Quality Prediction Model Based on Variable-Learning-Rate Neural Networks in Tobacco Redrying Process

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ABSTRACT: *As tobacco redrying process has characteristics of multi-interference, strong coupling, great hysteresis, nonlinear and uncertainty, it is very difficult to establish the physical model. This paper presented an innovative method with the variable-learning-rate-based back propagation neural network (BPNN) for establishing the quality prediction model of tobacco redrying process. First, characteristics of the process and correlation of the process variables are analyzed, and determine eight input parameters and two output quality indicators of model. Then, a quality prediction model of tobacco redrying process is established by using the BPNN structure. In the process of network training, BP algorithm is improved by using the method of variable learning rate, and satisfactory prediction results are obtained. Finally, in order to verify the effectiveness of this method, the improved BPNN model is applied for simulation experiment, and is compared with ordinary BPNN. The prediction results show that the improved model possesses strong self-learning function and higher prediction accuracy.*

Keywords: Tobacco; Drying Process; Back Propagation Neural Network; Variable Learning Rate; Quality Prediction Model

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1. Introduction

Tobacco redrying is a re-curing process after the tobacco drying for the first time, which has direct impact on the production quality of cigarette industries. This process includes three phases: drying, cooling and moisture regain [1, 2]. Quality control is one of the research emphasis during tobacco redrying process, and the method of intelligent control is usually applied to the quality control of tobacco re-dryer to realize that the parameters of every PID control link of tobacco re-dryer are automatically adjusted on line, and that the output tobacco moisture and temperature is controlled at the range of technology demand [3]. However, currently re-dryer control rely on manual setting every PID control link parameters, adjustment of re-dryer completely depend on the experience of operator, besides tobacco redrying process is an uncertain time-delay systems, so the moisture and temperature of tobacco are unstable at the exit of re-dryer. Based on this, Liu and Lu proposed a new kind of control method using the predictive controller based on fuzzy internal mode to solve the lagging problem of the tobacco

redrying process effectively [4]. Ihosvany and Orestes devoted to the application of the fuzzy control based technology to the drying process of tobacco leaves [5]. However, these methods are basically local optimal control. Meanwhile, some scholars also proposed global optimal control method based on model predictive control [6, 7]. Regardless of any intelligent control method which has been used, especially model predictive control, the key of the intelligent control is to establish quality prediction model. Because only the predictions on quality parameters for future products are made, the production process can be adjusted before product quality problems occurs and the goal of improving product quality can be achieved. But, current literatures in this area are less.

The method for establishing quality prediction model can be divided into two categories [8]. The first category is the physical method, which is according to the analysis of physical process to determine the form of model; then through experiment to determine the model coefficients. The second category is experimental method, which is, according to specific process equipment, through a large number of experiments to obtain the process conditions and the corresponding process parameter data. Efremov and Kudra discussed a modified quasi-stationary equation for drying kinetics to develop a method allowing calculation of the effective diffusion coefficient and tracing its variation with drying time, established physical model of the drying process [9]. However, comparing with other process based industries, tobacco redrying process has obvious characteristics of multi-interference, strong coupling, great hysteresis, nonlinear and uncertainty. Consequently, it is very difficult to establish the physical model. Therefore, we must find a new way to create the quality prediction model of tobacco drying process.

The neural network method can describe the characteristics of objects without establishing the physical model, and it has the advantages of parallel processing, strong learning ability and good robustness. Therefore it has been widely used in complex systems [10, 11]. In recent years, many scholars have put forward the method that combines physical analysis and neural network to apply in object of industrial production modeling, and which has achieved significant control effectiveness [12-14].

