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Predicting Pulverized Coal Plasma Ignition Performance by BP Neural Network

Lei SHI*, Yi ZHANG, Yu-bin MEN and Ji CHENG
Aero Engine Corporation of China, Shenyang Engine Research Institute, Shenyang, China
*Corresponding author

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Abstract. To make sure the major factors and their influence for pulverized coal plasma ignition(PCPI), the way predicting the PCPI was investigated in this paper. The back propagation(BP) neural network was used to established a prediction model which can study by itself for PCPI. Then the sample database was set up by simulating the PCPI in kinds of conditions. After that, the prediction model was trained by sample database to improve the prediction level. At last, the prediction model was used to predict the PCPI in new conditions and the prediction error is under 0.004. The research show that the BP neural network can predict the PCPI correctly. In this paper, the BP neural network was applied to predict the PCPI innovatively, and the prediction efficiency increase highly and the prediction accurancy does not deline.

Introduction

During the operation PCPI, plasma torch injects into the pulverized coal stream to form a stable flame, which is poured into the furnace of boiler. PCPI technology has attracted attentions worldwide because it can be used in the pulverized coal fired boilers to realize the startup or stable combustion in part load operation. It has been a promising way to reduce oil consumption in coal fired power plants. Up to now, PCPI systems have been used in about 550 boilers in China, which have a total capability of near 230 GW.

The PCPI processes have been investigated. Among these, Masaya Sugimoto et al.[1] investigated the ignition processes with different coal in a drop tube, discussed the power demand to realize the success of ignition under differential excess air ratio. E.I. Karpenko et al. [2], focused on a 200 MW boiler, studied the plasma ignition processes with Reynolds Average Navier Stocks (RANS) simulation and experiments in this boiler. Zhang xiaoyong et al. [3], studied how to design the multistep plasma ignition burner with RANS and experiments.

With the development of PCPI both in practical applications and theory investigations, how to predict the main parameters of the PCPI becomes a challengeing problem. Traditional simulation methods, such as RANS and LES, can not meet command in practice because of prediction efficiendy. The back propagation(BP) neural network is an proper approach to slove this problem. It has been used in both laminar and turbulent reactive flows, as an alternative to the conventional kinetics evaluation, which can reduce the CPU cost largely [4~7]. But the applicability of BP neural network in two phase flows, especially in the pulverized coal combustion processes, still remains to be demonstrated. How to predict the PCPI by BP neural network was investigated in this paper.

Establish Prediction Model

The back propagation(BP) neural network is the most popular network architecture now. The transfer function of the neurons in BP neural network is Sigmoid differentiable function, so it can deal with the nonlinear mapping problems.

The momentum—adaptive learning rate method is used to improve the performance of algorithm. This improved BP algorithm is to add a proportion which is proportional to the variable quantity of last weight to each weight adjustment quantity and adjust the learning rate automatic in the learning iteration process. After one cycle of the learning sample, the learning rate will change according the variation of errors. Because of momentum coefficient, the network can avoid the trap of local minima and get global minima. The learning rate can change properly by variation trend of error surface to accelerate the learning speed.

The hidden nodes which can realize and restore the inherent law of the samples play a very important role in network. They can make influence on many characters of the network. The fault tolerance of the multi-layer perceptron is strongly related to its hidden nodes. Increasing hidden nodes may provide the advantage of higher degree of fault tolerance but have the disadvantage of higher computation and hardware complexities. Generally the numbers of hidden nodes is related to the numbers of input and output layer nodes. The variation of hidden nodes numbers range from $\frac{n}{2}+1$ to $2n+1$, n refers to the number of input nodes. Based on many training for network the number of hidden nodes is 20 in present study.

The prediction model is three-layer BP neural network in this paper. The number of input nodes, output nodes and hidden nodes is 11, 5 and 20. The structure of the network is 11*20*5. Look Fig.1. The transfer functions of hidden nodes and output nodes are Tansig and Purelin. And the training function of the network is traingdx [8~9].

