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ENHANCING UNDERSTANDING OF MOISTURE DIFFUSION IN WOOD: NUMERICAL APPROACH AND DIFFUSION PARAMETER OPTIMIZATION

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Abstract. Wood, an environmentally friendly construction material, is characterized by a critical attribute that significantly influences its mechanical properties and durability: its moisture absorption behavior. This study expands upon an existing one-dimensional model to develop an innovative two-dimensional numerical framework for simulating moisture propagation within wood. Utilizing the finite difference method, this approach offers a more detailed analysis of moisture behavior in wood structures. The research adopts an inverse modeling technique, integrating a simplex optimization algorithm programmed in VBA software. This algorithm is employed to deduce diffusion parameters from the evolution of moisture content over time. Focusing on the analysis of moisture diffusion parameters, the study examines both longitudinal and transverse directions in two temperate species (Beech and Fir) and two tropical species (Moabi and Ozigo). The findings provide insightful data on the hygroscopic behavior of these woods, revealing significant distinctions between temperate and tropical species. This research offers valuable information for the application of these wood species in construction and other fields, enhancing the understanding of their moisture-related properties.

Keywords: Wood, hygroscopic, moisture diffusion, finite difference method, Simplex algorithm.

1. INTRODUCTION

In a favorable environmental context promoting the utilization of materials with low embodied energy in civil engineering structures, wood emerges with significant advantages, even to the point of acting as a carbon sink. Although wood has always been a part of the construction material spectrum, it has frequently occupied secondary roles. Presently, the prospects of placing wood at the forefront face challenges stemming from its intricate characteristics (such as material orthotropy, viscoelasticity, thermo and hygro sensitivity, water diffusion, etc.), as well as durability concerns within humid settings and its susceptibility to cracking under dry conditions. Nonetheless, recent history has borne witness to unconventional designs that elevate wood to the role of primary structural material. Particularly in architectural endeavors, forward-thinking project leaders have made extraordinary choices by adopting wood as the central material for structural integrity.

Wood, as a hygroscopic material, is significantly influenced by moisture diffusion, which greatly impacts its durability [1], [2]. Acquiring knowledge about diffusion parameters is imperative for accurately modeling and forecasting the moisture changes in outdoor structures subjected to wetting and drying cycles. Additionally, this understanding helps identify the risks associated with low moisture levels, as cracking, as well as the risks associated with high moisture levels, such as biological attacks [3].

The hygroscopic properties of various wood types exhibit distinct characteristics along three axes: longitudinal, tangential, and radial. Notably, moisture diffusion occurs most rapidly along the longitudinal axis in comparison to the other two orientations [4]. The diffusion rate is governed by moisture diffusion coefficients, contingent upon both the wood's material composition and its prevailing MC. In the context of scientific investigation, inverse methods are employed [5-7], employing optimization algorithms to align numerical models with experimental data - a technique widely embraced within research endeavors. Among these methods, the gravimetric approach is a prevalent choice for monitoring temporal shifts in average MC. Nevertheless, the precision of computation outcomes, as derived from optimization algorithms, remains contingent upon the data's degree of conformity with the model.

The first section of the paper presents the theoretical foundations of moisture diffusion processes in wood materials. The following section introduces experimental setup examining the temporal variations in average MC of temperate and tropical wood species, considering different geometric dimensions, various orientations, and distinct relative humidity phases. Then, a numerical model simulating the moisture diffusion process in two dimensions based on finite difference methods is constructed and integrated into an inverse modeling framework using the Simplex optimization algorithm to determine the moisture diffusion coefficients. Next, datasets are employed for analysis to assess the minimum information requirements necessary to ensure the accuracy of the optimized model. The final part comprises conclusions and a discussion of the computed results pertaining to the longitudinal and transversal moisture diffusion coefficients for the studied wood types.

2. THEORETICAL BACKGROUND

The mass diffusivity is a fundamental property that describes the capacity of a substance to facilitate the movement of water from areas of higher moisture to areas of lower moisture. In the case of wood, which falls within the hygroscopic realm, this pertains to the migration of water vapor through the voids between cells and the movement of bound water within the cell walls, driven by variations in MC. The diffusion equation, known as the first law of Fick [8], establishes a mathematical relationship between the gradient in MC and the resulting flux. In its uniaxial form, it can be represented as follows:

$$j = \lambda \frac{dw}{dx} \tag{1}$$

j is the mass flux (kg/m²s);

λ is the diffusion coefficient (kg/ms);

w is the MC (kg/kg);

x represents the direction of diffusion (m).

In order to highlight the time evolution of the induced flux, Fick established a second law by using the principle of mass conservation [9]–[11]. This law states that the sum of the incoming and outgoing mass fluxes from any volume enclosed by a closed surface is equal to the rate of change of the quantity of matter present in the volume. When expressed in terms of MC, this law can be written as follows:

$$\frac{dw}{dt} = div\left(\overline{\overline{D_w}}.\vec{\nabla} w\right) \tag{2}$$

The tensor of moisture diffusion $\overline{\overline{D_w}}$ is diagonal in the coordinate system associated with the principal directions of orthotropy. The components of the tensor in the longitudinal (D_w^L), radial (D_w^R), and tangential (D_w^T) directions are represented by:

The non-linearity of the MC diffusion can be introduced as follows:

$$D_w^{\alpha}(w) = D_0^{\alpha}.\exp(k_\alpha w) \text{ with } \alpha \in \{L, R, T\} \tag{3}$$

D_0^{α} is the diffusion coefficient in the anhydrous state of the material (m^2/s), and k_α is a non-linearity parameter [12]. The diffusion coefficient value showed a notable disparity between the longitudinal and transversal directions [13], [14].

