Modeling and Simulation Comparison of Real-time Monitoring of Particleboard Hot-Pressing Thermal Conductivity

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Abstract. In this paper we present a new measure method for real-time monitor of thermal conductivity of the hot-pressing process applied to particleboard. In the particleboard hot-pressing process, the monitoring data of thermal conductivity was modeled and forecasted based on BP neural network and ELM algorithm. The trained network can both accurately harmonize different sets of experimental data and precisely predict the dynamic indexes of thermal conductivity. Simulation results show that ELM prediction method not only overcome the shortcoming of the traditional real-time monitoring mechanism in precision but also avoid the problems of depending on a large number of data with high quality in existing BP network learning.

Keywords: Particleboard hot-pressing; thermal conductivity; BP neural network; ELM

1. Introduction

During the manufacturing of particleboard, it is difficult to online detect the relevant parameters because of the economic and technical reasons. There are some trouble in solving real-time control and realizing accurate measurement. But soft sensing technique is an effective method for solving above problems [1, 2]. BP neural network that has many merits is the most widespread applications in the soft sensing modeling [3, 4]. However, BP neural network has some disadvantages, such as slow convergent speed and easy convergence to the local minimum points, to limit the development and application. Extreme Learning Machine (ELM) is recently proposed a new Single-hidden Layer Feed forward Neural Networks (SLFNs) learning method [5]. This learning method has ensuring that the network has good generalization ability, while a great extent improved the feed-forward neural network learning speed and avoid many problems of learning method based on gradient descent [6, 7]. The scholars in the detection methods of particleboard hot-pressing are used thermocouple for temperature measurement sensors. They make a deep researched on the heat and mass transfer mechanism of the particleboard hot-pressing [8-10]. But their measurements are difficult to apply to actual production. This paper proposes a new predication model of hot-pressing soft sensing. This model through experimental measured data fits the relevant parameters of hot-pressing slab, such as thermal conductivity and thermal diffusivity. Simulation results show the correctness and effectiveness of the proposed method. So, the prediction method of real-time monitoring will be helpful to the later manufacturing of particleboard hot-pressing.

2. The Modeling of Real-Time Monitoring of Particleboard Hot-Pressing

Heat transfer approximation for the one-dimensional non-steady process in the process of the particleboard hot-pressing, the thermal conductivity equation is [11]:

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$$\frac{\partial T}{\partial t} = \frac{k}{C_p \rho} \cdot \frac{\partial^2 T}{\partial x^2} \tag{1}$$

Where t is the heat transfer time; T is the temperature of t times; k is the thermal conductivity; C_p is the density of particleboard; x is the location.

Order $\alpha = k/C_p\rho$, the formula (1) can be rewritten

$$\frac{\partial T}{\partial t} = \alpha \cdot \frac{\partial^2 T}{\partial x^2} \tag{2}$$

Where α is the thermal diffusivity of particleboard. As is shown in Figure 1, boundary conditions of the parallel plate is: $X = 0$, $X = 2R$, $T = T_n$ (Hot-pressing plate temperature). Initial condition is $t = 0$, then $T = T_0$ (The initial temperature of slab).

Figure 1.   Particleboard Profile

So (2) the solution is

$$\frac{T_n - T}{T_n - T_0} = \frac{2}{\pi}\sum_{a=1}^{n}[1-(-1)^a]\frac{1}{\alpha} \cdot (exp - (a\alpha\pi/k)^2 t)\,sin(a\alpha x/2R) \tag{3}$$

We can calculate the fourth parameter value just need to know three parameters among T_n, T_0, α and t, but (3) is very complex style to solve.

Artificial Neural Network (ANN) is a nonlinear modeling technique of rapid development and wide application in the late 1980s [12]. The most commonly used is the BP neural network model by the Rumelhart and McClelland proposed, it has a capability of non-linear large-scale parallel and distributed processing and function approximation, so it has been achieved the desired research results in many scientific fields. BP training method makes minimize the error sum of squares or smaller than a certain threshold between the actual output and expected output to the error through the reverse principle to constantly adjust the network weights. Usually it uses the method of gradient descent to iteratively adjust W: $W_k = W_{k-1} - \eta\frac{\partial E(W)}{\partial W}$, Where η represents the learning rate.

