ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 6, Issue 1, July 2016

Prediction Model Based on Artificial Neural Network for Industrial Bleaching and Degumming Process of Crude Palm Oil

Nu'man Abdul Hadi, Che Rahmat Che Mat
Engineering & Processing Research Division, Malaysian Palm Oil Board, 6, Persiaran Institusi, Bandar Baru Bangi, 43000 Kajang, Selangor, Malaysia

Abstract*— Degumming and bleaching are critical processes in the physical refining of crude palm oil. Both processes amass a high operating cost. The objective of this study is to develop an artificial neural network model for the prediction of phosphoric acid and bleaching earth consumption in palm oil refinery. A total of 38 sets of process parameters on bleaching and degumming processes from local palm oil refinery were collected and used to develop a prediction model based on a neural network architecture and feed-forward / back-propagation algorithms. The model performance was evaluated based on its root mean square error and its corresponding correlation coefficient (R^2). The model was developed and programmed in a MATLAB environment and further translated into a user interface program (UIP) in a convenient spreadsheet application. Multiple-input / single-output and multiple-input / multiple-output models with a multilayer perceptron were successfully developed and two best models were obtained having R^2 of 0.9370 and 0.9090, respectively. These models consist of 15 and 16 numbers of hidden nodes (respectively) with logsig functions responsible for the processing of data targeting the lowest RMSE. Consequently, a UIP was developed and has conveniently allowed users to key-in new data to obtain prediction values.

***Index Terms*— degumming, bleaching, refinery, artificial neural network, user interface program.**

I. INTRODUCTION

Palm oil is currently the world's most consumed vegetable oil followed by soybean, corn and rapeseed oil [1]. Crude palm oil (CPO) production has been growing vastly over the past 50 years [2]. Malaysia, the second-largest producer of CPO after Indonesia, produced 19.96 million t of CPO in 2015, a vast growth compared to 92,000 t of CPO produced in 1960 [2]–[3]. Palm oil refineries are part of the major contributors to the significant growth of the Malaysian oil palm industry, the other being palm oil mills. Generally, palm fruit undergone a series of extractions to produce two main raw products; i.e. CPO (extracted from the fibre of palm fruit) and palm kernel oil (extracted from the fruit seed). The CPO will be sent to palm oil refinery for further treatment to produce refined oil, namely olein and stearin.

David [4] describes palm oil refining as purification needed to reduce as far as possible the contaminants of the crude oil that will adversely affect the quality of the end product and the operation efficiency of the modification processes by fractionation, hydrogenation and esterification. Generally, two methods were used; physical and chemical treatment. The fatty acids are distilled off in the physical process, while in the chemical process they are neutralized using an alkaline reagent, thus forming soaps that are removed from the oil by phase separation [4]. In a refining process, there are many physical and chemical stages in which each stage have their own role in oil refining. The removal of contaminants is not restricted at one stage; instead, they undergo various steps or stages ensuring the contaminants to be removed effectively.

In palm oil refinery, degumming and bleaching process are the first two critical steps in the physical refining of the CPO. Both processes constitute a sizable operating cost due to the utilization of acid phosphoric acid and bleaching earth. It is estimated that about 20 % of the total operating cost are due to the bleaching and degumming process. Besides, total removal of proteinaceous matters in palm oil refining is not always preferred, instead, the quality of palm ought to be controlled corresponding to the demand of consumers [5]. In other words, the purpose of refining is to improve shelf-life and nutritive status of the resultant oils [6]. Currently, the standard method to determine the suitable dosage of reagents that should be used in a palm oil refinery is non-existent, though refiners normally estimated the dosage depending on the quality of crude palm oil feedstock. Hence, the purpose of this study is to develop a neural network model of degumming and bleaching process intelligent enough to predict the suitable dosage of reagents based on the desired quality of palm oil.

Over the past decades, neural networks have received a great deal of attention among scientists and engineers, and they are being touted as one of the greatest computational tools ever developed. A neural network is a computing system made up of a number of simple, highly interconnected nodes or processing elements, which processes information by its dynamic state response to external inputs [7]. Neural network are usually associated with network architecture such as input layers, hidden layers, output layers, number of nodes, weights, biases, transfer function and learning algorithm. In terms of learning algorithm, feed-forward network algorithm was the simplest type of artificial neural network where information moves in only a linear direction. To improve the model's learning capability, back-propagation is the most common supervised learning types of algorithm. Feed-forward / back-propagation (FFBP) network algorithm can be set by feeding a known input-output pattern. Then the parameter for

