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PREDICTING BOILER EMISSION BY USING ARTIFICIAL NEURAL NETWORKS

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Abstract. Palm oil is produced in palm oil mills, where palm oil waste can be used (shell and fibre) as fuel for the boilers for generating steam power plants. Unfortunately, the combustion products of these materials cause severe atmospheric pollutions. The emission released through the chimney can be monitored by modeling its process of input (in fuel, turbine, boiler) and output of the pollutants. In this paper, Artificial Neural Networks (ANN) is used to model the emission from the palm oil mill boiler. Multiple Linear Regression (MLR) is also applied to find the coefficient of the contributing element to the pollution in order to make comparison and validate the ANN results. In conclusion, the prediction made by ANN is better than MLR but both agrees well with the actual values collected from the mill.

Keywords: Artificial neural network; biomass boiler emission; multiple linear regression; prediction and comparison

Abstrak. Minyak sawit dihasilkan di kilang kelapa sawit yang dilengkapi loji kuasa stim tersendiri dan loji terbabit menggunakan bahan buangan kelapa sawit (sabut dan tempurung) sebagai bahan api dandang. Walau bagaimanapun, hasil pembakaran menyebabkan pencemaran ke atmosfera yang serius. Pelepasan asap melalui serobong boleh dipantau dengan menyelaku proses masukan (dalam bahan api, turbin, dandang) dan keluaran pencemar. Dalam kertas kerja ini, Rangkaian Neural Buatan (ANN) digunakan untuk menyelaku asap dari dandang kilang kelapa sawit. Regresi Lelurus Pelbagai (MLR) juga digunakan untuk mencari pekali unsur yang menyumbang kepada pelepasan setiap pencemar dan membanding dan mengesahkan keputusan ANN. Kesimpulannya, ramalan yang dibuat oleh ANN lebih baik daripada MLR tetapi keduanya menunjukkan keputusan yang hampir sama dengan nilai sebenar yang diperolehi dari kilang.

Kata kunci: Rangkaian neural buatan; emisi dandang biojisim; regrasi lelurus pelbagai; ramalan dan perbandingan

1.0 INTRODUCTION

Air pollution can never be totally eliminated, but it can be minimized [1]. Most of the palm oil mills have installed smoke density sensors which monitor the smoke

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production in units of opacity. Opacity is the degree of smoke that reduces the passage of light as determined by a certified observer. It is expressed numerically from 0 percent (fully transparent) to 100 percent (fully opaque). In Malaysia only industries that use process combustion such as power plants and palm oil mills are required to install smoke density sensor meter in order to comply with the ISO 1400 standard. On top of that, most power plants install a new system called Continuous Emission Monitoring System (CEMs) which monitors the pollution level released 'online'. The CEMs is better than smoke density as it can give the smoke composition and production level automatically. Palm oil mills however are not required and expected to install this system due to the high maintenance cost (US$10 000 per year) and its expensive initial installation cost (US$ 200 000).

Monitoring emission based on a Artificial Neural Networks (ANN) model is proposed in the current study. The proposed model can be classified as a part of a Predictive Emission Monitoring System (PEMs) that operates in the same function as Continuous Emission Monitoring System (CEMs) in terms of monitoring several types of pollutants from various processes. Its main advantage is that it is cheaper than CEMs in operation and maintenance. This current study discusses the possibilities and suitability of a ANN in predicting and monitoring the smoke emission from biomass steam power plant at palm oil mill. Multiple Linear Regression (MLR) is also applied to search the coefficient of the contributing factors to the pollution.

Grott [2] has reported successful boiler emission modelling in Rheinbran Corplent and Health Project in German and Ostrulak power plant in Poland. Other applications are petroleum refinery factory in Anaco, Texas city, Westinghouse power plant, Wisconcin electric plant, Florida and Pavilion power plant in USA. In Britain, similar successful projects are developed by BCURA (British Coal Utilization Research Association), GNOCIS (Generic NO_x Control Intelligent System) and DTI (Department Trade and Industry) [3 – 4]. Review such as those by Keller *et al.* [5], Tuma *et al.* [6], Lennox *et al.* and Lisboa [8] reported the successful application of ANN in boiler emission controlling.

