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IoT Network Based Analysis of Variations in Particulate Matter due to COVID-19 Lockdown

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***Abstract*—During the COVID-19 pandemic, India's complete lockdown was implemented from March 24 to May 3 2020, to minimize the effects of community transfer and control the rapidly growing rate of the virus spread. In this paper, we focus on quantifying the change in air pollution due to Hyderabad's lockdown, the capital of Telangana State. For this, two datasets are employed. The first dataset is from the Central Pollution Control Board (CPCB) stations in the city. In contrast, the second dataset is the dense IoT network of PM monitors deployed in the educational campus of IIITH in Gachibowli, Hyderabad. An analysis is done on the collected data to understand the effect of lockdown on PM values while considering the yearly and seasonal variations. It has been shown that while there has been a significant drop in PM values. However, through correlation analysis between the temperature and the PM values during the regular times, not all PM values decrease because of the lockdown.**

***Index Terms*—IoT, Air Pollution, COVID-19, Pandemic, PM2.5, PM10**

I. Introduction

Air pollution has been a cause of severe concern since long due to its hazardous effects on human health and the environment. There are several air pollutants in the atmosphere, out of which Particulate Matter (PM) has been identified as the most crucial contributor to air pollution [1]. Long term exposure to PM may increase the chances of severe respiratory and cardiovascular illness. A recent study has shown a correlation between PM (2.5 and 10) and mortality exposure due to the COVID-19 virus [2]. Localised and frequent monitoring of PM and other air pollutants is required for focused health advisories and intervention.

Internet of things (IoT) is the most preferred choice for air pollution monitoring due to its ability to sense and connect with the ambient surroundings and ease of interaction with users and other systems by employing an array of smart devices [3]. For example, Central Pollution Control Board (CPCB) has deployed six monitoring stations in Hyderabad measuring different pollution parameters linked to the Indian air quality index (AQI) including PM2.5, and PM10 [4]. These values are accessible to the general public through their website or downloaded by an APP through API. Although CPCB monitors are highly reliable, they are incredibly costly, and only a few can be deployed. For example, a large metropolitan city like Hyderabad spread across 650 km^2 has only six monitoring stations. This sparse deployment leads to the unavailability of pollution data at places of personal interest to the general public, such as residential areas, offices, and schools. This issue has paved the way for the low-cost but dense deployment of IoT networks for air pollution monitoring by researchers and institutions to understand local pollution. In our study a dense network of eight nodes in a small area of 66 acres was deployed in IIITH for monitoring PM2.5 and PM10 [5] as a pilot study. This paper focuses on the monitoring of PM2.5 and PM10 parameters.

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Significant contributors to the PM are vehicles, residential and industrial fuel burning, and dust [1], [6], [7]. After the outbreak of the corona pandemic in February 2020, governments worldwide have put several restrictions on human activities in public places as a measure to reduce the spread of the virus. In some countries, complete lockdown had been announced. The Indian Government announced a complete nationwide lockdown on March 24, 2020, which lasted till May 3, 2020. Due to the lockdown, the traffic, industrial, and other outdoor activities have dropped to a bare minimum. This has resulted in a significant drop in air pollution in several regions, including New Delhi, India [8], USA [9], and Europe [10]. The focus of this paper is on quantifying the effect of COVID-19 on the change of PM values in the southern Indian city of Hyderabad.

The specific contributions of this paper are

- Two datasets have been used for this analysis. The first dataset (data for one and half years) is from CPCB stations in the city [4], while the second dataset (data for six months) is from the dense IoT network of PM monitors deployed in the educational campus of IIITH in Gachibowli region of Hyderabad, a bustling IT and financial area [5].
- Differential analyses are done on the data to understand the effect of lockdown on PM values by factoring in the yearly and seasonal variations.
- The Welch's t-test is carried out to test whether the PM values have changed with respect to values in pre-lockdown time period.
- Pearson pair-wise correlation coefficient is estimated between PM and temperature values to show the effect of temperature changes on the PM values irrespective of lockdown.