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 6, Issue 1, July 2016

neural network is adjusted until each node produces an appropriate output. The FFBP usually consist of an input layer, one or more hidden layer, and one output layer. In a FFBP, the input quantities are transferred from the input layer to the nodes of a hidden layer after being multiplied by the weight factor. The weight is the connection between the nodes and it determines the strength of input signal. In the hidden layer, the nodes sums up the weighted input received from the nodes of previous layers associated with a bias before passing them to the next hidden layer or output layer through a non-liner transfer function. Artificial neural network has been demonstrated to be a valuable tool in many chemical and physical processes [8–12]. In fuel processing technology, neural network model has been used to predict polycyclic aromatic hydrocarbon formation in premixed n-heptane flames [8]. Neural network prediction model was also developed in the past to estimate the zeolite molar compositions that is formed from different reaction mixtures [9]. The closest work related to palm oil refining, as reported in [12], uses experimental bleaching and degumming data to develop a process model based on artificial neural network.

II. METHODOLOGY

A. Data Collection

A total of 38 sets of data were collected from FELDA Oil Products Sdn Bhd (FOP), Johor, Malaysia. The data consists of quality of CPO and pre-treated oil (PTO), and dosage of phosphoric acid (PA) and bleaching earth (BE). The quality of CPO and PTO, which measurement was done by workers at the FOP laboratory, are fatty acid content in CPO (FFACPO), free fatty acid content in PTO (FFAPTO) iodine value of CPO (IVCPO), peroxide value of CPO (PVCPO), moisture content in CPO (MCPO), deterioration of bleachability index (DOBI) of CPO (DOBICPO), discriminant function of CPO (DFCPO), free fatty acid content in PTO (FFAPTO) and red Lovibond color of PTO (RPTO). For the measurement of phosphoric acid and bleaching earth dosages, common practice of FOP is to monitor the level of phosphoric acid in its storage tank and the number of counts bleaching earth is blown. From that, the phosphoric acid and bleaching earth dosage (% wt.) were calculated as follows:

$$Y1 = \left[\left(\Delta Y1 \times \dot{m}\right)/\left(C \times SG\right)\right] \times 100\% \quad (1)$$

Where *Y1* is phosphoric acid dosage (% wt.), *ΔY1* is difference in acid level (cm), $\dot{m}$ is the amount of phosphoric acid (9.8 kg/cm), *C* is oil capacities (L) and *SG* is specific gravity of oil (kg/L).

$$Y2 = \left[\left(\Delta Y2 \times \dot{n}\right)/\left(C \times SG\right)\right] \times 100\% \quad (2)$$

Where *Y2* is bleaching earth dosage (% wt.), *ΔY2* is number of Counters (counts), $\dot{n}$ is the amount of bleaching earth (1.037 kg/counts), *C* is oil capacities (L) and *SG* is specific gravity of oil (kg/L).

Table 1 Input and output variables for model development

No.	Variables	Symbol
	Input	
1	FFA_{CPO}	X1
2	IV_{CPO}	X2
3	PV_{CPO}	X3
	M_{CPO}	X4
5	$DOBI_{CPO}$	X5
6	DF_{CPO}	X6
7	FFA_{PTO}	X7
8	RL_{PTO}	X8
	Output	
9	Phosphorus acid	Y1
10	Bleaching earth	Y2

B. Model Development

In the model development, variables are categorized into inputs and outputs. In this study, phosphoric acid and bleaching acid dosage are designated as model outputs, the rest of the variables as model inputs. Designation of input and output variables of the model are summarized in Table 1.

Four neural network models based on FFBP algorithms were developed in the MATLAB environment. Number of nodes in input/output layer depends on the input/output variables, and numbers of nodes in the hidden layer varied in the range of 8 to 24. Layers were connected through nodes using selected transfer functions, therefore obtaining multiple-input / single-output (MISO) and multiple-input / multiple-output (MIMO) models. The network architecture and interconnection of nodes between layers are as shown in Figs. 1 (a) and 1 (b).

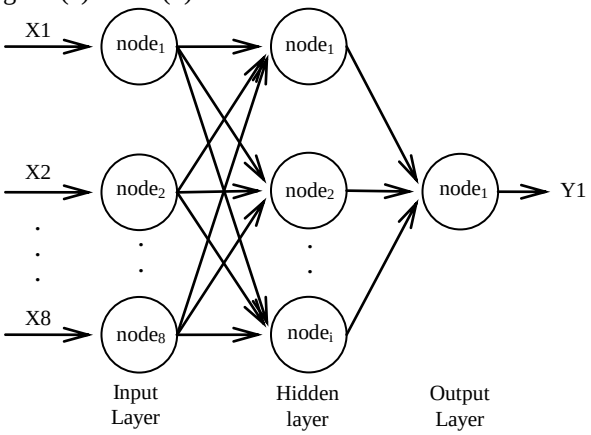


Fig. 1 (a) Multiple-input / single-output (MISO) model with interconnected nodes between layers

