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PREDICTING MODULUS OF RUPTURE OF HEAT-TREATED WOODS BY ARTIFICIAL NEURAL NETWORK COMBINED GENETIC ALGORITHM

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ABSTRACT: A total of 104 spruce and Larix gmelinii wood samples were employed to generate a reliable ANN-based model for estimating the Moment of Rupture (MOR) of heat-treated woods. Seventy percent of the samples were used for training, while the remaining thirty percent were used for testing phases of the data set. The Feed Forward network with five topologies was used, including heat treatment at various temperatures, durations, and relative humidity as input parameters. The weights of the artificial neural network are optimized by employing a genetic algorithm. The model's accuracy is assessed by comparing results with the particle swarm optimization-based neural network model. The study concluded that the genetic algorithm-based ANN model performed better by yielding results with reduced error.

KEYWORDS: Modulus of Rupture (MOR), Heat-Treated Woods, Artificial Neural Networks, Genetic Algorithm, Particle Swarm Optimization

1 INTRODUCTION

While timber is a distinctive, renewable, and sustainable construction material, it is biodegradable, mainly in open-air applications. Modifying timber's physical and mechanical properties improves its durability, preventing degrading agents. Wood modification methods are an evolving fashion and an eco-friendly substitute of chemicals for wood preservation procedures. During heat treatment processes, the wood is heated and modified in various atmospheres [1]. The material's structural performance and durability depend on numerous properties of heat-treated wood. Heat treatment dramatically lowers the wood's water absorption, equilibrium moisture content, and wettability, increasing its dimensional stability and biological endurance. Additionally, changes in the various characteristics of heat-treated wood affect the wood's performance in its application area.

Fernandez et al. (2012) determined the MOR and MOE of structural plywood using an artificial neural network and verified the results through the Multiple Linear Regression (MLR) model. The study considered thickness, moisture content, and density as the input variables for determining MOR and MOE. The results showed that the ANN model with three hidden layers has higher accuracy than the MLR model [2].

Yapıcı et al. (2012) employed Fuzzy Logic Classifier to determine the MOR and MOE of the heat-treated chestnut woods. The authors found that the developed model can calculate the MOR and MOE parameters of the test specimens with an accuracy of 92.64% and 90.35%, respectively, emphasizing its implementation in the wood industry manufacturing stages [3].

Yang et al. (2015) modified wood at high temperatures and under steam pressure. They created an ANN model to determine the mechanical properties of wood, considering temperature, time, and relative humidity as input parameters. The proposed ANN-based model yielded MOR and MOE values with reasonable accuracy [4].

Jiang et al. (2021) performed non-destructive testing of bamboo-based wood. The authors considered a duo Artificial Neural Network (ANN) and support vector machine (SVM) models to determine the MOR and MOE parameters. The outcomes of the study demonstrated that the SVM model with correlation coefficients of 0.90, 0.93, and 0.95 in the training, validation, and testing stages possesses higher accuracy than the ANN model [5].

The current study investigates the MOR of heat-treated woods employing Feed-Forward networks on the selected dataset. A genetic algorithm is used to optimize the weights of ANNs, followed by selecting the best-performed model among all samples of the same type. The proposed model is compared with the Particle Swarm Optimization (PSO) algorithm to evaluate its accuracy.

2 BACKGROUND

2.1 ARTIFICIAL NEURAL NETWORKS (ANN)

An artificial neural network (ANN) is a data model that can be taught from past experiences while implementing the outcomes to new data [6,7]. ANN is fabricated with neurons that work simultaneously to resolve a problem locally. Neural networks learn through typical computations describing the intrinsic mechanisms of the dataset in a reduced human brain-like manner. This study uses the Feed-Forward model comprising more than three layers, including input, hidden and output.