Hydraulic convection reflects the exchanges that occur between the material and the external environment through an exchange interface. The hydraulic fluxes prevailing at this interface are established either by condensation (in a more humid external environment) or by evaporation (in a more humid internal environment). Therefore, during operation, the moisture state at the core is conditioned by the hygroscopic equilibrium prevailing at the exchange surface.

The hydraulic flux is calculated using a convection coefficient that establishes a proportionality between the hygroscopic equilibrium at the surface and the relative humidity of the ambient air:

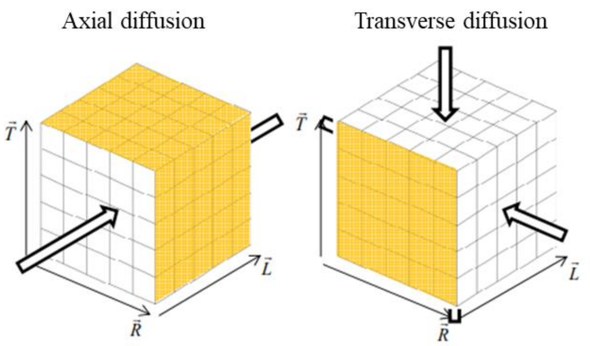
$$j = S.\left(w_{surf} - w_{eq}\right) \tag{4}$$

S is the surface exchange coefficient (m/s) [15], [16], w_{surf} is the MC prevailing at the wood surface, and w_{eq} is the hygroscopic equilibrium MC equivalent to the relative humidity of the ambient air. The surface emission coefficient decreased with relative humidity and increased with temperature [16]. This equilibrium MC is derived from the sorption isotherms [17].

3. EXPERIMENTAL PROTOCOL

The study conducted within the research by Manfoumbi N. [18] is predicated upon four discrete timber species, specifically the tropical varieties Baillonella toxisperma (Moabi) and Dacryodes buettneri (Ozigo), along with the temperate types Fagus sylvatica (Beech) and Abies alba (Fir). The primary aim of these experiments was to investigate and compare the sorption properties of these species under controlled conditions of humidity and temperature. The analysis was conducted in two directions: longitudinally, which involved studying unidirectional diffusion, and transversely, which involved examining simultaneous diffusion along both radial and tangential directions. This scientific investigation contributes to the understanding of the moisture sorption behavior of these selected timber species in different environments.

Two types of geometries measuring 15x15x15 mm^3 and 30x30x30 mm^3, as shown in Figure 1, were selected to obtain two distinct ratios between volume (mass diffusion) and surface area (surface exchanges) in order to facilitate their characterization. The samples were weighed and then sealed with a thin layer of paraffin to impose a diffusion direction for each group: longitudinal (L) or transverse (RT), as shown in Figure 1.



a) 4 waterproof sides b) 2 waterproof sides

Figure 1. Two types of geometries of cubic samples [18].

The choice of these geometries results from a compromise between, on the one hand, the diffusion rate that should not be too fast in order to measure masses at regular and well-spaced time intervals, and on the other hand, the time required for experimentation, which should not be too long either. The ratio between volume and exchange surface varies from one geometry to the other, ranging from a 1:2 ratio.

To account for non-linear diffusion, the experimental protocol was designed with varying relative humidity levels during both the adsorption and desorption processes. Initially, all samples (Figure 2c) including 48 samples per species (24 samples per dimensions) were conditioned in a dry environment set at 20°C and 30% relative humidity (RH). The sorption test involved placing these samples inside a climatic chamber (Figure 2b), subjecting them to two humidity ranges during the adsorption phase (65% RH and 90% RH) and the desorption phase (65% RH and 30% RH), while maintaining a constant temperature of 20°C. The average MC was measured by weighing the samples throughout the test (Figure 2b). Additionally, the anhydrous mass was determined by drying the samples in an oven at a temperature of 103°C.

(a) Climatic chamber (b) Balance (c) Samples

Figure 2. Experimental setup [18].

The variation in mass over time and the mass after drying allow for the calculation of MC changes over time for each test sample. Within the scope of this research, the authors used the average curve of MC of 24 samples (for each species and dimensions) over time to apply it to the computational model introduced in the following section. Figure 3 provides an example of the average curve of MC variation over time for Beech samples of dimensions 15x15x15mm^3 and 30x30x30mm^3.

