least square (PLS), artificial neural network (ANN), and PLS-ANN. A comparison has been made among models respectively obtained by PLS, ANN, PLS-ANN. Results show that with the unburned carbon in fly ash model based on ANN, accurate 2765 calculation can be achieved, proving the data mining model method to be effective and feasible.

7. References

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