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Feedforward Neural Network Modeling of Biomass Pyrolysis Process for Biochar Production

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Growing energy needs and increasing environmental issues are creating awareness for alternative energy which substitutes the non-renewable and polluting fossil fuels. Biomass is a good feedstock for biochar production through the pyrolysis process. There is potential to generate solid fuel from biomass, as there are large quantities of agricultural wastes available in Malaysia. This paper outlines the experimental study on the pyrolysis of durian rinds in Thermogravimetric Analyzer (TGA). The effects of temperatures on the yield of biochar from the durian rinds were investigated. Increasing temperature resulted in increasing weight loss of the biomass sample. The total weight loss at the end of 920 ºC was 86.9 %. This corresponds to the loss of water and volatile matter from the durian rinds. A multilayer feed-forward neural network (FANN) model was trained with an error back-propagation algorithm. Reaction time, temperature were used as the input parameters and weight loss was the output for the study. A FANN model with modeling performance of 2-20-1 was obtained for the study.

1. Introduction

Energy has become very important for industrial and social development. Life without electricity would be imaginary for most of modern mankind. The demand for energy increases dramatically as the population increases (Lee et al., 2007). Energy is largely consumed in the industry, where production is being carried out 24 h/d for 7 days a week. According to the World Energy Council, about 82 % of the world’s energy needs are currently covered by fossil resources such as petroleum, natural gas and coal (Soetaert and Vandamme, 2005). But the depletion of the world’s oil reserves has raised awareness on the importance of renewable energy (IEA, 2008). Fossil fuel combustion products are causing global problems, such as global warming, acid rains and urban air pollution (Nejat Veziroğlu and Şahin, 2008).
In recent years, power generation not only depended on coal, petroleum and natural gas, but also on some contributions from hydro, wind, solar and biomass. One renewable option is utilizing waste to generate energy. Biomass looks like a promising alternative to produce biofuels. Biofuels are considered to be carbon cycle neutral because CO_2 released into the atmosphere when burnt is fixed in the biomass by photosynthesis (Choi et al., 2014). Thus, it will have none or very small net carbon dioxide impact to the global warming compared to fossil fuels (Koroneos et al., 2008). Biomass is a complex resource that can be processed through biological routes that convert the carbohydrate portion of the lignocellulose into ethanol or thermochemical processes that generate char, liquid, syngas (Goyal et al., 2008) and clean conventional fuels (Chum and Overend, 2001).
Biomass wastes from the agriculture are well known for their wide availability, high moisture content and short shelf-life. They are considered low grade fuels compared to petroleum or coal. Nevertheless they can be upgraded by applying thermo-chemical treatment such as liquefaction (Wang et al., 2008,), pyrolysis and gasification (Wei et al., 2006). Biomass can be categorized as “young coal”. As coal takes millions of years to form, biomass is readily available in the form of agricultural wastes. Biomass has similar mechanism with coal when it is pyrolised or gasified. Figure 1 illustrates the thermal conversion of biomass.

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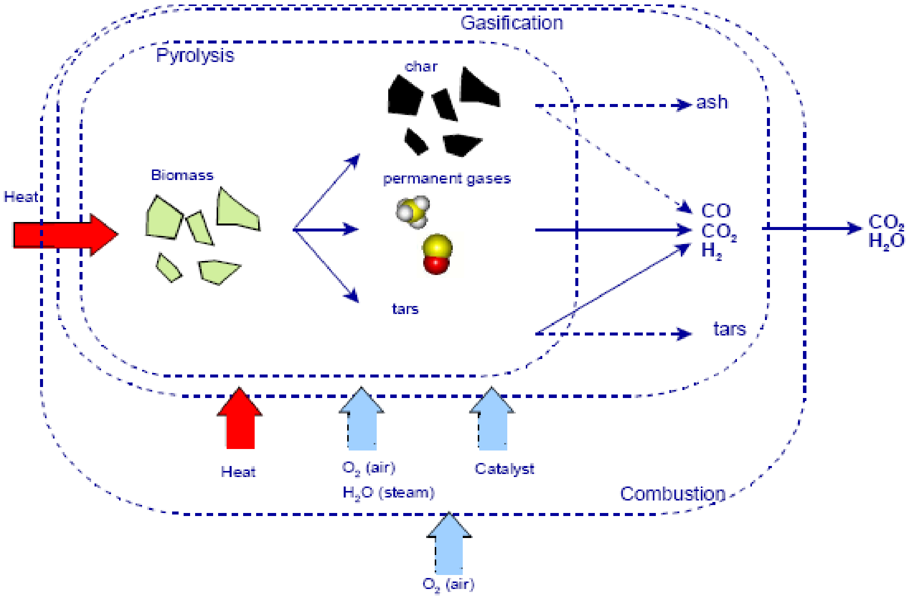