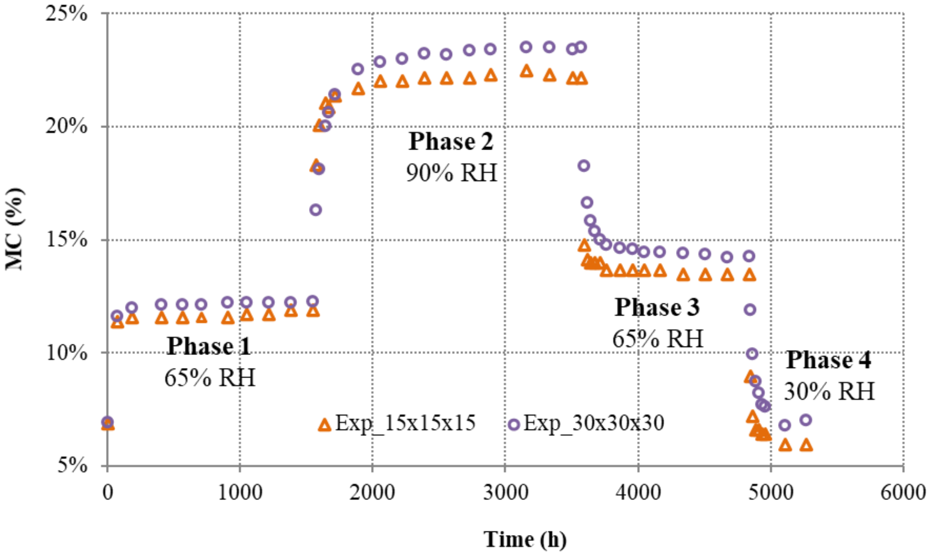


Figure 3. Average curve of MC variation over time for Beech samples of dimensions 15x15x15mm^3 and 30x30x30 mm^3.

4. NUMERICAL APPROACHES

4.1. Two-dimensional moisture diffusion modelling

Kucharczyk A. et al [14], Nguyen et al [19], Simpson W. T. et al [20] has constructed a model using the finite difference method to simulate the one-dimensional moisture diffusion in wood. This computational approach has been validated through comparisons with analytic method and finite element method [19], [21]. The advantage of this method lies in its simple calculation formulas, which significantly reduce the computation time.

In this research, moisture diffusion is simulated using finite difference methods in a two-dimensional moisture diffusion. The specimen is discretized into element of uniform thickness $m \times n$ (as shown in Figure 4), with each discrete point representing a specific MC value.

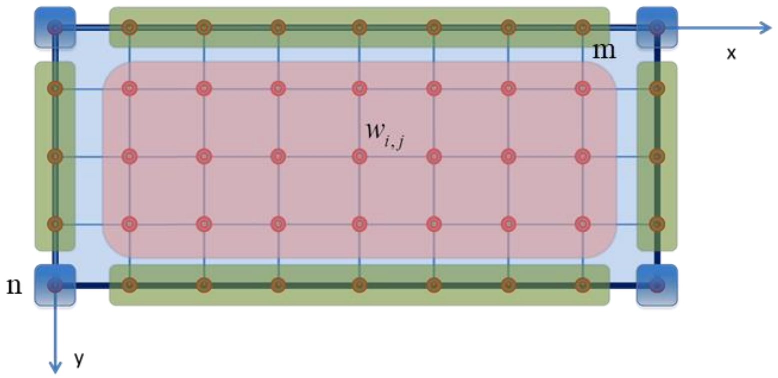


Figure 4. Samples discretization.

The subsequent step involves determining the distribution of moisture over both space and time within the sample. The sample is initially conditioned with a MC of w_{ini}. Starting from t = 0, an ambient virtual MC w_{eq} is applied to the non-sealed face. To discretize time, an explicit Euler scheme is utilized with a designated time step τ. The MC at position (i, j) and time t is denoted as $w_{i,j}^{t}$, and through temporal integration, The evolution of MC at position (i, j) can be observed as follows:

$$\begin{aligned} w_{i,j}^{t+\tau} = w_{i,j}^{t} + \frac{D_{0x}\tau \exp(kw_{i,j}^{t})}{4\Delta x^2}\left\{k(w_{i+1,j}^{t} - w_{i-1,j}^{t})^2 + 4(w_{i+1,j}^{t} - 2w_{i,j}^{t} + w_{i-1,j}^{t}\right\} \\ + \frac{D_{0y}\tau \exp(kw_{i,j}^{t})}{4\Delta y^2}\left\{k(w_{i,j+1}^{t} - w_{i,j-1}^{t})^2 + 4(w_{i,j+1}^{t} - 2w_{i,j}^{t} + w_{i,j-1}^{t}\right\} \end{aligned} \tag{5}$$

On the surface:

$$w_{n,j}^{t+\tau} = w_{n,j}^{t} + 2D_{0x}\tau \exp(kw_{n,j}^{t})\left[\frac{w_{n-1,j}^{t} - w_{n,j}^{t}}{\Delta x^2} + \frac{w_{n,j-1}^{t} - 2w_{n,j}^{t} + w_{n,j+1}^{t}}{\Delta y^2}\right] + \frac{2S_x\tau(w_{eq} - w_{n,j}^{t})}{\Delta x} \tag{6}$$

$$w_{i,m}^{t+\tau} = w_{i,m}^{t} + 2D_{0x}\tau \exp(kw_{i,m}^{t})\left[\frac{w_{i,m-1}^{t} - w_{i,m}^{t}}{\Delta x^2} + \frac{w_{i,m-1}^{t} - 2w_{i,m}^{t} + w_{i,m+1}^{t}}{\Delta y^2}\right] + \frac{2S_x\tau(w_{eq} - w_{i,m}^{t})}{\Delta x} \tag{7}$$

