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ORIGINAL PAPER

Process Modelling of Combined Degumming and Bleaching in Palm Oil Refining Using Artificial Neural Network

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Abstract Combined degumming and bleaching is the first stage of processing in a modern physical refining plant. In the current practice, the amount of phosphoric acid (degumming agent) and bleaching earth (bleaching agent) added during this process is usually fixed within a certain range. There is no system that can estimate the right amount of chemicals to be added in accordance with the quality of crude palm oil (CPO) used. The use of an Artificial Neural Network (ANN) for an improved operating procedure was explored in this process. A feed forward neural network was designed using a back-propagation training algorithm. The optimum network for the response factor of phosphoric acid and bleaching earth dosages prediction were selected from topologies with the smallest validation error. Comparisons of ANN predicted results with industrial practice were made. It is proven in this study that ANN can be effectively used to determine the phosphoric acid and bleaching earth dosages for the combined degumming and bleaching process. In fact, ANN gives much more precise required dosages depending on the quality of the CPO used as feedstock. Therefore, the combined degumming and bleaching process can be further optimised with savings in cost and time through the use of ANN.

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Keywords Phosphoric acid · Bleaching earth · CPO quality · ANN · Combined degumming and bleaching

Abbreviations

ANN	Artificial neural network
BE	Bleaching earth
CCD	Central composite design
CPO	Crude palm oil
DBPO	Degummed, bleached palm oil
DOBI	Deterioration of bleachability index
DOE	Design of experiment
Fe	Iron content
FFA	Free fatty acids
MISO	Multi-input single-output
MIMO	Multi-input multi-output
P	Phosphorus content
PA	Phosphoric acid
PV	Peroxide value
RBDPO	Refined bleached deodorised palm oil
RM	Ringgit Malaysia (1 USD = 3.4 RM)
RMSE	Root mean sum of squares of the errors
RSM	Response surface method
X	Independent experimental variables
Y_1	Response factor, phosphoric acid dosage
Y_2	Response factor, bleaching earth dosage

Introduction

Currently, the palm oil refining industry is among the most important manufacturing sectors in Malaysia. Besides contributing to the gross domestic product and increasing employment opportunities in the country, the refining sector has contributed significantly to the growth of the palm oil industry in Malaysia, [1]. In the refining process, combined degumming and bleaching is the first stage of processing in a modern physical refining plant. It is estimated about 20% of total operating cost of palm oil refining is due to this process. It was reported in [2] that bleaching during the refining of vegetable oils was cost-intensive mainly because of the consumption of expensive bleaching agents such as bleaching earth and activated carbon coupled with oil losses in the spent bleaching material. The prices of bleaching earth are RM 700–800 per metric tonne and RM 3,000 per metric tonne for phosphoric acid, respectively.

Combined degumming and bleaching is a batch process. The operating condition widely practised in the industry is at a temperature of 100 °C, pressure (7 kPa ~ 50 torr) and a contact time of 30 min [3]. The feed to the combined degumming and bleaching process is the crude palm oil (CPO) and the product is degummed, bleached, palm oil (DBPO) as shown in Fig. 1. Table 1 gives the minimum specification of the CPO and DBPO [4]. The minimum specification has to be met to avoid disruption in subsequent processing in refining which may result in compromised refined, bleached, deodorised palm oil (RBDPO) quality. RBDPO is the final product during palm oil refining.

At present, the amount of phosphoric acid (degumming agent) and bleaching earth (bleaching agent) added is usually a rough estimation of the quality of CPO as the feedstock used. The refineries use varied amounts of phosphoric acid between 0.5–1.0% wt/wt CPO and 1.0–2.0% wt/wt CPO for bleaching earth, respectively. The exact dosages of these two agents rely heavily on the plant supervisor's experience. In order to avoid conditions of non-compliance of minimum DBPO specification, extra dosages of both agents would do the trick. At times, the product from these processes in the form of DBPO will not be released to subsequent processing since the minimum quality is not met. This would incur additional dosages of both agents as well as an additional processing time.

