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Control modeling of ash wood drying using process neural networks

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ABSTRACT

For the control and system identification problems of the deceleration phase of the ash wood drying process, we propose a deceleration phase modeling method of ash wood drying using process neural networks with double hidden layers. This method applies time-varying characteristics of process neural networks and the ability to extract time-space cumulative effects. The time-varying characteristics of wood drying deceleration phase modeling under time series background are directly incorporated into the model. By comparison with traditional neural network modeling results, we prove that the model of process neural networks has better control accuracy, providing an idea to solve control and nonlinear system identification problems under a time series background.

1. Introduction

Wood drying is an important technique part of wood processing; the overall promotion of wood drying performance provides strong technical support for efficient utilization of wood resources. The main problems in computer-controlled wood drying are first, the temperature and humidity control model is used to characterize the relation between temperature and humidity, which is the foundation and basis of a wood drying modeling simulation and controller design. Secondly, the drying benchmark model and inverse model characterizes the nonlinear mapping relation of temperature, humidity and wood moisture content in the design of a computer control system. The benchmark model uses moisture content change to achieve control and prediction in the wood drying process by establishing a mapping model incorporating temperature, humidity, and moisture content.

The wood drying process is a complex strong coupling, nonlinear system with time-varying and uncertain characteristics. The main parameters characterizing the drying process are time-varying features, so the wood drying benchmark modeling and inverse modeling systems are part of a time series prediction control problem. The establishment of a drying benchmark model and an inverse model aims at computer control of the wood drying process by simulating the complex nonlinear relationship between temperature, humidity, and wood moisture content. The wood drying process can be divided into three stages: the preheating stage, a constant rate drying stage (moisture content is above fiber saturation point), and a deceleration drying stage (moisture content is below fiber saturation point). The water evaporation mechanism is different in each stage: the drying curve (i.e., moisture content changing with time) is approximately linear in a constant rate drying period, the corresponding model being relatively simple. The aim for the preheating stage is to raise the wood internal temperature quickly to a certain level and avoid premature water evaporation at the wood surface; this stage is relatively short. The deceleration drying stage mechanism is relatively complex. The wood drying segment model has been studied mostly for the deceleration stage. Cao Jun, Hu Kunlun et al.[1] studied the wood drying deceleration phase modeling by using traditional neural networks. In our paper, process neural networks were applied to wood drying modeling in the deceleration phase. The process neural network model was established for the ash wood drying deceleration phase. We compared and analyzed the performance, and achieved control of the wood drying process and system identification by using an extraction ability to achieve a time-space cumulative effect and strong nonlinearity of process neural networks.

2. Materials and methods

2.1. Data acquisition

Data were obtained using the following: a miniature industrial drying kiln of size 1.8 m × 1.7 m × 1.2 m; a detection device having two temperature sensors, two humidity and six wood moisture content sensors; a heating, spray and, moisture-discharging device. Under normal working conditions of the kiln, data were recorded

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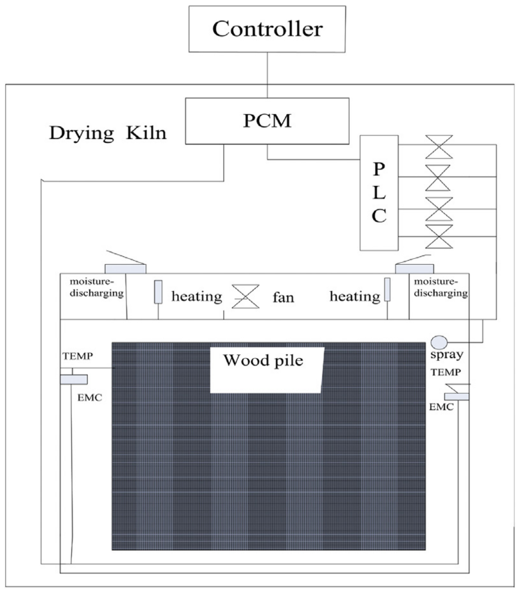

Fig. 1. Structure of drying kiln.

for temperature, humidity, wood moisture content, and the states of the spray valve, moisture-discharging valve and heating valve. The heater was a switch type for raising the temperature in the kiln. The spray and moisture-discharging valves were used to adjust the humidity in the kiln. A fan was used to accelerate air flow rate by running at full speed, so it would not be considered in the experiment.

