Study on Artificial Neural Network (ANN) for Pyrolysis of Sawdust

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Abstract—**The effects of emissions caused by the excessive usage of fossil fuel on global warming has became a global concern as the negative impacts continuously increase. One of the most recognized alternatives to the fossil derived energy was biofuel, which has been perceived as more environmentally friendly and used as product against climate change. Artificial neural network, ANN is a highly intelligent system that has been widely used to predict and analyze certain processes. With the aid of ANN, it is possible to model the pyrolysis of sawdust before being industrially applied and implemented. The predicted data from ANN fitting model in Matlab was determined with validation, R^2 achieved at 0.9811 and the MSE error was indicated at small difference of 4.9747 in validation result under 36 epochs at 25 hidden neurons. The modeling of ANN has shown great performance and potential for the application on real process modeling and control in biofuel production process.**

I. INTRODUCTION

Global effects due to climate changes and greenhouse gas emission have been increasing. Fossil fueled energy has caused a multitude of implications to the environment. The shortage of conventional fossil fuels and the global environment problems such as global warming and acid rain have become a serious issue. The focus on waste minimization to lower the dependence on fossil fuel derived energy has been researched [1]. One of the most recognized alternatives to the fossil derived energy was biofuel, which has been perceived as more environmentally friendly and used as product against climate change [2]. The utilization of biomass has great potential for reducing the dependence on fossil fuels and alleviating the burden of environmental degradation [3]. From a financial point of view, the shift towards the usage of biofuels can be justified if it offers cost and performance benefits of equal or extra value to their fossil-derived counterparts [4].

While having the same target of achieving a more environmental approach to fulfill energy demands, the technologies, ideas and processes have been considered. Multiple concepts such as waste in recycling, energy conversion, minimization and management are being applied to drive the biofuel initiative [5]. Hence, pyrolysis has been acknowledged as an efficient means of meeting these demands [6]. Pyrolysis is a type of thermolysis decomposition of organic material at elevated temperatures which produces char, condensable liquid and non-condensable gas products [7].

By duplicating the capabilities of a biological neurode, researchers have discovered that an artificial neural network (ANN) is able to simplify multiple processes. As ANN serves as an important companion practical guide and tool in developing estimated values based on input parameters, the estimated values for the biofuel yield from the pyrolysis process of sawdust can be achieved.

With the limiting ability of our human minds to compute and analyze, ANN have become the alternative to assist us in analyzing a multitude of problems. ANN are relatively new computational tools that have been extensively utilized in solving real-world problems. The attractiveness of ANN comes from their generalization capabilities to adapt and learn, alongside their remarkable information processing [8]. Development of ANN modelling in MATLAB has attained attention as real-time use of conventional methods in an energy management center can be difficult due to their significant large computational times [9]. With the aid of the highly intelligent system, it is possible to analyze multiple processes that could highly benefit and change the future of the chemical engineering field, such as analyzing and modelling the pyrolysis of sawdust before being industrially applied and implemented [10].

This study is aimed to measure the efficiency of development modelling for pyrolysis of sawdust and also to determine the optimum parameters of physical properties for pyrolysis of sawdust by ANN.

II. METHODOLOGY

A. Experimental Equipment

The equipment used for the ANN network modelling is MATLAB. MATLAB is a professionally developed and tested interactive application that enables us to see how the different algorithms work with our data. It is mainly used for data analytics and programming. MATLAB also enables exposure to real engineering instruments and devices through computing. The following are the commonly followed steps to produce a neural network [11].

