PLANNING MALAYSIA:
Journal of the Malaysian Institute of Planners
VOLUME 22 ISSUE 1 (2024), Page 394 – 408

TEMPORAL ANALYSIS AND PREDICTIVE MODELING OF AMBIENT AIR QUALITY IN HULU LANGAT DISTRICT, SELANGOR, MALAYSIA: A CHEMOMETRIC APPROACH

Aiman Abdullah[1], Ahmad Shakir Mohd Saudi[2], Nur Zahidah Shafii[3], Mohd Khairul Amri Kamarudin[4], Firdaus Muhammad-Sukki[5]

[1]*Environmental Health Section, Institute of Medical Science and Technology,*
UNIVERSITI KUALA LUMPUR, MALAYSIA
[2,3]*Center for Water Engineering Technology, Malaysia France Institute,*
UNIVERSITI KUALA LUMPUR, MALAYSIA
[4]*Faculty of Applied Social Sciences,*
UNIVERSITI SULTAN ZAINAL ABIDIN, MALAYSIA
[5]*School of Computing, Engineering and the Built Environment,*
EDINBURGH NAPIER UNIVERSITY, UNITED KINGDOM

Abstract

One of the most important environmental problems facing the globe today is air pollution. The centre area for the local populace is the Hulu Langat district, which borders Kuala Lumpur, the capital. The purpose of this study is to look at how the ambient air quality varies in Hulu Langat, Selangor. The Air Quality Division of the Malaysian Department of Environment provided five years' worth of secondary data on the air quality at Hulu Langat. The database included five primary air pollutant characteristics sulphur dioxide (SO_2), carbon monoxide (CO), ozone (O_3), nitrogen dioxide (NO_2), and particulate matter with a diameter of 10 microns or less (PM_{10}), in addition to data from the Air Pollutant Index (API). Chemometric analysis was used to examine the results. According to the results, SO_2, NO_2 and PM_{10} had the greatest correlations with API readings. A statistical process known as statistical control (SPC) showed that certain PM_{10} values were over national recommendations and control limits. The artificial neural network method's air quality prediction model demonstrated good accuracy with real data (R^2 = 0.9). The results of this investigation indicated a strong correlation between the Hulu Langat air quality data. In order to achieve sustainable environmental practices in the future, it is imperative to engage in extensive collaboration across environmental departments and relevant authorities and engage in continuous monitoring of air quality.

***Keywords**:* Air quality; Artificial neural network; Chemometrics; Correlation; Principal component analysis

[2] Lecturer at Universiti Kuala Lumpur. Email: ahmadshakir@unikl.edu.my

INTRODUCTION

Air pollution refers to the contamination of the indoor or outdoor ambient by chemical, biological or physical agents (WHO, 2016). Air pollution has been one of the world's most pressing environmental concerns. Exposure to air pollution can have immense damaging effects on the health of humans, livestock, plants, buildings, and the global environment (Azmi et al., 2010; Mustaffa et al., 2023; Saad et al., 2023). The main causes of air pollution in Malaysia include open burning, fixed sources, and mobile sources (Abdullah et al., 2012). Approximately 70% - 75% of total air pollution was caused by either public or privately owned motor vehicles, 20% - 25% by industrial and power generation plants and 3% - 5% by forest fires and transboundary haze (Abdullah et al., 2012; Azhari et al., 2016). It is widely reported that air pollution has harmful effects on human health. Studies have indicated that pollution haze is associated with impaired lung function and respiratory symptoms.

One of Malaysia's main districts is Hulu Langat, which has been subjected to potential poor air quality as it is located near Kuala Lumpur (Ling et al., 2010; 2014), the most populated city in the country. A study conducted in Hulu Langat found that pre-school kids living in the urban areas located close to industrial zones were more likely to experience coughing, chest tightness, and phlegm compared to kids in the non-urban areas (Kamaruddin et al., 2015). Urban regions in Malaysia tend to experience unhealthy air exposure and higher reported cases of respiratory-related illnesses.

Furthermore, with a population of approximately 1.5 million citizens, Hulu Langat is the fifth largest district in the state of Selangor. Hulu Langat's population is continuously rising as more urbanization in the region produces more housing and jobs. The population increase in certain areas directly influences the demand for basic needs and energy resources such as electricity, petrol, natural gases, and coal (Zabel, 2009). Therefore, there are more emissions of toxic air pollutants in the atmosphere that might also be affected by the transboundary dust and smoke from other industrially active regions. This study was conducted to determine the significant air quality parameters and investigate the trend of the main air pollutants that affect the ambient air quality status at Hulu Langat, Selangor, using chemometrics technique.

