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Moisture diffusion analysis for timber structures based on physics-informed neural network

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ABSTRACT: The moisture content greatly affects the long-term creep and time-dependent deformation of timber structures. Therefore, monitoring and predicting the moisture content of timber structures is crucial. The variation of moisture content was obtained through long-term service experiments. An analysis method based on the physics-informed neural networks (PINN) is proposed. The moisture diffusion model based on Fick's second diffusion law and the boundary condition are incorporated in the PINN simulation. The coefficients in the model are also set as trainable parameters, which simplifies calculations while ensuring accuracy. Additionally, transfer learning was applied to achieve satisfactory prediction with small data samples, and the predicted results were compared with the experiments. The PINN-based method shows higher efficiency and coefficient independence compared with the previous numerical models.

KEYWORDS: timber structures, moisture diffusion, physics-informed neural networks (PINN), transfer learning

1 INTRODUCTION

The duration of load effect and exposure to the environment can cause time-dependent deformation, creep and damage accumulation in timber structures, leading to a decrease in mechanical performance under long-term application. Analysis models have been proposed to evaluate the performance degradation. Among the proposed methods, the moisture diffusion analysis is an important module since the moisture content of timber greatly influences the creep and time-dependent deformation. The diffusion models have been established based on Fick's second diffusion law[1]. However, when solving the second-order partial differential equation (PDE) of the model, the parameters determined through empirical equations may not be accurate, and the calculation can be complicated [2,3].

Deep learning has achieved great success in engineering problems. The physics-informed neural networks (PINNs) can embed the physics information into the deep learning models, making it more interpretable and extensible. Compared with classical numerical models, PINNs could avoid complex mesh generation and errors caused by the difference schemes, identify the unknown parameters contained in the models and tackle high-dimensional problems governed by parameterized PDEs, showing high efficiency in solving both forward and inverse PDE problems[4,5].

In this study, a moisture diffusion model was established based on PINNs. The boundary condition laws and the PDE of Fick's second diffusion law were embedded in the neural networks. The diffusion and surface emissivity coefficients, two important parameters in Fick's second diffusion law, were set trainable in the network. This allowed the model to avoid complex calculations and ensured the accuracy of the model. The prediction obtained through the model was validated and verified through long-term experimental results of post-tensioned CLT shear walls [6].

2 EXPERIMENT SETTINGS AND MODEL SIMPLIFACTION

Three post-tensioned CLT shear walls were monitored to study the changing mechanical properties under varied environment [6]. The dimensions of the experimental post-tensioned CLT shear wall elements are 1,500 × 1,100 × 175 mm (height × width × depth). To monitor the moisture content variation, moisture electrodes were

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installed at different locations of the CLT shear walls. Two penetration depths of moisture electrodes (i.e., 30 and 45 mm) were chosen. The moisture content of timber can be assessed by a moisture meter based on the electrical resistance method. The test positions were named Wx-xx, where the number following 'W' is the number of the shear wall, and the number following '-' indicates the penetration depths.

Since the panel edges possess a small area and are often covered by adjacent floors and walls in real structures, and the thickness of CLT walls was much smaller than the width and the height of CLT walls, the CLT walls are assumed to mainly absorb or desorb moisture perpendicular to the panel surface. The influence of the glue layers was not considered since the glue layer only had little effect on the moisture diffusion behavior [7]. The experiment settings and model simplification was shown in Figure 1.

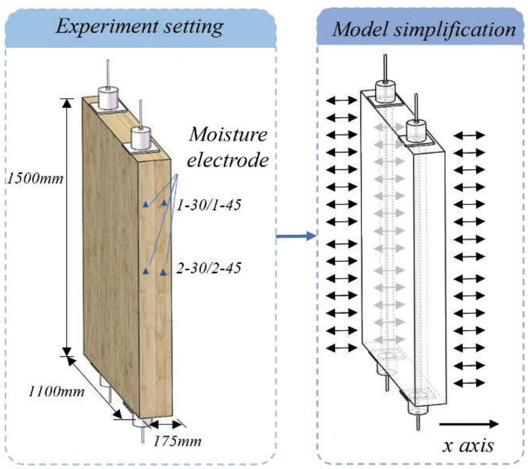

Figure 1 The experiment settings and model simplification

3 ESTABLISHMENT OF PINN MODEL

3.1 INSTRUCTION FOR THE PINN MODEL

The core of PINNs method is to convert the problems of solving partial differential equations to optimization problems. The general form of nonlinear partial differential equations can be expressed as:

$$\begin{cases} u + N[u,\lambda] = 0 \ , x \in \Omega, t \in [0, t_T] \\ u(x,0) = h(x) \ \ , x \in \Omega \\ u(x,t) = g(x,t), t \in [0, t_T], x \in \partial\Omega \end{cases} \tag{1}$$

Where, u is the solution of the partial differential equation, $N[u,\lambda]$ is a nonlinear operator with parameter λ, x and t are the spatial and temporal variables., Ω is the computational domain, t_T is the terminal time of analysis, $h(x)$ is the initial condition of the equation and $g(x,t)$ is the boundary condition of the equation.