Unlike the studies in [8]–[10], which only rely on the data publicly available for few sparsely placed nodes in a city, the contribution in this study is the data from a dense deploy-

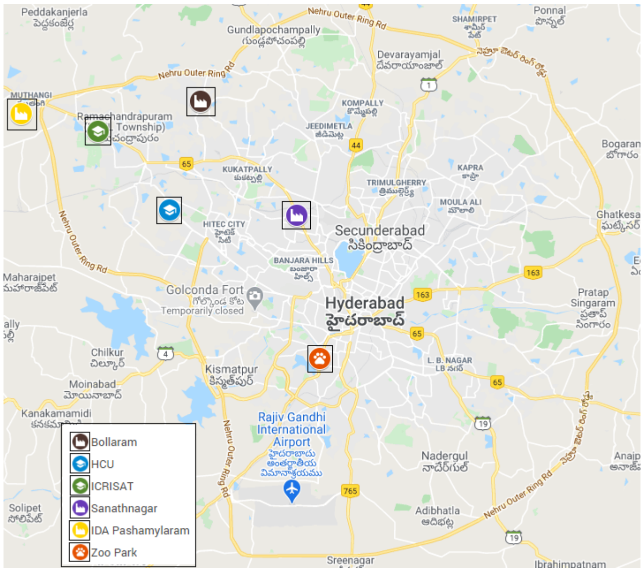


Fig. 1: Locations of CPCB pollution monitoring stations in Hyderabad.

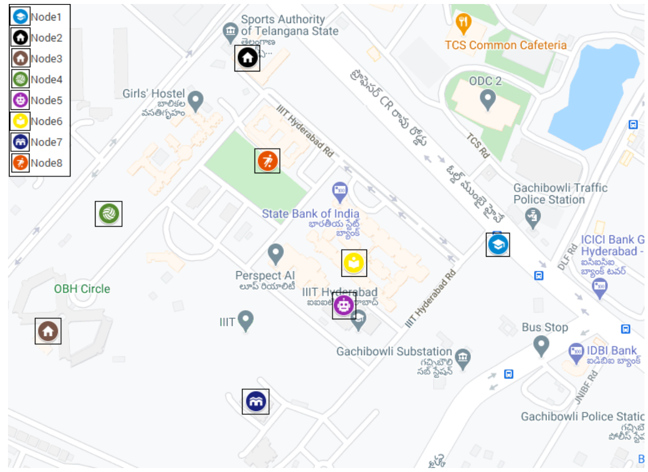


Fig. 2: Deployment of PM monitoring IoT network in the IIIT-H campus.

ment of low-cost sensors. Also, the seasonal variation and temperature effect have not been considered in the studies while calculating the impact of COVID-19 lockdown on the PM levels.

The rest of the paper is organized as follows. Section II describes the IoT network measurements for the CPCB stations and the IIIT-H campus IoT nodes. Section III talks about the analysis tools and techniques performed on the data collected from the two sources. Section IV discusses the analysis and results obtained, while Section V concludes the paper.

II. IoT Network Measurements

In this section, the measurement network for CPCB is explained first, followed by the details on the measurement network for the IIIT-H network.

A. CPCB nodes

Fig.1 shows the six pollution monitoring stations deployed in the Hyderabad city by CPCB [4] [11]. The node in Zoo Park was not functional for most of the measurement period, and hence, it has not been considered for analysis. Each of these stations uses PM sensors with a resolution of 0.5 $\mu g\,m^{-3}$, a precision of ±2 $\mu g\,m^{-3}$ (1-hour average), and accuracy of ±1% [12]. The CPCB website provide hourly averaged values for PM2.5 and PM10, both in $\mu g\,m^{-3}$, in the *csv* format. For CPCB nodes, the data is collected from January 1, 2019, to June 30, 2020.

B. IIIT-H nodes

Fig. 2 shows the deployment of PM monitoring nodes developed and deployed in IIIT-H [5] [11]. The objective of dense deployment (eight nodes in 66 acres) was to measure PM value with high spatio-temporal resolution. Out of these eight nodes, Node8 was not functional for most of the measurement period, and hence it has not been considered for analysis. Each node has a Nova PM SDS011 sensor, with a resolution of 0.3 $\mu g\,m^{-3}$ and a relative error of max. ±15% (±10 $\mu g\,m^{-3}$) [13]. Each node is connected to the internet through a WiFi connection to either IIIT-H routers or a 4G based WiFi router, as mentioned in [5]. The IIIT-H nodes' data have been collected using the REST API from ThingSpeak server [14], where the nodes dump the sensor data. Each node provides PM2.5 in $\mu g\,m^{-3}$, PM10 in $\mu g\,m^{-3}$, temperature in °C and relative humidity every 15 seconds with an additional network lag. For IIIT-H nodes, the data collection is ongoing since October 26, 2019, but the data considered for analysis in this paper is from January to June 2020.

