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SENSITIVITY ANALYSIS VIA ARTIFICIAL NEURAL NETWORK OF BIOMASS BOILER EMISSION

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ABSTRACT

According to a survey in 1999, only 76 % of the palm oil mills in Malaysia meet the regulation of Department of Environment (DOE) regarding emission. The emission is released through the chimney from the process of fuel combustion and steam generation in order to produce power to the mill. The complex and very highly non-linear process involves several variables in fuel, turbine and boiler as factors producing pollutants. Therefore, Sensitivity Analysis via Artificial Neural Networks (SAANN) and Correlation Coefficient (CC) were used to find the major and minor input variables to each pollutant from 15 input variables. The result shows the major and minor input variables for both methods are similar.

Keywords: *Correlation coefficient, sensitivity analysis, artificial neural networks, biomass boiler emission*

1.0 INTRODUCTION

The smoke emission factors are quite complex, and are influenced by many processes. There are no direct mathematical relationships available between the fuel combustions, boiler processes and power load produced by turbine. Even though factors such as combustion, boiler process and mill process are related to each other in producing emission from steam power plant.

The combustion of fibre and shell is recognized as the main factor for boiler emission. The inconsistency in fuel flow affects combustion feature, steam generation, electric energy output and finally the emission [1]. Despite the fuel transfer system being driven by a motor at constant speed to supply the fuel, problem exists as fibre and shell are not fed uniformly due to variation in the rate of loading to trolley. It will also cause fluctuating calorific value and moisture, or fuel quality, interrupting the combustion rate and temperature. Combustion furnace also needs to be cleaned from unburnt carbon that influences the combustion rate. Briefly, not only fuel capacity causes the emission, but also the fuel types and its quality play a role in the emission production and cannot be easily controlled.

Steam generation from palm waste material combustion depends on the power load required. The processes and power needed influence fuel inlet capacity, air and water [2]. When power is unstable, it influences other factors to change their parameters automatically. High power electricity requires low pressure and high temperature steam [1]. Therefore, the electrical energy generated from turbine is proportional to the mill operation which involves many processes.

The air supply system is automatically controlled by the fuel inlet and inlet water capacity. The air supply will increase when excess of water in boiler drum and fuel flows into the oven. Although excess air supply is to achieve complete combustion, it also causes low combustion temperature and in return produces NO_x gas. However, less air supply causes CO emission and water attendant in boiler lead to less steam generation due to incomplete combustion. It will decrease boiler efficiency, power generation and affect optimum heat transfer of fuel combustion, steam production and power generation.

Hence, the air capacity, temperature and excess air are extremely complex to control and optimize in order to minimize smoke production. These processes are related to each other and are highly non-linear. They cannot be illustrated by direct equations to forecast the emission.

The complex factors and contributors to many processes in the palm oil mill have no direct relationship in predicting the emission. The operations in the palm oil mill, the processes and operations involve the furnace, boiler and turbine which are closely related to each other. Figure 1 illustrates the complexity of factors which affect emission.

Each output depends on several input variables. Some variables might have great contribution or influence to certain specific output variables only, and some others might have less influence to those specific output variables. The input variables which have great an impact on a particular output variable are called major input variables whereas those which interactions with small impact on that particular output variable are called minor input variables. All 15 input parameters taken can be divided into major and minor variables with respect to each output variable. In order to identify and eliminate minor input variables, several methods have been proposed by many researchers through statistical and ANN simulation. Statistical methods for parameters reduction include principal component analysis (PCA), F-Test, correlation coefficient and optimal brain damage [3]. In ANN approaches, several methods can be used such as sequential zeroing weights (SZW), system variation variables (SVV), sensitivity analysis (SA), fuzzy curves, changing mean square error and analysis of effectiveness [3].

Two types of sensitivity analysis introduced by [3] are SVV and SZW. Most researchers such as [4-6] suggested using partial differential sensitivity analysis. Present study will used SAANN using partial differential approach as it was successfully used in simple mathematical functions as real engineering problem [4], exclusive OR (XOR) network with three additional random inputs [5] and steam generator which used enthalpy, steam pressure and primary outlet temperature as output parameters [6]. No researchers focus and study on SAANN for biomass boiler emission.

