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DETERMINATION OF SIGNIFICANT VARIABLES TO PARTICULATE MATTER (PM_{10}) VARIATIONS IN NORTHERN REGION, MALAYSIA DURING HAZE EPISODES (2006-2015)

K. M. K. Ku Yusof[1], A. Azid[1,2,*] and M. A. Jamalani[3]

[1]Faculty Bioresources and Food Industry, Universiti Sultan Zainal Abidin (UniSZA), Besut Campus, 22200 Besut, Terengganu, Malaysia

[2]UniSZA Science and Medicine Foundation Centre, Universiti Sultan Zainal Abidin (UniSZA), Gong Badak Campus, 21300 Kuala Nerus, Terengganu, Malaysia

[3]Faculty of Environmental Studies, Universiti Putra Malaysia (UPM), 43400 Serdang, Selangor, Malaysia

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ABSTRACT

The most substantial air pollutant variables during haze episode in Northern region for 10-consecutive years (2006-2015) were analyzed and highlighted. ANN together with SAPCR were integrated to identify the variables contributed to fluctuation of particulate matter (PM_{10}) during haze period. 13 variables including air pollutant and meteorological factor were included as explorable variables. The humidity, wind speed and ozone were recognized as determinant to PM_{10} variation during haze from 2006-2015. Three artificial neural models were created based on all parameters, leave-out method and PCR-factor loading. The best model will be selected based on a few criterions like determination of coefficient, R^2, root-mean-square-error and squared sum of all errors. ANN-HM-LO was a better model than ANN-HM-PCR in overall prediction performance with R^2 result for ANN-HM-LO was 0.839, whilst ANN-HM-PCR was just 0.801.

Keywords: haze studies; sensitivity analysis; artificial neural network; principal component regression.

Author Correspondence, e-mail: azmanazid@unisza.edu.my

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1. INTRODUCTION

Southeast (SE) Asia is well known as the region where the frequency of the haze rate is high as the rest of other region. Commonly, the haze in SE Asia was highly contributed from massive scale forest fire, yet the most cases of forest fires had happened on the peat soil-type. Started as biomass fires, the particulate matter (PM) emitted in smoke could be highly transported thousands miles away from the multi-origin point. The prolonged issues of haze could be blanketing neighboring countries by day, week or monthly time. Thus, haze issues are not only be considered as national agenda but more likely to be as regional conflict of interest [17]. The SE Asia haze history was started about two decades ago by Sumatera and Kalimantan areas but the intensity, frequency, duration and severity may be increased over time. The first case was recorded in 1983 and since then there were repetitive haze incident in 1990, 1991, 1994, 1997, and 1998 like been reported by [13]. They also regarded as 1997 and 1998 haze events were the worst case ever in SE Asia region.

Malaysia as one of the neighboring countries in SE Asia, has extremely affected by regional transboundary haze for past 20 years. The effect was not only to human health issues, but more widely concern into national income losses. The Department of Environment, Malaysia (DOE) has released the list which detailed out the year, exact situation and location affected during haze event started in year 1994 up to 2015. Thus, the imperative of study, identify and understand is crucial to avoid any undesirable circumstances in the future. In order to recognize of haze characteristics, in [2] has summarized that Particulate Matter (PM_{10}) and Carbon Monoxide (CO) were two main components are dominating in Malaysian Air Pollutant Index (MAPI) compare to the rest of other pollutant stated in API calculation. Factually, particulate matter with size less than 10μm could be referred as PM_{10} while particulate matter less than 2.5 μm in diameter as $PM_{2.5}$ [21]. Despite of consistently used as MAPI calculation, in [15, 18] emphasized that particulate matter smaller than 10 mm (PM_{10}) is actually act as a precursor to the haze formation throughout Malaysia. PM_{10} is easily dispersed in atmospheric, and it is highly correlated to meteorological process. An anomalous weather condition, for example, drier Southwest (SW) monsoon El-Nino Southern Oscillation (ENSO) and would exacerbate the PM_{10} level. Local anthropogenic factor like petroleum based emission, industrial and small-local agricultural activity are the contributor to elevation of PM_{10} during non-haze period. Therefore, application of statistical and modeling approach could be alternatives option to discover the variability of PM_{10} in the atmospheric circumstances, especially in Malaysia.

