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# ESTIMATION OF MASS YIELD OF TORREFIED BIOMASS USING ARTIFICIAL NEURAL NETWORK

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**Abstract -** In this study, Levenberg-Marquardt (L-M) algorithm with Multiple Input-Single Output (MISO) layer network was employed to predict the biomass Mass Yield using the carbon content (CC), torrefaction temperature (TFT), and torrefaction time (TT) as the input variables. Agro-waste biomass were the feedstocks considered. Around 150 datasets obtained from torrefaction experiments were trained using 8, 9, & 10 neurons in the hidden layer, respectively. The Input Variable Representation Technique- by-Visual Inspection Method (IVRT-VIM) was used for the model improvement. The coefficient of determination ($R^2$), Mean Square Error (MSE) and Partial Derivatives (PaD) method, were the matrixes used for the evaluation of the model and the most influential variable on the output, respectively. The $R^2$ obtained from TT, TFT, & CC, TT & TFT, and TFT & CC as inputs were in the range of 90 – 93.71 %, 88.61- 94.55%, & 90.40 – 97.14 %, respectively. From the sensitivity analysis, Carbon content (CC) was the most important variable affecting the Mass Yield (output) with Sum of Squares of Partial Derivatives (SSD) of 21.29. The results obtained have shown that ANN model is capable of predicting the mass yield of torrefied biomass.

**Keywords: Artificial Neural Network, Biomass, Mass Yield, Energy production, Torrefaction Plant.**

## 1. Introduction

Researchers around the globe are relentlessly studying the most effective means of energy generation. The studies are centered on renewable and non-renewable energy sources. Solar, hydro, wind, and biomass are promising sources of renewables while oil and gas (petroleum) and coal are potential for non-renewable sources. From the environmental point of few, renewable sources are more attractive than non-renewable sources (Hu et al., 2012).

Gaseous emissions into the environment are dependent on the energy conversion process used. The thermochemical energy production processes such as combustion, gasification and pyrolysis are promising systems for energy production (Chen et., 2018). The emissions arising from the processes varies. Biomass - a renewable source produces lower emissions when compared to coal, oil and gas, but its energy density is lower than that of the aforementioned fossil fuels. The emissions from coal including CO2, NOX and SOX are dangerous to the environment (Chen et., 2018). Biomass are organic materials obtained from living plants and biological wastes. They are clean source of fuel with low or zero amounts of Sulphur and contaminants (Hu et al., 2012). It is composed of cellulose, hemicelluse, lignin and extractives. The hemicellulose is the most reactive amongst the components of the fuel (Chen et., 2018). Similarly, Non-renewable fuels such as coal and petroleum are fast depleting, expensive, and produces dangerous emissions resulting to climate change (Paula et al., 2013).

In Nigeria, waste biomass materials including wheat straw, rice husk, corn cob, sugarcane bagasse, and wood sawdust are in abundant. They can be used to produce syngas used as fuel in gas turbines, fuel cells, and internal combustion engines to produce electricity. The quality of the syngas is dependent on the quality of the fuel. The quality of a fuel can be enhanced by torrefaction.

Torrefaction is a heat-treatment process whereby biomass is heated in an inert atmosphere using tubular or rotary furnace at suitable temperature and time to upgrade the fuel quality (Chen et al., 2017). The carbon content is one of the vital physiochemical properties of biomass that affects the energy value the fuel. The energy density of biomass is lower than that of coal, oil and gas, but emissions from these fossils limits there uses.

To achieve a high-quality biomass fuel via torrefaction, the process conditions have to be understood. The Mass Yield or Mass Loss of torrefied biomass is a critical parameter in biomass torrefaction plant. Campbell et al. (2018) has reported the co-relation of thermal degradation of the biomass and carbon content of the fuel with respect to the mass yield using experimental and linear regression model. Unfortunately, Laboratory experiments are not attractive due to time and high cost of experiments. In this study, Artificial Neural Network (ANN) model will be used to predict the mass yield of biomass.

