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Monitoring Air Quality Trends for Industrial and Urban Areas

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ABSTRACT. This study examines the trends of three air pollutants: Particulate Matter 10 (PM_{10}), Particulate Matter 2.5 ($PM_{2.5}$), and Nitrogen dioxide (NO_2) in industrial and urban regions. Although extensive air quality monitoring occurs in Malaysia, limited studies have employed statistical process control methods to analyze temporal pollution trends between industrial and urban areas, thereby constraining understanding of process stability and environmental performance. This study fills this gap by utilizing $\overline{X}$ and S charts, along with the Process Capability Ratio (PCR), to assess both pollutant levels and the efficacy of air quality monitoring systems across various land-use categories. This study creates a quality control chart for three primary pollutants, utilizing data sourced from the Department of Environment Malaysia (DoE) for Shah Alam and Kuala Lumpur, spanning the period from January 1 to December 31, 2022. The data was examined to assess the efficacy of air quality control systems and to confirm whether air quality monitoring devices identify pollutant levels within designated thresholds. Research reveals that pollution levels in Shah Alam exceeded expectations, likely attributable to its nearness to manufacturing facilities and contributions from vehicle emissions and transboundary pollution. This study highlights the significance of a comprehensive air quality monitoring network in protecting the environment and enhancing public health.

Key words: Air Pollution, Control Charts, Particulate Matter, Statistical Quality Control

1. INTRODUCTION

The Air Pollutant Index (API) in Malaysia is an essential instrument created by the Department of Environment (DoE) to assess and convey air quality to the public. It offers a streamlined assessment of pollution levels derived from principal pollutants, namely Carbon monoxide (CO), Sulphur dioxide (SO_2), Nitrogen dioxide (NO_2), Ozone (O_3), and Particulate Matter (PM_{10}). The API is determined by the maximum sub-index value of these pollutants and is classified into categories including Good, Moderate, Unhealthy, Very Unhealthy, and Hazardous (DoE, 2023; Redzuan et al., 2023; Mustakim et al., 2022). As Malaysia experiences swift urbanization and industrialization, a methodical evaluation of air quality is essential. The API system enables the government to monitor pollution levels and regulate activities that substantially affect air quality (Talib et al., 2022).

Industrial emissions and environmental variables persist in influencing air quality in Malaysia. Rahman et al. (2022) identified vehicular emissions and industrial activities as principal sources of pollution in urban areas like Kuala Lumpur and Penang, where pollution levels often fluctuate between moderate and unhealthy, particularly during peak traffic periods. Mustakim et al. (2022) investigated seasonal fluctuations in air pollutant data and determined that the southwest monsoon season, linked to agricultural burning, increases levels in southern and central Malaysia.

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Moreover, Hua et al. (2022) highlighted that transboundary haze events lead to detrimental air quality, primarily resulting from biomass combustion in adjacent nations, thereby intensifying pollution levels in Malaysia.

In addition to environmental issues, elevated air pollutant levels present considerable health hazards. Othman et al. (2023) performed an epidemiological study associating elevated API levels with a rise in hospital admissions for respiratory and cardiovascular ailments. Their findings indicate that even moderate levels of API can negatively affect at-risk populations, such as children, the elderly, and those with pre-existing health conditions. Tan et al. (2023) and Ramli et al. (2022) further corroborate this, demonstrating a direct correlation between API levels and elevated respiratory-related mortality rates in prominent Malaysian cities. These studies highlight the critical necessity for efficient air quality management to safeguard public health (Rahman et al., 2022).

In light of these concerns, ongoing air quality monitoring in industrial and urban regions is crucial to avert deteriorating pollution levels. This study examines Shah Alam and Kuala Lumpur as exemplars of industrial and urban settings, respectively. Shah Alam is marked by a significant concentration of factories, combustion processes, and vehicular emissions, whereas Kuala Lumpur, being Malaysia's most bustling metropolitan region, endures substantial traffic pollution. Examining air pollutant trends in these two cities yields insights into the determinants of air quality, considering their geographical proximity and differing environmental conditions. Comprehending these trends will facilitate initiatives to reduce pollution and enhance regulatory frameworks (Sentian et al., 2022).

Various policies have been implemented to mitigate air pollution. Ahmad et al. (2025) indicated that Malaysia has enacted more stringent emission regulations and encouraged the adoption of electric vehicles to mitigate industrial and vehicular emissions. Nevertheless, their study emphasized that enforcement is inconsistent and public awareness regarding air quality issues is comparatively low, despite these measures resulting in some enhancements.

Although extensive air quality monitoring occurs in Malaysia, limited studies have employed statistical process control methods to analyze temporal pollution trends in industrial and urban areas, thereby constraining understanding of process stability and environmental performance. To improve air quality management, enhanced enforcement, public education, and more effective pollution control strategies are necessary (Tan et al., 2023). This research seeks to evaluate the status of air pollutants in Malaysia's industrial and urban regions, assess current pollution control measures, and recommend more effective strategies for air pollution mitigation.