Artificial Neural Networks (ANN) was developed in 1950s as imitation a function of brain system, and it has been widely used to solve environmental issues. In [19] reported that ANN is useful tool to develop an efficient air quality analysis and future prediction models in Istanbul. In [12] on the other hand was using ANN as spatial modeling of Air Temperature (AT) and Relative Humidity (RH) in Greece. In Malaysia, in [4] able to predict daily maximum O_3 concentrations based on meteorological parameters. A good thing of ANN application in environmental is suited for large, complex multidimensionality non-linear data. Despite of having capabilities to process multidimensional data, the black box concept used as a replacement to input-output system will shorten the process period [12]. ANNs is an architecture structure, composed by input-ouput system, process and interconnected by multilayer neurons [20] which divided into three main processes; the train set, the test set and the validation set [11].

In this study, Sensitivity Analysis (SA) and Principal Component Regression (PCR) were used as additional tools in order to identify the best selection of air quality parameter. Once the parameter has been statistically identified, the parameters will be included as input into different type of ANN development models. The integration ANN-SA and ANN-PCR technique are rarely been used in air quality studies, but have been widely applied in other field studies [2]. The objective of this study is to identify the most significant variables contribution PM_{10} levels during haze period in Northern region during year 2006-2015.

2. METHODOLOGY

2.1 Study Area

The northern region is made from couple of states; the northernmost, Perlis and Kedah, followed by Penang and Perak. The synonym to this region is on their rice field. However, Perak has rocky part of limestone outcrop. Perlis is the smallest states (810 sq. km) while Perak has biggest areas among the rest. Northern region has approximately 20.7% of Malaysia's population or equal to 6.56×10^6 people. Perlis, Kedah and Perak are the only states share the land boundary to Southern part of Thailand, but all do share the same straits of Malacca. All twelve study areas as depicted in Fig. 1 are managed by Air Quality Division, Department of Environment, Malaysia but the installation and maintenance works are subjected onto Alam Sekitar Malaysia Sdn. Bhd. (ASMA). As this region is mostly filled with agricultural activities, the biomass fires are the cheapest and convenient way for farmers to manage their vegetation residual. Therefore, the deterioration of air quality in this area is crucial to be further studied. The details for study area are tabulated in Table 1.

Table 1. The coordinate for Continuous Air Quality Monitoring (CAQM) study area

Sampling ID	Sampling location	State	Latitude	Longitude
N1	Langkawi	Kedah	N 6.3317	E 099.8586
N2	Kangar	Perlis	N 6.4237	E 100.1841
N3	Alor Setar	Kedah	N 6.1370	E 100.3480
N4	Sungai Petani	Kedah	N 5.6314	E 100.4698
N5	Balik Pulau	Pulau Pinang	N 5.3588	E 100.2977
N6	Seberang Perai	Pulau Pinang	N 5.3912	E 100.3869
N7	Seberang Perai	Pulau Pinang	N 5.3982	E 100.4032
N8	Taiping	Perak	N 4.8990	E 100.6797
N9	Ipoh	Perak	N 4.6297	E 101.1161
N10	Ipoh	Perak	N 4.5526	E 101.0809
N11	Manjung	Perak	N 4.2006	E 100.6640
N12	Tanjung Malim	Perak	N 3.6878	E 101.5244

2.2. Data

The recorded hourly values for 13 air-pollutant parameters including atmospheric pollutant (particulate matter (PM_{10}), nitrogen oxide (NO_x), nitrogen monoxide (NO), methane (CH_4), non-methane hydrocarbon (NmHC), total hydrocarbon (THC), sulphur dioxide (SO_2), nitrogen dioxide (NO_2), ozone (O_3), carbon monoxide (CO) and meteorological factors (wind speed (WS), air temperature (AT), relative humidity (RH) and ultraviolet-b (UV_b)). All data were daily averaged and the only day which contained air pollutant and meteorological parameter subjected to PM_{10} levels above more than 150µg/m^3 (≥150µg/m^3) are selected for further analysis in this haze study. The selection for PM_{10} above than 150µg/m^3 (≥150µg/m^3) is being made due to stipulated standard limit in Recommended Malaysia Air Quality Guideline (RMAQG). A total of 2,591 out of 43,324 observation datasets are available after filtration for four states in Northern region.