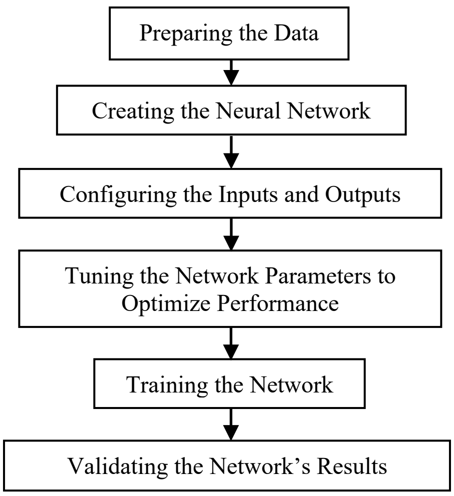

Figure 1: Workflow for Designing Neural Networks

B. Input-output Data Generation

A neuron has more than one input, hence multiple input signals were first selected as basis for the ANN modelling [12]. Several data such as the temperature, nitrogen flow and reaction time were selected to act as the input data. These data will then be used to simulate an ANN modelling and then compared with the actual experimental data.

Table 1: Input-output Data

Input	Output	No. of Samples	No. of Hidden Neurons
Temperature (ºC) Nitrogen Flow (L/min) Reaction Time (min)	Yield of Biofuel (wt%)	20	1 to 25

Table 2: Actual and Predicted Biofuel Yield

No.	Input 1 (ºC)	Input 2 (L/min)	Input 3 (min)	Actual (wt%)	Predicted (wt%)	Error
1	250	0.1	30	13.448	18.386	-4.938
2	350	0.1	30	18.966	22.237	-3.241
3	450	0.1	30	22.069	31.209	-9.14
4	550	0.1	30	34.138	27.15	6.988
5	650	0.1	30	41.379	38.845	2.534
6	750	0.1	30	54.138	59.659	-5.521
7	850	0.1	30	61.379	65.444	-4.065
8	950	0.1	30	63.103	65.884	-2.781
9	500	1	20	37.143	38.424	-1.281
10	500	2	20	32.857	20.722	12.135
11	500	4	20	38.571	39.473	-0.902
12	500	6	20	37.143	50.522	-13.379
13	400	0.025	30	31.379	30.83	0.549
14	450	0.025	30	29.815	34.219	-4.404
15	500	0.025	30	26.552	31.709	-5.157
16	550	0.025	30	24.655	29.302	-4.647
17	600	0.025	30	24.828	32.142	-7.314
18	450	0.4	5	22.250	22.78	-0.53
19	450	0.4	10	24.313	25.149	-0.836
20	450	0.4	15	31.250	32.579	-1.329

Table 3: Best Biofuel Yield

No.	Input 1 (ºC)	Input 2 (L/min)	Input 3 (min)	Actual (wt%)	Predicted (wt%)	Error
6	750	0.1	30	54.138	59.659	-5.521
7	850	0.1	30	61.379	65.444	-4.065
8	950	0.1	30	63.103	65.884	-2.781

Table 2 and 3 show the best amount of biofuel yield based on the three inputs. According to Yang H., et al, the highest biogas yield was the highest at 950 ºC, however the optimum pyrolysis range was from 450 to 650 ºC, for which the sawdust briquettes produced within this range had the highest calorific value (29.14 to 30.21 MJ/kg) while the liquid is useful for liquid fuels and other chemical materials, and the low heating value of the gaseous product was 11.79 to 14.85 KJ/Nm^3 in this temperature range. As the range of the error was still acceptable at ±5%, the samples can be weighted for the results of MSE and R^2 [13].

C. Development of Computational Program

The computational program, MATLAB is the main medium used in simulating the ANN modeling. The ANN network model for pyrolysis of sawdust, as shown in Fig. 2 and 3, was developed by computing the input data and obtaining the MSE and R^2 values. The samples in the ANN training (70%), validation (15%) and testing (15%) sets were weighted for the results of MSE and R^2. Based on the obtained MSE and R^2 values, the efficiency of the process can be predicted. Depending on the values and deviation, an ANN training sequence such as Figure 4 must be done to optimize the performance of the network.