Table 1 Typical composition of the main components of Malaysian CPO, DBPO and RBDPO [4]

Constituent	CPO	DBPO	RBDPO
Free fatty acids, FFA (%)	2–5	3–5	0.05
Red colour ($5^{1/4}$ in. Lovibond cell)	Orange red	–	~2.5
Moisture and impurities (%)	0.15–3.0	~0.2	~0.02
Peroxide value (PV) (meq/kg)	1–5	Nil	Nil
Anisidine value (AV)	2–6	2–6	~2.0
β-Carotene content (ppm)	500–700	–	–
Phosphorus (P) (ppm)	10–20	~4	~3
Iron (Fe) (ppm)	4–10	~0.15	~0.15

The current practice in combined degumming and bleaching is inefficient and needs to be reviewed and improved. In recent years, studies on optimisation and modelling of bleaching and degumming processes of vegetable oils have been conducted in order to improve the operating conditions [5–7]. This indicates that there is a need for optimisation of these two processes during vegetable oil refining. It therefore, becomes an interest to all refineries to optimise the consumption of bleaching earth and phosphoric acid. The use of artificial neural network (ANN) to optimise the dosages of bleaching and degumming agents with respect to CPO quality yet ensuring the desired quality of a DBPO will be explored in this study.

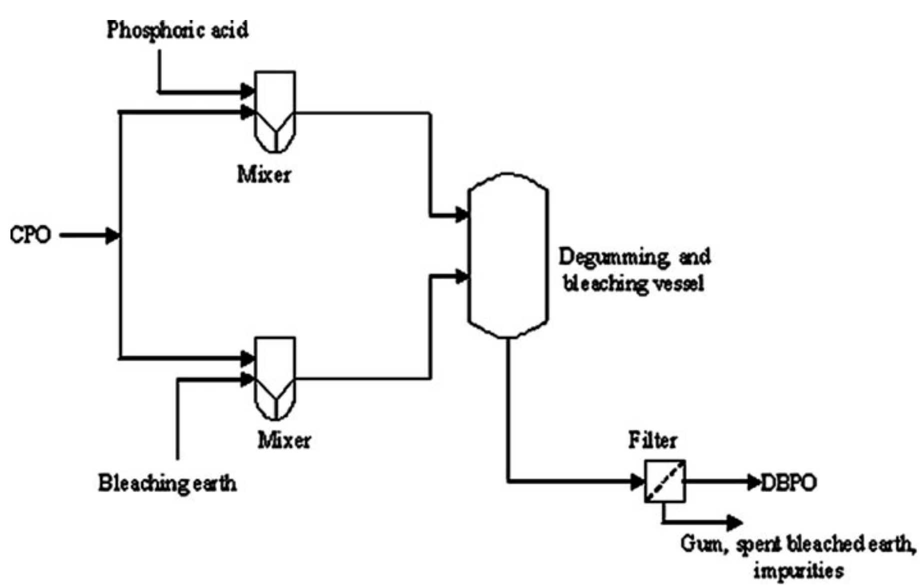

Fig. 1 Combined degumming and bleaching process of palm oil

Table 2 The three categories of CPO samples used in this study

Category	FFA content (%)	
A	<2.5	Golden Jomalina Food Industries Sdn Bhd, Banting, Selangor, Malaysia
B	2.6–3.5	Golden Jomalina Food Industries Sdn Bhd—samples left at room temperature ∼30 °C over a few days
C	>3.6	Pandamaran Delima Oil, Klang, Selangor

Source: Palm oil refinery

ANN has been demonstrated to be a valuable tool in both food and non-food application. ANN and genetic algorithm (GA) were proven to be successful in predicting the optimised pretreatment process parameters for biodiesel production using vegetable oils of varied quality including waste vegetable oils [8, 9]. This particular application of ANN and GA has reduced time and cost on expensive experiments.

