Technical report

Findings of a field study of low-cost air quality monitors

SHAKTI SUSTAINABLE ENERGY FOUNDATION

skymet weatherwise

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Abbreviation

BAM	: Beta Attenuation Monitor
CO	: Carbon Monoxide
CPCB	: Central Pollution Control Board
DTM	: DustTrak Monitor
NGO	: Non-Government Organization
NO	: Nitrogen Oxide
NO_2	: Nitrogen Dioxide
O_3	: Ozone
OPC	: Optical Particle Counter
PM	: Particulate Matter
RI	: Refractive Index
SOP	: Standard Operating Procedure
US EPA	: United States Environmental Protection Agency
WHO	: World Health Organization

1. Abstract

Air pollution control and air quality monitoring are needed to implement abatement strategies and stimulate environmental awareness among citizens. To meet this purpose, several techniques and technologies can be used to monitor air pollution (Penza et al., 2014). In this regard, Shakti Sustainable Energy Foundation (Shakti) supported a field trial to evaluate the performance of four low-cost air quality monitors in ambient Indian conditions. Renowned air quality experts who have extensive experience in designing, managing, and implementing air quality measurement programs provided technical and advisory support to undertake this study.

Skymet Weather Services Pvt. Ltd. conducted this field study at Pune and Noida from January to April 2018. Four low-cost air quality sensors were selected for the field study. To evaluate the performance of the low-cost air quality sensors at higher concentrations, simulations in laboratory were also performed (April 10, 2018 to May 3, 2018).

This study reveals better agreement of low-cost sensors for particulate matter at lower concentrations than at higher concentrations. Further, it shows that performance of low-cost sensors varies spatially and temporally as it depends on the atmospheric composition and meteorological conditions.

This study showed that low-cost sensors are capable and useful for deployment in the field to capture real-time particulate matter (PM) measurements. Based on the findings from this study, Plantower's PMS 7003 is recommended for the establishment of a network of low cost air quality monitors.

2. Introduction

Clean air is a basic requirement for human health. Urban air quality represents a major public health burden and is a long-standing concern to citizens. Air pollution is associated with a range of diseases, symptoms, and conditions that impair health and quality of life (e.g., Bentayeb et al., 2015; Pascal et al., 2013; Raaschou-Nielsen et al., 2016; Wu et al., 2016). As per the latest report published by the World Health Organisation (WHO), 91% of the world population was living in places where the WHO air quality guidelines levels were not met. Moreover, ambient (outdoor air pollution) in both cities and rural areas was estimated to cause 4.2 million premature deaths worldwide in 2016 (WHO, 2018).

Additionally, air pollution is responsible for global climate change (Rai et al., 2017; Ramanathan and Feng, 2009) and environmental problems such as acid rain (Menz and Seip, 2004), haze (Li and Zhang, 2014; Xu et al., 2013), depletion of ozone (Solomon, 1999; Solomon et al., 1986), and crop damage (Avnery et al., 2011a, 2011b; Van Dingenen et al., 2009). Therefore, there is a global drive to monitor and tackle this challenging problem (Rai et al., 2017; Fenger, 2009).

Air quality monitoring networks are essential to generate air quality data used to assess health risks due to air pollution and to understand the impact of control measures. Presently, real-time air quality monitoring by the pollution control boards is only conducted for a select number of Indian cities. Lack of real-time air quality monitoring implies that not enough air pollution data is generated to publish the Air Quality Index (AQI) for more than just a handful of cities. This is a critical data and knowledge gap which is impeding progress towards improving air quality management in cities and states.

The emergence of alternative air quality monitoring methods such as those based on the use of low-cost air quality monitors has provided an opportunity to address some of the existing data challenges. These monitors are affordable, easily deployable, and can generate independent, real-time air quality data to increase the existing pool of data and enhance public awareness in areas which are currently inadequately covered by the existing air quality monitoring networks of the pollution control boards. However, the reliability of such monitors and the quality of data they generate have not been studied in detail and remain an area which requires further investigation. Proper calibration of the instruments and adoption of standard operating procedures (SOPs) for monitor siting, data validation, and network maintenance can improve the reliability and quality of data from low-cost air quality monitors.

