Modeling of temperature-humidity for wood drying based on time-delay neural network

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Abstract: The temperature-humidity models of wood drying were developed based on Time-delay neural network and the identification structures of Time-delay neural network were given. The controlling model and the schedule model, which revealed the relation between controlling signal and temperature-humidity and the relation between wood moisture content and temperature-humidity of wood drying, were separately presented. The models were simulated by using the measured data of the experimental drying kiln. The numerical simulation results showed that the modeling method was feasible, and the models were effective.
Keywords: Wood drying; Temperature-humidity model; System identification; Time-Delay neural network
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Introduction

Wood drying is a strong coupling, big-lagged, complicated nonlinear system. External interference and model uncertainty always exist in the process of wood drying. To establish an effective drying model is an important part in the fundamental study of wood drying and is also a precondition in realizing fully automatic drying control, improving drying quality, reducing energy consumption, and shortening drying time. In recent years, the studies of the modeling of drying mainly focused on the mechanism models such as airflow and heating fluid flow models and thermodynamic models of heat and moisture transfer, and so on. Cloutier *et al*. (1993) established finite element model for isothermal drying and water transfer model to describe the characteristics of the process of wood drying based on water potential concept. Taking account of the vertical and horizontal conditions of wood, Salin (2001) established a model to predict transfer coefficient. Two-dimensional and three-dimensional heat and mass transfer models were also separately proposed by Perre *et al*. (1999) and Dedic *et al*. (2003) to identify the heat and mass transfer phenomena in the whole drying process. Pang (1996) developed a dynamic model to predict the conditions across a stack of softwood inside kiln. Hua *et al*. (1998) presented a numerical model to simulate the airflow distribution and to solve the flow distribution in a kiln according to its geometry. A formulation of a dynamic, kiln-wide drying model was described by Sun *et al*. (2000), and the model solves the unsteady-state mass, momentum and energy balance equations for both the airflow and the wood boards. Hukka (2000) studied a two-dimensional model for the stress analysis of drying wood, which can describe viscoelastic-mechanosorptive-plastic behavior, to predict deformation and optimize schedules. However, most of these models are difficult to actualize in practical control due to the fact that too much restrained conditions makes the models very complex, or very simple conditions makes the models inaccurate.

Many external factors can also affect the wood drying speed, of which, temperature, humidity (equilibrium moisture content) and airflow speed are the primary factors, and these three main factors decide the change of wood moisture content. Therefore, establishing a phenomenological model based on the relation between the macroscopical characteristics of wood expressing and drying conditions in the process of drying is also an important research direction of modeling. Using a minimum consumption of energy and minimum drying time with a constrain of wood quality as the performance index, Tarasiewicz *et al*. (1998) put forward a reference system model with a few partial differential equations, which can produce estimated state variables and estimated operating functions to compensate the time delay. Yan *et al*. (1999) established temperature control model to simulate the temperature optimization control based on recursive least squares estimator. Wang *et al*. (2001) developed an intelligential adaptive control system of an industrial lumber drying process, and established a single input and single output system model by using a system identification scheme based on the on-line input output data and knowledge accumulated through extensive lumber drying tests. This study presented temperature-humidity modeling of wood drying based on system identification of neural network, namely: (1) the controlling model of temperature-humidity (This model showed the relation between controlling signals and temperature-humidity); (2) the schedule model of wood drying (This model showed the relation between wood moisture content and temperature-humidity). With the help of studying input and output data directly, the network minimized objective error rule function to obtain the relation between input and output data hidden in the system, namely characteristic expression model. In our study, considering the actual wood drying process, we established the wood drying models based on Time-delay neural network for the identification and control, and the network can reflect the dynamic action of system preferably by the model.

Structure of wood drying model

A downscaled industrial drying kiln with dimensions of 1.8 m×1.7 m×1.2 m was used in this study. In the kiln, the temperature, humidity and airflow speed were controlled by the

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heat-valve, spray-valve, eliminating-damp-valve and the wind-machine, respectively. The heater was on-off type and used to increase the temperature. The spray-valve and the eliminating damp valve were used to adjust the humidity. The wind-machine accelerated the airflow of the kiln. The wind speed was not considered in this paper because the machine ran in full career all long. In this way, wood moisture content can be controlled by regulating the temperature and the humidity in the kiln. The measuring equipments had two temperature sensors, two humidity sensors and six moisture content sensors, and these were used to gather the experimental data at the normal running state of the kiln. In addition, input-output data for identification were obtained by recording the states of the heat-valve, spray-valve and the eliminating-damp-valve. The structure of wood drying model is shown as Fig. 1.