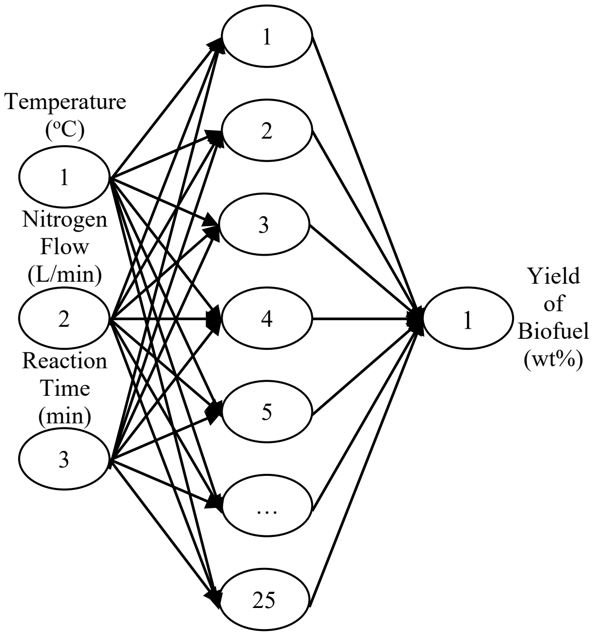

Figure 2: Artificial Neural Network

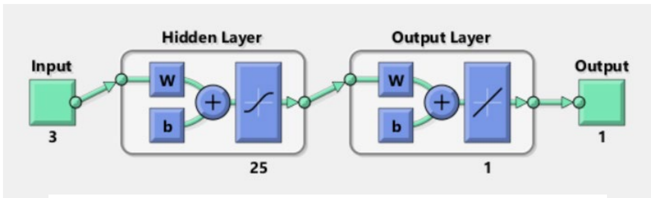

Figure 3: Artificial Neural Network Model

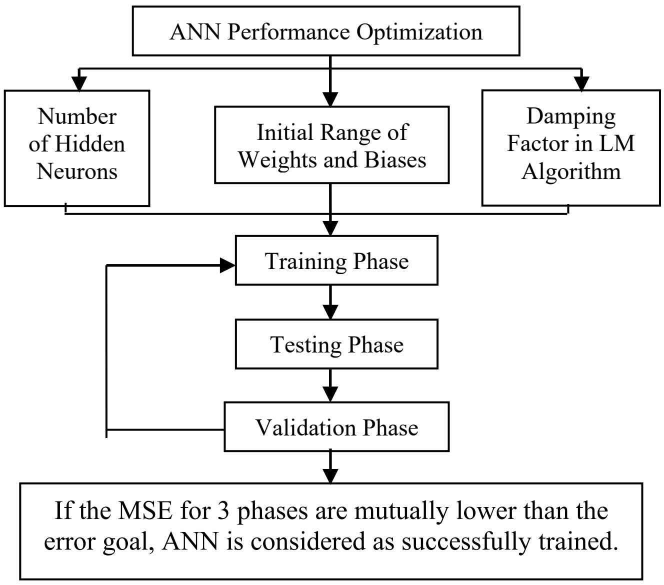

Figure 4: General ANN Training Sequences in Three Phases (Hui et al., 2016)

Based on Figure 4, the general performance of an ANN is affected by the number of hidden neurons, initial range of weights and biases, and the updating method of damping factor in Levenberg-Marquadt (LM) training algorithm [14]. After selecting the wanted parameters for each of the factors respectively, the training phase of the network was executed with the aid of LM algorithm to reduce possible errors. If the obtained MSE is lower than the targeted error, the network will be simulated with the weights and biases generated in the training phase. If the testing MSE is lower than the targeted error, the network undergoes the validation phase where it is simulated with validation data. If it does not achieve the targeted error, re-training will be prompted for the network [15].

