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AIR POLLUTION ASSESSMENT IN SOUTHERN PENINSULAR MALAYSIA USING ENVIRONMETRIC ANALYSIS

(Penilaian Pencemaran Udara Di Selatan Semenanjung Malaysia Menggunakan Analisis Environmetrik)

Haslinda Ab Malek, Nurul Nabila Natasha Jalaluddin, Sharifah Nadia Syed Hasan,Umi Amira Hassni, Isnewati Ab Malek*

Faculty of Computer and Mathematical Sciences
Universiti Teknologi MARA, Cawangan Negeri Sembilan, Kampus Seremban,
70300 Seremban, Negeri Sembilan, Malaysia

**Corresponding author: isnewati@uitm.edu.my*

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Abstract

Air pollution can be defined as the presence of toxic chemicals at levels that pose a health risk. Air quality plays an important role as polluted air could affect the environment. The air pollution problem has become a major issue in Malaysia for the past two decades. Thus, this study focused on the air pollution assessment in Southern Peninsular Malaysia based on the data obtained from the Department of Environment Malaysia. Six major air pollutants (PM_{10}, $PM_{2.5}$, SO_2, NO_2, CO and O_3) in five monitoring stations were measured hourly for the year 2018. Factor Analysis was used to identify the most dominant air pollutant to the air quality. It is found that PM_{10} and $PM_{2.5}$ were the most dominant air pollutants that contribute to the degradation of the air quality in Southern Peninsular Malaysia due to industrial activities. It is hoped that this study could help the authorities in controlling air pollution by determining the most dominant air pollutants involved.

Keywords: air pollution, air pollutant, air quality, factor analysis, dominant

Abstrak

Pencemaran udara dapat didefinisikan sebagai kehadiran bahan kimia beracun pada tahap yang menimbulkan risiko kesihatan. Kualiti udara memainkan peranan penting kerana udara yang tercemar dapat mempengaruhi persekitaran. Masalah pencemaran udara telah menjadi isu utama di Malaysia sejak dua dekad yang lalu. Oleh itu, kajian ini memfokuskan pada penilaian pencemaran udara di Selatan Semenanjung Malaysia berdasarkan data yang diperoleh dari Jabatan Alam Sekitar Malaysia. Enam pencemar udara utama (PM_{10}, $PM_{2.5}$, SO_2, NO_2, CO and O_3) di lima stesen pemantauan diukur setiap jam untuk tahun 2018. Analisis Faktor digunakan untuk mengenal pasti bahan pencemar udara yang paling dominan terhadap kualiti udara. Didapati bahawa PM_{10} dan $PM_{2.5}$ adalah bahan pencemar udara yang paling dominan menyumbang kepada penurunan kualiti udara di Selatan Semenanjung Malaysia kerana aktiviti perindustrian. Diharapkan kajian ini dapat membantu pihak berkuasa dalam mengawal pencemaran udara dengan menentukan bahan pencemar udara yang paling dominan.

Kata kunci: pencemaran udara, bahan pencemar udara, kualiti udara, analisis faktor, dominan

Introduction

Air is the unseen gaseous material that covers the earth, primarily a mixture of oxygen and nitrogen. Air pollution can be characterized as a situation in which high concentrations of air pollutants are present in the atmosphere above their normal ambient levels. In a broader sense, air pollution means the presence of chemicals or compounds in the air which are usually not present and lower the quality of the air that cause detrimental changes to the quality of life [1]. Air pollution sources include contaminants (such as ammonia, carbon monoxide, sulphur dioxide, nitrous oxides, methane and chlorofluorocarbons), particulate matter (both organic and inorganic), and biologic molecules. This can cause human diseases, allergies and even death. This can also damage other living creatures such as livestock and food crops and can affect the natural environment. In Malaysia, Air Pollution Index (API) is a simple and generalized way of describing air quality. The API was introduced as an index system for classifying and reporting the ambient air quality. The API for a given period is calculated based on the sub-index value (sub-API) for all the six air pollutants, namely particulate matter (PM_{10}) and ($PM_{2.5}$), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), carbon monoxide (CO), and ozone (O_3), which are included in the Malaysia API system. The API reference value has been based on the Recommended Malaysian Ambient Air Quality Guidelines (RMAQG) of 1989 as shown in Table1 [2].

