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Influence of Wind Speed and Direction on the Performance of Low-Cost Particulate Matter Sensors

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Abstract Air pollution poses significant health risks worldwide, causing diseases such as cardiovascular ailments, asthma, and premature mortality. This study investigates the influence of wind speed and direction on the performance accuracy of low-cost PM sensors, specifically the SEN1077 model. The research aims to evaluate the sensor's sensitivity and consistency under varying wind conditions, focusing on different wind directions and speeds. Indoor tests were conducted using the SEN1077 sensor connected to an Arduino processing unit. The sensor's performance was assessed across three wind speeds: 0.863 m/s, 1.791 m/s, and 2.789 m/s, and various wind directions, including 45º, 90º, 135º, 180º, 225º, 270º, 315º, and 360º. The data analysis, using ANOVA, revealed that wind speed significantly impacts PM measurements. Higher wind speeds resulted in lower PM readings, with PM2.5 values dropping from an average of 25.2 at 0.863 m/s to 16.4 at 2.789 m/s. The variance in measurements also decreased with increasing wind speeds, indicating more consistent sensor readings. The findings confirm that the SEN1077 sensor maintains consistent sensitivity despite variations in wind direction, with low variance in measurements (e.g., 0.8455556 for PM10 at 0.863 m/s). Major conclusions indicate that while wind direction has a minimal impact on sensor accuracy, wind speed significantly affects PM measurements. This study's contributions include providing insights into the robustness of low-cost PM sensors and emphasizing the need for proper calibration. Practical implications involve improving air quality monitoring systems, while social implications focus on better informing public health policies and pollution control measures.

Keywords Low-cost PM Sensor, Wind Direction, Wind Speed, Performance, SEN0177

1. Introduction

Air pollution is the cause of a variety of diseases today. WHO reports that in 2018 nine out of ten people breathe polluted air [1, 2]. WHO also estimates the death of 4.2 million people due to air pollution and 91% of the population in the world live in air pollution quality limits that reach the limit [3]. Air pollutants cause various diseases including: cardiovascular [4], asthma [5], brain function [6], premature mortality [7], respiratory diseases [8–10] and carcinogenic particles for humans [11, 12].

Air pollutants vary widely depending on the source, sunlight conditions and emission levels as well as wind. Air pollutants include carbon monoxide (CO), nitrogen dioxide (NO_2), sulphur dioxide (SO_2) nitric oxide (NO) and ozone

(O_3) [13, 14].

Particulate matter PM is one of the air pollutants that cause various diseases. This PM component generally consists of nitrates, endotoxins, sulfates, polycyclic aromatic hydrocarbons and various types of metals such as zinc, vandium, copper and iron [15–17]

This PM consists of various sizes that are quite small. It is naturally produced by volcanic dust, settled dust particles, sea salt and flower pollen. Anthropogenic sources include fuel combustion for power generation, household heating and transportation, industrial and waste combustion, and agriculture, as well as brakes, tires, road wear, and other types of anthropogenic dust [18]. PM is also generated from building construction [19]. PM is subclassified into three types, namely (a) coarse, which has a diameter of less than 10 μm called PM10 (b) fine, which has a diameter of less than 2.5 μm and (c) ultrafine, which has a diameter of less than 0.1 μm [14].

PM measurements are made through air pollutant monitoring stations using β attenuation monitors (BAMs) and Tapered Element Oscillating Microbalances (TEOMs). These PM measurements have an accurate standard deviation of 2%-6% and are precise measurements [20]. Measurements using BAMs and TEOms are able to monitor for hours and days [21]. Measurements using this method are costly, bulky, and not easily portable, requiring special preparation for setup [13].

