# Predicting Fiberboard Physical Properties using Multilayer Perceptron Neural Network

Faridah Sh. Ismail and Nordin Abu Bakar

**Abstract**— 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 most extensive procedures of BS EN standard are 24-hour thickness swelling, 24-hour water absorption and 48-hour moisture content. The aim of this research is to reduce testing time by excluding these lengthy tests. A model of each is produced to predict the properties of omitted tests using other properties of MDF, including fiberboard density and percentage of empty fruit bunch fiber. A prediction model was produced by the multilayer perceptron Neural Network containing seven input neurons for seven predictors. Only one hidden layer used with four neurons. Output layer contains three output neurons, one for each target. WA24hours obtained smallest SSE for both training and testing with 0.113 and 0.108 respectively. Prediction model has contributed to the increase in MDF testing efficiency based on British Standard European Norm (BS EN).

**Index Terms**— empty fruit bunch fiber, fiberboard, physical properties, prediction, neural network.

## 1 INTRODUCTION

IN the past few decades, Medium Density Fiberboard (MDF) industry has been in the furniture industry and becomes the competitor to solid wood products. It is made of fiber from wood leftovers and therefore it is cheaper. In Malaysia, main source of fiber normally comes from forest wood and rubber wood. Alternative sources of fiber can be obtained from oil palm biomass such as empty fruit bunch (EFB) [1],[2]. Malaysia has abundance of oil palm biomass due to being the largest producer of palm oil [3]. Among favourite fiber type is from EFB which is most available. This fiber is usually combined with rubber wood fiber to produce better quality.

The first phase in an MDF pilot plant is to produce a fiberboard. This is done by going through steps involving process parameters such as fiber mixing, pressing, gluing, forming and cutting. However, in any research-based pilot plant, process parameters are changed rapidly as required by research works.

Next is the testing phase, whereby fiberboard is needed to undergo series of testing procedures to obtain sample properties. As a non-solid wood panel, MDF has to conform to a standard to ensure the board strength. This is a very important step before being accepted for further manufacturing processes. According to the British Standard (BS-EN), there are four test procedures that will produce altogether eight properties.

- *Faridah Sh. Ismail is a lecturer of Universiti Kuala Lumpur, Malaysian Institute of Information Technology and currently pursuing PhD degree in Computer Science in the Universiti Teknologi MARA, Malaysia. E-mail: faridah@miit.unikl.edu.my*
- *Dr. Nordin Abu Bakar is the supervisor of the first author. He is an Associate Professor of Faculty of Computing and Mathematical Sciences, Universiti Teknologi MARA, Malaysia.*

Two test procedures for each mechanical and physical aspects of the board. Mechanical testing procedures will be on tensile (Internal Bonding test) and flexural (Bending Strength test) capabilities. On the other hand, physical tests focus more on the water resistant (Thickness Swelling test) and moisture features (Moisture Content test). Fig. 1 shows four tests that produce eight properties. Mechanical tests produce properties of Internal Bonding (IB), Modulus of Rupture (MOR) and Modulus of Elasticity (MOE). While, five other properties are obtained from physical tests, namely, Moisture Content (MC48hours), Thickness Swelling (TS2hours and TS24hours) and Water Absorption (WA2hours and WA24hours).

Time spent for physical tests is longer as compared to mechanical tests. TS test takes up to 24 hours, while MC test needs 48 hours to run. TS test involved soaking sample in water. Measurements on additional weight (WA) and additional thickness (TS) are taken after 2 hours and also after 24 hours. On top of that, MC test will need sample to be placed in an oven and monitor moisture changes for up to 48 hours.

Several attempts have been made to reduce pilot plant costs, especially for cost related to destruction materials and time. Most of research focused more on optimizing process parameters [4],[5],[6] and utilizing process parameters for prediction of IB using statistical methods [7],[8] and Neural Networks (NN) [9]. There was also an attempt to predict testing properties by utilizing other properties, such as MOE prediction [10], TS and WA prediction based on British standard [11] and MC prediction based on Spanish standard [12] using NN. Very few research found on reducing the time for lengthy physical testing according to BS EN which requires up to 48hours to be completed. Three separate single-output NN models were used by [13] to predict TS, WA and MC individually. However, this approach is found tedious and less effective because all models are having the same set of input variables as predictors.

This research aims to reduce time taken to run lengthy testing procedures for TS24hours, WA24hours and MC48hours properties. The focus is to utilize properties from the less extensive testing procedures in order to predict properties of the lengthy testing procedures.

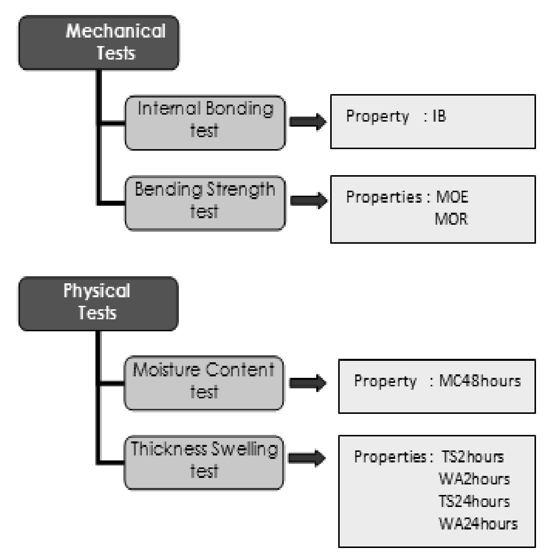


Fig. 1. Mechanical and Physical Tests. Each test produces one or more properties.