The data from 12 study areas for ten-year period (2006-2015) were obtained from Department of Environment, Malaysia as part of their long of period Continuous Air Quality Monitoring (CAQM) program. PM_{10} concentrations were monitored by using b-ray attenuation mass monitor (BAM-1020) as manufactured by Met One Instruments Inc. [7, 9]. The model equipped for continuously monitor for every single atmospheric pollutant and meteorological parameter are listed in Table 2.

Table 2. CAQM model equipment for each parameter

Parameter	Model Equipment
Wind Speed (WS)	Met One 010C
Air Temperature (AT)	Met One 062
Relative Humidity (RH)	Met One 083D
Nitrogen Oxide (NOx)	Teledyne API Model 200A/200E
Nitrogen Monoxide (NO)	Teledyne API Model 200A/200E
Ultraviolet-b (UV_b)	
Methane (CH_4)	Teledyne API M4020
Non-methane Hydrocarbon (NmHC)	Teledyne API M4020
Total Hydrocarbon (THC)	Teledyne API M4020
Sulphur Dioxide (SO_2)	Teledyne API Model 100A/100E
Nitrogen Dioxide (NO_2)	Teledyne API Model 200A/200E
Ozone (O_3)	Teledyne API Model 400/400E
Carbon Monoxide (CO)	Teledyne API Model 300/300E

2.3. Sensitivity Analysis (SA) and Artificial Neural Network (ANN)

Sensitivity analysis (SA) described by [10] is a data assimilation problem. The definition brought by [10] is where a function, x in which the gradient, S of interest or output. In addition, if the assimilation problem does not encounter any problem, the sensitivity analysis could be used as determinant to a model development [10]. In this study, sensitivity analysis is used to examines 13 parameter as input, while predicted PM_{10} is selected as output. As reference, sensitivity analysis will be integrated with artificial neural network to develop a haze model (HM) namely ANN-HM-AP.

