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Original Research Article

An experimental and theoretical examination of pine woods dried in the vacuum dryer by artificial neural network

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ABSTRACT

The drying characteristics of the pine woods were examined in the vacuum drying system under different operating conditions. Three drying temperatures (40, 50 and 60 ◦C), three operating pressures (0.6, 0.7 and 0.8 bar) and three times of exposure to vacuum (5, 10 and 15 minutes) were investigated. Experiments were carried out to obtain data from the sample moisture content. In this study, the application of Artificial Neural Network (ANN) to estimate pine woods' moisture content (output parameters for ANN modeling) was examined. Drying time, drying temperature, relative humidity, pressure and air temperature were accepted as the input parameters of the model. Training and validation were performed with great accuracy. The moisture content of woods is formulated by the ANN method. The proposed method offers more flexibility; therefore, the determination of the moisture content in pine woods is quite simpler.

Keywords: Artificial neural network; Modeling; Vacuum drying; Wood

1. Introduction

Drying is accepted as a complex, vague, and the nonlinear process is with several unknown factors which changes in time. Hence, it is difficult to determine the complex relationship between the input and output of a drying system based on analytical methods. Artificial Neural Network (ANN) have a high-level learning skills and the ability to determine and model the complex, nonlinear relations between the inputs and outputs of a system [1].

Recently, modeling of the drying process via ANN has been increasingly utilized. Pedreno-Molina et al. used ANN in microwave-assisted drying processes to estimate the temperature and drying curves and solve the reveres modeling equations [2]. Ceylan determined the drying characteristics of wood using ANN and mathematical models [3]. Poplar and pine woods were dried in a heat pump dryer. Menlik et al. used the ANN to determine the freeze-drying characteristics such as moisture content, moisture rate, and drying rates of apples [4].

Momenzadeh et al. investigated the drying characteristics of corn in a microwave-assisted fluidized bed dryer [5]. They used ANN to estimate the drying time. Strength of microwave, drying air temperature and grain moisture content was accepted as input parameters. Ceylan and Aktas utilized the ANN method for a PID-controlled heat pump. Upon the evaluation of experiment results via ANN, the drying air rates, moisture content of hazelnut, and total drying time were estimated [6]. Movagharnejad and Nikzad performed studies on drying tomatoes in a tray dryer which involves different parameters such as the power of the heater and the airflow rate [7]. The data was modeled using ANN and experimental mathematical equations. Esteban et al. estimated the elasticity module of wood via an artificial neural network through parameters of density, width, thickness, moisture content, dispersion velocity of ultrasonic waves, and visual assessment of test particles [8]. Lertworasirikul and Tipsuwan estimated the moisture content and water activity of semi-product cassava crackers which had been subjected to the hot-air drying process in a tray dryer using a multi-layer feed-forward neural network [9].

Tripathy and Kumar used ANN to estimate the temperature variations of the food product during an investigation of sun-drying [10]. They accepted the sun radiation and the environment air temperature as input parameters. Nazghelichi et al. used ANN to predict the energy and the exergy based on the parameters of drying time, drying air temperature, size of carrot cubes, and bed depth [11].

Topuz used the ANN method to estimate the drying characteristics of agricultural products such as hazelnut, bean, and chickpea [12]. Nazghelichi et al. utilized the ANN method to estimate the energy and the exergy of carrot cubes during the fluidized bed-drying. Drying time, drying air temperature, size of carrot cubes, and bed depth was accepted as input parameters [13]. Wu and Avramidis used ANN modeling to estimate the drying rates of the wood kiln. To estimate a single input, the average final moisture content, three-input ANN models were developed [14].

Çakmak and Yıldız used feed-forward ANN to model the nonlinear drying behavior of seeded grapes [15]. Cachim benefited from artificial neural networks to estimate the temperatures in wood under fire load [16]. Tiryaki and Aydın used the ANN and multiple-linear regression model to estimate the compressive strength of the heat-treated wood [17]. Khazaei et al. used an artificial visual and artificial neural networks to model and control the grape drying process [18]. Nadian et al. utilized ANN to associate drying parameters and drying time with color parameters and moisture content of apple wedges [19].

