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On Determination of Bio-Gasoline Octane Number Using Artificial Neural Network

Abdul Wahid, Bambang Heru Susanto, Hexi Trijati Rahayu, and Teguh Adilina

Chemical Process System Lab., Dept. of Chemical Engineering
Faculty of Engineering, University of Indonesia
Email: wahid@che.ui.edu

Abstract – **Artificial Neural Network (ANN) is used for determining octane number of bio-gasoline. The aim is to provide a solution for any alternative energy resources researcher of bio-gasoline in determining the bio-gasoline octane number more easily and accurately. The advantage of this method is it can recognize a relationship between input and output without knowing a mathematical equation of those input and output. ANN learns a relationship pattern of number of input and output data through training process, then predicts the output from a given new input. This research uses 43 data of bio-gasoline physical properties (density and 50% distillation temperature or TT50) as inputs and bio-gasoline octane numbers as outputs. Three ANN models of *multi-layer feed-forward* (MLFF), *generalized regression neural network* (GRNN), and *radial basis* (RB) are used in this research. The result shows RB is the best model with 0.07% average error. After that, the second is GRNN with 0.8% average error, and the last is MLFF with 1.6% average error. Except MLFF model, the other models can predict output very accurately (zero error). RB model has three points of five validation data and GRNN model in two points.**

I. INTRODUCTION

Consumption of gasoline in Indonesia is 39 thousands KL per day or more than 14 millions KL per year (2005) [1]. This is the huge numbers. Even, this will be 60 million KL if totalized with other fuel consumption. This causes Indonesia is a net importer country. Meanwhile, crude oil resources are limited that is shown by decreasing of the domestic oil production [2]. It is imperative to look for an alternative energy from a renewable material.

Indonesia is the second of the biggest producer country of CPO (crude palm oil) after Malaysia, that is 10 million tons/year. Even in 2010, Indonesia is predicted to the first of the biggest producer of CPO, producing 12 million tons/year [3]. Now, Indonesia's CPO is mostly (>90%) exported as a raw material without any advanced treatments. This is very different with Malaysia. The most production of Malaysia's CPO is treated in advance before exported to another country. This causes the increasing of an added value of the CPO.

There are many researches in bio-gasoline recently. They are according to encourage using of the alternative fuel and the design of automotive engine appropriate with bio-gasoline. The problem is how to determine octane number (ON) of bio-gasoline that is the important parameter of bio-gasoline quality. This is caused by the expensive of the ON testing cost and a little of ON testing tools. Using a model relating to physical properties of bio-gasoline and its ON is going to ease all of researchers developing bio-gasoline to determine bio-gasoline ON. In this research, we proposed *artificial neural networks* (ANN) to get an accurate result.

II. BASIC THEORY

There are four methods that is commonly used to determinate the bio-gasoline ON, those are:

1. Predicting it through cetane index (using temperature at 50% distillation or TT50 and then the cetane index is used to calculate bio-gasoline ON) [4].
2. Predicting it through FT-IR (Fourier Transform Infrared) method as proposed by Asfaha et.al. [5].
3. Using the ON-tester (by contacting directly with sensing device to bio-gasoline)
4. Using ASTM D 2699 method (using VCR (variable compression ratio) engine)

ANN can recognize the relationship between input and output without knowing the mathematical equation of the input and the output. This ability makes ANN can help the bio-gasoline researchers to determine bio-gasoline ON that has a complex relationship between its input and output (ON).

