Mugla Journal of Science and Technology, Vol 1, No 1, 2015, Pages 24-33

Mugla Journal of Science and Technology

ESTIMATION THE PROPERTIES OF PARTICLEBOARDS MANUFACTURED FROM VINE PRUNINGS STALKS USING ARTIFICIAL NEURAL NETWORKS

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Accepted: 07.04.2015
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Abstract

In this study, chips of vine pruning stalks and wood chips in five various proportions were used as the raw material for three-layer particleboards. Primarily, small size sample panels (56x56x2 cm) were manufactured. The physical (thickness swelling (TS), water absorption (WA), and mechanical (modulus of rupture (MOR), modulus of elasticity (MOE), internal bond (IB), screw holding (SH) properties of particleboards were determined. Although direct measurement is the most reliable method, it is very complex and time consuming. Also every proportion is not applicable. So that, soft computing methods which are the powerful tools for input-output mapping were preferred. Artificial neural networks (ANNs) were used to estimation. The results show that ANN system capable to predict properties of particleboards in a time and cost effective way.
Keywords: Neural networks, Agricultural residue, Particleboard, Prediction of properties

YAPAY SİNİR AĞLARI KULLANILARAK BAĞ BUDAMA ARTIKLARINDAN ÜRETİLEN YONGA LEVHALARIN ÖZELLİKLERİNİN TAHMİN EDİLMESİ

Özet

Bu çalışmada, yonga levha hammaddesi olarak beş farklı oranda, bağ budama yongaları ve odun yongaları kullanılmıştır. Öncelikle küçük boyutlu numune paneller üç katmanlı olarak (56x56x2 cm) üretilmiştir. Bu levhaların; fiziksel (kalınlığına şişme, su alma) ve mekaniksel (eğilme direnci, elastikiyet modülü, iç yapışma ve vida tutma) özellikleri belirlenmiştir. Direk ölçüm alma metodu en güvenilir metot olmasına rağmen çok karmaşık ve zaman alıcıdır. Üstelik her oran uygulanabilir değildir. Bu nedenle girdi-çıktı haritalamada en güçlü araçlar olan esnek (yazılımsal) hesaplama yöntemleri tercih edilmiştir. Bu aşamada, yapay sinir ağları (YSA) tahmin amaçlı kullanıldı. Sonuçlar yapay sinir ağları sisteminin zamandan ve maliyetten kazanç sağlayarak yonga levhaların özelliklerinin belirlenmesinde yetkin olduğunu göstermektedir.
Anahtar Kelimeler: Sinir ağları, Tarımsal atıklar, Yonga levha, Özelliklerin tahmini

1 Introduction

The increased demand for wood and agricultural land and the forest fires because of population expansion leads to a permanent decline in forest areas. Growing social demands for various wood products and especially wood-based panels leads to the continuous effort of finding new wood resources as an alternative to forest wood [1]. Many political, economic, social, geographic and environmental factors determine the availability and end use of natural, renewable resources throughout the world. Due to environmental movement, landfill regulations, recycling trends, green movement, the available supply of wood is becoming scarce in the developed countries. Developing countries have already poor resources of wood for particleboard manufacturing. As a result, non-wood fibers play a major role in providing the balance between supply and demand.

Within the last four decades, in the forest products industry, especially in products generally referred to as particleboards, many the successful developments have been reported [2]. A wide range of agri-residues and annual fiber crops could potentially be used for manufacturing composites such as particleboard [3]. Agricultural residues are plentiful, widespread, and easily accessible. Aside from their abundance and renewability, utilization of agricultural residues has advantages for economy, environment, and technology [4].

Researchers have worked on a wide variety of crops from many different regions of the world. Some of these plants are sunflower stalks [5], vine pruning [1], hazelnut husk [4], kenaf stalks [6], almond shell [7], wheat straw and corn pith [8], cotton carpel [9] coconut shell [10], flax shiv [3], castor stalks, rice husks, peanut shells, bamboo, waste tea leaves, cotton stalks, kiwi pruning etc.

One other lignocellulosic agricultural residue, which could replace wood as the raw material for particleboard production, is vine pruning. Turkey has approximately 484,000-hectare total area for vine cultivation (TSI 2007). The average pruning yield per hectare is approximately 5 tons, which is higher than the average wood yield of temperate forests [1]. Therefore, approximately 2,420,000 tons of vine pruning residues are produced annually in Turkey. Large quantities of lignocellulosic pruning remain in the fields every year in early spring after pruning.