Table 1 summarizes several papers related to current study of predicting boiler emission by using ANN. Several of them used ANN to control boiler emission as a substitute in using Continuous Emission Monitoring System (CEMs) at coal power plant. However, Briggs *et al.* [9] and Euhos & Blanc [10] implemented ANN at a paper mill boiler, Mill [11] used it at incinerator and Guo *et al.* [12] used ANN to predict biomass gasification. Therefore, most of the papers in Table 1 describe the utilization of ANN at coal power plant and only Guo *et al.* [12] focuses on biomass emission modelling. No one yet applies ANN to palm oil mill boiler emission that uses biomass as fuel.

Table 1 also shows the input and output variables, as obtained by the 18 researchers in ANN boiler emission modelling. Based on the papers, different researchers used different input variables to predict the same pollutants. For example, Briggs *et al.* [9] and Troncis *et al.* [25] focused on predicting CO and NO_x, but they used different input variables. However, the use of different input variables does not greatly affect the prediction accuracy as the input variables selected are major influence to the output variables. The accuracy percentage measures the ratio between predicted and actual values during testing period of ANN.

Based on the papers listed in Table 1, the number of times certain input and output variables used in the prediction can be counted. From the total of the last row in Table 1, fuel capacity and excess air are commonly used as input variables (total 10). The second commonly used input variables are air capacity, air fuel ratio, and combustion temperature. These variables are chosen depending on the processes and factors that contribute to the pollutants. For example, to model NO_x as an emission from coal boiler, Rowland [20] used air capacity, fuel capacity, excess air, ambient temperature and firing rate as input variables. However, Grott [2] found hooter flame temperature in combustion process caused NO_x released, while Euhos & Blanc [10] justified that NO_x emission was due to the pneumatic conveyer transportation system. As a result, Grott [2] used air capacity, air fuel ration, combustion temperature, firing rate and boiler efficiency, while Euhos & Blanc [10] employed air capacity, air temperature, fuel capacity, combustion temperature and excess air as input variables. Thus, the input variables cannot easily be determined and they depend on the processes and conditions contributing to the pollutants.

So far, to predict 8 output pollutants, the researchers have used 20 input variables as listed in Table 1. Radl [19] and Tronci *et al.* [25] focused on predicting CO and NO_x only, while Mill [11], Guo *et al.* [12], Booth & Roland [16] and Kamal [22] carried out to predict various pollutants. The production of NO_x, CO and particulate matter (PM) increase is due to the maximum combustion under unstable load contributed to fluctuating of air fuel ratio [22]. So far from the literature, nobody has compared the simulation boiler emission with 2 or more different mills as reported by EPAUSA. The successful Pavilion project installation of 200 PEM in USA used their own power plant data collection to validate RATA (Relative Accuracy Test Audit).

The input and output variables need to be measured during the data collection. There are online or offline data collection that can be carried out, but most researchers used online data collection as it can give data in real-time sequence. For input data collection, Laux [18] used electric charge transfer system (ECT); Hou *et al.* [24] applied digital computer signal (DCS) and other people employed sensor and gage that interface with software to collect the data through online. Most of the researchers used the available CEMs in order to determine the pollutants amount. Mill [11] used *Method-5* isokinetic source sampling and Kamal [22] used electric static precipitator to collect PM.

Table 1 Different types of input and output variable used in Predictive Emission Monitoring System (PEMs)