RESEARCH METHODOLOGY

Study area

The Hulu Langat district is located between Kuala Lumpur and Negeri Sembilan, in the southeastern corner of Selangor (Latitude: 3° 03' 18.5" N; Longitude: 101° 50' 43.5" E) with an area of 840 km^2 and a population of nearly 1.5 million people. Hulu Langat is the fifth largest district in the state of Selangor. As most people live in towns near Kuala Lumpur, it has both urban and rural settlements. These population centers have essentially become suburbs of the greater metropolitan area, such as Cheras and Ampang.

Data collection

The Department of Environment's (DOE) Air Quality Division provided secondary air quality data for this investigation, consisting of a four-year database (2014-2018) of the Hulu Langat air quality. Five primary air pollutant parameters: carbon monoxide (CO), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), ozone (O_3), and particulate matter with a diameter of 10 microns (PM_{10}) or less as well as data from the Air Pollutant Index (API) were included in the database. The total amount of data obtained was 251,094 data sets (41,849 hourly observations x 6 parameters).

Data analysis

The chemometrics technique was used for the statistical analysis of the database in this study. Chemometrics is an analytical method that utilises multivariate statistical modelling to solve huge and complex environmental databases (Shafii et al., 2019). Initially, the significant association between the parameters and the strength of the relationships was found using Spearman's correlation test. Consequently, the most important air contaminants influencing the API readings in Hulu Langat may be examined thanks to Principal Component Analysis (PCA).

Combusted pollutant patterns were examined using time series analysis based on the Statistical Process Control (SPC) to determine the air quality status in Hulu Langat. A prediction model of Hulu Langat’s air quality was conducted using the Artificial Neural Network (ANN) utilising the actual data (2014 - 2018).

(a) Spearman’s Correlation Test

The correlation test measured the important relationship between two variables and the strength of the relationship, denoted as the coefficient of correlation, r. In positive correlations, r showed that the two variables increased together in linear correlation, while negative correlations showed an increase of one variable and a decrease in the linear correlation (Saudi et. al., 2015).

The correlation of r values equal to or greater than 0.75 was deemed as a "strong correlation"; "moderate correlations" had r values ranging from 0.50 to 0.74; "fair correlations" had r values ranging from 0.26 to 0.49; and finally, a "weak correlation" was when r values range less than 0.26.

(b) Principal Component Analysis (PCA)

This method can trim down a large data set and was used to explain the variance of a wide set of interrelated variables by converting them into a smaller group of uncorrelated variables, known as Principal Components (PCs) (Sarwat & El-shanshoury, 2018). The equation is expressed as shown below:

$$Z_{ij} = \alpha_{i1}\chi_{1j} + \alpha_{i2}\chi_{2j} + \alpha_{i3}\chi_{3j} + \cdots \ldots\ldots.. + \alpha_{im}\chi_{mj} (1)$$

Where, Z is the component score, α is the component loading, X is the variable's measured value, i is the component number, j is the sample number, m is the total number of variables. In this study, the interrelated variable was interpreted using PCA to identify the parameter with the most significant influence on changing the API readings in Hulu Langat, Selangor.

(c) Statistical Process Control (SPC)

In this analysis, a five-year database time series (2014–2018) was utilised to assess the trend of the most important air contaminants affecting Hulu Langat, Selangor's air quality using statistical probability. The PCA's factor loading was used to extract the most important air contaminants. A straight line connected the subsequent points on the control graph, which displayed the characteristic levels of the air pollution over time. The Lower Control Limit (LCL), Central Line (CL), and Upper Control Limit (UCL) are represented by straight lines.

The Control Chart reveals trends and patterns, showing real data deviations from the historical baseline and the dynamic limit, identifying irregular usages of resources (Saudi et. al., 2015). It is thought to be the most effective baseline for illustrating how real data differs from the historical baseline. The national air quality standard limit and the control limitations were compared to the air pollution patterns.

(d) Artificial Neural Network (ANN)

Based on historical and present training data, an ANN algorithm is a machine learning algorithm that mimics human neural networks for prediction, grouping, and pattern recognition (Lee, 2019). In this study, ANN analysis was applied between the API and the air pollutant parameters to predict the air quality at Hulu Langat. The API as the air quality benchmark was analysed using 50% of the test set of the selected parameters to compute the predicted values. Both real data and the new predicted data were analysed using the ANN to measure the prediction models' fitness.

The Root Mean Square Error (RMSE) values were displayed alongside each trend's coefficient of determination (R2) scores in the model. The statistical measure of R2 indicates how closely the actual data points fit the regression predictions. The regression predictions nearly exactly match the actual data, as demonstrated by an R2 of 0.98 (Bloomenthal, 2020).

RESULT AND DISCUSSION

This The variables involved were API, CO, NO_2, SO_2, PM_{10}, and O_3, which were successfully analysed using XLSTAT software. The statistical analysis included descriptive analysis, Spearman's correlation test, PCA, SPC, and ANN.

