Adaptive Neuro Fuzzy Inference System (ANFIS) modelling for quality estimation in palm oil refining process

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ABSTRACT

Palm oil refining is a process of removing the unwanted compounds from crude palm oil to produce a refined, bleached and deodorized (RBD) palm oil. It consists of three main processes which are degumming, bleaching and deodorization. In this study, an adaptive neuro-fuzzy inference system was developed to predict the FFA content in the RBD palm oil. The FFA content is non-linearly correlated to the input quality and the operating condition at the refining processes. Feed flow rate, FFA content (input), moisture, IV, phosphoric acid, bleaching earth, bleaching temperature, bleaching vacuum pressure, deodorizer temperature, deodorizer vacuum pressure, heating temperature, sparging steam pressure, and pre-stripper sparging steam were used to build the ANFIS model. Subtractive clustering method was selected for the ANFIS model. The performance of the model was evaluated using RMSE and R^2 value. This study demonstrates that ANFIS are useful for estimating the FFA quality at the palm oil refining process.

Keywords: *Quality Estimation; ANFIS; Palm Oil; Refinery*

Introduction

Quality of the refined, bleached and deodorized (RBD) palm oil is the most crucial parameters in palm oil refining industry. The quality is determined by various factors and one of it is the free fatty acid (FFA) content in the refined oil. The FFA contents indicate the level of deterioration of the refined oil as well as contributes to objectionable odour, flavour and other characteristics. High amount of FFA content causes the refined oil to be circulated in order to achieve the desired quality or even worst being rejected. This will result in product downtime, increase the operating cost as well as reduce the profit's margin.

In real plant operation, the FFA content is checked offline through laboratory testing for every hour which is time consuming and labor intensive. The limitations of this method can be overcome by developing a fast and robust model to estimate the FFA content.

In the past few years, a significant number of works related to the quality of the refined, bleached and deodorized palm oil have been reported. For example, Sulaiman and Mohd-Yusof [1] developed artificial neural network (ANN) to predict the FFA content of the refined palm oil. In a similar work, Sulaiman and Mohd-Yusof [2] compared the performance of the ANN models for prediction of single output and multiple output for refined oil quality. In this study, the quality of the refined oil in terms of FFA content and color were selected as the output for the developed models. On the other hand, Noor et al. [3] developed multivariate statistical control to predict the quality of the palm oil such as the FFA content, moisture and iodine value to improve the refining process performance. Rashid et al. [4] developed principal component regression to forecast the quality of the refined palm oil. Although many researchers have investigated different models for quality prediction, none of these studies used adaptive neural fuzzy inference system (ANFIS) for quality estimation in palm oil refinery.

ANFIS which is a combination of fuzzy modelling and applied artificial neural network for learning algorithm was introduced by Jang [5]. It overcome the limitation of artificial neural network as a "black box" and fuzzy logic for its inefficient in learning by combining the advantageous of both methods [6]. ANFIS has been widely used in chemical processing such as in wastewater treatment plant [7-10], oil refinery as well as palm oil mill[11].

In this study, adaptive neural fuzzy inference systems (ANFIS) was developed to estimate the FFA content for refined, bleached and deodorized palm oil. A subtractive clustering-based fuzzy inference system (FIS) was developed. Good performance of the designed ANFIS ensures its capability as a promising tool for modelling the FFA content.

In the following, the process description of the palm oil refining is presented. Next, details of methodology of constructing the ANFIS model is discussed. The results for ANFIS model are described in the Results and Discussion section. Last, a conclusion of this study is drawn.

Process Description

The palm oil refining plant used in this study is the commercialize plant located in West Peninsular Malaysia. It is important to understand the overall palm oil refining process to determine the input and output variables involves for ANFIS model development.