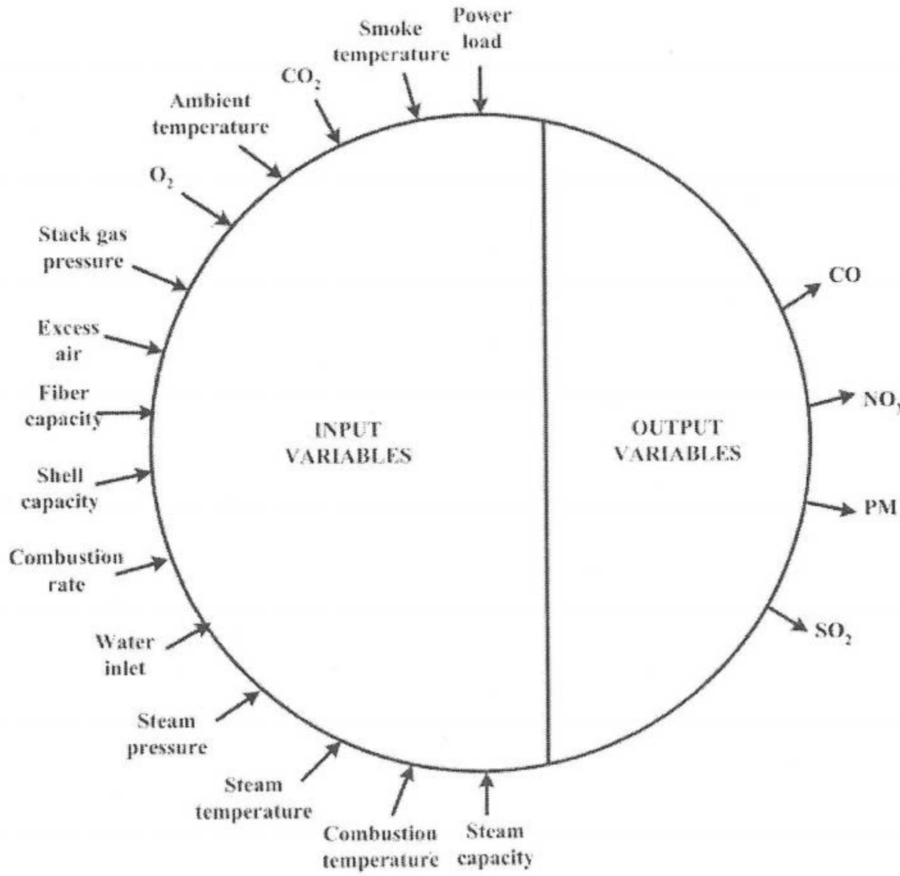

Figure 1 Input and output parameters for a typical boiler emission

The discussion on the input and output variables with respect to the pollution is simplified by the illustration shown in Figure 1. As discussed, the complex factors and contributors to many processes in the palm oil mill have no direct relationship in predicting the emission. The operations in the palm oil mill, the processes and operations involve the furnace, boiler and turbine which are closely related to each other. Figure 1 illustrates the complexity of factors which affect emission such as steam pressure (Sp), steam capacity (Sc), feed water (Fw), steam temperature (St), furnace combustion (Fc), boiler outlet (Bo), water level (Wl), ambient temperature (At), flue gas temperature (Ft), excess air (Ea), fibre flowrate (Ff), shell flowrate (Sf), power output (Po), oxygen (O_2) and carbon dioxide (CO_2). The output emissions include carbon monoxide (CO), nitrogen oxide (NO_x), sulphur dioxide (SO_2) and particulate matter (PM) which represent the pollutants as the effect from the boiler process while generating electricity.

As these parameters are highly complex and non-linear and in various interaction between factors inside the process can be regarded as a black box. The main concern from this process is to monitor and subsequently control the release of emission. As the whole process involves the cause and effect or input and output, Sensitivity Analysis via Artificial Neural Networks (SAANN) is found to be a feasible method to model the boiler emission from palm oil mill.

In this paper, Artificial Neural Networks (ANN) will be used to model combustion process consisting of input variables such Sp, St, Fw, *etc.* as input factors and pollutants such as CO, NO_x, SO_2 and PM as output variables. After that, SAANN can be used to recognize the major and minor contributors to the pollutants from input variables. The results were validated with correlation coefficient.