Figure 1 shows a simple ANN [6], where have 3 neurons of inputs (X_1, X_2, X_3), 1 neuron of output (Y) and relation weights of both inputs and outputs (W_1, W_2, W_3). Y receives inputs of X_1, X_2 and X_3 with the relation weights are W_1,W_2 and W_3, respectively. Three impulse of neurons are combined:

$$net = x_1 w_1 + x_2 w_2 + x_3 w_3 \qquad (1)$$

Magnitude of impulse received by Y follows activation function:

$$y = f(net) \quad (2)$$

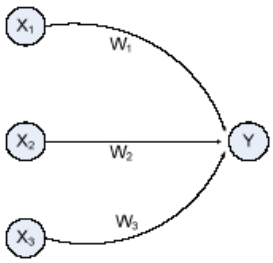

Figure 1. A simple artificial neural network

If value of activation function is strong enough, the signal will be continued. The value of activation function (output of network model) also can be used as basis to change the weights.

III. EXPERIMENT

In this research, the input data are physical properties data of bio-gasoline in the form of density and temperature of 50% distillation that is called TT50, meanwhile the output data are the bio-gasoline ON. Three ANN models are used in this research, they are *multi-layer feed-forward* (MLFF) that is a developing model from initial model of *back-propagation*; *radial basis* (RB) model, and *generalized regression neural network* (GRNN) model.

In the MLFF model, there is a training step to find number of an optimum layer and neuron. The optimum layer and neuron are used to predict the target (bio-gasoline ON). In the RB model, the network formation using two options: without (is called RB-WOGS) and with goal and spread parameters (is called RB-GS), while the GRNN model that is a developing model from RB model, uses the default function. All of models are processed using MATLAB® software.

IV. EXPERIMENTAL RESULTS

This research uses training data as shown by Figure 2, taken from the previous researches [7 – 10]. The data range are 0.73 – 0.8865 kg/m^3 for density, 249.8 - 320°C for TT50, and 72.53 – 92 for ON.

The results of training process to build ANN in MLFF model show that more number of neurons in a layer, the number of iteration is smaller. So, the training process is faster. But, if the number of neuron is too many, it causes unstability in the algorithm and the number of iteration is more. In this research, the optimum numbers of neuron in one hidden layer are 4 neurons. But, the number of hidden layer has a little effect to the number of iteration in the training process. This may be caused by unstability in the algorithm when the hidden layer is added, then increasing in the number of iteration. Thereby, it is able to say that MLFF model with one hidden layer has been an optimum, although sometimes adding a hidden layer can make the training process is better. The structure of MLFF model is shown by Table 1.

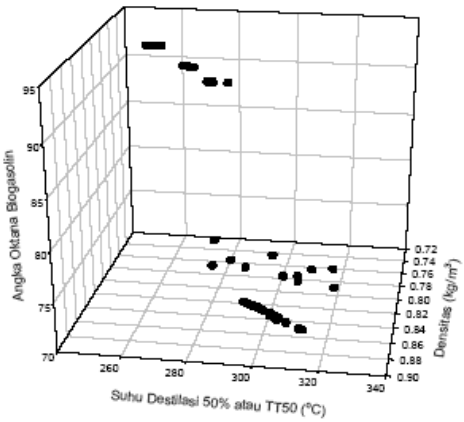

Figure 3. 43 data that is used in ANN training process

Table 1 The result of training process with MLFF model

Input : • Number of layer	1 (2 neurons)
Hidden layer : • Number of layer • Activation function	1 (4 neurons) Purelin
Output : • Number of layer • Activation function	1 (1 neuron) Purelin

A network model that is used in MLFF model is shown by Figure 3. MLFF network has one input layer with two neurons (X1 dan X2), one hidden layer with four neurons and one output layer (Y).

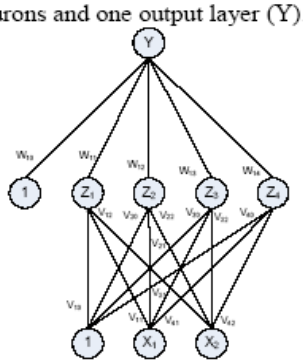

Figure 3 ANN architecture that is used in this research

The first test to validate the results of the three models uses the same data that is used in the training process. The purpose of this step is to ensure what the model can predict the target accurately. Figure 4 shows that RB model can predict the target accurately or the error is zero. This result can be achieved by RB-WOGS model as well as RB-GS model. GRNN model has 0.5% of average error, meanwhile MLFF model has 2.3% of average error.