ANN has been used in vision and speech recognition (Pandey et al., 2016). It is a data-driven technique that explores the complex relationships for different input and output variables without requiring the explanation of the mathematical phenomena or principles involved (Sunphorka et al., 2017). Also, it has been used due to its predictive accuracies and enhanced adaptability in energy science (Buratti et al., 2014). The ANN model has been used for estimating the gasification performance of gasification systems (Pandey et al., (2016); Ozonoh et al., (2020); and Ozonoh et al., (2020). Other researchers including Bach et al. (2017) and Nieto et al. (2018) reported the attractiveness of the model in predicting the lower heating value (LHV) of biomass during gasification reactions. Similarly, Tiwary et al., (2018) and George et al., (2018) employed the model to study the syngas yield, LHV of product gas, LHV of gasification products (e.g., char and tar) and gas composition (CO, $CO_2$, $CH_4$, $H_2$) during gasification experiments in a fluidized bed gasifier (FBG) and bubbling fluidized bed (BFB) gasifier, respectively.

The results from the aforementioned authors were promising, but unfortunately the prediction of mass yield of torrefied biomass samples using ANN model was not considered. A Multiple Input- Single-Output (MISO) layer network for predicting biomass Mass Yield is scarce in the literature. In this study, 150 different experimental dataset was used with carbon content (CC), torrefaction temperature (TFT) and torrefaction time (TT) as the input variables to predict the Mass Yield (MY)

- the output variable of the torrefied biomass. This study will promote the development of commercial biomass torrefaction plants, hence, resulting to energy production and sustainability. The study will also be instrumental to waste management in the country. It will equally assist stakeholders in decision making and as well, open a window for further R&D in this area.

## 2. Theory of Work

Electricity tariff and bills has continued to increase in Nigeria. It could be attributed to inefficient petroleum refineries in the country and over dependency in fossil fuels for electric power generation. Energy can be generated from both renewable and non-renewable sources as earlier explained in section 1. To enhance domestic and industrial operations in Nigeria, sustainable electricity sources and systems are crucial.

### 2.1. Biomass Torrefaction

Torrefaction of biomass upgrades the energy density of the fuel. The pre-treatment process creates an opportunity of substituting biomass with fossil fuels such as coal and petroleum that threatens the environment during energy conversion processes (Ozonoh et al., 2020). Biomass materials have important components as shown in Figure 1, but understanding the relationship between its composition and torrefaction process conditions may require several experiments. To save time and the cost of experiments, processing modelling is considered. ANN process modelling is effective for this purpose.

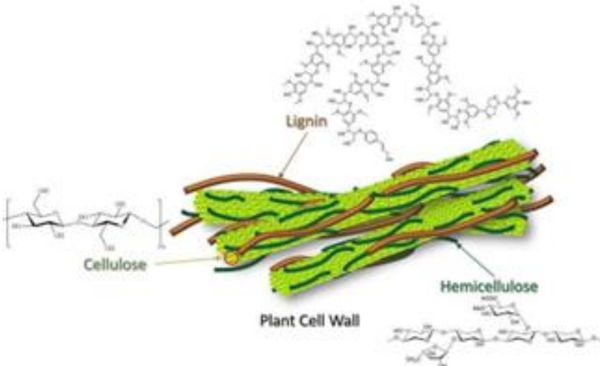


**Figure 1: Cell plant wall of lignocellulosic and its components (Chen et al., 2018).**

### 2.2. Physiochemical properties of Biomass

An overview of the physiochemical properties of raw and torrefied biomass materials are presented in Table 1.

**Table 1: Characteristics of biomass before and after Torrefied biomass**

| S/N | Raw biomass | Torrefied biomass |
|---|---|---|
| 1 | Higher moisture content | Lower moisture content |
| 2 | Lower energy density | Higher energy density |
| 3 | Lower heating value | Higher heating value |
| 4 | Higher O/C and H/C ratio | Lower O/C and H/C ratio |
| 5 | Hygroscopic | Hydrophobic |
| 6 | Non-uniform properties | More uniform properties |
| 7 | Difficult to grind | Easier to grind |

Torrefaction condition in the range of 200 - 300 $^{O}$C under nitrogen atmosphere

Mathematically, the mass yield during torrefaction is expressed in Equation (1):

$$Mass\ Yield = \frac{Mass\ of\ Biochar}{Mass\ of\ Raw\ Feedstock}\ X\ 100 \quad \textbf{(1)}$$

The mass Yield is in percentages (%) while the mass of biochar and Mass of raw feedstock are in gram (g).