ANN application to food process industry has been very promising [10–12]. Deniz et al. [11] had demonstrated the successful use of ANN for the estimation of the enzymatic reaction rate during hydrolysis of maltose using amylglucoside enzyme. The back-propagation ANN was proven to be a very useful algorithm for establishment of non-linear calibration models with near infrared spectroscopy to determine wheat protein [12]. There is no application of ANN to palm oil processes. In general, ANN has indeed been a valuable tool for assisting in complex processes [13]. Nevertheless, an ANN model has to be trained with sufficient experimental data for a reliable output; the accuracy of the predicted data improves with increasing training data.

Methodology

Combined degumming and bleaching experiments were performed on CPO samples. The CPO samples of this work were divided into three categories depending on the quality indicated by % free fatty acid (FFA) content as presented in Table 2. The quality of CPO and DBPO samples before and after the combined degumming and bleaching process were monitored through six different analytical tests which were; the FFA content, deterioration of bleachability index (DOBI) value, peroxide value (PV), phosphorus content (P), moisture content and iron content (Fe). The experimental methods used were described in [14, 15].

Design of experiments (DOE) through a central composite design (CCD) technique via a response surface method (RSM) using Minitab 14 environment determined the optimum number of experiments to be conducted. Using the DOE method, there are 20 sets of experiments on combined degumming and bleaching process. These experimental arrangements given by DOE had used the indicated dosages of phosphoric acid and bleaching earth is shown in Table 3. All the six quality analytical tests for both samples; pre (CPO) and post the experiment (DBPO) were performed. A total of 120 quality analytical tests for both CPO and DBPO were done with three repetitions each.

Table 3 The arrangement of experimental sequence given by DOE method

Run order	Bleaching earth dosage (wt%)	Phosphoric acid dosage (wt%)	FFA content (wt%)	CPO category
1	1.0	0.5	3	B
2	1.0	0.5	1	A
3	0.0	1.0	1	A
4	2.0	0.5	3	B
5	2.0	1.0	5	C
6	2.0	1.0	1	A
7	1.0	0.5	3	B
8	1.0	0.0	3	B
9	2.0	0.0	1	A
10	1.0	0.5	3	B
11	0.0	0.0	1	A
12	1.0	0.5	3	B
13	1.0	0.5	3	B
14	1.0	0.5	3	B
15	0.0	0.0	5	C
16	0.0	1.0	5	C
17	1.0	1.0	3	B
18	0.0	0.5	3	B
19	2.0	0.0	5	C
20	2.0	0.5	5	C

Figure 2 illustrates the use of ANN to predict the exact phosphoric acid and bleaching earth feed in accordance to the CPO quality. The dosages of bleaching earth and phosphoric acid used in industrial practice were obtained from some 24 palm oil refineries in Malaysia through a survey and visits [14] and were used to verify the ANN predicted data.

Model Development

A multi-layer perceptron feed forward neural network was designed in the MATLAB 7 environment employing the data obtained from experiments conducted. Three network

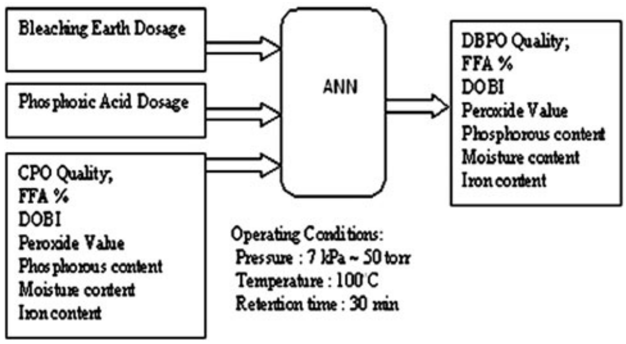

Fig. 2 ANN method to establish the exact phosphoric acid and bleaching earth dosages for combined degumming and bleaching process

topologies, two multi-input single-output (MISO1 and MISO2) and a multi-input multi-output (MIMO) were developed to predict phosphoric acid and bleaching earth dosages. Given the desired product (DBPO) quality and the CPO quality being processed, MISO1 was used to model phosphoric acid dosages. MISO2 was used to model bleaching earth dosages, while the MIMO network was used to predict both phosphoric acid and bleaching earth dosages simultaneously.