The drying kiln (Fig. 1) consisted of a controller, PCM (signal acquisition and processing module), PLC (control interface) and kiln facilities. The PCM collected the temperature, EMC (equilibrium moisture content), wood moisture content and other data for conversion to a digital signal, transmitted to the controller. According to the demand and current kiln states, the controller adjusted the fan, heating pipe, spray valve, and exhaust window, and ensured that the temperature and equilibrium moisture content met the requirements of the kiln. The controller continuously monitored PCM data, saved and recorded the drying kiln operation states, and enabled an efficient drying process.

30 mm thick ashes were selected to carry out a three-kiln drying and data-sampling experiment. All data were obtained under normal working conditions of the system. To generate the identification data, continuous step signals were applied to the kiln. This method maintained the integrity of the control system and control object; it activated all determinants of the process, and performed simultaneous sampling of temperature, humidity, wood moisture content and other data in the kiln, thus acquiring input and output data for identification and analyses.

2.2. Data selection

With airflow speed a determinant of the environment, external factors affecting the wood drying process were temperature and humidity of the medium [2]. Wood moisture content values characterized the drying effect after the wood drying process. Wood drying data from 30 mm thick ash obtained under the normal working conditions of the system were used as original data for control modeling. Ash wood drying data were as follows: the initial moisture content was 68.7%, the fiber saturation point was 30%, and the final moisture content was 8.9%. The deceleration drying stage data of one kiln (moisture content from 30.7 to 8%) were selected to form 59 sample sets, which were used as training samples. To verify the model's overall performance, kiln ash wood drying data (moisture content decreased from 30 to 8.9%) were selected to form 53 sample sets for testing. The temperature-humidity function was fitted by ten consecutive discrete temperature and humidity data sets, and wood moisture content function fitted by ten consecutive discrete moisture content data sets before a time-point was used as an input function. The wood moisture content value at the time-point was used as output. That is, the corresponding time-varying function was fitted by two-point temperature, humidity and wood moisture content consecutive data, before the time-point. The data were used as the inputs of process neural networks. The wood moisture content constant at the time point was used as the network output, as shown for a single sample in formula (1)

$$\{x_1(t), x_2(t), \ldots, x_i(t), \ldots, x_n(t), d\}, \tag{1}$$

where $x_i(t)(i=1, 2, \cdots, n)$ represents an arbitrary input function, which is fitted by a series of discrete input data, d is the desired output of network, n is the number of input neurons.

2.3. Data preprocessing

To reduce noise interference to the system identification and to improve convergence speed of the process neural networks, the following steps were adopted to realize data preprocessing: a logarithmic sigmoid function was used as an excitation function, its output in the range of (0, 1). If normalizing data to the [0,1] range directly by using standard formula, then there will be 0 and 1 values within each column. But close to the 0 and 1 values, the excitation function was not sensitive to input changes, so the network adjustment value to weight was rather small. Therefore, in the practice of data normalization, the normalized interval was adjusted to avoid the emergence of 0 and 1 values, so formula (2) was adopted to normalize data, with its interval in the range of [0.15, 0.85].

$$x^* = 1 - e^{-\left(0.1625 + \frac{(1.8971-0.1625)(x-x_{\min})}{x_{\max}-x_{\min}}\right)}, \tag{2}$$

where x is original data, x^* is the normalized data, x_{max} and x_{min} are the maximum and minimum of x, respectively. Note that if the original data dimension in each row or column was different, normalization should be carried out in each row and column of data, respectively.

In addition, after completing network training and testing, anti-normalization of response network output should be carried out. The specific formula is shown in formula (3).

$$x = x_{\min} + \frac{x_{\max} - x_{\min}}{1.8971 - 0.1625}\left(\ln \frac{1}{1-x^*} - 0.1625\right). \tag{3}$$

2.4. Drying deceleration phase modeling based on process neural network

2.4.1. Wood drying deceleration control model

The traditional neural network achieved better results in the wood drying control and system identification. But specific to the control and nonlinear system identification problems with a time series background, an important factor that cannot be ignored is the time-varying characteristics. Based on these characteristics, some researchers [3–14] had introduced delay neural networks and dynamic recurrent neural networks to solve time series control problems. At the same time nonlinear system identification was extended to the more general nonlinear time-varying problem. The purpose of using time delay neural networks and dynamic recurrent neural networks was to take time-varying characteristics into time series control and system identification by delay and feedback. Relatively, this is an indirect way and could not directly reflect the time-varying characteristics of system input. Based on the above analysis, this paper introduces two-hidden-layer feed-forward process neural networks to time series control and nonlinear system