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Construction of Air Pollution Index with the Inclusion of Aggregated Weights of the Pollutants

*[1]Nur Syamimi Muhamad Fauzi, [2]Maznah Mat Kasim &
[3]Nor Hasliza Mat Desa
[1&2]Department of Decision Science,
School of Quantitative Sciences,
Universiti Utara Malaysia, Malaysia
[3]Department of Statistics,
School of Quantitative Sciences,
Universiti Utara Malaysia, Malaysia

*nur_syamimi6@ahsgs.uum.edu.my;
maznah@uum.edu.my;
nliza@uum.edu.my
*corresponding author

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ABSTRACT

The ambient air quality measurement in Malaysia is described as Air Pollution Index (API). The existing API for a given period is defined as the maximum value of the sub-index values of six pollutants. Although research has demonstrated that long and short-term exposures to air-suspended toxicants have different toxicological impacts, the API still considers these pollutants as having equal hazardous effects on humans. Therefore, this study proposed a new API that includes weights representing different hazardous levels of pollutants in its calculation. Based on the secondary data of six pollutants' readings for 16 states and federal territories of Malaysia for the year 2018, the aggregated weights were computed by combining both weights obtained from the subjective experts' opinions and the objective data-driven methods, which balanced both perspectives of evaluations. Resultantly, the particulate matter with an aerodynamic diameter of less than 2.5 micrometres $(PM_{2.5})$ was the most hazardous pollutant since its aggregated weight value was the highest, whereas the distributions of the API readings for all 16 states and federal territories were found to be normal. The highest and lowest API readings occurred on 14th August 2018 and 10th March 2018, respectively. The new API readings are arguably more accurate and provide a clearer picture of the occurrence of air pollution, particularly in Malaysia. This study provides new insight into constructing API and contributes more comprehensive and precise air quality measurements to be analysed by the responsible authorities in their efforts towards a healthy environment.

Keywords: Aggregated weights, air pollution, hazardous levels, objective weighting method, subjective weighting method.

INTRODUCTION

Air pollution (AP) is a never-ending global problem as more new pollutants are known to threaten humans' lives and the environment (World Health Organization (WHO), 2020). AP is described as a change in air quality by measuring chemical, biological, or physical pollutants in the atmosphere. Malaysia's air quality is defined by the Department of Environment Malaysia (DOEM) in terms of the air pollution index (API) (Department of Environment (DOE), 2020). Currently, six major types of air pollutants are considered in determining the AP, comprising sulphur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO), ozone (O_3), particulate matter with an aerodynamic diameter less than 10 micrometres (PM_{10}), and particulate matter with an aerodynamic diameter less than 2.5 micrometres $(PM_{2.5})$.

Historically, DOEM issued the Recommended Malaysian Air Quality Guidelines (RMG) in 1989. The Malaysian Air Quality Index (MAQI) was later developed in 1993 to measure ambient air quality, which ranged from good to hazardous. Then, the Air Pollution Index (API) was established in 1996 that only considered five air pollutants and was defined as the maximum value of the sub-index values of the five pollutants. In August 2018, DOEM improved the calculation of API by considering $PM_{2.5}$.However, the API still considers all air pollutants as having the same hazardous effects on the environment and human life, in particular. Therefore, the API readings may be misleading and inaccurate.

Several reports have revealed the direct association between exposure to poor air quality and increasing morbidity and mortality rates, mostly due to cardiovascular and respiratory diseases (Ghorani-Azam et al., 2016; Boyandi et al., 2016; Sahu et al., 2014). Previous research also found that $PM_{2.5}$ is a very small particle that can lodge deeply in the lungs and disturb the respiration system, where a single strand of human hair is 30 times larger than these fine particles (DOE, 2020). Smaller particles reach the lower respiratory tract more easily and have a higher risk of causing lung and heart problems (Mannucci & Franchini, 2017). Consequently, fine particles such as $PM_{2.5}$ are thought to be the most dangerous air pollutant given their negative influence on human health, especially the cardiovascular and respiratory systems (Lei et al., 2017).