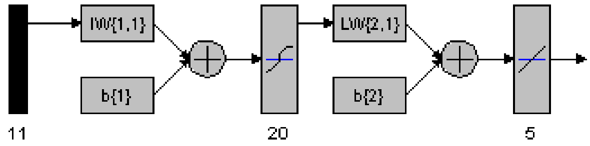

Figure 1. BP neural network topology

Set up Sample Database

In this paper, the plasma generator is axial arranged (Fig.2). There are four boundary conditions in the burner: primary air inlet, plasma inlet, flame outlet and the walls of this burner. In this paper, the primary air boundary includes the speed and temperature of coal stream. Plasma inlet boundary is also about speed and temperature which changes by the coordinate. The output boundary condition is outflow, the walls boundary is assumed to be adiabatic.

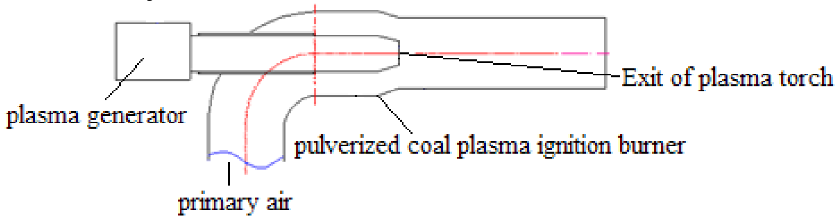

Figure 2. Schematic of the simulated burner

Simulating PCPI processes in kinds of conditions, the data of temperature distribution on the burner central vertical section, temperature distribution along the burner central axis, CO distribution on burner center longitudinal section, CO_2 distribution on burner center vertical section, O_2 distribution on burner center longitudinal section, the radial temperature distribution at the outlet, and so on, can be got. These data are collected and stored into neural network prediction model's databases.

Obviously not all of the parameters which make influence on plasma burner ignition can be the neural network prediction system's input parameters, choosing proper parameters is necessary. Taking consideration of the importance, practicality and accessibility, the primary air velocity(V), the primary air concentration(N), the power of plasma generator(P), the length of burner(L), the inlet angel of primary air(A) and the carbon content(Car), hydrogen content (Har),oxygen content(Oar), nitrogen content(Nar), volatile, low heating value($Q_{ar,net}$) of coal are chosen as the input parameters of prediction model.

There are many factors which can reflect the capability of plasma burner .The purpose of this paper is mainly about adjusting the equipment operating parameters based on the results predicted by the prediction model. By these adjusting operations, the ignition processes can be controlled under the safe and stable condition and improve burner work efficiency. Under these considerations, 5 characteristic parameters are taken as the output parameters of the prediction model. They are the temperature in the center of flame (T), the effective diameter of the flame (temperature above 1200k) (D), the temperature near the wall (TN), the mass fraction of CO in the peak value (M1), the mass fraction of CO_2 in its peak value (M2).

Based on the results of numerical simulation, we collected the value of input and outlet parameters of 69 different working conditions and then set up the database. The data of 69 different working conditions are divided into two groups. The first group consisted of the top 60 will be the training sample. The second group included the bottom 9 will be the testing sample.

Train and Check Prediction Model

The rationality of data preprocessing of sample relates to the learning speed, convergence and generalization ability of network. Hence this step is critical for learning of network. Now the original data of sample have to be transformed into new data in [-1, 1] by the following formula(1)

$$X_n = 2 * \frac{X_i - X_{i\min}}{X_{i\max} - X_{i\min}} - 1 \tag{1}$$

Here, X_i is original data before pretreatment, X_{imin} and X_{imax} are minimum and maximum of the original sample values [10]. The output values should be transferred to the original unit value by the inverse operation of normalizing.

Using new data and taking momentum and adaptive learning rate method, the prediction model was trained. The value of learning factor is 0.02, the original value of momentum factor is 0.8 and error performance regulation is 0.8. Then start iteration, stop the training at the number of 5626 epochs and then the mean square error value is 0.0067. The error curve of the system can be seen in Fig.3.

