APPLICATION OF BACK PROPAGATION NEURAL NETWORK IN PREDICTING PALM OIL MILL EMISSION

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ABSTRACT

The paper presents an approach to investigate and monitor the air pollution caused by the palm oil mill. A concept of dealing with the problem from its causes is used where the sources of pollution from the stack gases were examined. The main causes were from the combustion of shell fibre and of the palm oil. However, in the boiler itself, several parameters like steam load and pressure, fuel capacity and temperature also contribute to the pollution. The study uses Neural Network (NN) to simulate the process of combustion and stack gases. This neural network was trained by using the data on emission and combustion bed taken from local palm oil plant in Perak, Malaysia. The trained data by NN agrees well with the measured data, *i.e*. almost within 8% error for pollutants like CO, SO_2, NO_x and particulate matters.

Keywords : *palm oil mill, emission, neural network, air pollution, back propagation*

1. INTRODUCTION

In Malaysia, the palm oil industry is the most important industry for Malaysia and it is the main contributor to the national export. Malaysia is the largest producers of palm oil mill as shown in a pie chart of Figure 1. It shows that Malaysia contributes 66% of world production of palm oil. In the year 2000, Malaysian export income based on palm oil reaches RM 14.84 billion from the production of 10.8 billion ton of palm oil. To minimize the wastes, most of the palm oil mills utilize their palm oil wastes such as fibre and shell as their source of burnt fuel in the combustion bed of the boiler. It produces air pollution through emission that can cause health problem to the nearby community especially when the mixture of the fuel burnt are not in the correct proportion. The small particles from the black smoke are the primary component that

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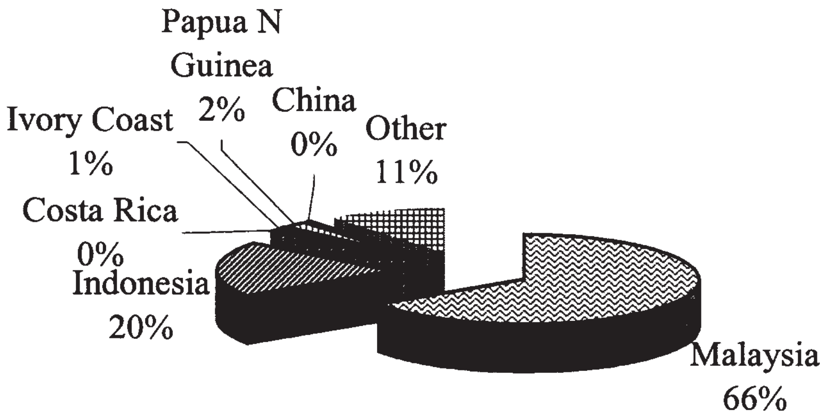


Country	Prod. Figure(000 tonnes)
Malaysia	7425
Indonesia	2252
Costa Rica	49
Ivory Coast	83
Papua N Guinea	235
China	35
Other	1228

Figure 1 : *World production of palm oil in 1998.*

can cause health hazard and should be given a full attention in the palm oil industry. This is due to the fact that the particles could be observed clearly with our naked eyes. The production of black smoke from the industry apparently shows that combustion is incomplete and that leads to the incorrect transfer of heat in the process.

A study of the boiler combustion technology shows that black smoke is formed when volatile matter from the burning bed is condensed into liquid aerosol and then heated to such high temperatures in a efficiency of oxygen that droplets are thermally decomposed, mainly to very fine carbon particles and other combustible materials[1-2]. Aggregate of smoke called soot, usually are relatively difficult to burn, requiring more rigorous conditions of mixing, residence time and temperature of combustion than other products of incomplete combustion, the particle sizes range is from 0.01 μm to 2 μm. Whereas the light-colored smoke (shades of brown to virtually white) or distillation smoke is essentially volatile matter that escapes the fuel bed and has not ignited. It occurs when a cold charge of solid fuel such as empty fruit bunch and kernel for palm oil mill boiler is dumped onto a burning fuel bed[2].

Gross estimation, for the particle from the black smoke release from the palm oil mill is 1.5 $gmN^{-1}m^{-3}$ at normal pressure and the rate of fruit production is 17,500,000 tones per year and this creates an average of 1-1.5 tones particles released into the open air everyday by every plant, or a total of 56,000 tones particle a year produced by approximately 220 oil palm processing plant in the country[1]. Therefore, it is necessity that the dark smoke and particulate emission of palm oil mill boilers in Malaysia be reduced either by using particulates removing devices or by improving the combustion efficiency of the boiler in used. Thus, a better control of smoke could lead to a less total of pollution. Some of the pollutants from the palm oil mill, which caused air pollution and unhealthy surrounding, are black particles that contain particulate matter (PM), sulphur dioxide (SO_2), nitrogen oxide (NO_x), carbon dioxide (CO_2), and carbon monoxide (CO)[3]. Nevertheless, the quantity of sulphur dioxide (SO_2) and nitrogen oxide (NO_x) are comparatively low and that the pollution caused by these gasses from the mill is usually not taken into account as a hazardous substance to the air pollution.

From economical aspect, the investigation on palm oil emission can help in monitoring air pollution caused by the palm oil mill by giving the optimum process without destroying the environment as it is an important income to Malaysia. During 1997 there were only 76% of the palm oil industry which obeyed the emission level as being enforced by the authority of Malaysia. All 309 palm oil mills do not have Continuous Emission Monitoring Systems (CEMS) as the cost to install and maintain these equipments together with their related software may be astronomical. As most of the palm oil mills are being operated by small organizations, the use of CEMS is unproductive. As a result, in order to oblige with the pollution limit and not to be fined by the authority, most of the palm oil mills tend to wait and see the emission being released. If there is complain from the public or the authority, the palm oil mill operators will reduce the emission level by reducing the amount of fuel. Since there is no special method to monitor the emission level from the palm oil mill in Malaysia, the investigation towards monitoring the stack gases released from the palm oil mill deems necessary.