Figure 1: Schematic diagram of thermal conversion process (Swaaij et al., 2002)

Pyrolysis is known as thermo-chemical decomposition of solid or liquid feedstocks. Chemical decomposition of organic materials occurs when heat is introduced in the absence of oxygen (Saxena et al., 2008). Pyrolysis generally produces char, oil/tar and syngas, which consist of CH_4, H_2, CO, CO_2 and also H_2O. In addition, pyrolysis of plant-derived biomass can also be taken as the decomposition of cellulose, hemi-cellulose and lignin. Therefore, pyrolysis can be applied to upgrade low grade fuels like biomass into combustible gases and char.

Pyrolysis processes can be categorized into slow pyrolysis, fast pyrolysis and flash pyrolysis. Among the processes, slow pyrolysis is normally chosen to obtain maximum char yield. Both, fast and flash pyrolysis, produce more bio-oil and syngas and result in lower yields of char from the rapid decomposition of cellulose, hemi-cellulose and lignin. The main operating parameters for all three pyrolysis process are shown in Table 1.

Table 1: Range of main operating parameters for pyrolysis process (Maschio et al., 1992)

	Slow pyrolysis	Fast pyrolysis	Flash pyrolysis
Operating Temperature (ºC)	300-700	600-1,000	800-1,000
Heating Rate (ºC/s)	0.1-1	10-200	≥ 1,000
Solid residence time (s)	600-6,000	0.5-5	< 0.5
Particle size (mm)	5-50	<1	Dust

Therefore, this paper describes the pyrolysis process adopted to produce biochar by adopting biomass as the feedstock. The objective of this paper was to develop a Feedforward Neural Network (FANN) model to predict the weight loss in the production of biochar at various temperatures and time period.

2. Materials and method

Durian rinds were chosen as the biomass for the pyrolysis process. Malaysia is one of the primary producers of durian. Total planted area was 116,280 ha and the production reached 303,717 t in 2003 (MARDI, 2003). For durian aril, the edible portion of the fruit accounts for only 15-30 % of the mass of the entire fruit. Thus, around 70 % of the total mass of the fruit, which includes the seed and the rinds are being discarded as wastes. As a large portion of the durian rinds are readily available as wastes, the durian rinds were chosen for the pyrolysis process. The samples of durian rinds were obtained from hypermarket in Balakong. As received durian rinds have high water content of around 80 %wt. As an initial step, the material was cut into smaller pieces ± 2 x 7 cm. Then the durian rinds were oven dried for 24 h at 70 ºC to reduce their moisture content to air-dried moisture content of around 10 %wt. After drying, the durian rinds were ground using a grinder Retsch model SM100 to a particle size of ≤ 5 mm. The samples were then sieved using sieves and a sieve shaker. Sieve sizes of 2 mm and 1 mm were used to segregate the samples. The samples fraction retained on the 1 mm sieve was used for the pyrolysis process. A thermogravimetric analyzer (Mettler Toledo, model TGA/DSC 1) had been used to carry out pyrolysis process. A slow pyrolysis adopted to obtain more char yield. 50 mg of durian rind sample was used and heated under nitrogen flow at 50 mL min^{-1} from room temperature to 920 ºC at a heating rate of 5 ºC min^{-1}. To obtain a higher char yield, a slow heating rate was used. Pyrolysis process need an inert environment, thus nitrogen was introduced. The weight loss corresponding to temperature was recorded every 2 minutes.

3. Feedforward Neural Network (FANN) Modelling

Artificial Neural Networks (ANN) technology offers an alternative method for the generation of process models. The advantages of using Artificial Neural Networks to represent a system are its ability to perform a nonlinear mapping between inputs and outputs and the necessity of requiring minimal prior knowledge of the system. ANN can learn complex functional relations by generalizing from a limited amount of training data. Hence, they can serve as black-box models of nonlinear, multivariable static and dynamic systems. They can be trained by input–output data observed on the system. The purpose of developing a Feedforward Neural Network (FANN) model was to predict the weight loss in the production of biochar at various temperatures and time periods.

