Study of Measurement and Inverse Prediction Methods of Heat Storage Efficiency for the Wood Heating Floor

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Abstract. Wood heating floor has been widely used today, but the performance evaluation system still needs to be further improved. The author's team developed the equipment for testing heat storage efficiency of wood floor. The basic principle is to calculate the heat storage efficiency of test samples by temperature field distribution which is measured by the sensor in closed cavity. Based on the study method for the inverse heat transfer problem, this paper proposed an inversion calculation method for the heat storage efficiency of the test sample according to the measured temperature field. BP neural network technique is adopted for the inversion calculation which is a nonlinear problem. Numerical model of the testing cavity is established with CFD software. The temperature field data of a single structure sample under different initial temperature range of 50 °C ~ 130 °C are obtained by simulation (different simulation conditions are divided by interval of 5 °C). After repeated training, a better neural network model is obtained. The average values of the calculation error and the fitting degree of the testing set are $MRE = 0.67\%$, $MAE = 19.68\%$, $MSE = 1.16\%$, $R^2 = 0.97$. It can be seen that, the well trained BP neural network model could predict out the heat storage of different wood floor samples, and provides support for the analysis of heat storage efficiency for wood heating floor.

Keywords: Wood floor · Heat storage performance · Heat transfer inverse problem · Neural network

1 Introduction

The wood heating floor has the advantages of thermal comfort, energy saving, environmental protection, which has been widely used in residential, office and public buildings in recent years [1]. The thermal storage efficiency of floor heating has an important influence on the thermal comfort degree, but there is no equipment and method to detect the thermal storage efficiency of the wood heating floor. The quantification of heat store efficiency for wood heating floor can enrich the evaluation system of different material floors, which is convenient for users to choose, and is also conducive to the promotion and application to wood heating floors. The author's research group has developed the

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testing equipment of the floor heat storage efficiency. The purpose of the equipment is to calculate the thermal storage performance of the test sample by the temperature field distribution measured by the temperature sensor inside the cavity. Because the heat transfer process inside the cavity is a composite heat transfer process, including heat conduction, convection and radiation heat transfer, causing the internal heat transfer process is very complex and difficult to quantify. It is difficult to solve this problem by forward heat transfer theory, so it can be transformed into the inverse problem of heat transfer in source seeking. The inverse problem is the relative positive problem, which usually has the characteristic of not being qualitative. Especially in the field of heat transfer, although the theory of forward heat transfer is very mature, but there are still many engineering problems in practical application cannot be solved by forward heat transfer theory, which leads to the research of inverse heat transfer problem in the ascendant. The current research focuses on heat transfer inverse problem include the determination of thermal physical parameters, the inversion of boundary conditions, the identification of heat source terms and the study of various inversion algorithms [2–4]. The inverse problem of heat transfer in source seeking is the identification of heat source item, mainly refers to the process of inversion or solution to the position or intensity of the heat source by collecting the research object's boundary or the internal quantity of the measured point temperature value.

Since most inverse heat transfer problems belong to non-linear problems and artificial neural networks is one of the effective measures to solve non-linear problems. It is a common mathematical method to use neural networks to solve inverse heat transfer problems. Ahamad and Balaji used artificial neural network to invert the intensity of three heat sources inside the ventilation chamber [5]. And the inversion results were verified by experiment and CFD simulation. Tahavvor and Mahmoud used artificial neural network to study the natural convection heat transfer and fluid flow around a cooling horizontal cylinder with constant surface temperature, and established the natural convection correlation of cooling horizontal cylinder [6]. In order to get the best position of the discrete heat source in the interior of the ventilating cavity, Rajeev Reddy and Balaji were studied by two-dimensional numerical simulation with artificial neural network and genetic algorithm [7]. Kumar and Balaji used artificial neural network and principal component analysis method to inverse the boundary heat flow problem of a two-dimensional square cavity with a known wall temperature [8]. Ozgur made a neural network analysis on the natural convection heat transfer problem of horizontal cylinders [9]. The results of network training are in good agreement with the experimental results. Compared with the study of inverse problem of single heat conduction process, the problem of natural convection heat transfer or radiation heat transfer, especially the inversion of the complex heat transfer process is more difficult.

In this paper, problem of testing and calculating the heat storage performance of ground heating floor is studied, that is, the heat transfer inverse problem inside the closed cavity with inner heat source in the field of thermal conduction, and the BP Neural network technique is used to calculate the heat source strength. Firstly, the numerical model of test cavity is established by CFD software, and the temperature field data of single sample structure under different initial temperature are simulated. Then the training set and test set are divided into neural network model, the neural network model is trained and validated. Finally, based on the neural network model, the temperature field data obtained by the test equipment are used to calculate the heat source strength, that is, the thermal storage efficiency of the test sample.

