# Prediction Control of Biomass Combustion Boiler based on Multilayer Perceptron Neural Network

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*Abstract*—**The structure of biomass direct fired boiler differs greatly from that of common fuel powder boiler, so the difference of operation process is great, which will inevitably lead to the difference of operation regulation law. Therefore, it is very important to analyze its technological process and combustion process in detail. All data were analyzed by SPSS17.0. We used the IBM SPSS Modeler 14.1data software to carry out modeling and prediction. The results show that there are 100 neurons in hidden layer and the area under the curve. The model accuracy, sensitivity and specific is 91.96%, 81.22% and 93.77%. Through validation data set validating, the model accuracy, sensitivity and specific is 92.15%, 80.32% and 94.01%. Therefore working process of biomass combustion boiler could accurately predict by MLP neural network model based on characteristics as the input layer variables of prediction model.**

*Keywords-Prediction Control; Multilayer Perceptron; Neural Network;Working Process; Biomass Combustion Boiler*

## I. INTRODUCTION

The boiler adopts a combustion mode of a vibrating grate. The boiler steam water system adopts natural circulation, and the outside of the boiler is centralized with the falling pipe structure[1]. The boiler adopts the "M" type arrangement, and the furnace and super heater channel adopt a fully sealed membrane wall structure, which ensures the boiler sealing performance well[2]. The superheated steam adopts four stage heating, and the three stage water spraying temperature reducing mode makes the superheated steam temperature have a great regulation margin to ensure the steam parameter of the boiler[3]. A two stage economizer, a first stage high-pressure smoke cooler and a two stage low-pressure flue gas cooler are arranged in the tail shaft. The air preheating is arranged outside and the flue is heated by water cooling, so that the low temperature corrosion of the tail flue can be avoided effectively. The boiler is started with light diesel oil and equipped with a starting burner on the right wall of the furnace.

The neural network prediction model of multilayer perceptron is a multilayer feed forward network model of one-way communication, which is one of the most basic network model in current research and application[4]. Under normal circumstances, the generalization ability of the model is improving with the training capacity of the network improving to some extent, considering the contradictory between generalization ability and training capacity of the network[5]. However, there is a limit about this trend, the generalization ability declines with the training ability improving when the model reaches this limit; the internal reason of this is the learning principle of model, when too much details of the sample is studied, the law will not be reflected by the network model. This study randomly selected the Holdout sample for preventing over-fitting, which is 20% of total.

Multilayer Prediction Artificial Neural Network (MLPANN) is a nonlinear mapping model of universal approximation[6], but Radial Basis Function Artificial Neural Network (RBFANN) is a nonlinear input-output mapping model of local approximation using local exponential decay function (such as Gauss function)[7]. In practical applications, RBFNN avoids the iterative process, so the learning speed is faster, but needs more training samples. MLPNN learning based on the theory of stochastic approximation, the convergence rate of which is slow, but the training samples number of which required less than RBFNN[8]. When a nonlinear input-output mapping approaching, the RBFANN needs more sample characteristic parameters than MLPANN at the same precision request. In this study, the input layer of the variables selected is line with the design principles, which can be applied to model. Compared with the RBFANN, the MLPANN requires less sample volume. So, we choose the MLPANN.

## II. BIOMASS BOILER COMBUSTION SYSTEM

Biomass boiler is a kind of boiler, and It is a boiler with biomass energy as fuel. Biomass boiler can be divided into biomass biomass steam boiler, hot water boiler, hot blast stove of biomass, biomass, biomass, and vertical furnace boiler horizontal biomass boiler etc.. At present, biomass boilers can be divided into two kinds according to their uses: one is biomass heat energy boiler, and the other is biomass energy electric boiler. The principle of the two is basically the same, that is, obtaining energy by burning biomass fuel. The first kind of boiler can acquire heat energy directly, while the second kind of boiler converts heat energy into electric energy. In these two boilers, the first is now the most widely used as relatively mature technology.

## A. Feeding System

Feeding system is made up of silo, vibrating feeder, screw feeder and spiral feeding pipe. In the factory, the processed BMF fuel is transferred to the storage bin via a belt conveyor, and then the BMF fuel supply burner in the bin is fired by a screw feeder. A vibration feeder is connected between the bin and the screw feeder for the stability of continuous blanking delivery.