III. Data Processing Techniques

A. Data pre-processing

The raw data collected from the CPCB and IIIT-H IoT networks must be pre-processed before any analysis can be done. In this paper, we have considered two methods. The first one involves removing null data points, while the second one consists of the removal of any possible outliers. This is necessary to avoid any unnecessary deviations caused by extreme values. For removing outliers, Z-score [15] is used.

B. Analysis techniques

In this section, four analysis techniques considered in this paper are briefly presented: averaging of data, evaluating seasonal and yearly variations, and significance test (Welch's t-test).

1) Averaging of data: Generally, a moving average is used for analyzing data. Averaging helps in smoothing out short-term variations and reveal the long term trends or patterns. In this paper, hourly averaged data is used for finding statistical quantities such as mean, variance, and correlation between different quantities. Weekly average plots have been used for easy visualization, while monthly average values have been used for the change analysis.

2) Change analysis: For performing change analysis, February 2020 and April 2020 have been considered to represent the pre-lockdown (normal) and total lockdown periods. The months of March and May in 2020 were not considered for the same because these were transitional months, i.e., lockdown happened during the last week of March 2020, and the Government began relaxing the total lockdown rules during May 2020. This made February and April the ideal months to highlight the contrast between pre-lockdown and complete lockdown and establish a comparative understanding.

To understand the seasonal variations, the change for the monthly average PM values in April w.r.t. February for the years 2019 and 2020 respectively are considered. For the yearly trend variations, the relative change for the monthly average PM values in 2020 w.r.t. 2019 for February and April, respectively, are considered.

In this paper, the definition of change Δ and relative change R between monthly average PM values of month $m1$ of year $y1$ w.r.t. the reference month $m0$ of the year $y0$ is given by

$$\Delta = M_{m1,y1} - M_{m0,y0} \tag{1}$$

and

$$R(\%) = \frac{\Delta}{M_{m0,y0}} \times 100, \tag{2}$$

where $M_{m,y}$ is the monthly average PM value for the month m in the year y.

3) t-test: The t test is used to decide if there is a significant difference between the means of two groups. Let us denote the first group or dataset $\mathcal{A}$ as the PM values change for April 2019 w.r.t. February 2019. This corresponds to seasonal change during normal times (without lockdown). Similarly, let us denote the dataset $\mathcal{B}$ containing the PM values change for April 2020 w.r.t. February 2020. This dataset refers to the seasonal change during lockdown (abnormal). Using these two data sets, the two hypotheses corresponding to the t-test are

$$\begin{aligned} H_n &: \mathcal{A} == \mathcal{B} \\ H_a &: \mathcal{A} \,!= \mathcal{B} \end{aligned} \tag{3}$$

where H_n is called the null hypothesis (signifies no effect of lockdown on the PM levels) while H_a is called the alternative hypothesis (signifies the effect of lockdown on the PM levels).

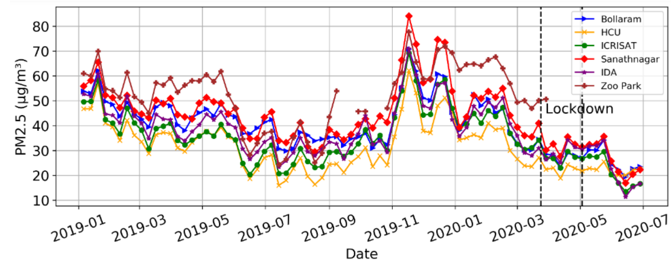
Given that the two sets might have different means and variances, we employ Welch's t-test, where the test statistic is given by [16]