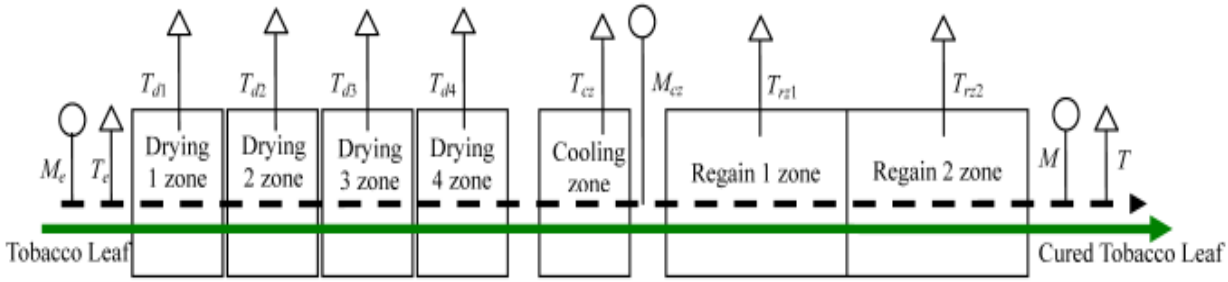
In this research, we developed a variable-learning-rate neural network based quality prediction model for tobacco redrying process. In the modeling process, characteristic of physical process and variables correlation are analyzed, and then eight manufacturing process parameters were dedicated to network training and testing. In addition, BP algorithm is improved by using the method of variable learning rate to enhance the network's learning ability. The rest of this article is organized as follows. In Section 2 physical description and characteristic analysis of tobacco redrying process is summarized. In Section 3 the design of neural network prediction model is shown. In Section 4 the results obtained are discussed. Conclusions are presented in the last section.

2. Process Description And Characteristic Analysis

In the tobacco redrying process, the most direct quality indicators are tobacco moisture and temperature. The technical index requires that tobacco moisture is controlled between 11.5% and 13.5%, and tobacco temperature is controlled between 50□ and 60□. The goal of production process control is that process parameters are adjusted to make the tobacco moisture and temperature meet the process index requirements.

2.1. Process description and impact factors

Tobacco redrying process usually carries out in redrying machine (shown in fig. 1). According to the technology characteristics, the redrying machine is mainly divided into three sections: drying section, cooling section and moisture regain section [1].



o- moisture tester; □- temperature tester

Figure 1. Tobacco redrying process

Drying section consists of four drying zone and moisture removal system, whose task is to bake the tobacco leaves flowing through and remove the moisture and mixed gas in tobacco leaves.

Cooling section is composed of cooling zone and ventilation system. The cooling air cools down the tobacco leaf after drying and makes the temperature reduce below 40□ for the benefit of moisture regain.

Moisture regain section consists of two moisture regain zones and moisture removal system. According to the technology indexes requirements, this section makes moisture regain treatment to tobacco leaf after cooling to control the tobacco moisture content at about 13% and the temperature at about 55□. Through this section, it is good for the preservation, Re-fermentation and reproduction of tobacco.

In actual production process, the moisture, temperature, planting area, variety and grade of tobacco at entrance have very important influence on the tobacco quality at exit; The pressure, temperature and saturation degree of heating steam and moisture regain steam directly influence the tobacco quality at exit; Ambient air temperature and humidity also have some indirect impact on the tobacco quality in cooling stage. Sometimes, under the influence of tobacco threshing process before, tobacco feed flow and the speed of transport car need to be adjusted to meet the continuous production, which leads to the changes of process dynamic characteristic. Meanwhile, tobacco redrying machine works at environment of high temperature, high humidity and dust, so that abnormal condition would occur on the equipment. In this case, the operators need to change technology parameters, which results in the diversity of process characteristics.

Based on the above analysis, and assuming the external environment of tobacco redrying is the same, and for tobacco is from the same planting area, the same variety and the same grade, the main influence factors of the tobacco moisture and temperature are: tobacco leaf moisture at entrance (M_e), tobacco temperature at entrance (T_e), tobacco feed flow (F_f), the speed of tobacco transport chain car (V), temperature of four drying sections (T_{d1}, T_{d2}, T_{d3}, T_{d4}), heating steam (S_h), moisture of cooling zone(M_{cz}), temperature of cooling zone(T_{cz}), water flow of moisture regain(F_r), steam of moisture regain(S_r), temperature of regain 1 zone(T_{rz1}), temperature of regain 2 zone(T_{rz2}) and so on, and there exists strong coupling between these factors.

2.2. Correlation analysis

500 groups sample data are obtained randomly from the historical database of tobacco redrying process of the same planting area, the same variety and the same grade. Which include 15 sample data: M_e, T_e, F_f, V, T_{d1}, T_{d2}, T_{d3}, T_{d4}, S_h, M_{cz}, T_{cz}, F_r, S_r, T_{rz1} and T_{rz2}. And then those samples are used for statistical analysis.