D. Network Performance Optimization

The simulation results were summarized in table and graphical form for better analysis. The ANN performance is examined based on the statistical data of MSE, R^2 and number of epochs. The equation of MSE and R^2 are related to the predicted and actual values as displayed in Equation 1 and 2 respectively.

$$MSE = \frac{1}{n}\sum_{1}^{n}(y_{\cdot i.act} - y_{\cdot i.pred})^2 \quad (1)$$

$$R^2 = \frac{\sum_1^n (y_{\cdot i.act} - y_{\cdot i.pred}) - (\sum y_{\cdot i.pred})(\sum y_{\cdot i.act})}{\sqrt{n\sum y_{\cdot i.pred}^2 - (\sum y_{\cdot i.pred})^2}\sqrt{n\sum y_{\cdot i.act}^2 - (\sum y_{\cdot i.act})^2}} \quad (2)$$

where

$y_{i.act}$ = actual value of variable, y

$y_{i.pred}$ = predicted value of variable, y

From the obtained values of MSE and R^2, the ANN network can be optimized by selecting the training parameters such as the number of hidden neurons, initial weights and biases, and the LM method. The variation of number of hidden neurons will change the structure of the network whereas changing the initial weights and biases will affect the LM algorithm.

III. RESULTS AND DISCUSSION

A. Comparison of Results

The network was simulated by varying the number of hidden neurons with a consistent input-output data to understand the limits of ANN over the change of hidden neurons. By following the conditions of the experimental pyrolysis, the operating conditions of the prediction values and the biofuel yield were predicted. This study is aimed to understand the effect of the number of hidden neurons to the performance of the network, shown in Table 4.

Table 4: ANN Performance

No. of Hidden Neurons	MSE	Correlation Coefficient, R^2	No. of Epochs
1	65.643	0.8640	12
2	52.8489	0.8688	16
3	44.7998	0.9012	10
4	45.1354	0.9102	6
5	40.5828	0.9285	10
7	19.4965	0.9339	10
10	11.9356	0.9417	11
15	12.7625	0.9620	8
20	9.0914	0.9722	10
25	4.9747	0.9812	36

Table 4 shows the result of the ANN performance based on the number of hidden neurons and the effect on the validation MSE, overall MSE, correlation coefficient, R^2 and the number of epochs. Generally, the value of MSE is inversely proportional to the value of R^2, hence a higher value of MSE produces a lower value of R^2. With 1 hidden neuron, the number of epochs and overall MSE value were relatively high at 12 and 65.643 respectively, where its R^2 value was the lowest at 0.8640. The values show significant and immediate increment as the number of hidden neurons is increased. At 5 hidden neurons, the MSE and R^2 values were at 40.5828 and 0.9285 respectively at 10 epochs while the values went to 11.9356 and 0.9417 at 10 hidden neurons. With 20 hidden neurons, the value of overall MSE was 9.0914 at 10 epochs, with the an R^2 value of 0.9722. However, when the number of neurons was increased to 25, the performance of the network further improved in which the MSE value decreased to 4.9747, R^2 value increased to 0.9812 at 36 epochs. Hence, the hidden layer with 25 neurons was selected as the most optimized ANN structure because the best fit of model represents an R^2 value of almost 1. Also, the deviation implies that the ANN model can predict the values with little inaccuracy [17].

Table 5: MSE and R^2 Outcomes at Optimal Hidden Neuron

	Samples	MSE	R^2
Training	14	4.9747	0.9812
Validation	3	12.2322	0.9808
Testing	3	114.3191	0.7861

B. Predictive Analysis of ANN Simulation

Based on the obtained results, the relationship between the number of epochs, MSE, R^2 and the number of hidden neurons can be seen as shown in Figure 5 and 6.