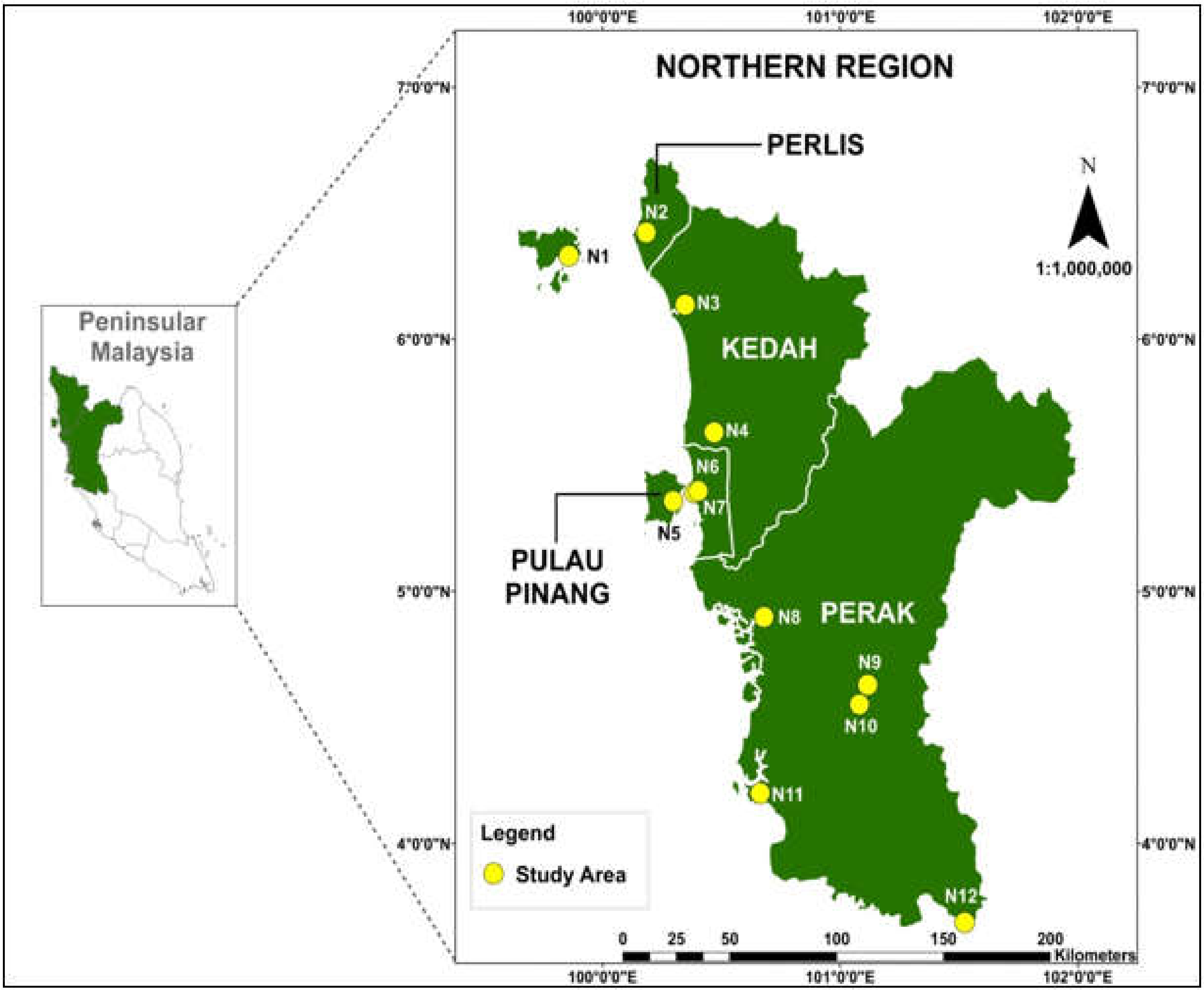

Fig.1. The location for 12 study areas (N1-N12) within Northern region used in this study

Therefore, coefficient of determination (R^2) was used as determinant to differentiate from other models. However, to determine the most significant parameter to be used in the second model, elimination of each parameter process will be manually calculated. Hence, R^2 values will be sort out from highest to smallest value by applying 'leave-one-out parameter" technique. The second model then named as artificial neural network-haze model-leave (parameter) or ANN-HM-L (parameter). For 13 parameters, including WS, AT, RH, NOx, NO, UVb, CH_4, NmHC, THC, SO_2, NO_2, O_3 and CO, then was namely ANN-HM-LWS, ANN-HM-LTemp, ANN-HM-LRH, ANN-HM-LNOx, ANN-HM-LNO, ANN-HM-LUVb, ANN-HM-LCH_4, ANN-HM-LNmHC, ANN-HM-LTHC, ANN-HM-LSO_2, ANN-HM-LNO_2, ANN-HM-LO_3 and ANN-HM-LCO. Hence, the percentage contribution of each variable is essential to recognize the highest contributor onto PM_{10} during haze episodes. The ANN diagram can be seen in Fig. 2.