2. METHODOLOGY

2.1. Source of Data

This study employs a quality control methodology to improve the precision and dependability of air pollutant data in Malaysia, concentrating on the systematic regulation and inspection of environmental monitoring systems. Data was collected daily from January 1 to December 31, 2022, with quality control measures instituted to reduce variations and errors. The Department of Energy's air quality monitoring system documents essential pollutants, such as PM_{10}, $PM_{2.5}$, NO_2, SO_2, and O_3, providing hourly and daily pollutant values obtained from urban, suburban, and rural stations. Shah Alam and Kuala Lumpur signify industrial and urban regions, respectively. $PM_{2.5}$, PM_{10}, and NO_2 were recognized as the most significant pollutants and designated as the primary parameters of the study. The normality of the pollutant data was assessed using the Shapiro-Wilk test, resulting in a p-value of 0.066, which surpasses the 0.05 threshold. This signifies that the data adheres to a normal distribution. The Q-Q plot in Figure 1 shows that the points closely follow the reference line, supporting the normality assumption. Therefore, the data is appropriate for the application of control charts.

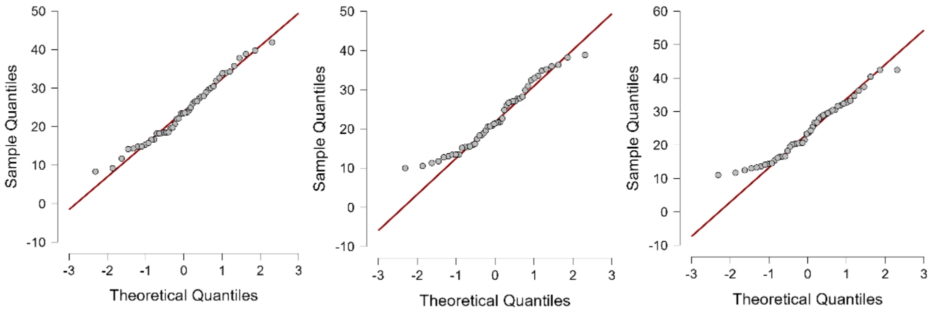


Figure 1. The Q-Q Plot for PM_{10} (left), $PM_{2.5}$ (middle), and NO_2 (right) in Kuala Lumpur and Shah Alam cities in the year of 2022

2.2. Assumption on SQC

The Normal Line Chart operates in statistical quality control analysis and time-series visualizations. The variation depends on the analytical application and methodology employed, necessitating the fulfillment of certain assumptions. The plotted variable must be continuous, and the data points should be recorded chronologically to illustrate temporal trends or patterns within the data. Statistical tests require normally distributed data, whereas visualizations can be conducted without this prerequisite, as normality is not essential for analysis.

SQC utilizes $\bar{X}$ and S charts to monitor process stability over time-based measurements. The charts are most effective for analyzing data derived from moderate to large sample sizes measured at predetermined intervals. The $\bar{X}$ chart monitors the mean values of processes to identify alterations in the central tendency of data. For sample sizes exceeding n = 10, the S chart offers enhanced monitoring of process standard deviation. The S chart effectively represents process variability as its calculation method incorporates all data points from each subgroup. The concurrent application of $\bar{X}$ and S charts benefits industries that emphasize quality control by ensuring process stability and minimizing variation. The following equations are utilized to determine the necessary values for these charts: mean ($\bar{X}$), standard deviation (S), Central Line (CL), Upper Control Limit (UCL), and Lower Control Limit (LCL).

Sample Mean ($\bar{X}$)

$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i \quad (1)$$

Where X_i are the individual sample values and n is the sample size.

Sample Standard Deviation (S)

$$S = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2} \tag{2}$$

$$\bar{\bar{X}} = \frac{\bar{X}_1 + \bar{X}_2 + \cdots + \bar{X}_m}{m} \tag{3}$$

$$\bar{S} = \frac{S_1 + S_2 + \cdots + S_m}{m} \tag{4}$$

Where X_i are the individual sample values, $\bar{X}$ is the sample mean, and n is the sample size and m is the sample subgroups.

Control Limit

S chart.

$$\bar{S} = \frac{S_1 + S_2 + \cdots + S_m}{m} \tag{5}$$

$$\text{UCL} = B_4 \cdot \bar{S} \tag{6}$$

$$\text{LCL} = B_3 \cdot \bar{S} \tag{7}$$

$\bar{X}$ chart.

$$\bar{\bar{X}} = \frac{\bar{X}_1 + \bar{X}_2 + \cdots + \bar{X}_m}{m} \tag{8}$$

$$\text{UCL} = \bar{\bar{X}} + A_3 \cdot \bar{S} \tag{9}$$

$$\text{LCL} = \bar{\bar{X}} - A_3 \cdot \bar{S} \tag{10}$$

The constants B_3, B_4, and A_3 are parameters in $\bar{X}$ and S charts, with their values contingent upon the sample size n. The fraction nonconforming (p) represents the proportion of points that exceed the control limits. Provided that air quality remains stable, the historical nonconformity fraction (p) may serve as an estimate for the future probability of nonconformity.