$PM_{2.5}$ can cause long term and short-term health impacts, such as irritation in the eyes, sneezing and shortness of breath while the worst scenarios can cause respiratory problems, such as asthma, chronic bronchitis, and heart disease. China is one of the countries listed as the most polluted by $PM_{2.5}$ [3]. This is supported by a case study in Beijing, which indicates $PM_{2.5}$ is one of the air pollutants which becomes an emerging public health issue, especially in China's mega-cities. Moreover, PM_{10} is the main component of dust fall, which comes from industrial activities and construction sites, the transportation exhaust emission and soil dust [4]. Other than that, NO_2 is a gaseous air pollutant formed when a high temperature consumes fossil fuels such as coal, oil, gas or diesel. NO_2 is one of the major indicators of outdoor air pollution in Shah Alam [5]. This is supported by the research done in the Northern Region of Peninsular Malaysia which concluded that NO_2 is one of the major pollutants that have contributed to degrading air quality in that area due to the combustion process from vehicles and industries [6].

Other than that, according to Ismail et al. [6], carbon monoxide (CO) is a poisonous gas made from incomplete combustion of vehicles, industries, and open burning activities. Moreover, research done by Zakaria et al. [5] has found that there is an association between CO and NO_2 which can be demonstrated by their source that came from industrial and traffic activities.

In addition, a study done by Isiyaka and Azid [7] has found that ozone (O_3) and particulate matter (PM_{10}) are the significant parameters influencing the value of the air pollution index (API) in Peninsular Malaysia. High concentration ozone in ambient air may adversely affect individuals and ecosystems. This is supported by Núñez-Alonso et al. [8] who claimed that ozone pollution appears to be the highest in rural areas outside the metropolitan region due to certain chemical that is more common in urban areas, such as nitrogen oxides which are found at lower concentration levels.

Sulphur dioxide (SO_2) is also one of the air pollutants. SO_2 is created when fuel containing sulphur, such as coal and oil is burnt which eventually may lead to air pollution. This gas can also be emitted by trains, large ships, lorries and other diesel equipment. A study done by Kamaruzzaman et al. [9] used multivariate statistics to identify the spatial variation of air quality in selected monitoring stations in Putrajaya, Wilayah Persekutuan, Malaysia. Principal Component Analysis (PCA) together with Factor Analysis indicated that only five parameters (wind speed, wind direction, SO_2, NO_2 and CO) had strong positive loadings (>0.75). Moreover, according to Isiyaka and Azid [7], who indicated that

SO_2 was one of the most parameters with a p-value less than 0.0001, which can be discriminated as the best in polluting the air. By using the principal component analysis, this research shows that SO_2 is one of the major possible air pollutants, which the total variance accounted for more than 58% and proves that SO_2 has a strong influence on the source of air pollution.

Air pollution in Southern Peninsular Malaysia is mainly due to rapid urbanization and industrialization as the region is surrounded by developing areas. The Southern region is mostly encircled by residential area which is nearby to major roads and industrial. This would potentially increase the exposure of the states in the Southern region with pollutants emitted from motor vehicles and industrial that surround the area. Hence, the urban area is considered as a prone zone to experience air quality problems, which would eventually affect human health, wildlife and plants as well as the global environment. A study done by Mohtar et al. [10] found that from 2005 to 2015, the ozone levels have generally increased in suburban areas. Air pollution is a serious issue which all relevant authorities around the globe need to give immediate and serious attention. Therefore, this study focuses on finding the most dominant air pollutant to the air quality in Southern Peninsular Malaysia. Air pollution research is an effort to create awareness in reducing emissions. Hence, it is hoped that this study could help the authorities in controlling the air pollution in Malaysia by determining the most dominant air pollutants involved.