### 2.3. Artificial Neural Network (ANN) concept

Understanding the basic structure is the first step in designing of the network, and it involves determining the number neurons and hidden layer in the input and output. According to Idioa et al., (2016), the input-output relationship of the ANN model is presented in Equation (2):

$$y = \boldsymbol{b_2} + LW * tansig\ (b_1 + IW * X) \quad \textbf{(2)}$$

where y and X represents the input and output vectors respectively; LW represents the connection matrix of weights with respect to all the arcs from the hidden layer; IW represents the connection matrix from the input layer to the hidden layer; b1 and b2 are respectively, the hidden and output layers' bias vectors.

Signals are received by the hidden layer and sent to the neuron of the output layer, but each unit (yj) of the network in the hidden layer, sums its weighted inputs and uses the activation function to generate the output signal. Equation (3) (Idoia et al., 2016) presents the activation function principles of the network.

$$y_j = f_{Activation}\left(\textstyle\sum_{I=1} W_{IJ}\, X_i + b_j\right) \quad (3)$$

Wij represents the weight of the connection between the i$^{th}$ input and the j$^{th}$ neuron of the hidden layer; bj represents the bias weight of the unit j. An example of activation function that can be used is shown in Equation (4), while its application is shown in Equation (5).

$$f_{Activation}(X) = \frac{1}{1+e^{-X}} \quad (4)$$

$$\mu K = f_{Activation}\left(\sum_{j=1} V_{jk}\, y_f + b_k\right) (5)$$

The statistical tools ($R^2$ and MSE) used for the overall model performance are expressed in Equation
(6) and Equation (7), respectively, and in this study, 8, 9 and 10 number of neurons in the hidden layer were considered, respectively.

$$R^2 = \left[\frac{\sum_{i=1}^{n}((E_i - E)(P_i - P)}{\sqrt{\sum_{i=1}^{n}(E_i - E)^2}\ \sqrt{\sum_{j=1}^{n}(P_i - P)^2}}\right]^2 \quad (6)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(E_i - P_1)^2 \; (7)$$

## 3. Materials and Method

### 3.1. Experimental data

In this study, 150 torrefied biomass samples were collected from the literature and were used for the estimation of the output variable (Ozonoh et al., 2020). The results of the torrefaction experiments were carried out in different torrefaction reactors and process conditions. The parameters considered were torrefaction temperature (TT), torrefaction time (TFT), biomass carbon content (CC), and biomass mass yield (MY). The data were divided into input and output variables as displayed in Table 2 in section 4.1.

### 3.2. Network Training Procedure

The 150 input-output patterns employed in the investigation was divided into three namely: 80 % (120 dataset), 10 % (15 dataset), and 10 % (15 dataset) for training validation and testing the model, respectively. Iterations were carried out using the input datasets that was randomized by the network. For effective training of the network and development of a better architecture, the number of neurons in the hidden layer was varied using tansigmoid transfer function expressed in Equation (2). A Multiple-Input-Single-Output (MISO) layer network was studied. For the model performance evaluation, an in-built statistical tool including the Mean Square Error (MSE) and coefficient of determination ($R^2$) were used. As the network training progressed, the result of the model was assessed based on the network with the lowest MSE and highest $R^2$ values, respectively.

A flow-chart presented in Figure 2 was used for the neural network training using 8, 9, and 10 number of neurons in the hidden layer following the steps shown in Figure 2.

