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REVEALING THE RELATION BETWEEN INDEPENDENT VARIABLES AND DRYING TIME IMPLEMENTED IN TORKSIM BY MEANS OF ARTIFICIAL NEURAL NETWORKS: A PRELIMINARY STUDY

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Abstract:
The purpose of this study was to reveal by means of artificial neural networks (ANN) the relation that is inside Torksim software between the independent variables (wood species, density, temperature, green moisture content, air velocity and drying schedule) and drying time in order to be incorporated in spreadsheet programs, which are used in sawmills for production planning. Different configurations of the ANN model were tested to find out the optimal structure. The optimal structure of the ANN model was 6-6-1 and was figured out based on both, the mean relative error (MRE= 1.30%) and coefficient of determination (R^2=0.998). The ANN model presented in this paper is capable to discover the valuable relation between independent variables and drying time in TORKSIM software. Consequently, it can be easily and fast integrated in spreadsheet programs that are used for production planning.

Key words: *wood drying; drying time; artificial neural networks.*

INTRODUCTION

Spreadsheet programs such as Microsoft Excel may be used in sawmills to support production planning. One example is the model proposed by Gjerdrum (2010) that contains a set of interlinked spreadsheet that can be used for calculating and planning kiln demand and capacity through the year. In one of the input spreadsheet the user can specify the drying time (Gjerdrum 2010). In the case of simulated drying times the user can apply the Torksim software to run different scenarios (Salin 2007). One lack of Torksim is that it cannot be integrated in a spreadsheet program for further calculation needed for production planning. Therefore, there is a need to reveal the relation that is implemented in Torksim between the independent variables and drying time in order to be incorporated in spreadsheet programs. The approach proposed in this work consists in using Artificial Neural Networks (ANN) - a computational structure that mimics the human brain - that can discover the relationship, by successive training, between the independent and dependent variables (Naguib and Sherbet 2001).

Artificial neural networks have a rather wide and diverse range of applications such as process control, medical diagnosis, weather forecasting, financial applications, investment analysis, food science, mechanical engineering etc (Huang *et al*. 2007, Benli 2013). Compared to other areas, the application of ANNs in the field of wood science is still in the early development stage. However, the ANNs have been used as an useful tool to model wood-water isotherm, water-vapor sorption in douglas-fir wood, nonisothermal diffusion of moisture in wood, wood thermal conductivity, drying rates, wood dielectric loss factor, temperature – humidity models for wood drying, and wood identification (Avramidis and Iliadis 2005a, Avramidis and Iliadis 2005b, Avramidis *et al*. 2006, Wu and Avramidis 2006, Zhang *et al*. 2006, Avramidis and Wu 2007, Esteban *et al*. 2009, Tekleyohannes 2010).

The common structure of an artificial neural network is formed of layers of neurons interconnected in different ways as it is pictured in Fig.1 (Sablani 2006). According to Huang *et al*. (2007), one of the most commonly used structures is the three layer feedforward network (Fig.1). In this kind of structure the neurons from the input layers receive the signals from the user and are carried to the hidden layer through the connections. From the hidden layer the signals are transmitted to the output layer which produces the network output. The number of neurons in the input and output layers correspond to the number of input and output variables. The number of hidden layers and the number of neurons in each hidden layer can be varied till the optimal configuration is obtained (Sablani 2006). The network shown in Fig.1 can be referred as a 4-5-1, namely, 4 input neurons in the first layer, 5 neurons in the hidden layer and 1 neuron in the output layer.

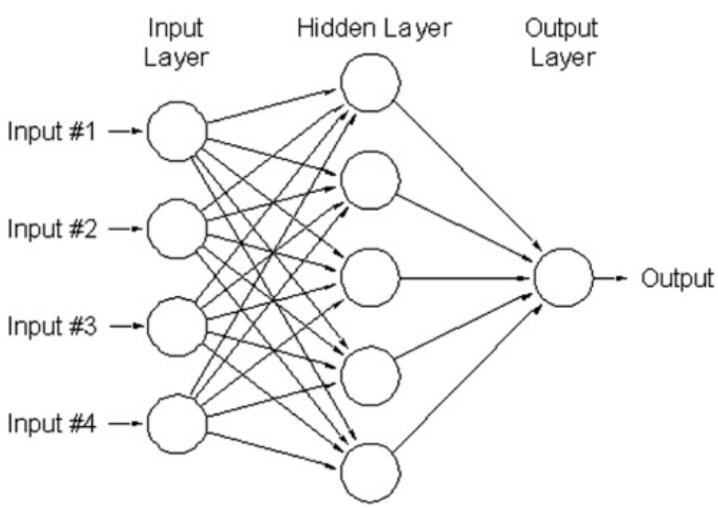

Fig. 1
(Zgoul 2012) Typical ANN model.