2.0 METHODOLOGY

The data collected from mill consists of 120 sets of input and output variables collected from palm oil mill at Nibong Tebal, Pulau Pinang during operation hour of 8 hours per day with 15 minutes interval time. The 15 input variables and 4 output variables (pollutants) which are arranged according to the time of the data collection. Data collection from steam plant palm oil mill is taken at five locations (turbine, boiler, fuel inlet, exhaust and stack chimney). These locations are chosen as the sources of the input and output variables selected based on the contributing factors to emission. Output variables of emission (CO, NO_x, SO_2 and PM) are collected from the stack chimney. The data at boiler and steam turbine are 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 are utilized at the stack chimney.

Data collection is utilized to model input and output variable using optimum structure of ANN. The models show relationship between input and output variable is establised when achieved 0.00001 mse. The established ANN model then applied with SA. SAANN can rank and select the major and input variables through its analysis. SA with partial differential is based on calculation of input, weights and output variables from the ANN simulation. The calculation of sensitivity, S is as follows [4]:

$$S = \frac{\partial O}{\partial I} = O' \sum_{J=1}^{J} \left(w_{ij}^{1} H' w_{ij}^{2} \right) \tag{1}$$

$$S = \frac{\partial f(O)}{\partial X} \sum_{J=1}^{J} \left(w_{ij}^{1} \frac{\partial f(H)}{\partial X} w_{ij}^{2} \right) \tag{2}$$

where O is output and H is a hidden node that have to be differentiated, w_{ij}^{1} and w_{ij}^{2} are the weights with respect to the first and second connection of hidden layer.

The first connection is for input and hidden layer and the second connection is for hidden node and output layer. It computes each set of input and output data. If the network has bias, the equation becomes:

$$S = O' \sum_{J=1}^{J} \left(\left(w_{ij}^{1} H' + b_{ij}^{1} \right) w_{ij}^{2} + b_{ij}^{2} \right) \tag{3}$$

$$S = \frac{\partial f(O)}{\partial X} \sum_{J=1}^{J} \left((w_{ij}^{1} \frac{\partial f(H)}{\partial X} + b_{ij}^{1}) w_{ij}^{2} + b_{ij}^{2} \right) \tag{4}$$

By using Equation 3, the value for each input corresponding to a single and multiple outputs can be obtained. All ANN models for sensitivity analysis use the training data to perform sensitivity value. By referring to sensitivity value, the input variables can be ranked for their contribution to the output. The results with a value more than 1 represent major factors and the value less than 1 represents minor factor.

Prior to ANN application, an approach is required to make the network structure optimum in order to achieve generalized and high accuracy network with less simulation time. During training, ANN will learn from input data and adjust the weight smoothly to give desired output. According to [7], the number of hidden layer depends on the data, which can be determined through training. More number of hidden layer cause long time for training and will produce unstable network [8] but it produces better results [9]. The suitability of time and accuracy must be considered. Trial and error method is usually applied to get the optimum nodes and layer numbers [7]. High number of hidden layer/nodes causes a slow time for training, but usually gives better prediction. In contrast to that, less number layer/node gives incorrect prediction. As a result, to find an optimum structure through the trial and error method, time for training, number of iterations and square error achieved by network with different hidden node as indicated by 'h' in Table 1 should be considered. In this research, only a single hidden layer is employed referring to Kolmogorov's theorem [9]. Briefly stated, Kolmogrov claimed that a single hidden layer or three layers back propagation network is enough to map any function to very high precision and better prediction.

After obtaining the optimum structure for all 5 models of simulation (4 for each output and 1 for all output), the SAANN are carried out. A ThinkPro software version 1.05 is itilized. This window base software provides the sensitivity analysis after data simulation by ANN. The software uses Artificial Neural Networks setting parameters as shown in Table 2. In this study, the Levenberg-Marquart algorithm is used as suggested and used by many researchers such as [8,11-14]. During this ANN process, the weights and bias are initialed in randomized order. For a 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 0.95 are utilized. Both values are applied as initial value 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 maximum epoch or when square error reaches a value of 0.00001 between the actual and predicted value.