Table 1. API Status Indicator

API	**Alert Level**	**Health Effect Descriptor**
0 – 50	No alert	Good
51 – 100	No alert	Moderate
101 – 150	Early alert	Unhealthy
151 – 200	Early alert	Unhealthy
201 – 300	On alert	Very unhealthy
301 – 500	Warning	Hazardous
>500	Emergency	Hazardous

Materials and Methods

Study area

This study used secondary data obtained from the Department of Environment (DOE) Malaysia, under supervision and control by Alam Sekitar Malaysia Berhad (ASMA). The data consists of hourly observations of the average concentration of air pollutants such as PM_{10}, $PM_{2.5}$, NO_2, SO_2, CO, and O_3 from January to December 2018. Five air quality monitoring sites in Table 2 were selected to give a general representation of the air pollution status in Southern Peninsular Malaysia.

Factor Analysis

Factor analysis is a multivariate analytical technique, which derives a subset of uncorrelated variables called factors that explain the variance observed in the original dataset [11]. The inter-correlation between air pollutants needs to be checked before conducting a factor analysis. It can be done by constructing the correlation matrix. With respect to the correlation matrix, the variables must be intercorrelated, but no multicollinearity exists and it should be a singularity. Multicollinearity can be detected via the determinant of the correlation matrix. If the determinant is greater than 0.00001, then there is no multicollinearity [12].

Meanwhile, Bartlett's test of sphericity determines whether the correlation matrix is an identity matrix, which would indicate that the factor model is inappropriate [13]. PCA can perform compression of the available information only if we reject the null hypothesis. The test statistic of Bartlett's test of sphericity is given in equation (1):

$$\chi^2 = -\left(n - 1 - \frac{2p+5}{6}\right) \times \ln|R| \qquad (1)$$

where n is number of samples, p is number of variables and R is correlation matrix of variables.

There are two main issues to take into consideration to determine whether a particular set of data is appropriate for factor analysis: the number of samples size should be a large sample (300 sample sizes) and the strength of the relationship between variables [14]. According to Kaiser [15], the adequacy of sampling is tested through Kaiser-Meyer-Olkin (KMO) as given by equation (2):

$$\mathrm{KMO} = \frac{\sum\sum_{j\neq k} r^2_{jk}}{\sum\sum_{j\neq k} r^2_{jk} + \sum\sum_{j\neq k} P^2_{jk}} \qquad (2)$$

The Kaiser-Meyer-Olkin criterion is calculated and values between 0 and 1 is obtained. Here, r_{jk} is the correlation between the air pollutant and P_{jk} is the partial correlation.

Moreover, Factor Extraction is the best approach to apply to a large amount of complex environmental monitoring data because they can avoid misinterpretation of results produced during data analysis [16]. The application of environmetric techniques such as PCA has been extensively applied in many scientific studies over the last few years, especially in air quality monitoring [16, 17]. In this study, the extraction of principal components or factors takes place by calculating the eigenvalues of the matrix. According to Rietveld and Hout [18], the number of positive eigenvalues determines the number of factors or components to be extracted. After constructing the factors, it is possible to determine the factor loadings by calculating the correlations between the original variables and the newly obtained factors or components.

In addition, Factor Rotation is used in this study in defining a small number of factors that can be used to best signify the whole relationship between air pollutants. Kaiser's criteria help in deciding to determine the smaller number of factors that should be retained. Under this criterion, components with an eigenvalue larger than 1 are retained [19]. In practice, only factor loading with absolute values greater than 0.5 is selected for the principal component interpretation. The higher the factor loading value, the more the air pollutant contributes to the variation attributed to the principal component [20].