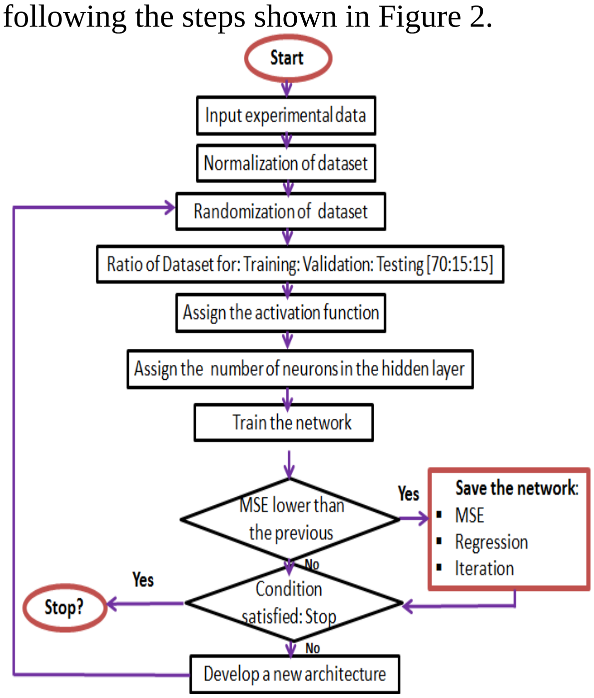


**Figure 2: ANN training procedure**

The Feed-forward neural network used in this study is shown in Figure 3.

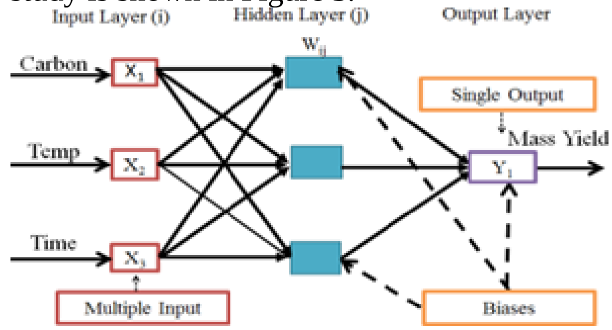


**Figure 3: A feed forward ANN: With 3 inputs and 1 output (MISO) layer.**

## 3. Sensitivity Analysis

A sensitivity analysis was carried out to determine the input variable with the highest effect on the output variable (Mass Yield - MY). In this study, partial derivative (PaD) method was used and the expression presented in Equation (8) and Equation (9) was employed.

$$SSD_I = \sum_P \left(\frac{\partial o_k^P}{\partial x_i^P}\right)^2 \quad (8)$$

The effect or contribution of each input variable on the output variable is shown in Equation (8):

$$\text{Contribution of the ith Variable} = \frac{\mathrm{SSD_i}}{\sum_\mathrm{i} \mathrm{SSD_i}} \quad (9)$$

Where, SSD represents the sum of square of the partial derivatives

## 4. Results and Discussion

### 4.1. Neural network model development and applications

The range of the input and output data employed is displayed in Table 2. The 20 – 98 data range is the range of data for the Mass Yield (the output variable) estimated in this study, while the 200 – 800, 10 – 100, and 23 – 80 were the range of data or values for the torrefaction temperature, torrefaction time, and carbon content of the different experiments carried out by different researchers and extracted in the literature (Ozonoh et al., 2020) for the current study.

**Table 2: Input and output variables used in the neural network**

| S/N | Input Variable | Data range | Output variable | Data range |
|---|---|---|---|---|
| 1 | Torrefaction temperature [ºC] | 200 – 800 | Mass yield (%) | 20 - 98 |
| 2 | Torrefaction time [min] | 10 – 100 | - | - |
| 3 | Carbon content [%] | 23 – 80 | - | - |

### 4.2. ANN Mass Yield (MY) Prediction

To determine the mass yield, different number of neurons in the hidden layer of the MISO layer network was used, while the Mean Square Error and the coefficient of determination ($R^2$) were used to evaluate the prediction accuracy of the model. The values of MSE and $R^2$ determine are used to assess the accuracy of the model (Dahunsi, 2019).

#### 4.2.1. Prediction of mass yield using TT, TFT, & CC

The TT, TFT, and CC were used to predict the mass yield. In this case, 8, 9, and 10 number of neurons in the hidden layer were studied. The convergence characteristics of the network obtained are shown in Figure 4 – Figure 6.