Several studies have been conducted to evaluate the performance of the low-cost air quality monitors. Rai et al., (2017) evaluated 24 identical units of commercial low-cost sensor platforms (AQMesh v3.5) against CEN (European Standardization Organization) reference analyzers. Their study evaluated measurement capability of low-cost air quality monitors over time and a range of environmental conditions. Gaseous pollutants (NO, NO2, O3, CO) were evaluated in the laboratory whereas particulate matter measurements were evaluated in the field. The result showed that performance of low-cost monitors varies spatially and temporally as it depends on the atmospheric composition and meteorological conditions. This study revealed better agreement of particulate matter at a lower concentration site than at a higher concentration site.

Borrego et al., 2016 assessed reliability and uncertainty of low-cost air quality sensors using a reference monitor. In this study, authors conclude that real-time data collected from microsensors combined with standard monitoring techniques have an enormous potential to be applied in new strategies for air quality control, rapid mapping of air pollution at high spatial detail, validation of atmospheric dispersion models, or evaluation of population exposure.

Mukherjee et al., 2017 quantified the performance of low-cost sensors (Alphasense OPC N2 and AirBeam) and presented the potential utility of measurements and deployment in an environment surrounded by hills and with no existing air quality monitoring station available (although a reference monitor was included in the study). Further, this study demonstrated the usefulness in the assessment of short-term changes in PM concentrations. Despite the limited accuracy of the Alphasense OPC-N2, the study showed a reasonable correlation between the sensor and the FEM BAM.

The United States Environmental Protection Agency (US EPA) evaluated various low-cost air quality sensors for gases and particulate matter (AGT Environmental Sensor). As a first step, they investigated how the low-cost sensor segment compares to recognized FRM/FEM specifications. They found not only encouraging but surprising results in many instances with respect to certain performance characteristics such as detection limit, linearity, precision, and rise and lag times.

Several more review articles have already addressed this emerging area of low-cost sensor-based air quality monitoring and are listed in Table I

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Table I: Summary of review article focused on the application of low-cost sensors for air pollution monitoring

Author and year	Study Focus
Aleixandre and Gerbolesb (2012)	Reviewed available commercial sensors for gaseous pollutants and compared their detection ranges with those specified in the European Directive on air quality 2008/50/EC.
White et al. (2012)	Highlighted the synergistic opportunities available between the sensor and wireless communication technologies for reducing human exposure to air pollutants.
Castell et al. (2013)	Reviewed potential application areas of sensor technologies for air quality management. The article also provided a critical analysis of commercially available sensors for gas measurements and emphasized the need for performance assessment of emerging sensor technologies under real-world conditions. Finally, the article summarized 24 different air quality management campaigns based on emerging sensor technologies.
Snyder et al. (2013)	Discussed the changing paradigm of air pollution monitoring due to the emergence of portable air quality sensors. The paper also illustrates a few application areas for such sensors in managing air quality issues together with key challenges and possible solutions.
Jovašević-Stojanović et al. (2015)	Assessed low-cost sensors for monitoring PM, including their specifications and general performance characteristics. They also reported measurements and modelling results to show validation methodology of a particular low-cost PM sensor.
Koehler and Peters (2015)	Reviewed personal exposure assessment to particulate air pollution by using novel sensors developed over last 5–10 years. They also discussed new metrics (that go beyond traditional mass measurements) for evaluating the relationship between particulate matter and its health impacts.
Kumar et al. (2015)	Reviewed the emergence of low-cost sensing technologies for managing air pollution in cities with respect to its need, state-of-the-art, opportunities, challenges, and future directions.