$$t = \frac{\bar{\mathcal{B}} - \bar{\mathcal{A}}}{s}. \tag{4}$$

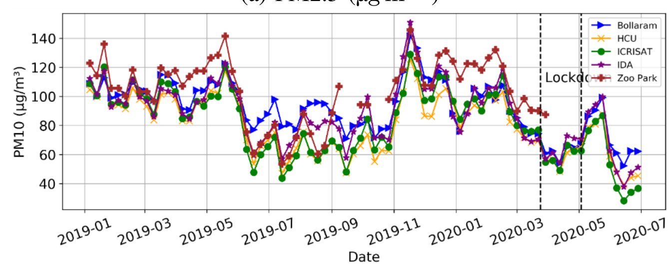
Here $\bar{\mathcal{A}}$ and $\bar{\mathcal{B}}$ are means of the sets $\mathcal{A}$ and $\mathcal{B}$, respectively and s is the scaling parameter given by

$$s = \sqrt{\frac{s_{\mathcal{A}}^2}{N_{\mathcal{A}}} + \frac{s_{\mathcal{B}}^2}{N_{\mathcal{B}}}} \tag{5}$$

with $N_{\mathcal{A}}$ and $N_{\mathcal{B}}$ are the number of samples and $s_{\mathcal{A}}$ and $s_{\mathcal{B}}$ are standard deviations for the sets $\mathcal{A}$ and $\mathcal{B}$, respectively.



(a) PM2.5 ($\mu g\, m^{-3}$)



(b) PM10 ($\mu g\, m^{-3}$)

Fig. 3: Central moving averages of PM values for the CPCB stations in Hyderabad with window length of 3 weeks.

The performance parameter in t-tests is p-value, which is the probability of correctly deciding the null hypothesis. A very small p-value means that such an extreme observed outcome would be improbable under the null hypothesis, implying the null hypothesis can be rejected.

IV. Analysis and Results

In this section, results are presented in two parts. Data from CPCB nodes is analyzed in the first part, followed by the analysis of data from the IIIT-H IoT network.

A. CPCB nodes

The CPCB data is analyzed by first plotting the central moving averages of PM values. Next, the change analysis is done taking seasonal and yearly variations into account, followed by the t-test.

1) Averaging of data: Fig. 3 presents the central moving averages over the window of three weeks for PM2.5 and PM10 values across the CPCB stations through January 1, 2019, to June 30, 2020. It can be observed that the PM values are at a peak during winters (November January). The PM values start decreasing with an increase in temperatures in February and keep dropping through summer before hitting the lowest values in Monsoon (June-September) because of rains. The values start increasing with the onset of winter in October and again hit a peak in November. It can be also observed from Fig. 3 that both the PM values are the lowest for the nodes at the HCU and ICRISAT. This is expected as HCU and ICRISAT are green institute campuses while other nodes are in industrial areas. Note that the graph of weekly average PM10 values for Sanathnagar station is missing in Fig. 3b due to data non-availability. It can be also observed that the data at the Zoo Park node is missing for February 2020 and hence it has been omitted in further analysis.

TABLE I: Monthly average PM values for CPCB stations

(a) PM2.5 ($\mu g\,m^{-3}$)

Station	Feb2019	Apr2019	Feb2020	Apr2020
Bollaram	46.15	40.12	42.88	27.75
HCU	37.48	31.23	35.13	23.06
ICRISAT	39.94	33.69	41.98	28.52
Sanathnagar	49.18	43.61	49.28	33.64
IDA	44.76	34.63	46.34	32.01

(b) PM10 ($\mu g\,m^{-3}$)

Station	Feb2019	Apr2019	Feb2020	Apr2020
Bollaram	105.74	94.65	98.46	61.94
HCU	98.79	86.67	93.33	59.31
ICRISAT	100.08	89.20	99.35	62.91
IDA	102.85	87.34	106.23	69.23

Table I shows the monthly average values of PM2.5 and PM10 for February 2019, April 2019, February 2020, and April 2020. Similar to Fig. 3, it can be observed that the PM values in general decrease going from February to April irrespective of the lockdown, though the difference is significantly high for the months in the year 2020. Therefore, to understand the effect of lockdown, we need to take into account yearly and seasonal variations.