In the corner position:

$$w_{n,m}^{t+\tau} = w_{n,m}^{t} + \exp(k w_{n,m}^{t}) \left(D_{0x} \tau \frac{w_{n-1,m}^{t} - w_{n,m}^{t}}{\Delta x^2} + D_{0y} \tau \frac{w_{n,m-1}^{t} - w_{n,m}^{t}}{\Delta y^2} \right) + (w_{eq} - w_{n,m}^{t}) \left(\frac{S_x \tau}{\Delta x} + \frac{S_y \tau}{\Delta y} \right) \tag{8}$$

Through knowledge of the MC value at time t, one can predict the MC towards the edge at time $t + \tau$. Once the initial MC profile of the sample is known at time $t = 0$, the MC for each element at the subsequent time $t + \tau$ can be calculated. The MC of each element is updated step by step for a given time. Ultimately, an iterative time process is employed to update the temporal distribution of MC.

Within the framework of this study, the theoretical equations mentioned earlier are utilized to develop a direct diffusion model programmed in VBA code. When the diffusion parameters, initial state, and equilibrium state of a sample are known, this direct model enables the representation of the average MC evolution, the variation of MC at each position throughout its thickness over time, and also the spatial MC profiles at a specific moment of investigation.

4.2. Diffusion parameters optimization

Nguyen T.A. et al [19] also developed an inverse model to determine the moisture transfer coefficients based on the Simplex optimization method [19], [22], [23]. The Simplex algorithm is used to minimize the difference between experimental data and the results obtained through the finite difference method. Among the minimization algorithms available in the literature, the Simplex algorithm is suitable for this case due to its advantage of not requiring the derivation of the objective function. In situations with a small number of parameters to be identified, this minimization technique exhibits better performance and faster computation compared to other methods .

Firstly, arbitrary input parameters are chosen, which can be initially determined empirically or referenced from bibliographic data. In the event that the discrepancy between experimental and numerical data is not minimal, the Simplex algorithm will recalculate a new set of parameters until achieving the minimum discrepancy between experimental and numerical data in terms of least squares. In this study, the algorithm is implemented in VBA code integrated with the Excel.

4.3. Objective function and stopping criteria

The objective function is defined by the least squares norm, which is the sum of the squares of the differences between the measured MC $\bar{w}_{mes}$ and the one calculated by the direct model $\bar{w}_{num}$.

$$f = \frac{1}{N} \times \sqrt{\sum_{i=1}^{N} \left(\bar{w}_{num}(t_i) - \bar{w}_{\exp}(t_i) \right)^2} \tag{9}$$

t_i: denotes the i^{th} measurement time, N is the total number of measurements

Commonly, the stopping criterion is proposed based on the objective function by considering a minimum value. Nevertheless, the value of the objective function heavily relies on the experimental data, and in cases of substantial deviation, the algorithm may not converge. Hence, an alternative criterion is proposed and applied, which considers the variation of parameters between two successive iterations. In this scenario, a normalized convergence criterion is chosen to assign equal importance to each model parameter.

However, the main drawback of this criterion is the risk of identifying local minima. An investigation of the parameter identification path is thus essential. The principle involves initially selecting several parameter vectors sufficiently distant from each other to ensure that the algorithm converges to the same solution. When two inversion paths converge to the same minimum of the objective function, the parameters are identified. Otherwise, it is necessary to randomly remove another starting solution and verify the value of the objective function. Although this process may take more time, it helps avoid local solutions and enhances the robustness of the inversion method.

5. RESULS AND DISCUSSION

5.1. Selection of experimental data for feeding the inversion algorithm

In this section, the detailed analysis is conducted only on the results obtained for Beech. Three inversion approaches are discussed. The first approach focuses on identifying parameters for each relative humidity level separately. The second approach involves a global identification that considers all the relative humidity levels collectively. Lastly, to incorporate scale phenomena, a multi-scale identification approach is proposed.

5.1.1. Identification on a level-by-level basis

The identification process focuses on each individual level by considering the initial equilibrium MC of each phase, which is assumed to be reached at the end of each level. The parameters to be identified include the anhydrous diffusion coefficient D_0, the non-linearity coefficient k, and the surface exchange coefficient S. It is worth noting that the boundary conditions for moisture exchange allow for the direct imposition of equilibrium humidity, which leads to the assumption of an infinite surface exchange coefficient.

In these conditions, the algorithm does not converge definitively. During the adsorption phases, a smaller value of the objective function is obtained when the anhydrous diffusion coefficient D_0 is higher and when the non-linearity coefficient k is negative. Conversely, during the desorption phases, the objective function value is smaller when D_0 is lower and k is positive (Figure 3). After 40 iterations, the algorithm is manually terminated. The identification results are presented in Table 1.

Table 1. Diffusion parameters identified on a level-by-level basis.