Figure 1 shows the continuous process of overall palm oil refining plant. This process has three main processes which are degumming, bleaching and deodorization. Initially, crude palm oil is treated with about 0.05% to 0.1% of phosphoric or citric acid at the degumming process. The acid disrupts non-hydratable phosphatides by decomposing the complex compounds before it is removed at the later process. It is important to degummed the crude oil to remove the unwanted compounds which will darken and cause a poor quality product when subjected to high temperature at deodorization process[12].
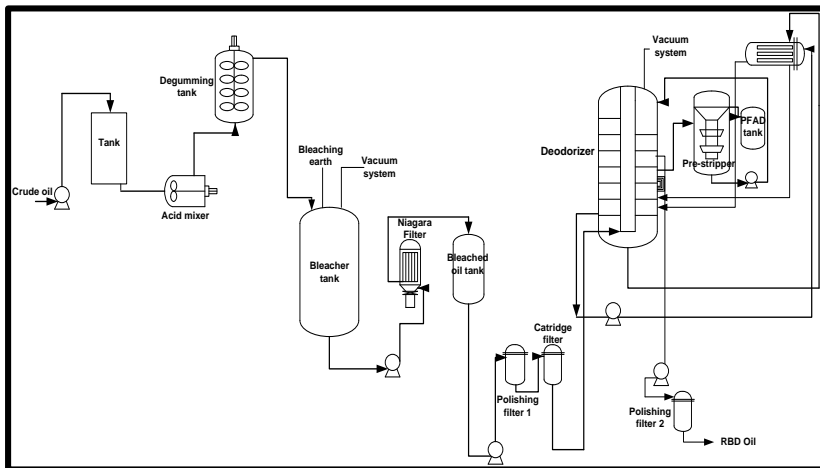

Figure 1: Overall palm oil refining process

Then, the processed oil is bleached using bleaching earth (1% to 2%) at the bleaching process at a temperature of 80 to 120ºC under vacuum condition. The degummed components are adsorbed at the surface of

bleaching earth and were filtered to separate the unwanted impurities from the processed oil.

Finally, the processed oil is deodorized to strip off the volatile components, removed the odoriferous components as well as thermal destruction of pigments while maintaining low side reactions [13]. In order to heat the processed oil to 250 to 260°C, the processed oil will be heated at the pre-stripper first. The volatile compound will be separated from the processed oil and collected at the palm fatty acid distillate (PFAD). Temperature, vacuum and sparging steam are three important variables that need to be maintained during this process. The processed oil is then sent to the top of deodorization column to further process. The refined, bleached and deodorized palm oil is collected after finishing all the processes.

Model Development

Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS is of the hybrid neuro-fuzzy system for function approximation created by Jang [5, 14]. It consists of special five layer of feedforward network architecture as shown in Figure 1. ANFIS has similar learning algorithm with neural network which are a combination of backpropagation and least square estimation [5]. It has five layers which are input layer, rule layer, normalization layer, defuzzification and output layer. For simplicity, ANFIS structure consists of two inputs, x_1 and x_2 and one output, z.

The ANFIS system contain two fuzzy if-then rules of Takagi-Sugeno's type:

Rule 1: If (x_1 is A_1) and (x_2 is B_1) then ($f_1 = p_1x_1 + q_1x_2 + r_1$)
Rule 2: If (x_1 is A_2) and (x_2 is B_2) then ($f_2 = p_2x_1 + q_2x_2 + r_2$)

where x_i is the inputs, A_i and B_i are the fuzzy sets and f_i are the outputs within the fuzzy region specified by the fuzzy rule, p_i, q_i and r_i are the design parameters that are determined during the training process.

Layer 1 Every node in this layer has a function to convert the input signal to fuzzy signal with a node function of:

$$O_i^1 = \mu_{A_i}(x_1), i = 1,2 \tag{1}$$
$$O_i^1 = \mu_{B_i}(x_2), i = 1,2 \tag{2}$$

where x_1 and x_2 are the input to layer 1, A_i and B_i are the linguistic labels, and μ_{A_i} and μ_{B_i} are the fuzzy membership function curve. In this case, the curve is performed based on Gaussian function using the following equations:

$$\mu_{A_i}(x_1) = exp\left[-0.5\left(\frac{x_1 - c_i}{b_i}\right)^2\right] \tag{3}$$

where c_i and b_i are the parameters for Gaussian membership function for the input variables.

Layer 2 is an output signal from layer 1 becomes and input signal to layer 2 which is the IF-THEN rule. The fuzzy signal is obtained using the following equation:

$$O_i^2 = w_i = \mu_{A_i}\mu_{B_i} \tag{4}$$

where w_i is the firing strength of the IF-THEN rule.