2) Yearly variations: Table II shows the yearly variation in the PM values regarding change and relative change. It can be seen that the PM2.5 values have slightly reduced in February, going from 2019 to 2020 in Bollaram and HCU while they have increased marginally for other stations. Similarly, PM10 values in February have decreased somewhat for Bollaram, HCU, and ICRISAT while showing a slight increase for other stations. For example, the relative change in PM2.5 varies from -7.07% to 5.11% , while for PM10, the relative change varies from -6.88% to 3.28%. However, the PM values have only decreased and that too significantly in April across the two years for all stations. For example, the relative change in PM2.5 varies from -30.83% to -7.58% while for PM10, the relative change varies from -20.73% to -34.55%. Thus, the effect of lockdown on reduction of pollution is visible in the yearly trends.

TABLE II: Yearly variation (2020 w.r.t. 2019)

(a) PM2.5

Station	Change (Feb) ($\mu g\,m^{-3}$)	Relative Change (Feb) (%)	Change (Apr) ($\mu g\,m^{-3}$)	Relative Change (Apr) (%)
Bollaram	-3.263	-7.07	-12.371	-30.83
HCU	-2.347	-6.26	-8.168	-26.14
ICRISAT	2.042	5.11	-5.168	-15.33
Sanathnagar	0.099	0.20	-9.972	-22.86
IDA	1.584	3.53	-2.626	-7.58

(b) PM10

Station	Change (Feb) ($\mu g\,m^{-3}$)	Relative Change (Feb) (%)	Change (Apr) ($\mu g\,m^{-3}$)	Relative Change (Apr) (%)
Bollaram	-7.279	-6.88	-32.705	-34.55
HCU	-5.458	-5.52	-27.358	-31.56
ICRISAT	-0.730	-0.72	-26.296	-29.47
IDA	3.382	3.28	-18.108	-20.73

TABLE III: Seasonal variation (April w.r.t. February)

(a) PM2.5

Station	Change (2019) ($\mu g\,m^{-3}$)	Relative Change (2019) (%)	Change (2020) ($\mu g\,m^{-3}$)	Relative Change (2020) (%)
Bollaram	-6.028	-13.06	-15.137	-35.29
HCU	-6.247	-16.66	-12.068	-34.34
ICRISAT	-6.248	-15.64	-13.459	-32.05
Sanathnagar	-5.570	-11.32	-15.641	-31.73
IDA	-10.123	-22.61	-14.334	-30.92

(b) PM10

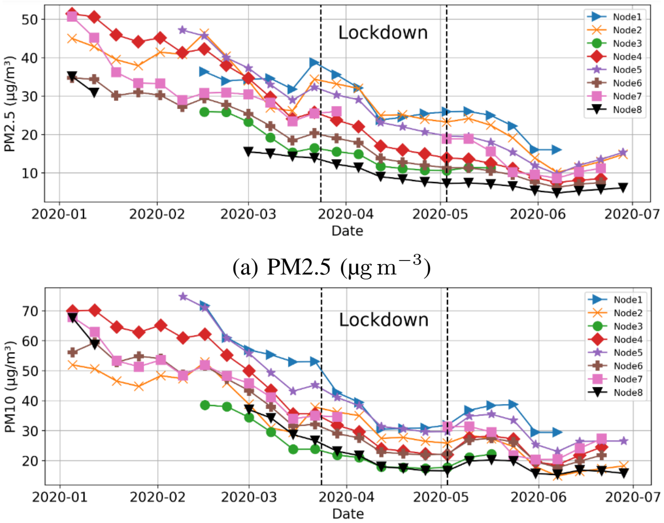
Station	Change (2019) ($\mu g\,m^{-3}$)	Relative Change (2019) (%)	Change (2020) ($\mu g\,m^{-3}$)	Relative Change (2020) (%)
Bollaram	-11.090	-10.48	-36.517	-37.08
HCU	-12.121	-12.26	-34.022	-36.45
ICRISAT	-10.871	-10.86	-36.437	-36.67
IDA	-15.507	-15.07	-36.998	-34.82

3) Seasonal variations: Table III shows the seasonal variations, i.e., change in the values of PM going from February to April in the same year. Here, the year 2019 serves as a reference year for normal times. It can be seen that the PM values decrease from February to April for both the years. This is as expected with the increase in temperatures and can also be seen from Fig.3. The relative decrease in the seasonal variation in 2019 ranges from 11.32% to 22.61% for PM2.5 and from 10.48% to 15.07% for PM10. However, the relative changes in the seasonal variation in 2020 are consistently show the relative decrease upwards of 30%. This shows the effect of lockdown on PM values, that is a decrease.