Phase	D_0 (m^2/s)	k	f
1	5.01×10^{-9}	-19.01	3.27×10^{-4}
2	8.73×10^{-9}	-18.33	4.36×10^{-4}
3	4.57×10^{-12}	28.05	3.75×10^{-4}
4	1.26×10^{-10}	17.14	4.51×10^{-4}

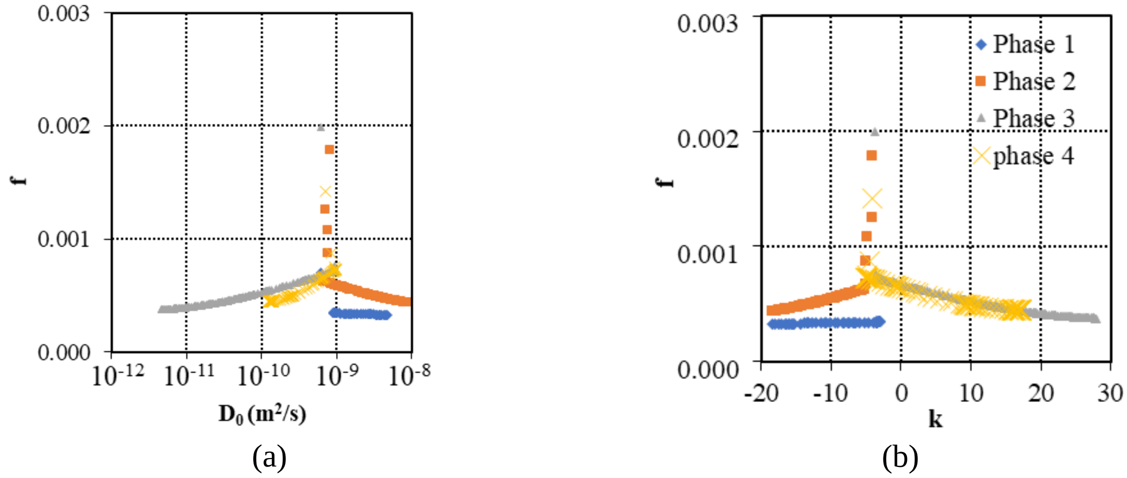


Figure 3. Identification path of diffusion parameters on a level-by-level basis.

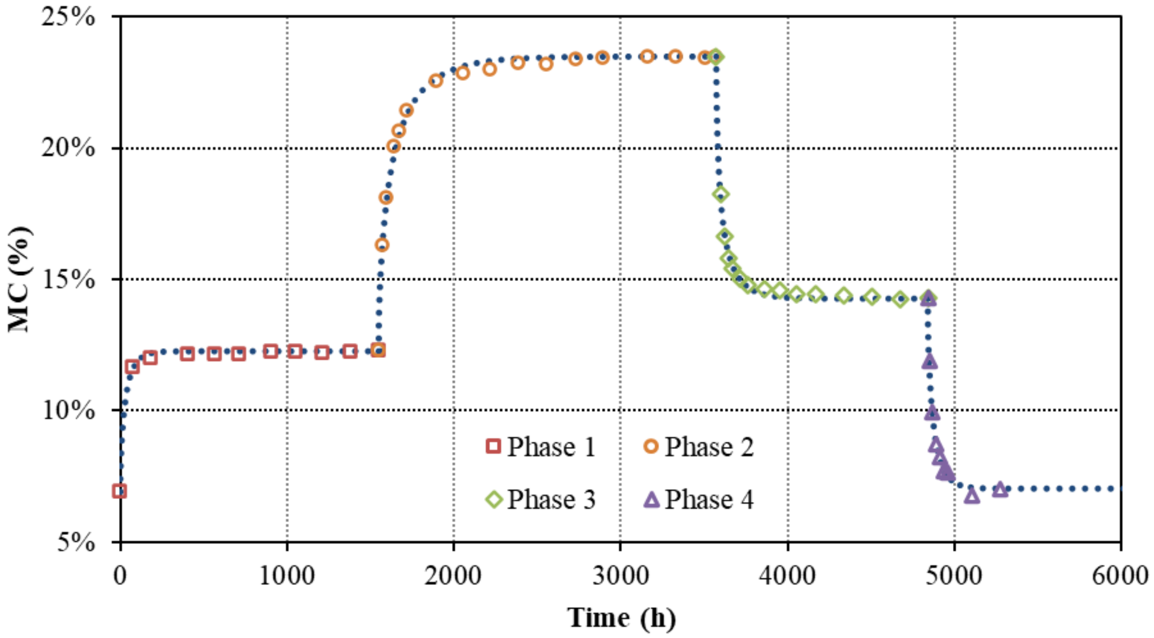


Figure 4. Evolution of experimental and numerical MC with diffusion parameters identified by level-by-level basis.

The diffusion coefficients obtained display a pronounced reliance on the chosen level, which contradicts the inherent nature of diffusion properties, as depicted in Table 1. However, Figure 4 illustrates a noteworthy agreement between the simulation and experimental MC. The observation implies the presence of numerous sets of moisture diffusion parameters that can fulfill the measured moisture values. In simpler terms, the available data lacks adequacy to precisely determine the diffusion parameter through inverse modeling.