NO	RESEARCHERS	INPUT PARAMETERS																				OUTPUT PARAMTERS								
		Power load	*Feed water*	*Air capacity*	*Air temperature*	*Fuel quality*	*Fuel capacity*	*Air fuel ratio*	*Steam capacity*	*Steam pressure*	*Steam*	*Combustion*	*Excess air*	*Stack pressure*	*Ambient temp.*	*Stack temp.*	*Firing/heat rate*	*Boiler efficiency*	*Slag/soot*	CO_2	O_2	CO	NO_x	PM	SO_2	CO_2	H_2	O_2	CH_4	Accuracy, %
1	Briggs *et al.* [19]										●		●				●						●					●		85
2	Bainess *et al.* [13]						●	●				●											●							95
3	Fisher [14]	●						●			●						●	●	●			●	●		●					–
4	Noble & Mayhew [15]			●			●			●	●		●										●							95
5	Booth & Roland [16]	●		●	●	●	●	●		●			●		●				●				●		●	●				80
6	Yu *et al.* [17]		●	●	●				●				●	●	●	●							●							95
7	Laux [18]			●		●	●								●								●					●		-
8	Radl [19]					●	●	●					●				●					●	●							-
9	Rowland [20]			●			●						●		●		●						●		●	●				-
10	Androscoggin [11]				●	●	●	●			●												●	●	●					-
11	Euhos & Blan [10]			●	●		●					●	●										●							93
12	Ikonen *et al.* [21]						●					●									●		●							95
13	Kamal [22]	●					●	●					●		●					●		●	●	●	●	●		●		-
14	Kersch *et al.* [23]							●					●	●		●	●						●							93
15	Grott [2]			●			●					●					●	●					●							-
16	Guo *et al.* [12]											●				●						●				●	●		●	-
17	Hou *et al.* [24]					●						●			●								●							97
18	Tronci *et al.* [25]	●					●			●		●	●	●								●	●							90
	Total	4	1	7	4	5	10	7	3	3	4	7	10	3	6	3	6	2	2	1	1	5	17	2	5	4	1	3	1	

2.0 METHODOLOGY

This section covers the methods used to develop boiler emission model. First, the industrial set up for data collection at palm oil mill is described. Second, MLR models and ANN used for boiler emission modelling are briefly described.

2.1 Industrial Set-up for Data Collection

The industrial set-up was prepared to collect data at palm oil mill in order to build up an ANN and MLR model. Data collection from steam plant palm oil mill was taken at five locations (turbine, boiler, fuel inlet, exhaust and stack chimney) as shown in Figure 1. Fifteen parameters taken as input variables to emission from four locations as shown by the chart in Figure 2. Output variables of emission (CO, NO_x, SO_2 and PM) were collected from the stack chimney. The data at boiler and steam turbine were directly taken from their reading display. However, for at fuel inlet capacity, the fibre and shell capacity have to be weighed manually since no automatic measurement is available. To measure the pollutant, gas analyser and isokinetic sources sampling were utilized at the stack chimney.

There are a variety of data collected by other researchers to model boiler emission. Yue *et al.* [17] gathered about 350 sets of data and Fisher-Rosemount [14] collected the data every minute for 2 and 4 weeks for boiler emission modelling. Most of the

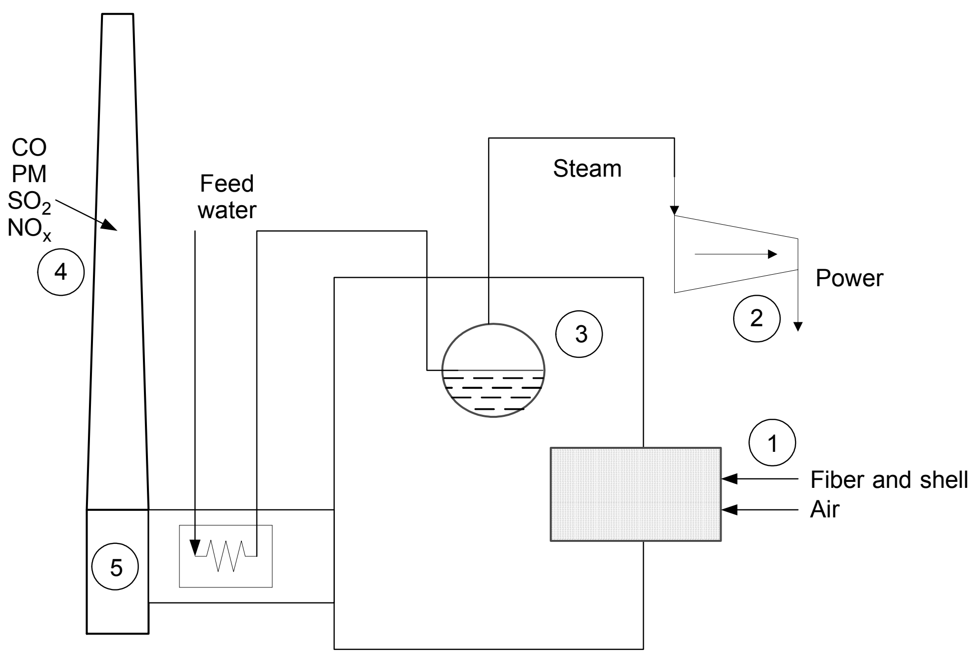

Figure 1 Location for data collection (1-Fuel inlet capacity, 2-Steam turbine, 3-Boiler display, 4-Stack chimney platform and 5-Exhaust)