The correlation between any two variables can be calculated by formula (1) [14]:

$$r = \frac{\sum XY - \frac{\sum X \sum Y}{N}}{\sqrt{\left(\sum X^2 - \frac{\left(\sum X\right)^2}{N}\right)\left(\sum Y^2 - \frac{\left(\sum Y\right)^2}{N}\right)}} \tag{1}$$

In the formula (1), r represents correlation coefficient, X and Y represent any of the two variables, and N represents number of samples. When the correlation coefficient of two variables r=1, it shows that the two variables are complete correlation; when r=0, it shows that the two variables aren't linear correlation; when r>0.7, it could be considered that the two variables exists strong correlation. According to the strong correlation coefficient standard 0.7, there is a strong correlation between S_h and T_{d1}, T_{d2}, T_{d3}, T_{d4}. Similarly, it can draw that there exist strong correlation between S_h and M_{cz}, S_h and T_{cz}, T_{d1} and T_{cz}, T_{d2} and T_{cz}, T_{d3} and T_{cz}, T_{d4} and T_{cz}, F_r and T_{rz1}, F_r and T_{rz2}, S_r and T_{rz1}, S_r and T_{rz2}. To ensure that the variables of neural network input layer have mutual independence, this paper chooses M_e, T_e, F_f, V, M_{cz}, T_{cz}, F_r and S_r as the input parameters of neural network model.

3. Neural Network Prediction Model

BPNN (Back Propagation Neural Network, BPNN) is a mature neural network. BP algorithm is essentially gradient descent

method, and the learning results exists local minimum problems inevitably. As the learning rate remains unchanged in the learning process, the algorithm convergence speed may be slow, or even non-convergence. Therefore, in order to improve training speed and the model accuracy, the ordinary BP algorithm must be improved. We adopted a method which was variable learning rate based.

3.1. Quality prediction model of tobacco redrying process

BPNN with 3-layer is adopted to establish prediction model. By section 2.2 the analysis of process variables correlation, the inputs of the neural network are determined to: M_e, T_e, F_f, V, M_{cz}, T_{cz}, F_r and S_r, and the model outputs are tobacco moisture and temperature of re-dryer exitÿrespectively as M and T □. So the neuron number of input and output are 8 and 2. And hidden layer neuron number is calculated to 20 according to empirical formula [15]. Neural network structure is shown in fig. 2.

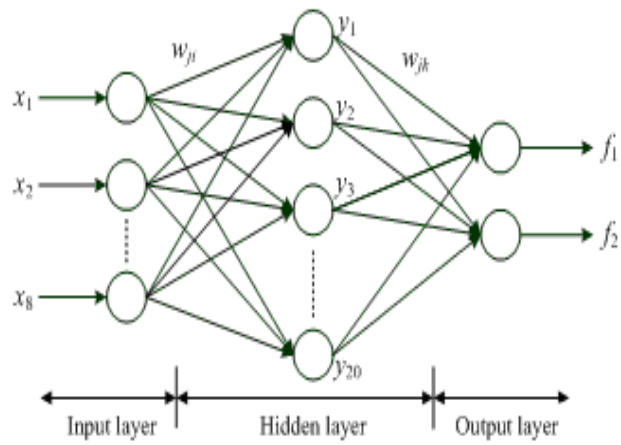


Figure 2. Tobacco redrying quality neural network model structure diagram

In fig. 2, x_i (i=1, 2, …, 8) is input layer variables, y_j (j=1, 2, …, 20) is hidden layer variables, f_k (k=1, 2) is output layer variables, w_{ji} is the weight value from the ith neurons of input layer to the jth neurons of hidden layer, w_{jk} is the weight value from the jth neurons of hidden layer to the kth neurons of output layer. By sigmoid-tansig non-linear activation function, the neural network structure of tobacco redrying process export moisture and temperature prediction model was determined as:

$$f_k = (M, T)^{\mathrm{T}} = \sum_{j=1}^{20} w_{jk} \tan sig\left(\sum_{i=1}^{8} w_{ji} x_i + b_j\right) + b_k \qquad (2)$$

In the formula (2), w_{ji} and w_{jk} represent the weight value, b_j represents the corresponding threshold value of the jth neurons of hidden layer, and b_k represents corresponding threshold value of the kth neurons of output layer. The weight value w_{ji}, w_{jk} and threshold value b_j, b_k were obtained from the training of BPNN.

3.2. BP algorithm of variable learning rate

Prediction model is the basis of parameter optimization, whose accuracy has great significance to ensure effectiveness and reliability of the optimization. Although the ordinary BP algorithm is effective, the convergence speed is very slow near target point. When describing complex systems, it always can't ensure the global convergence and falls into local minimum. Thereby ordinary BP algorithm needs to be improved. There are mainly two ways, using heuristic learning method and using more efficient optimization algorithm, to improve BP algorithm. Usually, two optimization algorithms of increasing momentum terms and changing learning rate are adopted to improve network training performance [14, 15]. This paper uses variable-learning-rate-based BP algorithm training equation (2).