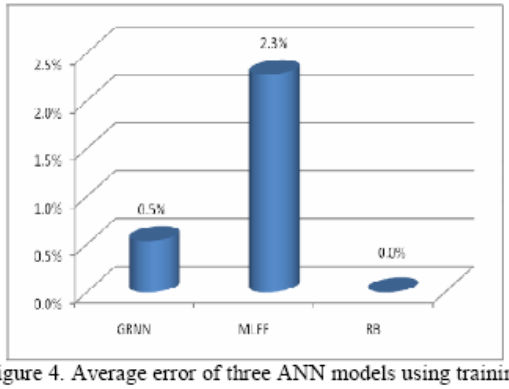

Figure 4. Average error of three ANN models using training data

How if the validation test uses new data, not the training data?

The test uses data that is not used in the training step is called validation step. The purpose of the validation step is to show the ability and stability of ANN performance in predicting the bio-gasoline ON. Table 2 shows the result of ON prediction uses the three ANN models.

Table 2 shows that the best model is RB with 0.07% of average error. GRNN model places the second with 0.8% of average error, and the end is MLFF model with 1.6% of average error. RB model can predict accurately in the three points of five validation data, GRNN model has two accurate point, and MLFF model has no any accurate point.

In addition, the results in the Table 2, for RB model uses RB-GS with goal parameter is 2 and spread value is 0.01 or called G1S.01. Those values are the optimum value as shown by Figure 5, because the average error is the smallest. If we use RB-WOGS the average error is huge (5702%). This is caused by the prediction result of the fifth point of validation data (density: 0.8298 and TT50: 330°C) is far away from the target, that is -20,567.

Table 2 Validation data and ON calculation results using three ANN models

DATA VALIDASI			GRNN		MLFF		RB	
Density	TT 50 (°C)	ON	ON	Error	ON	Error	ON	Error
0.7400	251	92.00	92	0.0%	90.8179	1.3%	92	0.0%
0.7300	269.6	88.00	88.0001	0.0%	87.3169	0.8%	88	0.0%
0.8278	313	74.68	73.661	1.4%	73.7902	1.2%	74.68	0.0%
0.8848	307	73.85	73.593	0.3%	72.7186	1.5%	73.68	0.02%
0.8298	330	72.39	74.065	2.3%	70.0063	3.3%	72.15	0.33%
Average Error				0.8%		1.6%		0.07%

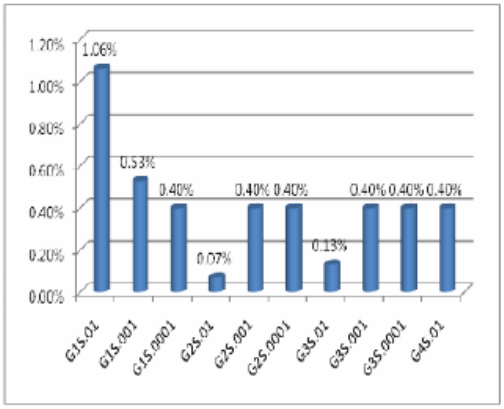

Figure 5. Average error of RB-GS model based on G and S values

V. CONCLUSIONS

ANN can be used to predict bio-gasoline octane number by using its physical properties (density and TT50). The validation results of three ANN models show that the ANN can predict the bio-gasoline ON better with the average error has range 0.07% - 1.6%. The result shows that RB model with G = 2 and S = 0.01 is the best model with 0.07% average error. After that, the second is GRNN with 0.8% average error, and the last is MLFF with 1.6% average error. Except MLFF model, the other models can predict output very accurately (zero error). RB model has three points of five validation data and GRNN model in two points.

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