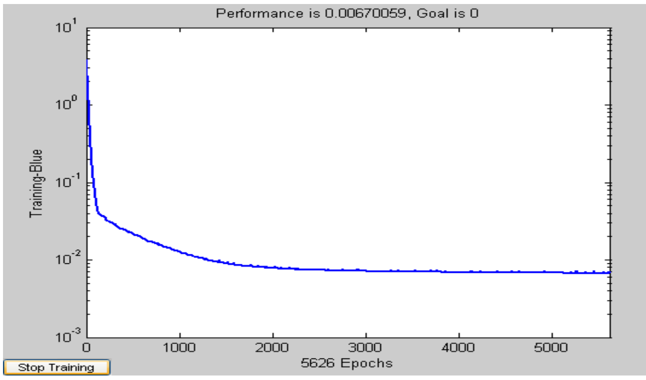

Figure 3. Error curve of BP neural network training

The prediction values and expected values of 5 output parameters of the prediction model in the training processes are analyzed by linear regression. The trace rate is 0.996 and prediction error is under 0.004. Prediction errors of all output parameters can be seen in Fig.4.

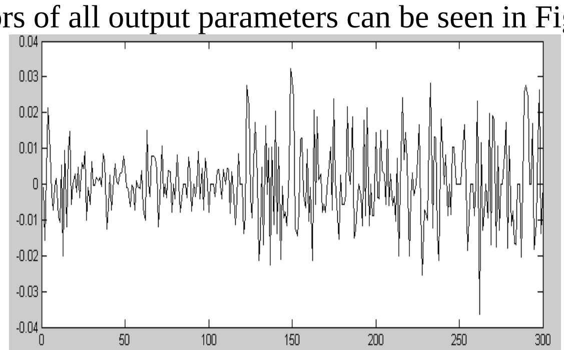

Figure 4. Prediction error of all output parameters

By analyzing prediction value and real value of test sample with linear regression method, the prediction performance of the prediction model can be tested. Taking the temperature of flame center at burner exit(T) for example, look Fig. 5, it can be seen that the prediction level of the model is 0.997, the errors is under 0.003. The prediction error is in Fig .6

Hence the prediction model in this paper has good generalization ability; it can predict the combustion characters of plasma burner in a large scale of new working condition.

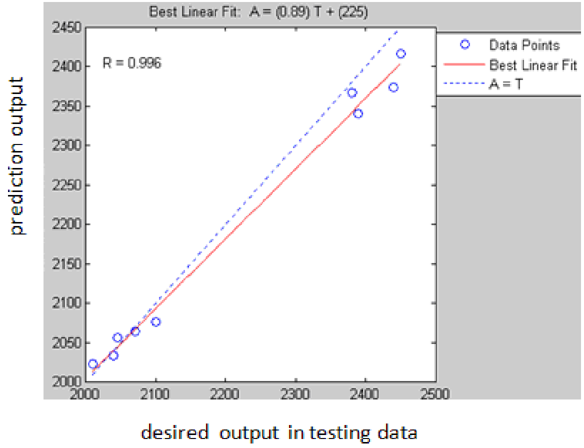

Figure 5. Linear regression analysis of T predict and aspiration values

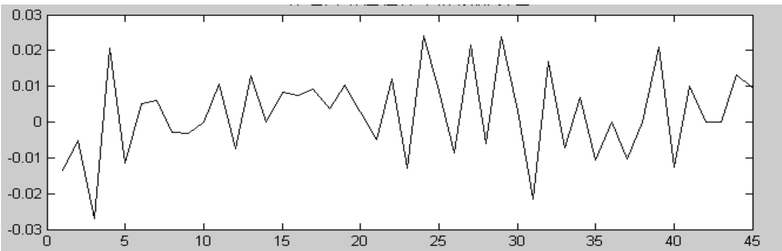

Figure 6. Prediction error of BP neural network training sample

Conclusion

The BP neural network was used to predict the PCPI in this paper. The prediction model which could study by itself was established by this approach. The sample database is set up by simulating the PCPI in kinds of conditions. The parameters of input and output of the prediction model were confirmed by analyzing the PCPI. The prediction error of model is 0.0067 after training. The model predict PCPI in new conditions and the prediction error is under 0.004. In conclusion, the BP neural network is one good way to predict the PCPI correctly and fastly.

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