In a feed forward multi-layer perceptron network, the structure consists of three fundamental layers;

(1) an input layer, where each neuron is associated with an experimental factor and receive information/signal from outside world, usually in the form of a data file.
(2) layers of processing neurons, called hidden layers or intermediate neurons contained in one or more hidden layers allow nonlinearity in the data processing.
(3) an output layer, where each neuron is associated to the response and provide an answer for a given set of input values.

The signal moves from the input layer towards the output layer and in this process each neuron uploads all the neurons of the successive layers, transferring a portion of the signal that has been accumulated. The portion of signal transferred is regulated by a transfer function [16].

From the 20 sets of experiments arranged by RSM, 14 experimental data were employed for model development (training) and 6 experimental data were for validation (generalisation), based on rule of thumb of ratio 70:30. The overall steps of neural network modelling are shown in the flowcharts of Fig. 3.

In this study, there were 12 independent experimental variables identified based on the six quality parameters for both CPO and DBPO pre and post the combined degumming and bleaching process, respectively. The independent variables (X) and the response factors or outputs were

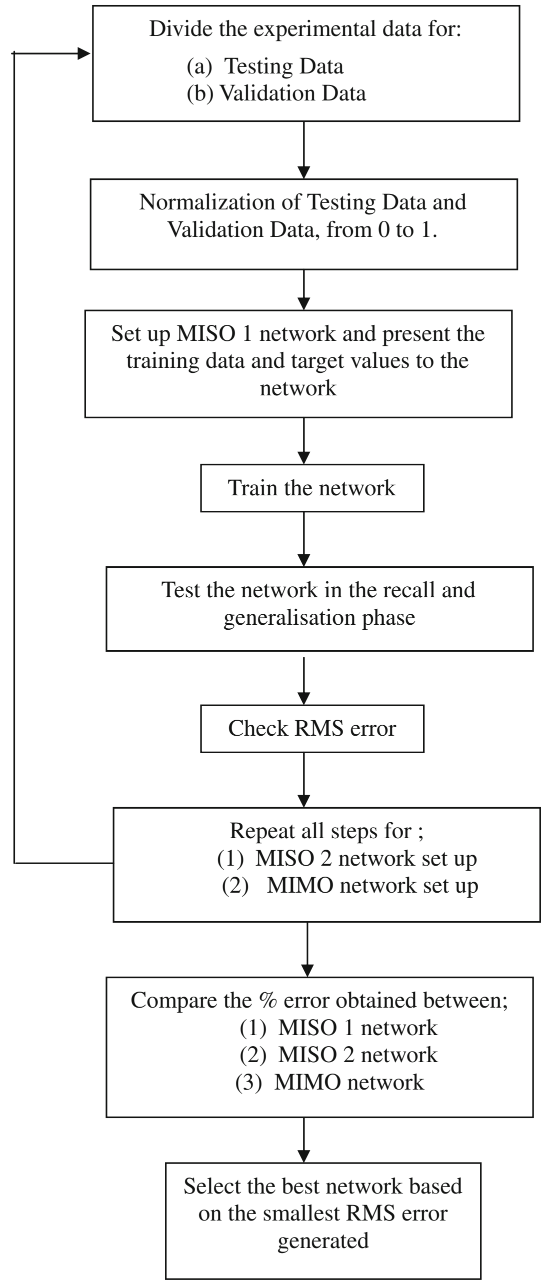

Fig. 3 Methodology for modelling a network for predicting phosphoric acid and bleaching earth dosages for varied CPO quality

phosphoric acid dosage (Y_1) and bleaching earth dosage (Y_2) are as listed in Table 4. Table 5 depicts the input independent variables and output response factors for the 14 model development and six model validation data sets.

