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# Tensile strength prediction of empty palm oil bunch fiber composite with artificial neural network

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***Abstract***

*As the leading global producer of palm oil, Indonesia encounters substantial environmental challenges arising from the waste generated by empty palm oil fruit bunches (EPOFB). This research aims to develop an accurate Artificial Neural Network (ANN) model to predict the tensile strength of EPOFB fiber-reinforced composites. The method involves two types of ANN, namely Radial Basis Function (RBF) and Backpropagation, with testing using variations in immersion time, volume fraction, and length of EPOFB fibers. The research results show that both ANN models can predict tensile strength with a Mean Absolute Error (MAE) below 10%. However, the Backpropagation ANN shows superior performance with a training MAE of 0.0078 and a testing MAE of 0.45, compared to the RBF ANN, which has a training MAE of 0.371 and a testing MAE of 0.53. In conclusion, ANN Backpropagation is superior in prediction accuracy and characterization efficiency of EFB fiber-reinforced composites, offering an economical solution and supporting sustainable palm oil waste management.*

***Keywords**: Artificial Neural Network (ANN); Backpropagation; Palm Oil Empty Bunches (POEB); Radial Basis Function (RBF)*

## 1. INTRODUCTION

Indonesia is one of the world's leading producers of palm oil, producing millions of tons of palm oil every year (1). However, this abundance of palm oil production also causes significant environmental problems, especially from the solid waste produced, such as empty oil palm fruit bunches (EFB) (2). This waste is often not utilized optimally and only accumulates rubbish in the environment. One potential solution to overcome the problem of EFB waste is to use it as a reinforcing material in making composites (3). Palm oil empty fruit bunch fiber-reinforced composites have great potential due to their excellent mechanical properties and abundant availability (4). However, composites reinforced with empty fruit bunch fibers generally have much lower mechanical strength compared to composites reinforced with synthetic fibers (5,6). Furthermore, the characterization of these composites often poses challenges, primarily due to the high costs and time required for laboratory testing. One way to reduce characterization costs is through the use of prediction techniques (7–9). In addition, composites reinforced with empty fruit bunch fibers have also been researched for applications such as ship hulls and sound-dampening systems (10–12). However, studies on using empty fruit bunch fibers for ship hull applications have shown that it is not feasible because the mechanical strength does not meet the required standards.

On the other hand, the rapid development of artificial intelligence (AI) technology offers various innovative solutions in the prediction field. One prominent AI method is Artificial

Neural Network (ANN). ANN has been used in various fields to predict various parameters with high accuracy, including in health, finance, and engineering (13–18). In materials, ANN has also been used for tensile strength prediction for friction stir welding aluminum alloy and produces good prediction results with an error of only 1.13% (19). However, ANN has been widely applied in various fields, and its application for the characterization of palm oil empty fruit bunch fiber composite materials still needs to be improved. Research on the use of ANN to predict the characterization of composite materials is still rare, so it needs to be developed, which is expected to reduce the costs and time required for conventional composite characterization.

This research includes the development of an accurate ANN model to predict the tensile strength of palm oil empty fruit bunch fiber-reinforced composites. In addition, this research provides an alternative composite characterization method that is more efficient and economical. By increasing the added value of empty palm oil bunch waste as a composite reinforcement material, this research contributes to more sustainable palm oil waste management. Thus, this research offers innovative solutions in composite materials while contributing to better waste management practices in the palm oil industry.

## 2. Methods

The research process involved developing an artificial neural network using experimental data. The neural network development process involved training and testing using the same dataset. The research methodology can be seen in Figure 1.