In this study a 6-6-1 ANN model for predicting the drying time based on data generated by Torksim was developed and validated. The independent variables were the same with those used in the TORKSIM software, namely, wood species, wood density, wood temperature, green moisture content, air velocity and the drying schedule too. The output variable was the drying time. The resulted ANN model can be easily integrated in the Microsoft Excel program to perform further calculations needed by production planning.

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OBJECTIVES

The purpose of this study was to develop and validate an ANN model that can predict the drying time based on the unknown relationship that exists between independent and dependent variables in the Torksim software.

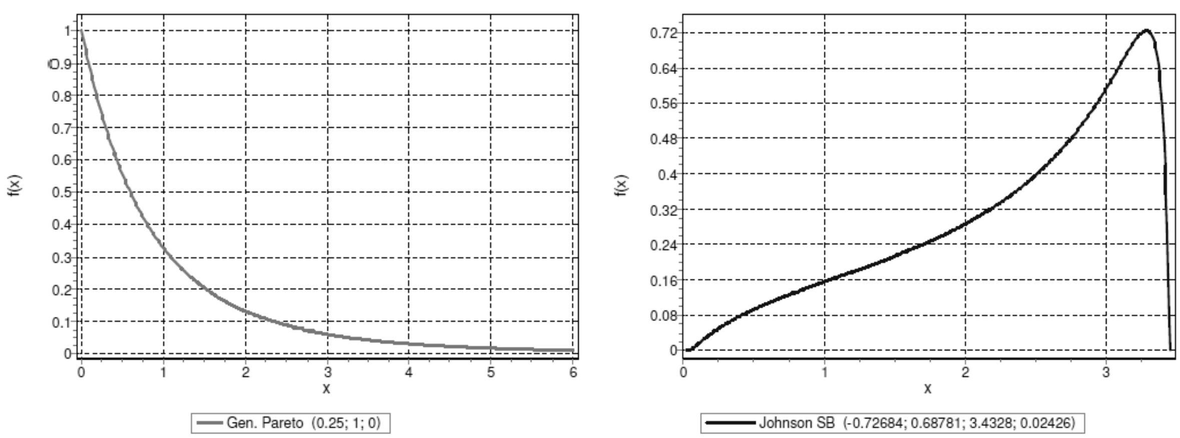
METHOD, MATERIALS AND EQUIPMENT

In order to generate the data for the model, 360 runs were performed with Torksim, only for softwood boards with the thickness of 50mm. The values of the independent variables are presented in Table 1. The time based drying schedules that were used in the simulation are shown in Tables 2, 3 and 4. The schedules were generated based on the Schedule suggestion option that is available in Torksim software. The values of air velocity and green moisture content were generated using random values. Prior to generate random values, the data measured by Bedelean (2009) for both, air velocity and green moisture content were used to select the probability distribution that fits the data. The selection of the probability distribution function (PDF) was done based on the Kolmogorov-Smirnov test – using EasyFit software - that is the most widely used goodness of fit test (Mathwave Technologies 2011). The resulted PDFs are presented in Fig. 2. Once the dataset was gathered, it was divided in three sub-sets, namely, 60% of cases for training, 20% of cases for testing and 20% of cases for validation (Avramidis and Wu 2007).

Table 1

Range of variables used in the simulations

Variables	Value / Range
Species	Spruce (*Picea abies*), Pine (*Pinus silvestris*)
Density, kg/m^3	385, 430
Initial wood temperature, °C	35, 45, 65
Drying schedule	RM1, RM2, RM3
Green moisture content, %	23.21 – 143.29
Air velocity, m/s	0.1-3.44



a **b**

Fig.2
The Probabilty density function of independent variables:
a – green moisture content; b – air velocity.

