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Stochastic numerical model for conventional kiln drying of timbers

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Abstract A numerical model that predicts the stochastic dispersion associated with industrial kiln drying of timber was adapted to conventional drying and evaluated with experimental data. The theoretical aspects of the model are briefly explained, a selection of the calibration parameters was carried out, and a new empirical dispersion factor is proposed to account for all unknown sources of random behavior. The model was calibrated with six experimental runs of western hemlock and amabilis fir (116 mm^2 timbers) to an average moisture content (target) of 14%–20%. It was found that with implementation of the dispersion factor, the number of required simulations is considerably reduced, the calibration results are consistent for all the experimental runs, and the target moisture content along with its standard deviation can be well reproduced using the all-run average parameters.

Key words Conventional wood drying · Numeric stochastic model · Moisture dispersion prediction

Introduction

Conventional drying of wood is a process of random characteristics. In one commercial run, thousands of pieces are dried simultaneously, all with a varied degree of difference in their thermophysical properties and initial moisture content (M_i). Furthermore, ambient air conditions are not completely homogeneous throughout the kiln where temperature and relative humidity usually oscillate in time and space due to control system limitations. As a result, timber positioning inside the kiln also affects the drying rate, and the surface or internal checks that appear in some or all of the timbers could change their internal heat and mass transfer characteristics.

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As a result of these random factors, the final moisture content (M_f) is not an exact value but a distribution within a certain range of dispersion. The understanding and prediction of this intrinsic characteristic of the drying process is a real challenge to both structural timber producers and users, as the M_f range of dispersion is maintained within specific limits (13%–19%); otherwise, thick timbers could exhibit unacceptable degradation (related to over-dried timber; i.e., $M_f < 13\%$) or structural instability (related to wet timber; i.e., $M_f > 19\%$). Different sort-out procedures have been proposed and tested to reduce the M_f range of dispersion,[1,2] but they require appropriate optimization to ensure that revenues due to the improved quality of the timber will cover the costs on the extra labor and equipment requirements. Therefore, an accurate stochastic prediction model would be useful for the optimization of these timber-drying strategies and the development of new ones.

Although some other methods have been proposed to simulate stochastic drying of timber, such as the Monte Carlo model proposed by Kayihan,[3] they are based on a piece-by-piece random simulation, so they produce a slightly different result each time the model is applied to the same initial conditions. Because of this, the results with these models are also uncertain, so there is no easy way they can be implemented in an optimization procedure. Therefore, the stochastic model described in Elustondo et al.[4,5] was adapted to simulate conventional drying of timber. The model is briefly described and then considerably simplified by introducing of a new empirical dispersion parameter. Finally, it is calibrated with experimental data and used to predict conventional drying of timber for a process in which the targeted M_f is changed arbitrarily.

Theory

Stochastic model

It is generally accepted in the wood-drying research community that the Monte Carlo method[3] is a standard proce-

dure to analyze the outcome of stochastic processes.[6] The goal of this method is to generate a piece-by-piece random simulation by considering different locations inside the kiln and different timber thermophysical properties. Stochastic behavior is generated by a computer based on a random-number generator, and Weibull and Gauss probability distribution curves are used to describe M_i and model parameter dispersions, respectively. Although realistic, this approach produces a different result each time a new run is performed. The method is equivalent to the measurement of a sample containing a limited number of timbers, 250 in the case of Kayihan.[3] For this study, the stochastic model is developed to simulate not a particular experiment but the most probable result as if the data were averaged for an infinite number of runs. The proposed method is not far different from the Monte Carlo one; but instead of repeating the simulations several times using random sequences of parameter values, the method takes samples from all the probability space to represent totally the possible parameter combinations.

The theoretical foundation of the method is explained by Elustondo et al.[2] Basically, the multidimensional space described by the model parameters is divided into a set of subspaces associated with a parameter combination (normally the center point of the subspace) and a probability to occur. All generated parameter combinations are concurrently simulated, and the resulting M_f versus probability points are combined to obtain the M_f distribution. Green M_i distribution, another stochastic parameter, is treated differently by the method to increase the efficiency of the simulation. As explained by Elustondo and Avramidis,[5] the M_i distribution is also divided into a set of M_i subintervals not associated with the center point but to the limits of each subinterval.