The study presented here is to monitor the release of the emission from boiler at the palm oil mill. The process relates to the knowledge of the source of air pollution from burning material, operational process of the boiler and a thorough study on the fuel characteristics used in the boiler to generate steam. The pollution caused by the boiler are identified by measuring the contents in the combustion bed. The neural network is applied in order to control and monitor the release of pollution from this palm oil mill. The study can later be used to build up an accurate tool to foresee the effect of changing various input parameters that cause the pollution on emission parameters of the palm oil mill.

2. NEURAL NETWORK

Neural network is in the group of artificial intelligence that tries to mimic the brain's operation in learning and making decision. It consists of a number of nodes with neuron connection between the nodes. When training process is being conducted, the neural network learns from the input data and gradually adjusts its neurons to reflect the desired output[4]. There are several types of architecture and learning algorithm to train the network[5,6]. The most popular network include Multi Layer Perceptron (MLP)[7-9], Madaline[10], Hopfield[11], Neocognition[12], Functional Link[13], CMAC[14], Radial Basis Function (RBF)[15], Sigma-Pi[16] and B-Spline[17]. In this research MLP is used for simulation of the boiler emission.

The multilayered perceptron network trained by the means of back propagation algorithm is used here. A multilayered neural network is made up of one or more hidden layers placed between the input layer and output layer as shown in Figure 2. Each layer has a number of nodes connected with each other layer. Thus the node in the lower layer is connected with each of the nodes in the other layer. The information flow is only allowed in one direction during the training process, from input layer to the output layer through the hidden layers. Each of the first layer obtains some information signals from the input layer nodes, and then the output of the layer gives some information signals into the second layer nodes and so on.

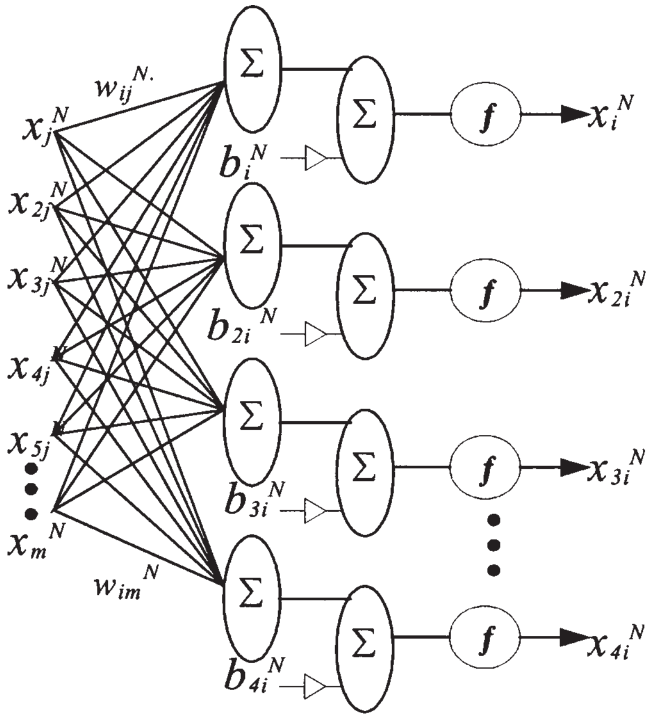


Figure 2 : *Multilayered back propagation Neural Network*

As shown in Figure 2, each node *j* of the input value, x_j^N in the layer *N* is connected with each node *i* in the proceeding layer *N* through a connection of weight w_{ij}^N. The multiplying of input value and weight with added by bias give the output value x_i^N through the equation (the figure' s flow is from left to right side)

$$x_i^N = f\Sigma\left(\sum_{j=1}^{m} w_{ij}^N x_j^N + b_i^N\right) \tag{1}$$

Where b_i^n is a threshold or bias of the *i-th* neuron in the layer *N*. The *N* = 1 is the input layer and the function f on the right hand side is called the output node activation function for x_i^N and assumed to be differentiable. For the hidden layers, the activation function is adopted to be sigmoid function refer to activation function.

$$f\left(x_i^N\right) = \frac{1}{1+\exp(x_i^N)} \tag{2}$$

For minimizing the error seen at the output nodes, the back propagation neural network algorithm is used here. The structure and algorithm is very widely used due to its successes in several applications[18-23]. The method is used in training is a gradient descent search in order to minimize an error defined as the sum square error (*sse*) difference between supervised output data x_i^N. (predicted output) and actual output data x_i^F, i.e. the error E is given as

$$E(sse) = \sum_m \sum_i (x_i^N - x_i^F)^2 \tag{3}$$

where i is the number of output nodes, and n is the number of input/output patterns.

The back propagation process to compute the error is written from equation (3) as

$$\delta_i^N = \sum (x_j^N - x_i^F) f_i'(x_i^N) \tag{4}$$

where $f_i'(x_i^N)$ is partial derivative of sigmoid function is given by $\dfrac{\partial f}{\partial x_i^N} = \dfrac{e^{-x_i^N}}{1+e^{-x_i^N}}$

and the error in any layer with the starting value of the Equation (4) is derived as

$$\delta_i^N = -\frac{dE}{\overline{\overline{dx_i^F}}} = f_i'(x_i^N) \sum_{j=1}^{m} (\delta_i^N w_{ij}^N) \tag{5}$$

The error δ_i^N must be calculated from the known final error, δ_i^F at the output layer. The errors are passed backwards from output layer, layer by layer. The threshold is adjusted in the same way as the connection weights. Then the new weights W_{ij}^N is calculated by using Equation (6)

$$\Delta w_{ij}^{N\cdot}(k+1) = \bar{\eta}\delta_i^N x_j^N + \alpha \Delta w_{ij}^{n-1}(k) \tag{6}$$

Where $\bar{\eta}$ is termed a learning rate, which is chosen to be large as possible and α is a momentum term. Knowing the weight changes, therefore weights are updated using the equation

$$w_{ij}^N = \Delta w_{ij}^{N-1} + \Delta w_{ij}^N \tag{7}$$

w_{ij}^N is the connection weight. The equations (1) to (7) are repeated to train all pattern input node, x_j^N to last input node x_m^N until the acquired error is sufficiently low.