For a proportion, the confidence interval can be calculated using the normal approximation method:

$$p\emptyset\left(Z<\frac{x-\mu}{\sigma}\right)+\left(Z>\frac{x-\mu}{\sigma}\right) \tag{11}$$

where Z is a standard normal variable. The Average Run Length (ARL) is a key concept in statistical process control (SPC). It refers to the average number of samples taken before a control chart signals an out-of-control condition. ARL is crucial for understanding the sensitivity and performance of a control chart. In-Control ARL (ARL_0) is the average number of points plotted on the control chart before a false alarm. It indicates the rate at which a control chart will incorrectly signal that a process is out of control. Out-of-Control ARL (ARL_1) is the average number of points plotted on the control chart before it correctly signals an out-of-control condition when the process is out of control. It reflects how quickly a control chart can detect a real shift in the process. Below is the calculation used for ARL.

$$ARL=\frac{1}{P(X<LSL)+P(X>USL)} \tag{12}$$

Probability calculation:

$$P(X<LSL)=\emptyset\left(\frac{LSL-\mu}{\sigma}\right) \tag{13}$$

$$P(X>USL)=1-\emptyset\left(\frac{USL-\mu}{\sigma}\right) \tag{14}$$

Process Capability Analysis (PCR) is essential as it enables the assessment of the degree to which products can be manufactured within defined limits, thereby consistently ensuring quality. The study seeks to regulate air quality to the standards established by the Department of Environment (2023). This procedure entails computing the Process Capability Ratio (C_P) and the Process Capability Index (C_{PK}) using the equations below:

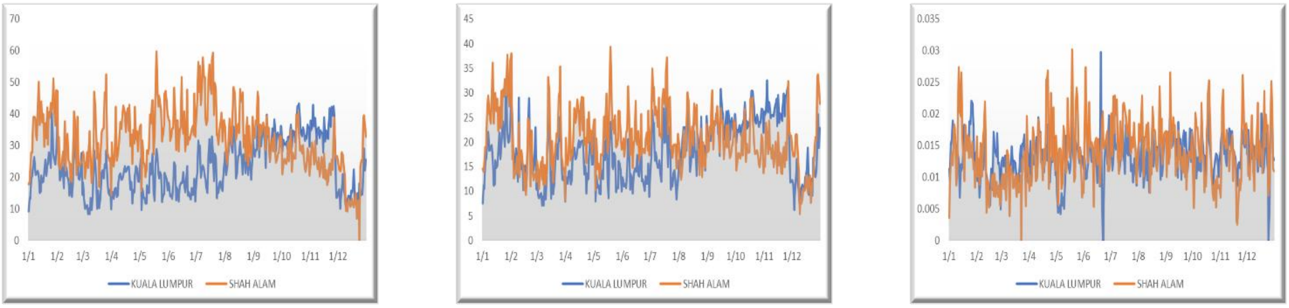
$$C_P=\frac{USL-LSL}{6\sigma} \tag{15}$$

$$C_{PK}=min\left[\frac{USL-\sigma}{3\sigma},\frac{\sigma-LSL}{3\sigma}\right] \tag{16}$$

3. RESULTS AND DISCUSSION

3.1. Trend Analysis

This section elucidates the findings subsequent to the examination of the research questions. The discussion underscores the necessity for action in the event of uncontrollable circumstances. The chapter concludes with a summary highlighting the pertinent information regarding the effectiveness and compliance of the process, followed by the presentation of optimal actionable recommendations.



(a) (b) (c)

Figure 2. Mean concentration of a) PM_{10}, b) $PM_{2.5}$, and c) NO_2 in both cities of Kuala Lumpur and Shah Alam in the year of 2022

Figure 2a clearly indicates that PM_{10} levels in Shah Alam consistently exceed those in Kuala Lumpur for the majority of the year. PM_{10} concentrations in Shah Alam exhibit periodic surges, attaining levels close to 50-60 µg/m³ during the mid-year and experiencing additional peaks towards the year's conclusion. In Kuala Lumpur, the data indicates generally lower PM_{10} concentration values, averaging approximately 20-40 µg/m³. Kuala Lumpur exhibits fewer and smaller spikes in comparison to Shah Alam, yet it is gradually surpassing the levels observed in Shah Alam as the year concludes. The $PM_{2.5}$ levels exhibit marked differences between Kuala Lumpur and Shah Alam, as illustrated in Figure 2b. The concentration in Kuala Lumpur varies from 7 to 28 µg/m³, whereas in Shah Alam, it attains levels up to 40 µg/m³, exhibiting significant peaks towards the year's conclusion. Like PM_{10}, $PM_{2.5}$ concentrations are consistently elevated in Shah Alam relative to Kuala Lumpur, indicating distinct sources and effects of fine particulate matter in both regions. This may be attributed to local pollution sources, such as vehicular emissions and industrial operations.