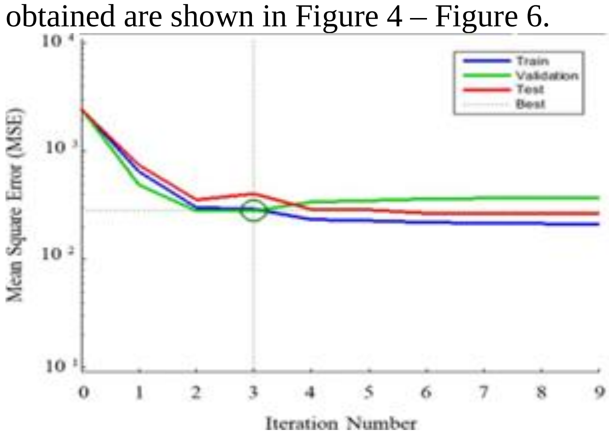


**Figure 4: Convergence characteristics of MISO layer network using TT, TFT, & CC: [8 neurons]**

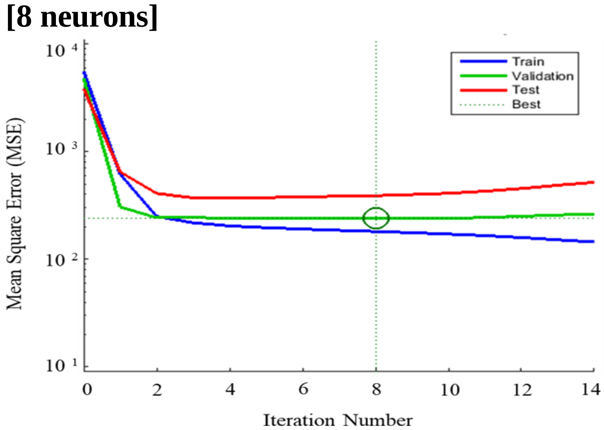


**Figure 5: Convergence characteristics of MISO layer network using TT, TFT, & CC: [9 neurons]**

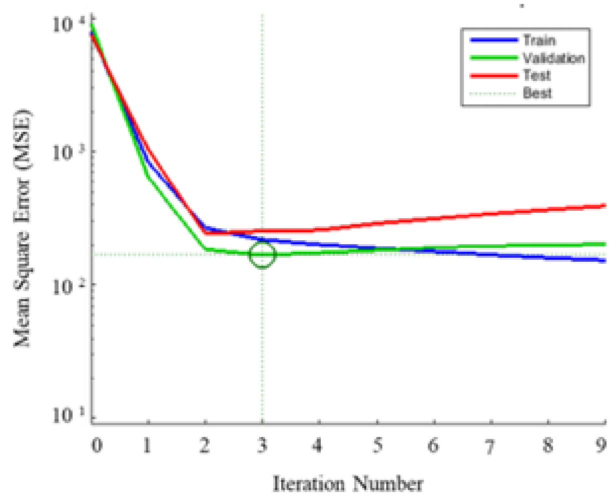


**Figure 6: Convergence characteristics of MISO layer network using TT, TFT, & CC: [10 neurons]**

From Figure 4 it can be seen that there was a perfect fitting in terms of the training, testing, and validation of the network, but the testing curve slightly shifted from that of training and validation at epoch 2, but the best fittings were achieved at epoch 3. The shift observed may be attributed to noise from the network. From Figure 5 and Figure 6, the convergence characteristics were very stable till epochs 8 and 3 respectively, but the stability obtained from figure 7 was better than that of Figure 6. The MSE obtained from using 8, 9, and 10 number of neurons were 28.53, 237.98, and 167.37, while the $R^2$ for training, validation and testing is in the range of 90.24 – 93.71 %, respectively.

#### 4.2.2. Prediction of mass yield using TT and TFT

Based on the high MSE obtained in section 4.2.1, the number of input variables used for the mass yield estimation was reduced from 3 to 2 to test the model improvement. In this study, Input Variable Representation Technique-by-Visual Inspection Method (IVRT-VIM) was employed (Ozonoh et al., 2020). The result obtained is presented in Figure 7 through Figure 9. From Figure 7, the number of iterations encountered by the network during the learning was 11, while the best fitting was achieved at epoch 5. The implication was that the model was able to respond accurately with the input dataset as evidenced in the convergence curves for fitting, validation and testing, respectively.