Zhou et al. (2015)	Reviewed state of the art and future perspectives for different types of chemosensors for monitoring gases involved in environmental exhausts (CO2, SO2, NOx, VOCs), biological signalling (H2S, NO, O2), and toxic use (nerve gases, sulphur mustard).
Bhanarkar et al. (2016)	Reviewed the issues and challenges in the design and deployment of wireless sensor nodes for outdoor air pollution monitoring.
Kumar et al. (2016a)	Focused on solving the typical problem of deteriorating indoor air quality (IAQ) in building management programs aimed at conserving energy by proposing to use real-time sensing.
Kumar et al. (2016b)	Highlighted the needs, benefits, challenges, and future outlook of monitoring indoor air quality (IAQ) using real-time sensors. The review also critically analysed the currently available sensor technologies available for monitoring different types of gaseous and particulate air pollutants.
Thompson (2016)	Reviewed current and emerging areas of analytical chemistry and sensor technology suitable for the development of a low-cost sensing platform for monitoring air quality together with a summary of recent crowd-sourced sensing efforts.

**Table adopted from Rai et al., 2017*

3. Objectives of the Study

1. To identify and select three to five different types of low-cost air quality monitors capable of measuring and reporting real-time concentrations of the pollutants $PM_{2.5}$ and PM_{10} that will be tested under a range of weather and air quality conditions.

2. Test the performance of the selected low-cost air quality monitors over a field trial that extends a minimum of three months. The performance of the low-cost air quality monitors will be compared against a high-grade comparison monitor. For this study, DustTrak was procured as a comparison instrument. Based on the results of the field study, the best performing air quality monitor will be selected for wide-scale deployment.

4. Experimental Materials and Methods

4.1 OPC N2

Alphasense's OPC-N2 (http://www.alphasense.com) is a low-cost particulate matter sensor which measures $PM_{2.5}$ and PM_{10}. The OPC-N2 measures particles from 0.38 micron to 17 microns in diameter using the patented 'pumpless' design. Like conventional optical particle counters, the OPC-N2 measures the light scattered by individual particles carried in a sample air stream through a laser beam. These measurements are used to determine the particle size (related to the intensity of light scattered via a calibration based on Mie scattering theory) and particle number concentration. Particle concentrations- PM_1, $PM_{2.5}$, or PM_{10}, are then calculated from the particle size spectra and count data, assuming a particle density and refractive index (RI).

Figure 1: Alphasense OPC N2

Technical details of OPC N2 are as follows:

Particle range (μm)	Spherical equivalent size (based on RI of 1.5)	0.38 to 17
Size categorisation (standard)	Number of software bins	16
Sampling interval (seconds)	Histogram period	1.4 to 10
Total Flow rate (typical)	L/ min	1.2
Sample flow rate (typical)	mL/ min	220

Max particle count rate	Particles/ second	10,000
Coincidence probability	% at 106 particles/L	0.84
Measurement mode	mA (typical)	175
Non-measurement mode	mA (typical) Laser at minimum power; fan off	95
Transient power on start-up	mW for 1 ms	<5000
Voltage range	V DC	4.8 to 5.2
Digital Interface		SPI (Mode 1), USB 2.0
Data storage	micro SD	16 GB
USB VID		Ox04D8
USB PID		OxF3D5
Laser classification	as enclosed housing	Class 1
Temperature range	°C	-20 to 50
Humidity range	% rh (continuous)	0 to 95 (non-condensing)
Weight	g	< 105

4.2 SDS 011

The unit SDS 011 from Nova Fitness Co. Ltd. measures $PM_{2.5}$ and PM_{10} concentrations. The SDS011, using the principle of laser scattering, can measure particle sizes between 0.3 to 10μm in the air. Light scattering is induced when particles go through the detecting area. The scattered light is transformed into electrical signals and these signals are amplified and processed. The number and diameter of particles can be obtained by analysis because of the signal waveform's relationship with particle diameter.