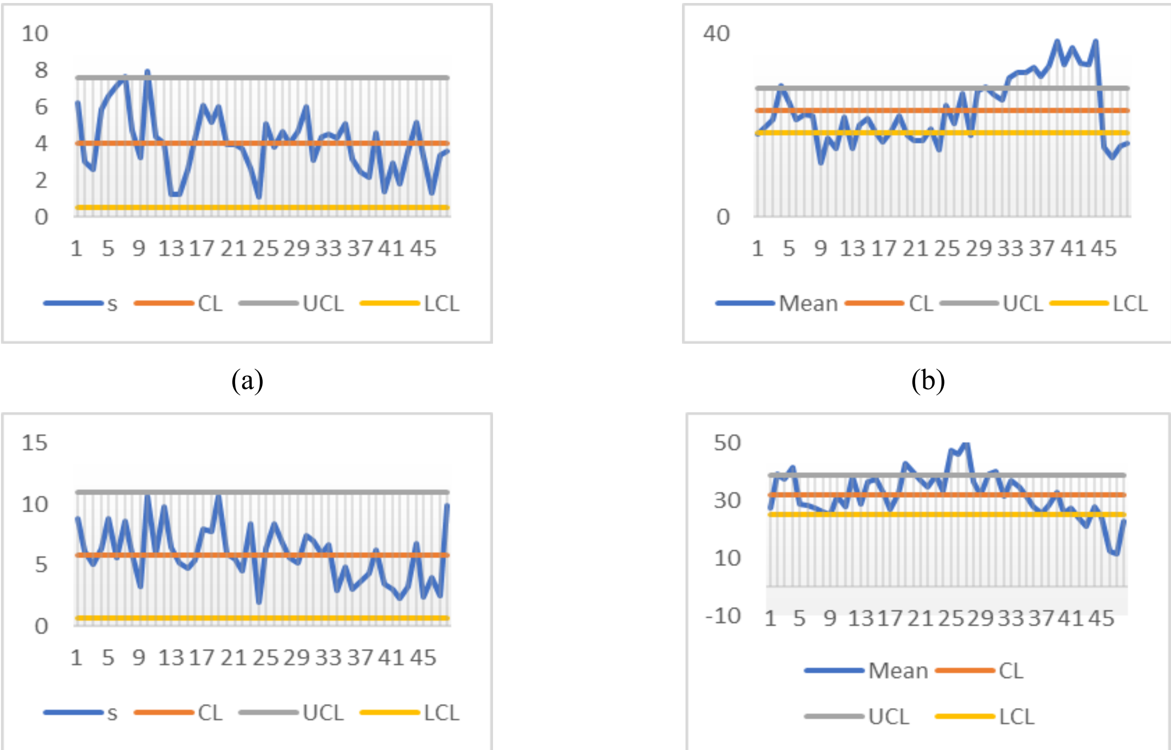
Figure 2c indicates that Shah Alam consistently exhibits elevated average NO_2 levels in comparison to Kuala Lumpur. The concentration level in Shah Alam varies between 0.015 and 0.03 parts per million (ppm), with intermittent surges surpassing 0.03 ppm. Meanwhile, Kuala Lumpur displays lower NO_2 concentrations, approximately 0.01-0.02 ppm, with infrequent declines and rare surges. Nonetheless, there are significant transient declines in Kuala Lumpur and Shah Alam during the mid-year and end-year periods. NO_2 is an atmospheric contaminant commonly released by industrial operations, vehicular emissions, and combustion activities. Given that the concentrations of PM_{10}, $PM_{2.5}$, and NO_2 are consistently elevated in Shah Alam, it can be inferred that Shah Alam generally exhibits inferior air quality relative to Kuala Lumpur. The industrial emissions may influence this, as Shah Alam has a high concentration of factories that typically contribute to elevated levels of air pollutants. Nonetheless, the patterns indicate a substantial decline towards the year's conclusion for PM_{10} and $PM_{2.5}$. It is thought to be affected by the monsoon season, which typically occurs at the end of each year. This event may decrease the concentration of air pollutants and indirectly result in improved air quality.

3.2. Control Chart

The air pollutants data for the year 2022 is examined and analyzed for both Kuala Lumpur and Shah Alam. These charts aid in detecting methods by which a process is not in statistical control. It can also facilitate continuous improvement processes by identifying trends, shifts, or patterns that require attention. $\bar{X}$ and S charts serve as effective and precise instruments for maintaining process stability and improving quality with an emphasis on consistency.

Table 1. The Summary of Results from $\bar{X}$ and S charts for PM_{10}.

Parameter	Kuala Lumpur	Shah Alam
Mean, $\bar{X}$	23.30	32.15
Standard Deviation, S	4.05	5.87
Control Limit R chart	UCL = 7.63	UCL = 11.06
	CL = 4.05	CL = 5.87
	LCL = 0.84	LCL = 0.69
Control Limit $\bar{X}$ chart	UCL = 28.09	UCL = 39.10
	CL = 23.30	CL = 32.15
	LCL = 18.51	LCL = 25.21



(a) (b)

(c) (d)

Figure 3. The a) S chart in Kuala Lumpur, b) $\bar{X}$ chart in Kuala Lumpur, c) S chart in Shah Alam, and d) $\bar{X}$ chart in Shah Alam for PM_{10} concentration.

According to Table 1, the average standard deviation of PM_{10} in Kuala Lumpur is 4.05, which is designated as the control limit for the S chart. The Upper Control Limit (UCL) is 7.63, and the Lower Control Limit (LCL) is 0.48. Figure 3a illustrates that all points remain within the Upper Control Limit (UCL) and Lower Control Limit (LCL), with the exception of a single point during week 10, signifying that the process variability is stable. Significant periodic spikes are evident in the initial stages, specifically from week 1 to 17, but these fluctuations stabilize in the latter portion of the chart. The study advanced by generating the $\bar{X}$ chart, as the S chart indicated that the process was in control. The average PM_{10} concentration in Kuala Lumpur is 23.30, serving as the control limit for the $\bar{X}$ chart. According to Figure 3b, nearly 50% of the chart indicates out-of-control conditions, specifically points 4, 9, 11, 13, 17, 22, 24, 29, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 46, 47, and 48. Particularly near the conclusion, the mean declines precipitously beneath the lower control limit. However, values exceeding the LCL are not of concern to researchers, as low PM10 levels indicate that the air quality is safe. Consequently, the process is deemed stable as the majority of points outside the control limit fall beyond the lower control limit (LCL).