Soft computing methods are often used in agricultural applications [11], [12] developed soft computing applications in agricultural and biological engineering. ANNs were used for corn and soybean yield prediction [13]. Expert systems and neural networks were applied to learn site-specific conditions [14].

Most recent scientific applications involve the determination of direct relationships between input parameters and a known target response [15]. They used the methods of fuzzy logic, artificial neural networks, genetic algorithms, decision trees, and support vector machines to study soil and water regimes, analyze the operation of food processing, and support decision-making in precision farming [16] used decision support system to develop land suitability for agriculture.

Jia and Davalos [17] have developed of an artificial neural network (ANN) method for the analysis of load ratio effects on fatigue of interfaces for phenolic fiber reinforced polymer (FRP) composite bonded to red maple wood. Yapici et al [18] created a model based on fuzzy logic classifier in order to determine the values of modulus of elasticity (MOE) and modulus of rupture (MOR) of flakeboards. Riegler et al [19] simulated a real-time process adaptation of an industrial scale fiber-board manufacturing process. Demirkir et al [20] designed an ANN capable of predicting the optimum manufacturing parameters without spending much time and loss bonding strength. A dissertation study [21] related to improving the knowledge of forest products manufacturers by a contemporary DM method related to decision theory is decision trees (DTs). Andre et al [22] presented a genetic algorithms (GA) based multivariate calibration models for predicting internal bond strength from medium density fiberboard (MDF) process variables.

Medium Density Fiberboard (MDF) is an engineered wood used in furniture industry as an alternative to solid wood. Besides using forest wood and rubber wood as the main source of fiber, oil palm biomass was proven as an excellent substitute. Regardless of any fiber used, identifying its strength level is the main issue. Therefore, prior to releasing processed fiberboards for manufacturing use, boards need to undergo test procedures for mechanical and physical properties as set by the standard. These tests are timely, especially to research institutions which involve various characteristics of boards.

The aim of this research is to reduce testing time by excluding these lengthy tests. The study consists of two parts. First, Turkey Aegean region of grapevine plants (Vitis vinifera L. cv. Sultanas) was tested to determine if it is suitable to be raw particleboard materials. Then, the second part of the study a prediction model was produced to predict properties of particleboards. In this model, feed-forward back-propagation network was trained with supervised learning method. Wherein, the network learns the relationship between the input and the output information. The training of the network is carried out by the arrangement of the weight between neurons of each layer. Feed-forward networks are allowed to move in one direction, from input to output. Back-propagation algorithm is the process that the regulation of weight backward to minimize errors in the output layer [23], [24] **.**

2 Artificial Neural Networks

ANNs are typically designed to perform a nonlinear mapping from a set of inputs to a set of outputs. ANNs are developed to try to achieve biological system type performance using a dense interconnection of simple processing elements analogous to biological neurons. ANNs are information driven rather than data driven. ANNs offer certain advantages over conventional techniques. These advantages are the generalization capability, parallelism, distributed memory, redundancy, and learning [25].

Neural networks were firstly emerged after the introduction of simplified neurons by McCulloch and Pitts [26]. Rumelhart and McClelland [27] introduced the back-propagation learning algorithm for complex multilayer networks.

All neural network models share a common building block, known as a neuron and a networked interconnection structure [28]. ANNs are composed of a number of nodes or units, connected by links. Each link has a numeric weight associated with it [29]. The most widely used neuron model is illustrated in Figure 1.

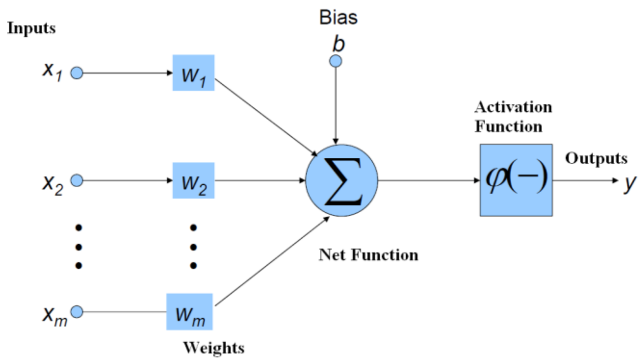

Figure 1. The basic neuron structure.