Table 2. Location, coordinates, and area status of a monitoring station

Station ID	Location	Coordinates		Area Status
		Latitude	Longitude	
S1	Nilai, Negeri Sembilan	2.82	101.81	Industrial
S2	Seremban, Negeri Sembilan	2.72	102.24	Urban
S3	Bandar Melaka, Melaka	2.22	102.24	Urban
S4	Kota Tinggi, Johor	1.56	104.23	Urban
S5	Pasir Gudang, Johor	1.47	103.91	Industrial

Source: Department of Environment (DOE) Malaysia

Results and Discussion

Descriptive analysis

Descriptive statistics including minimum, maximum and mean of six air pollutants studied have been carried out. Table 3 shows that the maximum concentration of SO_2, NO_2, and CO are 0.020 ppm, 0.077 ppm and 4.229 ppm respectively. The value of these three pollutants did not exceed the approved level of air pollutants concentration limit based on RMAQG which are 0.13 ppm, 0.17 ppm and 30.00 ppm respectively. However, the concentration of PM_{10} and O_3 overshoot the approved level of RMAQG. The maximum value of PM_{10} is 319.871 µg/m3, which is greater than the RMAQG approved level of 150.00 µg/m3. Even though the value is quite high from the permitted level, but it does not exceed the hazardous level of PM_{10} that is 600 µg/m3. Meanwhile, the maximum value of O_3 is 0.12 ppm which surpass the approved level by RMAQG, 0.10 ppm.

Correlation analysis

The intercorrelation between the concentration of air pollutants needs to be checked before the factor analysis can be carried out. The top half of Table 4 contains the correlation coefficient between air pollutants whereas the bottom half contains the p-value of each coefficient. The p-value that is less than 0.05 indicated that the correlation is significant with each other. The value of correlation coefficient for all pair of air pollutants are below 0.9 except for PM_{10} and $PM_{2.5}$ with strong correlation coefficient (r = 0.944). Hence, the determinant of the correlation matrix is needed to check the existence of multicollinearity in the data. Since the determinant value is 0.043 which is greater than 0.00001, therefore multicollinearity is not a problem for this data. Factor Analysis seems to be appropriate and suitable for this study as there is an inter-correlation between the air pollutants and no multicollinearity exists.

The strong correlation between PM_{10} and $PM_{2.5}$ illustrated that the dispersion of PM_{10} from the industrial activities in the study area also affected $PM_{2.5}$. PM_{10} and $PM_{2.5}$ concentrations are highly correlated (r = 0.944) because emission sources are mainly the same for the different measures (mobile sources and agricultural activities) [21].

Sampling adequacy

Table 5 shows the value of the Kaiser-Meyer-Olkin (KMO) and Bartlett's test. The value of KMO is 0.646 which is greater than 0.5. According to Kaiser [15], the acceptance value for KMO is greater than 0.5. Hence, it can be concluded that factor analysis is appropriate for this data. In addition, Bartlett's test of sphericity is measured to ensure that the R-matrix is not equal to the identity matrix. Since the p-value (0.000) is less than the significant value (α=0.05), it can be indicated that the R-matrix is not equal to the identity matrix and factor analysis is appropriate.

Table 3. Summary statistics of the air pollutants concentrations

	Minimum	Maximum	Mean
PM_{10}	0.874	319.871	26.7888
$PM_{2.5}$	0.066	305.648	18.511
SO_2	0.000	0.020	0.001
NO_2	0.000	0.077	0.010
O_3	0.000	0.122	0.019
CO	0.040	4.229	0.633