According to Table 1, the average standard deviation of PM10 in Shah Alam is 5.87, which denotes the control limit for the S chart. Figure 3c indicates the absence of any out-of-control conditions, as all points reside within the Upper Control Limit (UCL) of 11.06 and the Lower Control Limit (LCL) of 0.69. The fluctuations seem consistent, with no unusual patterns observed throughout the year, suggesting that process variability is stable. Following the S chart, the investigation proceeded to develop the $\bar{X}$ chart for PM_{10} in Shah Alam. The mean value for $\bar{X}$ is 32.15, which represents the center line (CL) for the $\bar{X}$ chart. According to Figure 3 d), only a limited number of points have surpassed the control limit, specifically points 2, 4, 19, 25, 26, 27, 43, 46, and 47, indicating an out-of-control signal. The remaining points demonstrate a state of control, as they are plotted within the Upper Control Limit (UCL) of 39.10 and the Lower Control Limit (LCL) of 25.21. Nonetheless, a substantial shift occurs at the chart's endpoint 42, descending below the LCL.

Table 2. The Summary of Results from $\bar{X}$ and S charts for $PM_{2.5}$.

Parameter	Kuala Lumpur	Shah Alam
Mean, $\bar{X}$	18.23	20.58
Standard Deviation, S	3.42	4.24
Control Limit R chart	UCL = 6.44 CL = 3.42 LCL = 0.40	UCL = 7.99 CL = 4.24 LCL = 0.50
Control Limit $\bar{X}$ chart	UCL = 22.27 CL = 18.23 LCL = 14.18	UCL = 25.59 CL = 20.58 LCL = 15.56