Figure 2_ Nova SDS 011

Technical details of SDS 011 are as follows:

Parameter	Description
Measurement parameters	$PM_{2.5}$, PM_{10}
Range	0.0-999.9 μg/m^3
Rated voltage	5V
Rated current	70mA±10mA
Sleep current	<4 mA
Temperature range	Storage environment -20 ~ to +60℃
	Work environment -10 ~ to +50℃
Humidity range	Storage environment Max 90%
	Work environment : Max 70%
Air pressure	86KPa~110KPa
Corresponding time	1s
Serial data output frequency	1Hz
Minimum resolution of particle	0.3 μm
Counting yield	70%@0.3μm
	98%@0.5μm
Relative error	Maximum of ± 15% and ±10μg/m^3

Product size	71x70x23mm
Certification	CE/FCC/RoHS

4.3 FRT RDM 202

FRT RDM 202 from Fronttech Beijing Ltd., adopts the laser scattering method to measure $PM_{2.5}$ and PM_{10} concentrations in the ambient environment. RDM 202 is suitable for battery power supply system. Its industrial protective shell can ensure long term life of the sensor.

Technical details of FRT RDM 202 are as follows:

Parameter	Description
Measurement method	Laser scattering/Fan
Measurement range	0 to 1000 μg/m^3
Sensitivity	0.3 μg/m^3
Accuracy	15% or 10 μg/m^3

4.4 Plantower PMS 7003

Plantower PMS 7003 is a digital and universal particle concentration sensor, which can be used to obtain the number of suspended particles in the air, i.e., the concentrations of particles, and output them in the form of a digital interface

The laser scattering principle is used for this sensor, i.e., a laser is used to produce scattering from suspended particles in the air, then the sensor collects scattered light at a certain angle and obtains the curve of scattering light changes as a function of time. In the end, equivalent particle diameter and the number of particles with different diameters per unit volume can be calculated by an onboard microprocessor based on Mie's theory (Mie scattering occurs when the dimensions of the scattered is much larger than the wavelength of the incident electromagnetic radiation. An example is when light is scattered by small particles in the atmosphere)

The sensor output is the quality and number of each particle with different size per unit volume, the unit volume of particle number is 0.1L, and the unit of mass concentration is μg/m³. There are two options for digital output: passive and active. The default mode is active after power up. In this mode, the sensor sends serial data to the host automatically. The active mode is divided into two sub-modes: stable mode and fast mode. If the concentration change is small, the sensor runs at stable mode with the real-time interval of 2.3s. If the change is large, the sensor switches to fast mode automatically with the interval of 200~800ms. The higher of the concentration, the shorter the interval.

Parameter	Description
Measurement method	Laser scattering/Fan
Measurement range	Effective: 0 to 500 μg/m³ Maximum: ≥ 1000 μg/m³
Resolution	1 μg/m³
Accuracy	±10 μg/m³

The Plantower PMS 7003 sensor was also tested to investigate its performance against the RDM202 system.

4.5 Dusttrak DRX

The Dusttrak DRX was used as the comparison monitor for this evaluation of low-cost air quality monitors. The DustTrak DRX desktop monitor is a battery operated, data-logging, light-scattering laser photometer that provides real-time aerosol mass readings. It uses a sheath air system that isolates the aerosol in the optics chamber to keep the optics clean for improved reliability and low maintenance.

The DustTrak DRX laser photometers simultaneously measure five size-segregated mass fraction concentrations at once. The desktop model with external pump is a continuous, real-time, 90°, light-scattering laser photometer that simultaneously measures size-segregated mass fraction concentrations corresponding to PM_1, $PM_{2.5}$, Respirable, PM_{10}, and total PM. They combine both particle cloud (total area of scattered light) and single particle detection to achieve mass fraction measurements. This size-segregated mass fraction measurement technique is superior to either a basic photometer or optical particle counter (OPC). It delivers the mass concentrations of a photometer and the size resolution of an OPC. Typically, photometers can be used at high mass concentrations, but they do not give any size information (unless used with size selective inlet conditioners) and significantly underestimate large particle mass concentrations. OPC's provide size and count information; however, they do not provide any mass concentration information and cannot be used in high mass concentration environments.