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Each layer carries a set of nodes known as neurons connected to the layer above it. Weights, biases, and an activation function that can be continuous, linear, or nonlinear frame the neurons in the hidden and output layers. Once the structure is framed for Feed-Forward training, several procedures will be implemented to optimize the weight and bias levels. The study employs, The Levenberg Marquardt technique for distributing the error to yield the best fit with the least error [8,9].

2.2 GENETIC ALGORITHM (GA)

GA is thoroughly described considering biological concepts, including genetics and evolution. An individual is a candidate solution (typically a parameter vector), and a gene is a component of an individual, while a population is a collection of candidate solutions. An algorithm iteration is generally referred to as a generation, as such, a candidate solution or parent is modified in some way to generate a new candidate solution or child, followed by the algorithm's execution [10]. The standard GA algorithm comprises three genetic operators, including selection, crossover, and mutation. The selection operator is used to pick parents during each generation. The individuals with higher fitness levels have a greater chance of selecting the operator, followed by producing additional individuals or children [10].

3 METHODS AND MATERIALS

3.1 DATASET

In this study, the required data set is extracted from past studies [4,11]. In all, 104 samples of heat-treated woods were studied. The Feed-Forward network, considering temperature, time, and relative humidity as input parameters, was implemented on the dataset to determine the MOR of heat-treated wood. The statistical properties of the input and output parameters are shown in Table 1. While Figures 1 and 2 illustrate the box normal plot and histogram of the MOR parameter, indicating the cluster of MOR values between 60 to 70 MPa.

Table 1:*Input and output parameters in heat-treated wood* [4,11]

Num	Parameter	Unit	Type	MIN	MAX
1	Temperature	°C	Input	120	210
2	Time	hrs	Input	0.5	9
3	Relative Humidity	%	Input	0	100
4	Modulus of Rupture	MPa	Output	45.1	78.2

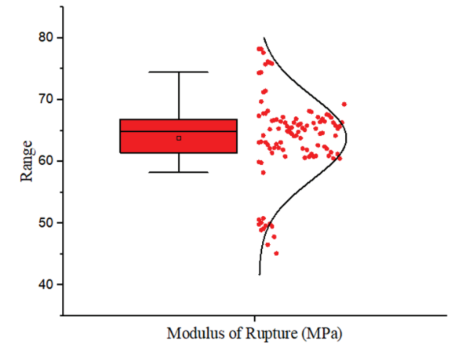

Figure 1: *Box normal plot of experimental data for MOR*

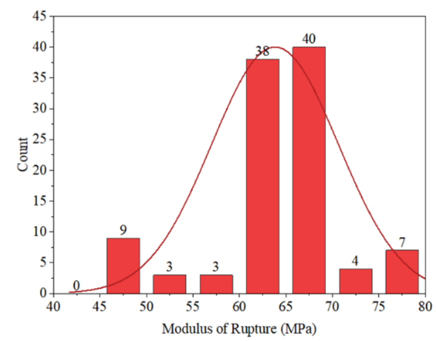

Figure 2: *MOR plot for experimental data histogram*

3.2 ANN MODEL COMBINED WITH GENETIC ALGORITHM

Of 104, 73 samples (70%) were used for training, and the remaining 31 (30%) contributed to testing the data. Two-layer neural networks with different transfer functions suggested the various topologies, as presented in Table 2. The weights and biases of the models were reduced by employing a genetic algorithm. Table 3 displays various properties of the genetic algorithm.

Table 2: *Different topologies used in ANNs*

No	Topology	Hidden and Output Activations
1	3-4-3-1	PURELIN-PURELIN-PURELIN
2	3-4-2-1	POSLIN-POSLIN-PURELIN
3	3-3-4-1	LOGSIG-LOGSIG-PURELIN
4	3-3-3-1	POSLIN-POSLIN-PURELIN
5	3-3-2-1	TANSIG-TANSIG-PURELIN

Table 3: *Genetic algorithm (GA) parameters* [12]

Parameter	Value	Parameter	Value
Crossover (%)	50	Max generations	150
Crossover method	single point	Recombination (%)	15
Lower bound	-1	Selection Mode	1
Upper bound	+1	Population Size	150