4) t-test: All the results presented till now are based on observing the differences in the monthly averages. To be sure that there is indeed change in the PM values, we consider t-test, which takes into account the standard deviations of the two data sets. The data for set $\mathcal{A}$ belongs to the change in the hourly averaged PM values for April 2019 w.r.t. February 2019. The data for set $\mathcal{B}$ belongs to the change in the hourly averaged PM values for April 2020 w.r.t. February 2020. Table IV presents the t-test results for the same. It can be seen that the null hypothesis is rejected with more than 99.99% confidence for all the stations for both PM2.5 and PM10 values validating the decrease in the PM values observed in the Tables II and III caused because of the lockdown. Only exception is IDA which is also rejecting the null hypothesis with 95% confidence. The CPCB stations at the industrial locations of Bollaram and Sanathnagar show the biggest variation followed by the greener institute HCU and ICRISAT. IDA, which is an industrial area at the outskirt of the city, is showing the least variation.

TABLE IV: t-test analysis

Station	t-value (PM2.5)	p-value (PM2.5)	t-value (PM10)	p-value (PM10)
Bollaram	-8.043	2.38e-15	-9.597	5.60e-21
HCU	-3.862	0.00011	-7.331	4.88e-13
ICRISAT	-5.455	6.26e-08	-7.050	3.62e-12
Sanathnagar	-7.663	4.81e-14	-	-
IDA	-2.039	0.0417	-5.817	8.60e-09



(a) PM2.5 ($\mu g\,m^{-3}$)

(b) PM10 ($\mu g\,m^{-3}$)

Fig. 4: Central moving average plot with window length of 3 weeks for IIIT-H IoT nodes.

TABLE V: Pearson's r correlation coefficient analysis for Jan 2020 to Mar 2020 variation (Temperature vs PM)

Pearson's r	**Node1**	**Node2**	**Node3**	**Node4**	**Node5**	**Node6**	**Node7**
PM2.5	-0.67	-0.58	-0.80	-0.81	-0.37	-0.85	-0.74
PM10	-0.86	-0.64	-0.87	-0.80	-0.42	-0.83	-0.74

B. IIIT-H IoT network

The IIIT-H IoT network data is analyzed in three parts: averaging of data, Pearson r correlation, and seasonal variation analysis. As the historical data of 2019 is not available, analyses corresponding to yearly variations and t-test have not been carried out. Pearson's r correlation analysis has been performed to establish the correlation between temperature variation and PM values change.

1) Averaging of data: Fig. 4 presents the weekly average variation in PM2.5 and PM10 from January to July 2020. The weekly average PM values are least for Node3 (located at the most interior part of the campus) and highest for Node1 (situated in the campus's main entrance gate). Of the seven nodes, Node4 shows the steepest descent, especially after the lockdown happened, which implies that the most significant decrease was recorded in Node4. The slope for the graphs of Node3 and Node7 remained almost constant during the lockdown period, which denotes that these two nodes did not record any significant change during the lockdown. It can be seen that data from Node8 is missing for the entire February and has not been considered for further analysis.

2) Pearson's r correlation analysis: From Table V, it can be seen that there is a strong negative correlation between temperature and PM values across all the nodes. It demonstrates that the PM values, even in normal times, decrease with increase in temperature values going from winter to summer. This shows that although there is a significant decrease in the PM values during the lockdown, not all PM values reduction can be attributed to the lockdown. Therefore the seasonal and yearly variations along with t-test analysis are essential.

3) Seasonal Variation: Table VI shows the comparison of the decrease of PM values in April 2020 with respect to February 2020 in terms of concentration Change ($\mu g\,m^{-3}$) and Relative Change (%). It has been observed that the decrease is noticeably different for both PM10 and PM2.5 for the seven node locations. The relative change for 7 Nodes in the IIIT-H campus ranged from -31.3% to -55.05% in case of PM2.5 and -39.26% to -56.94% for PM10. The difference in the values for the seven nodes is significant and considering that all nodes are in a small area of 66 acres shows the variation in the level of human activities in a small campus and the need for a dense deployment of PM monitoring nodes for localizing the events of cause for the PM values.