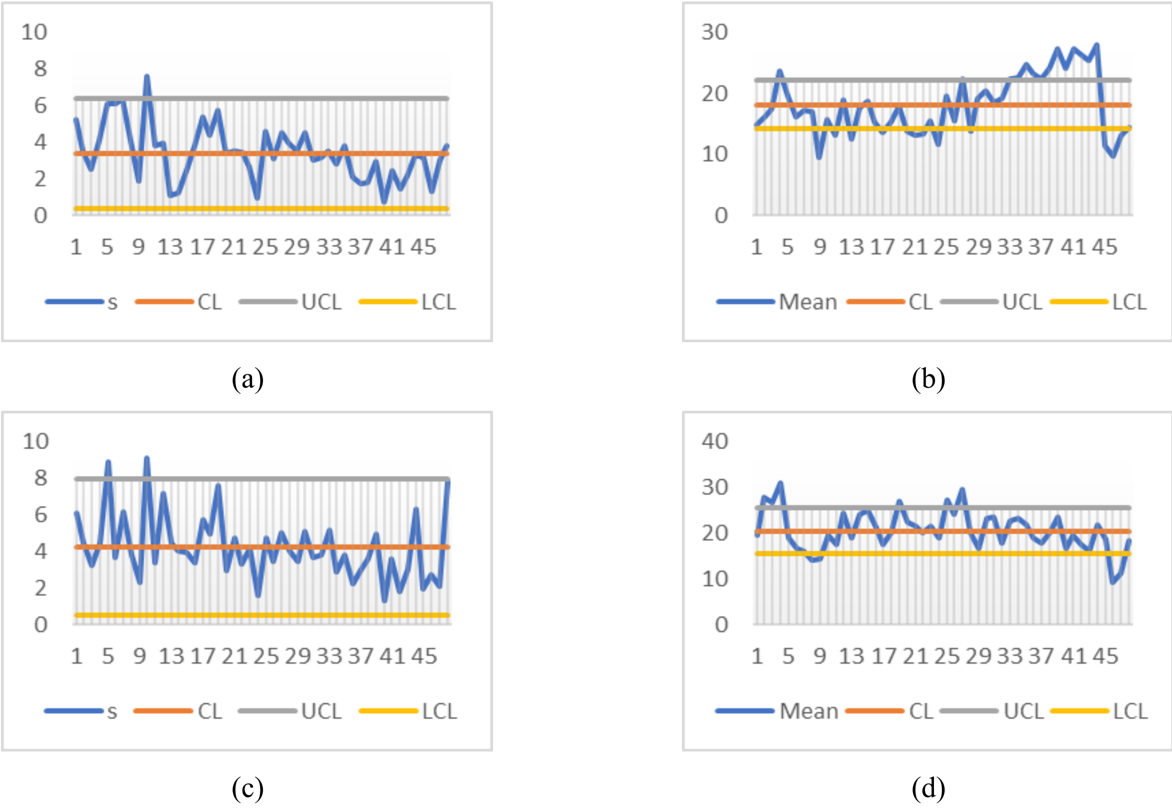


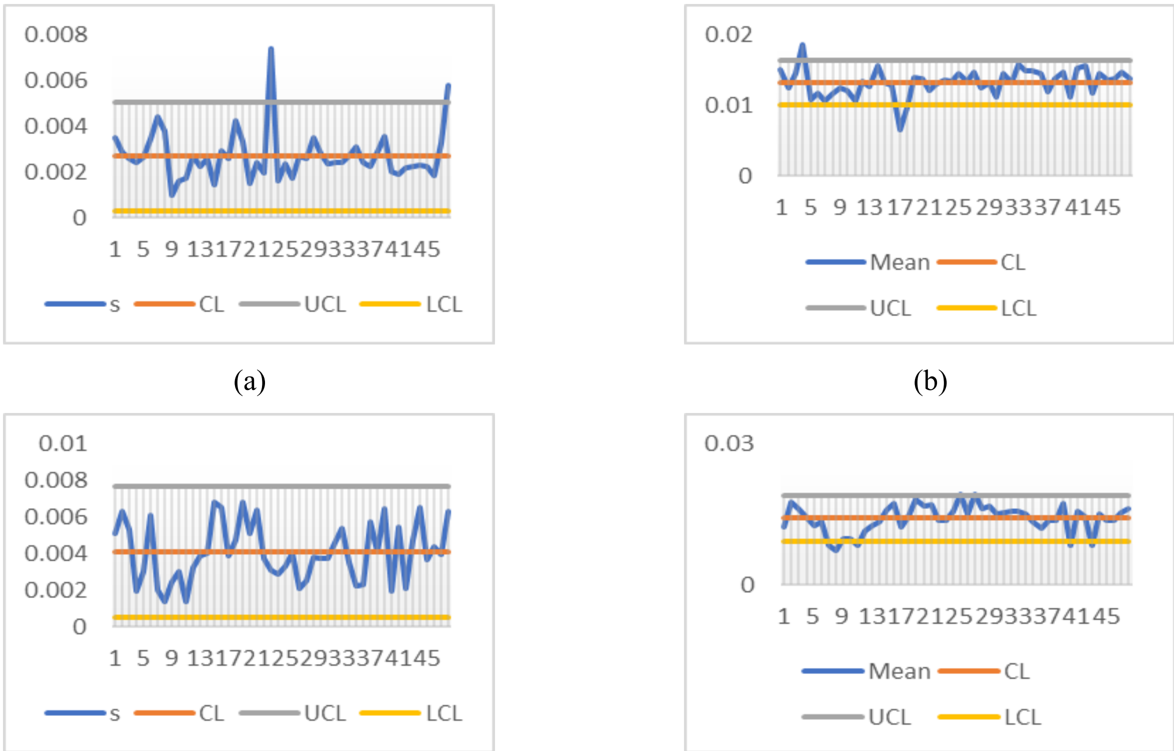
Figure 4. The a) S chart in Kuala Lumpur, b) $\bar{X}$ chart in Kuala Lumpur, c) S chart in Shah Alam, and d) $\bar{X}$ chart in Shah Alam for $PM_{2.5}$ concentration.

According to Table 2, the average standard deviation for $PM_{2.5}$ in Kuala Lumpur is 3.42, indicating the control limit for the S chart. Figure 4a illustrates solely point 10, which lies outside the Upper Control Limit (UCL) of 6.44 and the Lower Control Limit (LCL) of 0.40. The remaining points signify conditions under control, as they are plotted within the control limits. Nonetheless, there are pronounced periodic spikes in the initial half of the chart, signifying considerable variability within that subgroup. The variability has decreased, as the spikes have consistently diminished over the past six months, indicating a stable process. The research subsequently involved the creation of an $\bar{X}$ chart for $PM_{2.5}$ in Kuala Lumpur. The mean value is 18.23, designated as the control limit for the $\bar{X}$ chart. Figure 4b indicates that several points, specifically points 4, 9, 11, 13, 17, 21, 22, 24, 28, 29, 35, 37, 39, 40, 41, 42, 43, 44, 45, and 46, have surpassed the Upper Control Limit (UCL) and Lower Control Limit (LCL), signalling an out-of-control condition. The remainder remains within the control limit. As previously stated, values exceeding LCL are not a concern as they signify reduced air pollution concentration. The values surpassing the UCL are likely attributable to a significant rise in $PM_{2.5}$ indices.

According to Table 2, the mean standard deviation is 4.24, signifying the control limit of the S chart. All data points lie within the Upper Control Limit and Lower Control Limit, with the exception of weeks 5 and 10. Analogous to the chart in Kuala Lumpur, the periodic spikes are markedly elevated during the initial phases of the chart, signifying considerable variability. Nonetheless, the fluctuations stabilize over time, indicating that the process depicted in Figure 4 c) is regulated. The research proceeded with the development of the $\bar{X}$ chart for $PM_{2.5}$ in Shah Alam. Most of the points oscillate around the mean value of 20.58. Nevertheless, several points are plotted above the upper control limit of 25.59, specifically points 2, 3, 4, 19, 25, and 27. Points 8, 9, 46, and 47 have surpassed the lower control limit of 15.56. Figure 4 d) indicates that the spikes remain consistently normal throughout the majority of the year, with no extreme variations observed, suggesting that the chart is in control.

Table 3. The Summary of Results from $\bar{X}$ and S charts for NO_2.

Parameter	Kuala Lumpur	Shah Alam
Mean, $\bar{X}$	0.0133	0.0142
Standard Deviation, S	0.0027	0.0041
Control Limit R chart	UCL = 0.0051	UCL = 0.0077
	CL = 0.0027	CL = 0.0041
	LCL = 0.0003	LCL = 0.0005
Control Limit $\bar{X}$ chart	UCL = 0.0165	UCL = 0.0190
	CL = 0.0133	CL = 0.0142
	LCL = 0.0101	LCL = 0.0094



(a) (b) (c) (d)

Figure 5. The a) S chart in Kuala Lumpur, b) $\bar{X}$ chart in Kuala Lumpur, c) S chart in Shah Alam, and d) $\bar{X}$ chart in Shah Alam for NO_2 concentration.