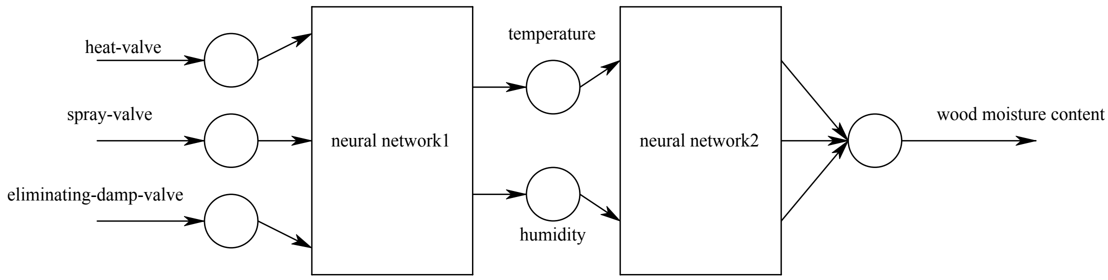

Fig.1 Structure of wood drying model

Time-delay neural network and the identification structure

Two methods are usually used for the identification of dynamic system: One is to apply the dynamic characteristic of system to the network directly such as the recurrent network model and the dynamic neural network model; the other is to consider the dynamic factors of system in the input signals of network, i.e., to add the lagged signals of input and output to the input of system, which ensures that the output of network includes the former input-output information (Kumpati *et al*. 1990; Kaiser 1994; Shi *et al*. 2002), so as to simulate discrete dynamic system. The latter method was adopted in this study.

Time-delay neural network

Time-delay neural network is expanded from feed-forward network (such as multilayer BP network, RBF network and CMAC network) after TDL-Tapped Delay line was introduced. It is described as:

$$y_{NN}(k) = F[x(k), x(k-1), x(k-2), \cdots x(k-n); \\ y(k-1), y(k-2), \cdots y(k-m)] \quad (1)$$

In fact, time-delay neural network can solve dynamic problems by static network. The dynamic time-list can be solved by spreading the input signals simply according to time-coordinates. All the information spread is regarded as the input mode of the static network. In other words, time is added to the import of neural network as another input signal to approach the dynamic time-list system by the static network. In this way the time information of the neural network can be emphasized adequately. However, in fact, the input time-list only can be spread to limited dimensional input signals. The training method entirely uses the traditional BP algorithm because there is no feedback.

Identification structure of neural network

For the relation between the input-output of neural network (model P') and the identification system (model P), there are two identification structure: parallel linking type and series-parallel linking type, which separately corresponds to the parallel model (PM) and the series- parallel model (SMP) (Xu 1999; He *et al*. 2000). Parallel model (PM) can be realized by inner time-delay network or output feedback network, and it can be described Equation 2 and its structure is shown as Fig. 2

$$y_N(k) = NN_f[y_N(k-1), \cdots, y_N(k-n)] + \\ NN_g[u(k), u(k-1), \cdots, u(k-m)] \quad (2)$$

Where, y_N(k) is the output of identification model, NN_f and NN_g are the arithmetic operators gained by the neural network. The output at moment k relies on the input of itself and the output of the system before the moment k. Though the identification system is supposed steady, at the beginning of the study, it can not assure the y_N approaches y. If there is any error, it will produce accumulated domino effect during recurrent process. Thus the structure is possibly unsteady.

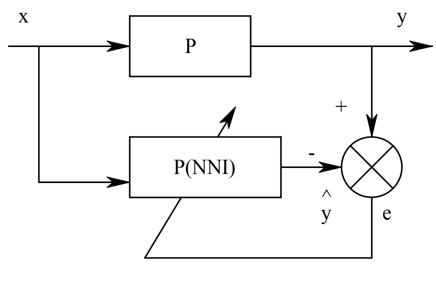

Fig. 2 Identification structure of parallel model

The series-parallel model (SMP) is obtained by time-delay neural network (Fig. 3) and described as Equation (3).

$$y_N(k) = NN_f[y(k-1), \cdots, y(k-n)] + \\ NN_g[u(k), u(k-1), \cdots, u(k-m)] \quad (3)$$

The output at moment k depends on the input and output of the system before the moment k. Because the series-parallel structure trains the network by regarding the input and output as the identification information synchronously, it is possible to assure the constringency and stability of the identification model. Thus this structure is frequently adopted.