Overview Descriptive Analysis of Hulu Langat's Air Quality Data

The results in Table 1 showed that the API recorded maximum and minimum values of 323.00 and 1.00, respectively. The mean for API was 56.431 ± (17.883). The maximum and minimum value of O_3 was 0.149 ppm and 0.00 ppm, respectively. The mean value for O_3 was 0.022 ppm ± (0.022). Meanwhile, CO recorded the maximum and minimum values of 5.658 ppm and 0.00 ppm, respectively. The mean value for CO was 0.702 ppm ± (0.359). SO_2 registered a mean value of 0.003 ppm ± (0.003) with a maximum value of 0.084 ppm and a minimum value of 0.00 ppm. NO_2 recorded the maximum and minimum values of 1.325 ppm and 0.00 ppm, respectively.

The mean value for NO_2 was 0.013 ppm ± (0.026). Lastly, PM_{10} recorded a mean value of 51.886 µg/m^3 ± (33.742) with a maximum value of 438.610 µg/m^3 and a minimum value of 0.114 µg/m^3. The mean values for all parameters were within the Recommended Malaysia Air Quality Guidelines (RMAQG) permissible levels. However, both the API and the PM_{10} hit their maximum values on 14th March 2014, which were classified as heavily polluted. Smoke from a forest fire in Indonesia caused the API to increase (Lim, 2014; Ministry of Education (MOE), 2014).

Table 1: Descriptive statistics of Hulu Langat air quality data

Parameter	Minimum	Maximum	Mean	Standard Deviation	RMAQG
API	1.000	323.000	56.431	17.883	50.000
O_3 (ppm)	0.000	0.149	0.022	0.022	0.100
CO (ppm)	0.000	5.658	0.702	0.359	30.000
SO_2 (ppm)	0.000	0.084	0.003	0.003	0.130
NO_2 (ppm)	0.000	1.325	0.013	0.026	0.170
PM_{10}(µg/m^3)	0.114	438.610	51.866	33.741	150.000

Note: RMAQG=Recommended Malaysia Air Quality Guidelines; API=Air Pollutant Index

Spearman's Correlation Between Air Quality Parameters and API in Hulu Langat

The non-parametric Spearman's correlation test was used to identify the parameters with the strongest positive associations with changing API readings. The result in Table 2 shows that PM_{10} has the highest value recorded with moderate positive correlation scores ($r = 0.490$, $p < 0.0001$). SO_2 has the second-highest value affecting the API reading with ($r = 0.266$, $p < 0.0001$), followed by NO_2 ($r = 0.220$, $p < 0.0001$). The parameters that have the lowest impact on API readings were CO with moderate negative correlation scores ($r = -0.028$, $p < 0.0001$) followed by O_3 ($r = -0.016$, $p < 0.0001$).

Table 2: Spearman's correlation between parameters and Air Pollutant Index (API)

Parameter	API
API	1
O_3	-0.016
CO	-0.028
SO_2	0.266
NO_2	0.220
PM_{10}	0.490

Note: API=Air Pollutant Index

Identifying the most significant air quality parameters that contribute to the API readings

In this study, PCA determined the factor loading scores of the parameters that significantly impact the API. The resulting analysis of PCA in Figure 1 shows that F1 (2.721) and F2 (1.506) gained an eigenvalue of more than one (> 1.0), and the cumulative variability justified the value of 70.439%. Therefore, after determining the stable number of eigenvalues, the PCs were picked to carry out the varimax rotation operation. The varimax rotation approach was used because it streamlines the factor's structure, facilitating a more straightforward and precise examination. Due to the primary factors' duplication, PCs with eigenvalues less than one (< 1.0) were eliminated (Azid et al., 2015). The threshold for the strong criteria chosen for interpretation was found using the scree plot diagram (Figure 1).

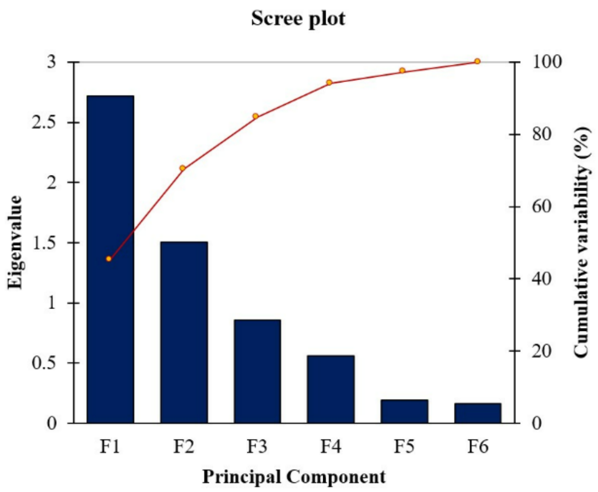

Figure 1: The resulting analysis of PCA

Findings shown in Figure 2 presents factor loadings after Varimax Rotation. In the first factor-loading (F1), O_3 is the highest, corresponding to the component changes with the positive correlation of coefficient scores (0.845) followed by CO (0.812). Meanwhile, PM_{10} has a moderate value that corresponds to the coefficient score (0.734). In this factor, NO_2 has a strong negative value that corresponds to the component changes correlating to coefficient scores (-0.825).