The transfer functions employed in the networks were log-sigmoid transfer function (for nodes in the hidden layer) and purelin transfer function (for the output layer). All the networks were trained using the Levenberg–Marquardt learning algorithm (Trainlm). The overall MISO and MIMO network topologies are shown in Fig. 4.

Table 4 List of independent experimental variables and outputs

No.	Independent variables	Symbol
1	FFA_{CPO}	X_1
2	FFA_{DBPO}	X_2
3	$DOBI_{CPO}$	X_3
4	$DOBI_{DBPO}$	X_4
5	PV_{CPO}	X_5
6	PV_{DBPO}	X_6
7	P_{CPO}	X_7
8	P_{DBPO}	X_8
9	$Moisture_{CPO}$	X_9
10	$Moisture_{DBPO}$	X_{10}
11	Fe_{CPO}	X_{11}
12	Fe_{DBPO}	X_{12}
	Outputs	Symbol
1	Phosphoric acid dosage	Y_1
2	Bleaching earth dosage	Y_2

Model Selection

In order to select the best network topology, a systematic trial and error was utilised where each of the studied neural network topology was run 10 times. The network with smallest root mean sum of squares of the errors (RMSE) was selected to represent the process. The values of weights and biases associated to each connection between neurons of adjacent layers of the chosen network were obtained. The RMSE was defined as

$$\mathrm{RMSE} = \sqrt{\frac{\sum (\text{observed} - \text{predicted})^2}{\text{No. of data}}} \tag{1}$$

Weight and Bias

The model equation of a single neuron can be written as follows:

$$y_{pi}^{l} = \sum_{i=1}^{n} \left(w_{ij} a_{ij} \right) + b_j \tag{2}$$

where w_{ij}, a_{ij}, and b_j represent weight, input and bias, respectively, of i row in j layer. Once the node was calculated, it passed the result to the transfer function, $f(y)$. The functions used in this study were sigmoidal function and purelin function because the normalisation value of training and validation data for this simulation were in the range of 0–1. Thus, the complete node calculation for a sigmoidal function was:

$$f(y) = \frac{1}{1 + \mathrm{e}^{-y}} \tag{3}$$

and for purelin function was:

$$f(y) = y \tag{4}$$

As a result, the model equation of each response factor was presented in a value of weight of each layer. The initial value of weights and biases were set to 0 for all MISO and MIMO networks.

Results and Discussion

The experimental results were extensively discussed in [14, 15]. The experimental results generated in this study were used in the three ANN models established. In utilising ANN in this study, three layers of MIMO and MISO network models were developed for the prediction of phosphoric acid and bleaching earth dosages required to process varied CPO quality to produce the desired DBPO quality.

ANN models developed were evaluated based on the training and validation errors obtained. In this model development networks, each model was trained with several different number of hidden nodes (22, 23, 24, 25, and 26). Table 6 illustrates the training and validation errors of MISO and MIMO networks in this study. Interesting observation was obtained in which the validation and training errors increased as the number of nodes increased after the network reached its optimum (judged by the smallest validation error calculated using RMSE). Note that these were the errors calculated based on the prediction given by the network of data that had not been used for training.

For the training error, the same trend as validation error was observed for MISO1 and MISO2 networks, where training error decreased when the number of hidden nodes increased from 22 to 24 but re-increased when the number of hidden nodes rose from 24 to 26. However, MIMO network performance was different. The training error fluctuated as the number of hidden nodes increased. As the number of hidden nodes in MIMO network model for Y_2 was increased from 22 to 23, the training error dropped from 1.46×10^{-7} to 4.40×10^{-10}. In contrast, as the number of nodes increased from 24 to 26, the training error for Y_2 decreased from 1.02×10^{-8} to 5.74×10^{-11}.