Table 2 Typical Artificial Neural Networks setup for CO model

Structure	Feedforward
Algorithm	Back propagation
Type of algorithm training	Trainlm
Network structure	[15, 27, 1]
Transfer function	Sigmoid and linear
Number of iterations	1000 (max epoch)
Performance function	Mean square error (mse)=1×10^{-3}
Data scaling	Standard deviation and mean
Learning rate	0.01
Momentum	0.95

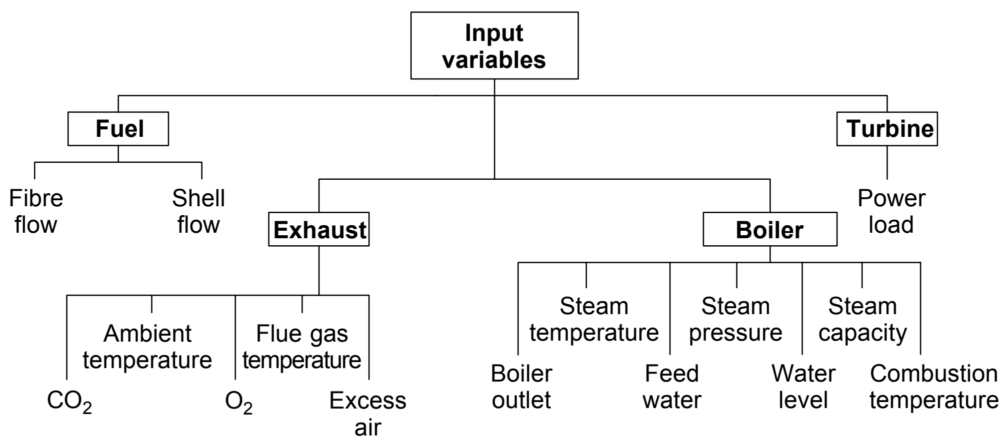

Figure 2 Selected input variables for fuel, exhaust, turbine and boiler parameters

researchers gathered data every hour (24 hours) for a month through online method [2, 16, 18 – 19, 21 – 23]. However, Baines *et al.* [13] collected the data in every hour for 3 months, *i.e.* 720 sets. In this study, by considering the equipment provided and the time operation for palm oil mill power plant (8 hours per day and 5 days per week), the data were collected 120 sets in 15 minutes interval time.

2.2 Artificial Neural Networks (ANN)

The concepts of Artificial Intelligent have given the possibility of realising machine learning based on human thinking method. According to Bartos [26], Artificial Intelligence group comprises of ANN, expert system (ES), fuzzy logic (FL), Genetic Algorithms (GA) and other combination of AI like fuzzy neuro, neuro genetic and fuzzy genetic system. ANN is adapted from the human biological neuron that reacts to give an output result after receiving the information [28]. Actually, this ANN is based on signal processing using mathematical formulae that function as a human nerve. ANN must learn how to process input before they can be utilized in an application. The process of training an ANN involves adjusting the input weights on each neuron such that the output of the network is consistent with the desired output. This involves the development of a training file, which consists of data for each input node and the correct or desired response for each of the network's output nodes. Once the network is trained, only the input data are provided to the network, which then recalls the response of the network learned during training.

Matlab 6.0 software was used with its Neural Networks Toolbox, and setting parameters as shown in Table 3. In this study, the Levenberg-Marquart algorithm (Trainlm) was used as suggested and used by many researchers such as Ref. [3, 29 – 32] due to its successful applications in various field. In the process, the weights and bias are initialed in randomized order. For the present task, to minimize the time taken for simulation, and also to follow a common practice regarded to be successful, the learning rate value of 0.01 and momentum value of 0.95 are utilized. Both values are applied as initial value for a network that can be adjusted during training. The weights are automatically adjusted depending on the learning rate and momentum to obtain minimum difference value between actual and predicted output using back propagation method. The simulation stops after reaching 1000 epoch or when square error reaches a value of 0.001 between the actual and predicted value. The boiler emission model simulation process uses training, validation and testing in order to obtain a generalized model [13]. Training period is an initial approach to create randomized weights that will be adjusted to achieve a certain square error between actual and predicted values. Sigmoid and linear transfer functions were utilized for connecting input layer to hidden layer and hidden layer and output layer respectively.