Table 1 Typical ANN setup for CO model of sensitivity analysis

Structure	Feedforward
Algorithm	Back propagation
Type of training	Trainlm
Network structure	15, h and 1
Transfer function	Sigmoid and linear
Number of iterations	1000 (max epoch)
Performance function	Mean square error (mse)=0.00001
Data scaling	Standard deviation and mean
Learning rate	0.01
Momentum	0.95

Statistical method offers a tool to analyse raw data from experiment and dividing data into uniform distribution lead to generalized model. This statistical method can be used to filter outlier or minor input variables from the raw data [15-17]. Thus, the correlation coefficient is used for measuring the linear relationship between input and output parameters in order to remove minor variables as employed by [17]. The correlation measured with r-value (correlation) is based on Equation 5 [18] as:

$$r = \frac{\sum_{x=1}^{120}(x-\mu_x)(y-\mu_y)}{(n-1)\sigma_x\sigma_y} \tag{5}$$

In this equation, x is the input variable, y is the output variable, μ_x is defined as mean value of input variable, μ_y is defined as mean value of output variable, σ_x refers to standard deviation of input variable, σ_y refers to standard deviation of output variable and n is the number of data sets used. By using Microsoft Excel software, the correlation coefficient of the input and output are analyzed to establish a degree of relationship. The r-value can determine whether the relationship between single input and single output is strong, weak, moderate or no relation at all as shown in Table 2 [19,20]. If it shows no relationship, it will be defined as a minor variable and other relationship (strong, weak and moderate) illustrate major input variables corresponding to the output variable.

Table 2 Relationship and determination of correlation coefficient [18,20]

r-value	Types of relationship	Classification
$r \leq 0.8$ or $r \leq -0.8$	Strong	Major
$0.5 < r < 0.8$ or $-0.5 < r < -0.8$	Moderate	Major
$-0.5 \leq r \leq 0.5$	Weak	Major
$r < 0.1$ or $r > -0.1$	No Relationship	Minor

3.0 RESULT AND DISCUSSIONS

To construct generalized and accurate ANN model, all 15 input variables need to be classified into minor and major variables that contribute to the emission. The raw data are analyzed using simulation of ANN with sensitivity analysis and correlation coefficient analysis.

Prior to the sensitivity analysis, trial and error method is employed to optimize the ANN structure. For example, Figure 2 shows the results of trial and error method for CO. From the graph, the optimum structure can be determined from the minimum mean square error of 0.0089239 at the value of 27 (number of hidden neuron). So, the optimum structure for CO model is 15, 27 and 1. The first column refers to the input neuron number, the second column for the number of hidden nodes and the third column for the number of output nodes. A large hidden node shows the complexity of the network during simulation [7]. Similar procedure is carried out for other output variables to find optimum structure of ANN and the results are in Table 3:

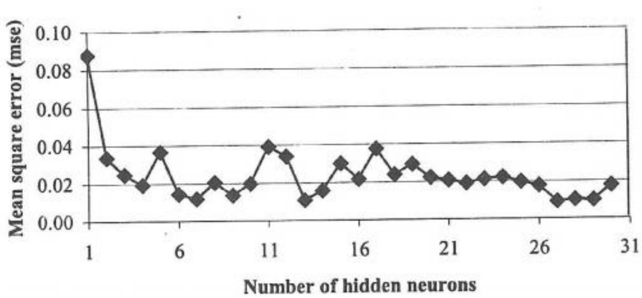

Figure 2 Number of hidden neurons for CO model

Table 3 Optimum structure of models

Model	Input neuron number	Hidden neuron number	Output neuron number
NO_x	15	27	1
SO_2	15	28	1
PM	15	26	1

Figure 3 shows the results of trial and error method for multiple outputs. It shows minimum mean square error (mse) of 0.0109490 represented by number of hidden neuron with value of 30. The optimum structure of multiple output model is 15, 30 and 4. The minimum mse for multiple output is slightly bigger than that for single output because of more than one output neurons used in the output layer make the network difficult for prediction. The maximum hidden nodes are always used to predict the multiple output [21].

The SAANN is carried out to find the major and minor input variables to the emission released based on the above optimum model structures. The analysis is carried out by 'ThinkPro' software using all sets of data and the results are shown in Table 3. Based on the sensitivity analysis as in Equation 3, the ranking of all input parameters for each pollutant is established based on sensitivity analysis value; the higher value indicates the higher ranking of input parameter [3]. Minor input variables are represented by the value less than 1, while major input variables are indicated by the value more than 1. The SAANN values with the bold show the major input variables for the corresponding output.