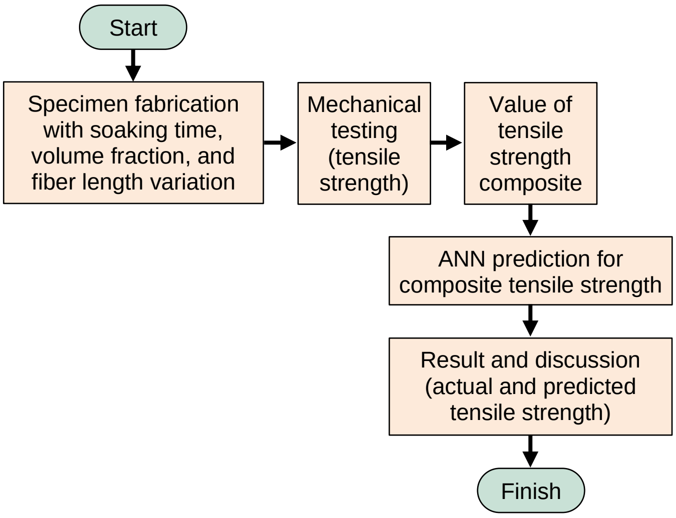


*Figure 1. Flowchart of this research*

Figure 1 shows the research starting with fabricating composite specimens with variations in soaking time, volume fraction, and fiber length, followed by mechanical testing to determine their tensile strength. After obtaining the tensile strength values, an Artificial Neural Network (ANN) is used to predict the tensile strength of the composites. Finally, the actual tensile strength values from testing are compared with the predicted values from the ANN, and the results are analyzed and discussed.

### 2.1. Test data

This test was conducted on soaking time, volume fraction of Palm Oil Empty Bunches (POEB) fiber, and length of POEB fiber. Those used orthogonal array L9 (3x3) as seen in Table 1.

*Table 1. Variation of testing*

| Soaking time (h) | Volume fraction (%) | Fiber length (cm) |
|---|---|---|
| 6 | 10 | 3 |
| 8 | 20 | 5 |
| 10 | 30 | 7 |

### 2.2. Artificial Neural Networks

An Artificial Neural Network (ANN) with a radial basis function (RBF) is an artificial neural network that uses a radial basis function as an activation function. ANN RBF usually consists of three layers: an input layer, a hidden layer, and an output layer. The input layer receives the signal and passes it to the hidden layer. Each neuron in the hidden layer uses a radial basis function, usually a Gaussian function, to measure the distance between the input and the center (centroid) of the neuron. The output of the neurons in this layer is the value of the radial basis function applied over that distance. Neurons in the output layer produce the network output by performing a linear combination of the outputs of the hidden layers. The main advantage of ANN RBF is its ability to handle classification and regression problems with good performance. ANN RBF is often used because of its ability to interpolate data, namely estimating values between known data points, and fast learning, which makes the ANN RBF training process more efficient (20).

Backpropagation ANN is an artificial neural network that uses a backpropagation algorithm to train the network. This network consists of an input layer, one or more hidden layers, and an output layer. In Backpropagation ANN, each neuron in hidden and output layers uses an activation function, such as sigmoid or ReLU, to produce output. The Backpropagation ANN training process involves two main stages: feedforward and backpropagation. In the feedforward stage, input is forwarded through the network to produce output. In the backpropagation stage, the error or difference between the expected output and the resulting output is calculated and used to update the network weights gradually through backpropagation from the output layer to the input layer. The backpropagation algorithm uses a gradient descent method to minimize error by adjusting weights iteratively. Backpropagation ANNs are popular due to their ability to learn complex patterns and perform accurate predictions in various applications, including pattern recognition, timing prediction, and classification. The advantage of ANN Backpropagation is its flexibility in handling several types of data and problems and its ability to adjust network weights to improve prediction accuracy over time automatically (21).

## 3. Result and Discussion

The procedure for making predictions with an artificial neural network (ANN) consists of two main stages. The first step is the training phase, where the system develops the neural network by learning using the given input data. The next step involves evaluating the performance of the developed neural network through testing.

### 3.1. Tensile strength

The tensile strength obtained from experimental testing is presented in the data shown in Table 2. The result indicates that soaking time, fiber volume fraction, and fiber length all have significant effects on the tensile strength of the composite material. Generally, composites with higher fiber volume fractions (30% and 40%) exhibit higher tensile strength values, with the highest strength recorded at 5.60 Mpa for a 6-hour soaking time, 30% fiber volume fraction, and 7 cm fiber length. The fiber length also plays a crucial role, with longer fibers (5-7 cm) contributing to higher tensile strength compared to shorter fibers (3 cm). For example, at a 6-hour soaking time and 40% fiber volume fraction, increasing fiber length from 3 cm to 7 cm increases tensile strength from 2.51 Mpa to 6.01 Mpa. The soaking time shows variable effects; for instance, while 6-hour soaking times tend to produce higher tensile strength in some cases, 10-hour soaking times do not consistently increase strength. This suggests that a balance of soaking time, fiber volume fraction, and fiber length is essential for optimizing tensile strength.