Table VIb show that almost every node deployed in the campus of IIIT-H show a consistent relative change (%) of at least 39% to maximum of 56% which is a variation of 16%. But in Table VIa it can be observed that the decrease in PM2.5 values show a similar trend as the CPCB stations deployed across the city, with few nodes showing a comparatively slighter decrease in terms of change ($\mu g\,m^{-3}$) even though the relative change (%) is higher.The relative change is from a minimum of around 31% to a maximum of 55% which amounts to a difference in around 24% of relative change in the campus. Consideration of the sources of PM2.5 in the surroundings of the respective nodes can give a possible explanation of the low or high drop of the PM2.5 values measured by the individual nodes in these locations.

- Node1 and Node2, even though being the closest to the vehicular pollution from the six-lane road in front of the campus, do not show a substantial decrease in terms of change ($\mu g\,m^{-3}$) and relative change (%) because of the

TABLE VI: Nodewise monthly average, change and relative change values for PM in IIIT nodes.

(a) PM2.5

Node ID	**Feb 2020** ($\mu g\,m^{-3}$)	**Apr 2020** ($\mu g\,m^{-3}$)	**Change** ($\mu g\,m^{-3}$)	**Relative Change (%)**
Node1	40.28	27.21	-13.07	-32.44
Node2	42.58	27.38	-15.20	-35.71
Node3	25.882	12.75	-13.12	-50.72
Node4	41.78	18.78	**-23.00**	**-55.05**
Node5	36.74	25.24	-11.50	-31.3
Node6	31.79	15.19	-16.60	-52.22
Node7	28.25	17.73	-10.51	-37.22

(b) PM10

Node ID	**Feb 2020** ($\mu g\,m^{-3}$)	**Apr 2020** ($\mu g\,m^{-3}$)	**Change** ($\mu g\,m^{-3}$)	**Relative Change (%)**
Node1	73.132	33.843	**-39.289**	-53.72
Node2	49.578	30.112	-19.466	-39.26
Node3	37.838	18.901	-18.937	-50.05
Node4	60.772	26.171	-34.601	**-56.94**
Node5	58.371	33.803	-24.568	-42.09
Node6	54.989	24.365	-30.624	-55.69
Node7	47.001	25.134	-21.867	-46.52

construction and repair of the same road taken up by the Greater Hyderabad Municipal Corporation (GHMC, the civic body that oversees the city of Hyderabad) during lockdown [17], which provided uninterrupted access to the repair and construction of the roads and flyovers. These construction hampered the expected decrease of the PM2.5 values even without the significant source of pollutants, vehicles being absent during the lockdown.

- Node4 shows the maximum decrease in both changes of -23.0 $\mu g\, m^{-3}$ and relative change of -55.05 % during the lockdown. The area surrounding Node4 is an online food and other e-commerce order delivery point and is busy round the clock with delivery vehicles before the lockdown and has a football ground nearby, typically used for sports activities before the lockdown. During the lockdown period, the area around Node4 is completely idle with no above mentioned human activities.
- Node6 shows the second-highest relative change of -52.22 % and change of -16.60 $\mu g\, m^{-3}$ during the lockdown. The node is located where the sources contributing to the PM2.5 values such as massive scale and round the clock fuel burning for cooking in the canteen just beside and dispersion of settled dust by people moving around during the rush hours of classes throughout the day have been entirely devoid due to the suspension of classes, and a closure of the canteen during the lockdown period, contributed to a higher decrease in PM2.5 values.
- Node3, Node5, and Node7 show the least amount of change around 10 $\mu g\, m^{-3}$. Node3 offers a higher relative change value of -50.72% even with a change of just -13.12 $\mu g\, m^{-3}$ as the initial value 25.882 $\mu g\, m^{-3}$ of this node is lowest the other nodes in February 2019 and are in locations where the human activities are much less even before the lockdown than the other nodes. Node3 and Node7 are in residential areas for students and faculty away from main activities, and Node5 is placed behind the research block, with low vehicle movement or construction activity,away from the significant PM values sources like vehicular pollution or large scale fuel burning for cooking. As the PM2.5 sources in these locations are already low even before the lockdown, the complete shutdown during the lockdown did not show substantial improvement in PM2.5 values.