2 Detection device and Data Acquisition

2.1 The Structure of Cavity

As shown in Fig. 1, the testing equipment is divided into upper and lower cavities, the lower cavity is a temperature regulating cavity, where are heating and refrigeration device located. The upper cavity is test cavity, which is an adiabatic closed cavity. There is a channel between the upper and lower cavities that controls the opening and closing, makes both cavities to be connected and isolated. There are 150 temperature sensors evenly distributed inside the test cavity where is divided into six temperature-measuring layers in perpendicular direction, and each of layers has 25 temperature sensors, as shown in Fig. 2. The cavity size, spacing of temperature measurement layer and the test piece size are shown in Table 1.

Fig. 1. Detection cavity

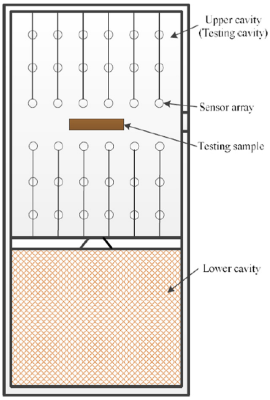


Fig. 2. Sensor array distribution

2.2 Materials

The laboratory is equipped with more than ten kinds of solid wood flooring of different kinds of materials. This experiment uses the solid wood flooring of four kinds of materials, such as *Betula platyphylla Suk.*, *Ash*, *Southwest birch* and *Eucalyptus*, which are more common in the market.

The wooden floor of different tree species is used in this research. For the convenience of operation, the wooden floor is processed into a test piece having a size of 100 × 60 × 15 mm. In this paper, the *Betula platyphylla Suk., Fraxinus mandshurica Rupr., Betula alnoides Buch. Ham. ex D. Don. and Xylosma racemosum* (*Sieb. et Zucc.*) *Miq.* are selected.

Table 1. Size information of the test device

Testing cavity size ($D \times H$)	Vertical spacing of upper cavity (d)	Distance of horizontal concentric circle(c)	Size of samples ($l \times w \times h$)
200 × 200 mm	20 mm	25 mm	100 × 60 × 15 mm

The test method is as follows: a wooden floor sample heated to the certain temperature is placed into the center of testing cavity. It is used as an internal heat source to release heat into the cavity space, and the temperature values of each measurement point in the closed space are collected in real time. The collected values are used as the basis data for calculating the heat storage efficiency of the test piece.

In order to obtain the temperature field distribution data of the test sample, the test cavity (Upper cavity) needs to be initialized, that is, the channel between the upper and lower cavity is opened, and the temperature control cavity (Lower cavity) is utilized. The heating and cooling device makes the temperature in the test cavity uniformly constant at 20 °C. Then, the passages between upper and lower cavity is closed, and wood heating floor sample heated to a certain initial temperature is pushed into the test cavity by the pneumatic device through inlet which is opened quickly. The inlet of testing cavity is closed. The before process is completed in a very short time (1.5 s) to reduce initial temperature fluctuations. The sample to be tested and pushing device are shown in Fig. 3.

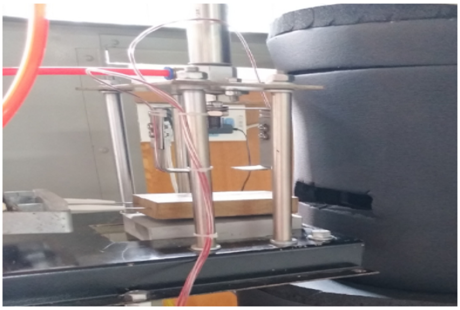


Fig. 3. Sample and push device

2.3 Data Acquisition

Bus type temperature sensors are selected in the test cavity. The controller consists of 12 digital inputs, 4 analog inputs, 9 switches, 2 analog outputs and 1 RS232 serial network communication. It can achieve the functions of collecting, transmitting and saving the temperature sensor array data, and also can realize the operation of terminal actuator, data collect and communication with the host computer.

3 Decomposition of Composite Heat Transfer Process

In order to clearly show the heat transfer relationship between each link in the compound heat transfer process in the test cavity. The test cavity can be simplified to a closed cavity with an internal heat source, as shown in Fig. 4. According to the basic laws of heat transfer, the thermal resistance network diagram of a closed cavity can be listed, as shown in Fig. 5.