Regional tropical factors, such as the consequences of burning biomass and solar UV radiation, were primarily responsible for the high coefficient connection found between O_3 and PM_{10} levels in Hulu Langat (Binyehmedet al., 2016). Generally speaking, photochemical oxidation and the primary cause of haze were linked to O_3 aggregation into the atmosphere (Banan et al., 2013). Along with SO_2 emitted by industrial activities, there were air pollutants such as mononitrogen oxide (NOx), which is frequently caused by urban and suburban activities (Wei et al., 2014). It was discovered that these two pollutants raised the atmospheric concentrations of O_3 (Hua, 2018).

The second factor-loading (F2) group shows that API has the highest factor loadings (0.927). At the same time, PM_{10} showed the highest positive correlation of coefficient affecting API reading changes (0.565) followed by SO_2 with a medium positive coefficient (0.482). PM10 pollutions in the Lembah Klang area were potentially caused by industrial pollution, heavy construction projects, and transboundary haze (Abdullah et al., 2012). Meanwhile, the elevated SO could be associated with the power plants' activities and industrial pollution, as well as the great traffic congestion of Kuala Lumpur (Binyehmed et al., 2016).

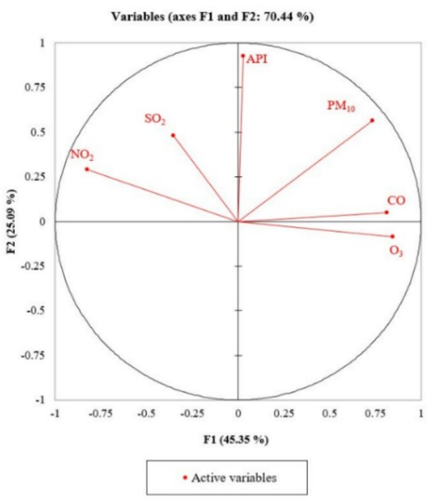

Figure 2: The factor loadings after Varimax Rotation

Pattern of the main air pollutants affecting API readings in Hulu Langat, Selangor

Based on the PCA, this study was able to analyse the most significant parameters in affecting API readings. Therefore, SPC analysis was carried out, and the control chart set the limit control. Accordingly, the SO_2 and PM_{10} were identified as the main factors contributing to the reading of API in the study area. The control chart (Figure 3) of each parameter was extracted to evaluate the time series of concentrations of real-time air pollutants and distinguish the presence of any alarming pollutant values exceeding the permissible values.

Figure 3(a) illustrates the control chart's findings in monitoring the trend of SO_2 at Hulu Langat (2014 - 2018). With an upper control limit (UCL) and lower control limit (LCL) ranging from 0.006 ppm to 0.001 ppm, the control limit (CL) value for SO_2 was 0.003 ppm. The highest value of SO_2 was 0.084 ppm on 6th April 2018, which was mainly associated with industrial activities and traffic congestions across the city in hot weather (Azid et al., 2015).

Besides, there were at least 20 metal, electrical and chemical industries within a 5 km radius of the monitoring station. According to the findings, SO_2 pollutant drastically rise in early 2017, probably due to a 7.9% growth in Selangor's manufacturing industry in 2017, compared to the 4.3% in 2016, where industries are mainly powered by sub-sectors of electrical and electronic goods, motor vehicles and transport equipment (DOSM, 2017). From 2000 to 2010, Selangor experienced an annual population increase of 3.17%, and of 2.78% in Hulu Langat. Likewise, motor-powered vehicles increased in 2017 with approximately 1.5 million units compared to 2016 (Mahidin, 2018).

Findings in Figure 3(b) indicate that the PM_{10} concentration control chart had a few significant spikes. PM_{10} had a CL of 51.866 μg/m^3, an LCL of 43.460 μg/m^3, and a UCL of 60.273 μg/m^3. More than 934 observations exceeded the acceptable levels of the RMAQG, 150 μg/m^3. The highest peak of PM_{10} occurred on 14th March 2014, with a PM_{10} concentration of 438.61 μg/m^3. Figure 4 below illustrates the result of the PM10 trend in Hulu Langat (2014 - 2018).

The highest PM_{10} spike recorded was influenced by the transboundary smoke from the Indonesian forest fire, which caused increased air pollution in the Malaysian atmosphere [15]. The same incident caused a second high spike of PM_{10} readings in October 2015 that reached 386.49 μg/m^3 (DOE, 2015). However, the PM_{10} pollution started to decline drastically in mid-2017, because the Indonesian government started to implement a stricter judicial system aimed at changing the long-lived tradition of slashing and burning and gave more incentives in order to switch to a more expensive land-clearing method (Haan, 2017). In addition, interventions decreased the number of fires from 5,000 fires (2001) to 647 fires (2017).