For the three networks used in this study, the validation errors decreased when the number of hidden nodes increased from 22 to 24. However, it increased again when the number of hidden nodes rose from 24 to 26. For example, in the MISO1 network, the validation errors decreased from 0.0404 to 0.0271 for the number of nodes in hidden layers of 22 to 24, respectively. However, the

Table 5 Input variables and output response factors for model development data and model validation data

No.	FFA_{CPO} X_1 (%)	FFA_{DBPO} X_2 (%)	$DOBI_{CPO}$ X_3	$DOBI_{DBPO}$ X_4	$Moisture_{CPO}$ X_5 (%)	$Moisture_{DBPO}$ X_6 (%)	PV_{CPO} X_7	PV_{DBPO} X_8	P_{CPO} X_9 (ppm)	P_{DBPO} X_{10} (ppm)	Fe_{CPO} X_{11} (ppm)	Fe_{DBPO} X_{12} (ppm)	PA Y_1 (wt%)	BE Y_2 (wt%)
Model development data set														
1	3.05	3.40	3.000	1.798	2.11	0.17	1.97	0	10.18	4.14	0.15	0.11	0.5	1
2	1.21	1.42	3.835	1.610	0.92	0.16	2.4	0	10.3	4.18	0.54	0.28	0.5	1
3	1.35	1.42	2.375	1.972	0.1	0.98	2.9	2.83	12.02	10.5	0.65	0.04	1	0
4	2.90	3.14	2.345	1.622	0.75	0.19	2.11	0	10.72	3.52	0.23	0.12	0.5	2
5	3.69	4.48	2.218	1.578	2.51	0.20	3.29	0	16.84	3.1	4.59	2.07	1	2
6	1.48	2.30	3.203	1.920	2.26	0.19	1.4	0	10.46	3.14	0.34	0.24	1	2
7	3.12	3.32	2.980	1.810	2.08	0.25	2.04	0	11.14	4.21	0.17	0.13	0.5	1
8	3.23	3.84	2.222	2.030	0.94	0.63	1.17	0	10.46	10.24	0.38	0.13	0	1
9	1.36	1.39	3.038	3.808	2.54	2.46	2.84	2.64	11.06	10.18	0.78	0.49	0	0
10	3.09	3.46	2.986	1.813	2.05	0.24	1.84	0	10.51	4.21	0.17	0.12	0.5	1
11	2.90	3.30	2.977	1.805	2.10	0.29	2.17	0	11.03	4.11	0.21	0.18	0.5	1
12	3.76	3.97	2.380	2.788	2.99	2.82	3.63	3.32	16	15.4	3.2	3.19	0	0
13	3.81	4.07	2.390	2.047	2.78	3.57	3.38	3.14	18.2	16.7	3.96	0.44	1	0
14	3.65	3.87	3.001	1.820	0.41	0.15	3.43	0	13.44	11.88	4.09	1.31	0	2
Validation data														
1	1.25	1.40	2.851	1.938	0.34	0.18	2.33	0	10.52	8.16	0.68	0.28	0	2
2	2.94	3.37	3.030	1.779	2.14	0.31	2.24	0	11.24	3.87	0.19	0.16	0.5	1
3	3.10	3.50	3.019	1.910	2.12	0.26	2.09	0	11.17	4.19	0.25	0.21	0.5	1
4	3.04	3.11	3.172	1.994	2.05	0.14	1.46	0	11.38	3.54	0.44	0.29	1	1
5	2.84	3.28	2.43	1.978	1.87	2.38	1.78	1.53	11.05	9.87	0.28	0.15	0.5	0
6	3.74	3.97	3.000	2.214	0.42	0.19	3.41	0	14.2	4.1	4.56	0.63	0.5	1

validation errors increased from 0.0271 to 0.0597 when the number of hidden nodes rose from 24 to 26 correspondingly. The reason for increased validation errors as the number of nodes were increased in the hidden layers after the networks reached its minimum validation error may be attributed to the network becoming more complicated due to the increasing number of weight and biases in the network that were linked to each other.