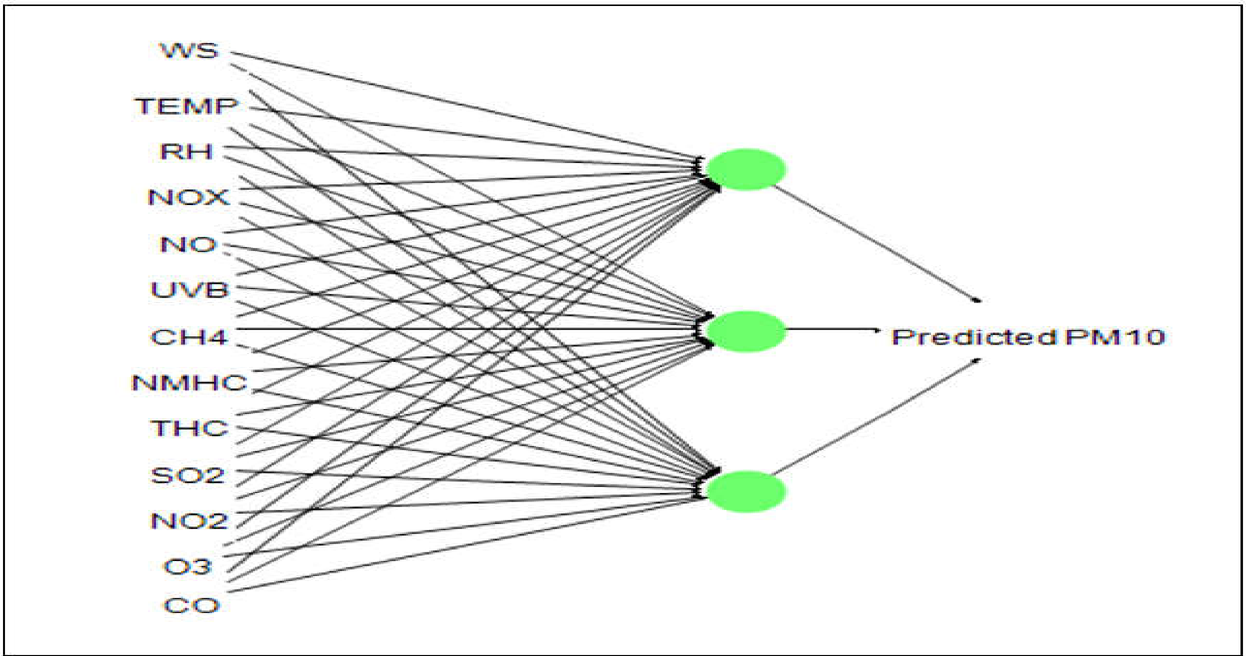

Fig.2. ANN multilayer perceptron [28] for PM_{10} prediction

2.4. Haze Model Development by Integrating ANN as Predictor

The integration of ANN in the model development is to determine the most substantial model that affecting PM_{10} during haze period. Three different types of models were developed and briefly described as below:

Full model	:	This model based on all thirteen parameters and recognized as ANN-HM-AP
Selected Model	:	This models is developed by selection parameter based on highest contribution to PM10 variations during haze event (ANN-HM-LO)
PCR model	:	This model is developed based on two factor loading comprise of 9 parameters (ANN-HM-PCR). The factor loading with values more than 0.70 (≥ 0.70) were selected as input in this model [3] (see Table 5 and Table 6)

2.5. Determination of Best Input Selection for Haze Model

To evaluate the ANN performance, three statistical indices were used: the coefficient of determination (R^2), the Root Mean Square Error (RMSE), the Sum Square Error (SSE), derived by statistical calculation based on output result. The formulas were expressed as below [1, 19, 22]:

$$R^2 = 1 \frac{\sum(x_i - y_i)^2}{\sum y_i^2 - \frac{\sum y_i^2}{n}} \quad (1)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2} \quad (2)$$

$$SSE = \sum_{i=1}^{n}(x_i - y_i)^2 \quad (3)$$

where in Equation (1)-(3), x_i = the observed data, y_i = the predicted data and n = the observation number.

The range calculation for R^2 is in between 0.0-1.0. The lowest value of R^2 explained that model considered as weak, whilst the highest value ($R^2 = 1.0$) is indicates the suitability to be chosen as the best predictor [6, 14].

3. RESULTS AND DISCUSSION

3.1. Leave-One-Out Results

The "leave-one-out technique" was used by using sensitivity analysis to produce the R^2 results. From the R^2 results, the percentage (%) contribution was manually calculated and the parameters were ranked from the highest contribution till the least percentage. 13 parameters were selected as input to predict the PM_{10} value during haze study. From the results, only three parameters have showed a convincing performance; relative humidity (33.251%), followed by wind speed (29.640%) and ozone (18.017%). Despite of having the highest contribution by three parameters earlier, the parameters namely AT (9.017%), SO_2 (6.504%), CO (1.881%), UV_b (0.658%), NO_x (0.576%), NmHC (0.200%), CH_4 (0.145%), NO (0.066%), NO_2 (0.023%) and THC (0.021%), respectively were classified as least contributor to PM_{10} variations during haze period in northern region. The full contribution results are shown in Table 3.