As seen in the literature studies above, the ANN method has been widely used to estimate the characteristics of the drying process. However, most of these studies have used tray dryers and fluidized bed dryers as the drying technology. And most of them have investigated the drying characteristics of agricultural products with ANN methods. On the other hand, there are no studies using ANN to investigate the drying characteristics of pine woods dried in vacuum dryers. This study examined the drying behavior of pine woods in vacuum dryers under different operating conditions and made an effort to develop and evaluate the ANN model of this drying configuration to estimate the moisture content (MC) of pine wood. The results obtained by the ANN model were compared to the results of the experiment. The MC values of pine woods were estimated with the ANN model accurately. Moreover, new formulas obtained from the ANN were presented to calculate the MC values. This model will help designers estimate the MC values of woods accurately and quickly beforehand.

2. Experimental Procedure

A testing apparatus was designed and applied to vacuum-dry the woods. The testing apparatus used in the research is shown in Figure 1. Pinewood was chosen as the drying material. Basically, the apparatus is composed of a fan, two heaters, a vacuum pump, a drying chamber, and measuring tools. A programmable logic controller (PLC) was added to the vacuum dryer. The experiments were conducted at different temperatures, pressures, and at different times of exposure to vacuum. All data collected during the drying was recorded on the computer and the PLC. For more details on the experimental procedure, please refer to the related reference [20].

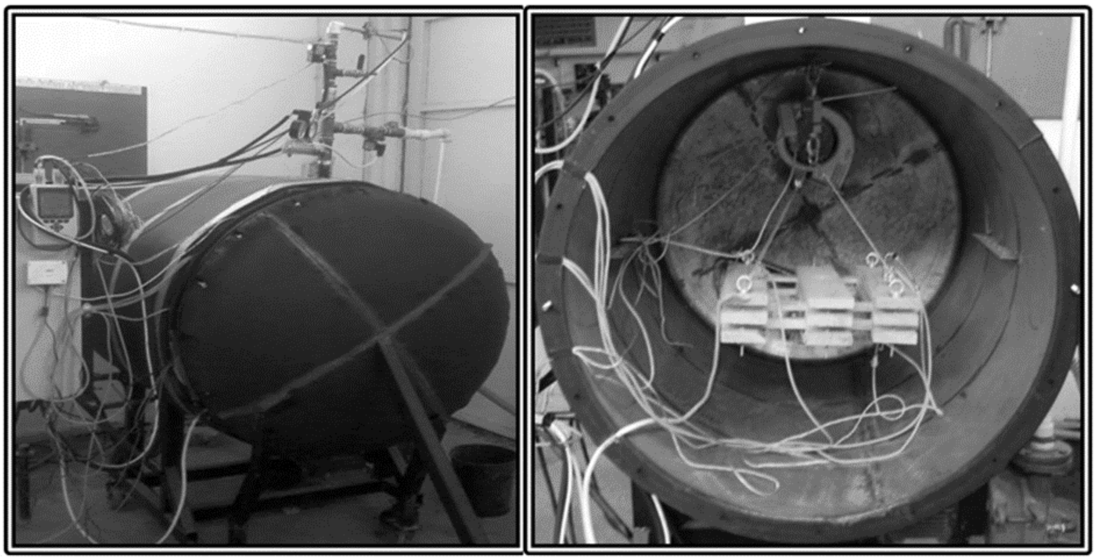

Fig.1. The experimental apparatus

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An experiment system was designed to vacuum-dry the woods. The experiments were conducted at different temperatures, pressures, and at different times of exposure to vacuum. Different operating conditions configured in the PLC system and properties of the woods are shown in Table 1.