The Bias is used to model the threshold. The Net functions can be used as linear, higher order, delta (∑, ∏) and neuron activation functions can be sigmoid, hyperbolic tangent, inverse tangent, threshold, Gaussian radial basis and linear [30].

Several architectures and algorithms have been developed in the literature for solving different problems. The main ones are multilayer perceptron, radial basis function network, and recurrent neural network [31]-[34].

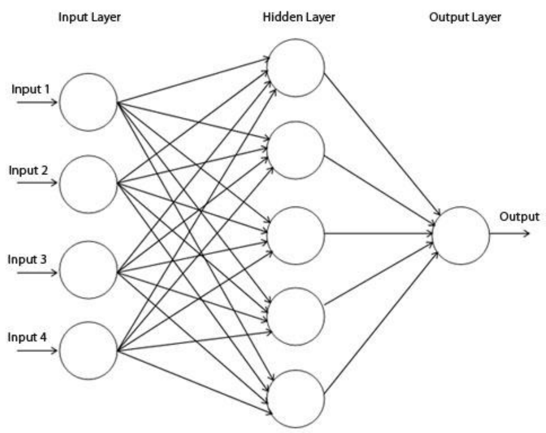

Figure 2. Basic Artificial Neural Networks Model

ANN basically consists of three layers as shown in Figure 2. The first layer consists of processing units related to input variables (cell or neuron); this section is called input layer. The function of input layer is to transmit the input variables to hidden layer coming after itself in the network. The final layer consists of output variables called the output layer. The layer consisting of the processing units between the input layer and the output layer is called the hidden layer. The presence of the hidden layer is useful in the modeling of the complex relations [35].

The number of the neurons in the layers varies depending on the complexity of the problem. Links coming out of each neuron of the input layer have weights; and the weights connecting z_h hidden layer with x_j input layer are labeled as w_{ij}. Each hidden layer neuron calculates the weighted sum of the neurons in the input layer; and this is given in Eq. 1:

$$Input_j^s = \sum w_{kj} x_k^i \qquad (1)$$

Outputs corresponding to these layers are obtained as a result of the implementation of the function known as activation or transfer function to inputs. An ANN with randomly set weights is "dull" but can be trained by successive repetitions of the same problem. A network "learns" by iteratively correcting the weights (the only adjustable parameters) so as to produce the previously specified output values (target sets) for as many input sets as possible.

If the difference between these values designed as output and actual values is at the desired level, the algorithm is terminated; otherwise, the weights are updated in such a way that the default between these values is minimized. This algorithm is called back propagation; and this is the most commonly used learning algorithm in ANN [29], [31], [34].

A commonly used equation for calculating the error of a network is given in Eq. 2:

$$E = \frac{1}{2}\sum_j (t_j - Output_j)^2 \qquad (2)$$

t_j and $output_j$ are the actual and desired values of unit j in the output layer. The weights are updated according to the so-called delta-rule of learning:

$$\Delta w_{ij} = \eta \delta_i o_i \qquad (3)$$

Where η > 0 is the learning rate, δ_i is a correction term, and o_j is the output of unit i in the previous layer. The value of δ_i should be proportional to the output-error. In the back-propagation algorithm the correction-term is obtained by applying the so-called gradient descent method, which leads to the following expression for the delta-term of an output unit:

$$\delta_i = (\partial E / \partial o_j)(\partial o_j / \partial I_j) = (t_j - o_j^{out}) o_j (1 - o_j) \qquad (4)$$

The following recursive formula is applied to calculate the correction term for a hidden unit:

$$\delta_j = o_j (1 - o_j) \sum_k \delta_k w_{kj} \qquad (5)$$

It has been found that the performance and also the stability of a training process are greatly enhanced if a so-called momentum term is added to the learning rule:

$$\Delta w_{ij} = \eta \delta_i o_i + \mu \Delta w_{ij}^{prev} \qquad (6)$$

Where 0< μ < 1 is a constant called momentum, and Δw_{ij}^{prev} is the adjustment to the same weight in the previous iteration cycle [29], [31], [34].

3 The process of the particleboard manufacturing

The raw material for this study consisted of vine pruning (*Vitis vinifera* L. *cv.* Sultani) and Scots pine (*Pinus sylvestris* L.), were utilized as the raw material for particleboard manufacturing. The target dimensions of panels were 56 × 56 × 2 cm. and density for all board types was 0.70 g/cm3. Various mixtures of vine prunings (VP) particles and pine wood (PW) chips were used as furnishes for three-layer particleboards. All layers consisted of various proportions of mixed VP and PW (Table 1). For each mixed model, three experimental panels were manufactured. After pressing, panels were conditioned at a temperature of 20 °C and 65% relative humidity, edge trimmed to 55 × 55 cm. For further detail of the steps of the particleboard production see [36].

