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Research Article

Use of Radial Basis Function Neural Network in Estimating Wood Composite Materials According to Mechanical and Physical Properties

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Abstract
Knowing the mechanical and physical properties of a material is the most important criteria for engineers and designers interested in determining the intended use of the material. The prediction of wood composite materials based on their mechanical and physical properties plays an important role in their future application. In this study, radial basis function network approach was employed for prediction according to mechanical and physical properties of wood composite materials such as particleboard, fiberboard, oriented strand board and plywood, which have widespread use in the furniture industry and construction sector. Four physical and mechanical properties were used as the board density, bending strength, bending elastic modulus and tensile strength in the prediction of the wood composite materials. This study will assist wood composite users in the selection of wood composite materials that will provide the mechanical and physical properties determined in advance for any construction. Moreover, the present study will fill this gap in literature.

Keywords: Physico-mechanical properties, Plywood, Fiberboard, Radial basis function neural network, Particleboard, Oriented strand board

Ahşap Kompozit Malzemelerin Mekanik ve Fiziksel Özelliklerine göre Tahmininde Radyal Temelli Fonksiyon Sinir Ağının Kullanımı

Öz
Mühendisler ve tasarımcılar açısından bir malzemenin mekanik ve fiziksel özelliklerinin bilinmesi malzemenin kullanım amacının belirlenmesinde en önemli kriterlerdendir. Ahşap kompozit malzemelerin mekanik ve fiziksel özelliklere göre tahmini, gelecekteki ahşap kompozit malzeme uygulamalarında önemli bir rol oynayacaktır. Bu çalışmada mobilya endüstrisinde ve inşaat sektöründe yaygın kullanıma sahip olan yonga levha, lif levha, yönlendirilmiş yonga levha ve kontrplak gibi ahşap kompozit malzemelerin mekanik özelliklerine göre tahmin işlemi radyal temelli fonksiyon ağı ile gerçekleştirilmiştir. Ahşap kompozit malzemelerin tahmininde levha yoğunluğu, eğilme direnci, eğilme elastikiyet direnci ve çekme direnci olarak dört fiziksel ve mekanik özellik kullanılmıştır. Bu çalışma, ahşap kompozit malzeme kullanıcılarının herhangi bir konstrüksiyon için önceden belirledikleri mekanik ve fiziksel özellikleri sağlayacak ahşap kompozit malzemenin seçiminde yardımcı olacaktır. Ayrıca, bu çalışma literatürdeki bu boşluğu dolduracaktır.

Anahtar Kelimeler: Fiziko-mekanik özellikler, Kontrplak, Lif levha, Radyal temelli fonksiyon sinir ağı, Yonga levha, Yönlendirilmiş yonga levha

1. Introduction

Over time, increasing global forest loss and rising wood prices have led to the development of wood composite materials, parallel to the development of the chemical and glue industry. The composite term is

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being used to describe any wood material adhesive-bonded together. (Cai and Ross, 2010). These materials have begun to be widely used as engineering design board products that meet consumer demands. Because they eliminate defects of solid wood materials and they are more homogeneous and durable. Thus, wood-based composite materials that are alternative to wood materials have been developed and a wide variety of wood materials have been produced according to the intended use with engineering design. Wood composites are more economical and more useful in many areas than natural wood materials because of the lack of growth defects such as twisted fibers, knots, decay.

A wide variety of engineering properties are used to characterize the performance of wood-based composites. The knowledge of the mechanical properties of these products is critical to their proper use. The mechanical properties of wood composites depend on several factors such as wood species, forest management regimes, the type of adhesive used to bind the wood elements together, geometry of the wood elements and density of the final product. Mechanical properties are typically used most commonly for evaluating wood-based composites for structural and non-structural applications (Cai and Ross, 2010).

There are a growing number of papers in the field of wood science employing artificial neural network (ANN), such as predicting physical and mechanical properties in wood and wood composites (Fernandez et al., 2008; Fernandez et al., 2012; Melo and Miguel, 2016; Ilkucar et al., 2018; Miguel et al., 2018), calculating wood thermal conductivity (Avradimis and Iliadis, 2005; Xu et al., 2007), classifying wood defects (Marcano-Cedeño et al., 2009; Shahnorbanun et al., 2010; Qayyum et al., 2016), optimizing of bonding strength of the various wood products (Cook and Chiu, 1997; Tiryaki et al., 2014) and analysing of moisture in wood (Zhang et al., 2006; Esteban et al., 2010; Özşahin, 2012).

The aim of the paper is to predict wood composite materials such as particleboard, fiberboard, oriented strand board and plywood by using radial basis function (RBF) neural network. Particleboard, fiberboard, oriented strand board and plywood used in this study are shown in Fig. 1. Four physical and mechanical properties such as the board density, bending strength, bending elastic modulus and tensile strength were used in the prediction of the wood composite materials.

Fig. 1. Wood Composite Materials.

The remainder of this paper is organized in the following way. The next section outlines the main idea of the RBF neural network. Section 3 presents the prediction of wood composite materials. Finally, conclusions are drawn in Section 4.