During validation stage, the final weights from training period will be updated using simulation for new sets of validation data obtained from lower square error than training period. This is also known as generalization phase in which a wider range of data value is used than in the training period. In order to verify the network either successful or not, the testing period data is needed. In this testing period, input data that are excluded from both training and validation periods are used. The training and validation periods are needed to increase the network capability, accuracy and will solve the overfitting problem that is always faced by feed forward

Table 3 Regression analysis single model of Artificial Neural Networks

	r-value			
	CO	**NO_x**	**SO_2**	**PM**
Training	1	1	1	1
Validation	1	1	1	1
Testing	0.9964	0.9946	0.9968	0.9527

back propagation. Overfitting problem happen when the error shown during training is small, but large error occurs during testing section [28, 33]. A low error between actual and predicted output indicates the accuracy of the model. All 15 input parameters as mention in Figure 2 and four output parameters (CO, NO_x, SO_2 and PM) were used in prediction of boiler emission using ANN. Each data is divided into 60 sets for training period, 40 sets for validation period and 20 for testing period.

2.3 Multiple Linear Regression (MLR) Model

A relationship of the model can be made in the form of mathematical equation when the experimental data is analyzed by MLR. The equations can be used to calculate the output when knowing all the input values. Before obtaining the equations, all the variables should be in original logarithm value in order to create a narrow range data value. The model development depends on the variation, pattern of data and number of observation [34]. However, regression models are known to give some deviation from actual data. The error margin determines the regression model quality. Lu *et al.* [35] and Rushyendran [36] have obtained Multiple Linear Regression (MLR) model by using Microsoft Excel. The current study also utilizes Microsoft Excel, but it is supported by software called 'Analyse-it' that is commonly used for statistical problem. A basic equation of MLR as follow:

$$y = A * x_1^{B_1} * x_2^{B_2} * x_3^{B_3} * \cdots \quad (1)$$

where the y is the output value, A is the intersection at y axis (output variable), x is defined input variable and B refers to power coefficient for input variable. By using the Excel software, the model gives the coefficient of each input depending on the output. From the coefficient and intersection of the output value, the equations can be derived, but the equation is valid for that range of data only. By using training data and unknown data, the equation can be validated and tested respectively. MLR was utilized 15 input parameters to predict four output parameters, but employed 100 data for training and 20 data for testing due to MLR does not have validation period.

3.0 RESULTS AND DISCUSSIONS

Data collection from palm oil mill boiler is modeled using ANN and MLR. ANN results are discussed based on regression analysis for training, validation and testing section. These results are compared with MLR results.

Single output model for each pollutant is developed. The regression analysis between actual and predicted output is applied to demonstrate the accuracy of the models as shown in Table 3. It shows the r-value for training, validation and testing period for both models. All models show accurate prediction during training and validation and a slight deviation for regression value (r-value) in the testing segment. However, the network can predict well unseen data during testing section [3, 34 – 35].

From the data partition, 4 models of MLR are constructed with all input variables. The models for each pollutant are then examined using testing data sets after applying them for simulation data. All 4-emission models are constructed after getting the coefficients or powers for each input variable and its corresponding output. The results for the models are illustrated by the equations below.

$$CO\left(ppm\right) = 1.16563 * 10^{-9} * Sp^{0.0635} * Sc^{-1.9875} * Fw^{-0.4530} * St^{3.2266} * Fc^{-0.0569} * Bo^{0.1523} * Wl^{2.3059} * At^{-2.7079} * Ft^{2.5889} * Ea^{-0.2798} * Ff^{0.2100} * Sf^{0.0266} * Po^{0.0294} * O_2^{-0.7332} * CO_2^{0.3605} \quad (2)$$