The optimum network model based on the smallest validation error was selected from the MISO1 and MISO2 networks with topologies of one output, 12 inputs, 24 hidden layers nodes.

To further verify the MISO neural network model, comparisons were made with plant data. Figure 5, illustrates the dosages of phosphoric acid and bleaching earth predicted using the ANN models compared to the current industrial practice. The shaded region is the range of dosages of both bleaching and degumming agents currently used for the various qualities of CPO. The ranges of dosages of these two agents are widely used in the industry because the exact dosages depend on the on duty supervisor. This corresponds to a survey conducted in this study whereby 24 palm oil refineries in Malaysia took part [14]. Each refinery has estimated the required dosages of phosphoric acid and bleaching earth based on the FFA content in CPO as feedstock and this is between 0.5–1.0% wt/wt CPO for phosphoric acid and 1.0–2.0% wt/wt CPO for bleaching earth. The usual preference is to err on the side of putting both agents in excess of requirements to ensure that the desired quality is met, even if it is more than what is required.

It is the non-specificity of the dosages of degumming and bleaching agents used during this process and the variation within the palm oil refineries practice that this study wishes to address. From Fig. 5, the ANN models predicted dosages are precisely and clearly distinguish between the three categories of CPO as indicated by A, B, and C. Even though, the ANN predicted dosages for CPO quality in categories B and C are within the range of the current industrial practice. The amount required for both agents indicate a significant difference of approximately 0.1% wt/wt CPO for phosphoric acid and 0.2% wt/wt CPO for bleaching earth required between categories B and C of oils. This is estimated from an average of 0.65% wt/wt CPO for phosphoric acid and 1.3% wt/wt CPO for bleaching earth for category B of CPO and 0.75% wt/wt

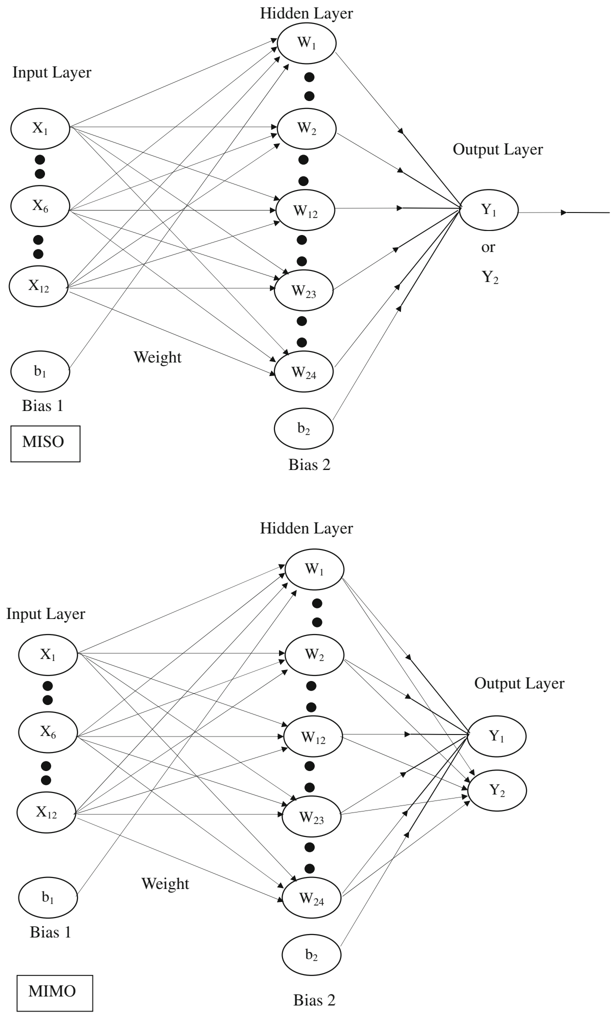

Fig. 4 Back-propagation feed forward topology of MISO and MIMO neural networks

CPO for phosphoric acid and 1.5% wt/wt CPO for bleaching earth for category C of CPO for ANN predicted dosages as in Fig. 5.