5.1.2. Multi-phases identification

To determine diffusion parameters common to each level, the objective function is calculated using all experimental data from the four levels. In order to test the robustness of the method, two sets of initial parameters converge to the same final solution (Figure 5). Therefore, it can be concluded that the identification results are optimized (Table 2).

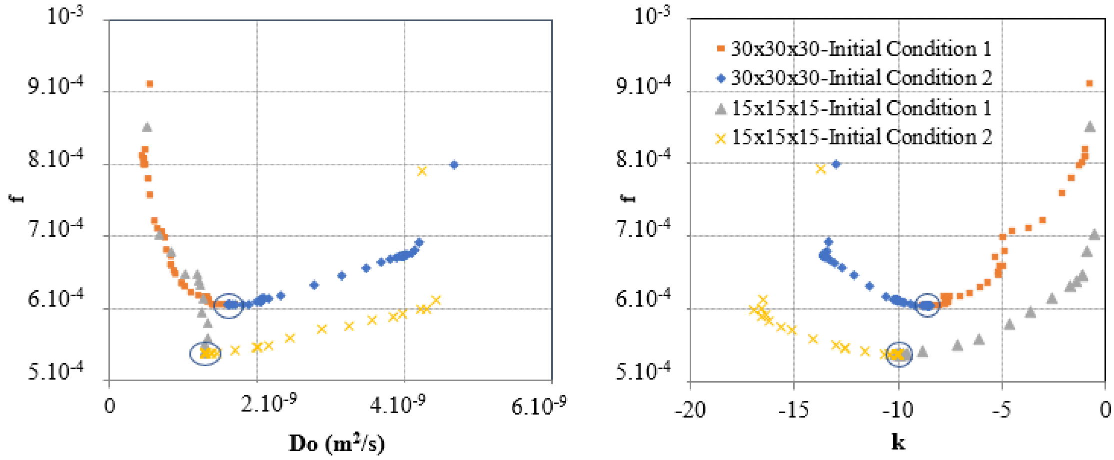


Figure 5. Multi-phases identification path of the diffusion parameters.

Table 2. Multi-phase identification of diffusion parameters.

	D_0(m²/s)	k	f
Beech 30x30x30 mm³	1.62×10^{-9}	-8.53	5.93×10^{-4}
Beech 15x15x15 mm³	1.31×10^{-9}	-10.05	5.38×10^{-4}

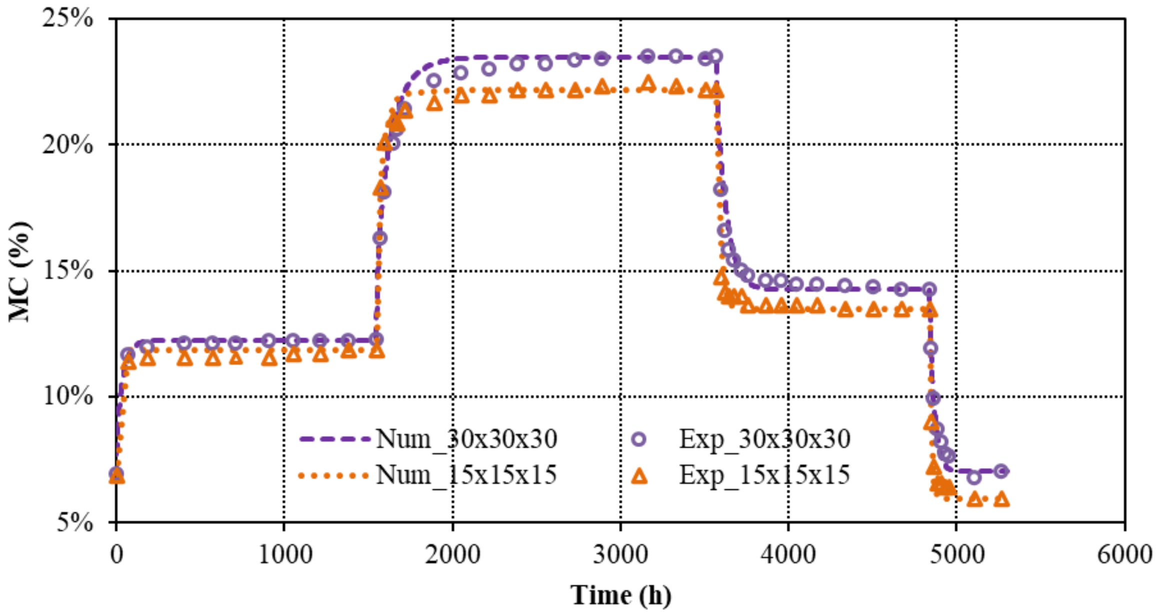


Figure 6. Evolution of experimental and numerical MC with of diffusion parameters identified by multi-phases experimental data.

The highly satisfactory results underscore the intrinsic nature of the characterization, as depicted in Figure 6. Indeed, the achieved multi-phases optimization yields a model that closely matches the experimental data using a single dataset, as illustrated in Figure 6. It will be demonstrated later that the integration of as many experimental data as possible into the inversion algorithm is crucial. This is because, as shown in Figure 5, the inversion method may favor numerous parameters sets that are consistent with the experimental test but do not meet the criteria for intrinsic parameter characterization.