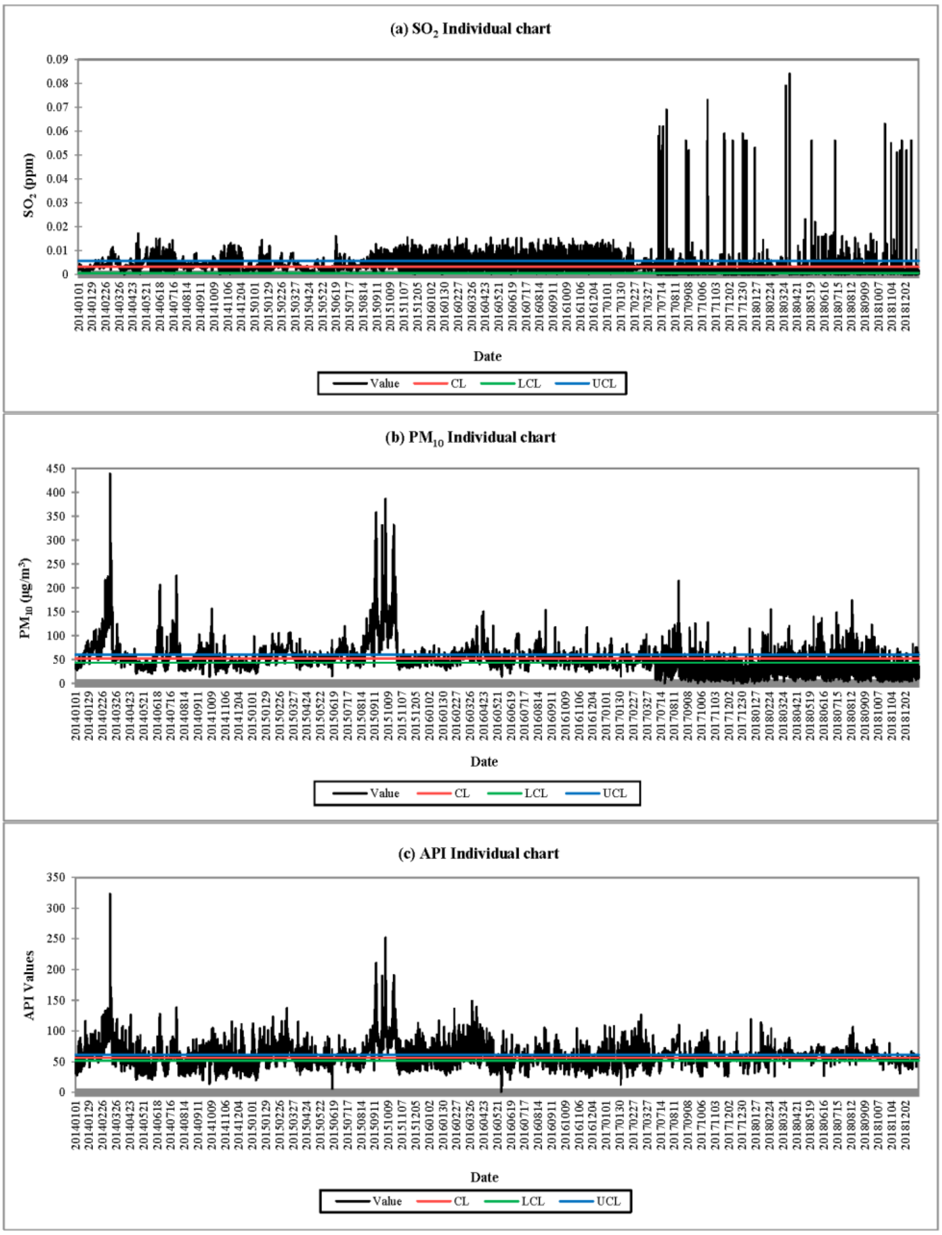

Figure 3: The control chart of each parameter for the time series of concentrations of real-time air pollutants

Figure 3(c) illustrates the control chart in monitoring API's trend at Hulu Langat (2014 - 2018). The CL value for API was 56.431, while the UCL and the LCL were 61.143 and 51.720, respectively. The highest API value was 323.0 on 14th March 2018, and the highest PM_{10} was recorded on the same date. There was a strong correlation of PM_{10} that affected API readings, as shown in factor loading (F2). In observation number 15526, the API spiked again to 252 in October 2015, due to the haze but later gradually declined at the end of the month after heavy rains in Sumatran that significantly reduced the size and number of forest fires (Cochrane, 2018). According to the results, from 2017 to 2018 there were only 44 observations with APIs higher than 100. These were due to the massive reduction of forest fire occurrences in the Sumatran rainforest because of the Indonesian government's intervention (Haan, 2017).