According to Table 3, the mean standard deviation of NO_2 in Kuala Lumpur is 0.0027. Figure 5a indicates that the majority of points reside within the control limits, implying that process variability remains consistent across most weeks. It is evident that two notable subgroups exhibit variability exceeding the upper control limit, particularly at points 23 and 48. These levels suggest the presence of special causes of variation within the process. The remaining subgroups exhibit minimal variation in process times, suggesting that process variability is effectively controlled. The majority of points falling within control limits indicates that the process exhibits a stable level of variability. The study involved the derivation of the $\bar{X}$ chart for NO_2 in Kuala Lumpur. According to Table 3, the mean value is 0.0133, which denotes the center line (CL) for the $\bar{X}$ chart. Figure 5 b) illustrates that the fluctuations remain consistently stable for the majority of the year. Point 4 has surpassed the upper control limit of 0.0165, whereas point 17 is below the lower control limit of 0.0101. These outliers may signify unique factors influencing both the mean and variability concurrently. The remaining points remain within the control limits, signifying that the process is in control.

According to Table 3, the mean concentration of NO2 in Shah Alam is 0.0041, which serves as the control limit for the S chart. Figure 5c demonstrates that there are no data points exceeding the Upper Control Limit (UCL) of 0.0225 and the Lower Control Limit (LCL) of 0.0009, signifying that the process variability is within control limits. The standard deviation values exhibit consistent fluctuations throughout the year, indicating a lack of unusual variability or significant disturbances during this period. The measurements are consistently reliable over time. The study advanced with the derivation of the $\bar{X}$ chart for NO_2 in Shah Alam based on the results. Table 3 indicates that the mean value over 48 weeks is 0.0142, which serves as the control limit for the $\bar{X}$ chart. According to Figure 5d, all points lie within the Upper Control Limit (UCL) of 0.0191 and the Lower Control Limit (LCL) of 0.0093, with the exception of points 7, 8, 11, 25, 27, 40, and 43. The mean appears to fluctuate slightly above and below the center line, which is deemed out of control, although the variations do not seem to be extreme. The chart reveals no notable shifts or trends, indicating a stable process mean.

3.3. Process Capability Ratio (PCR)

The Process Capability Ratio (PCR) was evaluated to determine the process's potential to meet defined limits under stable conditions. The PCR is operational to evaluate the efficacy of the proposed control chart. This ratio elucidated the extent to which the process spread conformed to the specification limits. This study calculated the PCR using the ratio of specification width to process spread, defined by six standard deviations of the process distribution. The study assessed the PCR to ascertain if the process could reliably generate results within acceptable air quality limits. The findings emphasized the extent of variability in the process and its capacity to adhere to regulatory standards.

This analysis considered the specification limits according to the guidelines established by the DoE. It encompasses various categories for air pollution conditions based on their levels. The specification limit is established according to the 'Good' category to obtain the PCR value prior to determining the efficacy of the control charts.

Table 4. API guidelines from Department of Environment (2020)

Category	Parameter Breakpoint		
	PM_{10} (µg/m^3)	$PM_{2.5}$ (µg/m^3)	NO_2 (ppm)
Good	0-40	0.0-15.0	0.000-0.030
Moderate	41-154	15.1-35.4	0.031-0.100
Unhealthy	155-354	35.5-55.4	0.101-0.360
Very unhealthy	355-424	(55.5-250.4)^3	0.361-1.249
Hazardous	425-504	(250.5-350.4)^3	1.250-1.649

Table 5. The Summary of Results for PCR.

		Specification Limit	Fraction Nonconforming	Average Run Length (ARL)	Capability Analysis
Kuala Lumpur	PM_{10} (µg/m^3)	USL = 40 LSL = 0	0.000044	22,727.27	C_p = 1.58 C_{pK} = 0.33
	$PM_{2.5}$ (µg/m^3)	USL = 15 LSL = 0	0.8186	1.22	C_p = 0.7 C_{pK} = 0.33
	NO_2 (ppm)	USL = 0.03 LSL = 0	0	-	C_p = 1.79 C_{pK} = 0.33
Shah Alam	PM_{10} (µg/m^3)	USL = 40 LSL = 0	0.1003	9.97	C_p = 1.09 C_{pK} = 0.33
	$PM_{2.5}$ (µg/m^3)	USL = 15 LSL = 0	0.8962	1.12	C_p = 0.57 C_{pK} = 0.33
	NO_2 (ppm)	USL = 0.03 LSL = 0	0.00012	8,333.33	C_p = 1.16 C_{pK} = 0.33

Table 5 summarizes the results of air pollutants in Kuala Lumpur and Shah Alam. The results were derived from the Fraction Nonconforming, Average Run Length, and Process Capability Analysis conducted using Microsoft Excel software. The specification limits are established according to the air quality guidelines provided by the Department of Environment. The analysis of PM_{10} in Kuala Lumpur indicated a high process capability index (Cp) of 1.58, contrasted by a lower process capability performance index (CpK) of 0.33. This suggests that while the process variability conforms to the specification limits, it is not centred appropriately. The ARL of 22,727.27 indicated a remarkably low probability of nonconformance, quantified as 0.000044. This indicates that the control chart is anticipated to require 22,727 observations to identify an out-of-control condition, which is excessively slow for detecting changes. In contrast, Shah Alam exhibits a lower Cp of 1.09 and a comparable CpK value of 0.33, with an ARL of 9.97 and a higher fraction of nonconformance at 0.1003, indicating a marginally less robust process than that of Kuala Lumpur. Consequently, the control chart demonstrates greater efficacy in Shah Alam, whereas it is ineffective in Kuala Lumpur.