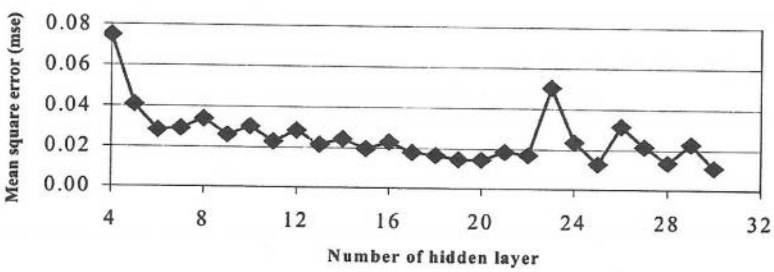

Figure 3 Number of hidden neurons for multiple model

As shown in Table 3, about 40 % from all input variables are major input variables to CO, while about 47 % to NO_x. However, the percentage of major input variables increase for both PM and SO_2, i.e. about 60 %. For multiple output model, about 60 % from all input variables are major input variables. These major input variables are slightly be different from the single model. SAANN is based on the calculation of Equation 3 where it depends on the data and ANN simulation to determine weights [4].

Table 4 shows the r-value for each of 15 input variables against 4 output variables using the whole data. The relationship between the input and output variables are determined from their correlation coefficient. The results indicate the relationship between the input variables and the emission according to Table 4 based on their r-value. The correlation coefficient (r-value) indicates the level of relationship such as strong, moderate, poor or no relationship between particular input and output variables. As shown in Table 4, only steam temperature (Sf) as input variable for CO, shows the strong relationship.

Table 3 Sensitivity Analysis and their ranking of input variables contribution to the emission

Variables	CO	Rank	NO_x	Rank	SO_2	Rank	PM	Rank	Multiple	Rank
Steam pressure	0.8668	12	**1.5530**	1	**1.0797**	5	0.9040	12	**1.2035**	1
Steam capacity	**1.0686**	4	0.9932	8	**1.0324**	8	0.9924	11	0.8387	14
Feed water	0.9648	10	0.9257	11	**1.3069**	1	**1.0392**	8	**1.1440**	2
Steam temperature	**1.0574**	5	0.9898	9	**1.1048**	3	0.9016	13	**1.0685**	5
Furnace combustion	0.9989	7	**1.0099**	6	**1.0873**	4	**1.2287**	1	**1.0017**	9
Boiler outlet	0.9930	8	0.7331	14	0.7166	15	**1.0927**	4	**1.0261**	7
Water level	0.9915	9	0.7175	15	0.7270	14	**1.0545**	6	0.8017	15
Ambient temperature	0.8278	13	0.8646	13	0.9575	10	**1.0001**	9	0.9444	10
Flue temperature	0.7376	15	0.9733	10	**1.0792**	6	**1.0516**	7	0.8885	13
Excess air	0.9635	11	**1.0062**	7	0.9331	12	0.7739	15	0.9280	11
Fiber flow	**1.0067**	6	**1.0774**	5	**1.0327**	7	**1.0632**	3	**1.0370**	6
Shell flow	**1.1421**	3	**1.0813**	4	**1.0113**	9	**1.1097**	2	**1.0191**	8
Power	**1.1781**	2	**1.4555**	2	**1.1837**	2	0.9998	10	**1.0874**	3
Oxygen	**1.5843**	1	0.9166	12	0.9536	11	**1.0570**	5	**1.0846**	4
Carbon dioxide	0.8122	14	**1.1030**	3	0.8943	13	0.8319	14	0.9270	12

From the result, out of 15 input variables, there are 29 variables showing no relationship, 20 variables showing weak relationship and 10 variables showing moderate relationship between the input and output variables. Poor relationship input variables are given by Fw, Ea, O_2 and CO_2 respectively. As for PM, most input variables demonstrate either no relationship or weak relationship between the variables while most inputs for NO_x and SO_2 illustrate weak, moderate and no relationships. According to [17] the variables with correlation coefficient less than 0.1 or no relationship are required to be discarded from the models. These variables are called minor input variables. In this case, as shown in Table 4, the variables indicated in bold letter represent the major input variables to the corresponding output and the minor input variables are represented by no relationship which r-value is less than 0.1. The results obtained by CC to determine whether the input variables major or minor depend very much on the data input of high or low contribution to the output [19].