The meteorological factors like wind speed and relative humidity were dominated the highest rank to PM_{10} variations especially during the hazy days from 2006 to 2015 period. The studies conducted by groups of scholars have proved that wind speed and relative humidity are strongly related to PM_{10} [16, 18]. The anomalous drier weather phenomenon like ENSO are affecting the meteorological factors and indirectly speed up the PM_{10} concentration process during haze [23]. On the other hand, in [5] wrote that the only two parameters have high contributor to atmospheric pollutant, namely PM_{10} and ozone (O_3). The O_3 result in the northern region proved that PM_{10} was not the only parameter polluted the atmosphere, but also with O_3 levels.

3.2. Comparison of ANN Models for Haze Model Prediction

Three different models were carried out, namely full, selected and PCR model. In order to maximize the probability in producing the best input selection for PM_{10} prediction, three statistical indices were calculated and to evaluate the model performance, expressed by R^2, RMSE and SSE. To verify the model fitness, the train set and the validation set also included in this study. All criterions for the models are presented in Table 4.

The first model comprises of all 13 parameters. This model was primarily developed and entitled as full model in order to be a reference for two other models. The different approach used in each models are only for input and output, while the number nodes was fixed to three hidden nodes. As reference model used all 13 parameters, selected model and PCR model was using three and nine parameters only, respectively. From the results, both RMSE and SSE result for full model are the lowest with the result of RMSE and SSE is 2.15×10^{-13} and 5.38×10^{-24} respectively. Contrarily with selected and PCR model, the R^2, RMSE and SSE values are 0.839, 2.885, 965.418 and 0.801, 3.160, 1158.274 respectively. The selected model nevertheless has R^2, RMSE and SSE was within full and PCR model, it considered as the best model compared than two other models. Not only with high R^2 result, selected model has proved that with only three selected parameter, it was adequate to predict the variation of PM_{10} during hazy days in northern region.

Table 3. Percentage contribution to PM_{10} based on sensitivity analysis result

Model	R^2	Difference R^2	% Contribution
ANN-HM-LWS	0.8969	0.1031	29.6395
ANN-HM-LAT	0.9686	0.0314	9.0170
ANN-HM-LRH	0.8843	0.1157	33.2511
ANN-HM-LNO_X	0.9980	0.0020	0.5762
ANN-HM-LNO	0.9998	0.0002	0.0662
ANN-HM-LUV_b	0.9977	0.0023	0.6582
ANN-HM-LCH_4	0.9995	0.0005	0.1448
ANN-HM-LNmHC	0.9993	0.0007	0.1996
ANN-HM-LTHC	0.9999	0.0001	0.0214
ANN-HM-LSO_2	0.9774	0.0226	6.5041
ANN-HM-LNO_2	0.9999	0.0001	0.0229
ANN-HM-LO_3	0.9373	0.0627	18.0175
ANN-HM-LCO	0.9935	0.0065	1.8815
Total		0.348	100.000

Table 4. Performance fitness for each model development

	Training			Validation		
	R^2	**RMSE**	**SSE**	**R^2**	**RMSE**	**SSE**
Full Model	1.000	2.15×10^{-13}	5.38×10^{-24}	1.000	$3.65E\times 10^{-13}$	7.71×10^{-13}
Selected Model	0.839	2.885	965.418	0.840	3.175	584.531
PCR Model	0.801	3.160	1158.274	0.844	3.269	619.675

Table 5. Eigenvalue result

	F1	**F2**
Eigenvalue	**7.177**	**1.711**
Variability (%)	55.208	13.164
Cumulative %	55.208	68.372