Based on gradient descent of BP have the following shortcomings [13]:

- Training is slow. Because it needs much iteration, so it is consuming a very long time;
- Parameters are very sensitive, we must select appropriate initial value of η and W in order to achieve the desired results. If the learning rate η is too small, the learning algorithm converges very slowly. However, if η is too large, the algorithm becomes unstable and diverges;
- Local minimum. As $E(W)$ non-convex, so it may fall into local minimum in the process decreased, and cannot achieve the global minimum;
- The transition fitting. It could lead to the transition fitting only with the objective of minimizing the training error when it trains in a limited sample.

In order to solve this problem, Huang et al proposed a new algorithm against Single-hidden Layer Feed forward Neural Network (SLFN) - Extreme Learning Machine (ELM) [14]. ELM needs set the appropriate hidden layer nodes, and input random assignment for input power and the hidden layer bias hidden layer, then obtain the output layer weights through the least square method. The whole process is completed in one time without iteration, and it is usually more than 10 times compared to the speed of BP.

There are N different samples (x_i, t_i), among, $x_i = [x_{i1}, x_{i2}, \cdots, x_{in}]^T \epsilon R^n$, $t_i = [t_{i1}, t_{i2}, \cdots, t_{im}]^T \epsilon R^m$, A hidden layer node number is $\widetilde{N}$, the unified model of activation function $g(x)$ is:

$$\sum_{i=1}^{\widetilde{N}} \beta_i\, g_i(x_i) = \sum_{i=1}^{\widetilde{N}} \beta_i\, g(a_i \cdot x_j + b_i) = \quad t_j, j = 1,2,\cdots,N \tag{4}$$

$a_i = [a_{i1}, a_{i2}, \cdots, a_{in}]^T$ is the input weights of consecutive ith node in the hidden layer in (4); b_i is the bias of the hidden layer node of ith; $\beta_i = [\beta_{i1}, \beta_{i2}, \cdots, \beta_{im}]^T$ is the output weight of the hidden layer nodes of ith; $a_i \cdot x_j$ represents the inner product of a_i and x_j. Excitation function $g(x)$ is "Sigmoid".

So the N-matrix equations can be written as $H\beta = T$, which

$$H(a_1, \cdots, a_{\tilde{N}}, b_1, \cdots, b_{\tilde{N}}, x_1, \cdots, x_N) = \begin{bmatrix} g(a_1 \cdot x_1 + b_1) & \cdots & g(a_{\tilde{N}} \cdot x_1 + b_{\tilde{N}}) \\ \vdots & \cdots & \vdots \\ g(a_1 \cdot x_N + b_1) & \cdots & g(a_{\tilde{N}} \cdot x_N + b_{\tilde{N}}) \end{bmatrix}_{N \times \tilde{N}},$$

$$\beta = [\beta_1^T, \cdots, \beta_{\tilde{N}}^T]_{\tilde{N} \times m}, T = [t_1^T, \cdots, t_N^T]_{N \times m} \tag{5}$$

$E(W)$ expresses error sum of squares between the expectations and the actual value, problem solving is to find the optimal value $W = (a, b, c)$ and to make the $E(W)$ is the minimum cost function, the mathematical model can be expressed as:

$$arg \min_{W=(a,b,\beta)} E(W) = arg \min_{W=(a,b,\beta)} \|\varepsilon\|^2,$$

$$s.t. \sum_{i=1}^{\tilde{N}} \beta_i \, g(a_i \cdot x_j + b_i) - t_j = \varepsilon_j, j = 1,2,\cdots,N \tag{6}$$

Which $\varepsilon_j = [\varepsilon_{j1}, \varepsilon_{j2}, \cdots, \varepsilon_{jm}]$ is the ith sample of the error.

Huang proposed ELM learning algorithm based on the following lemmas.

Lemma 1: For any N different samples (x_i, t_i), which $x_i = [x_{i1}, x_{i2}, \cdots, x_{in}]^T \epsilon R^n$, $t_i = [t_{i1}, t_{i2}, \cdots, t_{im}]^T \epsilon R^m$, N-node of hidden layer and an arbitrary interval infinitely mediated activation function for the $g: R \to R$, $a_i \epsilon R^n$ and $b_i \epsilon R$ is in the case of any assignment in SLFN, the formation matrix H of the hidden layer is invertible, that the equations have exact solutions, the cost function $E(W) = 0$.