Table 4 presents the output of five GA based models, GA-ANN, created to determine the MOR of the heat-treated wood samples. Five different topologies, as illustrated in

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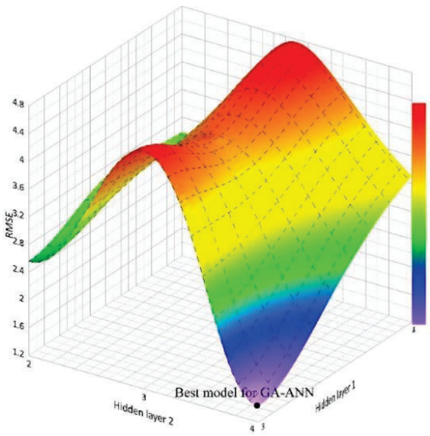
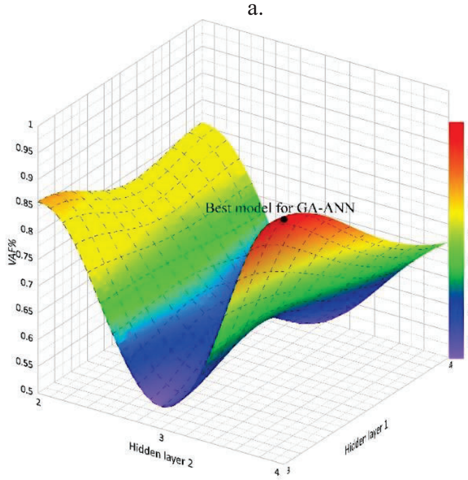
Figure 3, were evaluated on the measures of Variance Account Factor (VAF) and Root Mean Squared Error (RMSE) values. The results indicated that the network with the GA-ANN 2L topology (3-4) design achieved the lowest RMSE error rates and the highest VAF percent when estimating the output parameters.



a.



b.

Figure 3: *Statistical values for the proposed topologies in all data: a) RMSE, b) VAF%*

Further, as presented in Table 4, the Feed-Forward network with a GA-ANN 2L topology (3-4) has the lowest value of the RMSE index in the training (1.28) and testing (1.75) phases. Additionally, the model with the same topology maintained the highest VAF value in the training (96%) and the testing (94%) phases indicating the least error among other topologies of the same algorithm. The GA-ANN 2L network topology (3-4) is shown in Figure 4.

Table 4: *Statistics of ANNs combined with the genetic algorithm (GA) for the MOR parameter*

Model Name	Hidden layer 1	Hidden layer 2	Train		Test		All	
			RMSE	VAF%	RMSE	VAF%	RMSE	VAF%
GA-ANN 2L(4-3)	4	3	4.59	51	5.15	46	4.76	51
GA-ANN 2L(4-2)	4	2	2.95	80	3.04	81	2.98	81
GA-ANN 2L(3-4)	3	4	1.28	96	1.75	94	1.43	96
GA-ANN 2L(3-3)	3	3	4.37	56	5.18	47	4.63	54
GA-ANN 2L(3-2)	3	2	2.78	82	1.95	92	2.56	86