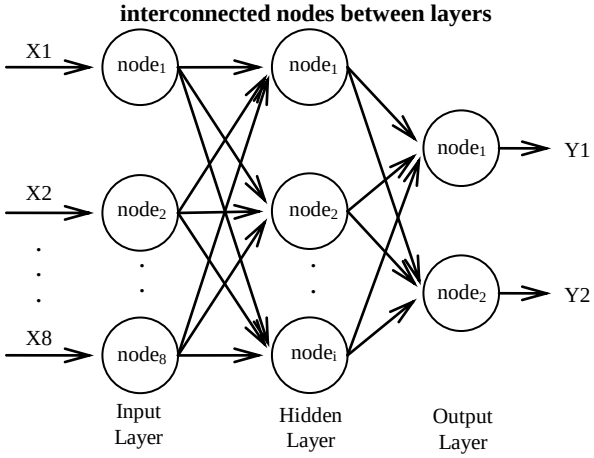


Fig. 1 (b) Multiple-input / multiple-output (MIMO) model with interconnected nodes between layers

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 6, Issue 1, July 2016

Nodes, which function as manipulators of the input to give the output, are regarded as the fundamental of a neural network. The output of a single node is affected by the weight factors, internal thresholds or biases, and the transfer function [13]. In mathematical terms, a node is described by the following equation [14]:

$$y = \sum_{i=1}^{n} \left(w_{ij} a_{ij} \right) + b_j \quad (3)$$

where w_{ij} is weight of i node in j layer, a_{ij} is input of i node in j layer, and b_j is bias of node in j layer.

Initially, weights and biases were introduced randomly to the network. Once the node was calculated, it passed the result to the transfer function, *f(y)*. The transfer functions used in this study were sigmoidal (*logsig*) function for the hidden layer nodes and linear (*purelin*) function for the output layer nodes. The node calculation for the sigmoidal function was:

$$f(y) = 1/\left(1 + e^{-y}\right) \quad (4)$$

and for the linear function was:

$$f(y) = y \quad (5)$$

The above transfer functions require input to be normalized in the range of 0 to 1 where the following normalization equation was used:

$$X_n^{'} = \left(X_n - X_{n,\min}\right)/\left(X_{n,\max} - X_{n,\min}\right) \quad (6)$$

where $X_n^{'}$ is normalized variable value, X_n is actual variable value $X_{n,min}$ is minimum variable value in the dataset, and $X_{n,max}$ is maximum variable value in the dataset.

The network model is then trained with a training dataset and tested with a testing dataset. During training, the model processed input variables and produced a set of model output at which it was compared with the targeted value (actual variable value). Its weights and biases were recalculated until the error (RMSE) between model output and targeted value reduced to below than $1x10^{-8}$. The trained network was then tested using another set of testing data. During testing, input training data was introduced to the network, then it was processed, the output data was produced and was compared with targeted output value from the testing data set.

The deviation between the model output (predicted) and the targeted output (actual) was measured by calculating the root mean square error (RMSE) and correlation coefficient (R2) as shown in equations (7) and (8).

$$RMSE = \sqrt{\left[\sum_{i=1}^{n} \left(actual - predicted\right)^2\right] / n} \quad (7)$$

$$R^2 = \sum_{i=1}^{n} \left(Z_{actual} Z_{predicted}\right)/\left(n-1\right) \quad (8)$$

The best network is selected based on the highest correlation and the smallest error generated. The overall steps of neural network development can be depicted in a flowchart as showed in Fig. 2.