Layer 3 is a normalization stage. An output signal from layer 2 becomes an input signal to layer 3. In this stage, the signal is obtained by calculating the ratio of the input signal, w_i of the firing strength to the sum of all the firing strength by the following equation:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} \tag{5}$$

Layer 4 is the defuzzification process of the output signal from layer 3. In this layer, the output is gained from a linear equation that is formed from the membership function of the output signal in the following equation:

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i \left[p_i x_1 + q_i x_2 + r_i\right] \tag{6}$$

where p_i, q_i, and r_i are the membership parameters for the linear signal.

Layer 5 is the final layer labelled as Σ, which computes the overall output from layer 4 as shown below:

$$O_i^5 = y = \sum \overline{w}_i f_i \tag{7}$$
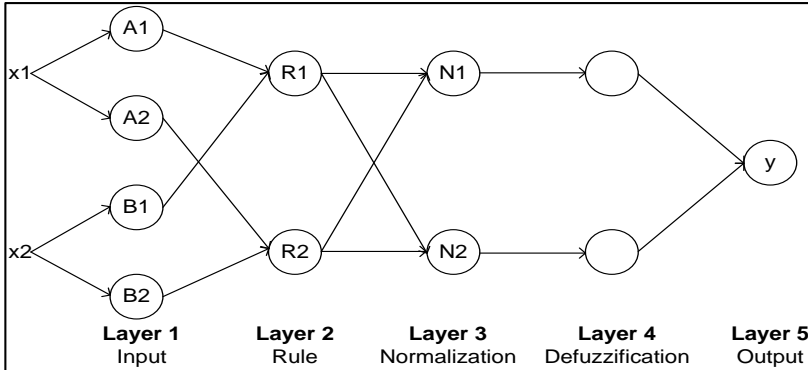
where y is the predicted value.

Figure 2: ANFIS architecture

Input and Output Data Selection

In order to develop the ANFIS model for FFA content's prediction, the data collected is distributed into two categories which are input and output. Selected inputs are the variables that might influenced the removal of FFA content in the RBDPO. Table 1 shows the selected input and output for this study.

Table 1: Input and output variables for ANFIS model

Symbols	Input and output variables
X1	FFA content of CPO (%)
X2	DOBI
X3	Moisture
X4	IV
X5	CPO flow rate (ton/hr)
X6	Degumming temperature ($^{\circ}$C)
X7	Phosphoric acid dosage (wt%)
X8	Bleaching earth dosage (wt%)
X9	Bleaching temperature ($^{\circ}$C)
X10	Bleacher vacuum pressure (mbarA)
X11	Heating tray temperature ($^{\circ}$C)
X12	Pre-stripper sparging steam pressure (bar)
X13	Deodorizer temperature ($^{\circ}$C)
X14	Deodorizer sparging steam pressure (bar)
Y	FFA content of RBDPO (%)

Data pre-processing

Prior to ANFIS model development, the input and output data were normalized due to large data variations in the data sets. The normalization also can be used to correct the different units in measuring each variable. The inputs and outputs data sets in this study were normalized based on the formula:

$$x_i = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{8}$$

where x_i is the normalized input x at $i= 1,2,….,$n. x is the x unnormalized value, x_{min} is the minimum value of x in the data sets and x_{max} is the maximum value of x in the data sets. All the input and output variables were normalized to have a value between 0 to 1.

The normalized data is then prepared for training and testing using cross validation method. In cross validation method, the k-1 fold is used for training the model while the remaining for testing. In each iteration, the data is segmented into k-1 fold for training and kth fold testing based on k-fold. Next, the partitioned data undergoes training and testing phase in the ANFIS model. The iteration stopped when all the kth fold has been tested. Figure 3 summarized the steps for ANFIS model for prediction of FFA content.
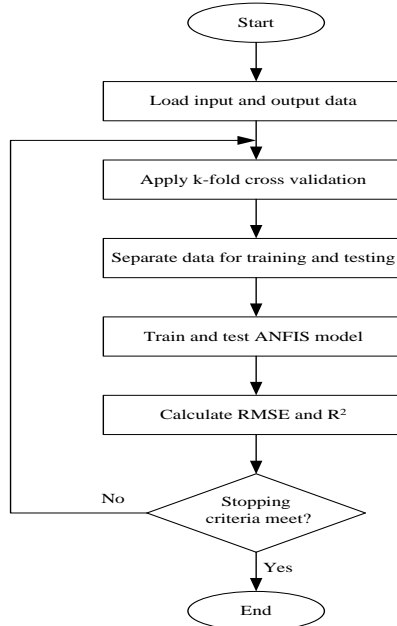