Through the adjustment of network weight value w to the error function decrease along the negative gradient direction:

$$w(k+1) = w(k) - \eta(t)\frac{\partial E}{\partial w(k)} \qquad (3)$$

In the equation (3), $E = \frac{1}{N}\sum_{k=1}^{N}\left[x_0(k) - \hat{x}_0(k)\right]^2$, N is learning sample number, $x_0(k)$ □ $\hat{x}_0(k)$ are network output value and expected value of the kth sample. The goal of network training is to minimize E through adjusting weight value and threshold value constantly.

When adjusting network weight value, it assumes that learning rate η is a linear function of the number of iterative learning (expressed as t), the maximum learning rate is η_{max} □ and the minimum learning rate is η_{min}. After each learning, the learning rate variable quantity is defined to:

$$\Delta\eta = \left(\eta_{max} - \eta_{min}\right)/t_{max} \tag{4}$$

Then the learning rate of the tth time learning is:

$$\eta(t) = \eta_{max} - \Delta\eta \times t = \eta_{max} - \left(\eta_{max} - \eta_{min}\right) \times t / t_{max} \tag{5}$$

In the equation, t_{max} and η are obtained empirically. Through experiment, when η □ [0.1, 0.9] better results can be achieved.

3.3. Network Learning

The steps of improving BP network training are:

Step 1: Initializing weights and thresholds. Giving the initial value of weights and thresholds between -1 and 1 at Random, and initial raw data of input and output;

Step 2: Providing learning sample of network training;

Step 3: According to equation (2), calculate the actual output of the network;

Step 4: Comparing the current training error and the last time training error, and adjust weight according to equation (3);

Step 5: Judging whether the error meets the scheduled accuracy. If satisfied, the training ends, then take the determined weight and threshold value into equation (2), and output prediction results. Otherwise return to step 2.

4. Results And Discussion

This research presented a variable-learning-rate-based approach to create a tobacco redrying process quality predictor. Eight BPNN manufacturing process parameters and two quality indicators were dedicated to train and test the network.

The neural networks were first trained using 450 samples of training data, then 50 samples of verifying data were used to make predictions, and the network performance was obtained by calculating the Root Mean Square Error (RMSE). The BPNN performance is shown in Table 1.

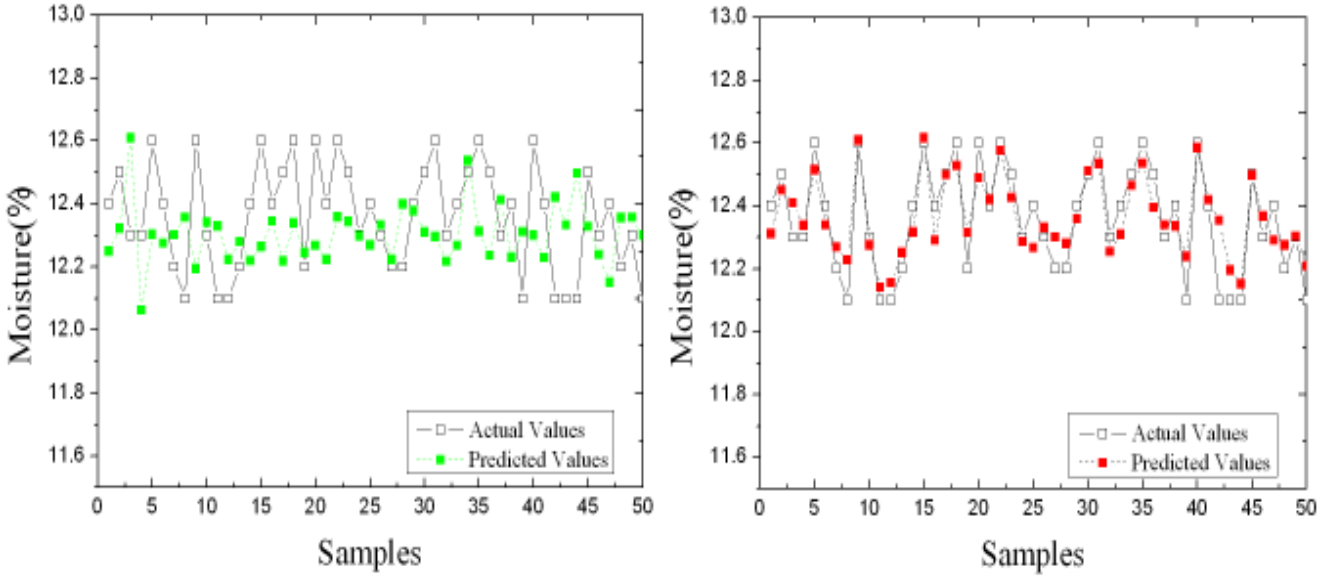
Item		Improved BPNN	Ordinary BPNN
Moisture predictor	Training RMSE	0.020	0.045
	Testing RMSE	0.012	0.027
Temperature predictor	Training RMSE	0.0076	0.010
	Testing RMSE	0.0066	0.017