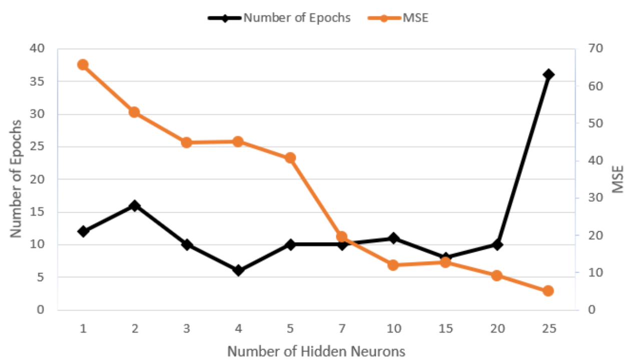

Figure 5: ANN Performance Based on Number of Epochs and MSE

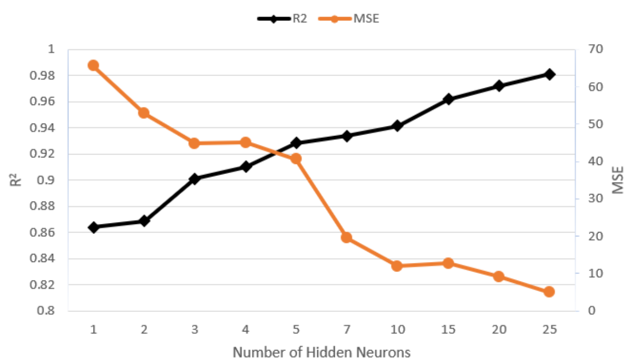

Figure 6: Trend of MSE and R^2 with Variation of Hidden Neurons

Based on Figure 5, the number of epochs increases to 16 epochs at 2 hidden neurons, and greatly decreases into 6 epochs at 4 hidden neurons. The number of epochs then resolves between 8 and 11. However, the number of epochs spiked to 36 when 25 hidden neurons were used. On the other hand, the value of MSE continuously decreased as the number of hidden neurons increased, going from 65.643 to 4.9747. Based on Figure 6, the correlation coefficient, R^2 continuously increases as the number of hidden neurons used increase until the optimal neuron is obtained.

Moreover, from the training results, four graphs were obtained; performance, training state, error histogram and regression as shown in Figures 4.3 to 4.6. The graphs displayed the values of the performance function versus the epochs. Figure 7 showed that the 36 epochs were performed and achieved the best validation performance at MSE of 12.2322 and R^2 computed to 0.9812 while the training state graphs in Figure 8 demonstrated the progress of other training variables, such as the gradient magnitude and validation checks. In the error histogram plot of Figure 8, the distribution of the network errors in 20 samples were shown. The error was calculated by subtracting the output (predicted) from the target (experimental) value. Finally, the regression plot in Figure 10 expressed the regression between the network outputs and targets. The perfect fit between the ANN model predictions equaled to the experimental data with a solid line of overall R^2 computed to 0.9333.