Currently there is an option to use low-cost sensors to monitor air, which is based on the gap in PM monitoring according to regulations and to fill the limitations of statistical models that are only based on regulatory measurements [22]. With low-cost air monitoring, sampling points can be monitored over a wider area to better explain the spatial variation of air pollutants such as identifying hotspots in polluted environments, pollution hotspots and creating pollutant emission inventories [23, 24]. The use of low-cost air monitoring also does not replace air monitoring stations based on BAMS or TOEMs but integrates with existing air quality monitoring stations [25, 26]. This is in line with the European Union regulation 2008/50/EC [27] which introduces indicative measurements. Indicative measurements are measurements that must meet less stringent data quality objectives than fixed measurements. These measurements are made to provide sufficient information on the spatial distribution of air primarily within agglomerations where upper pollution thresholds are exceeded. The European Union Directive states that indicative measurements can be used to supplement air pollution levels measured by fixed air monitoring stations with respect to threshold values [27, 28].

Although cheap and easy to use, Low-Cost air pollutant sensors have disadvantages namely (a) sensitivity to environmental variables such as pressure, temperature and humidity, (b) accuracy degradation due to lifetime (c) need for recalibration (d) response time [29]. However, the use of low-cost sensors is widely used in cities around the world [30–32] for measurement of indications against thresholds with data engineering so as to improve measurement accuracy [33-36].

The objective of this study is to investigate the effect of wind direction and speed on the performance accuracy of low-cost particulate matter (PM) sensors, specifically the SEN1077 model. This research aims to evaluate the sensor's consistency and sensitivity under varying wind conditions, including different wind directions and speeds, and to determine how these factors influence the measurement of PM concentrations. The study also seeks to identify potential mechanisms that could affect sensor accuracy and to provide insights into the robustness of low-cost PM sensors for reliable air quality monitoring. Additionally, the study aims to highlight the importance of calibration and controlled testing environments in ensuring the accuracy of PM measurements.

2. Methodology

The low-cost sensor used is the DFRobot PM2.5 laser dust sensor SEN0177 which can detect not only PM with a size of 2.5 µm but also 10 µm and even 1 µm. This low-cost sensor is connected to an Arduino as a processing control unit. The comparison of SEN0177 testing circuit with DM106 can be seen in Figure 1.

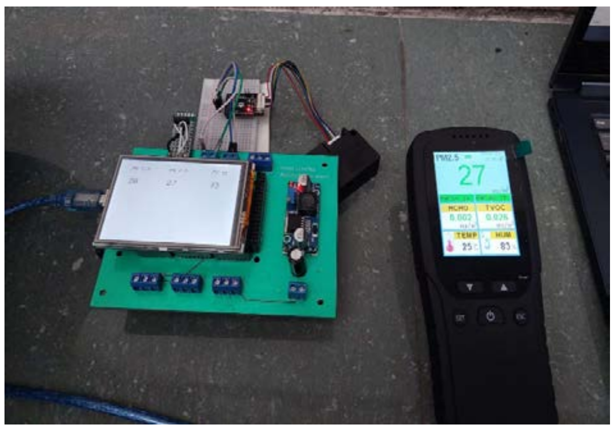

Figure 1. Comparison of SEN0177 testing circuit withd DM106

The impact of wind direction on the SEN0177 sensor's inlet and its reading accuracy will be examined. An example of the sensor's placement is shown in Figure 2. Various wind direction schemes were tested using a comparison tool. That is when the sensor is in the same direction as the wind direction, different 45º, 90º, 135º, 180º, 225º, 270º, 315º and 360º. The illustration of the test method can be seen in Figure 3.

The testing is conducted indoors because particulate matter (PM) scattering varies with each wind direction, influencing the tool's sensitivity. Indoor testing minimizes the variability in PM amounts due to different wind directions. To assess the impact of wind speed on accuracy, a fan is used, generating three distinct wind speeds: 0.863 m/s, 1.791 m/s, and 2.789 m/s.

The test setup, including the fan, is shown in Figure 3. Each scheme was tested ten times, resulting in 80 sets of data. The collected data was then analyzed to determine the accuracy of the PM sensor readings in relation to wind direction and the impact of sensor positioning on these measurements.