Neural Network has successfully been applied to many fields due to its ability to make prediction accurately. These fields include: aerospace and robotic[7-9]; automotive process and manufacturing[24-27]; management, banking and finance[28]; defence, environment and safety[23,29-33]; and electronics and communication[18,21,34-35]. In modelling, the input and output variables are important variables. These variables should be able to adequately establish the process behavior of related activities in releasing the emission from the palm oil mill. In order to achieve this, real data are collected from one of the local palm oil mills in Malaysia.

3. DATA COLLECTION AND NETWORK TRAINING

To properly simulate the whole process by using Neural Network, the readout for the input and output from the boiler need to be taken. Other parameters considered to have an effect on the emission either directly or indirectly are also recorded. The data collection points are shown schematically in Figure 3. As shown, there are 4 collecting points deem necessary for contribution to the emission. These points are combustion bed as fuel inlet, power generator (turbine), boiler, and chimney, and are numbered 1 to 4 respectively. Fuel (fibre and shell) and air in certain ratio are fed into the combustion bed and they heat up the water into steam in the boiler. The steam with high temperature and pressure will generate the steam turbine and produce electricity[36]. The exhaust gas after the combustion of fuel is then expelled to the atmosphere through the stack gas. In the combustion bed where the fuel are burnt, the inlet of shell and fibre is weighed manually. This has to be done because automatic weighting system is not available. As there is not any device readily installed to measure the stack gases released continuously, gas analyser and particulate matter collector are used at the chimney to take the data manually. For other variables that contribute to the emission, the read out from the boiler and turbine displays such as steam capacity, boiler pressure and power produced from the steam turbine, are recorded. All these parameters are taken at the same time continuously. As the palm oil mill usually operates after nine o'clock in the morning, the data are taken every 20 minutes from 10 a.m. to 3. p.m with a break during lunch hour. From the boiler, furnace and

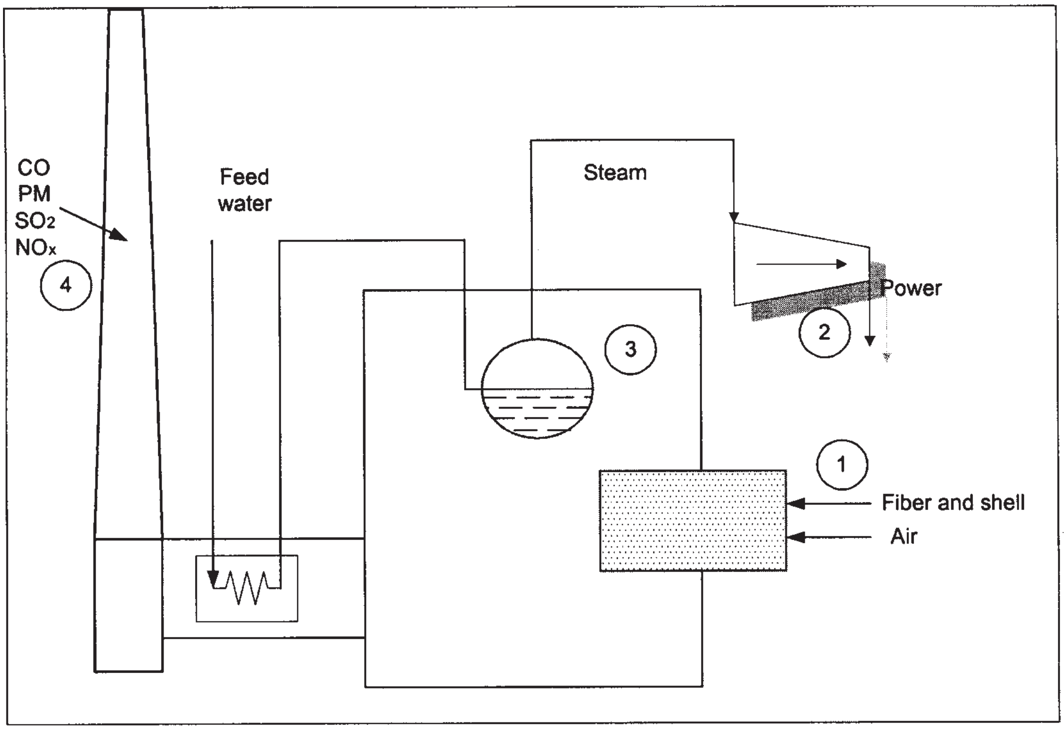


Figure 3 : *Schematic diagram of typical palm oil mill for data collection points*

turbine, the processes involved in emitting the pollutants from the chimney is called input variables while the pollutants released from the chimney are called output variables. The input process parameters are steam capacity, steam pressure, feed water from boiler parameters, fuel flow capacity as fibre and shell, power output and main pressure in steam turbine process. The output variables are then flue gas temperature and 4 kind of emissions: particulate matter (PM), carbon monoxide (CO), sulphur dioxide (SO_2), and nitrogen oxide (NO_x).

Programming language of MATLAB version 6.0 and Neural Network Toolbox from Mathworks Inc.[4] are used to generate Neural Network modelling. From the measured value taken from the palm oil mill, 12 set data points are obtained for each pollutant for neural network modelling. This is a network of 8 inputs from fuel, turbine, and boiler and 4 output containing the pollutants (CO, NO_x, SO_2 and PM) as shown in Figure 4. The simulation process stops when the maximum epoch is reached or when the difference sum square error of the actual and predict values achieved. The network stops at 156 epoch with sum square error of 1e-5 with computational time of 14.88 seconds only.