## 2 Problem Formulation

The response variables, as outlined in previous section, will be the timely test properties, TS24hours, WA24hours and MC48hours. A total of seven inputs are identified as potential predictors for the response variables. Properties obtained from mechanical tests and 2-hour-properties of TS test are utilized in the analysis. On top of that, density and fiber composition are also included. These two process parameters are best to portray fiber characteristics. Board samples have various densities within the range of medium density. The higher the density will produce higher strength. Fiberboard analyzed contained a combination of fiber from two sources, rubber wood and EFB. Fiber data used is the amount of EFB percentage in the fiber combination. Fig. 2 depicts the predictors which are inputs to the model, and response variables which are prediction outputs.

Multilayer Perceptron Neural Network is responsible to produce a prediction model for the targets. There are three layers involved as shown in Fig. 3. The Input Layer (IL) contains seven neurons to accept input from seven predictors. Covariates are rescaled using normalized method so that values will be between 0.0 and 1.0. Batch training criteria is used with gradient descent optimization algorithm. The inputs are feed forward to Hidden Layer (HL) and Output Layer (OL). Only one HL is used having four neurons. Sigmoid activation function is best applied for both HL and OL [13]. Since there are three targets, OL is designed to have three neurons, one for each response variable. This is more efficient than having separate models for each target as used in [13].

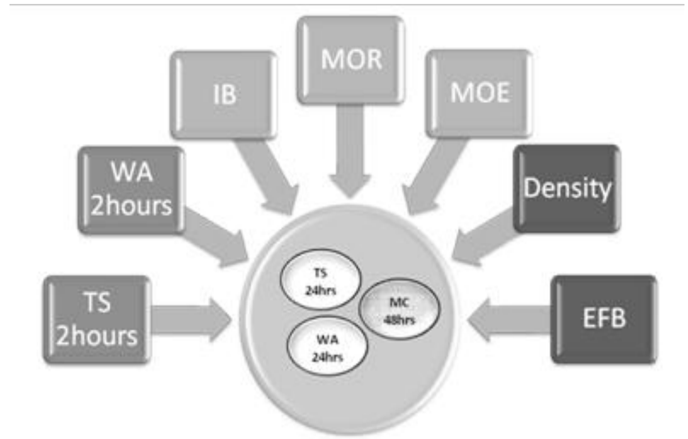


Fig. 2. Response variables and predictors. Response variables are placed in circles while the predictors in rectangle boxes

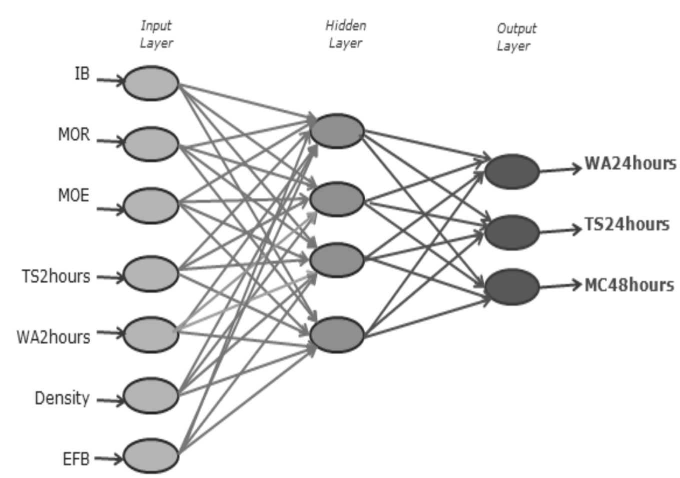


Fig. 3. Multilayer Perceptron Neural Network model. This model contains seven inputs and three outputs.

TABLE 1
ERROR ANALYSIS

| *Activity* | *Dependents* | *SSE* | *RMSE* |
|---|---|---|---|
| Training | Overall | 0.876 | 0.082 |
| | WA24hours | 0.113 | 0.029 |
| | TS24hours | 0.129 | 0.031 |
| | MC48hours | 0.610 | 0.068 |
| Testing | Overall | 0.484 | 0.089 |
| | WA24hours | 0.108 | 0.042 |
| | TS24hours | 0.207 | 0.058 |
| | MC48hours | 0.714 | 0.108 |