It is critical that the existing API calculation method be revised for the various levels of harm these pollutants contribute to human health. This study aims to construct a new API by considering the different hazardous levels that the six pollutants could bring to humans. Since subjective and objective approaches (Ma et al., 1999; Kasim, 2020) are available to weigh the hazardous levels, this article proposes the use of aggregated weights that are determined via the aggregation of subjective and objective weights (Desa et al., 2015) of the air pollutants. The resulting weights are argued to be optimal since both approaches complement each other's weaknesses. The resulting weight of each air pollutant represents the relative significance of the air pollutants towards the occurrence of air pollution (Choo et al., 1999; Zardari et al., 2015). The daily air pollution data of 16 states including three federal territories in Malaysia for 2018 were analysed in constructing the new API. In achieving the aim of this study, this article is presented in five main sections: introduction, a short review of the criteria weighting methods and index construction, methodology of the study, results and discussion, and conclusion.

CRITERIA WEIGHTING METHODS AND INDEX CONSTRUCTION

This section provides a general discussion about methods to weigh the criteria representing the degree of importance towards the concept under study. The two main approaches are subjective and objective, and once the weights of criteria are determined, those weight values are to be used in constructing the API index.

Subjective Weighting Approaches

Subjective techniques determine the criteria weights primarily based on the decision maker's or expert's judgments. Several subjective methods are available, such as the popular Analytic Hierarchy Process (AHP) (Saaty, 2000), rank-based technique (Barron & Barrett, 1996), swing methods (Von Winterfeldt & Edwards, 1986), graphical weighting (GW) method (Hajkowicz et al., 2000), Delphi method (Chang et al., 2008), and point allocation method (Bottomley et al., 2000). The point allocation (PA) method was selected as the subjective weighting method for this study due to its reliability and simple application compared to AHP that involves pairwise comparison among the criteria, leading to inconsistent evaluation. PA is a more straightforward method, where experts can allocate points to the criteria according to their significance to the concept under study.

Objective Weighting Approaches

Determining objective weights of criteria is performed by mathematically manipulating the intrinsic information of the data in the criteria. Several objective weighting methods are available such as standard deviation and coefficient of variation (Kasim, 2018), CRiteria Importance Through Inter-Criteria Correlation (CRITIC) (Krishnan et al., 2021), and entropy method (Kasim, 2020).

The entropy concept was firstly introduced by Shannon and Weaver (1949) to represent messages in the communication theory. Thereafter, Zeleny (1982) used the entropy concept as a proxy measure of criteria weights. Various entropy-based criteria weighting techniques are available, including those developed by Zeleny himself, Hwang and Yoon (1981), Chen and He (1997), and Desa et al. (2015). The concept of entropy is synonymous with uncertainty or vagueness. As the air pollution data are usually uncertain due to many factors, such as weather and temperature, the entropy method is used in this study as the objective weighting technique to calculate the hazardous levels of the six pollutants being investigated. All four entropy-based criteria were used, and the optimal objective entropy-based weights were chosen for the new API construction.

Construction of Index

A composite index, or simply an index, refers to a single measure or value determined by combining a set of measures according to a certain mathematical formula. The index is the final values resulting from the combination or aggregation of the values and weights of the criteria. In the case of API construction, the daily values of each pollutant should be combined with the pollutants' weights. According to Kasim et al. (2011), two aggregation methods are available: Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Simple Additive Weighting (SAW). This study employed the SAW method since it is highly established (Triantaphyllou, 2000) and uncomplicated. The following section explains the methodology of this study, which comprises the study area and data collection, the proposed aggregated weights of each air pollutant, and the construction of the new API.

METHODOLOGY

Study Area and Data Collection

As previously mentioned, this study considered six air pollutants, namely SO_2, NO_2, CO, O_3, and particulate matters with PM_{10} and $PM_{2.5}$. DOEM provided the daily readings of these six pollutants for all 13 states and three federal territories in Malaysia for 2018. The data were selected due to the improvement of the API calculation method made by DOEM in 2018 with the consideration of $PM_{2.5}$. The air quality data were collected daily for 365 days. Besides, a total of 15 experienced staff of DOEM were asked to evaluate the hazardous levels of the six air pollutants. Their evaluations were used as a basis to calculate the subjective weights of the pollutants.

The data were arranged in a decision matrix as illustrated in Figure 1, in which P_j represents pollutant type j, where j = 1, …,6, and x_{ij} represents the reading of pollutant type j on day i, where i = 1, …,365. Since this study considers data for 16 states and federal territories in Malaysia, the 16 decision matrices for all the areas were analysed.