It can be observed from Fig. 5, for high grade CPO, grade A, the dosages of phosphoric acid predicted is 0.4% wt/wt CPO which is less than the amounts currently used in practice at 0.5% wt/wt CPO; i.e. a reduction of 0.1% wt/wt CPO. Nevertheless, the amount of bleaching earth required as predicted by ANN model is the same as currently used in industry for this category of oil. This shows that all this while, the amounts of phosphoric acid could have been reduced for category A of CPO.

It is estimated that a reduction of 0.5 wt% bleaching earth would save RM 3,500/day while a reduction of 0.1 wt% phosphoric acid would save RM 3,000/day for a refinery with a capacity of 1,000 metric tonne CPO/day. This is crucial for an industry with a low profit margin since the operating costs of a palm oil refinery are relatively high.

Table 6 Training and validation errors of MISO and MIMO networks for various numbers of nodes in hidden layers

Network structure	No. of Nodes 22		23		24		25		26	
	Training error (RMSE)	Validation error (RMSE)	Training error (RMSE)	Validation error (RMSE)	Training error (RMSE)	Validation error (RMSE)	Training error (RMSE)	Validation error (RMSE)	Training error (RMSE)	Validation error (RMSE)
MISO1, Y_1	3.12×10^{-8}	0.0404	1.49×10^{-10}	0.0321	1.72×10^{-11}	0.0271	1.11×10^{-10}	0.0534	2.16×10^{-10}	0.0597
MISO2, Y_2	7.49×10^{-9}	0.0394	8.08×10^{-9}	0.0383	8.01×10^{-13}	0.0360	1.54×10^{-9}	0.0519	1.55×10^{-11}	0.0908
MIMO, Y_1	5.09×10^{-8}	0.0305	3.66×10^{-10}	0.0397	7.78×10^{-8}	0.0118	3.71×10^{-11}	0.0256	8.06×10^{-8}	0.0430
Y_2	1.46×10^{-7}	0.1113	4.40×10^{-10}	0.0969	1.02×10^{-8}	0.0883	3.79×10^{-10}	0.1126	5.74×10^{-11}	0.1043
Average		0.0709		0.0683	4.40×10^{-8}	0.0500		0.0691		0.0737

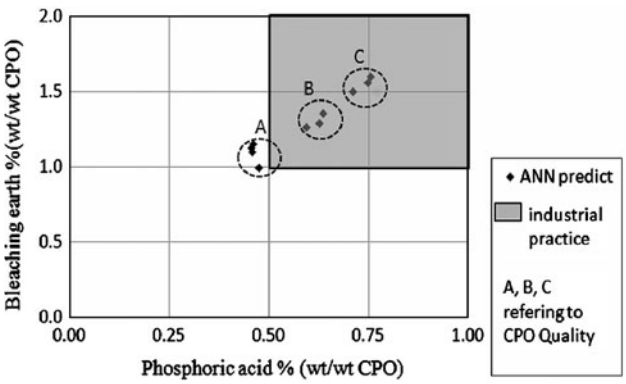

Fig. 5 Comparison of actual industrial practice and ANN predicted dosages for phosphoric acid and bleaching earth for varied CPO quality

The ANN model has demonstrated that it can predict precise amounts of degumming and bleaching agents which depends greatly on the quality of CPO as the feedstock. The dosages of degumming and bleaching agents predicted by ANN model would not compromise on the quality of BDPO produced since the required oil specification as indicated by Table 1, is built into the model.

Conclusion

The MISO1 and MISO2 models have demonstrated that predictions of the precise amounts of degumming and bleaching agents according to the quality of CPO as the feedstock are feasible. All results point towards a possible optimisation for combined degumming and bleaching which can be translated into significant savings in cost and time through the use of ANN models.

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