Additionally, this study shows that transboundary haze pollution, a persistent problem in South East Asia since 1997, has an impact on the air quality in Hulu Langat, Selangor. In order to maintain ASEAN as a haze-free region, the Association of Southeast Asian Nations (ASEAN) developed the ASEAN Peatland Management Strategy 2006 - 2020 (APMS) and the Agreement on Transboundary Haze Pollution (AATHP) (ASEAN, 2014; 2016). Even though the AATHP lacked enforceable mandatory provisions, it remained a valuable tool for regional cooperation in fighting transboundary haze pollution (Nazeer & Furuoka, 2017). These interventions showed that the collaboration between regional countries was effective and bringing more promising future results.

Prediction Models of Hulu Langat Air Quality

Based on the PCA, the API was the standard for observing the correlation of other parameters' coefficient values towards the component changes. In this study, the Artificial Neural Network (ANN) was conducted between API readings and parameters to predict the pollution trend of parameters. The process was performed separately, one parameter after another. Approximately 50% of each parameter's total actual data was analysed with API, and a set of predicted data was later produced. The predicted data was combined with the other 50% of the actual data to form a parameter's complete data set. The ANN analysed the new data set again with the parameter's actual data set. This process produced new predicted data for the respective parameter.

The study found that the prediction model through this technique had almost 90% accuracy with the actual data. This was proven as 50% of the predicted data produced was very similar to the actual data when compared together statistically with a coefficient of determination value, R^2 of 0.9 (Table III). Coefficient of determination (R^2) is a statistical measure of how well the regression predictions match the real data points. An R^2 of 0.98 indicates that the regression predictions almost perfectly match the actual data.

In Figure 4, the predicted trends by the ANN were later plotted on the graphs of the actual data (2014 - 2017) to observe the comparison between the actual data and the predicted data. These future predictions of the parameters' pollutions would be used in the future. If the existing data is used for a period of four years with this method, it is only possible to predict the data trend for four years ahead. In this study, a four-year existing air quality data (2014 - 2017) was utilised in the ANN analysis. Therefore, the prediction of air quality trend for the next four years (2018 - 2021) was referring to the new predicted data produced from this analysis. To produce prediction data, the historical data needed to have the same amount of data as those predicted.

This study found that the prediction model was remarkably as accurate as the prediction trend of air parameters, which almost perfectly matched the actual data. Environmental monitoring and modelling using chemometrics were conclusively determined the sources of contaminants for air pollutants which mainly originated from emissions of transportation and industrial activities as well as transboundary haze pollution in Indonesia. Therefore, this environmental modelling is very useful and beneficial to the industry as it could be implemented for other environmental aspects for future monitoring purposes.

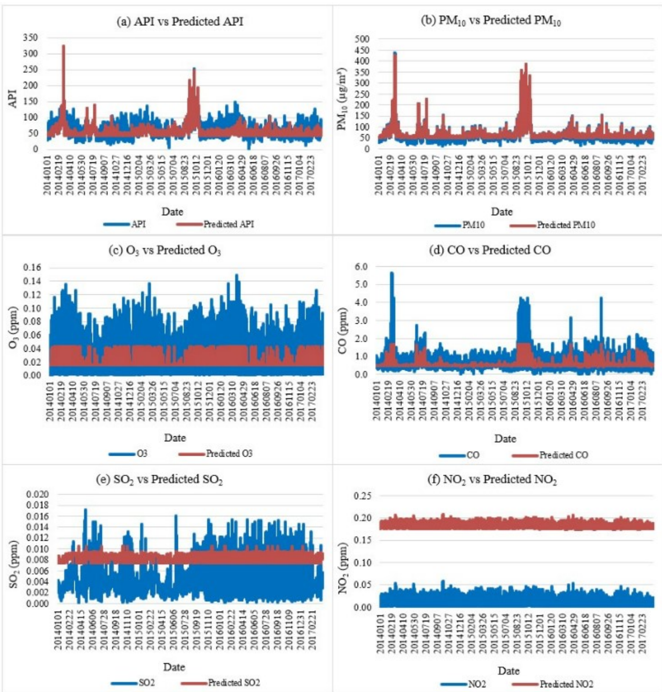

Figure 4: The predicted trends by the ANN of the actual data (2014 - 2017)

Limitations and Future Recommendation

This study utilised the secondary data that was provided by the DOE to analyse air quality in Hulu Langat, Selangor for 5 years (2014 - 2018). Although the air quality status in Hulu Langat varied between good and moderate levels for the period, the trends of air quality should be constantly monitored in order to prevent and control air pollution effectively. Besides, the analysis was based on five major air quality parameters that were accessible throughout the 5 years. The air quality parameters included were API, PM_{10}, CO, O_3, SO_2, and NO_2. The data for atmospheric particulate matter (PM) with a diameter of less than 2.5 micrometres ($PM_{2.5}$) was omitted because it was limited and only recently available from the second half of 2017. Nonetheless, it was suggested that future research incorporate other air pollutants such as $PM_{2.5}$, which has been shown to have greater impacts on human health and the environment compared to PM_{10} (How & Ling (2016). Additionally, more statistical and environmental techniques should be applied for future studies to gain a better insight and understanding of Malaysia's environmental issues, particularly air quality and pollution.