## B. Burning System

The combustion system includes a burner, a blower, an igniter, etc. Biomass fuel in the burner has a warm-up process, and then the fuel is transported to the furnace for combustion through the fan. BMF fuel contains very high volatile components. When the temperature in the furnace reaches the temperature of its volatile emission, the ignition fuel can be ignited rapidly under the condition of air supply. The temperature control of the burner is based on the internal temperature of the furnace, and the temperature is related to the amount of gas supplied by the fuel gasification. The adjustment of boiler load is controlled by the adjustment of feed quantity. After combustion, the flue gas enters the convection flue through the furnace chamber for heat exchange, then it enters the dust collector for purification treatment, and finally discharges to complete the whole combustion and heat transfer process.

## C. Smoke Air System

The boiler air supply system and the burner are arranged in an integrated way, and the air is sent to the hearth by the blower through the burner to achieve the function of conveying fuel and supporting combustion. Under the influence of the draft fan, the high temperature smoke generated by the combustion is converted into the dust collector by convection heat transfer in the smoke pipe, which can blow the furnace and smoke pipe regularly to ensure that no ash deposits occur on the surface of the smoke pipe, and finally the draft fan is discharged from the chimney.

## D. Operating System

The man-machine interface is used to exchange information with the boiler user to realize the fully automatic operation of the BMF boiler.

## III. The Controller of the Neural Network Model

The neural network model is an integration science of neuroscience, information science, and computer science. At present, it is a common method for nonlinear prediction[9]. Artificial neural network is a nonlinear simulation system of an information processing model currently[10]. The network generalization is an important indicator of evaluating performance, which refers to the ability of constructing the correct input-output relations about the non-training sample. The model of artificial neural network can save manpower and material resources, and the model is effective and feasible, therefore, both building a neural network model and solving practical problems are the attention focus for the prediction control of biomass combustion boiler.

## A. Statistical Analysis

The software of IBM SPSS Modeler 14.1 can be started by the starting menu or the desktop shortcuts, then the main page can be entered. All data were analyzed by Spss17.0. Different occupational characteristics of working procedure, such as the furnace temperature, the furnace load and so on, are analyzed in single factor analysis of variance. The IBM SPSS Modeler 14.1data mining software can be used to carry out modeling and prediction.

## B. Modeling Steps

The modeling steps are as followed.

Step1. Clicking on the **new stream**, **flowed save as** in the File pull-down menu.

Step2. Clicking the **source** button in the bottom of the main page, you can select the type of data source.

Step3. Clicking the **field option** button, you can select the type nodes of data.

Step4. Clicking the **modeling** button, you can select the type modeling, the type iron of modeling can be dragged into the main operating page.

Step5. Double-clicking on the **data source** nodes, you can edit the source and type of the data.

Step6. Clicking the **modeling** button, we can edit the model.

Step7. Predictive analysis, clicking the **output** button.

The symbolic description in mathematical mode is shown in Tab.1.

TABLE I.    SYMBOLIC DESCRIPTION IN MATHEMATICAL MODE

| Symbol | Symbolic significance |
|---|---|
| $x_1, x_2, \cdots, x_n$ | The input part of the neuron, which is information given at the last stage. |
| $\theta_i$ | Threshold of neurons |
| $y_i$ | Output of the neuron |
| $f[u_1]$ | Excitation function |

$f[u_1]$ determines the output form of reaching threshold value $\theta_i$ under the joint action of $x_1, x_2, \cdots, x_n$. The model used in this study is the second excitation function.

$$u_i = \sum_j w_{ij} x_i - \theta_i \tag{1}$$

Therefore

$$y_i = f[u_i] = f\left(\sum_j w_{ij} - \theta_i\right) \tag{2}$$

Formula (2) is a complete mathematical model expression of individual neuron.