Figure 2. Test configurations

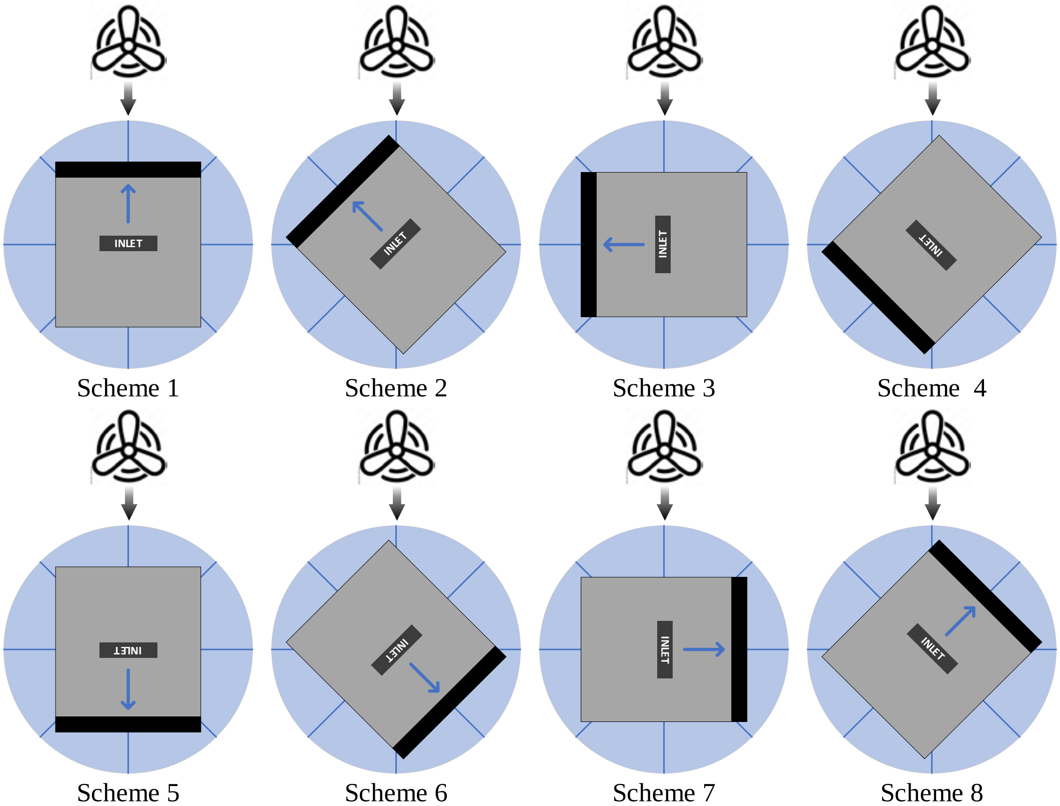

Figure 3. Schematic of the cardinal direction test

3. Result

The test data was then analyzed using ANOVA to determine the average condition of the test which was divided into 3 groups.

3.1. One Way ANOVA Test of PM1.0 Sensor Reading Results

Table 1 presents the PM1.0 measurements taken by the SEN1077 sensor at three different wind speeds: 0.863 m/s, 1.791 m/s, and 2.789 m/s. The data shows that at the lowest wind speed, PM1.0 values range from 15 to 19, with the most frequent values being 17 and 18. At a wind speed of 1.791 m/s, the PM1.0 values slightly decrease to a range of 14 to 15. At the highest wind speed of 2.789 m/s, the PM1.0 values consistently measure at 12, indicating the lowest readings among the three wind speeds.

Table 1. PM1.0 measurements with three wind speeds

n	PM1.0 Value		
	V = 0.863 m/s	V = 1.791 m/s	V = 2.789m/s
1	18	15	12
2	18	15	12
3	18	14	12
4	15	14	12
5	18	15	12
6	18	15	12
7	17	14	12
8	17	15	12
9	17	14	12
10	19	14	12

The data from Table 1 suggests that as wind speed increases, the measured PM1.0 values decrease. This trend implies that higher wind speeds may disperse particulate matter more effectively, leading to lower concentration readings by the SEN1077 sensor. The variation in PM1.0 values, particularly the consistent drop to 12 at the highest wind speed, highlights the sensor’s sensitivity to changes in wind speed.