Table 1. Experimental design and composition of the core of three-layer particleboards

Board Type	Raw material usage (%) (Vine pruning: wood)	Pressure time (min)	Density (kg/m^3)	Adhesive type	Adhesive (%)		Proportion (%)	
					Surface	Middle	Surface	Middle
A	100:0	7	700	UF	10	8	35	65
B	75:25	7	700	UF	10	8	35	65
C	50:50	7	700	UF	10	8	35	65
D	25:75	7	700	UF	10	8	35	65
E	0:100	7	700	UF	10	8	35	65

Test samples were cut from the boards and the following properties were determined in accordance with appropriate EN and TS standards: density (TS EN 322; EN 1993), static bending (modulus of rupture (MOR), modulus of elasticity (MOE) (TS EN 310; EN 1993), internal bond (IB) (TS EN 319; EN 1993), thickness swelling (TS), water absorption (WA) (TS EN 317; EN 1993) and screw holding strength (SHS) (TS EN 32). All results were statistically analyzed by using the analysis of variance (ANOVA) and Turkey's mean separation tests. Figure 3 and Figure 4 show just the specific samples of the construction of vertical tensile test to the board surface and he bending strength and modulus of elasticity test, respectively.

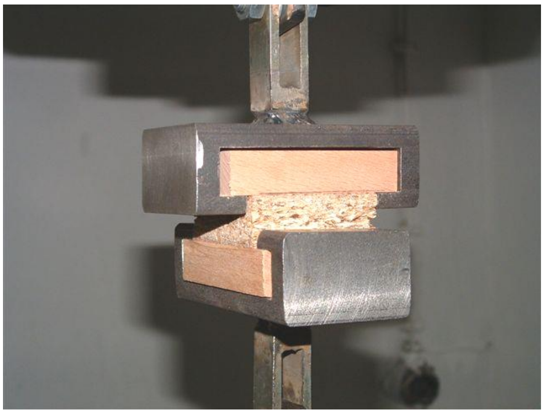

Figure 3. The construction of vertical tensile test to the board surface

Figure 4. The bending strength and modulus of elasticity test

Table 2 and Table 3 present the hygroscopic and mechanical properties of three-layer boards containing various proportions of Scots pine wood and vine pruning particles.

Table 2. Physical properties of three-layer particleboards made from various mixtures of Scots pine wood and vine pruning particles

Physical properties	Board type	N	Mean	S.D.^{w}	S.E.^{x}	X min^{y}	X max^{z}	p
Density (kg/m^3)	A	18	646.90^{b}	67.15	15.82	476.21	733.92	
	B	18	723.94^{a}	60.34	14.22	552.16	790.37	
	C	18	735.68^{a}	37.56	8.85	662.48	796.74	*
	D	18	700.06^{ab}	76.35	17.99	485.23	798.14	
	E	18	706.66^{a}	21.68	5.11	673.20	756.66	
Thickness swelling 2 h (%)	A	24	18.33^{a}	7.76	1.58	10	40	
	B	24	31.13^{d}	4.19	0.86	23	42	
	C	24	35.33^{de}	5.58	1.14	25	47	*
	D	24	23.42^{b}	4.15	0.85	16	32	
	E	24	38.50^{e}	6.16	1.26	27	52	
Thickness swelling 24 h (%)	A	24	22.79^{a}	5.79	1.18	12	32	
	B	24	34.29^{b}	4.43	0.90	25	43	
	C	24	37.04^{b}	5.61	1.14	28	48	*
	D	24	25.63^{a}	3.39	0.69	19	34	
	E	24	41.00^{c}	6.11	1.25	30	53	
Water absorption 2 h (%)	A	5	115.40^{d}	2.6077	1.1662	112.00	118.00	
	B	5	96.00^{b}	3.1623	1.4142	93.00	101.00	
	C	5	86.80^{a}	1.4832	0.6633	85.00	89.00	*
	D	5	104.00^{c}	5.2440	2.3452	99.00	112.00	
	E	5	99.20^{bc}	3.5637	1.5937	94.00	104.00	
Water absorption 24 h (%)	A	5	133.23^{c}	2.8281	1.2648	130.00	137.00	
	B	5	121.40^{b}	3.2863	1.4697	119.00	127.00	
	C	5	105.60^{a}	2.0736	0.9274	103.00	108.00	*
	D	5	124.40^{b}	5.5498	2.4819	117.00	131.00	
	E	5	121.40^{b}	3.2094	1.4353	117.00	125.00	

a, b, c, d, e values having the same letter are not significantly different and vice versa (for Turkey test).
w Standard deviation.
x Sampling error.
y Minimum value.
z Maximum value.
* Significance level of 0.05 (for ANOVA)