$$NO_x\left(ppm\right) = 3.5238 * 10^{-4} * Sp^{4.0023} * Sc^{-0.3618} * Fw^{3.7598} * St^{0.9747} * Fc^{0.4721} * Bo^{0.4102} * Wl^{-0.9336} * At^{-2.9836} * Ft^{-4.1752} * Ea^{-1.5893} * Ff^{0.0055} * Sf^{0.2537} * Po^{-0.1076} * O_2^{3.2552} * CO_2^{-0.4255} \quad (3)$$

$$SO_2\left(ppm\right) = 6.4305 * 10^{-10} * Sp^{-1.3655} * Sc^{-4.0653} * Fw^{0.6131} * St^{3.9415} * Fc^{-0.4240} * Bo^{0.3374} * Wl^{1.9220} * At^{-3.7723} * Ft^{3.5320} * Ea^{-0.2289} * Ff^{0.2506} * Sf^{-0.1495} * Po^{0.1097} * O_2^{-0.9999} * CO_2^{-0.1783} \quad (4)$$

$$PM\left(mg / Nm^3\right) = 4.6860 * 10^{9} * Sp^{0.5748} * Sc^{-0.6396} * Fw^{-0.2586} * St^{0.2216} * Fc^{0.0239} * Bo^{0.2929} * Wl^{-0.3523} * At^{-0.4641} * Ft^{-0.3363} * Ea^{-0.3107} * Ff^{-0.0233} * Sf^{0.1030} * Po^{-0.1146} * O_2^{0.2616} * CO_2^{0.2150} \quad (5)$$

Where *Sp* is steam pressure, *Sc* is steam capacity, *Fw* is feed water, *St* is steam temperature, *Fc* is furnace combustion, *Bo* is boiler outlet, *Wl* is water level, *At* is ambient temperature, *Ft* is furnace temperature, *Ea* is excess air, *Ff* is fiber flowrate, *Sf* is shell flowrate, *Po* is power load, O_2 is oxygen and O_2 is carbon dioxide.

Figures 3, 4, 5 and 6 show the comparison values between actual and predicted values by ANN and MLR for CO, NO_x, SO_2 and PM respectively. The predicted values of CO by ANN are almost at the same values with the actual value collected from the mill. High accuracy is obtained where the average error is only 0.1 percent. The maximum percentage error in testing part is about 5.4 percent at the 110th data point. For NO_x, the same pattern for both the actual and predicted values is obtained. The average error is 0.5 percent and the maximum error of 5.8 percent occurs at data point number 97. High accuracy of prediction is also obtained for SO_2 and PM.

The average error for both predictions is less than 1 percent and the maximum percentage error for both predictions is less than 8.5%. The error is quite high for SO_2 due to the low value of emission released [9].

The CO prediction average percentage error for ANN and MLR model is 0.2 percent and 0.5 percent respectively. For NO_x model, it shows comparison between MLR and ANN model which demonstrates slightly higher error results than CO model. The MLR percentage average error is 1.7 percent, while ANN shows average error less than 1.4 percent. SO_2 model results comparison between MLR and ANN model is shown in Figure 3. The MLR model shows average percentage error of 2.6 percent during training, while ANN makes good prediction for the training and validation segment with less than 1.5 percent average error. However, for the PM results; the average percentage for MLR model is 4.8 percent and the prediction by ANN model gives average percentage error of less than 2.5 percent. In short, the comparison results are shown in Table 4.

All output models demonstrate that the single ANN model is better than MLR model. As boiler emission model is complex and highly non-linear, ANN is more suitable tool than MLR [19] to predict the emission from the palm oil mill boiler. Hence, ANN forecasting results are better in accuracy for all pollutants. Even though MLR modelling shows less accuracy than ANN, the prediction is still within acceptable error. ANN boiler emission model is a complex and highly non-linear prediction capability; consequently, ANN is more accurate tool than MLR to predict the emission from the palm oil mill boiler.