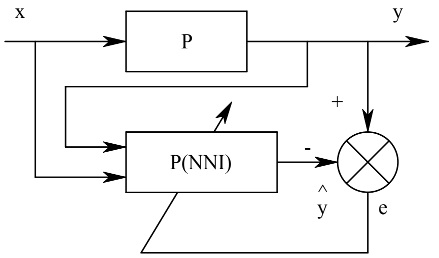

Fig.3 Identification structure of series-parallel model

A time-delay neural network structure of wood drying is shown as Fig. 4. *X* is the input, *y* the output of the network, *x*(*k*) and *y*(*k*) separately current state of variables; *x*(*k-1*), …, *x*(*k-n*) the historic state of the input vector, *y*(*k-1*), …, *y*(*k-m*) the historic state of the output vector, y_{NN} is the output of the neural network.

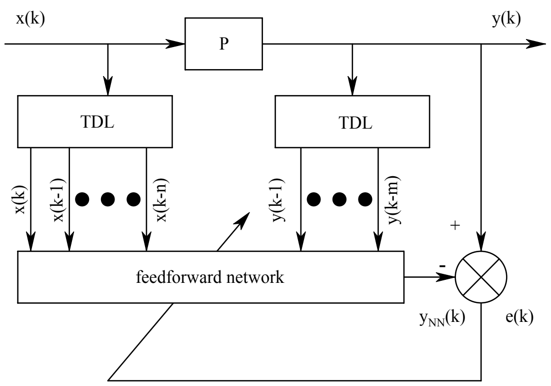

Fig.4 Identification structure of Time-Delay Neural Network

Modeling and simulation results

Temperature-humidity controlling model and the test results

The temperature-humidity controlling model revealed the relation among heat-valve, spray-valve, eliminating-damp-valve and temperature, humidity. For the identification problem of multi-input and multi-output, firstly the *m* and *n* are presumed based on precious knowledge. Then we obtained the most satisfying result by repeated presuming. Finally, *m* is 2 and *n* is 2 in Equation (1), thus there are 13 input nodes (3 current input states, 6 historic inputs, 4 historic outputs) and 2 output nodes in the feed-forward network. The training swatches are the data of *F. mandshurica* during one drying stage: 253 pairs of data including the temperature from 33.7ºC to 60.4 ºC (discontinuous rising), and the humidity from 20.9% to 7.1% (discontinuous falling). Training was made according to the neural network structure and algorithms mentioned. The parameters of the network are: the hidden nodes are 20, the study ratio is 0.7, the active function of the hidden cell and output cell is sigmoid function $f(x)=\frac{1}{1+e^{-x}}$, the initial weights are chosen randomly in 0 and 1, and the final study error (E) is 0.01. Repeated tests indicated that the above parameters can quicken the convergent speed of network and gained better approaching precision. At the end of the training, the weight matrix was obtained (input layer-hidden layer was 13×20, hidden layer-output layer was 20×2), that was input-output model. To validate the model's accuracy, 135 pairs of swatches data of *Fraxinus mandshurica* including temperature from 34.1ºC to 59.65ºC, humidity from 21.75% to 14.45%, and 217 pairs of swatches data of *Betula platyphylla* including temperature from 41.8ºC to 60.2ºC, humidity from 5.7% to 21.7%, were used to measure the states of the heat-valve, spray-valve and eliminating-damp-valve as inputs of the network to gain the outputs. The temperature and humidity curves of the network outputs (1) and actual system outputs (2) are separately shown as Fig. 5, Fig. 6, Fig. 7, and Fig. 8. The outputs approached the real values precisely except for separate swatches, which showed that the neural network model could preferably approach the real system.

Drying schedule model and the experimental results

To control wood drying by computer, the first problem to solve is how to transform drying schedule to a mathematical model. This study adopted moisture content schedule as the schedule to carry out computer control. The established model can supply the current drying temperature and humidity according to the current wood moisture content, these meant transforming the traditional stage drying to continuous drying, so as to improve quality and output and save energy. There are three stages during the process of wood drying: warm-up, uniform velocity drying (moisture content upwards the fibre saturation point) and decelerating drying stages (moisture content downwards the fibre saturation point). The moisture evaporation mechanism is not the same at each stage, and neither is the corresponding model. At uniform velocity drying stage, the drying curve (relating to both moisture content and time) is approximately linear, so the model is relatively simple; however, at the decelerating drying stage, the model is comparatively complicated, the schedule model of the decelerating drying stage is identified in this study.