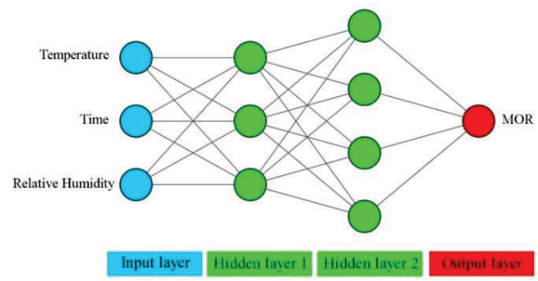
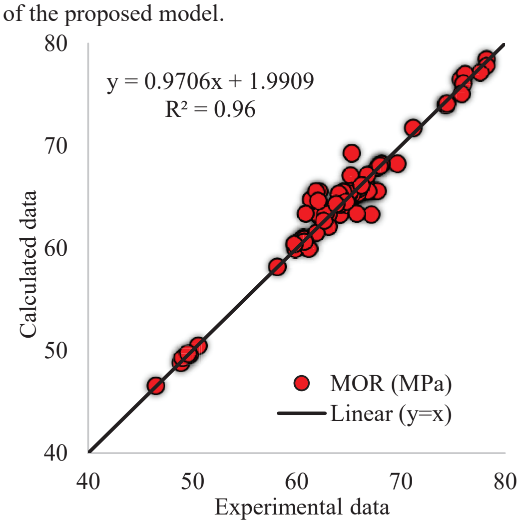
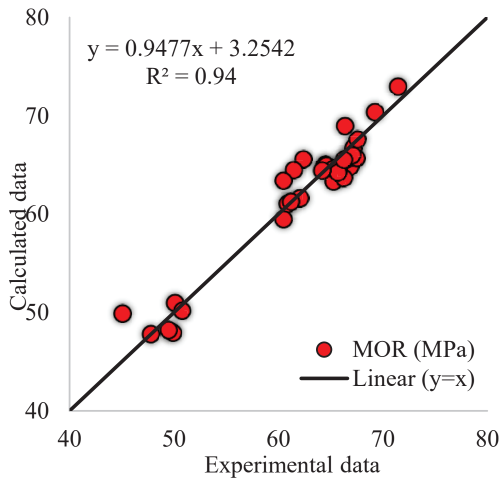


Figure 4: *The architecture of the ANN with the 3-3-4-1 topology*

Figure 5 illustrates the best performance of GA-ANN 2L (3-4), as depicted in the calculated values versus their experimental counterparts in the testing and training phases. The model's projected values fall in the vicinity of the line *(y=x)*, indicating the model's accuracy. Further, the R^2 value for the training and testing phases are found as 0.96 and 0.94, respectively, demonstrating the accuracy of the proposed model.



a.



b.

Figure 5: *Experimental vs. predicted values of MOR for the GA-ANN 2L(3-4) model: a) training, b) testing*

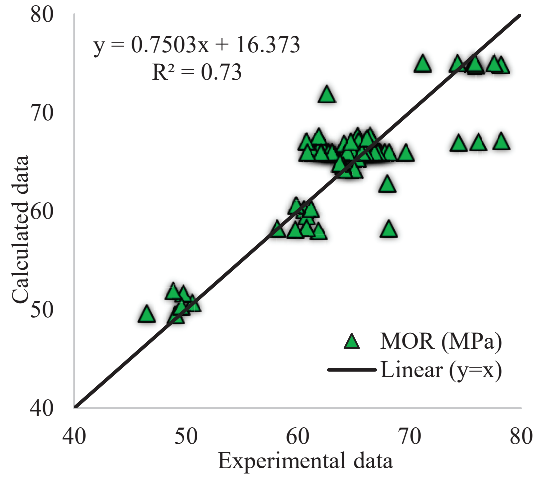
3.3 ANN MODEL COMBINED WITH PARTICLE SWARM OPTIMIZATION

The study employs a PSO-optimized ANN to calculate the MOR variable. Similar to GA based models, five topologies presented in Table 2 were used, creating various models for estimating the output parameters.

The models with PSO-ANN 2L(4-2) topology best calculated the required parameter (MOR), as indicated in Table 5 and Figure 6. The testing and training outputs for VAF and RMSE indicators confirm the lowest error rate of the model compared to the experimental data. Also, as indicated in the figure, the R^2 values of the training and testing phases are found to be 0.73 and 0.86, respectively, indicating the model's appropriate accuracy.