CONCLUSION

The results of this investigation indicated a strong correlation between the Hulu Langat air quality data. The study shows that SO_2, NO_2 and PM_{10} were positively correlated with API readings, whereas O_3 and CO negatively correlated with API readings. Furthermore, the API level in Hulu Langat correlated significantly with PM_{10} compared to other parameters. According to PCA, the two main air pollutants influencing the API readings at Hulu Langat were PM_{10} and SO_2. The primary sources of these toxins are industrial and transportation emissions, as well as pollution from transboundary haze.

All air pollution levels, with the exception of PM_{10}, which was caused by many transboundary haze pollution episodes in Indonesia and by intense traffic congestion emissions in Hulu Langat, were overall in compliance with the RMAQG. The results of this investigation also showed that the PM_{10} and API patterns in Hulu Langat were extremely similar. The methodology used in this study to predict models was considered as accurate as of the prediction trend of air parameters, which almost perfectly matched the actual data. Thus, active collaboration between all environmental agencies and departments is required to ensure efficient air quality management to guarantee a safer and healthier environment in the future.

ACKNOWLEDGEMENT

The team members of Universiti Kuala Lumpur (UniKL), Universiti Sains Islam Malaysia (USIM), Universiti Sultan Zainal Abidin (UniSZA), and Edinburgh Napier University are all appreciated by the authors for their unwavering commitment, direction, counsel, and support during this research project. We would especially like to thank the Malaysian Department of Environment (DOE) for providing us with access to the relevant air quality database, which was essential to the success of our study. Finally, we would like to express our gratitude to the National Institute of Occupational Safety and Health (NIOSH) Malaysia for providing the funding and opportunity for this study. The authors affirm that there is no conflict of interest associated with this paper's publication.

REFERENCES

Abdullah A. M., Abu Samah M. A., Jun T. Y. (2012). An overview of the air pollution trend in Klang Valley, Malaysia. *Open Environ. Sci. 6*, 13–19. doi: 10.2174/1876325101206010013.

ASEAN (Association of Southeast Asian Nations), (2014). ASEAN Peatland Management Strategy 2006-2020. ASEAN Secretariat, Jakarta, April 2014.

ASEAN (Association of Southeast Asian Nations), (2016). ASEAN Agreement on Transboundary Haze Pollution. ASEAN Secretariat, Jakarta, July 2016.

Azhari A. Z., Mohamed A. F., Latif M. T. (2016). Carbon emission from vehicular source in selected industrial areas in Malaysia. *International Journal of the Malay World and Civilisation*. 4(1), 89-93.

Azid A., Juahir H., Toriman M. E., Endut A., Kamarudin M. K. A., Rahman M. N. A… (2015). Source apportionment of air pollution: A case study in Malaysia. *J. Teknol.,72,* 83–88. doi: 10.11113/jt.v72.2934.

Azmi S. Z, Latif M. T, Ismail A. S., Juneng L, Jemain A. A. (2010). Trend and status of air quality at three different monitoring stations in the Klang Valley, Malaysia. *Air Qual., Atmos. Health. 3,* 53–64. doi: 10.1007/s11869-009-0051-1.

Banan N., Latif M. T., Juneng L., Ahamad F. (2013). Characteristics of surface ozone concentrations at stations with different backgrounds in the Malaysian Peninsula. *Aerosol Air Qual. Res. 13,* 1090–1106. doi: 10.4209/aaqr.2012.09.0259.

Binyehmed F. M., Abdullah A. M., Zainal Z. (2016). Trend and Status of SO_2 Pollution as a Corrosive Agent at Four Different Monitoring Stations in the Klang Valley. *Int. J. Adv. Sci. Res. 3,* 302–317.

Bloomenthal A. (2020). [Internet] Coefficient of Determination: Overview. Investopedia, July 2020. Available from: https://www.investopedia.com/terms/c/coefficient-of-determination.asp

Cochrane J. (2018). Rain in Indonesia Dampens Forest Fires That Spread Toxic Haze. The New York Times, New York, October 2018. Available from: https://www.nytimes.com/2015/10/29/world/asia/indonesia-forest-fire-toxic-haze.html

DOE (Department of Environment), (2015). [Internet]. KENYATAAN MEDIA. Available from: http://apims.doe.gov.my/v2/

DOSM (Department of Statistics Malaysia), (2017). [Internet]. State Socioeconomic Report 2017. Department of Statistics Malaysia Official Portal, Malaysia, 2017. Available from: https://www.dosm.gov.my/v1/

Haan J. (2017). [Internet]. Indonesia: Fire Count at Record Low for 2017. Future Directions International, Australia, November 2017. Available from: https://www.futuredirections.org.au/publication/indonesia-fire-count-record-low-2017/

How C. Y, Ling Y. E. (2016). The influence of $PM_{2.5}$ and PM_{10} on Air Pollution Index (API). Environmental Engineering, Hydraulics and Hydrology: Proceeding of Civil Engineering, Universiti Teknologi Malaysia, Johor, Malaysia. 2016 Jun;3:132.