The number of simulations required for this method is equal to the product of the number of points used to describe each stochastic parameter. In practice, acceptable histograms can be obtained using five points for the timber properties and six points for the green M_i distribution. This means that for a two-parameter model (such as the one proposed by Kayihan[3]) 150 simulations are required. Although more points could be used in the representation of the stochastic parameters, the model considers all possible combinations, so the average and range of dispersion of the results is always more or less well represented.

Intrinsic dispersion

Conventional drying is affected by the differences in the timber characteristics, the kiln nonhomogeneous drying environment, the instability in the kiln-controlled variables, the differences in the sticker channels among successive timber packs, and the timbers with three faces instead of two exposed to the air, to name a few. For this reason, the stochastic model was complemented with an additional intrinsic dispersion parameter representing all unknown sources of random behavior. This unknown source of dispersion is applied to each simulated M_f before the M_f histogram is generated, so it does not increase the number of parallel simulations. For this particular study, the standard deviation of the intrinsic dispersion (δ) is assumed to be directly proportional to the amount of evaporated water.

$$\ddot{a} = S_{\ddot{a}}(M_i - M) \tag{1}$$

Even though this is an empirical relation (which proved to be enough to predict M data dispersion under the conditions of this study), Eq. 1 can be derived by assuming that the drying rate range of dispersion on timbers starting with a similar M_i is proportional to their average drying rate.

Deterministic conventional model

The described method incorporates stochastic behavior through the parameters of a deterministic model, but selection of the deterministic model, simple or complicated, is a question of convenience. In the case of this study, the timber model is based on well-known heat and mass transfer differential balances for porous materials.[7–9] The model is a set of three differential equations taking into account heat, vapor, and air balances; and for kiln drying it is solved with regard to the internal moisture content (M), temperature, and pressure profiles. Heat flux is replaced by Newton's law, bound water and binary vapor-air diffusions are replaced by Fick's law, capillary water and total gas fluxes are replaced by Darcy's law, vapor equilibrium and capillary gradient pressures are replaced by their partial derivatives with respect to the temperature and M, and the ideal gas law is assumed for the gas phase. Finally, and after mathematical rearrangement and some minor simplifications, the following set of differential equations is obtained.

$$\frac{\partial M}{\partial t} = \nabla \cdot A_{XX}\nabla M + \nabla \cdot A_{XT}\nabla T + \nabla \cdot A_{XP}\nabla P_g \tag{2}$$

$$\rho C_p \frac{\partial T}{\partial t} = \nabla \cdot A_{TX}\nabla M + \nabla \cdot A_{TT}\nabla T + \nabla \cdot A_{TP}\nabla P_g \tag{3}$$

$$0 = \nabla \cdot A_{PX}\nabla M + \nabla \cdot A_{PT}\nabla T + \nabla \cdot A_{PP}\nabla P_g \tag{4}$$

where the values of the coefficients are, above the fiber saturation point:

$$A_{XX} = -B_1 \frac{\partial P_c}{\partial X}$$

$$A_{XT} = -B_1 \frac{\partial P_c}{\partial T} + \frac{P_g}{\rho_0} B_3 \frac{\partial P^{eq}}{\partial T}$$

$$A_{XP} = B_1 + \frac{W_v P_v}{\rho_0} B_2 - \frac{P_v}{\rho_0} B_3$$

$$A_{TX} = 0$$

$$A_{TT} = k + \Delta H P_g B_3 \frac{\partial P^{eq}}{\partial T}$$

$$A_{TP} = \Delta H W_v P_v B_2 - \Delta H P_v B_3$$

$$A_{PX} = 0$$

$$A_{PT} = -P_g B_3 \frac{\partial P^{eq}}{\partial T}$$

$$A_{PP} = W_a\left(P_g - P_v\right)B_2 + P_v B_3$$

and below the fiber saturation point:

$$A_{XX} = D_b + \frac{P_g}{\rho_0} B_3 \frac{\partial P^{eq}}{\partial X}$$

$$A_{XT} = \frac{P_g}{\rho_0} B_3 \frac{\partial P^{eq}}{\partial T}$$

$$A_{XP} = \frac{W_v P_v}{\rho_0} B_2 - \frac{P_v}{\rho_0} B_3$$

$$A_{TX} = \Delta H P_g B_3 \frac{\partial P^{eq}}{\partial X}$$

$$A_{TT} = k + \Delta H P_g B_3 \frac{\partial P^{eq}}{\partial T}$$

$$A_{TP} = \Delta H W_v P_v B_2 - \Delta H P_v B_3$$

$$A_{PX} = -P_g B_3 \frac{\partial P^{eq}}{\partial X}$$

$$A_{PT} = -P_g B_3 \frac{\partial P^{eq}}{\partial T}$$

$$A_{PP} = W_a\left(P_g - P_v\right)B_2 + P_v B_3$$

The parameters B_1, B_2, and B_3 are represented by the following expression:

$$B_1 = \frac{\rho_l}{\rho_0} \frac{K_l K_{rl}}{\mu_l}$$

$$B_2 = \frac{1}{RT} \frac{K_g K_{rg}}{\mu_g}$$

$$B_3 = \frac{D_{eff}}{RT} \frac{W_v W_a}{\left[W_a\left(P_g - P_v\right) + W_v P_v\right]}$$

For the boundary conditions (on the external timber surfaces), heat and vapor fluxes are assumed to be proportional to external heat and mass transfer coefficients, and the gas pressure is assumed to be equal to the kiln pressure.

$$q = H_q\left(T_{(\infty)} - T_{(s)}\right) \tag{5}$$

$$j = H_j\left(P_{v(\infty)} - P^{eq}_{(s)}\right) \tag{6}$$

$$0 = P_{g(\infty)} - P_{g(s)} \tag{7}$$

Stochastic parameters

Because most of the model parameters produce similar effects in the final result, calibration is performed by manipulating a small number of them but with significant and dissimilar effects on the final result. It is normally accepted that conventional drying is characterized by three periods:[10] a constant drying rate period, the first decreasing drying rate period (in which an internal wet zone with capillary water and an external dried zone with adsorbed water are formed), and a second decreasing drying period (when all the water is in the hygroscopic domain). Therefore, the following parameters were considered to calibrate the model. (There is also an initial warm-up period, but it cannot be calibrated from the final M data.)

1. During the constant drying rate period, the drying rate depends on external factors (i.e., external heat and mass transfer coefficients and dry and wet bulb temperatures); thus a proportional factor (S_H) multiplying both heat and mass transfer coefficients is used. The adjustment used for the external heat transfer coefficient is shown in the following equation; and because the analogy between heat and mass was applied,[3] the same adjustment was used for the external mass transfer coefficient.

$$H_{q(stochastic)} = S_H H_q \tag{8}$$

2. The first decreasing drying rate period is controlled by heat and mass transfer throughout a dried zone that appears between the external surface and the still wet timber interior; and because heat and vapor fluxes are related by way of the enthalpy of vaporization, only the diffusive component was adjusted. Choong[11] found a linear relation between the logarithm of the bound water diffusion coefficient and the reciprocal of the absolute temperature. Based on this relation, Kayihan[3] suggested that the random variation of the bound water diffusion coefficient (D_b) can be predicted with the following correction factor (S_b).

$$D_{b(stochastic)} = D_b e^{(S_b)} \tag{9}$$

3. Lastly, during the second decreasing drying rate period, it reduces rapidly as M tends to the equilibrium condition; and this is approximately dependent on the wood-water activity (á). Thermodynamics indicates that the natural logarithm of the water activity is directly proportional to the difference in free energy between absorbed and pure water (ΔG).

$$\frac{\Delta G}{RT} = \ln(\alpha) \tag{10}$$

Because free energy change represents changes on internal reversible energies, for water absorption it can be assumed to be approximately equal to the heat of sorption.[12] Therefore, the following correction factor ($S_á$), proportional to the heat of sorption, was used to adjust the water activity.

$$\alpha_{(stochastic)} = e^{[S_\alpha \ln(\alpha)]} \tag{11}$$

Kiln simulation

For conventional drying, timbers are placed in horizontal parallel layers separated by a small distance to allow pas-

sage of the drying air; and as the hot and dry air passes between timber layers, its sensible heat decreases to evaporate water and its relative humidity increases owing to absorption of the produced vapor. These changes occur in the direction of the air circulation, generating a difference between measured and actual temperatures at different positions inside the kiln. So this difference is not mistakenly attributed to the external heat and mass transfer coefficient, the following heat and mass transfer differential equations are implemented to simulate the changes in the direction of the air flow:

$$h\rho_g v_g Cp_g \frac{\partial T_\infty}{\partial x} = -2q + 2jC\mathrm{p}_v\left(T_\infty - T_s\right) \quad (14)$$

$$h\frac{\partial\left(\rho_g v_g\right)}{\partial x} = -2j \quad (15)$$

where the number "2" takes into account that evaporation occurs in both upper and lower timber surfaces.