Lemma 2: Given N different random samples (x_i, t_i), any small error e > 0, and infinitely differentiable in any interval of the activation function $g: R \to R$, there is always contains the $\tilde{N}(\tilde{N} \le N)$-node SLFN of hidden layer, and makes the error $E(W) \le e$ in the any case between $a_i \epsilon R^n$ and $b_i \epsilon R$.

Lemmas state that: As long as the hidden layer nodes are enough, SLFN will be able to approach any continuous function in the case of the input power randomly assign. In order to SLFN has good generalization performance, usually $\tilde{N} \le N$. The hidden layer matrix H is a definite matrix after the input power to be determined by the method of random assignment, so the training SLFN into calculations the least squares problem of $H\beta = T$. Compared with BP ELM need to adjust the parameters compare with BP are only the number of hidden layer nodes $\tilde{N}$, although there is no method to accurately estimate $\tilde{N}$ in the current, $\tilde{N} \le N$ is much smaller search, $\tilde{N}$ can be determined by cross validation in practical application.

The moisture content of the slab, board density, thickness and other factors have different levels of impact on the slab heating rate in the process of the particleboard hot-pressing, and these parameters are different in the operation period of time, and hardly to describe using the mathematical equations accurately. Therefore, the development of a reasonable thermal conductivity prediction model has a great significance for real-time accurate control of the particleboard hot-pressing.

We select the test data of the document [15] in the paper, and use 3 input nodes, 20 the hidden layer nodes, 2 the output node (thermal conductivity and thermal diffusivity) in the BP network and the ELM network prediction model. Particleboard hot-pressing neural network structure is shown in Figure 2.
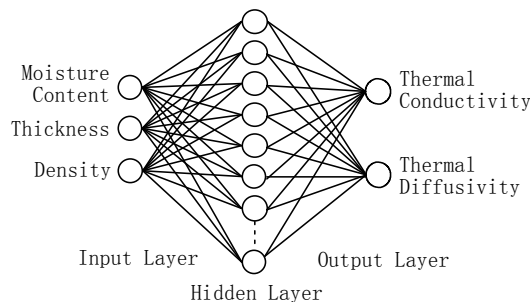

Figure 2.   Particleboard Hot-Pressing Neural Network Structure

As the three parameters of the input node have different spaces, in order to reduce the network's training time and reduce calculation errors, and prevent the neurons have reached over saturation, it is need to

normalize for the sample data of building, and make the data into [0, 1] interval. Meanwhile, the network output data must also be an anti-normalization, and make the data restore to the values of original physical space. Normalized and the anti-normalization followed by the following two equations [16]:

$$P_n = \frac{P_m - P_{min}}{P_{max} - P_{min}} \tag{7}$$

$$P_m = P_{min} + P_n(P_{max} - P_{min}) \tag{8}$$

Which, P_m is a set of data before normalized, P_n is a set of data after normalized, P_{max} is the maximum value of P_m, P_{min} is the minimum value of P_m.

3. Particleboard Hot-pressing Thermal Conductivity Predictive Evaluation

Here we compared the performance with BP and ELM through the experimental results. ELM algorithm source codes can be downloaded from Huang's personal home page directly. BP algorithm has been built-in Matlab neural network toolbox, can be used directly.

The hidden layer neurons use the S-tangent function tansig as the transfer function in the network model; the output layer neurons use the logarithmic function of S-type logsig as the transfer function. Its corresponding training function is trainscg, learning function is learngdm, the maximum training times of the network is set to 10,000 times, Training objectives error is set to 10^{-5}, learning rate is set to 0.1, and other parameters take default values.