2. Radial Basis Function (RBF) Neural Network

There are many types of ANN architectures, such as Multi-Layer Perceptron (MLP), Long Short-Term Memory (LSTM), Recursive Neural Network (RNN), Convolutional Neural Network (CNN), Self-Organizing Map (SOM) Network and Radial Basis Function Neural Network (Tchircoff, 2018). Different types of network architectures are preferred for solving different problems in the literature. Networks with different architectures can be used as alternatives to each other to solve the same problems. Depending on the resources (RAM, processor etc.) used and the calculation method, one can be preferred to the other. MLP and RBF neural networks are alternatives to each other in solving problems such as classification and prediction. The RBF network comes to the forefront in solving problems such as classification and prediction, with fewer resources and ease of calculation. Compared with the other ANN, the RBF neural network has a simple structure and the advantage of faster learning speed. The RBF neural networks as shown in Fig. 2 consist of three layers, the first layer considered as input layer, second layer as hidden layer and third layer as output layer

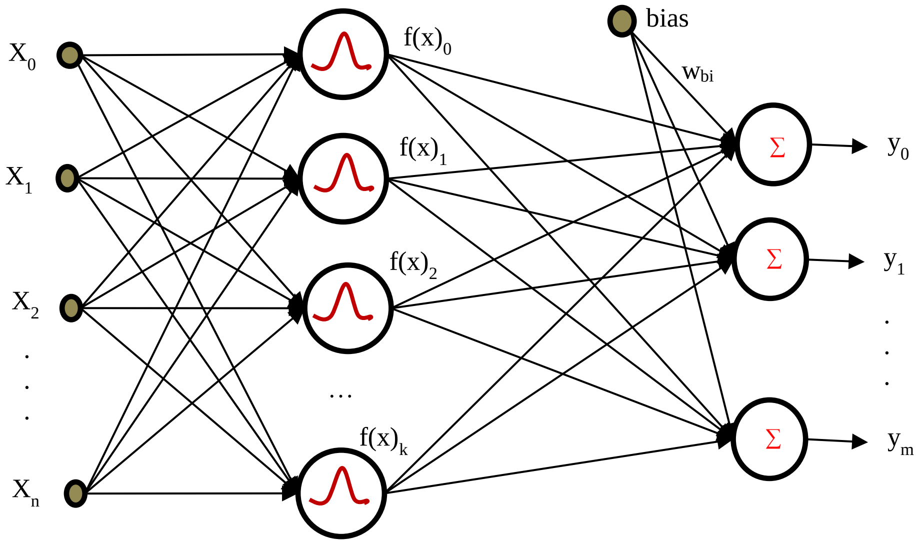

Fig. 2. The RBF Neural Network Structure

In the input layer-hidden layer and hidden layer-output layer, all nodes are interconnected. Only connections between the hidden layer and the output layer have weight (w) values. Since each hidden layer node represents a class (centrality), the number of nodes in the hidden layer must be greater than the number of nodes in the input layer. Different radial functions (Gaussian radial function, Thin plate spline, Quadratic, Inverse quadratic) are used as hidden layer transfer function (Behera, 2018). The most popular radial function is Gaussian radial function defined by Eq. (1).

$$f(x)_i = \exp^{\left(-\frac{\|x_i - c_i\|^2}{2\sigma_i^2}\right)} \quad (1)$$

where σ_i is the ith centrality distance, c_i is ith centrality. The output of the RBF neural network can be formed by a linear function of the hidden layer responses, which is shown as follows:

$$y_i = b + \sum_{i=0}^{m}(w_i * f(x)_i) \quad (2)$$

The network learning process is the process of determining weight values to minimize the amount of output error. Therefore, any optimization method can be used for this process. Different algorithms such as Pseudo-Inverse Technique, Hybrid Learning, Levenberg-Marquardt and Gradient Descent Learning are used for the RBF network supervised learning method in the literature (Godoy et al., 2014; Behera, 2018). Gradient Descent Learning algorithm is preferred in this study. The output function of the network is reflected back to the weight and centrality values and it is computed as follows:

Mean Absolute Error

$$(MAE) = \frac{1}{n}\sum_{i=1}^{n}|d_i - y_i| \quad (3)$$

where d_i indicates desired output value, y_i denotes calculated output value for input data (x_i). These values are updated and learning is performed. The amount of the output error determines the performance of the network. Accordingly, in order to obtain the minimum error value, the training process is performed by changing the weight and centrality values taking into account the derivation of the error function and the learning coefficient data according to the gradient descent learning method (Eq. (4) and Eq. (5)).

$$w_{(n+1)} = w_n + \eta\left(\frac{\partial E}{\partial w}\right) \quad (4)$$

$$C_{(n+1)} = C_n + \eta\left(\frac{\partial E}{\partial C}\right) \quad (5)$$

where η is the learning rate. Additional studies of the RBF neural network can be found in (Parsaie and Haghiabi, 2015; Montazer and Giveki, 2015; Zhao et al., 2015; Tatar et al., 2015), and the references cited therein.