Figure 3: Flowchart for FFA content prediction using ANFIS model

Model Implementation

In this study, the quality of the crude palm oil and the operating conditions at the degumming, bleaching and deodorization processes in palm oil refining were taken as the input variables for ANFIS model development. Meanwhile the FFA content of the RBDPO was used as the output for the model. A total of 1684 data samples were used for the ANFIS model.

The prediction capability of the ANFIS model was assessed and verified using the root mean square error (RMSE) and correlation coefficient (R-squared). The equation for the RMSE and R^2 values is shown as below:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - A_i)^2}{n}} \qquad (9)$$

where P_i is the predicted value from the model for $i= 1,2,3,\ldots,n$ and A_i is the actual value and n is the number of data points used in the study.

Results and Discussion

The ANFIS model is built to create the fuzzy inference system for estimating the final quality of FFA content in the RBDPO. The architecture of ANFIS based subtractive clustering for modelling the FFA quality used in this study is illustrated in Figure 4.
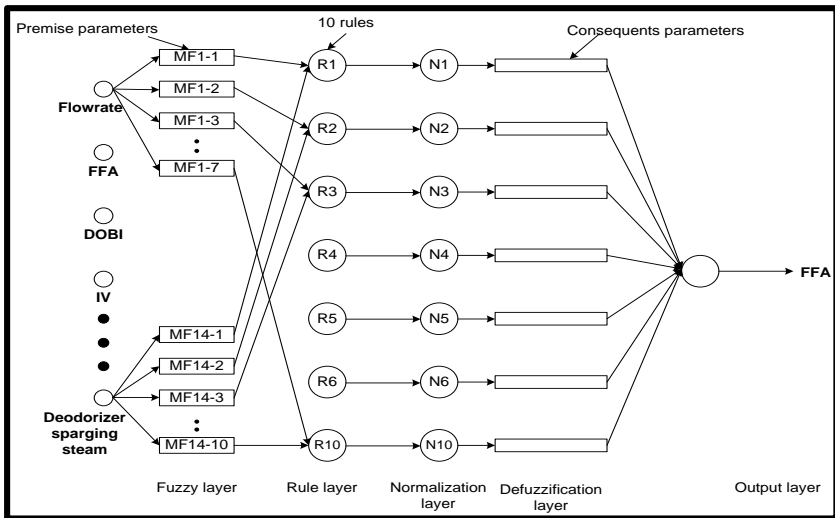

Figure 4: ANFIS architecture for subtractive clustering with 14 input variables and ten rules for modelling FFA quality.

In this study, ANFIS model based on subtractive clustering were developed using MATLAB R2018a environment. The model consists of fourteen input and one output variables. The input variables are quality of crude palm oil and operating condition at the palm oil refinery process and the free fatty acid content for refined palm oil is taken as the output variable. The input membership function is generated based on the subtractive clustering methods where Gaussian membership function was assigned.

The fuzzy system for ANFIS subtractive clustering method, the cluster formed are associated to the fuzzy rules. The numbers of clusters formed has been determined experimentally and the rules and consequent parameters formed has been investigated by developing various ANFIS models. Table 2 shows the number of parameters formed for the ANFIS model. It can be seen that, the number of parameters increases as the cluster radius decreases.

Table 2: Numbers of parameters for ANFIS model with different cluster radius

Parameters	Radius			
	0.5	0.6	0.7	0.8
NLP	615	300	150	105
NNLP	1148	560	280	196
TNP	1763	860	430	301

NLP number of linear parameters; NNLP number of nonlinear parameters; TNP total number of parameters

Meanwhile Table 3 discusses on the performances of the ANFIS model based on subtractive clustering method for predicting the FFA content in the refined palm oil. The performance of the model is evaluated using RMSE, MSE and R^2 for the training and testing phase. The appropriate cluster for the model resulted to be ten. Although R^2 for radius 0.6 is slightly higher than radius of 0.7 due to lowest RMSE and MSE for the testing phase.