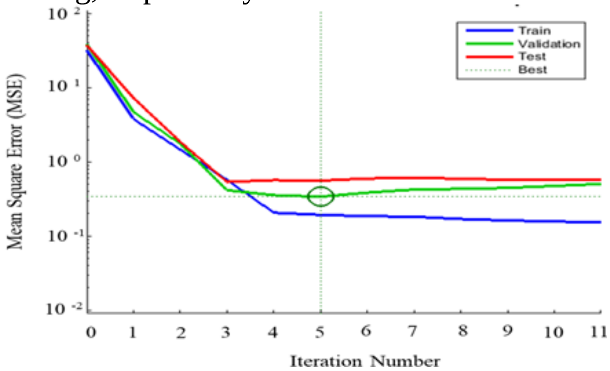


**Figure 7: Convergence characteristics of MISO layer network using TT and TFT: [8 neurons]**

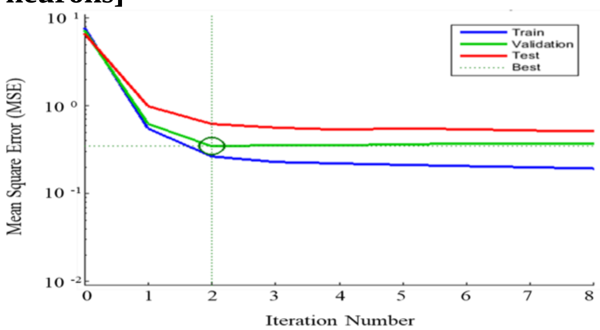


**Figure 8: Convergence characteristics of MISO layer network using TT and TFT: [9 neurons]**

From Figure 8 and Figure 9, it can be observed that 8 and 12 number of iterations was used by the neural network to predict the mass yield, but the best fittings were obtained at epochs 2 and 6, respectively. Larger value of epoch is preferred because it defines the stability of the characteristics curve; therefore, the model result obtained in Figure 9 is better than that of Figure 8. Furthermore, the accuracy of the result is evidenced in the MSE obtained from the networks, and from figures 4, 5, and 6, the MSE were 0.75, 0.62, and 0.50 respectively, while the $R^2$ was in the range of 88.61 – 94.55 %. A MSE tending to zero (0) is better (Cheng et al., 2018), it can be seen that the $R^2$ slightly reduced to 88.61 % when compared to when TT, TFT, and CC were used in the prediction, but there was considerable reduction in the MSE from TT & TFT input set. However, efforts were made to balance the two-evaluation metrics (i.e., MSE and $R^2$) to enhance the model results.

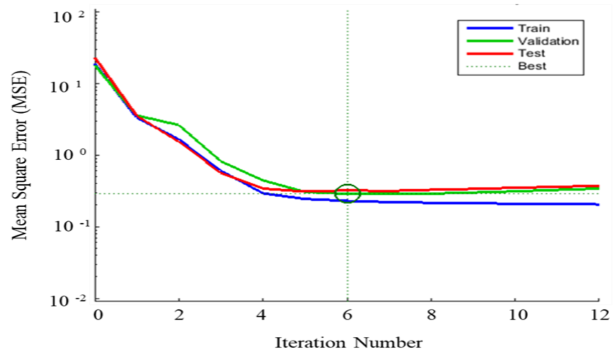


**Figure 9: Convergence characteristics of MISO layer network using TT and TFT: [10 neurons]**

**4.2.3. Prediction of mass yield using TFT and CC**

The IVRT-VIM was equally used here but, in this case, the torrefaction time (TT) was replaced with carbon content (CC). The essence of which was to determine if the CC has much influence on the mass yield than the TT, and check if the substitution of TT with CC, could help in the improvement of the model result. Figure 10 through Figure 12 presents the result obtained when only TFT and CC were used for the evaluation. The convergence characteristics for the training carried out with the two input variables displayed some considerable stability. The values or number of epochs produced from 8, 9, and 10 number of neurons were 7, 3, and 6 respectively, while considerable reductions in the MSE were equally recorded. The MSE from this training (TT and CC) was lower than that of TT, TFT, and CC and TT, TFT respectively. The indication was that the individual data contained in the overall experimental dataset from TT and CC were better than the others.