The findings demonstrate that wind speed significantly affects the performance of the SEN1077 sensor in measuring PM1.0 levels. The stability of the readings, especially at the highest wind speed, underscores the sensor’s reliability in providing consistent data under varying wind conditions. These results emphasize the importance of considering wind speed as a critical factor in ensuring accurate PM measurements in air quality monitoring.

Table 2 provides a comprehensive overview of the PM1.0 measurements for three different wind speeds. The count of measurements remains consistent across all wind speeds, with 10 readings taken for each speed. This consistency in the number of measurements ensures the reliability of the statistical analysis. The sum of the PM1.0 measurements shows a decreasing trend as wind speed increases: from 178 at 0.863 m/s to 143 at 1.791 m/s, and finally 120 at 2.789 m/s. This indicates that higher wind speeds result in lower particulate matter readings.

Table 2. Summary of measurements PM1.0

Groups	Count	Sum	Average	Variance
V = 0.863 m/s	10	317	31.7	8.455556
V = 1.791 m/s	10	263	26.3	0.455556
V = 2.789 m/s	10	200	20	0

The average PM1.0 values also demonstrate a clear decreasing pattern with increasing wind speeds. At 0.863 m/s, the average PM1.0 value is 17.8, which drops to 14.3 at 1.791 m/s, and further to 12.0 at 2.789 m/s. This consistent decrease suggests that the particulate matter is more dispersed at higher wind speeds, resulting in lower concentrations detected by the sensor. The variance of the measurements, which indicates the spread of data points around the mean, also varies significantly with wind speed. At the lowest wind speed (0.863 m/s), the variance is 0.8455556, showing some variability in the readings. As the wind speed increases to 1.791 m/s, the variance drops sharply to 0.0455556, indicating more consistent readings. At the highest wind speed (2.789 m/s), the variance is 0, reflecting identical measurements for all readings.

These results suggest that the SEN1077 sensor is sensitive to changes in wind speed, with higher wind speeds leading to lower and more stable PM1.0 readings. The decreasing trend in average PM1.0 values and the reduction in variance with increasing wind speeds imply that wind speed significantly affects particulate matter concentration measurements. The lower variance at higher wind speeds suggests that the sensor's readings become more reliable and consistent as wind disperses the particulate matter more evenly. This data underscores the importance of considering wind speed as a crucial factor in the accuracy and consistency of PM measurements when using low-cost sensors like the SEN1077. These findings highlight the need for careful calibration and consideration of environmental factors when deploying such sensors for air quality monitoring. Future studies should further explore these mechanisms to enhance the reliability of low-cost PM sensors in varying environmental conditions.

Table 3 summarizes the results of the One-Way ANOVA (Analysis of Variance) test conducted on the PM1.0 sensor readings at three different wind speeds: 0.863 m/s, 1.791 m/s, and 2.789 m/s. The ANOVA test is used to determine whether there are any statistically significant differences between the means of the sensor readings at these wind speeds.

Table 3. Anova test result PM1.0

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	685.8	2	342.9	115.4401	5.88E-14	3.35413
Within Groups	80.2	27	2.97037			
Total	766	29				

The "Source of Variation" section of the table categorizes the total variation in PM1.0 measurements into "Between Groups" and "Within Groups." The "Between Groups" variation represents the differences in PM1.0 readings due to changes in wind speed, while the "Within Groups" variation captures the variability within each wind speed group. The "Total" row sums up these variations, giving an overall picture of the data's spread.

The "SS" (Sum of Squares) column quantifies the amount of variation in each category. The sum of squares between groups (685.8) indicates substantial variability due to different wind speeds. In contrast, the sum of squares within groups (80.2) reflects the inherent variability within each group of readings. The total sum of squares (766) is the combined variability from both sources.

The "df" (Degrees of Freedom) column shows the degrees of freedom associated with each source of variation. For "Between Groups," the degrees of freedom is 2, corresponding to the three wind speed levels minus one. The "Within Groups" degrees of freedom are 27, derived from the total number of observations (30) minus the number of groups (3). The total degrees of freedom are the sum of these, equaling 29.