Table 3: Performances of ANFIS model based on subtractive clustering for different cluster influence range

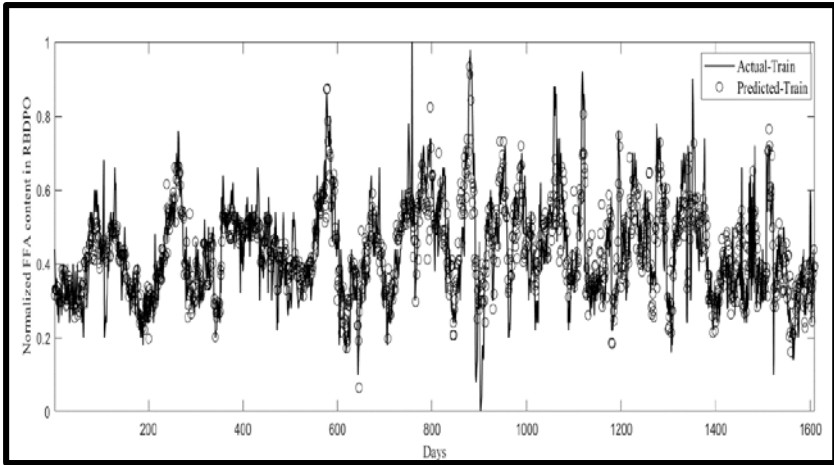| Radius	Rule	MF	Training			Testing		
			RMSE	MSE	R^2	RMSE	MSE	R^2
0.5	41	41	0.05200	0.0027	0.93420	0.15712	0.02469	0.52107
0.6	20	20	0.07050	0.0049	0.87359	0.12057	0.01454	0.62059
0.7	**10**	**10**	**0.09150**	**0.0084**	**0.77863**	**0.11903**	**0.01420**	**0.60438**
0.8	7	7	0.10012	0.0100	0.72725	0.12706	0.01614	0.54492

Figure 5: Comparisons of predicted and actual for ANFIS modelling in training phase
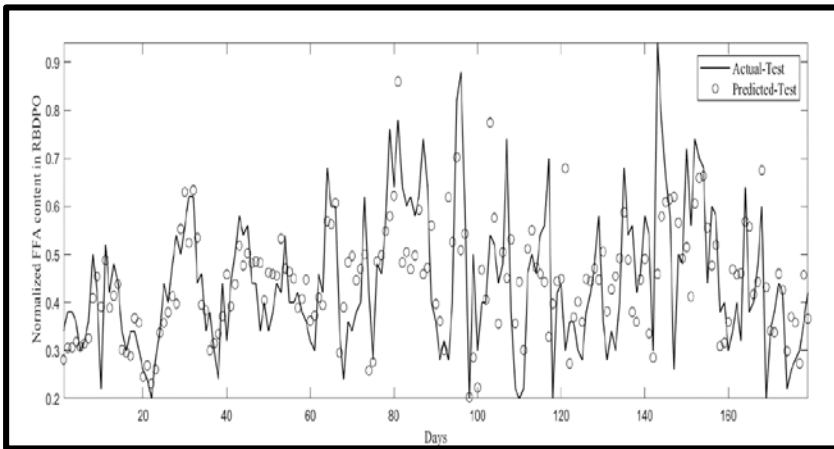

Figure 6: Comparisons of predicted and actual for ANFIS modelling in testing phase

On the other hand, Figure 5 and 6 shows the scatterplots of actual versus predicted of FFA content in the RBDPO. The figure demonstrates that the model performances are accurate in the training phase where all the predicted data fall on the actual data. Meanwhile, a satisfactory model performances for testing phase.

Conclusion

In this study, ANFIS based subtractive clustering method was developed to predict the FFA content of refined palm oil. The model was trained using backpropagation and gradient descent method and the result shows that cluster influence range of 0.7 and epoch number of 100 provide the best performance of the model. Overall, the result shows that the ANFIS model was able to make a good prediction for FFA content of the refined palm oil. Therefore, it has great potential to making predictions for other qualities of the refined, bleached and deodorized palm oil.

Acknowledgment

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