Table 3. Mechanical properties of three-layer particleboards made from various mixtures of Scots pine wood and vine pruning particles

Mechanical properties	Board type	N	Mean	S.D.[w]	S.E.[x]	X min[y]	X max[z]	p
Static bending (MOR) (N/mm^2)	A	18	12.38[a]	2.2	0.52	10.29	17.65	*
	B	18	12.78[a]	2.4	0.57	8.82	16.91	
	C	18	13.27[a]	1.9	0.45	9.56	17.65	
	D	18	13.36[a]	2.4	0.58	8.82	16.91	
	E	18	7.96[b]	6.3	1.14	6.61	8.82	
Elasticity (MOE) (N/mm^2)	A	18	2841.88[bc]	1421.44	335.03	1618.00	7845.00	*
	B	18	3336.61[bc]	966.65	227.84	1949.00	5044.00	
	C	18	3927.05[b]	1021.38	240.74	2351.00	6193.00	
	D	18	5252.88[a]	1887.20	444.81	2464.00	8387.00	
	E	18	2409.11[c]	624.18	147.12	1570.00	3924.00	
Internal bound strength (N/mm^2)	A	24	0.52[bc]	0.27	0.05	0.14	1.06	*
	B	24	0.45[c]	0.14	0.02	0.22	0.72	
	C	24	0.67[ab]	0.21	0.04	0.33	1.10	
	D	24	0.79[a]	0.24	0.05	0.28	1.20	
	E	24	0.21[d]	0.05	0.01	0.12	3.13	
Screw holding strength ⊥ (N/mm^2)	A	15	3.24[abc]	0.98	0.25	0.58	4.21	*
	B	15	3.13[bc]	0.58	0.15	2.64	5.00	
	C	15	3.44[abc]	0.92	0.23	0.78	4.60	
	D	15	4.07[a]	0.96	0.24	2.94	5.98	
	E	15	2.54[c]	0.71	0.18	1.56	3.53	
Screw holding strength // (N/mm^2)	A	30	2.02[c]	1.00	0.18	0.49	4.21	*
	B	30	2.3[bc]	0.80	0.14	0.68	4.31	
	C	30	2.92[ab]	0.82	0.15	1.47	4.90	
	D	30	3.47[a]	2.11	0.38	0.49	12.05	
	E	30	0.93[d]	0.43	0.08	0.39	1.66	

a, b, c, d, e values having the same letter are not significantly different and vice versa (for Turkey test).
w Standard deviation.
x Sampling error.
y Minimum value.
z Maximum value.
* Significance level of 0.05 (for ANOVA)

The results indicated that all mechanical properties (bending strength, internal bond, elasticity and screw holding strength) generally decreased as the amount of vine pruning particles increased in the range from 25 to 100%.

The static bending strength values of all experimental panels varied from 7.96 to 13.36 N/mm^2. The bending strengths of all panels met the minimum bending strength value (11.5 N/mm^2) required in TS-EN 312-2 standard for general purpose particleboards with the exception of the E (100% wood) type panels, having density of 0.706 g/cm^3. The highest bending strength value (13.36 N/mm^2) was measured for the particleboard having density of 0.700 g/cm^3, the lowest one (7.96 N/mm^2) is for board having a density of 0.706 g/cm^3, thus showing that density is not a clear factor on the bending strength. The reduction in bending strength for the E type board that constructed from 100% wood is probably attributable to manufacturing parameters which is consistent but incomparable to standard particleboard manufacturing. The negative effect of vine particles on board bending strength is partially attributable to their lower length to thickness (slenderness) ratio in comparison to wood particles. The negative effect of vine pruning particles was not only evident on bending strength but on all mechanical properties which is probably because of the fact that they incorporate certain amounts of pith particles. According to a previous research, vine pruning particles were characterized by higher bulk density and lower slenderness ratio than industrial wood particles [1].