Table 4. Correlation Matrix

		PM_{10}	**$PM_{2.5}$**	**SO_2**	**NO_2**	**O_3**	**CO**
Correlation	PM_{10}	1.000	0.944	0.130	0.489	-0.168	0.364
	$PM_{2.5}$	0.944	1.000	0.104	0.488	-0.119	0.343
	SO_2	0.130	0.104	1.000	0.132	0.108	0.024
	NO_2	0.489	0.488	0.132	1.000	-0.516	0.479
	O_3	-0.168	-0.119	0.108	-0.516	1.000	-0.418
	CO	0.364	0.343	0.024	0.479	-0.418	1.000
Sig.	PM_{10}		0.000	0.000	0.000	0.000	0.000
	$PM_{2.5}$	0.000		0.000	0.000	0.000	0.000
	SO_2	0.000	0.000		0.000	0.000	0.000
	NO_2	0.000	0.000	0.000		0.000	0.000
	O_3	0.000	0.000	0.000	0.000		0.000
	CO	0.000	0.000	0.000	0.000	0.000	

a. Determinant = .043

Table 5. Kaiser-Meyer-Olkin and Bartlett's test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.646
Bartlett's Test of Sphericity	**Approx. Chi-Square**	120603.42
	df	15
	Sig.	000

Factor Extraction

Total Variance Explained in Table 6 represents the lists of eigenvalues associated with each linear component before and after extraction as well as after rotation. Before extraction, there are six linear components identified within the dataset. The number of linear components identified is similar to the number of variables in the dataset (PM_{10}, $PM_{2.5}$, SO_2, NO_2, CO, and O_3). The initial eigenvalues represent the variance explained by that specific linear component of each factor. It shows that factor 1 explains 46.003% of the total variance.

The Extraction Sums of Squared Loadings extract all factors with eigenvalues greater than 1 based on Kaiser's criterion. The extracted factor with eigenvalues over 1 specifies that the three factors should be retained in the model. Therefore, in this factor analysis, only the first three linear components are extracted and contribute most to the total variance. Meanwhile, the Rotation Sums of Squared Loadings optimize the factor structure and equalize the relative importance of the three factors. Before rotation, Factor 1 accounted for relatively more variance than the remaining two with 46.003% compared to 20.491% and 16.682%, respectively. However, after rotation, it accounts for only 35.859% of the variance for Factor 1 followed by 29.456% and 17.862% for the other two factors, respectively.

The output of Communalities in Table 7 shows the proportion of each variable's variance that can be explained by the underlying factors. The initial value of all communalities is 1, which demonstrates that all variance is common with the work of PCA. The communalities value after extraction (PM_{10} = 0.947, $PM_{2.5}$ = 0.954, SO_2 = 0.968, NO_2 = 0.744, O_3 = 0.779, and CO = 0.599) indicate that the amount of variance in each variable explained by the included factors. Thus, it can be concluded that 94.7% of the variance correlated with PM_{10} is a common variance.

Table 8 represents the factor loading before and after rotation. This study uses varimax rotation to redistribute the factor loading that reflects the variables common characteristics. It finds that the rotation minimizes the complexity of the factor loadings to make the structure simpler to interpret within each component. These factors loading of each variable are supposed to measure each factor precisely. There are three factors extracted as shown in Table 8. The blank spaces denote the loading that is less than 0.4. Loading less than 0.4 is suppressed in the output to increase a value reflecting the expected value of a significant factor loading.

In the factor loading after rotation, the first component is most highly correlated with $PM_{2.5}$ and PM_{10} with the correlation of 0.967 and 0.957, respectively. These pollutants come from a variety of sources such as all modes of transportation, factories, construction sites and open burning. Generally, PM_{10} and $PM_{2.5}$ are mainly from industrial activities and construction sites [22].

The second component is most highly correlated with O_3, CO and NO_2 with a correlation coefficient of 0.861, 0.701 and 0.697, respectively. O_3 is not emitted directly from automobiles, the unstable compound is formed in the atmosphere through a complex set of chemical reactions involving hydrocarbons, oxides of nitrogen, and sunlight. The rate at which the reactions proceed is related to both the temperature and intensity of the sunlight. Because of this, problematic ozone levels occur most frequently during afternoons [23]. CO is the pollutant that comes from the incomplete combustion of vehicles, industries, and open burning activities [24]. Meanwhile, NO_2 is made up of the largest sources of emissions released by cars, trucks, buses and many of which come from indoor and outdoor. NO_2 emission in Malaysia proves that power stations and industrial activities released about 69% of this pollutant to the air, while 28% is from motor vehicles and the remaining 3% is from other sources [25].