A deep neural network $n(x,t;\theta)$ is established to approximate the solution u. The loss function defined as Equation (2) ,as shown below, can be calculated with the approximated results of u.

$$\begin{aligned} L(\theta,\lambda) := L_{u_0}(\theta,\lambda) + L_{u_b}(\theta,\lambda) \\ + L_f(\theta,\lambda) + L_u(\theta,\lambda) \end{aligned} \tag{2}$$

As shown in Equation (2), the loss function comprises of four parts. The $L_{u_0}(\theta,\lambda)$ is the residual of initial condition, $L_{u_b}(\theta,\lambda)$ is the residual of boundary condition, $L_f(\theta,\lambda)$ is the residual of partial differential equation, and $L_u(\theta,\lambda)$ is the residual of training data. The residual of the partial differential equation $L_{u_b}(\theta,\lambda)$ embeds the physical laws represented by the partial differential equation into the deep network. It enhances the generalization ability of the network.

Based on the constructed loss function, the deep network and the parameter of the equation λ are trained using the gradient descent method, as shown in Equation (3). The appropriate θ and λ can be found for minimizing the loss equation through training.

$$\begin{cases} \theta_{n+1} = \theta_n - \eta \nabla_\theta L(\theta_n, \lambda_n) \\ \lambda_{n+1} = \lambda_n - \eta \nabla_\lambda L(\theta_n, \lambda_n) \end{cases} \tag{3}$$

3.2 THE ESTABLISHMENT OF THE PINN MODEL

Moisture diffusion analysis

The numerical model for moisture transfer was developed based on Fick's second diffusion law given by Equation (4), describing the moisture diffusion under an unsteady state.

$$\frac{\partial u}{\partial t} = D_x \frac{\partial^2 u}{\partial x^2} \tag{4}$$

Where u is the moisture content of timber, t is time, x is the distance in the direction perpendicular to the wall surface, and D_x is diffusion coefficient.

Moreover, the boundary condition based on Fick's first diffusion law was shown in Equation (5), showing the moisture flux at the surface is related to the difference of the moisture content and the moisture content of both the environment and at the surface.

$$-D_x \cdot \nabla u = S(u_{air} - u_{surf}) \tag{5}$$

Where S is surface emissivity, u_{air} and u_{surf} are the moisture content corresponding to the ambient environment and moisture content at the surface of CLT walls, respectively. The u_{air} can be obtained by Equation

(6), a function of environmental relative humidity and temperature [8].

$$
\begin{aligned}
u_{air} &= \frac{1800}{W}\left(\frac{kh}{1-kh} + \frac{k_1kh + 2k_1k_2k^2h^2}{1+k_1kh+k_1k_2k^2h^2}\right) \\
W &= 330 + 0.452T + 0.00415T^2 \\
k &= 0.791 + 4.63\times10^{-4}T - 8.44\times10^{-7}T^2 \\
k_1 &= 6.34 + 7.75\times10^{-4}T - 9.35\times10^{-5}T^2 \\
k_2 &= 1.09 + 2.84\times10^{-2}T - 9.04\times10^{-5}T^2
\end{aligned} \tag{6}
$$

The diffusion coefficient D_x and the surface emissivity S can be obtained through Equation (7) and Equation (8) according to previous research [9,10].

$$D_x(u) = 2.0736\times10^{-5}e^{4u}m^2/day \tag{7}$$

$$S(u) = 2.7650\times10^{-3}e^{4u}m/day \tag{8}$$

The framework of the PINN model

Based on the numerical analysis model, the PINN model predicting the moisture content of the timber element is established and its frame work is shown in Figure 2. The model comprises of two main modules, the neural network and the physics constraint. The distance in the direction perpendicular to the wall surface (x) and time (t) were inputs of the neural network (*NN*). The moisture contents (u) at any given point and any time of the CLT shear walls were the output, obtained by the inputs trained in a fully connected neural network approximation function.