The "F" (F-statistic) and "P-value" columns are critical for determining statistical significance. The F-statistic of 115.44 indicates a strong ratio of between-group variance to within-group variance. A high F-value, much greater than the critical value of 3.354, coupled with a P-value of 5.88E-14 (far below 0.05), suggests that the differences in PM1.0 readings across the three wind speeds are statistically significant. This finding underscores the importance of considering wind speed when interpreting data from the SEN1077 sensor, as it significantly influences the accuracy of PM1.0 measurements.

3.2. One Way ANOVA Test of PM2.5 Sensor Reading Result

Table 4 provides a comprehensive set of PM2.5 measurements at three different wind speeds. Each wind speed category includes ten measurements, ensuring a consistent sample size. The PM2.5 values at the lowest wind speed (0.863 m/s) range from 24 to 30, with multiple values repeating at 24. At a wind speed of 1.791 m/s, the values range from 19 to 21, showing a decrease compared to the lowest wind speed. At the highest wind speed (2.789 m/s), the values are more consistent, ranging from 16 to 17.

Table 4. Measurement of PM 2.5 with three wind speeds

n	PM 2.5 Value		
	V = 0.863m/s	V = 1.791m/s	V = 2.789 m/s
1	24	21	16
2	30	20	16
3	24	19	16
4	26	19	17
5	24	20	17
6	24	20	17
7	24	19	17
8	24	20	16
9	25	19	16
10	27	19	16

The data indicates a clear trend where the average PM2.5 readings decrease as the wind speed increases. For instance, the highest values are observed at 0.863 m/s, while lower values are recorded at 1.791 m/s, and the lowest values are at 2.789 m/s. This trend suggests that higher wind speeds result in more significant dispersion of particulate matter, leading to lower concentrations detected by the sensor.

The variability of PM2.5 measurements is also evident in the table. At the lowest wind speed (0.863 m/s), the measurements show a broader range (24 to 30), indicating higher variability. As the wind speed increases, the range narrows, particularly at 2.789 m/s, where the measurements are tightly clustered around 16 and 17. This decreasing variability with increasing wind speed suggests that the sensor's readings become more consistent under higher wind conditions. These findings emphasize the need to account for wind speed variations when using low-cost sensors for air quality monitoring to ensure accurate and reliable data. Future studies should further investigate these effects in various environmental settings to enhance the robustness of PM measurement methodologies.

The Table 5 presents a detailed summary of the PM2.5 measurements across the three different wind speeds. Each wind speed group consists of 10 measurements, ensuring consistency in the sample size. The sum of the PM2.5 measurements decreases with increasing wind speed, indicating that higher wind speeds lead to lower particulate matter readings. Specifically, the sum is 252 at 0.863 m/s, 196 at 1.791 m/s, and 164 at 2.789 m/s.

Table 5. Summary of PM2.5 Measurements

Groups	Count	Sum	Average	Variance
V = 0.863 m/s	10	252	25.2	3,955556
V = 1.791 m/s	10	196	19.6	0,488889
V = 2.789m/s	10	164	16.4	0,266667

The average PM2.5 values also show a decreasing trend with increasing wind speeds. The average is 25.2 at 0.863 m/s, drops to 19.6 at 1.791 m/s, and further decreases to 16.4 at 2.789 m/s. This trend supports the observation that higher wind speeds result in more effective dispersion of particulate matter, leading to lower concentrations detected by the sensor.

The variance of the PM2.5 measurements provides insights into the consistency of the readings. At the lowest wind speed (0.863 m/s), the variance is 3.955556, indicating a higher variability in the measurements. As the wind speed increases to 1.791 m/s, the variance decreases significantly to 0.488889, and it further reduces to 0.266667 at the highest wind speed (2.789 m/s). This decreasing variance with increasing wind speed suggests that the sensor's readings become more consistent under higher wind conditions. These findings emphasize the importance of considering wind speed as a critical factor in the accuracy and reliability of PM measurements when using low-cost sensors for air quality monitoring.