5.1.3. Combination of multi-phases and multi-geometries identification

In order to study the impact of a scale change, this approach relies on a complete curve's identification in terms of both hydric and dimensional thresholds (4 phases of the 30x30x30 mm^3 sample and 4 phases of the 15x15x15 mm^3 sample). The evolution of the identified parameters, according to the objective function, shows that the identification converges towards an optimal set of parameters, as shown in Figure 7. The identification results incorporating both geometries are presented in Table 3.

Table 3. Combination of multi-phases and multi-geometries identification of diffusion parameters.

D_0 (m^2/s)	**k**	**f**
1.67×10^{-9}	-8.86	4.06×10^{-4}

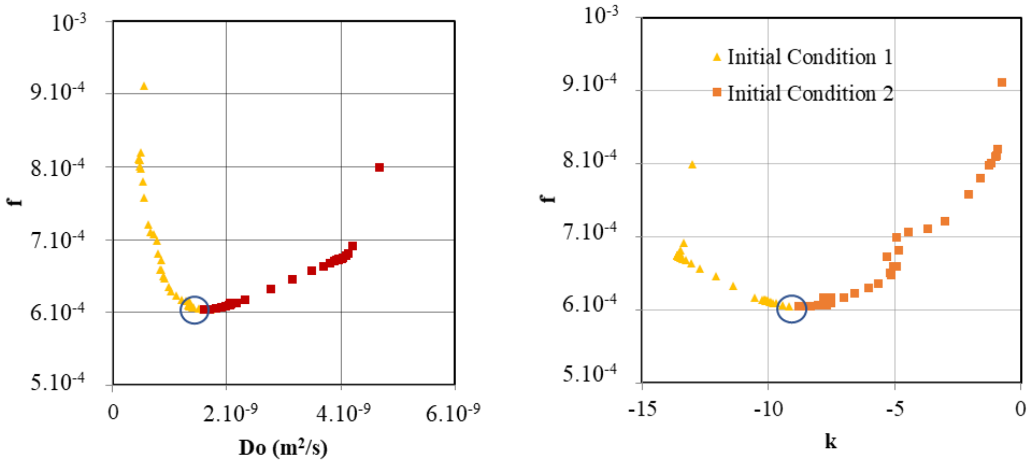


Figure 7. The path of the diffusion parameters identified by a combination of multi-phases and multi-geometries of experimental MC.

By employing measurement data acquired from two distinct sample dimensions, the inverse model produces optimal results for the parameters D_0 and k (Table 3). The diffusion coefficient values presented in Table 3 exhibit similarities to the dataset showcased in Table 2. It's important to highlight, however, that these values are not mere averages of discrete values obtained from individual geometric dimensions. The diffusion coefficients determined by multi-phases and multi-geometries not only display a harmonious alignment concerning moisture evaluation in relation to both the numerical model and empirical measurement, akin to the representation depicted in Figure 8, but also achieve a minimized value for the optimal objective function. Through the amalgamation of data from the two dimensions, the entirety of measurement points is effectively harnessed, thereby facilitating the derivation of diffusion parameters that effectively fulfill the entirety of the experimental dataset.

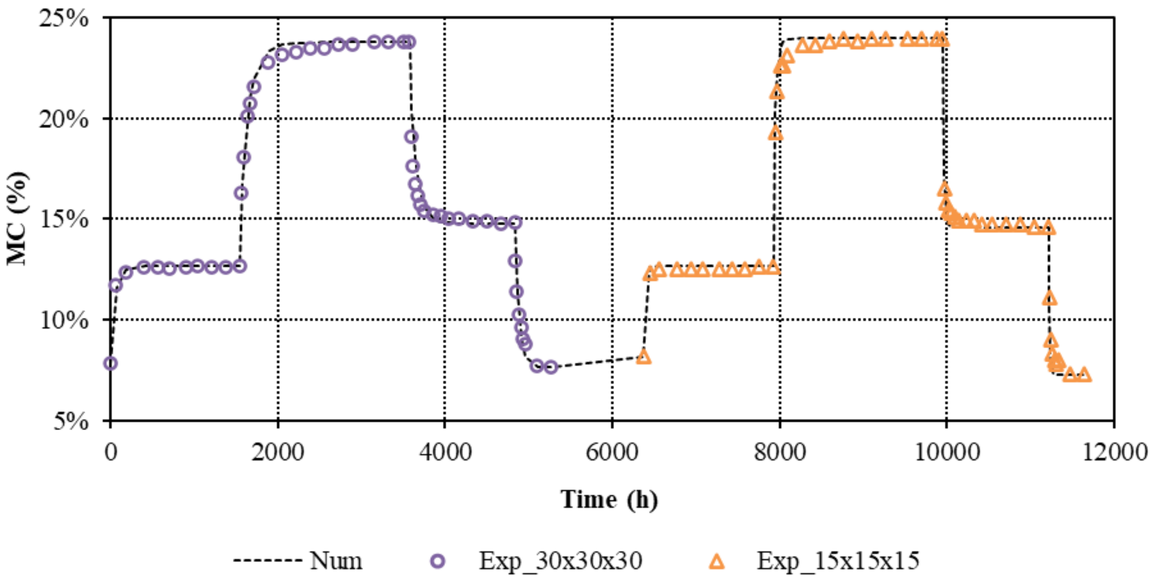


Figure 8. Evolution of experimental and numerical MC with of diffusion parameters identified by a combination of multi-phases and multi-geometries of experimental MC.