Table 1. The operation conditions adjusted in the PLC automation system and properties of timbers

	Explanation	Drying temperature			The residence time in vacuum			Pressure		
		Test 1	Test 2	Test 3	Test 4	Test 5	Test 6	Test 7	Test 8	Test 9
Kiln Working setting	Drying temperature of kiln (T_{ik})[ºC]	40	50	60	50			50		
	Pressure of kiln (P_{ik}) [kPa]	80			80			60	70	80
	The residence time in vacuum (t_w)[minute]	10			5	10	15	10		
	Fan speed [m/s]	≈ 2.8								
	Vacuum pressure (P_v) [kPa]	25								
Timbers	Dimensions of timbers [cm]	2x9x55 (nine samples)			2x9x50 (nine samples)			2x9x60 (nine samples)		
	Initial weight [kg]	9.58	9.65	9.35	6.65	6.49	6.71	8.95	8.90	8.86
	Initial relative humidity [%]	66	67	62	26	24	28	42	41	40
	Final weight [kg]	6.23	6.27	6.29	5.67	5.69	5.68	6.87	6.85	6.89
	Final relative humidity [%]	8.1	8.7	9	8.2	8.5	8.3	9	9	9

Figure 2 shows the variation of the MC as a function of the drying time at different drying temperatures. As shown in Figure 2, the drying time of the wood decreases as the drying temperature goes up. Also, the MC values also decrease while the drying continues.

Figure 3 shows the variations of the MC as a function of the drying time at different drying temperatures for the time of exposure to a vacuum. As seen in Figure 3, the woods were dried faster in 5 minutes of exposure to vacuum. Also the MC also decrease while the drying continues.

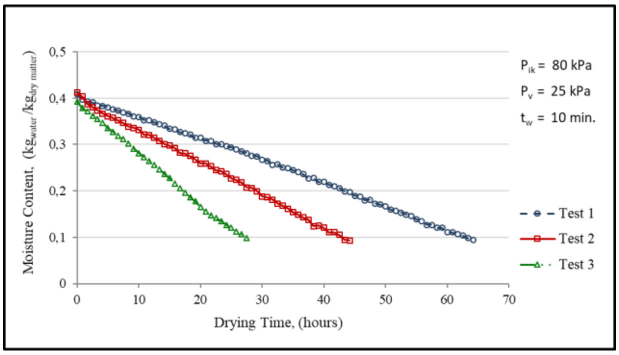

Fig. 2. Variation of moisture content with drying time for different drying temperature

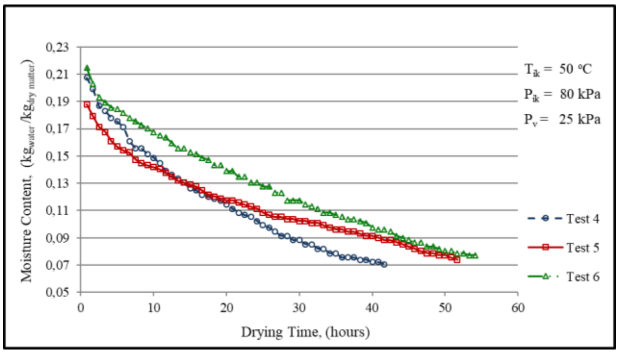

Fig. 3. Variation of moisture content with drying time for residence time in vacuum

Figure 4 shows the variations of the MC as a function of the drying time at different operating pressures. The drying times of the woods are almost the same at different operating pressures. On the other hand, the woods were dried a little faster at the pressure of 80 kPa.

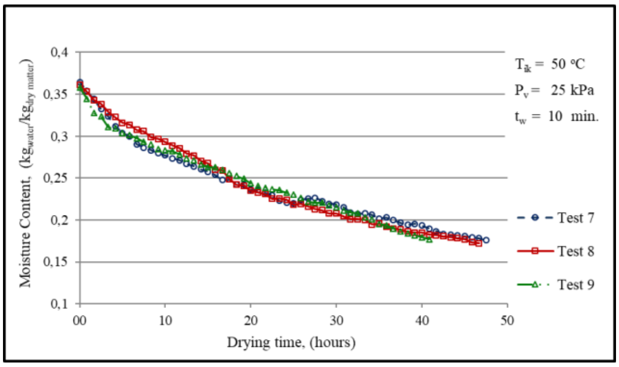

Fig. 4. Variation of moisture content with drying time for different operating pressure

3. ANN Modeling

ANN can be used in a lot engineering areas. ANN learns the relationship between controlled and uncontrolled parameters through input parameters by examining the pre-recorded data as the nonlinear regression does. Another advantage of using ANN is its ability to manage large and complex systems through several relevant parameters. They seem to be concentrated on more important inputs rather than considering the less important data [21-23].