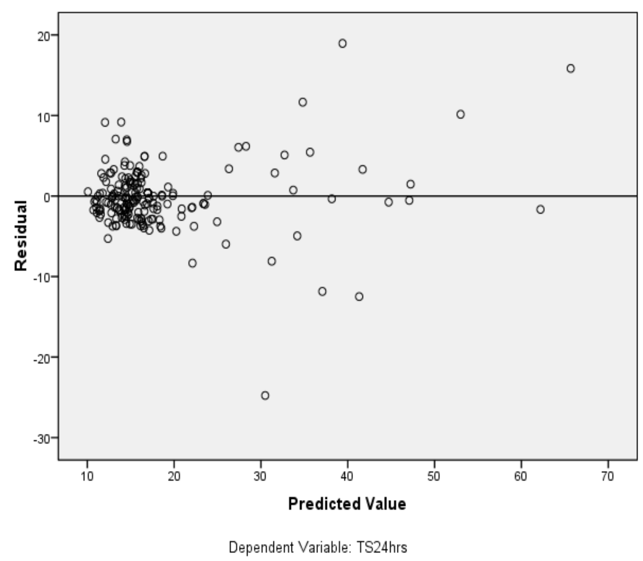


Fig. 5. Residual Scatter Plot of TS24hours Prediction.

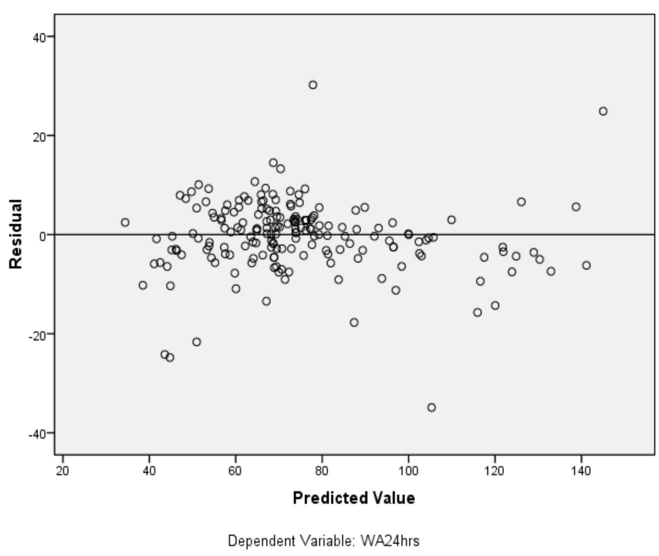


Fig. 4. Residual Scatter Plot of WA24hours Prediction.

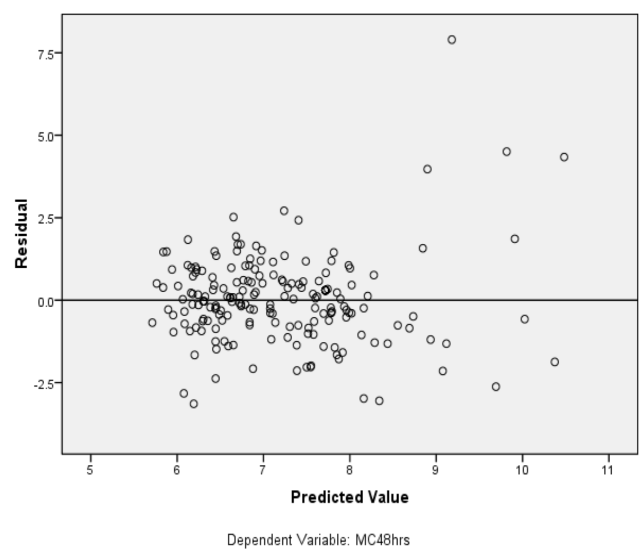


Fig. 6. Residual Scatter Plot of MC48hours Prediction.

Backpropagation algorithm is used to handle error during training. These errors are related to the differences between actual value and predicted value of supervised learning. The purpose of this algorithm is to reduce the error by adjusting the weights so that error is minimized to allow prediction to be closest possible to actual value. This is done in an iterative manner, until no reduction in error is seen.

## 3 Results and Discussion

The output from NN prediction model shows reliable results. Sum of Squared Error (SSE) and Root Mean Squared Error (RMSE) were calculated to verify prediction correctness. Table 1 outlines error during training as well as during testing, while Fig. 3, Fig. 4 and Fig. 5 are plots of residuals for each target. The overall SSE during training seemed to be higher as compared to during testing. However on average, testing has slightly higher error. Regardless of that, model has produced very small error.

Individual output error has shown no obvious difference between the two activities. This proves that no overfitting happens during training. Among others, WA24hours has the smallest error, next to TS24hours and MC48hours predictions. Figure 3 plots residuals of WA24hours prediction approaching horizontal line, confirming small error and high accuracy in prediction. Fig. 4 and Fig. 5 however shows comparatively more outlier plots which contributed to higher error.

## 4 Conclusion

Research has shown how testing time can be reduced using a prediction model. Physical property testing will need only 2 hours, instead of having to run for up to 48 hours. Omitting lengthy tests has caused more efficient in handling procedures where unavailable property values will be provided by the prediction model. Consequently, results of testing activities are produced faster.

Only one model is sufficient to produce three prediction output. The model proves to be excellent through its small RMSE both during training and testing. This also shows no over fitting happens and model has been well trained. Therefore, model is reliable to be used for properties prediction.

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