However, the third component is the most highly correlated with SO_2 with a strong correlation of 0.983. These sources of the pollutant are emitted by trains, large ships, lorries and other diesel equipment resulting in the high combustion of sulphur. In addition, the sources of SO_2 are resulted from the motor vehicles combustions, coal-powered power plants and uncontrolled burning of forests and dust storms from the neighboring country due to various activities [16]. According to Minnesota Pollution Control Agency [26], diesel vehicles and equipment have long been a major source of SO_2. Based on this finding, it shows that the most dominant air pollutant that affects the air quality in Southern Peninsular Malaysia are from the $PM_{2.5}$ and PM_{10}. These findings are in line with the result obtained in the research of assessment on air quality patterns in Putrajaya, Malaysia, which said that the major contributions are from automobiles, industries, power plants, transboundary sources and construction sites [9].

Table 6. Total Variance Explained

Factors	Initial Eigenvalues		Extraction Sum of Squared Loadings		Rotation Sum of Squared Loadings	
	Total	Variance (%)	Total	Variance (%)	Total	Variance (%)
1	2.760	46.003	2.760	46.003	2.152	35.859
2	1.229	20.491	1.229	20.491	1.767	29.456
3	1.001	16.682	1.001	16.682	1.072	17.862
4	0.572	9.532				
5	0.379	6.310				
6	0.059	0.981				

Table 7. Communalities

Variables	Initial	Extraction
PM_{10}	1.000	0.947
$PM_{2.5}$	1.000	0.954
O_3	1.000	0.968
CO	1.000	0.744
NO_2	1.000	0.779
SO_2	1.000	0.599

Table 8. Factors Loading for the air pollutants observations

Variables	Factor Loading Before Rotation			Factor Loading After Rotation		
	1	2	3	1	2	3
$PM_{2.5}$	0.862			0.967		
PM_{10}	0.846	0.405		0.957		
O_3	0.797				-0.861	
CO	0.682				0.701	
NO_2	-0.416	0.776		0.433	0.697	
SO_2			0.888			0.983

Conclusion

Air pollution can be defined as the presence of toxic chemicals or substances in the air which pose a health risk. It is one of the most serious environmental phenomena facing our society. This air pollution issue is usually caused by human activities, such as mining, construction, transport, factory work, agriculture, and smelting, which directly or indirectly affect the quality of air. The air pollutants including $PM_{2.5}$, PM_{10}, NO_2, SO_2, CO, and O_3 were obtained hourly from January to December 2018 by five air quality monitoring sites. This study is focused on determining the most dominant air pollutant in Southern Peninsular Malaysia by using Factor Analysis.

The descriptive analysis was used to describe the analysis of the hourly air quality concentration of major air pollutants. It found that the concentration of PM_{10} and O_3 overshoot the approved level of RMAQG. Based on the factor analysis, the most dominant air pollutant that affects the air quality in Southern Peninsular Malaysia are $PM_{2.5}$ and PM_{10} with a strong correlation of 0.967 and 0.957 respectively. The major contribution sources to these pollutants are from induced emission of industrial activities and construction sites. It is hoped that this research will help the authorities in controlling air pollution in Malaysia.

For further study, it is necessary to address a wider suite of components on a larger sample by covering more stations in identifying different sources of air pollution. Moreover, it is recommended that the study be replicated using PCA or Cluster Analysis to identify the correlation between different pollutants and to classify the different monitoring stations based on the different variables. In addition, the chemometric technique is a meaningful tool to disclose and justify significant spatial variability for the assessment of large and complex air quality data.

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