Table 6. Factor loading for PCR

	F1	**F2**
Wind Speed (WS)	**-0.710**	-0.187
Air Temperature (AT)	**-0.759**	-0.560
Relative Humidity (RH)	0.539	0.626
Nitrogen Oxide (NO_x)	**0.874**	-0.294
Nitrogen Monoxide (NO)	**0.761**	-0.279
Ultraviolet-b (UV_b)	-0.654	-0.519
Methane (CH_4)	**0.752**	-0.076
Non-methane Hydrocarbon (NmHC)	0.680	-0.411
Total Hydrocarbon (THC)	**0.837**	-0.268
Sulphur Dioxide (SO_2)	0.683	-0.161
Nitrogen Dioxide (NO_2)	**0.781**	-0.237
Ozone (O_3)	**-0.727**	-0.394
Carbon Monoxide (CO)	**0.839**	-0.232

4. CONCLUSION

The integration between sensitivity analysis (SA) and artificial neural network (ANN) [24-27] was an excellent statistical approach in producing a significant outcome to determine the most reliable factor to PM_{10} prediction during hazy days. The relative humidity leads the line with highest contribution to PM_{10}, followed by wind speed. Whilst, ozone is the only air pollutant involved for predicting PM_{10}. To be more precise, PM_{10} was not easily affected by fluctuations of other pollutant, but more onto meteorological factor. Based on three types of model development, the selected model (ANN-HM-LO) is the most suitable model to be considered. Compared to another models, ANN-HM-LO can give a reliable result with least parameter in predicting PM_{10}. Therefore, it is a very useful resource for Department of Environment Malaysia not only by using those three parameters as a precursor to haze episodes but more likely to national asset management.

5. REFERENCES

[1] Arhami M, Kamali N, Rajabi M M. Predicting hourly air pollutant levels using artificial neural networks coupled with uncertainty analysis by Monte Carlo simulations. Environmental Science and Pollution Research, 2013, 20(7):4777-4789

[2] Azid A, Juahir H, Toriman M E, Endut A, Rahman M N, Kamarudin M K, Latif M T, Saudi A S, Hasnam C N, Yunus K. Selection of the most significant variables of air pollutants using sensitivity analysis. Journal of Testing and Evaluation, 2015, 44(1):376-384

[3] Azid A, Juahir H, Toriman M E, Kamarudin M K, Saudi A S, Hasnam C N, Aziz N A, Azaman F, Latif M T, Zainuddin S F, Osman M R. Prediction of the level of air pollution using principal component analysis and artificial neural network techniques: A case study in Malaysia. Water, Air, and Soil Pollution, 2014, 225(8):1-14

[4] Banan N, Latif M T, Juneng L. An assessment of ozone levels in typical urban areas in the Malaysian Peninsular. Proceedings of World Academy of Science, Engineering and Technology, 2013, 74:147-151

[5] Demuzere M, Trigo R M, Vila-Guerau de Arellano J, Van Lipzig N P. The impact of weather and atmospheric circulation on O_3 and PM_{10} levels at a mid-latitude site. Atmospheric Chemistry and Physics Discussions, 2008, 8(6):21037-21088

[6] Hadzima-Nyarko M, Rabi A, Šperac M. Implementation of artificial neural networks in modeling the water-air temperature relationship of the River Drava. Water Resources Management, 2014, 28(5):1379-1394

[7] Juneng L, Latif M T, Tangang F. Factors influencing the variations of PM_{10} aerosol dust in Klang Valley, Malaysia during the summer. Atmospheric Environment, 2011, 45(26):4370-4378

[8] Oanh N T, Leelasakultum K. Analysis of meteorology and emission in haze episode prevalence over mountain-bounded region for early warning. Science of the Total

Environment, 2011, 409(11):2261-2271

[9] Latif M T, Dominick D, Ahamad F, Khan M F, Juneng L, Hamzah F M, Nadzir M S. Long term assessment of air quality from a background station on the Malaysian Peninsula. Science of the Total Environment, 2014, 482:336-348

[10] Le Dimet F X, Souopgui I, Ngodock H E. Sensitivity analysis applied to a variational data assimilation of a simulated pollution transport problem. International Journal for Numerical Methods in Fluids, 2017, 83(5):465-482

[11] Li F. Air quality prediction in Yinchuan by using neural networks. In Y. Tan, Y. Shi, & K. C. Tan (Eds.), Advances in swarm intelligence. Berlin: Springer, 2010, pp. 548-557