Based on the above CC and SAANN results, the major and minor input variables can be determined. All CC analyses show similar results of major and minor input variables to the SAANN analyses. Table 5 shows the major input variables for CO, NO_x, SO_2 and PM as obtained by CC and SAANN. Different emission outputs demonstrate different major input variables from all 15 input variables.

Table 4 Correlation Coefficient between input variables and output variables

Variables	CO			NO_x			SO_2			PM		
	r^2	r value	Relationship	r^2	r value	Relationship	r^2	r value	Relationship	r^2	r value	Relationship
Steam pressure	0.0088	0.09	No Relationship	0.3567	0.60	Moderate	0.26	0.51	Moderate	0.0051	0.07	No Relationship
Steam capacity	0.28808	0.54	Moderate	0.0061	0.08	No Relationship	0.0111	0.11	Weak	0.0052	0.07	No Relationship
Feed water	0.0039	0.06	No Relationship	0.0026	0.05	No Relationship	0.0181	0.13	Weak	0.0741	0.27	Weak
Steam temperature	0.6045	0.78	Strong	0.0024	0.05	No Relationship	0.4458	0.67	Moderate	0.0016	0.04	No Relationship
Furnace combustion	0.0072	0.08	No Relationship	0.0104	0.10	Weak	0.0140	0.12	Weak	0.0276	0.17	Weak
Boiler outlet	0.0082	0.09	No Relationship	0.0064	0.08	No Relationship	0.0004	0.02	No Relationship	0.119	0.34	Weak
Water level	0.0063	0.08	No Relationship	0.0021	0.05	No Relationship	0.0051	0.07	No Relationship	0.013	0.11	Weak
Ambient temperature	0.0085	0.09	No Relationship	0.0064	0.08	No Relationship	0.0058	0.08	No Relationship	0.0351	0.19	Weak
Flue temperature	0.0009	0.03	No Relationship	0.0003	0.02	No Relationship	0.3135	0.56	Moderate	0.122	0.35	Weak
Excess air	0.0025	0.05	No Relationship	0.3112	0.56	Moderate	0.0001	0.01	No Relationship	0.0053	0.07	No Relationship
Fiber flow	0.2687	0.52	Moderate	0.1138	0.34	Weak	0.1343	0.37	Weak	0.0854	0.29	Weak
Shell flow	0.1101	0.33	Weak	0.0395	0.20	Weak	0.1885	0.43	Weak	0.0985	0.31	Weak
Power	0.3829	0.62	Moderate	0.2493	0.50	Moderate	0.2868	0.54	Moderate	0.0533	0.23	No Relationship
Oxygen	0.0099	0.10	Weak	0.0047	0.07	No Relationship	0.0039	0.06	No Relationship	0.0156	0.12	Weak
Carbon dioxide	0.0086	0.09	No Relationship	0.0102	0.10	Weak	0.0078	0.09	No Relationship	0.0032	0.06	No Relationship

Table 5 Major input variables to the emission released

Input variables	Output variables				
	CO	NO_x	SO_2	PM	Multiple
Steam pressure		✓	✓		✓
Steam capacity	✓		✓		
Feed water			✓	✓	✓
Steam temperature	✓		✓		✓
Furnace combustion		✓	✓	✓	✓
Boiler outlet				✓	✓
Water level				✓	
Ambient temperature				✓	
Flue gas temperature			✓	✓	
Excess air		✓			
Fibre flowrate	✓	✓	✓	✓	✓
Shell flowrate	✓	✓	✓	✓	✓
Power output	✓	✓	✓		✓
Oxygen	✓			✓	✓
Carbon dioxide		✓			

4.0 CONCLUSION

From SAANN and CC analysis, fibre and shell appear as major contributors to all pollutants. For multiple output models, only 9 out of 15 input variables are found to be major input variables. The correlation coefficient can only determine major and minor variables for single input and single output only. It cannot determine major and minor interaction input variables for multiple output. SAANN is more suitable to determine major and minor input variables for both single and multiple input/output models. In conclusion, the main contributors to the emission come from fuel, turbine, air and boiler parameters.

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