In this study, networks with fixed identical structure were developed and trained by the Levenberg-Marquardt optimisation algorithm. Feed forward neural networks with two hidden layer was used. All simulation works were carried out using Matlab^{TM}R2012. In order to determine the number of hidden nodes in the hidden layer, neural networks with different numbers of hidden neurons were trained on the training data and tested on the testing data. The network with the lowest Sum Square Error (SSE) on the testing data was considered as having the best network topology. In assessing the developed models, Mean Square Error (MSE) and '*r*' value on the unseen validation data was used as the performance criterion. The static models for neural network development are shown below in Eq(1):

$$Y(t) = fn [u1(t) u2(t)] \tag{1}$$

where

Y(t) = Weight Loss
u1(t) = Temperature
u2(t) = Time

4. Results and Discussion

4.1 Weight loss prediction using Feed Forward Neural Network (FANN)

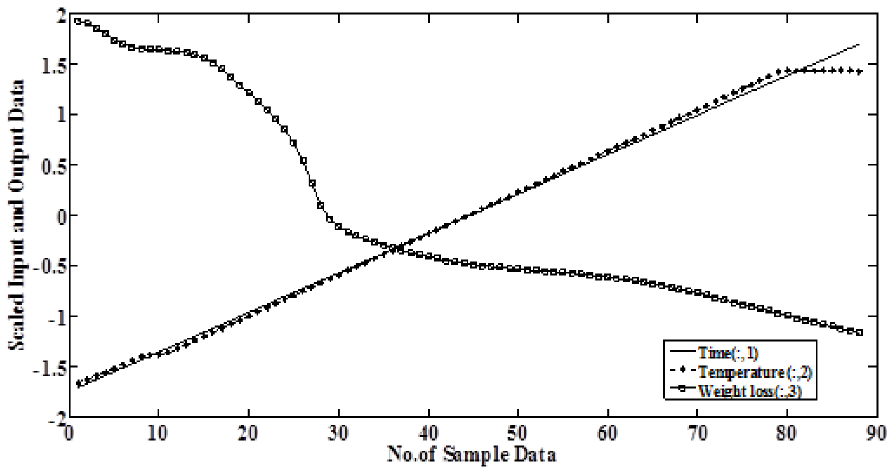

Figure 2: Scaled experimental data for biomass pyrolysis process

Figure 2 is the plot representing the scaled input and the output experimental data for the pyrolysis study. Time and temperatures were the inputs and the weight loss was the desired output. All the experimental data which includes the training, testing and validation data were normalized. This plot was obtained by finding the minimum and maximum of the data, and then for each data point, subtracting the minimum and divide by (max-min). 'zscore' function in MATLAB™ was used to perform the first type of scaling (zero mean, unit variance). From the plot it is clear that for each parameter, namely time and temperature are increasing and the weight loss is decreasing.

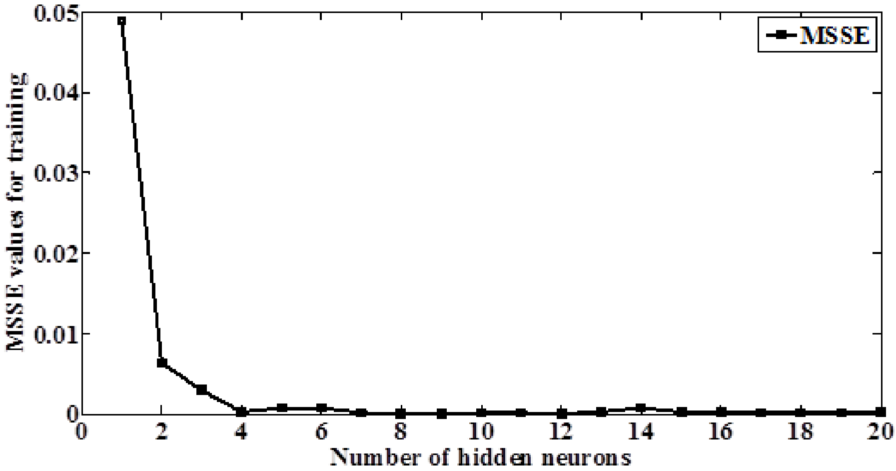

Figure 3: Variation of number of hidden nodes in hidden layers from training and testing data