When Table 2 is examined, the following is observed; for panels produced with five various proportions (A, B, C, D, E) the count of same type experimental materials, the received property values, the standard deviation of these property values, the margin of error, maximum and minimum values. For example, the intensity values of 18 different B-type panels that contain 75% of vineyards and 25% of pine content are from 476.21 to 733.92. The average value of these 18 values is 646.90; the standard deviation is 67.15; the margin of error is 15.82. Differences in the measured values of the panels are caused by physical differences involuntary realized. Therefore, it shows that a single measurement is not safe and adequate to describe the property value taken by the property.

4 Prediction of Mechanical and Physical Properties with an ANN Model

In this study, soft modeling methods that are able to make predictions using existing experimental data were preferred to determine what property values will be observed in other percentage mixtures apart from five different percentages of proportions. The difficulty of a mixture material production, time consuming, increasing cost and there exist some unintentional situations that occur in the experimental layout like differences and measurement errors. When these situations are taken into account, it demonstrates the value of the data obtained from the model. Scope of this study, feed-forward back-propagation neural network is used as flexible modeling (soft computing) method.

This study consists of 2 input vectors (the vineyard and pine percentage Mixing Ratio) and 10 output vectors (Table 2 Mechanical and physical properties). As seen at Table 2, analysis of 50 data belong to 5 different mixtures is considered. From these data, the value of 3 mixtures (A-C-E) used as training set and the value of 2 mixtures (B-D) used as test set.

In this study, Matlab neural network that has the lowest(or minimum) mean absolute percentage error in the test set after various attempts was realized with the parameters specified below. The details of the parameter values are given in Section 2. Figure 5 shows the ANN Model that was utilized.

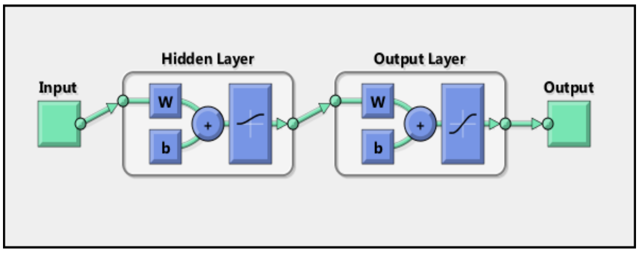

Figure 5. ANN Model

newff(minmax(pn),[6,4,10],{'tansig','tansig','logsig'},'traingdm','learngdm','mse')

The training parameter, 75, belonging to this network for the number of iterations was found adequate. Accordingly, the ANN model test results are given in Table 4.

Table 4. ANN test results

	Panel Type B			Panel Type D		
PROPERTY	**MEASURED**	**ESTIMATION**	**% MH**	**MEASURED**	**ESTIMATION**	**% MH**
D	700,06	718,46	2,63	735,68	735,36	0,04
SBS	13,36	13,349	0,08	13,27	13,326	0,42
E	5252,9	5248,5	0,08	3927,1	5249,4	33,67
IBS	0,79	0,78875	0,16	0,67	0,73311	9,42
SHS	4,07	3,9669	2,53	3,44	3,7906	10,19
SHS2	3,47	3,4477	0,64	2,92	3,1962	9,46
TS_2	23,42	35,263	50,57	35,33	31,533	10,75
TS_24	25,63	31,622	23,38	37,04	36,549	1,33
WA_2	86,8	86,825	0,03	86,8	86,826	0,03
WA_24	105,6	105,63	0,03	105,6	105,63	0,03
	% OMH		**8,01**			**7,53**
	r2		0,999992			0,998925

***epocs=75**

In this point, although, ANN showed high error in the less part of job, it showed very high consistency of estimating some properties of test panels. Especially, observing this situation on the same properties in the different mixtures of B and D type panels is an interesting case. Table 5 shows the estimated property values of the panels at an interval of 10% for untried mixture ratio as the purpose of the study.