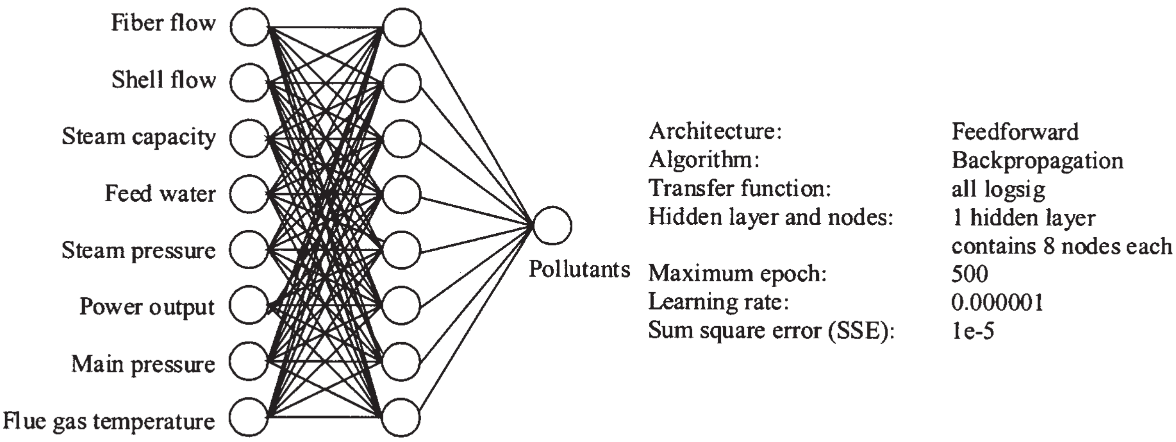


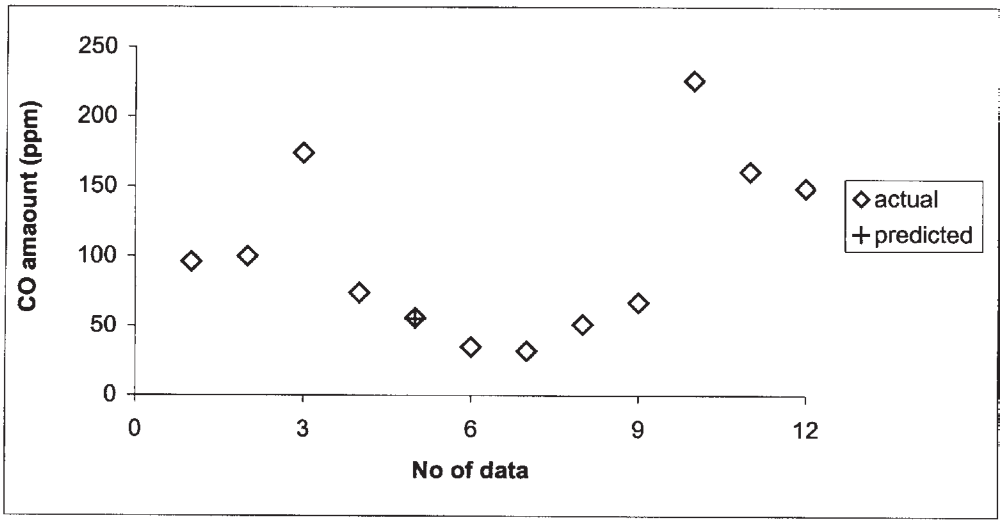
Figure 4 : *Illustration of the neural network modelling*

4. RESULT AND DISCUSSION

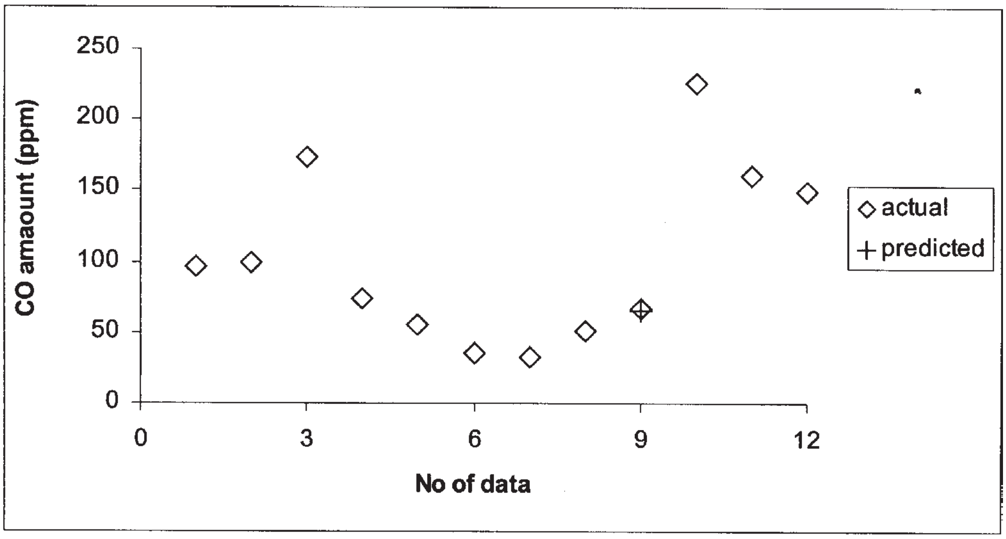
Since there are 4 emissions released from the chimney, the discussion will be done according to these 4 pollutants. The overall fluctuation of the data that can be observed is due to the different quantity of fuel that goes in the combustion bed resulted in different amount of pollutants being released from the chimney. It can also be observed that the general trend of the output pollutants to have minimum and maximum quantity of the data especially as shown for CO and NO_x.