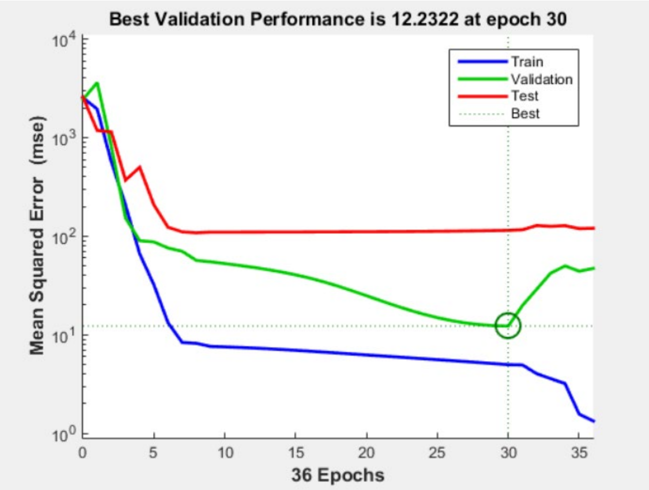

Figure 7: Performance Graph in 36 Epochs

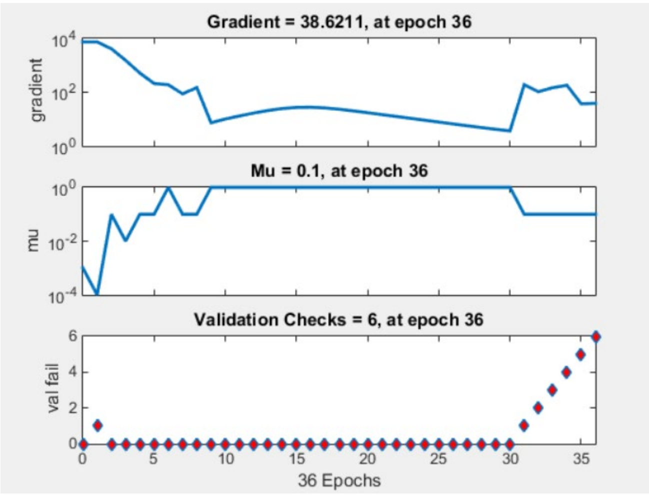

Figure 8: Training State in 4 Epochs

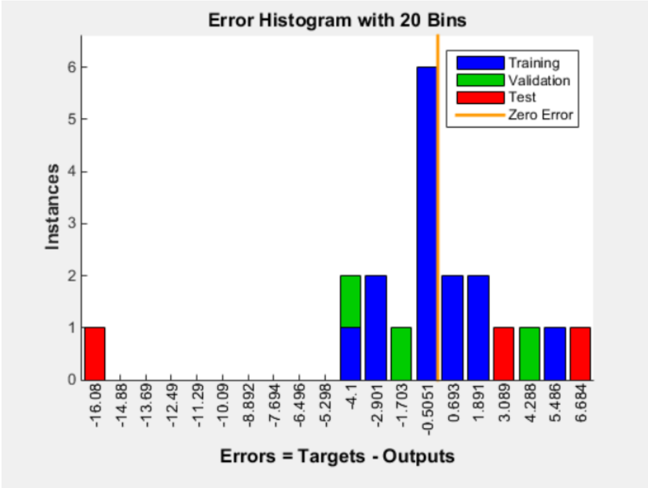

Figure 9: Error Histogram of 20 Samples

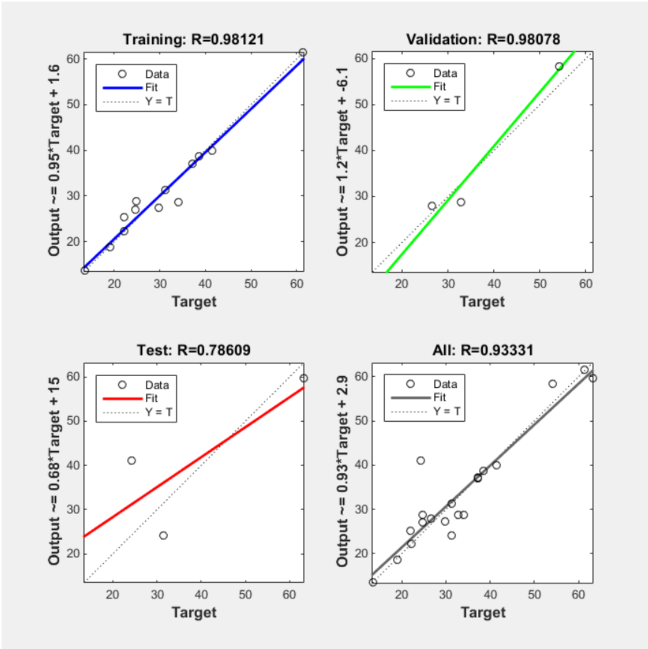

Figure 10: Best Fit of Regression Model

IV. Conclusion

The single hidden layered artificial neural network for the effect of temperature, nitrogen flow and reaction time for pyrolysis of sawdust process was generated using an engineering software, MATLAB r2014a. The ANN was trained based on the self-designed program and training sequences. The ANN performance optimization was conducted based on the number of hidden neurons, initial range of weights and biases. Based on the data, the best fit performance for yield achieved R^2 of 0.9818 with validation MSE value of 4.9747 under 36 epochs at 25 hidden neurons. It can be concluded that the modeling of the ANN was noted with high accuracy and robustness in simulating the sawdust pyrolysis process before proceeding to industrial processing.

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