*Table 2. Tensile strength of composite with POEB fiber*

| Soaking time (hours) | Fiber volume fraction (%) | Length of fiber (cm) | Tensile strength (MPa) |
|---|---|---|---|
| 6 | 10 | 3 | 2.62 |
| 6 | 10 | 5 | 2.68 |
| 6 | 10 | 7 | 3.03 |

| Soaking time (hours) | Fiber volume fraction (%) | Length of fiber (cm) | Tensile strength (MPa) |
|---|---|---|---|
| 6 | 30 | 3 | 2.37 |
| 6 | 30 | 5 | 3.65 |
| 6 | 30 | 7 | 5.60 |
| 6 | 40 | 3 | 2.51 |
| 6 | 40 | 5 | 4.31 |
| 6 | 40 | 7 | 6.01 |
| 8 | 10 | 3 | 2.41 |
| 8 | 10 | 5 | 2.11 |
| 8 | 10 | 7 | 2.22 |
| 8 | 30 | 3 | 2.43 |
| 8 | 30 | 5 | 2.57 |
| 8 | 30 | 7 | 2.94 |
| 8 | 40 | 3 | 2.50 |
| 8 | 40 | 5 | 3.29 |
| 8 | 40 | 7 | 4.02 |
| 10 | 10 | 3 | 1.63 |
| 10 | 10 | 5 | 2.50 |
| 10 | 10 | 7 | 3.33 |
| 10 | 30 | 3 | 2.05 |
| 10 | 30 | 5 | 3.26 |
| 10 | 30 | 7 | 4.23 |
| 10 | 40 | 3 | 4.54 |
| 10 | 40 | 5 | 4.86 |
| 10 | 40 | 7 | 5.24 |

### 3.2. Training

The training process for developing the neural network employs experimental data as mentioned in Table 2. The developed artificial neural network is subsequently evaluated using the training data to assess the accuracy of its predictions. The performance results of the training are illustrated in Figure 2.

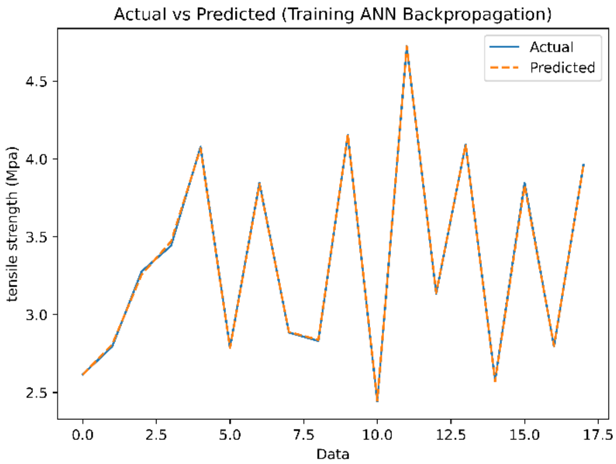


*Figure 2. ANN training data (ANN backpropagation)*

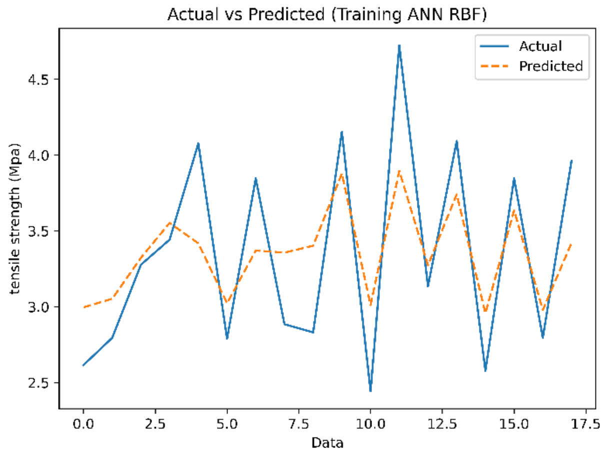


*Figure 3. ANN training data (ANN RBF)*

Figure 2 shows that the backpropagation ANN can follow the actual data trend, and the error is relatively minor compared to the RBF ANN. ANN backpropagation has an absolute error range from 0.00022 to 0.0279, while ANN RBF is between 0.046 and 0.83. The mean absolute error (MAE) training backpropagation is 0.0078, while the ANN RBF is 0.371. The backpropagation algorithm uses a gradient descent method to iteratively optimize network weights by minimizing error (22). This process allows for continuous adjustment of weights based on calculated errors, resulting in a more accurate model over time. Although radial basis function (RBF) networks use non-linear basis functions, having only one hidden layer limits their ability to capture complex non-linearities compared to deeper backpropagation networks (23).