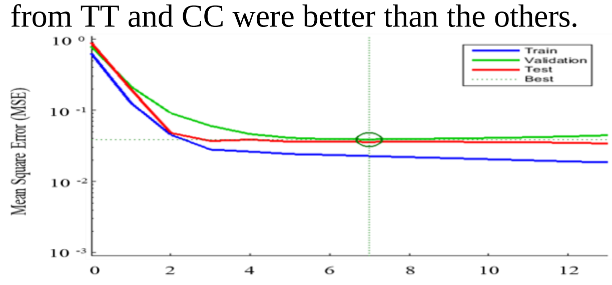


**Figure 10: Convergence characteristics of MISO layer network using TT and CC: [8 neurons]**

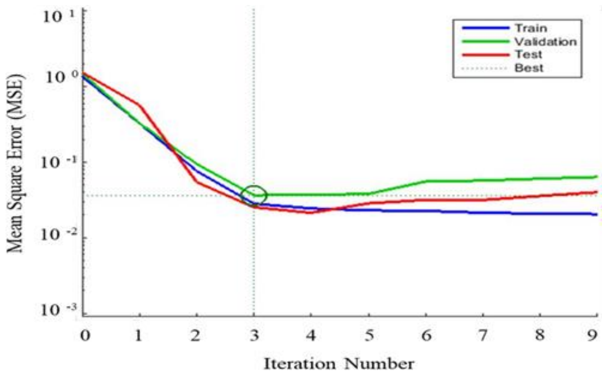


**Figure 11: Convergence characteristics of MISO layer network using TT and CC: [9 neurons]**

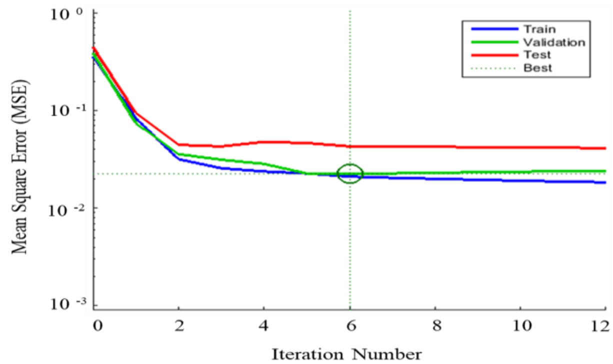


**Figure 12: Convergence characteristics of MISO layer network using TT and CC: [9 neurons]**

The summary result of the three classes of training carried out in this study to predict the mass yield of torrefied biomass materials is shown in Table 3.

**Table 3: Summary result: Prediction of mass yield using L-M MISO layer network**

| Input | Neurons | MSE | Epoch | Training | Validation | Testing | Out put |
|---|---|---|---|---|---|---|---|
| | | | L-M Algorithm MISO Layer Network: 2-Inputs & 1-Output | | | | |
| TT, TFT | 10 | 281.53 | 3 | 93.71 | 92.48 | 90.53 | Mass |
| and CC | 9 | 237.98 | 8 | 90.24 | 91.53 | 91.14 | Yield [%] |
| | 8 | 167.37 | 3 | 92.11 | 90.57 | 92.35 | |
| | | | L-M MISO Layer Network: 2-Inputs & 1-Output | | | | |
| TT and TFT | 10 | 0.50 | 5 | 94.55 | 93.75 | 90.66 | Mass Yield |
| | 9 | 0.62 | 2 | 90.38 | 91.50 | 89.46 | [%] |
| | 8 | 0.75 | 6 | 91.14 | 89.22 | 88.61 | |
| | | | L-M MISO Layer Network: 2-Inputs & 1-Output | | | | |
| TT and CC | 10 | 0.04 | 7 | 97.14 | 96.28 | 94.45 | Mass Yield |
| | 9 | 0.05 | 3 | 94.07 | 93.56 | 94.16 | [%] |
| | 8 | 0.06 | 6 | 92.21 | 91.25 | 90.40 | |

L-M: Levenberg Marquardt; MISO: Multiple Input-Single Output; TT: Torrefaction Temperature, TFT: Torrefaction Time; CC: Carbon Content.

### 4.4. Sensitivity analysis

Partial Derivative (PaD) method was used to determine the effect of the input variable on the output. The Pareto chart depicted in Figure 13 to Figure 15 describes the effects of the inputs on the output. The sensitivity analysis was based on the result obtained from the model improvement through IVRT-VIM method. The charts displayed the variable with the highest value of the Sum of Squares of the Partial derivatives (SSD), and which affirmed the most influential variable on the mass yield.