4.1 Carbon Monoxide (CO)

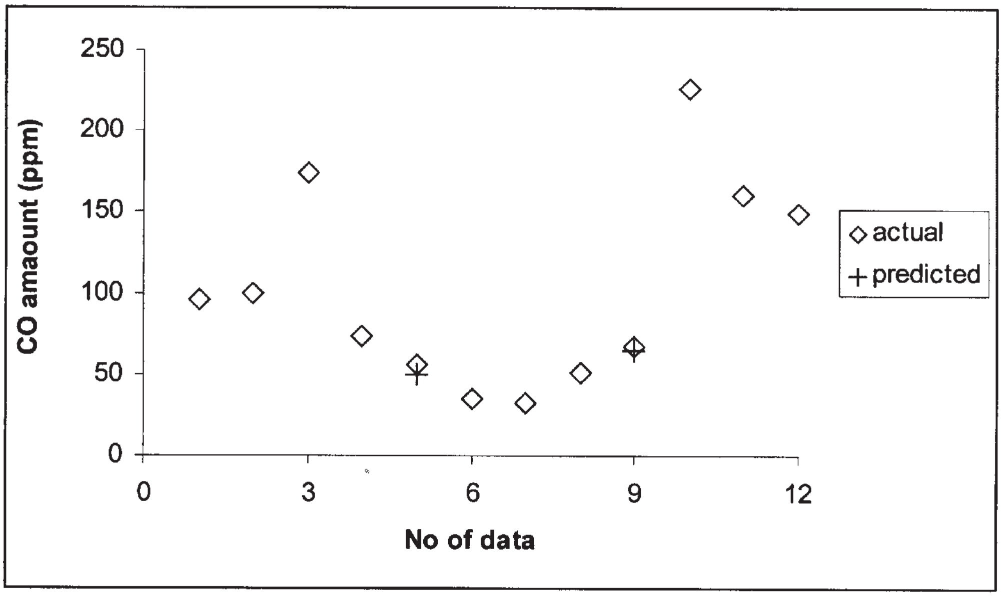
The number of points collected is however not too large in view of many practical difficulties encountered in the measurements. We have collected 12 points and used 11 points for training. The 12th point is predicted from the trained set and it is found that the prediction agrees well



(a)



(b)



(c)

Figure 5 : *Actual and predicted data of CO*

with the measured value as shown in Figure 5(a). The vertical axis is the quantity of CO in part per million (ppm) whereas the horizontal axis is the number of data collections. The data for experiment is indicated by a diamond symbol whereas the predicted data is indicated by '+' symbol. Here, the average error between the actual and predicted value is 1.3%. In order to see that the limited number of points gives enough data for training, we used another set of 11 points and the 12^{th} point (different from the previous one) is predicted as shown in Figure 5(b) and the prediction agrees well with the measured value with the average error of 3.48%. Further exercise is carried out to see whether ANN can make good prediction with the limited data as shown in Figure 5(c). With 10 points used for training, ANN can make reasonable predictions of the 11^{th} and 12^{th} data in which the average error is 3.25%. Therefore, these three exercises demonstrate that even with the limited points we are in a position to make predictions using ANN. As shown in Figure 5(c), in spite of two missing points, the prediction is still good. It may be mentioned here that in the case of electronic packaging industry, only 6 data points are used for training the ANN[34], thus paving way for using neural network with limited number of data points.

4.2 Nitrogen Oxide (NO_x)

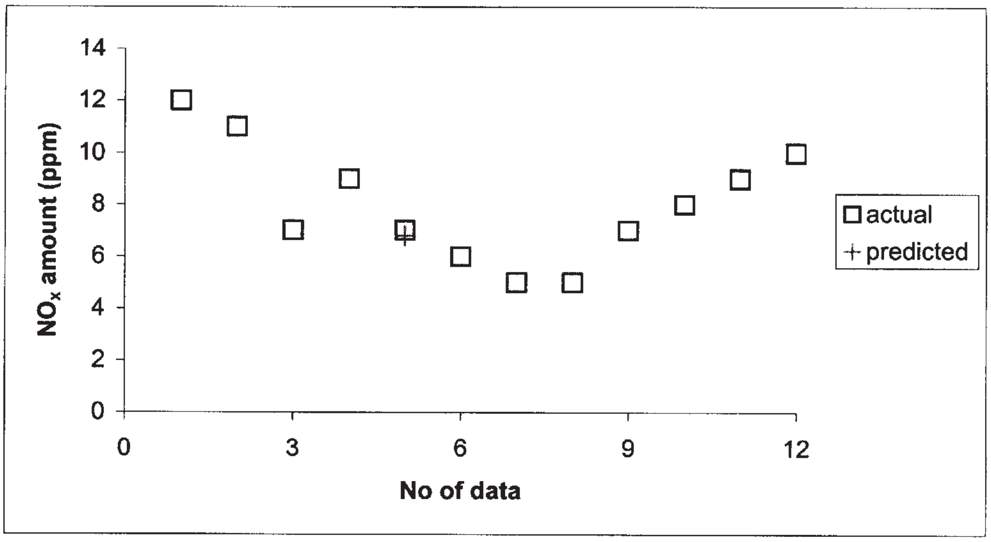
Similar exercises as in Section 4.1 are carried out with the limited data acquired. As shown in Figure 6(a) and Figure 6(b), by using 11 data points for training, the 12^{th} data point is predicted. The predicted value agrees well with the actual value with the average error for Figure 6(a) is 2.86% and 0.02% respectively. Very high accuracy is achieved for the second testing point since the training data points right before and following that particular point exhibit similar trend. ANN can also make accurate prediction with two missing points in training as demonstrated by Figure 6(c). The value for the average error is 2.36%.

4.3 Sulphur Dioxide (SO_2)

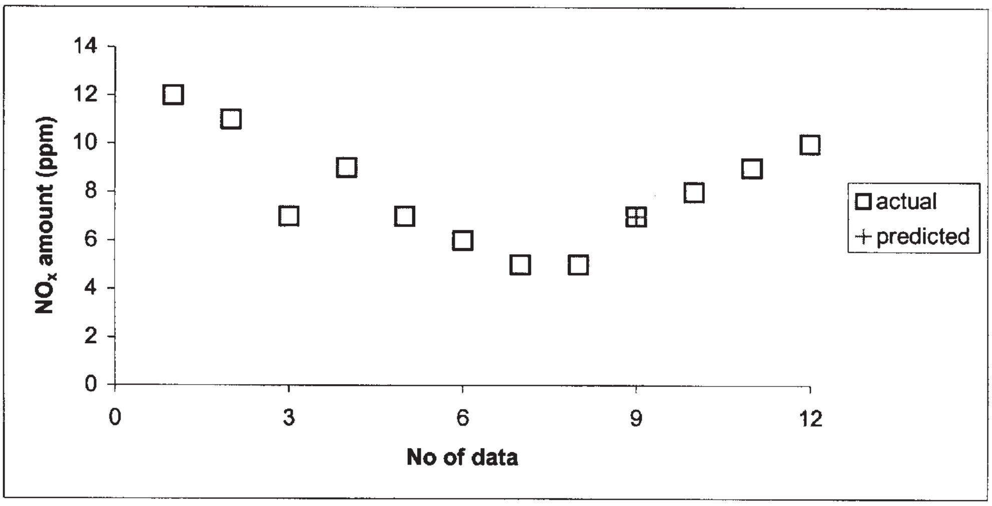
Figures 7 (a) and (b) show the actual and prediction values for SO_2. Similar exercises as before are carried out except now the exercise is extended to predict the data with only 9 points used for training. With two points missing in training, the average area is 2.43%. Even with three points missing in training, ANN shows good accuracy in predicting the data as shown in Figure 7 (b) where the average error is 3.14%.