Table 1. Comparison of the network performance between the improved BPNN and ordinary BPNN

It can be seen from Table 1 that, the training precision of the improved BPNN moisture and temperature quality predictor had an RMSE of up to 0.020 and 0.0076, and its testing precision amount was an RMSE of up to 0.012 and 0.0066, whereas the training precision of the ordinary BPNN moisture and temperature quality predictor had an RMSE of 0.045 and 0.010, and its

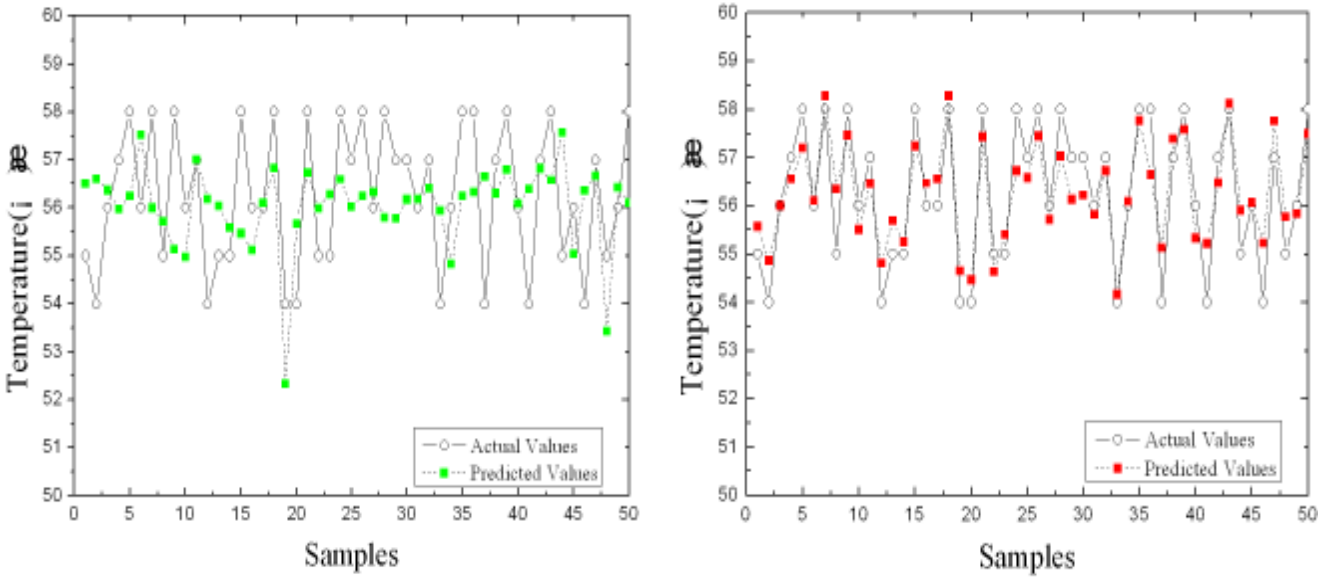
testing precision amount was an RMSE of 0.027 and 0.017. Apparently, the performance of the improved BPNN quality predictor was better than the ordinary BPNN quality predictor.

A comparison between the actual and predicted values via ordinary BPNN and improved BPNN moisture and temperature quality predictors are represented in Figs. 3 and 4. The results in Figs. 3 and 4 showed that the variable-learning-rate-based BPNN had better prediction effect than ordinary BPNN, the forecasting accuracy reached more than 90%, and can accurately reflect the quality trend of tobacco redrying machine exports moisture and temperature in normal production process. Based on these results, improved BPNN can provide effective guidance for solving the tobacco redrying machine quality optimal control problem.