The kiln width in the direction of the air circulation is divided into a number of sectors for which the homogeneous moisture content (M) distribution and drying air conditions are assumed. On each integration step, the average q and j fluxes on the layers are simulated simultaneously using several parallel stochastic models (one for each layer). The results are used to actualize the temperature and humidity profiles of the drying air. The air temperature (dry-bulb temperature) and humidity (or the equivalent wet-bulb temperature) are adjusted throughout according to a predetermined drying schedule, and the airflow direction is reversed several times during drying.

Materials and methods

Experimental data from six conventional dry kiln runs of mixed western hemlock [*Tsuga heterophylla* (Raf.) Sarg] and amabilis fir [*Abies amabilis* (Dougl.) Forbes], were used to adjust the stochastic model.[1] For each run, 160 pieces 116 × 116 mm in cross section and 2.44 m long were dried to a target between 14% and 20% in a 7.6 m^3 conventional kiln installed at the University of British Columbia's (UBC's) laboratory. Timbers were arranged in eight continuous 20-timber layers separated by 19-mm stickers and without chimney space. The drying schedule was intended to be conservative initially yet severe enough during the latter stages to get a response to the timber sorting regimens (Table 1). Fan speed was set to 3 m/s through the timber tiers, but the actual speed varied between 2.95 and 3.15 m/s when tested.

For determination of the M_i (green) distribution, 25 mm thick sections were cut from each end of each green timber. The volume of the sections was determined by the water displacement method; and after oven-drying they were reweighed to determine their oven-dried density (ρ_0). Green timber volumes were calculated from their rectangular dimensions, and timber weights were measured after and before drying using a digital balance. The experimental data were used later to calculate M.

Table 1. Kiln drying schedule

Step	Time (h)	Wet bulb (°C)	Dry bulb (°C)
1	6	49	49
2	24	51	52
3	24	53	55
4	24	55	58
5	24	57	62
6	24	59	66
7	24	61	70
8	24	63	74
9	90–212	65	78
10	12	74	78

Fitting to the experimental data was performed through numerical optimization (quasi-Newton method). In accordance with the most common M distribution curves found in the literature,[13,14] experimental data were fitted on the basis of three key histogram characteristics: the scale (equivalent to the average), the shape (equivalent to the standard deviation), and the threshold (which quantifies the fact that the M distribution has a positive lower boundary). Four independent variables were used on the numerical optimization, the stochastic parameters S_H, S_b, and S_α, and the intrinsic dispersion (δ) to fit the unknown sources of random behavior.

Results and discussion

In general, the higher the number of stochastic parameters, the better is the description of the final dispersion; however, the number of simulations increases rapidly with the parameters, and calibration becomes ambiguous if more than one have a similar effect on the model's results. Therefore, the optimum number of parameters is in fact the minimum required to provide consistent results under different experimental conditions. After experimenting with several possibilities, it was concluded that for the conditions of this work (same type of wood, similar schedules, and targets between 14% and 20%), the final moisture content distribution can be reasonably well predicted with the intrinsic dispersion parameter proposed in Eq. 1, so all data dispersion introduced by several random sources could be fitted with only one experimental parameter independent of the target. Because δ does not require more parallel simulations, the number of simulations is determined only by the M_i distribution points and the number of kiln subdivisions in the airflow direction. In this study three subdivisions (represented by three x points) were used for the kiln length and six subdivisions for the M_i distributions (represented by seven M_i points); thus, only 21 parallel simulations are required to account for the 3 × 7 possible combinations.

Two criteria were used to test the model. The first is a graphical comparison between experimental and simulated

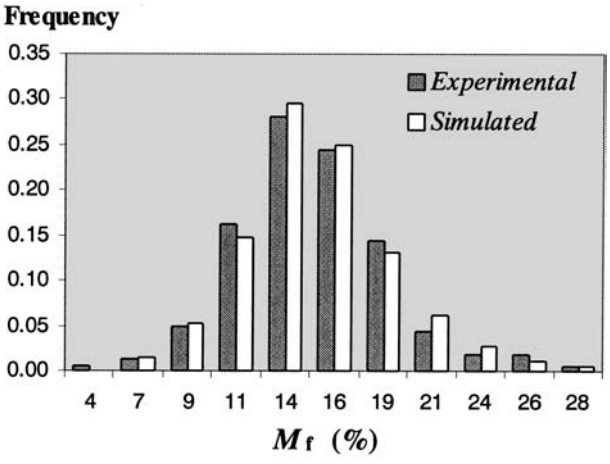

Fig. 1. Simulated and experimental final moisture content (M_f) distribution of run 1