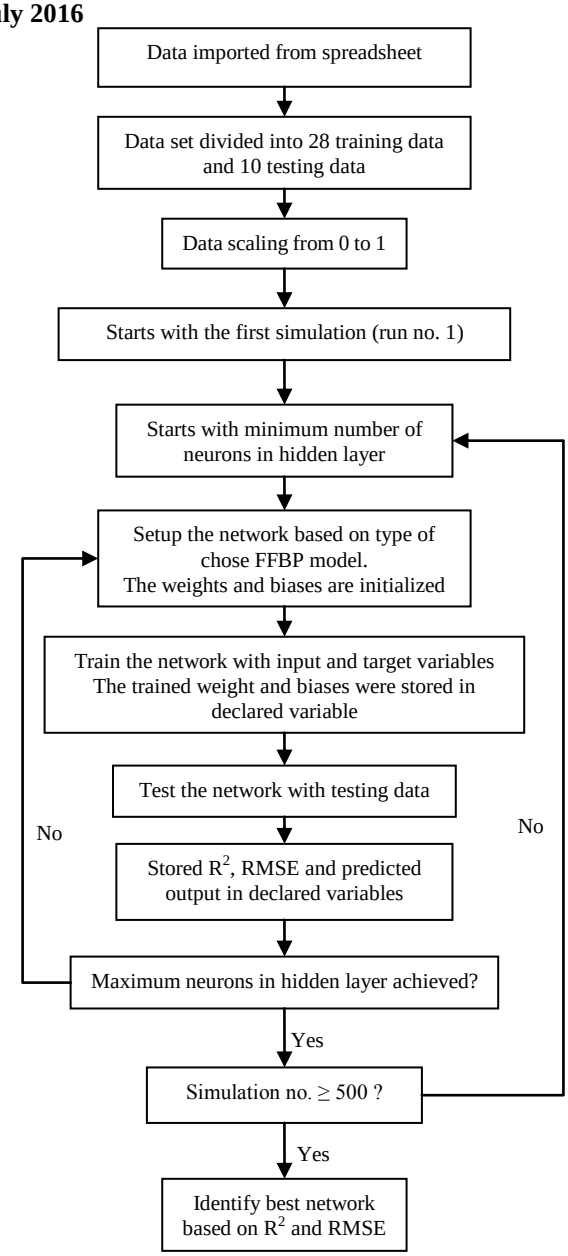


Fig. 2 Steps for the development of a neural network model

III. RESULTS AND DISCUSSION

A. Development of the Artificial Neural Network Model

Table 2 shows process parameters from actual bleaching and degumming process in the refining of CPO producing pre-treated oil (PTO). Due to a high cost of phosphoric acid and bleaching earth, the FOP usually uses not more than 0.06 % wt. of phosphoric acid and 2 % wt. of bleaching earth. However, depending on the quality of CPO received, refinery may need to increase the dosage of phosphoric acid and bleaching earth, therefore, accumulates a higher operating cost. Since currently there are no standard methods or guidelines to determine the dosage of phosphoric acid and bleaching earth needed to be used each time a new batch of CPO consignment is received at the refinery, development of a prediction model based on previous actual process parameters could be a helpful tool for refiners.

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 6, Issue 1, July 2016

Table 2 Actual process parameters on bleaching and degumming processes collected from the FOP

No.	PA (%)	BE (%)	FFA_{CPO} (%)	IV_{CPO}	PV_{CPO}	VM_{CPO} (%)	$DOBI_{CPO}$	DF_{CPO}	FFA_{PTO} (%)	R_{PTO}
	Y1	Y2	X1	X2	X3	X4	X5	X6	X7	X8
1	0.012	1.24	4.32	52.49	4.20	0.18	2.52	13.39	4.08	20.0
2	0.036	0.92	4.28	51.77	4.55	0.17	2.52	13.47	4.22	20.0
3	0.036	1.33	4.33	52.23	2.76	0.17	2.51	13.31	4.36	20.0
4	0.038	0.96	4.26	52.06	3.27	0.17	2.54	13.79	4.27	20.0
5	0.039	0.85	4.34	52.37	2.84	0.17	2.50	13.15	4.34	20.0
6	0.040	0.49	4.26	52.27	3.61	0.18	2.53	13.63	4.21	20.0
7	0.041	1.07	4.18	52.37	3.82	0.17	2.56	14.11	4.15	20.0
8	0.042	1.05	4.16	52.12	3.29	0.17	2.53	13.63	4.18	20.0
9	0.043	1.37	4.49	52.29	4.85	0.17	2.50	13.15	3.76	19.0
10	0.043	0.91	4.25	52.13	3.42	0.18	2.55	13.95	4.26	20.0
11	0.044	0.81	4.10	52.76	3.78	0.17	2.56	14.11	4.07	20.0
12	0.045	1.04	4.30	52.24	3.42	0.18	2.53	13.63	4.26	20.0
13	0.046	0.26	4.19	52.50	3.65	0.18	2.53	13.63	4.28	20.0
14	0.048	0.98	4.47	52.07	3.78	0.19	2.50	13.15	3.10	19.5
15	0.050	0.76	4.30	52.71	3.94	0.17	2.52	13.47	4.20	20.0
16	0.052	1.01	4.21	52.67	3.81	0.17	2.51	13.31	4.10	20.0
17	0.053	1.05	4.18	52.57	3.68	0.19	2.55	13.95	4.16	20.0
18	0.054	1.37	4.10	52.24	3.85	0.17	2.53	13.63	4.06	20.0
19	0.055	1.31	4.05	52.40	3.74	0.17	2.52	13.47	3.90	20.0
20	0.056	1.48	4.24	52.58	3.88	0.17	2.51	13.31	3.80	20.0
21	0.057	1.31	3.98	52.30	3.85	0.18	2.57	14.27	4.12	20.0
22	0.058	0.92	4.06	52.70	3.93	0.18	2.57	14.27	4.02	20.0
23	0.058	1.22	4.04	52.37	3.73	0.18	2.56	14.11	3.95	20.0
24	0.059	1.06	4.45	51.90	3.75	0.19	2.51	13.31	4.40	20.0
25	0.059	1.70	4.28	52.31	3.47	0.18	2.55	13.95	4.31	20.0
26	0.059	0.88	4.05	52.55	3.80	0.18	2.55	13.95	4.00	20.0
27	0.060	1.02	4.20	52.38	3.70	0.18	2.52	13.47	3.70	20.0
28	0.074	2.58	4.27	52.78	4.44	0.18	2.53	13.63	3.86	20.0
29	0.029	0.32	4.27	52.23	3.57	0.18	2.51	13.31	4.23	20.0
30	0.040	0.82	4.20	52.40	3.71	0.17	2.55	13.95	4.17	20.0
31	0.044	0.88	4.29	52.17	3.09	0.17	2.53	13.63	4.25	20.0
32	0.046	1.44	4.06	52.19	4.57	0.17	2.54	13.79	3.59	20.0
33	0.048	0.78	4.25	52.43	3.78	0.19	2.51	13.31	4.19	20.0
34	0.050	1.04	4.26	52.31	3.69	0.17	2.52	13.47	4.26	20.0
35	0.050	1.44	4.15	52.15	3.77	0.17	2.52	13.47	4.05	20.0
36	0.054	1.67	4.48	52.27	3.95	0.19	2.51	13.31	4.24	20.0
37	0.055	0.78	4.41	52.41	3.54	0.18	2.52	13.47	4.33	20.0
38	0.069	1.40	4.02	52.44	3.80	0.17	2.53	13.63	4.25	20.0