Use 10 groups of training samples after normalized data to train the network. BP training error curve as is shown in Figure 3. As can be seen from Figure 3, BP network convergence has achieved the set of the goals accuracy after 1581 iterations, while the ELM algorithm can only need 111 iterations.
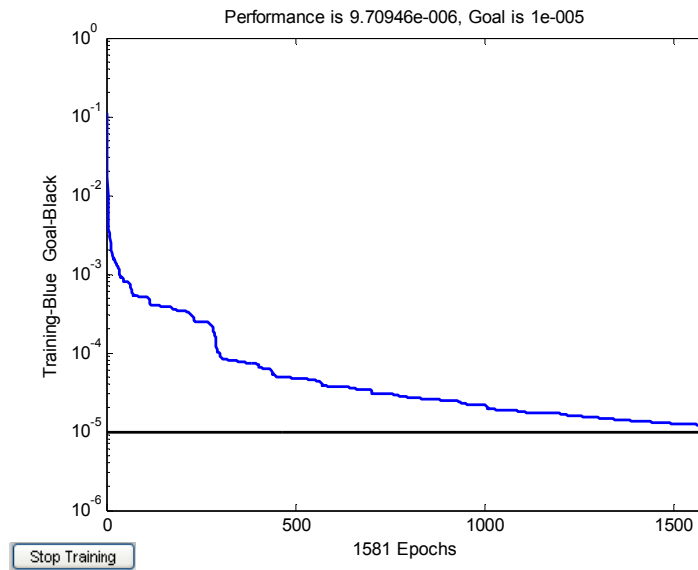

Figure 3. BP Neural Network Training Process Error Curve

We have verified the accuracy and reliability of the two kinds of neural network algorithm through the comparison and analysis among the BP neural network prediction value, ELM predictive value, and the test samples output value.

Through the predicted results of heat transfer coefficient and Transfer temperature coefficient as an example in the Performance of the particleboard hot-pressing, the results of comparison as is shown in Table 1.

Table 1 Prediction of Particleboard Hot-Pressing Thermal Conductivity

Number	Moisture Content (%)	Thickness (mm)	Density (kg/m3)	Thermal Conductivity (kcal/(m • h • ℃))			Thermal Diffusivity (1000/㎡/h)		
				Experiment	BP	ELM	Experiment	BP	ELM
1	4	14	700	0.137	0.1369	0.1368	0.23781	0.2379	0.2380
2	8	14	700	0.21	0.2141	0.2113	0.44577	0.4542	0.4449
3	15	14	700	0.216	0.2158	0.2159	0.52124	0.5217	0.5213

4	22	14	700	0.219	0.2190	0.2191	0.58808	0.5881	0.5881
7	8	12	700	0.224	0.2249	0.2242	0.478	0.4769	0.4770
5	8	16	700	0.200	0.2030	0.2021	0.42965	0.4268	0.4287
6	8	20	700	0.175	0.1729	0.1744	0.36982	0.3720	0.3696
8	8	14	500	0.165	0.1675	0.1659	0.3	0.3008	0.3001
9	8	14	600	0.197	0.1906	0.1953	0.34818	0.3436	0.3462
10	8	14	800	0.237	0.2344	0.2362	0.56862	0.5657	0.5674

Certain generalizations can be derived from comparison of test data results in table 1. The two predicted results and experimental values are very similar. The maximum difference of BP neural network is less than 0.032%, while the ELM only 0.0105%. The comparison results of prediction error are shown in Figure 4. We can prove that forecasts data of thermal conductivity of particleboard hot-pressing based on soft sensing are reliable and effective. It can achieve practical application accuracy.
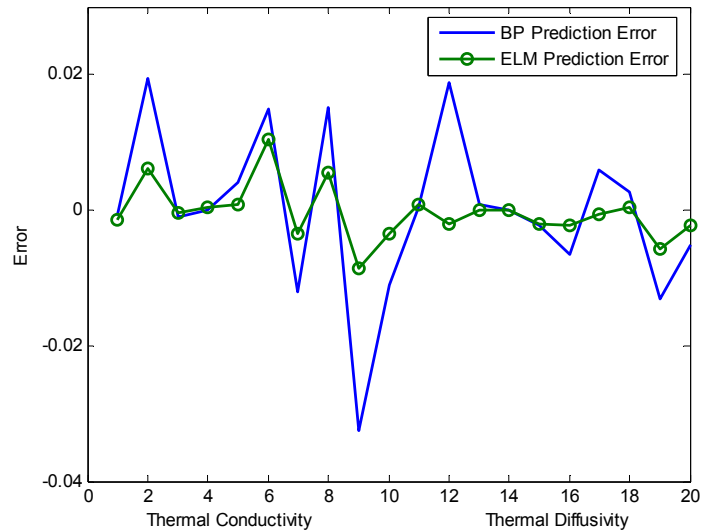