Figure 3 shows Mean Sum Squared Error (MSSE) for the variation of number of hidden nodes in the hidden layer. MSSE was obtained from sum of the squared error between the predicted result from the FANN model and the actual experimental result. Rule of thumb is that FANN model is normally assessed by the training and testing data. The performance of the whole model was seen in the results reflected by MSSE and correlation coefficient, '*r*' value. Therefore, in this case study, the number of hidden neuron used in the FANN models was 20. Modelling was carried out based on trial and error of the number of hidden layers. It was found that when the number of hidden neuron was 20, where the best performance was obtained in terms of MSE and r values. Lowest average mean square error (MSE) and correlation coefficient, '*r*' close to 1 was chosen as the optimum model. The optimum networks for Multi Input Single Output (MISO) model resulted to 2 input nodes, 20 hidden nodes and 1 output nodes [2-20-1]. The computational cost (or) the computational time can be referred as the time taken for the neuron to complete its training. The increase in computational time is due to the increase in the number of hidden neurons but its helps in achieving the accuracy.

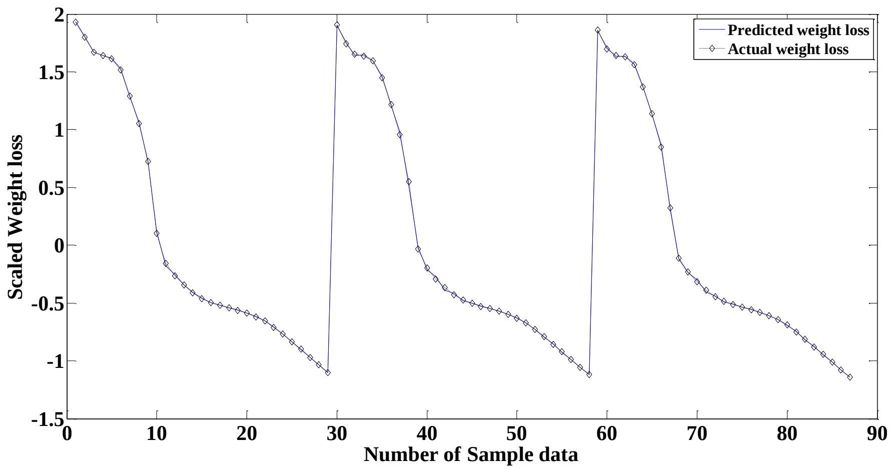

Figure 4: Plot comparing the predicted output with the actual output for pyrolysis study for combined data of training, testing and validation

Figure 4 shows the plot comparing the predicted output with the actual output in pyrolysis study which reveals the scaled weight loss for the biomass sample. The plot shows that the experimental data and the predicted data of combined data of training, testing and validation, match almost close to each other. The plot represents that the actual and predicted data are much synchronized. The plots are seen to be overlapping because of their similarity and it is a sign of an excellent representation of the process. These trends were supported by the '*r*' value on Table 2. SSE, MSE and '*r*' values are the renowned method of assessment for neural network model. The values of the above mentioned parameters can be seen in the Table 2.

Table 2: Correlation Coefficient Value and MSE for pyrolysis study

Data	**FANN (pyrolysis study)**	
	Correlation Coefficient, *r*	**MSE**
Training	0.999	0.0206
Testing	0.999	0.0083
Validation	0.999	0.0241

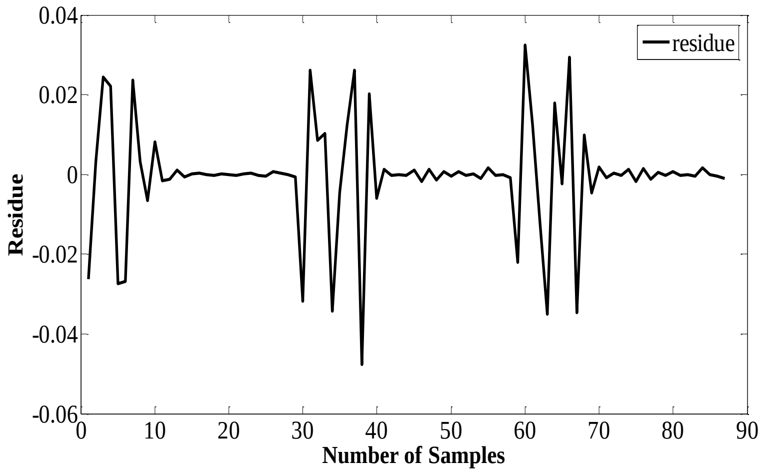

Figure 5: Residue plot for the model for pyrolysis study for combined data of training, testing and validation