Table 5: *Statistics of ANNs combined with the Particle Swarm Optimization algorithm for the MOR parameter*

Topology	Hidden layer 1	Hidden layer 2	Train		Test		All	
			RMSE	VAF%	RMSE	VAF%	RMSE	VAF%
PSO-ANN 2L(4-2)	4	2	3.43	73	2.79	85	3.25	77



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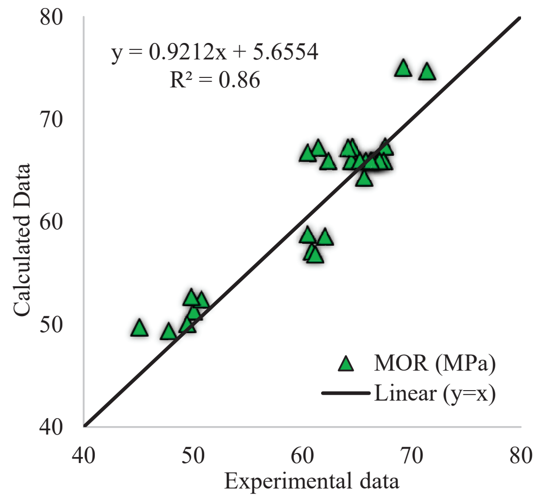

b.

Figure 6: *Experimental vs. predicted values of MOR for the PSO-ANN 2L(4-2) model: a) training, b) testing*

3.4 SELECTION OF THE BEST MODEL

Finally, the best-performed GA-ANN and PSO-ANN models are compared on equal measures for all the datasets. Figure 7 illustrates the comparative normal distribution of the best-performed models with their experimental counterparts. As displayed in the figure, the normal distribution of GA-ANN is closer to the experimental data than the PSO-ANN model indicating the higher accuracy of the GA-ANN model. The comparison of the two models, illustrated in Figure 8, confirms the relatively higher accuracy of the GA-ANN model over the PSO-ANN model.

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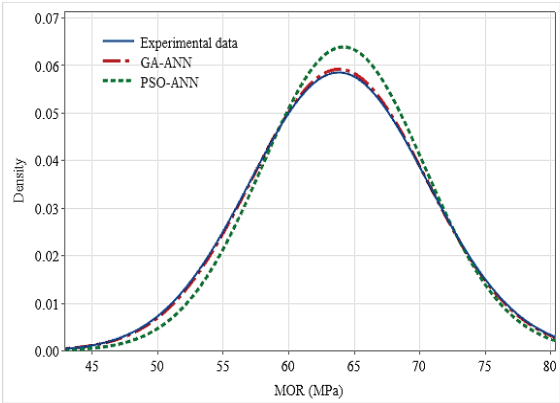

Figure 7: *Normal distribution of experimental data and GA-ANN and PSO-ANN models*

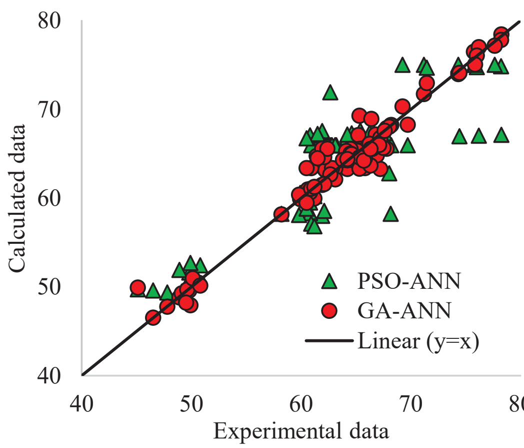

Figure 8: *Experimental vs. predicted values of MOR for different models*

4 CONCLUSION

A total of 104 experimental results obtained from spruce and Larix gmelinii woods were used to determine the MOR of the heat-treated woods. Artificial neural networks were optimized by employing genetic algorithms and particle swarm optimization to analyze the considered dataset. The analyses of the results suggested the better performance of GA-ANN over PSO-ANN for determining the modulus of rupture of the heat-treated woods.

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CONFLICT OF INTERESTS

The authors declare that they have no conflicting interests concerning the publication of this article.

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