Figure 4.   Comparison of Prediction Errors of BP Neural Network and ELM

Analysis has proved that the prediction error of BP neural networks mainly caused by insufficient training samples. This factor to bring about the neural network training is not sufficient. In addition, during the ELM prediction, the reasonable choice of the experimental data is possible to minimize effect of the individual errors on the final predicted result. Figure 5 and Figure 6 are respectively histogram predicted comparison of thermal conductivity and thermal diffusivity.
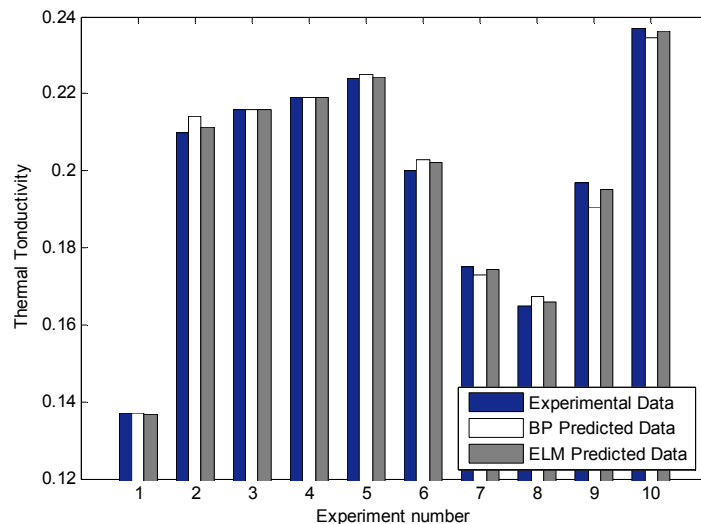

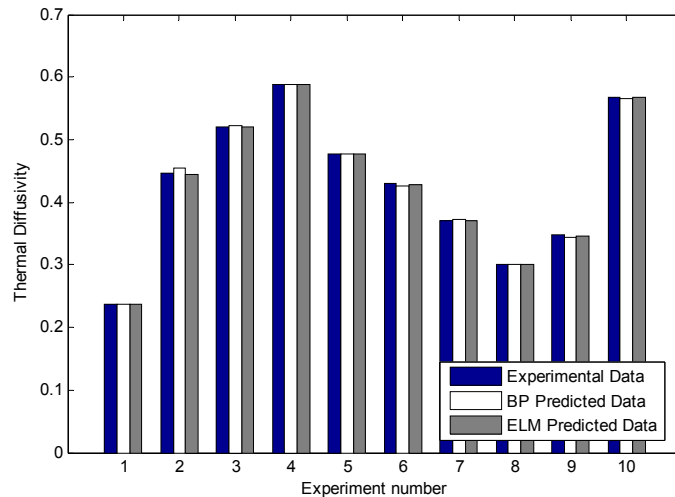Figure 5.   Predicted Comparison of Thermal Conductivity

Figure 6.   Predicted Comparison of Thermal Diffusivity

From Figure 5 and Figure 6 we can see this trend: In the first four sets of data, there were obvious positive correlations between the moisture content of the slab and thermal conductivity, thermal diffusivity. However, the thickness has positive correlation with thermal conductivity, thermal diffusivity in the middle of the three sets of data. The last three sets of data were obtained, density of panel pressed for thermal conductivity, thermal diffusivity also shows a positive correlation.

4.   Conclusion

Through the analysis of thermal conductivity during the particleboard hot pressing process, this paper presents a new neural network software measuring model. In this model, the inputs are moisture content of the slab, thickness and density of panel pressed; the outputs are thermal conductivity and thermal diffusivity. Experiment results and analysis showed that thermal conductivity prediction based on neural network is feasible and accurate in particleboard hot pressing. The artificial neural network has the perfect characteristics of self-learning. So this prediction model should be accurate and wide with more and more sampling date. It may be a valuable reference for the real-time monitoring deep study of particleboard hot-pressing in the future.

5.   Acknowledgment

6.   References

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