Figure 5 indicates the residue plot which is the difference between the actual and predicted data for the biomass pyrolysis study. The model residue is the method to portray the discrepancies between actual and predicted data for validation process. As can be seen in Figure 5, the discrepancies between the actual and predicted data are very small.

5. Conclusions

In this paper the effects of temperature and reaction time on the biochar yield was investigated. Increasing temperature resulted in increasing weight loss of the biomass sample. The total weight loss at the end of 920 ºC was 86.9 %. With increasing temperature, char yield decreased as the weight loss is higher primarily due to the initial large amount of volatiles that can be easily released. As the pyrolysis proceeded, the gas generated reduces the mass of the remaining biochar and also reduced the volatile matter of the biomass. Lower temperature of 300 to 500 ºC was desired for maximum biochar yield. FANN model with experimental input data namely reaction time, reaction temperature and output data weight loss was developed. The results of FANN predicted weight loss versus the experimental output were plotted. The results showed that a 2-20-1 gave best performance.

References

Chum H.L., Overend R.P., 2001, Biomass and renewable fuels, Fuel Processing Technology, 71, 187-195.

Goyal H.B., Seal D., Saxena R.C., 2008, Bio-fuels from thermochemical conversion of renewable resources: A review, Renewable and Sustainable Energy Reviews, 12, 504-517.

IEA (International Energy Agency), 2008, Key World Energy Statistics 2008. <www.iea.org/textbase/nppdf/free/2008/key_stats_2008.pdf> , assessed 19 April, 2010.

Choi J.H., Woo H.C., Suh D.J., 2014, Pyrolysis of Seaweeds for Bio-oil and Bio-char Production, Chemical Engineering Transactions, 37, 121-126

Koroneos C., Dompros A., Roumbas G., 2008, Hydrogen production via biomass gasification--A life cycle assessment approach, Chemical Engineering and Processing: Process Intensification, 47, 1261-1268.

Lee S., Speight J.G., Loyalka S.K., 2007, Handbook of Alternative Fuel Technologies. CRC Press, Taylor & Francis Group, Boca Raton, USA.

MARDI (Malaysian Agricultural Research and Development Institute), 2003, Fruit Crops Statistics Malaysia 2003. Malaysia: Department of Agriculture Peninsular Malaysia.

Maschio G., Koufopanos C., Lucchesi A., 1992, Pyrolysis, a promising route for biomass utilization, Bioresource Technology, 42, 219-231.

Saxena R.C., Seal D., Kumar S., Goyal H.B., 2008, Thermo-chemical routes for hydrogen rich gas from biomass: A review, Renewable and Sustainable Energy Reviews, 12, 1909-1927.

Soetaert W., and Vandamme E., 2005, Biofuel production from agricultural crops. In: Lens P., Westermann P., Haberbauer M., Moreno A., ed. Biofuels for Fuel Cells: Renewable energy from biomass fermentation, IWA Publishing, London, UK, 37-50.

Swaaij V., Stassen W., Prins H., 2002, Thermal conversion of biomass into secondary products-the case of gasification and pyrolysis, 12th European conference on Biomass and Waste. Amsterdam.

Nejat Veziroğlu T., Şahin S., 2008, 21st Century's energy: Hydrogen energy system, Energy Conversion and Management, 49, 1820-1831.

Wang L., Weller C.L., Jones D.D., Hanna M.A., 2008, Contemporary issues in thermal gasification of biomass and its application to electricity and fuel production, Biomass and Bioenergy, 32, 573-581.

Wei L., Xu S., Liu J., Lu C., Liu S., Liu C., 2006, A Novel Process of Biomass Gasification for Hydrogen-Rich Gas with Solid Heat Carrier: Preliminary Experimental Results, Energy & Fuels, 20, 2266-2273.