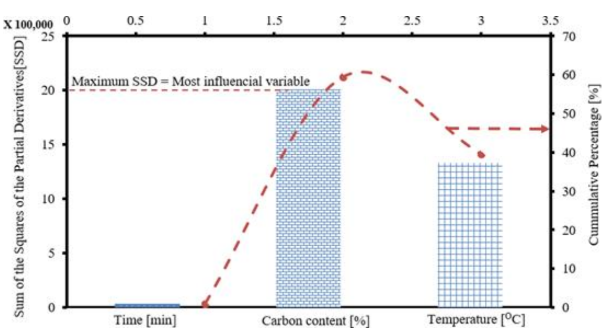


**Figure 13: Effect of time, temperature and carbon content on mass yield: [SSD = 20.06]**

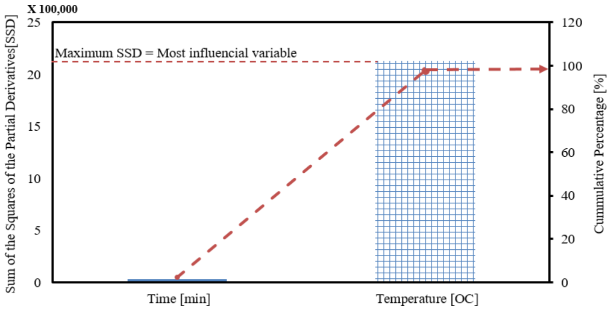


**Figure 14: Effect of time and temperature on mass yield: [SSD = 20.26]**

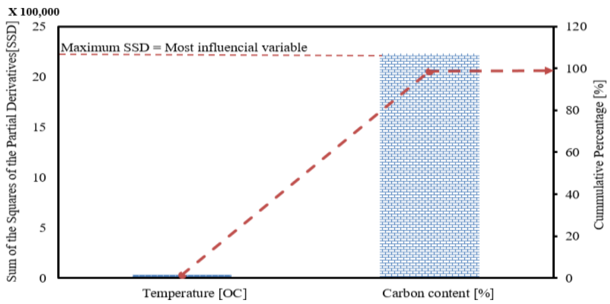


**Figure 15: Effect of temperature and carbon content on mass yield: [SSD = 21.29]**

From Figure 13 – Figure 15, the highest SSD was obtained when torrefaction temperature (TFT) and carbon content (CC) were used in the prediction of the mass yield; in this case, carbon (%) has the highest effect on the mass yield. This was expected because carbon content plays a very critical role in the energy content of a fuel and the mass loss of solid fuels during thermal degradation. Carbon is one of the major compositions of biomass (Fisher et al., 2018). The amount of carbon in a fuel also determines the calorific value (CV) of the fuel, and the change in the CV or higher heating value (HHV) of a fuel expressed by the enhancement factor (EF) equally influence the biomass Mass Yield (MY) during torrefaction (Ozonoh et al., 2018).

## 5. Conclusion

In this study, a Multiple-Input-Single-output (MISO) layer network was used to predict the mass yield of torrefied biomass. 150 experimental dataset obtained from different biomass torrefaction and process conditions were employed. Torrefaction temperature (TT), torrefaction time (TFT), carbon content (CC) of biomass, were used as the input variables to determine the output (mass yield). Three classes of ANN training using 8, 9, and 10 number of neurons in the hidden layer were considered, and the following conclusions were made:

- 8 number of neurons in the hidden layer produced the best model result.
- The $R^2$ from TT, TFT, & CC, TT & TFT, and TFT & CC were in the range of 90 % – 93.71 %, 88.61- 94.55 %, & 90.40 – 97.14 % respectively.
- The MSE obtained from TT, TFT, & CC training was high, but the MSE obtained from both TT & TFT and TFT & CC was considerably low, while the least MSE of about 0.04 was obtained from TFT & CC variable for mass yield prediction.
- The use of IVRT-VIM was effective for improvement of the ANN model result.
- Carbon content was the most important variable that influenced the mass yield (output) with Sum of Squares of Partial Derivatives (SSD) of 21.9.

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