Table 2

The RM1 drying schedule that were used in simulations

Time, hours	Temperature, °C	Relative humidity, %
0	66	92
10	70	79
20	70	76
30	73	68
40	77	58
50	80	45
60	80	36
70	80	29
80	80	25
160	80	25

Table 3

The RM2 drying schedule that were used in simulations

Time, hours	Temperature, °C	Relative humidity, %
0	46	95
10	49	79
19	49	78
67	49	79
76	49	79
96	49	78
105	49	76
115	50	73
125	51	70
134	52	66
144	53	61
153	55	56
163	56	52
172	58	46
182	61	39
191	64	34
350	65	33

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Table 4

The RM3 drying schedule that were used in simulations

Time, hours	Temperature, °C	Relative humidity, %
0	35	96
6	37	88
12	37	85
18	37	84
42	38	82
48	38	78
54	39	75
60	40	71
67	41	68
73	42	64
79	42	60
85	44	56
91	45	51
97	46	47
103	48	43
109	49	39
115	51	36
121	53	31
127	55	27
400	55	27

To develop a suitable ANN model and to facilitate an easy and fast integration in Microsoft Excel, the NeuralTools software (Palisade, NY) was used. A multi-layer feed forward network structure (MLF), which is the most popular in engineering applications, with one input, output and hidden layer was used in this study. Several MLF structures with 2,3,4,5 and 6 neurons in the hidden layer were tested to find out the optimal configuration of the ANN model. The input layer consisted of six neurons, namely, wood species, wood density, wood temperature, air velocity, green moisture content and drying schedule. The output layer consisted of one neuron, namely, drying time. The conjugate gradient algorithm was used for network training (Palisade 2013). The training time was two hours for each investigated configuration. The performance of several ANN configurations were analyzed based on the mean relative error (MRE) – Equation 1 – and the coefficient of determination, R^2, of the linear regression between the predicted values from the neural network model and the desired output (Islam *et al*. 2003, Sablani 2006, Wu and Avramidis 2007, Benli 2013). The optimal configuration was determined based on minimizing the MRE and maximizing the R^2 value, respectively.

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\frac{100 \cdot |a_i - p_i|}{a_i} \quad [\%] \qquad (1)$$

n - number of data points;
a_i - actual values of drying time, hours;
p_i - predicted values of drying time, hours.

RESULTS

Based on the values of MRE and R^2, the optimal configuration of the ANN model was 6-6-1, namely, six neurons in the input layer, six neurons in the hidden layer and one neuron in the output layer (Table 5). Its structure is presented in Fig. 3. The MRE for this configuration was 1.30% and the coefficient of determination R^2 =0.998, and therefore, the proposed model can be considered a good predictor (Table 5). To reveal the credibility of the prediction resulted from the ANN model, the drying time predicted by the proposed model is plotted against the values predicted by TORKSIM software (Fig. 4). In addition, a part of the predicted values using the selected configurations are presented in Table 6.

Table 5

Prediction errors in the drying time (to reduce moisture content from initial to 10%)

Neurons in each hidden layer	Drying time	
	MRE (%)	R^2
2	1.54	0.998
3	1.61	0.998
4	1.64	0.996
5	1.80	0.994
6	1.30	0.998

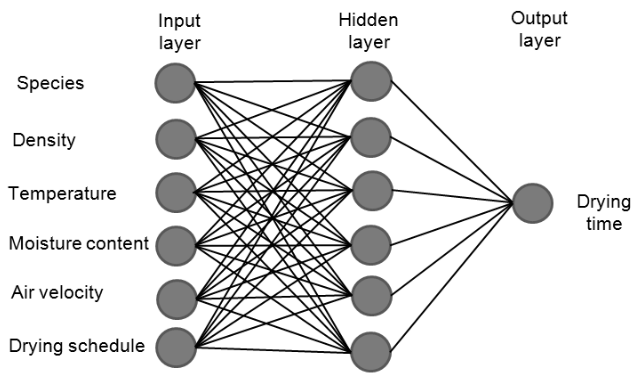

Fig. 3
The structure of the 6-6-1 ANN model.