The above points explain how PM2.5 decreased due to lockdown in only the human activities' locations (Node4 and Node6). Even with the primary source of PM2.5 values, i.e., vehicular pollution was nearly nil in Node1 and Node2, other human activities like construction of the road contributed to the PM2.5 values. Nodes with already lower values of PM2.5 even before the lockdown - Node3, Node5, and Node7 - did not show substantial change due to lockdown. Note that the variation across the different nodes for PM10 is not high when compared to PM2.5 which is a similar pattern seen in CPCB data. Hence, any explanation for PM10 has not been provided.

V. Conclusion

In this paper, by factoring in the yearly and seasonal trend analysis and applying t-test on the CPCB data, it has been demonstrated that there is a consistent decrease in the PM values across all the nodes because of the COVID-19 lockdown. A similar trend is observed for the data obtained for a smaller area of IIIT-H campus using the IoT sensor network deployed. However, the correlation analysis has shown a strong negative correlation between the temperature and the PM values demonstrating that not all the decrease in the PM values is because of lockdown. Moreover, the considerable variation in the effect of lockdown on the reduction in PM values in a small IIIT-H campus shows the importance of dense deployment for PM monitoring, identification of localised sources of pollution and the contribution of each source to the values.

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References

[1] K. Adams et al., "Particulate matter components, sources, and health: Systematic approaches to testing effects," *Journal of the Air and Waste Management Association*, pp. 544–558, 2015.

[2] X.Wu et al., " Exposure to air pollution and COVID-19 mortality in the United States," *medRxiv*, Apr 2020.

[3] S. Dhingra et al., "Internet of Things Mobile–Air Pollution Monitoring System (IoT-Mobair)," *IEEE Internet of Things Journal*, vol. 6, no. 3, pp. 5577–5584, June 2019.

[4] *CPCB website*, accessed 1 July 2020, https://www.cpcb.gov.in/.

[5] C. Rajashekar Reddy et al., "Improving Spatio-Temporal Understanding of Particulate Matter using Low-Cost IoT Sensors," *IEEE PIMRC*, 2020.

[6] H. Guo, S. Kota, S. Sahu, and H. Zhang, "Contributions of local and regional sources to pm2.5 and its health effects in north india," *Atmospheric Environment*, vol. 214, pp. 116867, 2019.

[7] I. Kheirbek et al., "The contribution of motor vehicle emissions to ambient fine particulate matter public health impacts in New York City: a health burden assessment," *Environ. Health*, 2016.

[8] S. Mahato et al., "Effect of lockdown amid COVID-19 pandemic on air quality of the megacity Delhi, India," *Elsevier*, Apr. 2020.

[9] J. Berman et al., "Changes in u.s. air pollution during the covid-19 pandemic," *Science of The Total Environment*, vol. 739, pp. 139864, 2020.

[10] L. Menut et al., "Impact of lockdown measures to combat covid-19 on air quality over western europe," *Science of The Total Environment*, vol. 741, pp. 140426, 2020.

[11] *Google Maps*, accessed 13 Sep. 2020, https://www.google.co.in/maps.

[12] *CPCB node sepcifications*, http://uppcb.com/pdf/volume_2_20nov14.pdf.

[13] *SDS011 Nova Sensor Specifications*, accessed 06 Aug. 2020, http://www.inovafitness.com/en/a/chanpinzhongxin/95.html.

[14] *ThingSpeak*, accessed 06 Aug. 2020, https://thingspeak.com/.

[15] C. Salgado, C. Azevedo, H. Proença, and S. Vieira, *Noise Versus Outliers*, pp. 163–183, Springer International Publishing, Cham, 2016.

[16] Zhenqiu Lu and Ke-Hai Yuan, *Welch's t test*, pp. 1620–1623, 01 2010.

[17] *Hyderabad making most of lockdown to build roads, flyovers*, 15 Apr. 2020, accessed 6 Jul. 2020, https://www.livemint.com/news/india/hyderabad-making-most-of-lockdown-to-build-roads-flyovers-11586959814540.html.