Table 3 Training data set and testing data set

Type of data	Data set no.
Training dataset	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28
Testing dataset	29, 30, 31, 32, 33, 34, 35, 36, 37, 38

Dataset from Table 2 was divided into a training dataset and testing dataset as shown in Table 3. The purpose of training is for the neural network to learn to recognize patterns in a given dataset. Neural networks are conceptually modelled from the human brain metaphor i.e. in decision making based on past experience trained from past actual data. Training of the model in this study serves as development of 'experiences' in order for the model to make a decision in the future; in other words, to predict the output that suits the new input. Therefore, in order for the network to make reliable

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 6, Issue 1, July 2016

predictions, a training dataset containing the upper and lower limit for each variable was selected. It is expected that the trained model would not give prediction beyond the actual data that is irrelevant.

Once the training is completed, the model can make predictions by identifying similar patterns in a new dataset. The model predicts the output by processing the testing dataset in nodes at each layer using the weights and biases obtained from the training activity.

Two MISO models; MISO Y1 and MISO Y2, and two MIMO models; MIMO Y1 and MIMO Y2 were developed in this study. The network specifications of each model are summarized in Table 4. Maximum number of nodes in the hidden layer was fixated at three times the number of input variables, i.e. 24 numbers of nodes.

Results were obtained after carrying out 500 numbers of simulations for each model developed. During the training activity, the simulation fits the input value with the targeted value and generates weights and biases accordingly. Training was considered sufficient after model error (RMSE) or deviation between the simulated value and the actual value in the training data set were reduced to less than $1x10^{-8}$. However, from Table 5, it was found that low RMSE generated during training does not necessarily produce low RMSE during testing. This is due to the weights and biases generated from training that are being utilized in testing, therefore higher error is possible. While the RMSE indicated training error, correlation coefficient (R2) generated from testing of model indicated actual performance of the model. Both the training RMSE and its corresponding R2 of the testing activity are as shown in Table 5.

From Table 5, for the prediction of phosphoric acid dosage, it shows that MISOY2 model outperformed MIMOY2 model with the R2 of 0.9090 and 0.8690, respectively. On the other hand, the MIMOY1 model outperformed MISOY1 model for the prediction of bleaching earth dosage with the R2 of 0.9370 and 0.8770, respectively.

MISOY1 model utilized all inputs and an output, i.e., phosphorus acid dosage (Y1) in the training and consequently the model was used to predict the phosphoric acid dosage. While MISOY1 predicts phosphoric acid dosage, MISOY2 predicts bleaching earth dosage. Whereas, MIMO model used the inputs and both outputs, i.e., phosphoric acid and bleaching earth dosages for training and the models were used to predict both the phosphoric acid and bleaching earth dosages. However, of all the 500 simulations run, there is almost no set of weights and biases that can satisfy the predicted outputs (Y1 and Y2) simultaneously, i.e. to obtain correlation coefficients of Y1 and Y2 above 0.85 at the same time. Instead, when one correlation coefficient was satisfied, the other was not. Therefore, the MIMO model was reported as predicting a single output (either Y1 or Y2), despite the training that utilized both outputs.