There are different learning algorithms to train this neural network. It is difficult to know which training algorithm is faster for a given problem and the best one is generally chosen with trial and error. Performance criteria's as root mean square error (RMSE), multiple determination coefficient (R^2) and variation coefficient (cov) can be used to compare the estimated and experimental data. RMSE is stated as follows:

$$RMSE = \sqrt{\frac{\sum_{m=1}^{n}\left(y_{p,m}-t_{e,m}\right)^2}{n}} \quad (1)$$

In addition, multiple determination coefficient (R^2) and variation coefficient (cov) is defined as follows:

$$R^2 = 1 - \frac{\sum_{m=1}^{n}\left(t_{e,m}-y_{p,m}\right)^2}{\sum_{m=1}^{n}\left(t_{e,m}-\bar{t}_{e,m}\right)^2} \quad (2)$$

$$cov = \frac{RMS}{\left|\bar{t}_{e,m}\right|} \quad (3)$$

n is data number; $y_{p,m}$ data point indicates the predicted value of m and $t_{e,m}$ represents the experimental value of m, and $\bar{t}_{e,m}$ is the mean value of all experimental data points.

To train the network the reference [20] experiment results were used. The inputs for the network are drying time, drying temperature, relative humidity, pressure, and air temperature; the output is the moisture content.

The back-propagation learning algorithm was used for the feed-forward, single-hidden-layer neural network. The variants used in the study are Levenberg–Marquardt (LM) and scaled conjugate gradient (SCG) algorithms. Inputs and outputs are normalized within the range of (0, 1). For both two hidden layers and output layers, the sigmoid (log-sig) transfer function was used. Here is the transfer function used:

$$F(z) = \frac{1}{1+e^{-z}} \quad (4)$$

z is the weighted total of the input.

The neural network toolbox in the MATLAB for analysis was used. Different numbers of neurons in the hidden layer were used. The data cluster included 87 data for the moisture content of the current pine woods. 70 data were used for training the network; the rest 17 data were randomly received to be used as test data clusters.

To obtain an optimal topology, different algorithms and numbers of hidden neurons were utilized. Performance criteria's as RMSE, R^2, and cov for the moisture content of the woods are given in Table 2.

Table 2. Statistical values for the moisture content estimation of timbers

Algorithm-neurons	RMSE	cov	R^2
LM-3	0.003720713	0.015192	0.99977
LM-4	**0.002866971**	**0.011706**	**0.999863**
LM-5	0.003229205	0.013186	0.999826
LM-6	0.004880268	0.019927	0.999604
LM-7	0.003119288	0.012737	0.999838
LM-8	0.006660886	0.027198	0.999261
LM-9	0.017353572	0.070858	0.994987
LM-10	0.009337086	0.038125	0.998549
LM-11	0.008383967	0.034234	0.99883
LM-12	0.03203099	0.130789	0.98292
SCG-3	0.003922099	0.016015	0.999744
SCG-4	0.004518904	0.018452	0.99966
SCG-5	0.003355301	0.0137	0.999813
SCG-6	0.004783316	0.019531	0.999619
SCG-7	0.003668946	0.014981	0.999776
SCG-8	0.004022043	0.016423	0.999731
SCG-9	0.008486241	0.034651	0.998801
SCG-10	0.007054376	0.028805	0.999172
SCG-11	0.005327015	0.021751	0.999528
SCG-12	0.004602209	0.018792	0.999647

It is understood from the data given in Table 1 that the most optimal topology is the four-neuron LM algorithm (LM-4) in the hidden layer to determine the moisture content.