3. Result and Discussion

In this study, the RBF neural network assisted with gradient descent learning algorithm was utilized to predict wood composite materials. Mechanical and physical properties such as full dry board density (gr/cm^3), bending strength (N/mm^2), bending elastic modulus (N/mm^2) and tensile strength (N/mm^2) of four different wood composite materials (particleboard, fiberboard, oriented strand board and plywood) were taken into account. The details of the data used in the study are listed in Table 1.

Table 1. Mechanical and physical properties of materials and numerical data.

Material	Data Count	Mechanical and Physical Properties	Standard Deviation	Maximum Value	Minimum Value
Fiberboard	31	Board Density	0,0035	0,85	0,67
		Bending Strength	5,82	47,04	23,27
		Bending Elastic Modulus	463,79	4602,35	2874,22
		Tensile Strength	113,41	632	0,25
Particleboard	29	Board Density	1,55	6,698	0,5
		Bending Strength	1,43	16,8	11,21
		Bending Elastic Modulus	165,88	2200	1595
		Tensile Strength	0,058	0,55	0,34
Oriented Strand Board	19	Board Density	129,08	650	65
		Bending Strength	2,29	24,12	16
		Bending Elastic Modulus	674,65	6301	3100
		Tensile Strength	0,066	0,45	0,22
Plywood	20	Board Density	0,0259	0,77	0,65
		Bending Strength	15,61	113,59	62
		Bending Elastic Modulus	1234,21	10000	5500
		Tensile Strength	0,77	3,4	0,71

Table 2. RBF network structure

Input Layer Nodes	Maximum Hidden Layer Nodes	Output Layer Nodes	Cost Function
4	75	1	MAE

The RBF network used in the study was trained by 90 iterations with 99 data sets and the performance graph is shown in Fig. 3

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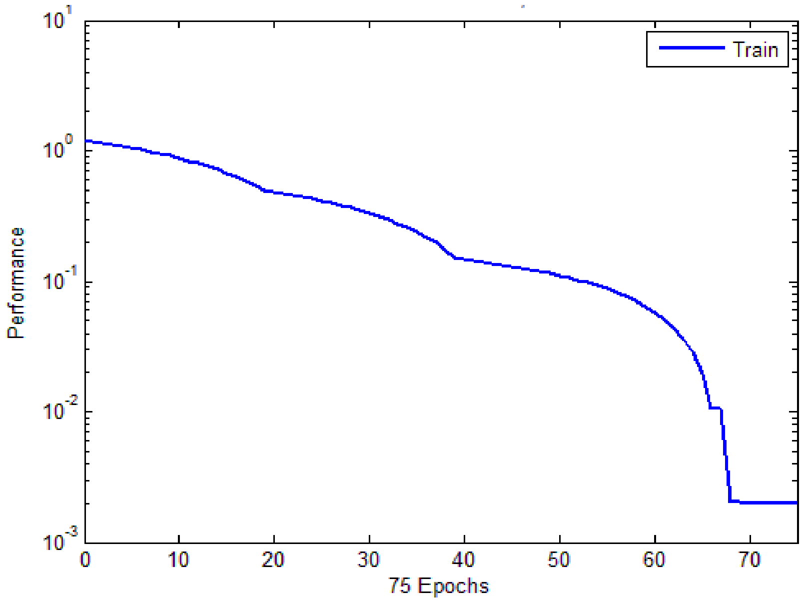

Fig. 3. Supervised Training Performance Graphic

The iterations after 90 iterations have been cut here because they have not been shown to have much effect on performance. During the iteration, the number of nodes in the hidden layer increased one by one starting from 4 and the optimal solution was obtained with 75 nodes. The RBF neural network learning parameters and performance value are shown in Tables 3.

70% of the data was used for training and remaining 30% was used for testing. The test data consisted of randomly selected data from the dataset that the network did not see previously. The network correctly predicted 28 of the 30 test data and viewed the two oriented strand boards as particleboard (Table 4). The test performance of the network was found at the accuracy levels of 93.3%. With 10-fold cross-validation, the network performance was found at the accuracy levels of 95.9%.

Table 3. The RBF network learning parameters and performance value

Spread Constant	MAE Goal	Maximum Number of Hidden Neuron	Performance
1	0.001	75	0.033

Table 4. Test data confusion matrix

Material	Fiberboard	Particleboard	Plywood	Oriented Strand Board
Fiberboard	11			
Particleboard		6		2
Plywood			5	
Oriented Strand Board				6

4. Conclusions

In this paper, the RBF neural network was employed for the prediction of wood composite materials such as particleboard, fiberboard, oriented strand board and plywood. Four physical and mechanical properties such as the board density, bending strength, bending elastic modulus and tensile strength were used in the prediction of the wood composite materials. The test performance of the network was found at the accuracy levels of 93.3%. With 10-fold cross-validation, the network performance was found at the accuracy levels of 95.9%. The results show that the RBF neural network can be used to predict wood composite materials based on their mechanical and physical properties. Moreover, this study will assist wood composite users in the selection of wood composite materials that will provide the mechanical and physical properties determined in advance for any construction.

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