### 3.3. Testing

The testing process was conducted to evaluate the performance of the established neural network in making predictions. The testing utilized the same data as the training data, but the directive given was specifically for testing. A total of nine data points were randomly selected to provide an overview of the performance of the developed Artificial Neural Network (ANN), with the results illustrated in Figure 3.

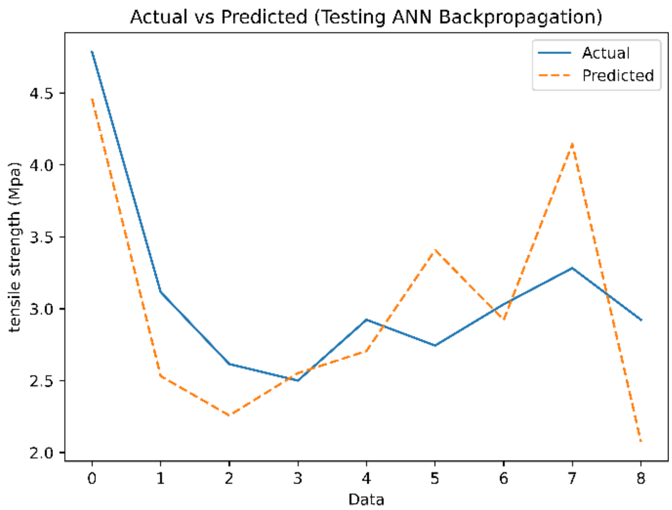


*Figure 4. Testing ANN (backpropagation)*

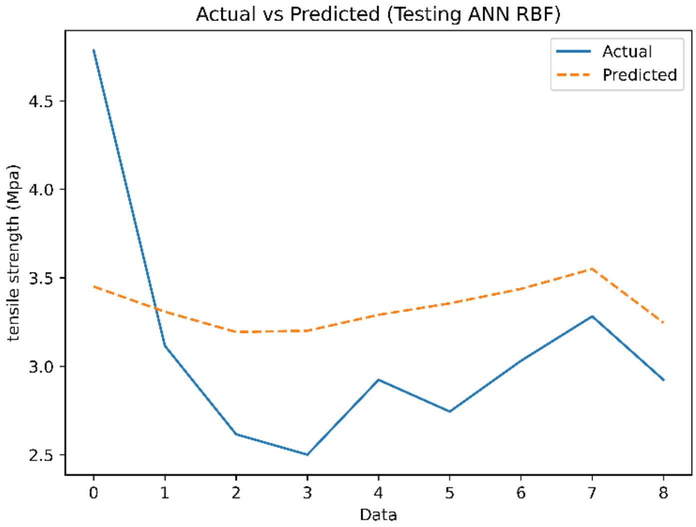


*Figure 5. Testing ANN (RBF)*

Since the RBF ANN exhibited a higher mean square error than the backpropagation ANN during training, the MAE was consequently greater when tested with different datasets. The absolute error range for the ANN backpropagation is between 0.052 to 0.86, while the ANN RBF error range is 0.19 to 1.3, and the MAE for the ANN backpropagation is 0.45 while the ANN RBF is 0.53. Even though the RBF ANN has a higher error than the backpropagation ANN, both have an MAE below 10% of the data so that the ANN can be used to predict the tensile strength of TKKS fiber-reinforced composites.

## 4. Conclusion

The use of ANN in prediction shows that both ANN Radial Basis Function (RBF) and ANN Backpropagation can predict the tensile strength of TKKS composites with a Mean Absolute Error (MAE) below 10%. This proves that both types of ANN can be used for this prediction purpose with acceptable accuracy. The accuracy of the Backpropagation ANN model is better than the RBF ANN, especially in following actual data trends and producing more minor errors during the training and testing process. The data shows that the MAE of ANN Backpropagation training is lower, 0.0078, compared to the MAE of ANN RBF training, which reaches 0.371. In addition, at the testing stage, the MAE of ANN Backpropagation was 0.45, which was also lower than the MAE of ANN RBF of 0.53. The higher performance of ANN Backpropagation shows its reliability in more accurate and consistent predictions.

## 5. ACKNOWLEDGEMENT

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