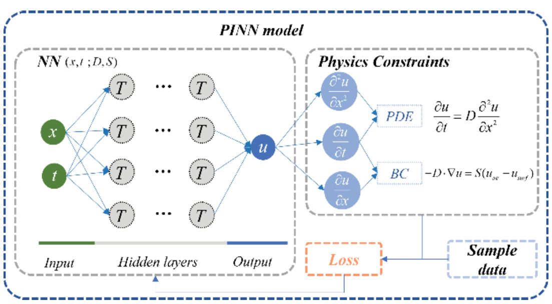

Figure 2 the framework of the PINN model

The *NN* module composed of three main layers: the input layer, hidden layers, and output layer. It can be defined by Equation (9)~(11), representing a mapping from the input layer $N^0 \in R^{din}$ to the output layer $N^{L+1} \in R^{dout}$. The first layer is the input layer, the input training data are a series of two dimensional space-time coordinates, and the format is shown as Equation (9). the w is the width of the CLT shear wall, and is 175 mm in this case; t_T is the terminal time of analysis, and is 368 days in this case. Equation (10) defines the hidden layer, where N^l is the nonlinear map for l^{th} hidden layer, W^l and b^l are the weights and biases of the transformation. They are also trainable, without being predefined. They are updated to be appropriate for each layer to achieve more accurate prediction. ϕ^l is the activation function acting on a vector element-wise. The output of each hidden layer is the input of the next hidden layer. The output layer is a fully connected layer, and the output of the prediction can be generated through Equation (11).

$$
\begin{gathered}
N^0(x,t) = (x,t) \in R^{din} \\
x \in \Omega = [0,w], t \in [0,t_T]
\end{gathered} \tag{9}
$$

$$N^l = \phi^l(W^l \cdot N^{l-1} + b^l) \tag{10}$$

$$N^{L+1} = \phi^{L+1}(W^{L+1}\cdot N^L + b^{L+1}) \in R^{dout} \tag{11}$$

The obtained output could then be used for the calculation of the loss function. The *NN* is trained by minimizing the loss function.

The activation function

The hyperbolic tangent function, shown as Equation (12), is chosen as the activation function in this research.

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{12}$$

The tanh activation function with a smooth gradient can prevent the abrupt gradient model training. Figure 3 shows the graph of the function and its gradient. As shown in the graph, the function outputs values in range (-1,1), and are symmetrical around zero, which helps faster convergence. Additionally, the tanh activation function has high gradient values around zero, resulting in higher updates in the weights of the network and big learning steps.

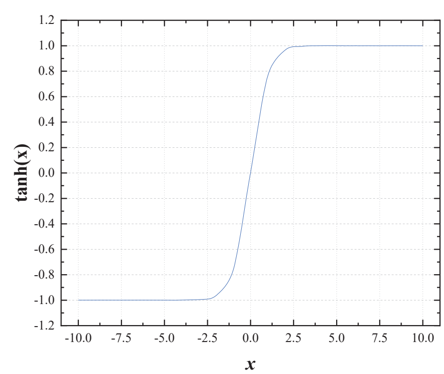

Figure 3 the graph of the activation function

The loss function

Equation (2) presents the composition of the loss function for a PINN model. In this research, the moisture content of two positions of the CLT shear wall was monitored, and the boundary condition can be calculated through Equation (5) and Equation (6). Thus, the residuals of the training data, the boundary conditions and the partial differential equations can be used for training the *NN*. However, the initial moisture content distribution of the

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CLT shear wall was unclear, the initial conditions can't be determined for training the *NN*.

The initial moisture content distributions of all the tested CLT shear walls were assumed to be the same in previous research and were 12.7% at all the points [6]. However, the monitored results present the moisture difference among the same positions of the three specimens. The moisture content at different points of the CLT shear walls also can't be the same. The assumed initial moisture content is inaccurate and will influence the prediction results.

Considering the available data, the loss function is established and it consists of three parts: the residuals of the training data L_u , the residuals of the boundary conditions L_{u_b} and the partial differential equations L_f , as shown in Equation (13).

$$L(x,t;D,s) = \omega_{u_b} L_{u_b} + \omega_f L_f + \omega_u L_u \quad (13)$$

Where, ω_{u_b} , ω_f and ω_u represents weights of each residual. Then the physical information residuals of the prediction results were obtained through the automatic differential algorithm and served as a regular term constraint in the loss function.