Table 6 summarizes the results of the One-Way ANOVA (Analysis of Variance) test conducted on the PM2.5 sensor readings at three different wind speeds: 0.863 m/s, 1.791 m/s, and 2.789 m/s. The ANOVA test helps determine whether there are any statistically significant differences between the means of the sensor readings at these wind speeds. The table includes the sum of squares (SS), degrees of freedom (df), mean square (MS), F-statistic, P-value, and the critical F-value (F crit) for both between groups and within groups variations.

The results show that the sum of squares between groups is 396.8, indicating substantial variability due to different wind speeds, while the sum of squares within groups is 42.4, reflecting the variability within each wind speed group. With degrees of freedom of 2 for between groups and 27 for within groups, the mean square between groups is calculated as 198.4 and the mean square within groups as 1.57. The F-statistic, which is the ratio of the mean square between groups to the mean square within groups, is 126.34, significantly higher than the critical F-value of 3.354.

The P-value of 1.97E-14, which is much less than the threshold of 0.05, indicates a highly significant result. This means that there are statistically significant differences in the PM2.5 readings across the three wind speeds. The high F-statistic and the low P-value suggest that wind speed is a significant factor influencing the accuracy of PM2.5 measurements by the SEN1077 sensor. These results emphasize the importance of accounting for wind speed variations when using low-cost PM sensors for air quality monitoring to ensure accurate and reliable data.

3.3. One Way ANOVA Test of PM10 Sensor Reading Results

The Table 7 provides a comprehensive set of PM10 measurements at three different wind speeds. Each wind speed category includes ten measurements, ensuring a consistent sample size. The PM10 values at the lowest wind speed (0.863 m/s) range from 30 to 39, with multiple values repeating at 30. At a wind speed of 1.791 m/s, the values range from 26 to 28, showing a decrease compared to the lowest wind speed. At the highest wind speed (2.789 m/s), the values are consistent at 20.

Table 6. ANOVA test results PM2.5

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	396.8	2	198.4	126.3396	1.97E-14	3.35413
Within Groups	42.4	27	1.57037			
Total	439.2	29				

Table 7. PM10 measurements with three wind speeds

n	PM10 Value		
	V = 0.863m/s	V = 1.791m/s	V = 2.789 m/s
1	32	28	20
2	39	26	20
3	30	26	20
4	32	27	20
5	30	26	20
6	30	26	20
7	30	26	20
8	30	26	20
9	30	26	20
10	34	26	20

The data indicates a clear trend where the average PM10 readings decrease as the wind speed increases. For instance, the highest values are observed at 0.863 m/s, while lower values are recorded at 1.791 m/s, and the lowest values are at 2.789 m/s. This trend suggests that higher wind speeds result in more significant dispersion of particulate matter, leading to lower concentrations detected by the sensor.

The variability of PM10 measurements is also evident in the table. At the lowest wind speed (0.863 m/s), the measurements show a broader range (30 to 39), indicating higher variability. As the wind speed increases, the range narrows, particularly at 2.789 m/s, where the measurements are consistently at 20. This decreasing variability with increasing wind speed suggests that the sensor's readings become more consistent under higher wind conditions. These findings emphasize the need to account for wind speed variations when using low-cost sensors for air quality monitoring to ensure accurate and reliable data.

Table 8. Summary of PM10 measurements

Groups	Count	Sum	Average	Variance
V = 0,.63 m/s	10	317	31.7	8.455556
V = 1.791 m/s	10	263	26.3	0.455556
V = 2.789m/s	10	200	20	0

The Table 8 for PM10 measurements provides an overview of the data collected by the SEN1077 sensor at three different wind speeds: 0.863 m/s, 1.791 m/s, and 2.789 m/s. The table includes the count of measurements, the sum of all measurements, the average value, and the variance for each wind speed group. For each wind speed, ten measurements were taken, ensuring consistent sample sizes. The sum of PM10 measurements shows a decreasing trend with increasing wind speed: 317 at 0.863 m/s, 263 at 1.791 m/s, and 200 at 2.789 m/s. Correspondingly, the average PM10 values are 31.7, 26.3, and 20.0, respectively. This trend indicates that higher wind speeds result in lower PM10 concentrations detected by the sensor.