Figs. 3 to 6 show individual model performance in terms of its R2 for phosphoric acid and bleaching earth dosages. Dotted lines were drawn showing actual process parameters to compare with the predicted values represented by the correlated straight line. The shaded area represents the area at which the model predicted lower dosage than the actual process parameters. It indicates that some of the phosphoric acid and bleaching earth actually needed lower dosages than the actual practice, therefore reducing the operation cost. The shaded area can be observed in Figs. 3, 4 and 6, but not in Fig. 5.

Table 4 Network specifications for the developed models

Network model	Network specifications				
	Transfer function (*hidden layer*)	Transfer function (*output layer*)	Hidden layer nodes	Output layer nodes	Training method
MISO Y1	Sigmoid (*logsig*)	Linear (*purelin*)	20	1	Levenberg-Marquardt (*trainlm*)
MISO Y2	Sigmoid (*logsig*)	Linear (*purelin*)	16	1	Levenberg-Marquardt (*trainlm*)
MIMO Y1	Sigmoid (*logsig*)	Linear (*purelin*)	15	2	Levenberg-Marquardt (*trainlm*)
MIMO Y2	Sigmoid (*logsig*)	Linear (*purelin*)	13	2	Levenberg-Marquardt (*trainlm*)

Table 5 Training error (RMSE) and correlation coefficient (R^2) generated during training and testing of network models, respectively

Network model	Training error (RMSE)	Correlation coefficient (R^2) of the tested model
MISO Y1	0.2576	0.8770
MISO Y2	0.1722	0.9090
MIMO Y1	0.0762	0.9370
MIMO Y2	0.2539	0.8690

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 6, Issue 1, July 2016

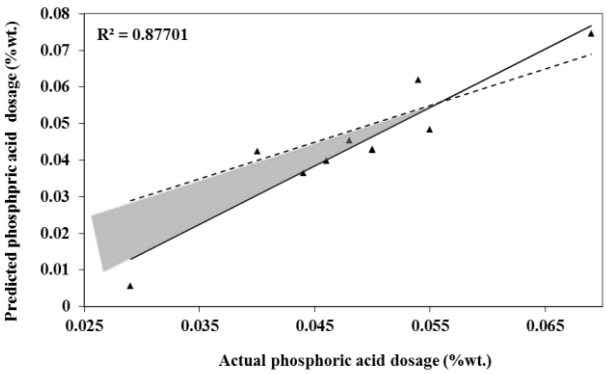


Fig. 3 Prediction performance of the MISOY1 model

Fig. 5 shows the performance of bleaching earth dosage predictions by MISOY2 model which has a correlation of more than 90 % with the actual process parameters. The predicted values however were higher that of the actual values.

The developed model is yet to give total satisfaction. It relies on the actual process parameters presented and utilized in developing a prediction model. If refiners happened to overvalued or undervalued a particular process parameter, the model treats the dataset as 'true' value and will decide similar process parameters in the future. Besides, the developed model based on artificial neural network possesses several disadvantages such as computational complexity, nonlinear process and noises and disturbances that have the potential to affect the model's performance. The operational 'error' caused by the action of the refiners could be minimized by sampling large amount of process parameters from the refinery plant, e.g. for 2 to 5 years of operation. Whereas, the mentioned disadvantages of artificial neural network structure could be improved by utilizing transfer function that fits closely with the trend of a particular process parameter, therefore improving the model's intelligence and preferences.