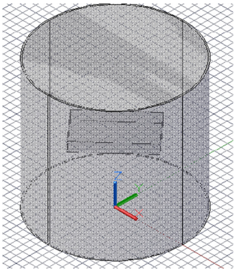


Fig. 4. Detection cavity

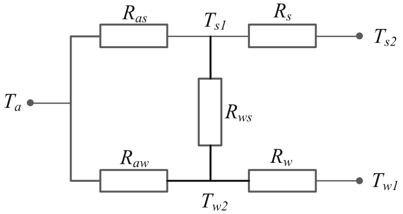


Fig. 5. Network diagram of thermal resistance

The meanings of the symbols in Fig. 5 are as follows:

T_s-Wall temperature of closed cavity, where, T_{s1}-The temperature of inner wall, T_{s2}-The temperature of outer wall;
T_w-Sample temperature, where, T_{w1}-The temperature inside the sample, T_{w2}-the temperature outside the sample;
T_a-Air temperature;
R_s-Thermal conductivity resistance of wall surface of closed cavity body;
R_w-Heat conduction resistance inside the sample;
R_{as}-Convective heat transfer resistance between air and inner wall surface;
R_{aw}-Convective heat transfer resistance between air and sample wall surface;
R_{ws}-Radiation heat transfers resistance between sample and wall surface of cavity.

According to the above thermal resistance network diagram, we can calculate the heat transfer of each part as shown below:

The heat conductivity of the sample itself:

$$Q_1 = (T_{w2} - T_{w1})/R_w \tag{1}$$

Heat conduction of the wall of the cavity body:

$$Q_5 = (T_{s2} - T_{s1})/R_s \tag{2}$$

Heat transfer between the sample wall surface and the air convection:

$$Q_2 = (T_{w2} - T_a)/R_{aw} \tag{3}$$

Convective heat transfer between the air and the wall of the cavity:

$$Q_3 = (T_{s1} - T_a)/R_{as} \tag{4}$$

Radiant heat transfer between the sample and the wall surface of the cavity:

$$Q_4 = (T_{s1} - T_{w2})/R_{ws} \tag{5}$$

According to the above formulas, if we want to obtain the heat transfer quantity of each part, we can calculate the heat resistance of each link only by calculating the heat resistance value of each link on the premise that the temperature of each link can be measured. Because the wood heating floor is porous medium material whose heat conduction coefficient value is affected by many factors, such as void ratio, moisture content and so on. These parameters are difficult to obtain, which causes its own heat resistance to be difficult to calculate theoretically. The convective heat transfer coefficient is affected by the distribution of air temperature inside the cavity and the size of the cavity, which increases the difficulty of calculating the heat transfer resistance. There are also many factors affecting the radiation heat transfer coefficient, which cannot be directly obtained by general theoretical calculation or measurement.

To summarize, it is not feasible to calculate the heat resistance of each part by the positive heat transfer theory and then to obtain the heat source strength. Therefore, the paper tries to solve the thermal storage performance of the test sample by solving the problem of heat transfer inversion.

4 The Inversion of Sample Regenerative Performance

4.1 Neural Network Model

Neural network BP algorithm has strong nonlinear fitting ability, and can calculate arbitrary nonlinear function with arbitrary accuracy [10]. The network algorithm is divided into two parts: information forward propagation and reverse propagation of error. The basic principle is that the information propagates from the input layer, the hidden layer to the output layer in turn, and then adjusts the weights and thresholds of the neurons in each layer according to the output error until the output results reach the expected value. The number of hidden layers and neurons has great influence on the prediction precision and computational efficiency of BP neural network. If the number of hidden neurons is too small, the computational efficiency can be improved, but the prediction accuracy will be reduced. On the contrary, the excessive number of neurons in the hidden layer will not only reduce the computational efficiency, but also may cause the problem of "excessive fitting" [11]. Therefore, it is necessary to compare the training of different structure models to obtain the best BP neural network model structure.

Because the conventional BP algorithm training speed is slow and also easy to appear the local minimization problem, this paper uses the numerical optimization algorithm Levenberfg Marguardt method. This algorithm calculates the convergence speed fast, and the stability is good, its weight and threshold adjustment formula is as follows:

$$X^{k+1} = X^k + S\left(X^k\right) \tag{6}$$

$$S\left(X^k\right) = \left(H^k + \lambda^k I\right)\nabla f\left(X^k\right) \tag{7}$$

Where $X(k)$ is the weight or threshold value of the time layer k; $H(k)$ is the Haisen matrix of the time layer of k; $f(X(k))$ is the objective function; I is the unit matrix (the same dimension as $H(k)$); $\lambda(k)$ is a positive number, and the program starts running with a larger value, which is gradually reduced to 0.