4.4 Particulate Matters (PM)

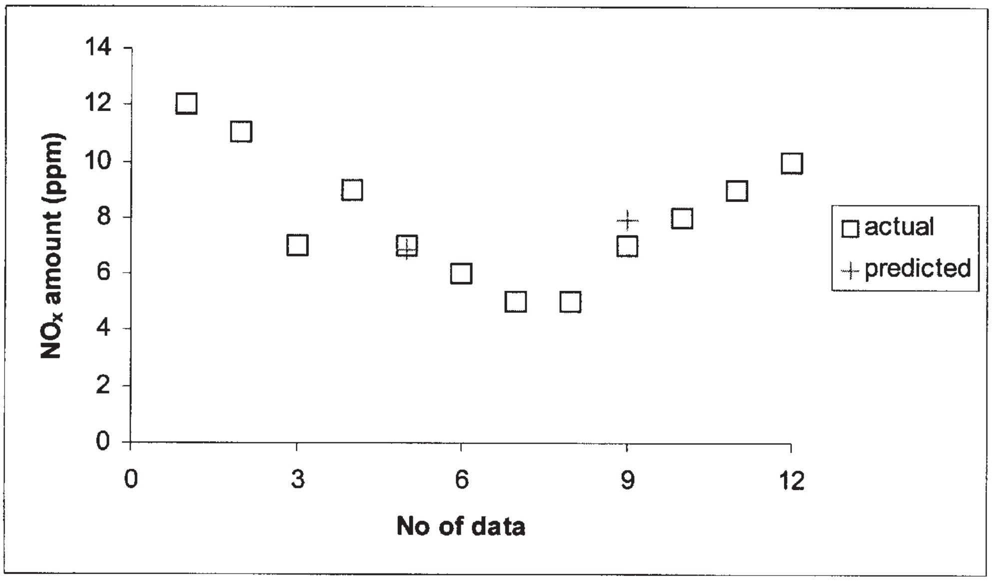
The particulate matter resulted form the combustion process varied from 0.2 $\frac{g}{Nm^3}$ to 1.8 $\frac{g}{Nm^3}$ as shown in Figure 8. The actual data is represented by a 'box' symbol, while the predicted data is represented by '+'. With 11 data points used for training, the 12^{th} value for PM is predicted well by using ANN with 5.18% and 7.86% of the average error for Figure 8(a) and Figure 8(b) respectively. With two points missing in training, the average error in prediction is 5.74%.



(a)

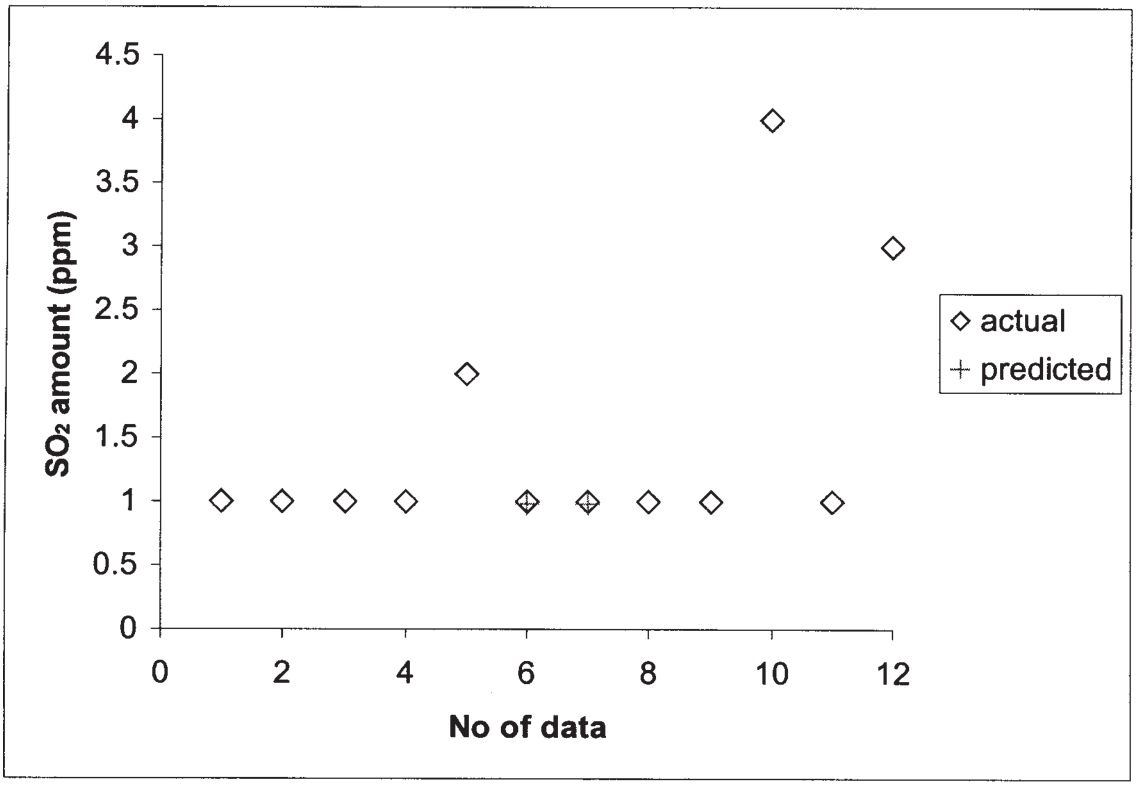


(b)