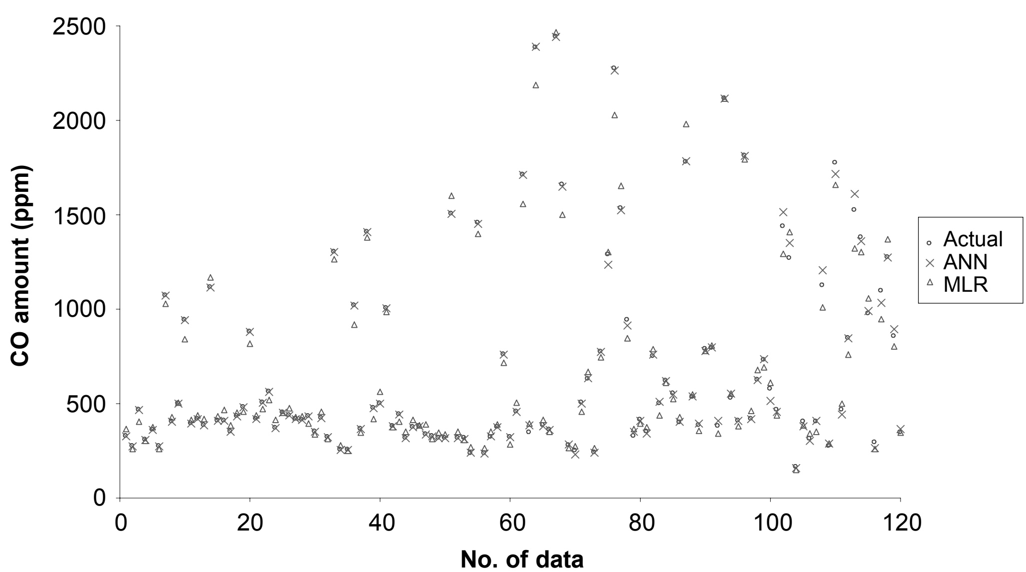

Figure 3 Comparison between actual, ANN and MLR for CO

Table 4 Comparison results between ANN and MLR

	Percent (%)			
	CO	**NO_x**	**SO_2**	**PM**
ANN	0.2	1.7	2.6	4.8
MLR	0.5	1.4	1.0	2.5