Figure 1

An Example of a Decision Matrix of Air Pollution Data of Six Pollutants

$$
X = \begin{array}{c c}
 & \begin{array}{ccccc} P_1 & \cdots & P_j & \cdots & P_6 \end{array} \\
\begin{array}{c} A_1 \\ \vdots \\ A_i \\ \vdots \\ A_{365} \end{array} &
\begin{bmatrix}
x_{11} & \cdots & x_{1j} & \cdots & x_{1,6} \\
\vdots & \ddots & \vdots & \ddots & \vdots \\
x_{i1} & \cdots & x_{ij} & \cdots & x_{i,6} \\
\vdots & \ddots & \vdots & \ddots & \vdots \\
x_{365,1} & \cdots & x_{365,j} & \cdots & x_{365,6}
\end{bmatrix}
\end{array}
$$

Data Normalisation

Prior to data analysis, the data were normalised to assure they were comparable since the six pollutants' data were with different scales and units of measurement. However, all data were in the same direction as they all represented cost data in which the lower values were better. The following Equation 1 was used to normalise the data.

$$r_{ij} = \frac{x_{ij} - x_{jmin}}{x_{j\,max} - x_{jmin}} \tag{1}$$

where,

r_{ij} = normalised value of ,
x_{jmax} = maximum value of pollutant *j*,
x_{jmin} = minimum value of pollutant *j*.

Besides, the range of r_{ij} is between zero and one.

Entropy-based Method as Objective Weighting Method

Objective weighting methods are data-driven methods, and one of them is the entropy method. Shannon and Weaver (1949) were the first to employ the entropy calculation method to measure the uncertainty associated with random occurrences. Other researchers have used the foundation of Shannon and Weaver's (1949) entropy approach to construct a new calculation method for entropy values to represent criteria weights. Therefore, four entropy calculation methods were used in this study. Hwang and Yoon (1981) suggested the entropy value calculation as in the following Equation 2:

$$E_j^{hy} = -k \sum_{i=1}^{365} \left(\frac{r_{ij}}{\sum_{i=1}^{365} r_{ij}} \right) \ln \left(\frac{r_{ij}}{\sum_{i=1}^{365} r_{ij}} \right) \tag{2}$$

Meanwhile, in 1982, Zeleny (1982) revised Shannon and Weaver's entropy formula, and the entropy value for pollutant *j* is calculated as indicated in Equation 3:

$$E_j^{z} = -k \sum_{i=1}^{365} \left(\frac{r_{ij}}{\hat{r}_j} \right) \ln \left(\frac{r_{ij}}{\hat{r}_j} \right) \tag{3}$$

where,

$$\hat{r}_j = \text{maximum of } r_{ij}.$$

Furthermore, Chen and He (1997) proposed that the entropy value should be calculated using the expression shown in Equation 4:

$$E_j^{ch} = -k \sum_{i=1}^{365} \left(\frac{|r_{ij} - \bar{r}_j|}{\sum_{i=1}^{365} |r_{ij} - \bar{r}_j|} \right) \ln \left(\frac{|r_{ij} - \bar{r}_j|}{\sum_{i=1}^{365} |r_{ij} - \bar{r}_j|} \right) \tag{4}$$

where,

$$\bar{r}_j = \frac{1}{n365} \sum_{i=1}^{365} r_{ij}.$$

The Gaussian kernel estimation proposed by Silverman (Silverman, 1986; Desa et al., 2015), as indicated in Equation 5, is the fourth entropy-based weighting method used in this study.

$$E_j^{s} = -k \sum_{i=1}^{365} \left(\frac{f_{ij}}{\sum_{i=1}^{365} f_{ij}} \right) \ln \left(\frac{f_{ij}}{\sum_{i=1}^{365} f_{ij}} \right) \tag{5}$$

where,

$$f_{ij} = \frac{1}{365h} \sum_{i=1}^{365} K\left(\frac{r_{ij} - r_{lj}}{h}\right),$$

$$K = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{r_{ij} - r_{lj}}{h}\right)^2\right),$$

$$h = 1.06\sigma n^{-\frac{1}{5}},$$

$$n = 365.$$

with f_{ij} representing the density estimation with a Gaussian kernel (Desa et al., 2015). Lastly, the objective weight for each air pollutant would be determined by Equation 6:

$$w_j^{obj} = \frac{1 - E_j}{\sum_{j=1}^{6} (1 - E_j)}, \; j = 1,2,\ldots,6, \quad 0 \le wj < 1, \; \sum_{j=1}^{6} w_j^{obj} = 1. \tag{6}$$

Since four sets of entropy-based weights were calculated, the optimal objective weights of the pollutants had to be determined. This study used accuracy methods in choosing the best entropy weighting method by comparing each set of weights with the 'true weights', which were defined as the average weights of the four weights (Mohammed et al., 2017). The accuracy (Kaur & Kumar, 2021) measurement methods used in this study were the mean absolute error (MAE), mean squared error (MSE), and mean absolute percentage error (MAPE) (Mohammed et al., 2020).