While studying the model, *n* and *m* were also equal to 2 in Equation (1), which indicated there were 8 input nodes and 1 output node in the feed-forward network. The experimental species was *F. mandshurica*, using the 397 pairs of data as training swatches whose moisture content was from 30% to 15%. Training was made according to the neural network structure and algorithm mentioned. The parameters were chosen as: the hidden layer nodes were 15, the studying ratio was 0.8, the active function of the hidden cell and output cell was sigmoid function, the initial weights were chosen randomly in 0 and 1, the final error (E) was 0.01. At the end of training, the weight matrix was obtained (input layer-hidden layer was 8×15, hidden layer-output layer was 15×1). To validate the accuracy of model, we used 1108 pairs of data of another kiln as swatches whose moisture content was from 30% to 7%. That is, we used the data of temperature and humidity measured as inputs to get the output of the network---wood moisture content. The output of network (1) and the actual output of system (2) are shown as Fig.9, the error between network output and actual output is shown as Fig.10. With the help of these curves, we concluded that the neural network model could reflect the characteristic of the actual system effectively, and had good extrapolating ability.

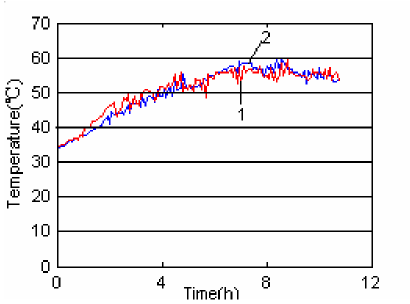

Fig. 5 Temperature comparison of network output and system output of *F. mandshurica*

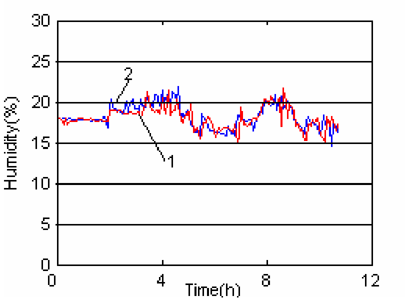

Fig.6 Humidity comparison of network output and system output of *F. mandshurica*

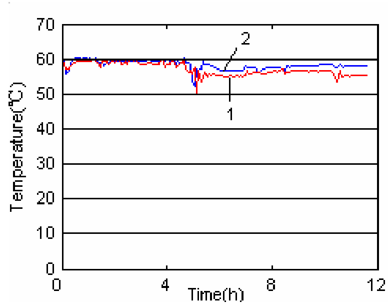

Fig.7 Temperature comparison of network output and system output of *B. platyphylla*

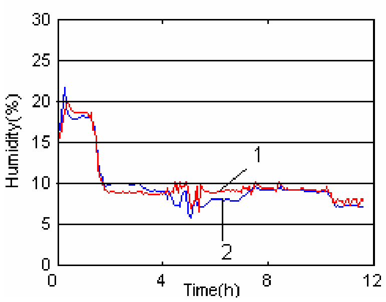

Fig. 8 Humidity comparison of network output and system output of *B. platyphylla*

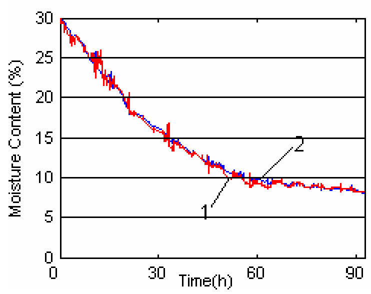

Fig.9 Drying curves of network output and system output

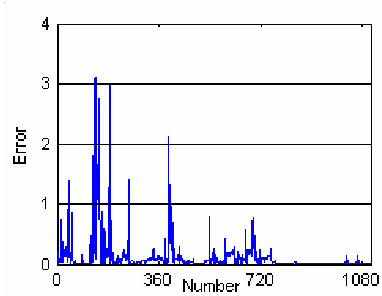

Fig.10 Error curve of network output and system output

Conclusions

Neural network was used at the identification of wood drying, with the advantages of parallel structure, parallel process, knowledge distributed storage, the ability of admitting error and self-adaptive. Considering actual situations such as lagged, parameters keeping invariable sometimes, and parameters jumping in determinate range, the time-delay neural network was adopted to realize the identification of drying dynamic system, so as to gain the drying control model (this model showed the relation between controlling signal and temperature-humidity) and the schedule model (this model showed the relation between wood moisture content and temperature-humidity) in this study. With the help of the simulation results, it can be concluded that the established models could reflect the characteristic of wood drying process effectively, which would provide advantageous and credible basis to realize fully automatic control and optimize drying schedule. It was of great importance for industry and application.

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