[12] Moustris K P, Ziomas I C, Paliatsos A G. 3-Day-ahead forecasting of regional pollution index for the pollutants NO_2, CO, SO_2, and O_3 using artificial neural networks in Athens, Greece. Water, Air, and Soil Pollution, 2010, 209(1-4):29-43

[13] Muraleedharan T R, Radojevic M, Waugh A, Caruana A. Chemical characterisation of the haze in Brunei Darussalam during the 1998 episode. Atmospheric Environment, 2000, 34(17):2725-2731

[14] Nagendra S S, Khare M. Modelling urban air quality using artificial neural network. Clean Technologies and Environmental Policy, 2005, 7(2):116-126

[15] Norela S, Saidah M S, Mahmud M. Chemical composition of the haze in Malaysia 2005. Atmospheric Environment, 2013, 77:1005-1010

[16] Payus C, Abdullah N, Sulaiman N. Airborne particulate matter and meteorological interactions during the haze period in Malaysia. International Journal of Environmental Science and Development, 2013, 4(4):398-402

[17] Radojevic M. Chemistry of forest fires and regional haze with emphasis on Southeast Asia. Pure and Applied Geophysics, 2003, 160(1-2):157-187

[18] Abas M R, Oros D R, Simoneit B R. Biomass burning as the main source of organic aerosol particulate matter in Malaysia during haze episodes. Chemosphere, 2004, 55(8):1089-1095

[19] Sahin U, Ucan O N, Bayat C, Oztorun N. Modeling of SO_2 distribution in Istanbul using artificial neural networks. Environmental Modeling and Assessment, 2005, 10(2):135-142

[20] Saraceno A, Aversa M, Curcio S. Advanced modeling of food convective drying: A comparison between artificial neural networks and hybrid approaches. Food and Bioprocess Technology, 2012, 5(5):1694-1705

[21] Shaadan N, Jemain A A, Latif M T, Deni S M. Anomaly detection and assessment of

PM_{10} functional data at several locations in the Klang Valley, Malaysia. Atmospheric Pollution Research, 2015, 6(2):365-375

[22] Sousa S I, Martins F G, Alvim-Ferraz M C, Pereira M C. Multiple linear regression and artificial neural networks based on principal components to predict ozone concentrations. Environmental Modelling and Software, 2007, 22(1):97-103

[23] Tangang F T, Juneng L, Salimun E, Vinayachandran P N, Seng Y K, Reason C J, Behera S K, Yasunari T. On the roles of the northeast cold surge, the Borneo vortex, the Madden-Julian Oscillation, and the Indian Ocean Dipole during the extreme 2006/2007 flood in southern Peninsular Malaysia. Geophysical Research Letters, 2008, 35(14):1-6

[24] Zabidi A, Yassin I M, Hassan H A, Ismail N, Hamzah M M, Rizman Z I, Abidin H Z. Detection of asphyxia in infants using deep learning convolutional neural network (CNN) trained on Mel frequency cepstrum coefficient (MFCC) features extracted from cry sounds. Journal of Fundamental and Applied Sciences, 2017, 9(3S):768-778

[25] Hashim F R, Daud N N, Ahmad K A, Adnan J, Rizman Z I. Prediction of rainfall based on weather parameter using artificial neural network. Journal of Fundamental and Applied Sciences, 2017, 9(3S):493-502

[26] Hashim F R, Adnan J, Ibrahim M M, Ishak M T, Din M F, Daud N G, Rizman Z I. Heart abnormality detection by using artificial neural network. Journal of Fundamental and Applied Sciences, 2017, 9(3S):1-10

[27] Mohd Yassin I, Jailani R, Ali M, Amin M S, Baharom R, Hassan A, Huzaifah A, Rizman Z I. Comparison between cascade forward and multi-layer perceptron neural networks for NARX functional electrical stimulation (FES)-based muscle model. International Journal on Advanced Science, Engineering and Information Technology, 2017, 7(1):215-221

[28] Adnan J, Daud N G, Mokhtar A S, Hashim F R, Ahmad S, Rashidi A F, Rizman Z I. Multilayer perceptron based activation function on heart abnormality activity. Journal of Fundamental and Applied Sciences, 2017, 9(3S):417-432

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