Point Allocation Method as Subjective Criteria Weighting Method

Besides objective weights, the study also determined the subjective weights by using the Point Allocation (PA) method. This method requires evaluations by experts. As previously mentioned, 15 DOEM staff were selected as the experts to answer a simple questionnaire that was developed and emailed to them. They were asked to allocate a budget of 100 points to the six pollutants. The outcome suggested that the more points a pollutant obtained, the larger its relative relevance to the occurrence of air pollution. In this study, let be the point allocated to pollutant j by expert l where $j = 1, 2, \dots, 6.$ and $l = 1, 2, \dots, 15.$ The allocated points given by an expert were used in the computation of a pollutant's weight as shown in the following Equation 7:

$$w_j^{l\,sub} = \sum_{j=1}^{6} \frac{a_j^l}{100} \tag{7}$$

Since the number of experts being considered in this study was 15 experts, the final subjective weight of pollutant j is determined as in Equation 8:

$$w_j^{sub} = \frac{\sum_{l=1}^{15} w_j^{l\,sub}}{15}, \; l = 1,2,\dots,15, \quad 0 \le w_j^{sub} \le 1 \tag{8}$$

where,

j = number of pollutants,

l = number of experts,

w_j^l = weight of pollutant j for expert l.

Aggregation of Objective and Subjective Weights

The aggregated weights, which combined subjective and objective weights, were proposed in this study. The proposed aggregation method presents a better way to reflect both weights, which can overcome the drawbacks of these two approaches separately (Desa et al., 2015). The aggregated weights of the pollutants were proposed in this study as in Equation 9:

$$w_j = \frac{{w_j}^{sub}.{w_j}^{obj}}{\sum_{j=1}^{6} {w_j}^{sub}.{w_j}^{obj}} \quad ,j = 1,2,\dots,6 \qquad 0 \le wj \le 1,\ \sum_{j=1}^{6} w_j = 1. \tag{9}$$

Construction of Air Pollution Index

Simple Additive Weighting (SAW) was used to create the daily API, API_i, i = 1,…,365, which is the sum of the normalised air pollutants' scores with the appropriate aggregated weights of each pollutant. The API_i score can be written mathematically as in Equations 10 and 11:

$$\mathrm{API}_i = w_1 r_{i1} + w_2 r_{i2} + w_3 r_{i3} + \cdots + w_{n6} r_{i,6} \tag{10}$$

$$\mathrm{API}_i = \sum_{j=1}^{6} w_j r_{ij} \tag{11}$$

where w_j is the aggregated weight of each pollutant j and r_{ij} is the normalised scores of the daily air pollutant readings. The API_i score ranges from zero to one, with a lower API_i score corresponding to lower air pollution and vice versa. A lower index value represents a good air quality status while a higher index value refers to a bad air quality status.

RESULTS AND DISCUSSION

This section provides the results and discussion of the study findings, where the daily readings of six air pollutants for 13 states and three federal territories in 2018 were analysed.

Result 1: Summary of the Raw Data

Table 1 summarises the descriptive statistics of the daily air pollutants readings in Malaysia over 365 days for the year 2018. The average contribution of PM_{10} towards the air quality was 44.0901 ± 10.1023 micrometres per day, $PM_{2.5}$ was 32.5476 ± 8.8071 micrometres per day, whereas that of $SO_2, NO_2, O_3,$ and CO were 0.0014 ± 0.0002, 0.0140 ± 0.0021,0.0391 ± 0.0074, and 0.9806 ± 0.0929 ppm per day, respectively. Meanwhile, the minimum daily concentration of PM_{10}

was 23.8895 micrometres, and its maximum concentration was 86.5853 micrometres. The minimum and maximum concentrations of $PM_{2.5}$ were 16.1943 and 67.9180 micrometres, respectively.