Optimization model is presented as

$$\mathbf{X} = (P_1, \quad P_2, \quad \dots \quad, P_{n-1}, \quad T_f)^{\mathrm{T}} \tag{3}$$

$$f(\mathbf{X}) = T_f \tag{4}$$

$$\text{S.T.} \quad h_1(P_1...P_{n-1}) = \dot{L}_{\backslash -,} \quad _- \tag{5}$$

$$h_2(P_1...P_{n-1}) = \dot{L}_{\backslash -,\prime} \quad _- \tag{6}$$

$$h_3(P_1...P_{n-1}) = \ddot{-}_{\backslash -,} \quad _- \tag{7}$$

$$h_4(P_1...P_{n-1}) = \ddot{-}_{\backslash -,\prime} \quad ) \tag{8}$$

$$\theta_{max} \le \theta_0 \tag{9}$$

$$\omega_{max} \le \omega_0 \tag{10}$$

Accordingly, it is possible to find a set of suitable controller gains $\mathbf{K} = (K_{pl}, K_{il}, K_{dl})^T$ to obtain the trade-off control effects by using optimization method. The controller design problem can be expressed as

$$\mathbf{K} = (K_{pl}, K_{il}, K_{dl})^T \tag{11}$$

$$f = \int_0^{T_0} e^2(t)dt \tag{12}$$

$$\text{S.T.} \quad t_s \le t^+ \tag{13}$$

$$\varsigma \le \varsigma^+ \tag{14}$$

$$\sigma_{max} \le \sigma^+ \tag{15}$$

Where $t_s$ is the adjusting time, $\varsigma$ is the steady error, and $\sigma_{max}$ is the maximum value of error. All constraints reflect the requirement of rapidity and accuracy of control system. If considering with the stability requirements, the follow ing formulas (16)~(17) should be added to the controller design model as inequality constraints. If the gains of PID controller $K_{pl}$, $K_{dl}$ and the constant $\varepsilon$ are chosen such that

$$0 < \varepsilon < \frac{\varepsilon K_{pl}(K_{dl} - a_3 b_1)}{K_{dl}^2 + K_{pl}^2 + 2K_{pl}a_2} \tag{16}$$

$$K_{pl} > \max(\frac{\varepsilon a_2^2}{a_1}, \frac{4\sqrt{a_3 c_1}}{\varepsilon}) \tag{17}$$

## IV. SIMULATION ANALYSIS

There were 3000 training records input as neural network. Then we get the index of sensitivity and specificity and determine the optimal curve, as shown Fig.1 and Fig.2. According to the curve of the model, we determine the optimal point of sensitivity the between 60 to 80 and the optimal point of specificity from 80 to 100. Comprehensively considering the sensitivity, specificity and accuracy, we decided 20 as point. The accuracy reached 91.96%. The sensitivity and specificity were 81.22% and 93.77%., respectively, as shown Fig.3 and Fig.4.
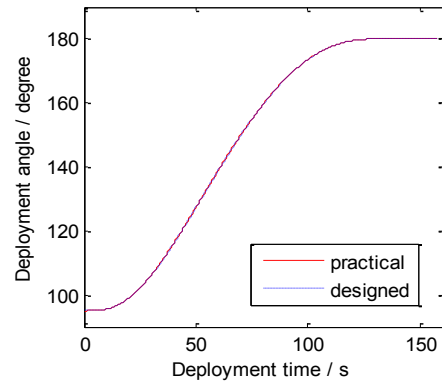


Figure 1.  The optimal deployment angle


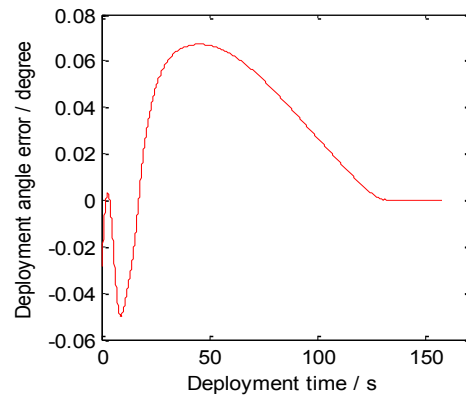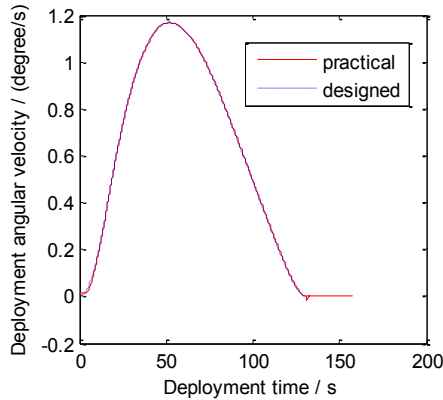
Figure 2.  The optimal deployment angle error