(a) Ordinary BPNN (b) Improved BPNN

Figure 3. Comparison between the predicted and actual moisture (%, wb) from (a) Ordinary BPNN and (b) Improved BPNN



(a) Ordinary BPNN (b) Improved BPNN

Figure 4. Comparison between the predicted and actual temperature (!) from (a) Ordinary BPNN and (b) Improved BPNN

However, because the actual tobacco production process is dynamic, the tobacco redrying process quality prediction BPNN model needs to be changed constantly as the sample keep updating. When model is doing self-learning, the latest samples joined into the self-learning library files, and the similar and earliest samples are eliminated, so that the model always keep uniform learning samples quantity. Therefore, in order to enhance the prediction precision of the product quality in the dynamic system, it is essential to extract the dynamic data of the process parameters.

5. Conclusions

Tobacco redrying process control and optimal parameter settings for the product properties require very accurate quality prediction. This research presented a variable-learning-rate back-propagation neural network (BPNN) based model for the tobacco redrying process dynamic quality prediction. With eight manufacturing process parameters and two quality indicators were dedicated to train and test the networks. In addition, another ordinary BPNN model was employed for comparison. The results revealed that the improved BPNN model proposed not only increased the prediction performance of product quality effectively and obtained more reliable product quality in advance, but also solved the problem of quality modeling difficulties of tobacco redrying process. In future extensions, the proposed approach will be employed to the process control for improving the prediction precision of the product quality in the tobacco redrying machine.

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References

[1] Wise, William B., Reaves, Dixie Watts. (1995). Potential Changes Facing Virginia Tobacco Producers. Virginia Cooperative Extension publication 448-307 / REAP P007, Virginia Polytechnic Institute and State University.

[2] Henk, Krijnen., Philip, Morris. (2003). Thermal mass flowmeters up accuracy, reliability in tobacco leaf drying process, *Control Solutions International* 76(5) 43.

[3] Pakowski, Z., Krupinska, B., Adamski, R. (2006). Sorption isobars of tobacco materials required for the superheated steam drying processes, *Inzynieria Chemiczna I Procesowa* 27(2) 507-517.

[4] Liu, S.F.; Lu, Y.Z.; Wang, A.H. 2004. The application of predictive controller based on fuzzy internal model to the tobacco redryingÿ, *Henan Science* 22(3) 321-324.

[5] Ihosvany, A.L., Orestes, L.S., Verdegay, J.L. (2005). Drying process of tobacco leaves by using a fuzzy controller, *Fuzzy Setsand Systems* 150 (3) 493-506.

[6] Wang, Y.H.; Han, G.S. 2000. The Humidity Control for Tobacco Drying Process, *Journal of Beijing Polytechnic University* 26 (4) 91-94.

[7] Chen, F., Qi, D.L. (2010). Robust low complexity predictive control of constrained piecewise affine systems with bounded disturbances, *International Journal of Control, Automation and Systems* 8(2) 439-444.

[8] Hanrahan, Robert, P. (1995). The IDEF Process Modeling Methodology. June.

[9] Efremov, G., Kudra, T. (2004). Calculation of the effective diffusion coefficients by applying a quasi-stationary equation for drying kinetics, *Drying Technology* 22(10) 2273-2279.

[10] Wilson, J.A., Zorzetto, L.R.M.(1997). A generalized approach to process state estimation using hybrid artificial neural network/mechanistic models, *Computer Chemistry Engineering* 21(9) 951-963.

[11] Hagan, M.T., Demuth, H.B.,Beale, M.H. (1996). Neural Network Design. Boston, USA: PWS Publishing.

[12] Yang, C.H., Deconinck, G. et al. (2002). An optimal power-dispatching system using neural network for the electrochemical process of zinc depending on varying prices of electricity, *IEEE Transactions on Neural Networks* 13(1) 229-236.

[13] Henriques, W.S, Cost, A.C.A., Alves, T.L.M. (1999). A hybrid neural model of ethanol production by zymomonas mobiles, *Applied Biochemistry and Biotechnology* 77(9) 277-297.

[14] Xu, C.H., Wu, M. (2009). Quantity-quality Prediction Model Based on Neural Networks in Lead-zinc Sintering Process, *Journal of System Simulation* 21(4) 1024-1028.

[15] Jacobs, R.A. (1988). Increased rates of convergence through learning rate adaptation, *Neural Networks* 1. 295-307