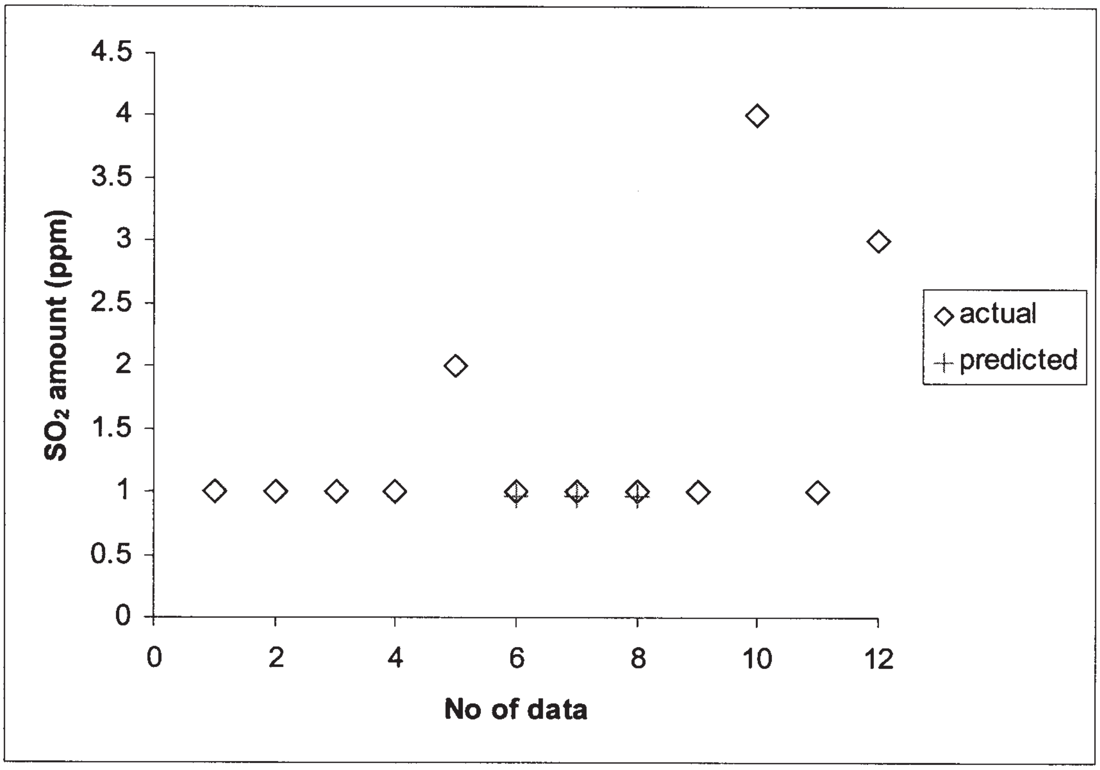


(c)

Figure 6 : *Actual and predicted data of* NO_x



(a)



(b)