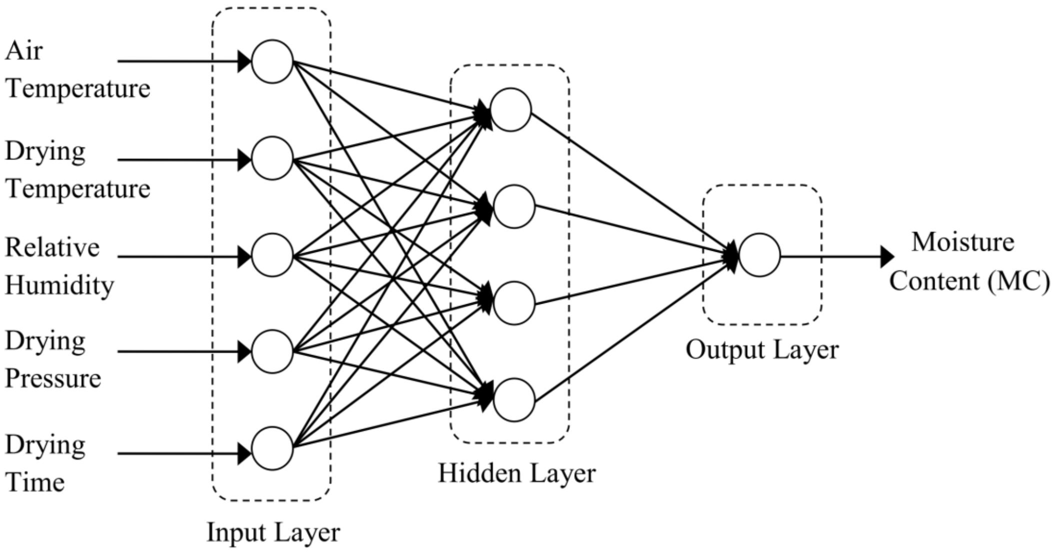

Fig. 5. ANN topology used for determining the moisture content

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The regression curve of the output parameter (moisture content) for the test data cluster is given in Figure 6. The correlation coefficient obtained in this case is a very satisfying value of 0.9987.

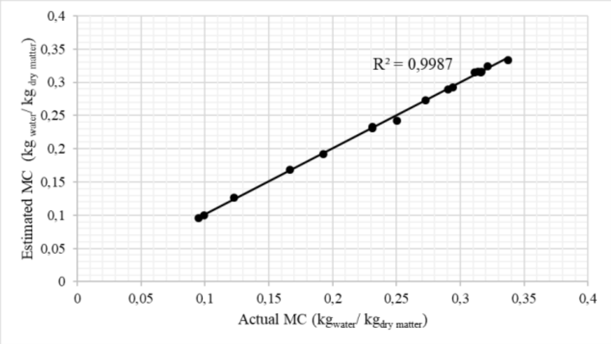

Fig. 6. Relationship between experimental results and ANN predicted results

4. Results and Discussion

The mathematical formulas derived from the ANN model are given here. The best approach that has the minimum error to determine the moisture content of the pine woods is the 4-neuron Levenberg–Marquardt (LM) algorithm. The log-sig activation was used both for the hidden layer and the output layer. The following equation was utilized to calculate the MC of the pine woods.

$$E_i = \sum_{n=1}^{4} I_n w_{ni} + b_n \quad (5)$$

$$F_i = \frac{1}{1+e^{-E_i}} \quad (6)$$

In the equations above, the first two values for E_i is the product of the weights in n position and the input parameters (I_n), and the last constant value represents the (b_n) bias term. The subscript i symbolizes the number of hidden neurons. The five input parameters are as follows:

I_1= Drying time (t)

I_2= Drying temperature (T)

I_3= Relative humidity (RH)

I_4= Drying pressure (P)

I_5= Air temperature (T_a)

4 hidden neurons are used for determining the moisture content of woods in the ANN; hence, four double equations, that is, E_1 - E_4 and F_1 - F_4 are necessary to symbolize the total and activation of each neuron of a hidden layer respectively. Coefficients of equation (5) are shown in Table 3.