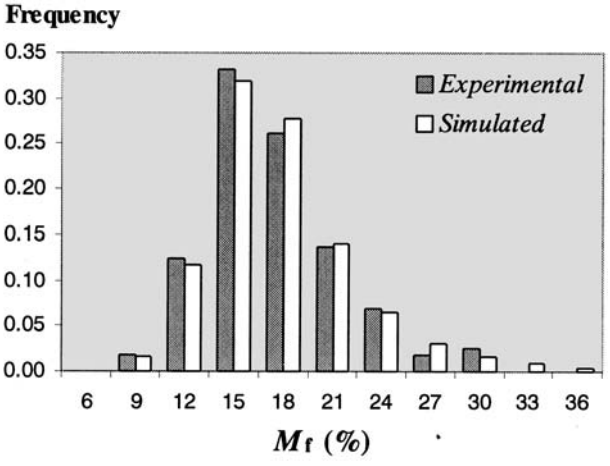

Fig. 2. Simulated and experimental M_f distribution of run 2

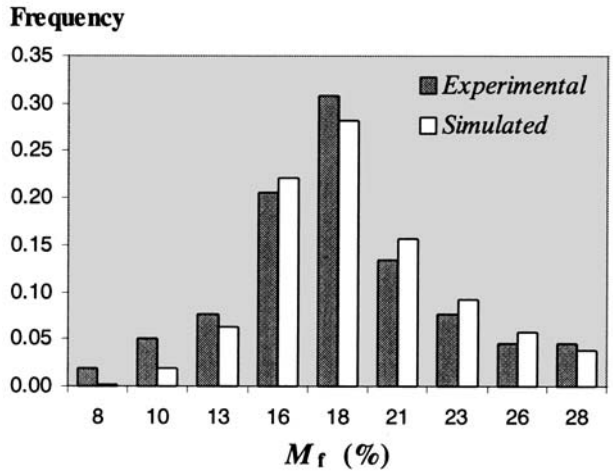

Fig. 3. Simulated and experimental M_f distribution of run 3

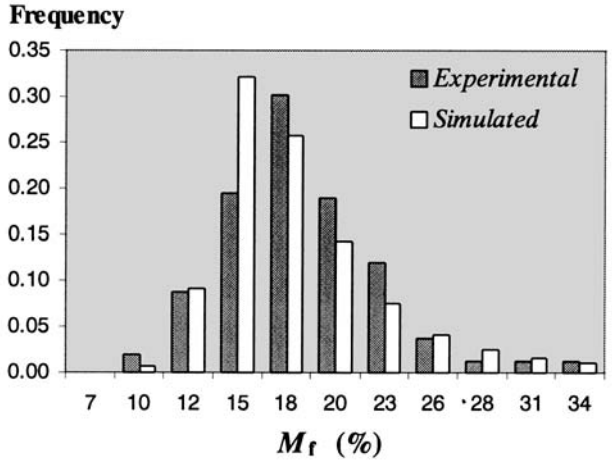

Fig. 4. Simulated and experimental M_f distribution of run 4

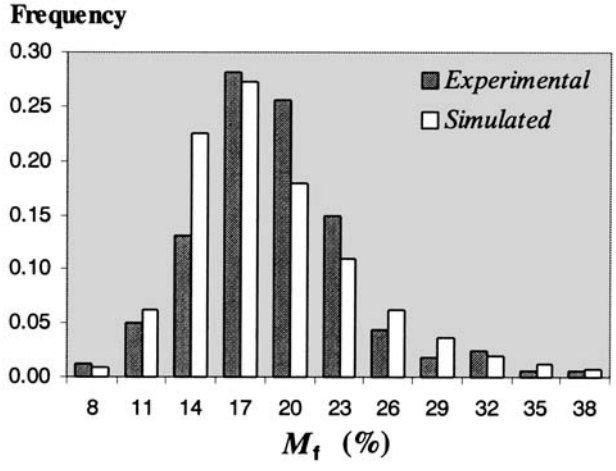

Fig. 5. Simulated and experimental M_f distribution of run 5

histograms, which although qualitative was found to be more indicative of the quality of the results than other statistical indexes such as the mean ($\bar{X}$) and standard deviation ($\acute{o}$). The latter indexes were in fact used to fit the data, so fitted $\bar{X}$ and $\acute{o}$ are in all cases close to the experimental ones. Graphical comparisons between experimental and simulated M_i histograms of runs 1, 2, 3, 4, 5, and 6 are shown in Figs. 1, 2, 3, 4, 5, and 6, respectively. It can be observed that an acceptable agreement exists. Exact agreement is not expected because the proposed model provides only the most probable output (the one that will be obtained after infinite repetitions of the same run), and the experimental data represent only a particular case.