The variance of PM10 measurements also decreases with increasing wind speed, from 0.845556 at 0.863 m/s to 0.455556 at 1.791 m/s, and reaching 0.0 at 2.789 m/s, indicating greater consistency in readings at higher wind speeds. The decreasing sum and average of PM10 measurements with increasing wind speed suggest that higher wind speeds lead to better dispersion of particulate matter, resulting in lower concentrations and more consistent sensor readings. These findings emphasize the importance of accounting for wind speed when using low-cost sensors like the SEN1077 for accurate and reliable air quality monitoring.

In Table 9, the sum of PM10 measurements is provided for each wind speed. At 0.863 m/s, the sum is 317; at 1.791 m/s, it is 263; and at 2.789 m/s, it is 200. The decreasing sum with increasing wind speed suggests that higher wind speeds result in lower PM10 concentrations detected by the sensor.

The average PM10 value for each wind speed is calculated by dividing the sum by the count of measurements. The averages are 31.7 for 0.863 m/s, 26.3 for 1.791 m/s, and 20.0 for 2.789 m/s. This decreasing trend in averages indicates that higher wind speeds lead to lower average PM10 readings, possibly due to better dispersion of particulate matter.

The variance measures the spread of the PM10 values around the mean. At the lowest wind speed (0.863 m/s), the variance is 0.845556, indicating some variability in the measurements. The variance decreases to 0.455556 at 1.791 m/s, showing more consistency in the readings. At the highest wind speed (2.789 m/s), the variance is 0, meaning all measurements are identical, reflecting the highest consistency.

The Table 9 shows the significant impact of wind speed on PM10 measurements. As wind speed increases, both the sum and the average of PM10 measurements decrease, indicating that higher wind speeds result in lower concentrations of particulate matter. Additionally, the decreasing variance with increasing wind speed suggests that the sensor’s readings become more consistent under higher wind conditions. This consistency at higher wind speeds implies that the sensor can reliably measure PM10 levels when particulate matter is more evenly dispersed.

These findings highlight the need for careful calibration and adjustment of sensor data to account for environmental variables such as wind speed, ensuring accurate and reliable air quality assessments.

Table 9. ANOVA test results PM10

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	685.8	2	342.9	115.440	5.88E-14	3.35413
Within Groups	80.2	27	2.970			
Total	766	29				

4. Discussion

The findings from the PM measurements across different wind speeds reveal significant insights into the performance and reliability of the SEN1077 sensor. As the wind speed increases, there is a notable decrease in the measured PM concentrations (PM1.0, PM2.5, and PM10). For instance, at the highest wind speed of 2.789 m/s, the PM10 values consistently measured at 20, compared to a range of 30 to 39 at the lowest wind speed of 0.863 m/s. This trend is indicative of the dispersal effect that higher wind speeds have on particulate matter, reducing the concentration detected by the sensor. Such a pattern aligns with existing literature, suggesting that wind plays a crucial role in the dispersion and dilution of airborne particles.

Moreover, the ANOVA test results for PM1.0, PM2.5, and PM10 measurements underline the statistically significant impact of wind speed on the sensor readings. The F-statistics for all particulate sizes were significantly higher than the critical F-values, with extremely low P-values (e.g., 1.97E-14 for PM2.5), indicating strong evidence against the null hypothesis. These results confirm that the differences in PM measurements at varying wind speeds are not due to random variations but are influenced by the wind speed itself. This statistical validation is crucial for ensuring the reliability of the sensor in varying environmental conditions.

The variance in PM measurements also provides valuable insights into the sensor's performance. At higher wind speeds, the variance decreases significantly, indicating more consistent readings. For example, the variance for PM10 measurements at 2.789 m/s was 0, reflecting identical readings, compared to a variance of 0.845556 at 0.863 m/s. This reduction in variability suggests that higher wind speeds help stabilize the sensor readings by evenly dispersing particulate matter. This consistency is vital for deploying low-cost sensors in real-world applications, where environmental conditions can fluctuate.