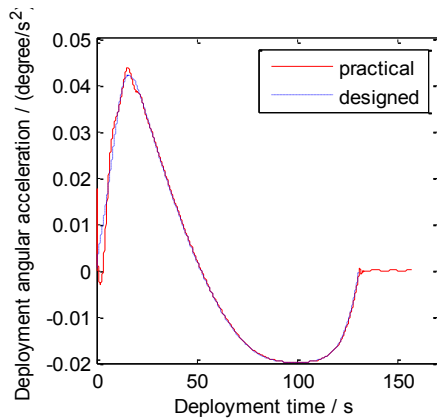Figure 3. The optimal deployment angular velocity



Figure 4. The optimal deployment angular acceleration

## V. CONCLUSIONS

We could accurately predict working process of biomass combustion boiler by MLP neural network model based on some characteristic quantities as the transport layer variables of prediction model. After the model established, we determined inspection standards of the optimal cut-off point. We obtained curves of ROC which is given about working procedure with different classification results. Then we get the index of sensitivity and specificity and determine the optimal cut-off point, which is used to evaluate the degree of accuracy of the prediction model. We use sensitivity, specificity and accuracy to evaluate the model whether it is suitable for predicting.

## REFERENCES

[1] LJR Nunes, JCO Matias and JPS Catalão, "Biomass combustion systems: a review on the physical and chemical properties of the ashes.," Renewable & Sustainable Energy Reviews, vol. 53, issue 15, pp. 235-242, 2016.

[2] M Opydo, R Kobyłecki, A Dudek and Z Bis, "The effect of biomass co-combustion in a CFB boiler on solids accumulation on surfaces of P91 steel tube samples," Biomass & Bioenergy, vol. 85, issue 3, pp. 61-68, 2016.

[3] J Capablo and J Salvadó, "Estimating heat transfer losses caused by alkali salt deposits in biomass combustion," Renewable Energy, vol. 105, issue 28, pp. 449–457, 2017.

[4] MA Gómez, J Porteiro, D Patiño and JL Míguez, "Eulerian CFD modelling for biomass combustion. Transient simulation of an underfeed pellet boiler," Energy Conversion & Management, vol. 101, issue 12, pp. 666-680, 2015.

[5] L Febrero, E Granada, D Patiño, P Eguía, A Regueiro, "A comparative study of fouling and bottom ash from woody biomass combustion in a fixed-bed small-scale boiler and evaluation of the analytical techniques used," Sustainability, vol. 7, issue 5, pp. 5819-5837, 2015.

[6] Lai CY, Xiang C and Lee TH, "Data-based identification and control of nonlinear systems via piecewise affine approximation," Neural Networks IEEE Transactions on, vol. 22, issue 5, pp. 2189-2200, 2011.

[7] Hagan MT, Demuth HB, Beale MH, and De Jesús O. Neural network design. Boston, PWS publishing company, 2000.

[8] Dehkordi AN, Kamali-Asl A, Ewing JR, Wen N, Chetty IJ, and Bagher-Ebadian H. "An adaptive model for rapid and direct estimation of extravascular extracellular space in dynamic contrast enhanced MRI studies," NMR Biomed, vol. 30, issue 5, pp. 118-127, 2017.

[9] Kosic D.,"Fast clustered radial basis function network as an adaptive predictive controller," Neural Networks, vol. 63, issue 8, pp. 79-86, 2015.

[10] X. Hong, "A fast identification algorithm for Box-Cox transformation based radial basis function neural network," IEEE Trans Neural Netw, vol. 17, issue 4, pp. 1064-1079, 2006.