4.2 Inversion Calculation

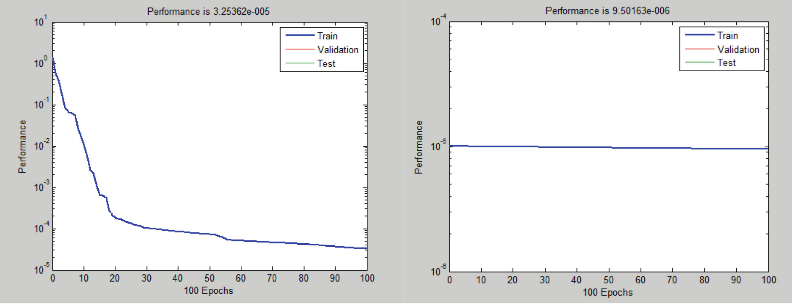
Because the wood heating floor belongs to the porous heterogeneous material which is a composite medium composed of solid skeleton and fluid, the void distribution is messy and the internal structure is complex. That cause the heat storage is difficult to be measured directly. In addition, the distribution of temperature field in the closed cavity will be changed by the change of the heat storage in the measured sample. Therefore, the distribution of temperature field can be measured, and then the heat storage of the tested sample can be inversed by neural network. However, the training process of the neural network model needs to know the input and output parameters, that is, the heat storage of the sample and the corresponding temperature field which cannot be realized by the experiment. It is necessary to simulate the temperature field of the samples with known heat storage by means of CFD simulation to obtain the sample training set and test set. Because the model of porous media is difficult to construct in CFD software, but the ideal sample of a single structure does not exist in the reality. So this paper uses Gambit 2.4 of CFD software to modeling and Fluent 6.3 of CFD software to simulate the different heat storage structure of a single sample temperature field. Then the neural network model training optimization, in which the temperature of the test as input, the sample of stored heat as output.

Since the thermal property parameters such as specific heat capacity and density are constant to the single sample of the structure in CFD simulation. According to the heat calculation formula $Q = \mathrm{cm}(T_0 - T_1)$ the sample heat storage amount Q and the temperature difference $T_0 - T_1$ are proportional. Letting the temperature $T_1 = 0$ °C before the sample is heated; the stored heat quantity Q is proportional to the temperature T_0 after the sample is heated (The initial temperature of the sample in the test chamber). Therefore, the sample initial temperature T_0 can characterize its stored heat quantity Q, and the heat storage performance of different samples can be used as a characterization parameter by the ratio of sample stored heat to sample temperature Q/T_0. The thermal property parameters are difficult to measure because of realistic porous media samples, and the ratio can also be used as the heat storage performance characterization parameter while the sample temperature is known.

1) Training and verification of neural network model.

In this paper, in order to obtain the obvious temperature field change of the air in the cavity, a sample initial temperature is set as a CFD simulation condition at intervals of 5 °C in the range of 50~130 °C under the premise that the sample thermal property parameters are constant and known. The initial temperature is the 50°C/60°C/70°C/80°C/90°C/100°C/110°C/120°C/130°C temperature field distribution data as the training set, the initial temperature is the

55°C/65°C/75°C/85°C/95°C/105°C/115°C/125°C temperature field distribution data as the test set. During the training process of the above neural network model, the temperature field data and the spatial coordinates of the measuring points are taken as the input, and the initial temperature as the output. However, in order to establish the inverse relationship between heat storage and temperature field, it is necessary to convert the initial temperature into heat storage by the heat calculation formula ($Q = \mathrm{cm}\Delta t$), and then take the heat storage as the final output of the neural network model.



a. The first stage **b.** The last stage

Fig. 6. Training curve

In order to avoid the accuracy of the analysis result caused by the large difference of order of magnitude in the inversion calculation, the data should be normalized to make each dimension in the same magnitude. By using the method of deviation standardization, the normalized values are mapped between [−1, 1] or [0, 1]. In the process of sample training, the strategy of step-by-step training is used, the total number of training times is 800 times, and 100 times per training is a stage, which stage outputs a weight and a threshold as the initial weight and threshold of the next stage. So the training model can achieve better training effect. As shown in Fig. 6, (a) for the first stage of the training curve; (b) for the last phase of the training curve, visible at the last stage, the performance of the model has stabilized at 10–5 levels, indicating that the model has been convergent.