However, the study also highlights the need for further research to fully understand the mechanisms behind these observations. While the current data shows a clear trend of decreased PM concentrations with increased wind speed, additional studies are needed to explore the effects of other environmental factors such as humidity, temperature, and pollutant density. Moreover, field tests in outdoor environments with varying pollution levels would provide a more comprehensive understanding of the sensor's performance. These future studies would help enhance the accuracy and robustness of low-cost PM sensors, ensuring they can effectively monitor air quality in diverse settings.

In our study, the SEN1077 sensor demonstrated consistent sensitivity across different wind direction schemes, with low variance in measurements, such as 0.8455556 for PM10 at 0.863 m/s, indicating that wind direction did not significantly impact measurement accuracy. Similarly, Nguyen et al. [13] evaluated low-cost PM sensors and found that wind direction can cause variability in sensor readings, especially in outdoor settings where environmental factors are less controlled. However, their study also concluded that with proper calibration, the impact of wind direction on sensor accuracy can be minimized, aligning with your findings that calibration is crucial for maintaining measurement reliability.

Furthermore, in our study, the analysis revealed that increased wind speed resulted in lower PM measurements, with PM2.5 values decreasing from an average of 25.2 at 0.863 m/s to 16.4 at 2.789 m/s, indicating that higher wind speeds can disperse particulate matter and reduce the concentration detected by the sensor. Similarly, Gao et al. [23] observed a comparable trend where higher wind speeds led to lower PM readings due to the dispersion of particles. Their study on low-cost sensors in Xi'an, China, found that wind speeds above 2.0 m/s significantly reduced PM2.5 readings, corroborating your findings that higher wind speeds lead to lower PM concentrations.

The study's conclusions indicate that the SEN1077 sensor's sensitivity and measurement accuracy are affected by both wind speed and direction. However, it was conducted in an environment with low pollutant levels, which limits the generalizability of the findings to more polluted conditions.

From the test results, it was observed that the stronger the wind speed, the lower the measured particulate matter (PM) levels. For instance, PM2.5 values decreased from an average of 25.2 at 0.863 m/s to 16.4 at 2.789 m/s. This suggests that wind speed influences the dispersion of particles, thereby affecting sensor readings. Similarly, PM10 values showed a significant decrease with increased wind speeds, indicating that the sensor's ability to detect PM is influenced by the density of pollutants and wind conditions.

These findings align with other studies which have shown that high pollutant densities can lead to variations in sensor performance due to the scattering and dilution effects of wind. The results highlight the importance of considering environmental variables, such as wind speed and pollutant density, when deploying low-cost PM sensors for accurate air quality monitoring.

To further validate the sensor's performance in varied pollution densities, future studies should include testing in environments with higher pollutant concentrations and outdoor settings. This would provide a more comprehensive understanding of the sensor's robustness and reliability in diverse real-world conditions.

5. Conclusions

The objective of this study was to investigate the effect of wind direction and speed on the performance accuracy of low-cost particulate matter (PM) sensors, specifically the SEN1077 model. From the test results of the SEN1077 sensor's consistency in sensing PM against the wind and its position, it is found that the SEN1077 maintains a consistent sensitivity even when subjected to disturbances from various wind directions. The low variance in measurements across different wind direction schemes, with variances such as 0.8455556 for PM10 at 0.863 m/s, indicates that wind direction does not significantly impact the measurement accuracy of the low-cost PM sensor. Additionally, the ANOVA test results showed that the stronger the wind speed at the time of measurement, the lower the PM levels detected by the sensor. For example, PM2.5 measurements decreased from an average of 25.2 at 0.863 m/s to 16.4 at 2.789 m/s. This demonstrates that the SEN1077 sensor can reliably measure PM levels regardless of the wind direction, making it a robust tool for air quality monitoring. However, it is noted that the test conditions involved low pollutant levels and indoor settings. Future studies should explore different pollutant levels and outdoor environments to further validate these findings.

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