Figure 7 : *Actual and predicted data of SO_2*

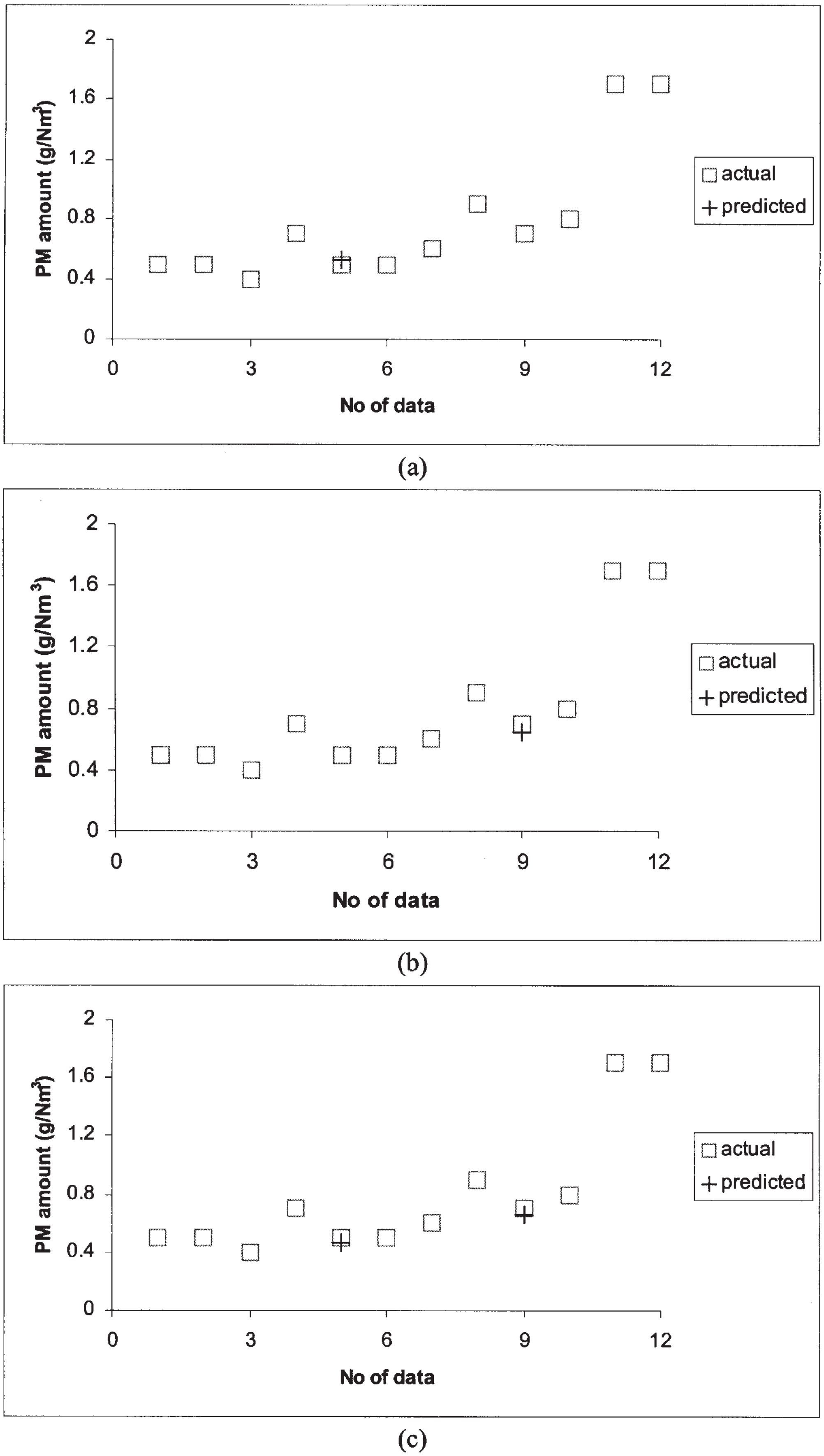


Figure 8 : *Actual and predicted data PM*

4.5 Coefficient of Regression between Experimental and Predicted Data

The accuracy of the pollutants between the actual data and simulation data, can be measured by introducing the coefficient of regression, r for the relationship between these two data. Table 1 shows this relationship. A value of 1 implies that all the predicted data perfectly match with actual data. As shown, the accuracy of CO, NO_X and SO_2 are very good, as r slightly lower than 1, while low accuracy is achieved for PM result. Figure 9 shows a plot of simulation points against the actual points for one of the pollutants, i.e. NO_X. A linear relationship can be derived and from this plot, the coefficient of regression of 0.995 is achieved.

Table 1 : *The accuracy measurement between experiment and simulation result.*

	Pollutants results			
	CO	**NO_x**	**SO_2**	**PM**
Regression coefficient, r	0.999	0.005	0.969	0.753

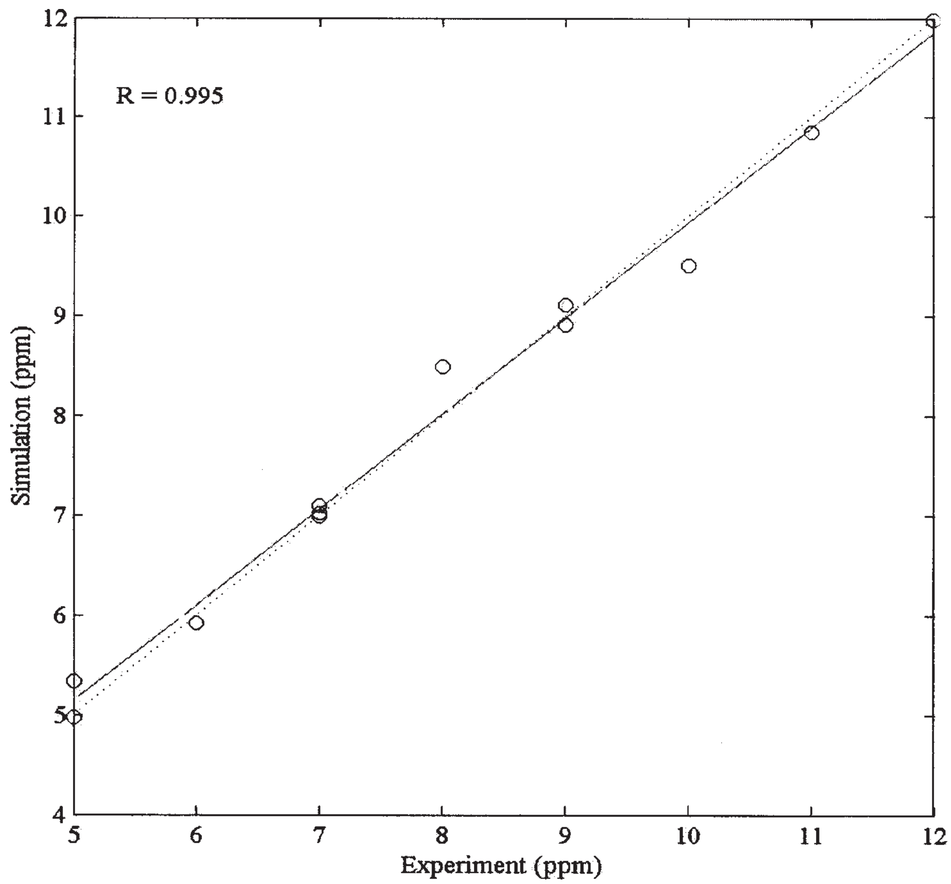


Figure 9 : *Deriving linear regression coefficient of actual and predicted data for NO_X*

5. CONCLUSION

This study was undertaken to monitor palm oil mill emission from the boiler to the atmosphere, as for the palm oil mill in Malaysia, there is no systematic means of controlling pollutants from being released from the chimney. It is also carried out to explore the capability of using Neural Network analysis in conjunction with the emission produced and the fuel being used in the combustion bed for palm oil mill. The study showed that back propagation Neural Network can accurately predict the quantity of pollutants, as the average percentage error is less than 8%. High accuracy of prediction is achieved for CO and NO_x, while good accuracy is achieved for both SO_2 and PM. The trained network can be further evaluated by sensitivity analysis, so that the relationship between the pollutants and input variable from boiler, fuel, and turbine can be examined and determined to control the pollution. The networking of the output pollution can be also be used to predict the emission that are produced by changing the input parameters. Thus, this simulation can be employed in a deterministic manner to infer the emission from chimney for given variations in any of the input parameters. A database of the output emission for the given flow rate of fuel, steam capacity and pressure, power output, exhaust gas temperature, turbine inlet, and outlet pressure can be built from this technique. With this combination of the input and output parameters, any desired results of the increase or decrease of pollution level can be acquired within a few seconds. From this modeling, the emission can be control to be at certain limit via controlling the input parameters and an optimum condition can be achieved. The approach of using Neural Network appears to be a useful tool in helping to understand and later, to determine the highly complex relationships between the boiler parameter and emissions produced from the palm oil mill. In short, back propagation Neural Network proves to be able to offer an alternative approach for effective emissions monitoring with reduced cost and efficient time.

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