Table 5. ANN results belonging to mixtures at an interval of 10%

	Vine Pruning Rate – Scotch Pine Rate (%)										
PROPERTY	**0–100**	**10–90**	**20–80**	**30–70**	**40–60**	**50–50**	**60–40**	**70–30**	**80–20**	**90–10**	**100–0**
D	715,08	723,71	723,92	723,91	723,83	723,49	722,33	713,36	696,81	694,5	694,36
SBS	10,370	10,370	10,370	10,370	10,370	10,37	10,371	10,372	10,381	10,422	10,459
E	3336,5	3336,5	3336,3	3336,2	3336,2	3336,3	3336,4	3336,5	3336,5	3336,5	3336,5
IBS	0,37151	0,36547	0,36508	0,36513	0,36557	0,36718	0,37233	0,40693	0,48955	0,51004	0,51307
VSHS	2,8904	2,8927	2,8997	2,902	2,9025	2,9004	2,8981	2,8949	2,8962	2,9045	2,9103
PSHS	2,2992	2,2984	2,2962	2,2961	2,2966	2,2972	2,2976	2,2983	2,2968	2,2888	2,2817
TS_2	35,406	32,233	31,193	30,248	29,388	29,120	29,032	28,960	28,823	28,729	28,702
TS_24	38,683	32,607	32,000	32,095	32,775	34,386	36,613	39,572	40,650	40,781	40,808
WA_2	107,08	105,80	105,73	105,75	105,83	106,01	106,32	107,37	110,68	113,19	113,81
WA_24	133,25	133,25	133,25	133,25	133,25	133,24	133,23	133,18	133,11	133,10	133,11

In this study, correlation coefficient (r2) was used as a statistical method to evaluate the performances of the established models, Mean Absolute Error (MAE) method was used to get information about distribution of the error. Evaluation of the performance of the models is given in Table 6. When the results of the test group performance evaluated, ANN, exhibits a reassuring situation.

Table 6. ANN performance

		Panel Type B	**Panel Type D**
YSA	**% OMH**	**8,01***	**7,53***
	r^2	0,999992*	0,998925*

*The best values

5 Result and Suggestions

In this study, using a neural network modeling method, the three-layered particle boards produced in the various mixture ratios from yellow pine wood chips and vine pruning's chips have attempted to estimate the mechanical and physical properties. Considering the performance ratings of the test sets, ANN was seen as appropriate. However, it is necessary to achieve measurements belonging to more input values. What's more, the measurement values used in the model training is the average value of the plurality of particle board pieces of the same characteristics. Table 2, shows the standard deviation of the data. Here, the standard deviation is the differences that occur involuntarily. Consisting of a lower values of standard deviation will allow a more accurate result for the established models.

At one side, producing particle board using a mixture of material in a given ratio is time consuming and costly, but at the other side, ANN was considered very encouraging for similar studies because of its success to estimate the changes in the measured values. These changes are the differences that occur during the production process.

ANNs are now widely used in science. Not only are they able to learn by inspection of data rather than having to be told what to do, but also they can construct a suitable relationship between input data and the target responses without any need for a theoretical or mathematical model. Unlike many conventional methods, they are able to assess absorption spectra without knowing about the underlying line shape of a spectral feature [15].

6 Discussion

In general, the evaluation of the mechanical and hygroscopic properties of experimental panels showed that partial substitution of wood by vine prunings negatively affects the board properties. The particleboards A, C, and D were the three types that met the minimum requirement for the heavy duty load bearing boards. But the E- type particleboards resulted in lower bending and internal bond strength values. Based on all mechanical tests, the D type (25% VP/75% W) board is to be an appropriate mixture.

The particleboards manufactured utilizing vine prunings gave relatively high thickness swelling and water absorption values. Adding water repellent chemicals such as paraffin during the board production could easily reduce the rate of thickness swelling and water absorption.

For enhancing the properties of vine prunings particleboard, as Ntalos suggested (2002), further research should be carried out in order to find appropriate methods for pith separation from the whole stalk. In addition, properties of vine prunings particleboard can be enhanced by alternative resins, such as isocyanates, and/or a reduction in furnish particle size, or involvement of plastic, fiber and or other materials in panels during manufacturing.

The results indicated that it is possible to produce particleboard from the chips of vine pruning stalks (*Vitis vinifera* L. *cv.* Sultani*).* When the amount of the waste material is considered, it is always reasonable to strive to convert vine pruning to a valuable raw material for composite particleboard production

7 Acknowledgement

This manuscript is prepared from the outcome of the project (105O513) that was supported by The Scientific and Technological Research Council of Turkey (TÜBİTAK), and titled "Investigating the usage of vine pruning stalks (*Vitis vinifera* L. *cv.* Sultani*)* as a raw material for particleboard manufacturing".

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