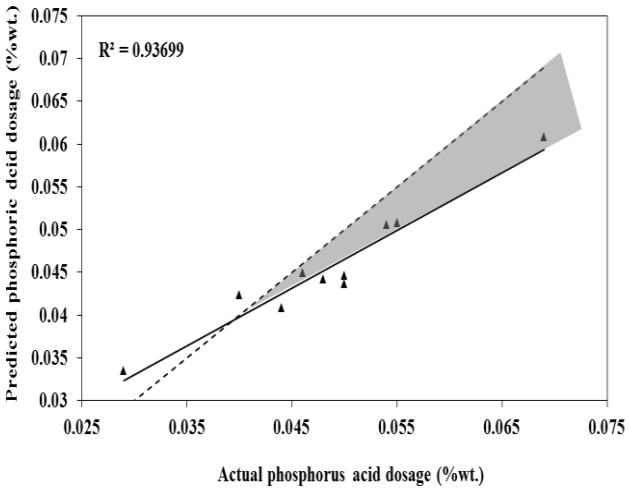


Fig. 4 Prediction performance of the MIMOY1 model

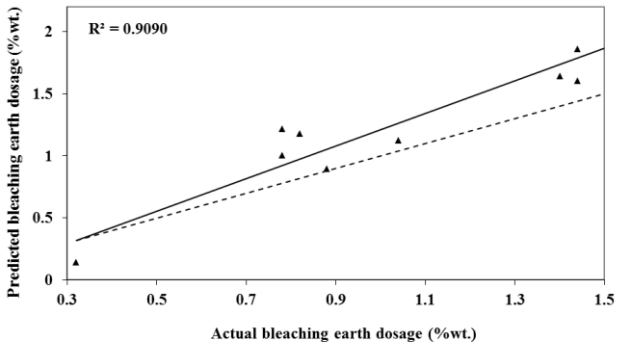


Fig. 5 Prediction performance of the MISOY2 model

A. User Interface Program

Many models were developed based on a particular environment, e.g. Visual Studio, Glade and MATLAB due to its ability to program the developed model at ease. However, they are not convenient to common users where translating the program into a user-friendly program is necessary. In this study, a spreadsheet file was created using Microsoft Excel program and linked to the MATLAB environment where the model was developed and programmed.

Fig. 7 shows the user interface program (UIP) developed in the Microsoft Excel spreadsheet. Using a simple coding, the spreadsheet allows common users to key-in the input data in an allocated spreadsheet cell. Consequently, due to the linkage between the spreadsheet and the MATLAB, prediction values are returned to the same spreadsheet file. While the spreadsheet conveniently allows users to key-in the input data and shortly obtain the prediction values, the MATLAB does all the calculation, i.e. processing the input in the neural network nodes using the transfer function and the saved weights and biases.

IV. CONCLUSION

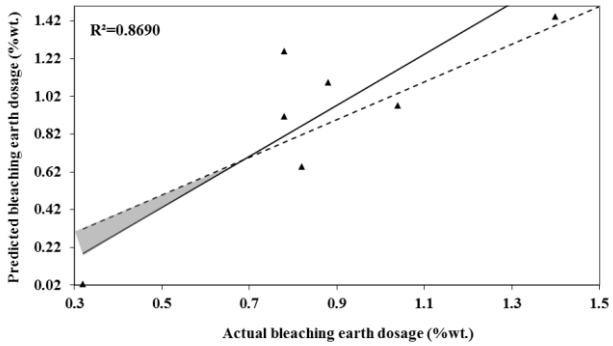
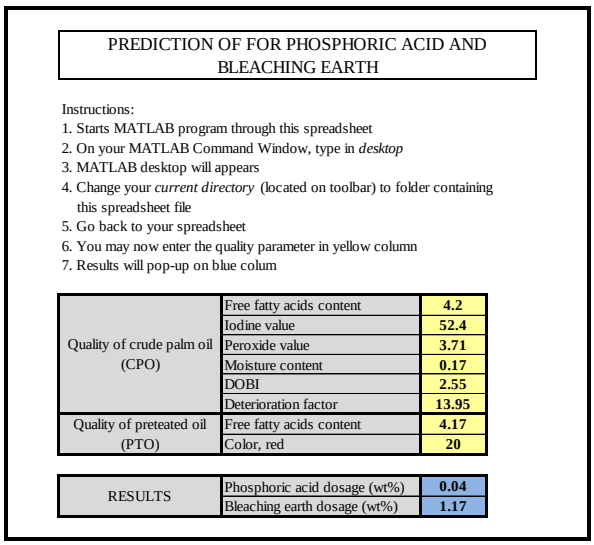


Fig. 6 Prediction performance of the MIMOY2 model

Prediction model for the bleaching and degumming of CPO in palm oil refinery was developed based on neural network architecture. Feed-forward and back-propogation algorithms consist of input layer, hidden layer and output layer were used in developing the model. Actual process data from the refining activities were utilized to train and to test the developed model. A good correlation between the actual

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 6, Issue 1, July 2016

values and predicted values were obtained for the prediction of PA and BE dosages, having R2 of 0.9370 and 0.9090 respectively. The developed models were embedded to the UIP in the form of a spreadsheet program which could be a useful tool for the refiners.



PREDICTION OF FOR PHOSPHORIC ACID AND BLEACHING EARTH

Instructions:
1. Starts MATLAB program through this spreadsheet
2. On your MATLAB Command Window, type in *desktop*
3. MATLAB desktop will appears
4. Change your *current directory* (located on toolbar) to folder containing this spreadsheet file
5. Go back to your spreadsheet
6. You may now enter the quality parameter in yellow column
7. Results will pop-up on blue colum

Quality of crude palm oil (CPO)	Free fatty acids content	4.2
	Iodine value	52.4
	Peroxide value	3.71
	Moisture content	0.17
	DOBI	2.55
	Deterioration factor	13.95
Quality of preteated oil (PTO)	Free fatty acids content	4.17
	Color, red	20

RESULTS	Phosphoric acid dosage (wt%)	0.04
	Bleaching earth dosage (wt%)	1.17

Fig. 7 User interface program for the prediction of PA and BE dosage developed on a simple spreadsheet program.