5.2. Identification results

Based on the conducted identification results for Beech, the optimization process of moisture diffusion parameters using a combination of multi-phases and multi-geometries of experimental MC is performed on 4 species: Beech, Fir, Moabi, Ozigo. For the general case, all 3 moisture transmission parameters are determined: D_0, S, k.

5.2.1. Longitudinal diffusion parameters

Note that the coefficients of anhydrous diffusion, non-linearity, and surface exchange in the longitudinal direction are denoted as D_0^L, k^L, S^L. These identified parameters are presented in Table 4 below:

Table 4. Longitudinal diffusion parameter.

	Beech	**Fir**	**Ozigo**	**Moabi**
D_0^L (m^2/s)	1.90×10^{-9}	3.39×10^{-9}	9.38×10^{-10}	7.81×10^{-11}
k^L	-9.58	-10.20	-6.60	5.78
S^L (m/s)	2.86×10^{-6}	4.75×10^{-6}	5.86×10^{-6}	1.82×10^{-7}

The identification results in Table 4 reveal that the moisture diffusion parameters along the longitudinal direction of tropical wood species are significantly lower than those of temperate species. Through a comparison between the Beech and Moabi species (which possess approximately similar densities), it becomes evident that Beech exhibits a longitudinal diffusion rate that is 24 times more significant.

In the cases of Beech, Fir, and Ozigo, their nonlinearity coefficients are negative, unlike Moabi, which has a positive coefficient. This implies that for Beech, Fir, and Ozigo, an increase in MC leads to a reduction in the moisture diffusion coefficient, while the opposite trend holds true for Moabi.

Relative to the other three wood species, Moabi demonstrates the lowest longitudinal moisture diffusion coefficient and the lowest surface exchange coefficient. Consequently, this results in the most sluggish moisture propagation within Moabi when compared to the remaining three wood types.

5.3. Transverse diffusion parameters

This section addresses the determination of two-dimensional diffusion properties in the transverse direction, specifically in the tangential and radial directions. To address the limited information available for monitoring MC evolution, several assumptions are made:

- Firstly, it is assumed that the surface exchange coefficients are uniform in both the radial and tangential directions. The surface exchange coefficient in the transverse direction is denoted as S^{RT} .
- Secondly, the diffusion process in the transverse sections exhibits orthotropy. In this study, a constant orthotropic ratio of 2 is assumed between the diffusion rates in the radial and tangential directions [4].

$$D_0^R = 2 \cdot D_0^T \tag{10}$$

$$\text{and } k^R = k^T \tag{11}$$

Therefore, the identification of diffusion parameters in the tangential direction is performed with 3 unknowns: D_0^T, k^T and S^{RT}. The identification results are presented in Table 5.

Table 5. Tangential diffusion parameters.

	Beech	**Fir**	**Ozigo**	**Moabi**
D_0^T (m^2/s)	2.01×10^{-11}	1.63×10^{-11}	4.86×10^{-12}	7.73×10^{-12}
$k^R = k^T$	8.23	13.20	11.27	11.50
S^{RT} (m/s)	8.49×10^{-8}	9.36×10^{-8}	8.12×10^{-8}	6.73×10^{-8}

The findings of the identification process indicate that, within the transverse orientation, the anhydrous state moisture diffusion coefficient is notably less than in the longitudinal orientation.

Similar to the longitudinal direction, in the transverse orientation, both the diffusion coefficient and the surface exchange coefficient of temperate species are significantly higher than those of tropical species. However, the nonlinearity coefficients for all four species are positive, indicating that the moisture diffusion coefficient increases as MC rises.

Along the longitudinal axis, Beech exhibits an anhydrous moisture diffusion coefficient almost 100 times greater than that observed in the tangential direction; Fir's diffusion coefficient surpasses 200 times, while for Ozigo, the ratio is nearly 200 times, and for Moabi, it exceeds 100 times. This is consistent with previous studies and can be attributed to the lumen structure of the wood.

6. CONCLUSION

Based on the finite difference method and Simplex algorithm optimization, an inverse model utilizing the was developed. By comparing the numerical model with experimental MC, this approach enables the determination of moisture diffusion parameters of the materials along both longitudinal and transverse directions.

In the context of the inverse model's input data, the evolution of MC is taken into account. The study further highlights the necessity of having a comprehensive set of input data to obtain the most accurate diffusion parameters. Within this investigation, a dataset encompassing moisture progression measurements across a combination of multi-phases and multi-geometries was employed. This dataset facilitated the precise determination of optimal moisture diffusion parameters.

The identification results of moisture diffusion parameters for the 4 wood species: Beech, Fir, Moabi, and Ozigo, indicate that, firstly, the longitudinal moisture diffusion is consistently significantly higher than the transverse diffusion. Secondly, the moisture diffusion parameters of temperate species are higher than those of tropical species, implying that the moisture diffusion for temperate wood species occurs more rapidly and intensively, both longitudinally and transversely.

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