Table 1

Descriptive Statistics for Daily Air Pollutants Contribution towards Malaysia's Air Quality in 2018

Air Pollutants	Mean ± SD	Minimum	Median	Maximum
	44.0901 ± 10.1023	23.8895	41.5995	86.5853
	32.5476 ± 8.8071	16.1943	30.6785	67.9180
	0.0014 ± 0.0002	0.0010	0.0014	0.0023
	0.0140 ± 0.0021	0.0069	0.0139	0.0219
	0.0391 ± 0.0074	0.0208	0.0391	0.0622
	0.9806 ± 0.0929	0.7178	0.9728	1.2815

Result 2: Subjective Weights

Table 2 depicts the point allocated by the experts and the resulting subjective weights of each air pollutant. The experts allocated points according to the significance of the air pollutants towards AP based on their opinions. Specifically, 53 percent of the experts recommended that $PM_{2.5}$ was the most significant air pollutant towards the occurrence of AP in Malaysia. However, Expert 2 believed that *CO* was the most important air pollutant.

Then, the subjective weight of each air pollutant was calculated by considering all the allocated points given by the experts. Resultantly, $PM_{2.5}$ had the highest weightage and represented the most hazardous air pollutant towards AP with a value of 0.2647, followed by PM_{10} with a weight value of 0.2147, SO_2, with a value of 0.1607, O_3, with a value of 0.1307, and NO_2, with a value of 0.1200. The least significant air pollutant was *CO* with a value of 0.1093.

Table 2

Allocated Points by Experts and Final Subjective Weights of Air Pollutants

Expert	PM_{10}	$PM_{2.5}$	SO_2	NO_2	O_3	CO
1	20	35	17	10	13	5
2	12	12	12	7	7	50
3	25	35	10	10	10	10
4	25	35	10	10	10	10
5	20	30	20	10	10	10
6	5	5	20	15	50	5
7	30	20	20	10	10	10
8	20	50	10	10	5	5
9	10	20	20	15	25	10
10	25	30	15	10	15	5
11	15	20	30	25	8	2
12	35	20	17	10	13	5
13	40	15	15	10	5	15
14	20	35	10	13	5	17
15	20	35	15	15	10	5
Subjective Weights	0.2147	0.2647	0.1607	0.1200	0.1307	0.1093
Rank	2	1	3	5	4	6

Result 3: Objective Weights

The results of objective weights obtained using four different entropy calculations are presented in Table 3. Hwang and Yoon (1981and Chen and He's (1997) methods allocated the same rank to the pollutants, as SO_2had the highest weight, followed by$PM_{2.5}$, PM_{10}, CO, NO_2 ,and the lowest weight was O_3. Meanwhile, Zeleny's (1982) method gave$CO$and SO_2 as the highest and lowest weight of air pollutants contributing to the air quality. On the other hand, $PM_{2.5}$ represented the highest objective weight by the Gaussian kernel method. In summary, the pollutant with the highest contribution to air quality was$SO_2$with a value of 0.1914, followed by $PM_{2.5}$ with 0.1841, CO with 0.1702, PM_{10} with 0.1683,NO_2 with 0.1535, and O_3 with 0.1324. Therefore, the objective weights were recorded to give a different ranking of the six air pollutants compared to subjective weights.

Table 3

Objective Weights of Each Air Pollutant

Entropy Method	PM_{10}	$PM_{2.5}$	SO_2	NO_2	O_3	CO
Hwang and Yoon (1981)	0.1861	0.2064	0.2330	0.1362	0.0962	0.1420
Zeleny (1982)	0.1537	0.1497	0.1463	0.1792	0.1839	0.1872
Chen and He (1997)	0.1769	0.1792	0.1910	0.1565	0.1388	0.1576
Gaussian Kernel	0.1566	0.2010	0.1954	0.1422	0.1108	0.1939
Average Weight	0.1683	0.1841	0.1914	0.1535	0.1324	0.1702
Rank	4	2	1	5	6	3

The best weights needed to be chosen since only one set of objectives was required. The accuracy of each set of weights was calculated by finding the mean absolute error (MAE), mean squared error (MSE), and mean absolute percentage error (MAPE). Table 4 shows the results of the accuracy measurement, where Chen and He's (1997) method was the best entropy method with the smallest value of MAE, MSE, and MAPE. Therefore, the objective weights obtained by Chen and He's (1997) method were considered the objective weights of this study.