Furthermore, the diffusion coefficient (*D*) and surface emissivity (*S*) are related to the moisture content *u*. The moisture content *u* has different values, resulting in different values of the two parameters at different points. Thus, the determination of the two parameters requires a large amount of calculation. However, PINN shows great advantages in solving inverse problems. The optimal solution and parameter values can be obtained simultaneously by minimizing the loss function. In this case, the two parameters were set trainable, avoiding complex and inaccurate calculations based on empirical formulas. The gradient descent algorithm was applied to train the neural network connection weight parameters and deviation vectors until the residual reached the convergence condition.

3.3 TRANSFER LEARNING

The training data has characteristics of small sample and sparseness, leading to easy over-fitting, poor generalization ability and limited application scope of machine learning models in the engineering fields. This is also true for the case in this research. The transfer learning methods can apply the existing knowledge to a related new area, and get a good training model without requirements of abundant training samples. Figure 4 shows the schematic diagram of transfer learning.

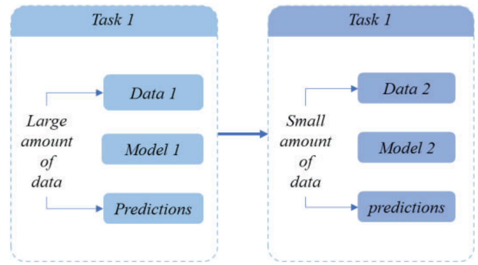

Figure 4 the schematic diagram of transfer learning

In this research, to achieve good prediction with fewer data samples. transfer learning was also applied. The NN was trained with one CLT shear wall first. Based on the trained network, models for predicting other walls were trained and verified.

4 TRAINING PINN

4.1 DATA PREPROCESSING

The input data used for training the PINN model contains the moisture content u_{air} and u , each corresponding to the ambient environment and the one monitored at specific positions. However, the two series of input data highly exceed the range (-1.7,1.7), where the activation function presents nonlinearity. Moreover, the u_{air} obtained through Equation (6) is higher than the moisture content with the timber. This will result in problems including the small weight of the NN, invalid neuron initialization, large gradient, improper learning rate and unequal roles of the input data in the analysis process.

As mentioned in section 3.2, big learning steps can be achieved around zero. Thus the data is preprocessed through normalization before training the *NN*.

4.2 NN SETTING AND THE APPLICATION OF TRANSFER LEARNING

The establishment of the *NN* has been illustrated in Section 3.2. The moisture diffusion analysis was first conducted on W1. A total of four hidden layers were contained, with three neurons in each hidden layer. Adam optimizer was applied, the learning rate was 0.001 and the number of iteration is 600.

The moisture content of the tested CLT shear walls were monitored over 1 year, the training model faces challenges of small data. However, the prediction models of the three shear walls have the same forms of input and output, only differing the training data, thus the transfer learning could achieve training the model with small data samples. 20% and 35% of the tested data of W1 were used to train the *NN* for predicting the moisture diffusion. Results indicate satisfactory results can be achieved when 35% of the tested data were used for training. The trained NN was then transferred to W2 and W3, only 15% of the tested data were used for training the *NN* for each shear wall.

5 PREDICTION RESULTS

The prediction results of the PINN model were compared with the numerical simulation and experimental results. The numerical simulation method was proposed in previous research[6]. Figure 5~10 shows the comparison between the two prediction methods and the experimental results of the two positions of each shear wall. Considering the different initial moisture content of the tested shear walls, the moisture content values rather than the relative values were compared.