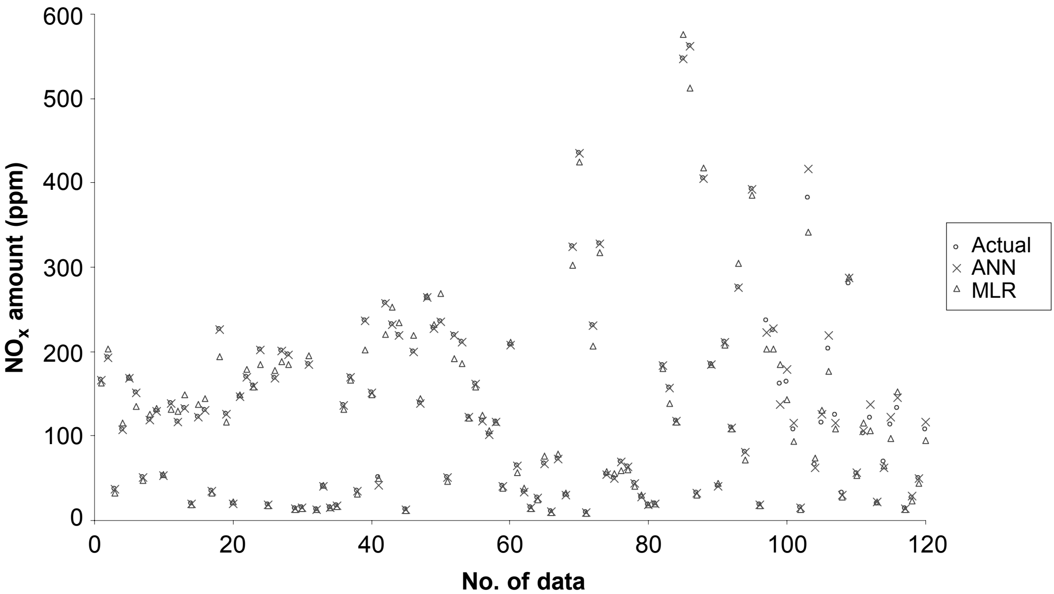

Figure 4 Comparison between actual, ANN and MLR for NO_x

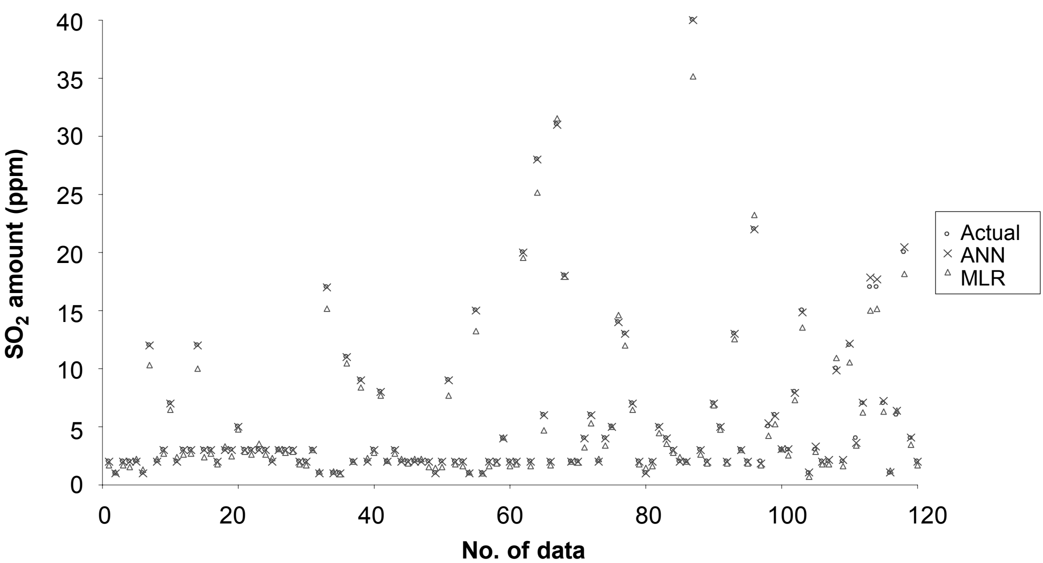

Figure 5 Comparison between actual, ANN and MLR for SO_2

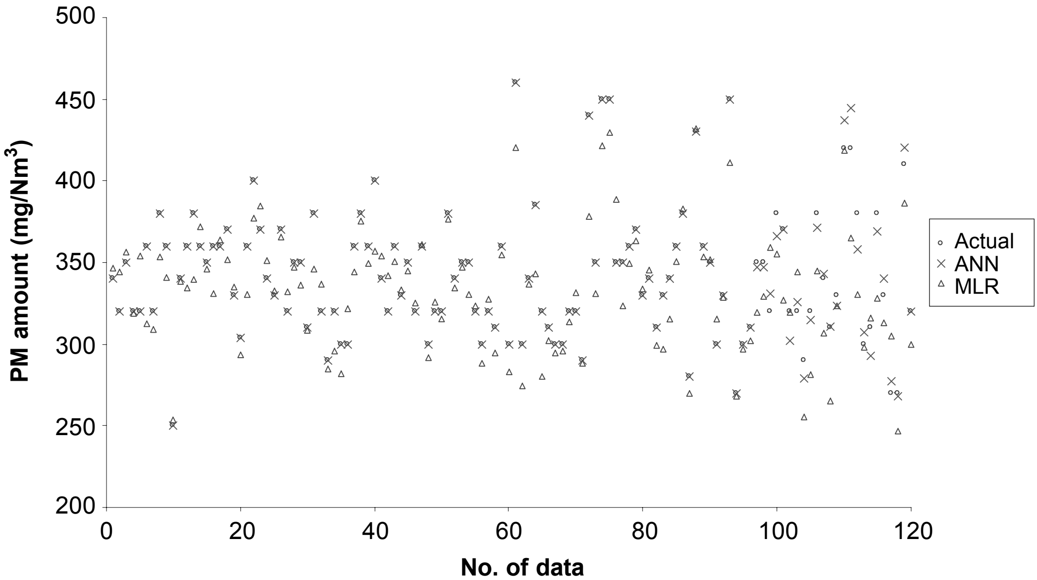

Figure 6 Comparison between actual, ANN and MLR for PM

4.0 CONCLUSION

In conclusion, the ANN modelling shows higher in accuracy than MLR in training, validation and testing periods. The error for MLR (5 percent) is slightly higher than the error obtained for ANN (2.5 percent) as the flexibility and capability of ANN are more than MLR in predicting emission which is very complex and non-linear process. However, MLR gives acceptable error in predicting the pollutants for all periods. The result shows that for a highly nonlinear relationship as in this modelling emission from palm oil mill, ANN can predict better than MLR.

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