The average relative error (*MRE*), the maximum relative error (*MAE*), the mean square error (*MSE*) and the fitting R^2 are introduced in this paper for the effective training model parameters, prediction performance of the model, the formulas for calculating the error and fitting degree are as follows:

$$MRE\ (\%) = \frac{1}{n}\sum_{i=1}^{n}\frac{|T_{ANN} - T_{CFD}|}{(T_{CFD-\max} - T_{CFD-\min})} \times 100 \tag{8}$$

$$MAE\ (\%) = Max\left(\frac{|T_{ANN} - T_{CFD}|}{T_{CFD-\max} - T_{CFD-\min}}\right) \times 100 \tag{9}$$

$$MSE\ (\%) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(T_{ANN} - T_{CFD})^2/(T_{CFD-\max} - T_{CFD-\min})} \times 100 \tag{10}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (T_{ANN} - T_{CFD})^2}{\sum_{i=1}^{n} (T_{ANN} - T_{ANN-mean})^2} \tag{11}$$

TANN is the predicted temperature value of the model; TCFD represents the temperature sample extracted from CFD; TANN-mean is the model to predict the average temperature. The Table 2 is the result of the prediction error of the test set. The average relative error $MRE = 0.67\%$, the maximum relative error $MAE = 19.68\%$, the mean square error $MSE = 1.16\%$ and the fitting $R^2 = 0.97$ are shown by averaging the error and fitting degree of the test set. It can be seen that the test set of each error is small; especially *MRE* and *MSE* values are around 1%. For most test sets, the R^2 value representing the accuracy of the model approximates 1, which shows the effectiveness of the neural network model.

Table 2. Training output error of the ANN model

Testing set	*MRE %*	*MAE %*	*MSE %*	R^2
55 °C	1.1695	15.5895	1.6775	0.8385
65 °C	0.7386	18.2635	1.2356	0.9905
75 °C	0.6052	19.6989	1.1213	0.9917
85 °C	0.5601	20.3211	1.1062	0.9921
95 °C	0.5321	20.9612	1.0254	0.9915
105 °C	0.5296	21.5012	1.0256	0.9913
115 °C	0.5923	19.3321	1.0451	0.9906
125 °C	0.6429	21.7658	1.0539	0.9913
Average value	0.6713	19.6792	1.1613	0.9722

5 Calculation of Heat Storage Inversion

Based on the trained neural network model, the temperature data and the corresponding coordinate values obtained from the test equipment for the thermal storage performance of wood heating floor can be input to predict the heat storage of the test samples. It is difficult to obtain the thermal physical parameters because of samples are porous heterogeneous materials, but the sample temperature is measurable. Therefore, each sample can be heated to a constant temperature and placed inside the chamber of the ground heating floor heat storage performance tester, then the temperature field distribution data can be measured. The measured temperature field data is used as the input of the neural network model which is trained in the preceding test, and then heat storage of the sample is inversely calculated. In this experiment, the samples of four kinds of floor heating floors of *Betula platyphylla Suk.*, *Fraxinus mandshurica Rupr.*, *Betula alnoides Buch. Ham. ex D. Don* and *Xylosma racemosum* (*Sieb. et Zucc.*) *Miq* are tested and retrieved. The results were shown in Table 3.

Table 3. Prediction results of heat storage performance

Testing sample	Initial temperature(T0)	Heat storage(Q)	Heat storage performance J/°C(Q/ T0)
Betula platyphylla Suk.	*70*	*4784*	*84*
Fraxinus mandshurica Rupr.	65	5493	98
Betula alnoides Buch. Ham. ex D. Don.	70	6061	101
Xylosma racemosum (Sieb. et Zucc.) Miq.	75	6792	103

Table 3 is established based on the prediction results of the test sample's heat storage and thermal storage performance gotten from the neural network model in the previous paper. It can be seen that the heat storage performance of the floor samples of four different materials is *Xylosma racemosum* (*Sieb. et Zucc.*) *Miq.* > *Betula alnoides Buch. Ham. ex D. Don.* > *Fraxinus mandshurica Rupr.* > *Betula platyphylla Suk.*. Thus, the neural network model established in this paper can effectively calculate the heat storage performance of the floor with different materials.

6 Conclusion

In view of the heat transfer problem in the thermal storage performance testing device of the ground heating floor, this paper calculates the regenerative performance of the sample by using the inverse problem method of the source heat transfer. The inversion is carried out by CFD simulation combined with neural network. Firstly, the corresponding CFD model is established, and the sample training set and test set of neural network are obtained by using the model. After repeated training, the test fitting degree of the neural network model can reach more than 0.97, which fully demonstrates the accuracy and credibility of the model. The prediction results show that the neural network model can be used to calculate the regenerative performance of wood heating floor, and the heat storage performance of different heating floors may be divided effectively, so as to provide theoretical and methodological support for the analysis and identification of the thermal storage performance to wood heating floors of different timber.

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