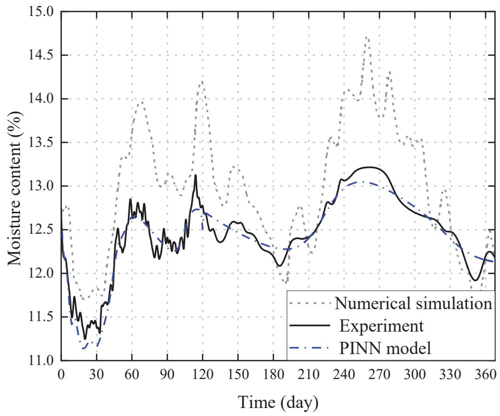

Figure 5 Results comparison of W1-30

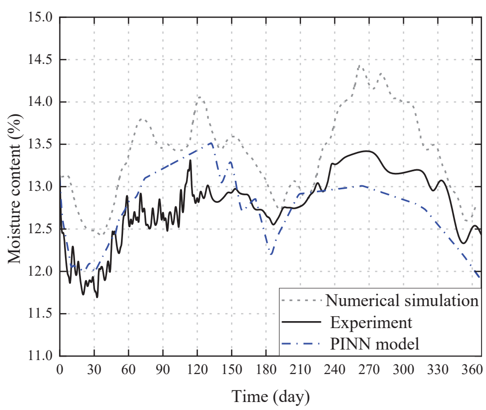

Figure 6 Results comparison of W1-45

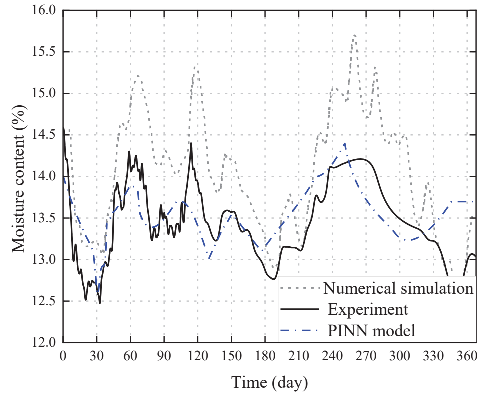

Figure 7 Results comparison of W2-30

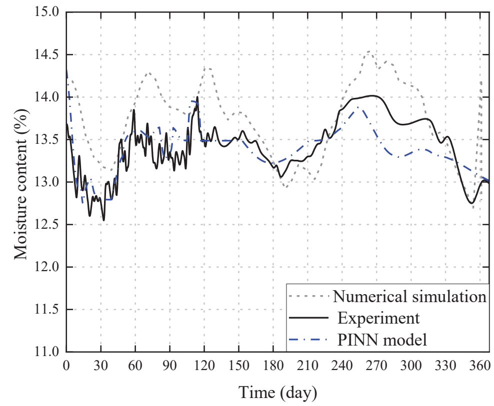

Figure 8 Results comparison of W2-45

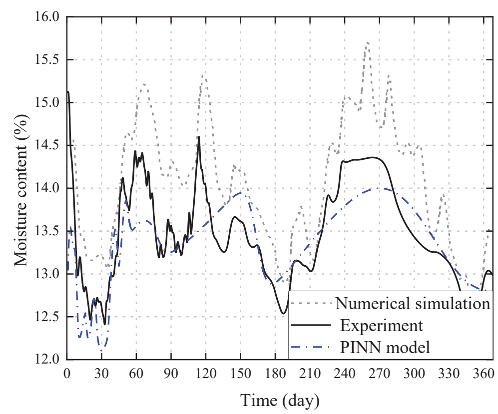

Figure 9 Results comparison of W3-30

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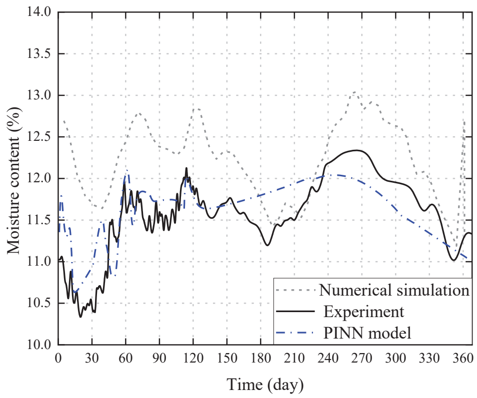

Figure 10 Results comparison of W3-45

The experiment data exhibited minor fluctuations resembling small saw-tooth patterns at early time points due to the intensive measurement of moisture content in the experiments. Although the other two methods didn't show the small saw-tooth patterns, the accuracy and effectivity were validated [6]. The MSE of different methods for each tested position were calculated, as shown in Table 1. The MSEs of the PINN model were all smaller than those of the numerical models, indicating the good performance and higher accuracy of the PINN model.

Table 1 The MSE of two methods

	Numerical simulation	PINN model
W1-30	0.458	0.063
W1-45	0.510	0.130
W2-30	0.555	0.132
W2-45	0.228	0.054
W3-30	0.499	0.139
W3-45	0.593	0.114

6 – CONCLUSION

A moisture diffusion model was established based on the physics-informed neural networks. The model was applied to three CLT shear walls, which have been monitored the moisture content for over one year. Considering the small data sample, the model was first trained with the tested data. of W1. Then transfer learning was applied, and the prediction models for another two shear walls were trained based on the *NN* trained for W1. The prediction results of the PINN model were compared with the results of the experiment and numerical model proposed in previous research. The PINN model can avoid complex mesh generation and determination of the unknown parameters contained in the models. Results show the PINN model agrees well with the experiments.

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