ACKNOWLEDGMENT

I wish to express my sincere appreciation to my former major supervisor, Dr. Khairiyah Mohd Yusof from Universiti Technology Malaysia, for her encouragement, guidance and criticism during which the project is carried out. I am also thankful to Mr. Noordin Basir, Plant Manager of FOP and staff at FOP for their helps and guidance.

REFERENCES

[1] D'Antone, S.; Spencer, R. Organizing for sustainable palm oil consumption: a market-based approach. Consumption Markets & Culture, **2015**, 18, 55–71.

[2] Ramli, A. World palm oil supply, demand, price and prospects - focus on Malaysian and Indonesian palm oil industries. Oil Palm Industry Economic Journal, **2011**, 11, 13–25.

[3] Production of crude palm oil 2015. Available online: http://bepi.mpob.gov.my/index.php/statistics/production/135-production-2015/736-production-of-crude-oil-palm-2015.html (accessed on 1 April 2016).

[4] David, A.A. Refining. In Lipid Technologies and Applications, 1st ed.; Gunstone, F.D.; Padley, F. B. New York: Marcel Dekker, Inc., 1997, pp. 137–168.

[5] Chikoti, G. Commercial production of cooking oil at premium oil industries. In Zambia Workshop on Oilseed Expression. Kafue, Zambia, 27–30 October 1987.

[6] Haraldsson, G. 1983. Degumming, dewaxing and refining. Journal of the American Oil Chemist's Society, **1983**, 60, 251–256.

[7] Hecht-Nielson, R.Neurocomputing. Reading: Addison-Wesley, 1990.

[8] Inal, F. Artificial neural network predictions of polycyclic aromatic hydrocarbon formation in premixed n-heptane flames. Fuel Processing Technology, **2006**, 87, 1031–1036.

[9] Tatlier, M.; Cigizoglu, H.K.; Erdem-Senatalar, A. Artificial neural network methods for the estimation of zeolite molar compositions that form from different reaction mixtures. Computer and Chemical Engineering, **2005**, 30, 137–146.

[10] Willis, M.; Di Massimo, C.; Montague, G.; Tham, M.; Morris, A. Artificial neural network in process engineering. IEE Proceedings D - Control Theory and Applications, **1991**, 138, 256–266.

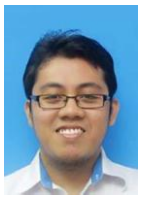
[11] Mohd. Yusof, K.; Idris, A.; Jet Siong, L.; Hun Mun, W.; Morad, N.A. Artificial neural network modelling of steady state chemical engineering system. In Malaysia-Japan Seminar on Artificial Intelligence Applications in Industry. Kuala Lumpur, Malaysia, 24–25 June 2003.

[12] Morad, N.A.; Mohd Zin, R.; Mohd Yusof, K.; Abdul Aziz, M.K. Process modeling of combined degumming and bleaching in palm oil refining using artificial neural network. Journal of the American Oil Chemist's Society, **2010**, 87, 1381–1388.

[13] Baughman, D.R. and Y.A. Liu. 1995. Neural Networks in Bioprocessing and Chemical Engineering. San Diego: Academic Press, Inc

[14] Vaziri, N.; Hojabri, A.; Erfani, A.; Monsefi, A.; Nilforooshan, B. Critical heat flux prediction by using radial basis function and multilayer perceptron neural networks: a comparison study. Nuclear Engineering and Design, **2006**, 4567, 1–9.

AUTHORS BIOGRAPHY



Nu'man Abdul Hadi received his Bachelor of Engineering (Chemical) from Universiti Teknologi Malaysia, Malaysia. He is currently working at Malaysian Palm Oil Board as a Research Officer. He has an expertise in process simulation and waste management system. He is also a Graduate Member of The Institution of Engineers (IEM), Malaysia and Board of Engineers Malaysia (BEM).

Che Rahmat Che Mat received his Bachelor of Engineering (Chemical) from Universiti Teknologi MARA, Malaysia. He is currently working at Malaysian Palm Oil Board as a Research Officer. He has an expertise in palm oil processing and enhanced oil extraction technologies. He is also a Graduate Member of The Institution of Engineers (IEM), Malaysia and Board of Engineers Malaysia (BEM).