Figure 3: Image of the comparison monitor used in the evaluation study

4.6 Field Experiment set up

To evaluate the performance of low-cost PM sensors against the standard comparison monitor, a field study was conducted from 1 January to 31 March 2018 at two different locations: Pune (1 Jan 2018 to 22 Jan 2018) and Noida (1 Feb 2018 to 31 March 2018). Eight low-cost PM sensors were used for this evaluation study. For comparison purposes, the sensors were grouped as follows:

1. Group A: OPC N2_A, SDS 011_A and RDM 202_A
2. Group B: OPC N2_B, SDS 011_B and RDM 202_B

3. Group C: SDS 011_C and RDM 202_C

These groups were collocated with the Dusttrak DRX at both Pune and Noida. Two-meter distance from the sensor to the comparison instrument was maintained in each group. Figure 4 and figure 5 pictorially represent the set-up at the two sites:

Figure 4: Field Experiment set up at Pune

Figure 5: Field Experiment set up at Noida.

4.7 Laboratory simulation set up

To assess the performance of the sensors at higher concentrations of the PM concentrations, a laboratory simulation was performed for the period of 10th April 2018 to 3rd May 2018. Smoke was generated in the laboratory by burning various sources such as incense sticks dry tree sticks and leaves. Additionally, some particles in the form of talcum powder was also sprayed. The mixture of the particles from different sources was made homogeneous using fans. Smoke generation and aerosol spraying process continued till the concentration achieved up to 1000 µg/m^3 to 1500 µg/m^3. After achieving the desired PM concentration, burning and spraying process stopped till the concentration reached normal level. This process was repeated two to three times per day.

Figure 6: Simulation set up in the laboratory

5. Consultations with external air quality experts

Throughout the field study, Skymet regularly consulted air quality experts who provided advice and shared recommendations to improve the field trial.

6. Performance Assessment Approach

For assessing the performance of the low-cost sensors selected for the field trial, a 'performance assessment approach' was developed in consultation with the experts. The approach listed specific tasks and metrics to evaluate the sensor performance. According to this approach, the bias, relative mean bias, precision, and relative precision was determined as follows:

$$\text{Bias} = \frac{1}{n}\sum_{1}^{n}(S-R)$$

$$\text{Relative Mean Bias} = \frac{\sum_{1}^{n}(S-R)}{\sum_{1}^{n}R}$$

$$\text{Precision} = \sqrt{\frac{\sum_{1}^{n}(S-R)^2}{n}}$$

$$\text{Relative Precision} = \frac{\sum_{1}^{n}|S-R|}{\sum_{1}^{n}R}$$

Where S is the sensor value, R is the reference value, and n is the number of samples.

7. Results and discussion

7.1 Hourly mean variation of PM concentration at Pune and Noida

Figure 7 and 8 represent hourly mean $PM_{2.5}$ and PM_{10} concentration respectively at Pune while Figure 9 and 10 reveals hourly mean $PM_{2.5}$ and PM_{10} concentration respectively at Noida. Figure 7 and 8 shows that, at Pune CPCB analyser and OPC N2_A report lower values of $PM_{2.5}$ and PM_{10} concentration with respect to DTM. $PM_{2.5}$ concentration reported by CPCB analyser at Pune was ranging from 18.07 μg/m^3 to 52.32 μg/m^3 corresponding concentration of PM_{10} was 45.16 μg/m^3 to 130.81 μg/m^3. Similarly, $PM_{2.5}$ and PM_{10} concentration measured by OPC N2_A ranges from 4.47 μg/m^3 to 99.46 μg/m3 and 12.57 μg/m3 to 82. 22 μg/m3 respectively.

Other sensors and comparison monitor DTM follow similar trend at Pune for $PM_{2.5}$ and PM_{10} ranging from 16.10 μg/m^3 to 233.32 μg/m^3 and 23.00 μg/m^3 to 279.74 μg/m^3 respectively.