Conversely, $PM_{2.5}$ exhibited markedly lower Cp values for both Kuala Lumpur and Shah Alam, recorded at 0.7 and 0.57 respectively, signifying considerable variability that surpassed the upper specification limit of 15. The process was not centred, as the CpK values for both locations were consistently 0.33. The fraction of nonconformance was significantly elevated, with 81.86% in Kuala Lumpur and 89.62% in Shah Alam, resulting in ARL values of 1.22 and 1.12, respectively. This indicates that the process cannot sustain compliance, resulting in recurrent deviations beyond the specification limits for this pollutant. The low ARLs suggest that $PM_{2.5}$ concentrations vary considerably and frequently surpass thresholds, rendering the control chart ineffective for monitoring process stability in both Kuala Lumpur and Shah Alam. Kuala Lumpur exhibited the highest Cp value for NO_2 at 1.79, signifying favourable process variability; however, the CpK value of 0.33 indicates a deficiency in centering. The fraction of nonconformities was 0, leading to an undefined Average Run Length due to the absence of deviations. Simultaneously, Shah Alam exhibited a marginally lower Cp value of 1.16 while sustaining an equivalent CpK value of 0.33. The nonconforming fraction was 0.00012, resulting in an ARL of 8,333.33, which still signified a highly controlled process for this pollutant. Consequently, the control charts are exceptionally effective for both Kuala Lumpur and Shah Alam.

4. Discussion

The air quality results for the $\bar{X}$ and S charts in Kuala Lumpur and Shah Alam appeared to be within acceptable limits. Nevertheless, the PM_{10} and $PM_{2.5}$ concentrations in Kuala Lumpur rose from October to November in comparison to Shah Alam. This phenomenon may result from construction activities and urban heat island effects. Although both cities encounter difficulties in sustaining air quality, the urban attributes of Kuala Lumpur exert a greater influence during this time. Moreover, the levels of air pollutants diminished considerably beneath the lower control limit by year-end in both cities. The process may be influenced by the monsoon season, which typically occurs at the year's end. The increased precipitation and vigorous winds further diminish air pollutant concentrations during this period, elucidating the downward trends in the graphs for PM_{10} and $PM_{2.5}$. Notwithstanding the controlled conditions, the results demonstrated that the mean value and standard deviation in Shah Alam are generally superior to those in Kuala Lumpur. This can be primarily attributed to industrial emissions, a high volume of vehicles, and geographical constraints that impede the dispersion of pollutants.

To address these issues, it is recommended that stakeholders, including government agencies, local authorities, industries, and the public, undertake specific actions such as improving industrial emission regulation. Some of the actions to be taken such as i) Enhance the policy through regular inspections and biennial assessments of industrial instruments and structures to ascertain adherence to the emission standard. ii) Implement pollution taxes on industries that have not adhered to emission standards. iii) Offers financial incentives to industries to foster green technology and innovation.

5. CONCLUSION

The study employed various statistical techniques, including control charts and capability analysis, to monitor and analyse air quality data. This approach enabled the analysis of patterns and frequency of air pollution levels, particularly in cities like Shah Alam and Kuala Lumpur. This study demonstrates that urbanization and industrialization indices contribute to pollutant emissions, specifically those categorized as PM_{10} and $PM_{2.5}$, corroborating the predictions of Koo et al. (2020) and Leh et al. (2020). This study revealed that the average levels of PM_{10}, $PM_{2.5}$, and NO_2 in Shah Alam were markedly elevated in comparison to those in Kuala Lumpur, suggesting distinct pollution sources. Given the proximity of these two cities, it can be inferred that varying environmental factors influenced the levels of air pollutants, indicating that industrial emissions had a greater impact on air quality. Nonetheless, the pollutants in these two cities are categorized as good, with the exception of $PM_{2.5}$, which is classified as moderate. The appropriate specification limits for PM_{10}, $PM_{2.5}$, and NO_2 are 40 (µg/m3), 15 (µg/m3), and 0.03 (ppm), respectively. The control charts developed in this study effectively represent the process, although they all exhibit a lack of centering. Although it is environmentally safe, air pollution remains a concern as it may evolve over time. This study highlighted the necessity for enhanced community awareness regarding air quality issues and the need for improved environmental management strategies. The results of this study may provide significant insights for policymakers in developing sustainable air quality strategies.

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AUTHOR CONTRIBUTIONS

Muhammad Hummam Adnan is responsible for data application, analysis, and preparation of the initial draft.
Noryanti Nasir supervises the research, guided manuscript development, checking language and grammar.

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DATA AVAILABILITY

Data is available on request.

COMPETING INTEREST

The authors declare that there are no competing interests.

COMPLIANCE OF ETHICAL STANDARDS

We comply with ethical standards by adhering to regulations, policies, and a commitment to integrity in all our actions.

SUPPLEMENTARY MATERIAL

Not applicable.

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