The second criterion considered is the consistency of the results. Even when some experimental discrepancies are expected due to the limited number of samples used on each run, the fitted coefficients for the six experimental runs must be similar to ensure that the model can be applied to predict a process with a variable target. The numerical results for the fitted S_H, S_b, S_α, and δ coefficients obtained for

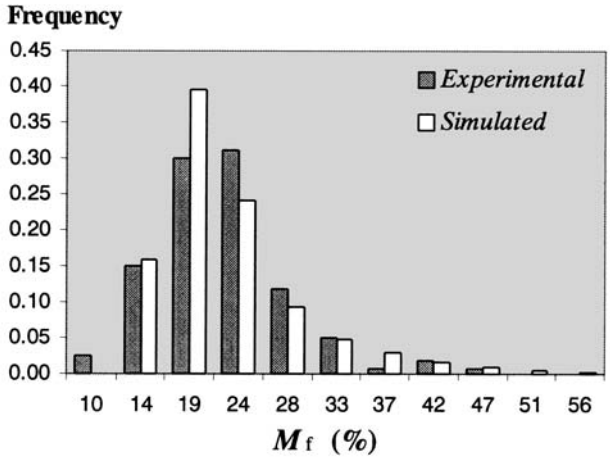

Fig. 6. Simulated and experimental M_f distribution of run 6

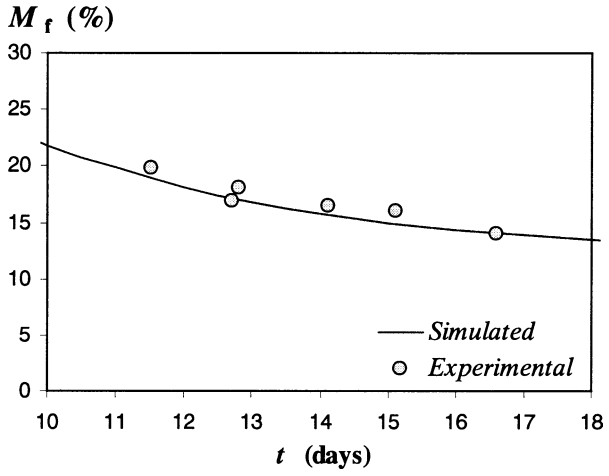

Fig. 7. Simulated and experimental M_f as a function of the drying time

Table 2. Basic data and fitted stochastic parameters for the six experimental runs

Run	Time days	M_f (%)	$ó$ (%)	S_H	S_b	S_α	δ
1	16.6	14.0	4.09	2.98	1.47	1.56	0.064
2	15.1	16.1	4.65	2.99	1.37	1.55	0.062
3	14.1	16.5	5.36	3.16	1.49	1.46	0.076
4	12.7	17.0	4.63	3.00	1.49	1.51	0.063
5	12.8	18.2	5.51	3.03	1.34	1.55	0.090
6	11.5	19.9	7.00	2.93	1.40	1.45	0.076
Mean				3.01	1.43	1.51	0.072

M_f, final moisture content; $ó$, standard deviation; δ, intrinsic dispersion; S_H, proportional factor; S_b and S_α, stochastic parameters