Table 3. Weight coefficients and bias values of the ANN for the estimations of woods' MC

Neuron position (w_{ni})	I_1 (t)	I_2 (T)	I_3 (RH)	I_4 (P)	I_5 (T_a)	b_n
1	1.7019	0.28597	0.07564	-0.07113	0.0043338	-6.3615
2	-48.3714	-82.0443	117.5112	-150.8556	-95.0195	140.895
3	3.9273	-20.8271	55.6927	-85.5887	-1.9469	30.6768
4	70.9568	90.4657	-184.0242	220.44	83.3259	-138.175

In addition, actual input data of several parameters need to be normalized as shown in Table 4.

Table 4. Normalization coefficients for the input parameters

Input Parameter	Coefficient
Drying time(t)	4400
Dryingtemperature (T)	45
Relative humidity (RH)	97
Dryingpressure (P)	1
Air temperature (T_a)	30

The wood moisture content can be calculated as follows:

$$E_5 = F_1*(-209.3615)+F_2*(0.17184)+F_3*(0.19448)+ +F_4*(0.16726)-0.37275 \quad (7)$$

$$The\ moisture\ content = \left(\frac{1}{1+e^{-E_5}}\right) \text{(MC)} \quad (8)$$

Table 5 presents a comparison of the MC estimated by the equation derived in the ANN of the pine woods and the actual MC. The error is on a minor level as can be seen.

5. Conclusion

In this study, the ANN was successfully applied to determine the wood moisture content. The data obtained from the vacuum-drying system were utilized to train the network. Mathematical formulas were derived from the ANN model to calculate the MC values of the woods. Obtained values by the ANN formulas were found to be compatible with the experimental data.

The presented ANN model can be easily used without the need for a mathematical model of the process. The procedure offered here can be of help for researchers to estimate the pinewood moisture content very accurately and fast.

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Conflict of interest

This study did not lead to any individual or institutional/organizational conflict of interest.

Authorship contribution statement for Contributor Roles Taxonomy

Erkan Dikmen: Writing - original draft, Investigation, Visualization, Supervision – review & editing. Arzu Şencan Şahin: Investigation, Supervision, Writing, Conceptualization, Methodology, Software, Formal analysis. Ali Kemal Yakut: Investigation, Supervision, Conceptualization, Methodology.

Table 5. A comparison of the MC estimated by the equation derived in the ANN and the actual MC

t (min.)	T (ºC)	RH (%)	P (bar)	T_a (ºC)	Actual MC (kg_{water}/ $kg_{dry\ matter}$)	Obtained MC from ANN	Error
200	40.49	79.01	0.58	25.3	0.337349	0.33316	0.004189
450	37.05	88.84	0.68	24.7	0.321632	0.32427	-0.00264
700	27.07	95.13	0.897	22.2	0.316444	0.31583	0.000614
750	25.97	95.58	0.897	21.6	0.315789	0.31453	0.001259
1050	21.46	96.59	0.897	19.4	0.31382	0.31574	-0.00192
1300	34.52	81.63	0.414	22.6	0.311175	0.31511	-0.00393
1550	40.99	77.29	0.578	23.3	0.294176	0.29287	0.001306
1600	40.94	77.87	0.578	23.4	0.290675	0.28938	0.001295
1850	38.22	78.7	0.399	22.1	0.272635	0.27303	-0.00040
2150	39.49	59.17	0.368	20.1	0.250524	0.24219	0.008334
2350	40.36	76.78	0.578	19.1	0.231183	0.23341	-0.00223
2400	38.72	81.67	0.583	19.0	0.231183	0.23072	0.000463
2850	40.41	76.14	0.581	21.3	0.193002	0.19174	0.001262
3150	37.9	82.2	0.569	21.5	0.166667	0.16847	-0.00180
3650	39.45	74.33	0.578	19.7	0.122699	0.12596	-0.00326
4000	38.06	64.43	0.395	17.9	0.099496	0.099292	0.000204
4050	38.27	62.06	0.389	18.3	0.094937	0.09557	-0.00063

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