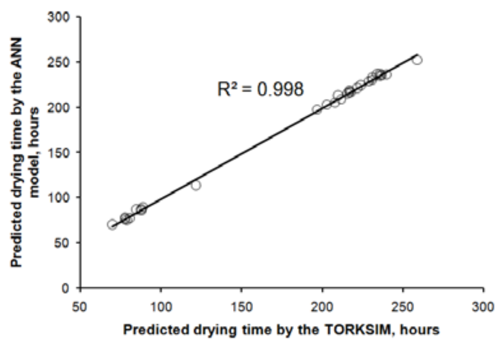

Fig. 4
Correlation of values predicted by TORKSIM versus the values predicted by the ANN model.

CONCLUSIONS

In this study, an ANN model was developed to predict the drying time of 50mm softwood boards for six input variables, namely, wood species, wood density, initial wood temperature, green moisture content, air velocity and three different drying schedules. The ANN model presented in this paper discovered the valuable relation used in TORKSIM software between independent variables and drying time. The 6-6-1 ANN model predicted the drying time with a mean relative error (MRE) of 1.30% and a coefficient of determination (R^2) of 0.998. Therefore, the model can be easily integrated in Microsoft Excel and used for further calculation needed for production planning (i.e. kiln demand and capacity through the year). A further study is needed to figure out the network weights and coefficients associated with the optimal ANN model. Once revealed, these data can be presented in the form of simple algebraic equations, so that the resulted equations can be used for further predictions without the need of the neural network program that was used for modeling. Also, we plan to take in consideration different thicknesses of boards.

Table 6

Comparison of Torksim and ANN predicted data for drying time – MRE (%)=1.30

Independent variables						Dependent variable		Relative error (%)
Species	Density, kg/m^3	Wood temperature, °C	Drying schedule	Green moisture content, %	Air velocity, m/s	TORKSIM predicted drying time (hours)	ANN predicted drying time (hours)	
Spruce	385	65	RM1	43.20	1.51	78	77.92	0.10
Spruce	385	65	RM1	51.49	1.02	85	87.03	2.38
Spruce	385	65	RM1	24.99	2.15	70	70.16	0.22
Spruce	385	65	RM1	92.19	1.95	88	85.75	2.55
Spruce	385	65	RM1	32.58	0.1	122	113.48	6.98
Pine	430	65	RM1	45.78	1.98	88	87.43	0.64
Pine	430	65	RM1	64.71	2.68	89	89.47	0.52
Pine	430	65	RM1	29.99	3.00	79	75.38	4.58
Pine	430	65	RM1	40.10	3.39	81	77.37	4.48
Pine	430	65	RM1	26.85	2.64	78	76.19	2.32
Spruce	385	45	RM2	35.13	2.82	216	215.34	0.30
Spruce	385	45	RM2	50.01	3.40	217	216.85	0.06
Spruce	385	45	RM2	91.49	1.46	236	234.81	0.50
Spruce	385	45	RM2	63.93	2.37	222	221.48	0.23
Spruce	385	45	RM2	135.25	2.93	231	232.91	0.82
Pine	430	45	RM2	28.37	3.35	224	224.38	0.17
Pine	430	45	RM2	32.19	2.22	229	228.73	0.11
Pine	430	45	RM2	55.61	2.08	237	235.43	0.66
Pine	430	45	RM2	30.96	1.37	236	237.07	0.45
Pine	430	45	RM2	38.47	2.18	231	230.11	0.38
Spruce	385	35	RM3	66.45	3.04	212	208.71	1.55
Spruce	385	35	RM3	30.92	3.04	197	197.51	0.25
Spruce	385	35	RM3	40.78	2.88	203	202.90	0.04
Spruce	385	35	RM3	95.63	3.16	218	216.39	0.73
Spruce	385	35	RM3	57.65	3.33	208	204.84	1.51
Pine	430	35	RM3	29.09	3.21	210	213.04	1.44
Pine	430	35	RM3	81.72	2.79	234	236.65	1.13
Pine	430	35	RM3	47.07	1.49	240	236.27	1.55
Pine	430	35	RM3	52.79	0.97	259	251.95	2.72
Pine	430	35	RM3	31.24	2.42	217	218.51	0.69

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