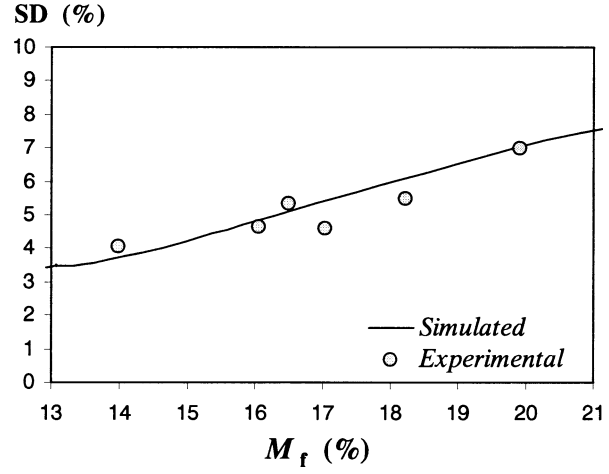

Fig. 8. Simulated and experimental standard deviation (SD) as a function of M_f

the six runs, together with the experimental values of drying time, average M_f, and $ó$ are listed in Table 2. It can be seen that the average S_H, S_b, S_α, and δ values are 3.01, 1.43, 1.51, and 0.0717, respectively; and the differences among individual runs are small. For example, the $ó$ among each six parameters are 2.57%, 4.52%, and 3.08% for S_H, S_b, and S_α, respectively, demonstrating the consistency of the results. In the case of δ, the $ó$ of the six fitted values is higher, 15.58%, with respect to the $\bar{X}$, but it is still acceptable when taking into account that δ incorporates all the random factors affecting each particular run.

Finally, the model is tested to predict target moisture content and its $ó$ using the six-run average stochastic parameters and the six-run average M_i distribution. Two comparisons were performed between the model and the experimental data, namely, the average M_f as a function of drying time (where time is only changed in step 9 of Table 1), and $ó$ as a function of the average M_f. The comparisons are shown in Figs. 7 and 8, respectively, where good agreement between model prediction and experimental data is observed. Therefore, in the range of conditions for which the model was adjusted, the average stochastic model can be used to predict conventional drying with a variable target.

Conclusions

In this work, a stochastic model developed in previous works was simplified and applied to conventional drying of mixed western hemlock and amabilis fir timbers. Contrary to other, more realistic stochastic models based on a piece-by-piece random simulation, the proposed method takes samples of all the multidimensional parameter probability space. This new approach has two advantages: The model gives the same result for the same initial conditions, and the average and range of dispersion of the results is more or less well represented independent of the number of discrete parameter points. The stochastic model also requires implementation of a deterministic timber drying model, which was simulated using heat and mass differential balances for both the timbers and the drying air. These balances are complicated to solve, but they incorporate flexibility to predict new hypothetical situations and give information about the timbers internal M profiles.

It was found that when applied to conventional drying the proposed stochastic model can be considerably simplified by introducing a new empirical factor that takes into account all sources of unknown random behavior. This new factor does not increase the number of simulations, so the model required only 21 parallel simulations to account for the six discrete M_i subintervals and the three-length subdivisions in the direction of the airflow. The model was tested with six experimental conventional runs to targets between 14% and 20%. The results showed that the fitted parameters and intrinsic dispersion were consistent for all runs, and experimental averages and standard deviations can be well reproduced using the six-run average parameters.

Appendix: nomenclature

D	diffusion coefficient (m^2/s)
Cp	heat capacity at constant pressure ($J/m^3.K$)
G	free energy (J/kg)
H_j	external mass transfer coefficient (s/m)
H_q	external heat transfer coefficient ($W/m^2.K$)
h	separation between parallel wood layers (m)
j	external vapor flux ($kg/m^2.s$)
K	intrinsic permeability of wood (m^2)
K_r	relative permeability
k	thermal conductivity (W/m.K)
M	water moisture content (dimensionless in the model equations) (%)
P	pressure (Pa)
P^{eq}	vapor equilibrium pressure (Pa)
q	external heat flux (W/m^2)
R	universal gas constant (J/mol.K)
S	stochastic correction factor
T	temperature (K)
$\bar{X}$	population mean value
t	time (s)
v	velocity (m/s)
W	molecular weight (kg/mol)
x	longitudinal in the direction of the airflow (m)
á	water activity
δ	standard deviation for the unknown random dispersion
ρ	density (kg/m^2)
$ó$	moisture content standard deviation
ΔH	water latent heat of evaporation (J/kg)

Subscripts

a = relative to the air
b = relative to the bound water diffusion coefficient
c = relative to the capillary pressure
eff = relative to the effective air-vapor diffusion coefficient
f = relative to the final of drying
g = relative to the gas (air-vapor mixture)
H = relative to the external heat and mass transfer coefficient
i = relative to the starting of drying
l = relative to the free water
s = relative to the timber external surface
v = relative to the water vapor
á = relative to the water activity
δ = relative to the intrinsic dispersion
∞ = relative to the external drying air
0 = relative to the oven-dried density

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