Table 4

Accuracy Measurement of the Entropy Methods

Entropy Method	MAE	MSE	MAPE
Hwang and Yoon (1981)	0.02826	0.00093	17.21535
Zeleny (1982)	0.03038	0.00103	18.48943
Chen and He (1997)	0.00212	0.00001	1.27408
Gaussian Kernel	0.01489	0.00027	9.31605

Result 4: Comparison of Subjective, Objective, and Aggregated Weights of the Six Pollutants

Table 5 shows the aggregated weights obtained by aggregating subjective weights as in Table 2 and Chen and He's (1997) objective weights as in Table 3. The aggregated weights recorded that $PM_{2.5}$ had the highest value, which meant that this pollutant was the most significant or hazardous air pollutant towards AP with a weight value of 0.2786. The second most hazardous pollutant was PM_{10} with an aggregated weight value of 0.2231, followed by SO_2 with 0.1803, NO_2 with 0.1103, and O_3 with 0.1065. Meanwhile, *CO* was the least significant air pollutant towards AP. The aggregated weight of each air pollutant was used in constructing the new API, as discussed in the following subsection.

Table 5

Subjective, Objective, and Aggregated Weights of Each Air Pollutant

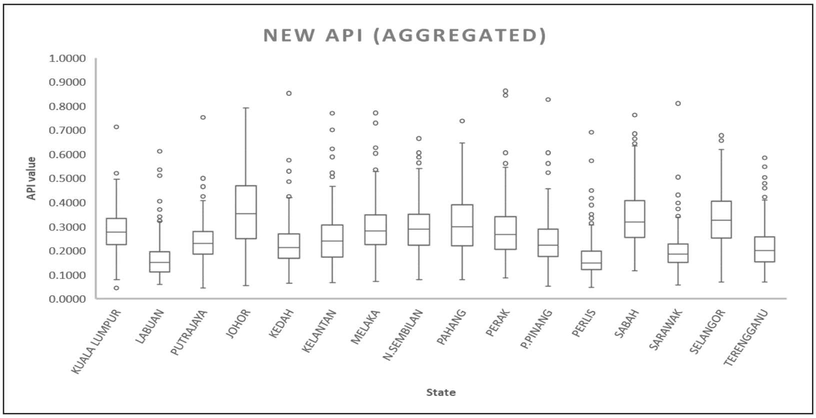
	Weights			
Air Pollutants	Subjective	Objective	Aggregated	Rank of Aggregated Weights
	0.2147	0.1769	0.2231	2
	0.2647	0.1792	0.2786	1
	0.1607	0.1910	0.1803	3
	0.1200	0.1565	0.1103	4
	0.1307	0.1388	0.1065	5
	0.1093	0.1576	0.1012	6

Result 5: The Air Pollution Index for Malaysia

The API is a daily index that ranges from zero (good air quality) to one (worst air quality). This index is constructed by considering the hazardous levels of the air pollutants towards AP, where the lowest value of API shows a lower AP level and vice versa. The API is visualised for each state in Malaysia as in Figure 2, reflecting the daily box-plots of API readings for each state and federal territory in Malaysia.

Figure 2

The Box-Plots of API Readings for the 16 States and Federal Territories in Malaysia for the Year 2018



Overall, most of the states had approximately normal API distribution. Johor was the only state that had no outliers, with slightly different mean and median API corresponding to 0.3604 and 0.3516, respectively. Among all the states, the highest API for 2018 was 0.8624 in Perak, which took place on 14th August 2018. The second highest API was in Kedah with a value of 0.8526 on 15th August 2018. Meanwhile, the lowest API value was recorded in Putrajaya with a value of 0.042, followed by Kuala Lumpur with a value of 0.0433 occurring on the same date, 10th March 2018.

CONCLUSION

This study has given a new insight into constructing a new API, particularly for 16 states including three federal territories of Malaysia, by considering the hazardous levels of the pollutants based on the 2018 data. The hazardous levels of the six pollutants were estimated by aggregating subjective and objective weights of the pollutants. This new API is arguably better than the existing API, which refers only to the maximum sub-index value of five pollutants, and all pollutants were treated as having the same toxicological level. The findings revealed that the smallest particle, , had the highest contribution towards air pollution in Malaysia compared to the other air pollutants. This result is consistent with previous findings that small or ultrafine particles have the worst health impact since they can remain in the deepest section of the airways or even reach the bloodstream directly. Furthermore, the findings depict that higher API values were found in August 2018 and the northern region of Malaysia, while the lower API values were discovered in March 2018 and the central region. Practically, the findings of this study could help the Ministry of Health and Ministry of Environment and Water to take the correct intervention actions according to the air pollution situation. Besides, the new API readings might provide more accurate information about the air quality status in Malaysia and help the community to adjust their daily activities accordingly.

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