Hua K. (2018). Applied Chemometric Approach in Identification Sources of Air Quality Pattern in Selangor, Malaysia. *Sains Malays. 47,* 471–479. doi: 10.17576/jsm-2018-4703-06.

Kamaruddin A. S., Jalaludin J., Choo C. P. (2015). Indoor air quality and its association with respiratory health among Malay preschool children in Shah Alam and Hulu Langat, Selangor. *Adv. Environ. Biol. 9*, 17-26.

Lee S, Jung S, Lee J. (2019). Prediction model based on an artificial neural network for user-based building energy consumption in South Korea. Energies, 12, 608. doi: 10.3390/en12040608.

Lim S Y. (2014). [Internet]. Forest fires contributing to haze in Selangor. Malaymail. Available from: https://www.malaymail.com/news/malaysia/2014/03/13/forest-fires-contributing-to-haze-in-selangor/633995

Ling O. H. L, Musthafa S. N., Mohamed N. (2014). Air Quality and Land Use in Urban Region of Petaling Jaya, Shah Alam and Klang, Malaysia. EnvironmentAsia, 7(1), 1-12.

Ling O. H. L, Tin, K. H, Shaharuddin A, Kadaruddin A, Yaakob M. J. (2010). Urban Growth and Air Quality in Kuala Lumpur City, Malaysia. *Environmentasia,* 3, 123-128.

Mahidin M. U. (2018). *Malaysia Statistical Handbook. 53,* 1689–1699.

Ministry of Education (MOE). 2014. [Internet]. Kenyataan media: Kenyataan Akhbar oleh KPPM berkaitan tindakan pihak sekolah menangani fenomena jerebu yang melanda negara 2014. Ministry of Education, Malaysia, Mac 2014. Available from: https://www.moe.gov.my/pemberitahuan/kenyataan-media/kenyataan-akhbar-oleh-kppm-berkaitan-tindakan-pihak-sekolah-menangani-fenomena-jerebu-yang-melanda-negara-2014

Mustaffa, H., Kamarudin, M. K. A., Toriman, M. E., Rosli, M. H., Sunardi, S. (2023). Impact of Suspended Sediment on Pahang River Development using Geographic Information System. *Planning Malaysia, 21*(1), 116 – 133.

Nazeer N, Furuoka F. (2017). Overview of ASEAN environment, transboundary haze pollution agreement and public health. International Journal of Asia-Pacific Studies. 13, 73–94. doi: 10.21315/ijaps2017.13.1.4.

Saad, M. H. M., Kamarudin, M. K. A., Toriman, M. E., Wahab, N.A, Ata, F. M., Samah, M. A. A., Manoktong, S. N. (2023). Analysis of the Flash Flood Event and Rainfall Distribution Pattern on Relau River Basin Development, Penang, Malaysia. *Planning Malaysia*, *21*(1), 58-71.

Sarwat E., El-shanshoury G. I. (2018). Estimation of Air Quality Index by Merging Neural Network with Principal Component Analysis. *Int. J. Comput. Appl. 1,* 1-12. doi: 10.26808/rs.ca.i8v1.01.

Saudi A. S. M, Juahir H., Azid A., Toriman M. E., Kamarudin M. K. A., Saudi M. M. (2015). Flood risk pattern recognition by using environmetric technique: a case study in Langat river basin. *J. Teknol. 77,* 145–152. doi: 10.11113/jt.v77.4142.

Shafii N. Z., Saudi A. S. M., Pang J. C., Abu I. F., Sapawe N, Kamarudin M. K. A… (2019). Application of chemometrics techniques to solve environmental issues in Malaysia. *Heliyon,* 5:e02534. doi: 10.1016/j.heliyon.2019.e02534.

Wei J, Guo X, Marinova D, Fan J. (2014). Industrial SO_2 pollution and agricultural losses in China: Evidence from heavy air polluters. *J. Cleaner Prod. 64,* 404–413. doi: 10.1016/j.jclepro.2013.10.027.

WHO (World Health Organization). (2016). Ambient Air Pollution: A global assessment of exposure and burden of disease. World Health Organization: Geneva, Switzerland, 1-131. Available from: https://apps.who.int/iris/handle/10665/250141

Zabel G. (2009). Peak People: The Interrelationship between Population Growth and Energy Resources - Resilience. Energy Bulletin. Available from: https://www.resilience.org/stories/2009-04-20/peak-people-interrelationship-between-population-growth-and-energy-resources/

Received: 4th Jan 2024. Accepted: 23rd Jan 2024