On the other hand, at Noida all the sensors including CPCB analyser and DTM showing more or less similar trend with varying range of concentration. As shown in Figure 9 and 10; CPCB analyser's concentration range for $PM_{2.5}$ and PM_{10} was 61.86 µg/m³ to 204.95 µg/m³ and 240.31 µg/m³ to 403.81 µg/m³. Whereas, DTM concentration at Noida ranges from 59.07 µg/m³ to 249.15 µg/m³ for $PM_{2.5}$ and for PM_{10} it is 122.71 µg/m³ to 326.27 µg/m³.

A curious phenomenon was observed at Pune. The sensors showed morning peak from 0700 hrs to 0900 hrs while this peak was shifted in CPCB analyser it was started on 0900 hrs and last till 1100 hrs. Shifting of peak may be due to the variation in the location of CPCB analyser and the sensors. There was 10 km distance between CPCB monitoring station and Skymet monitoring location shown in Figure 11.

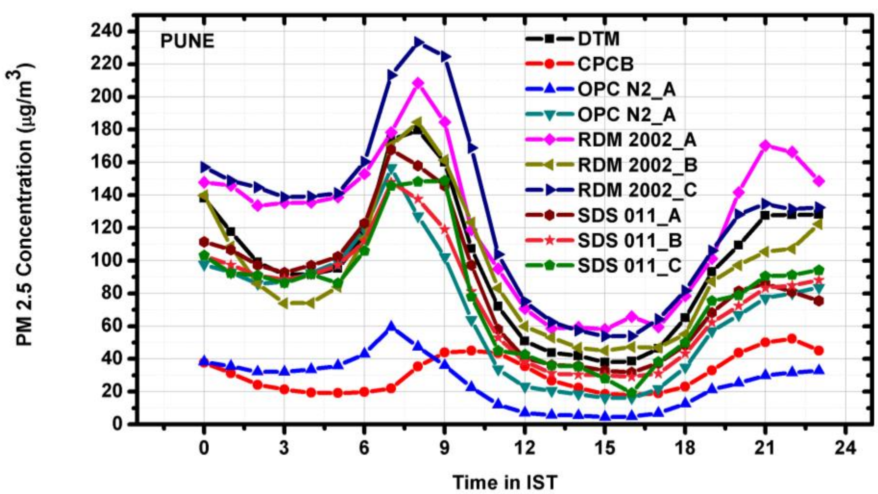

Figure 7: Hourly mean variation of $PM_{2.5}$ at Pune

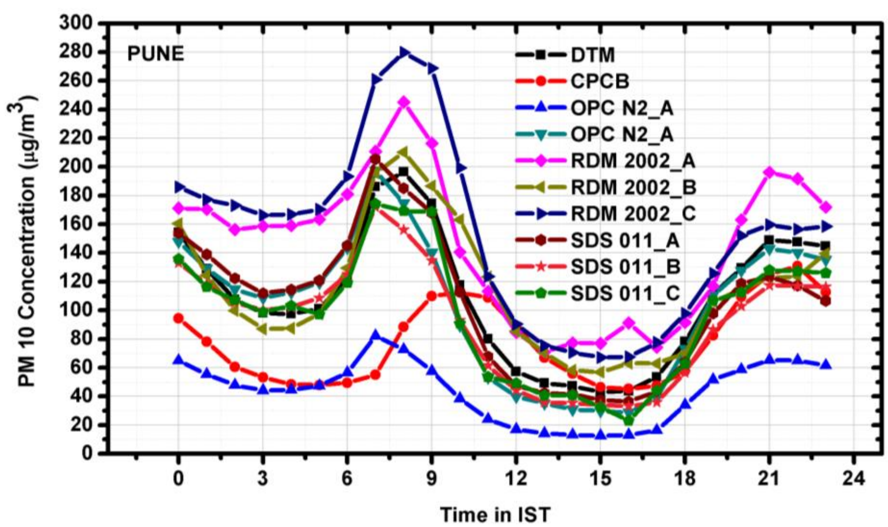

Figure 8: Hourly mean variation of PM_{10} at Pune

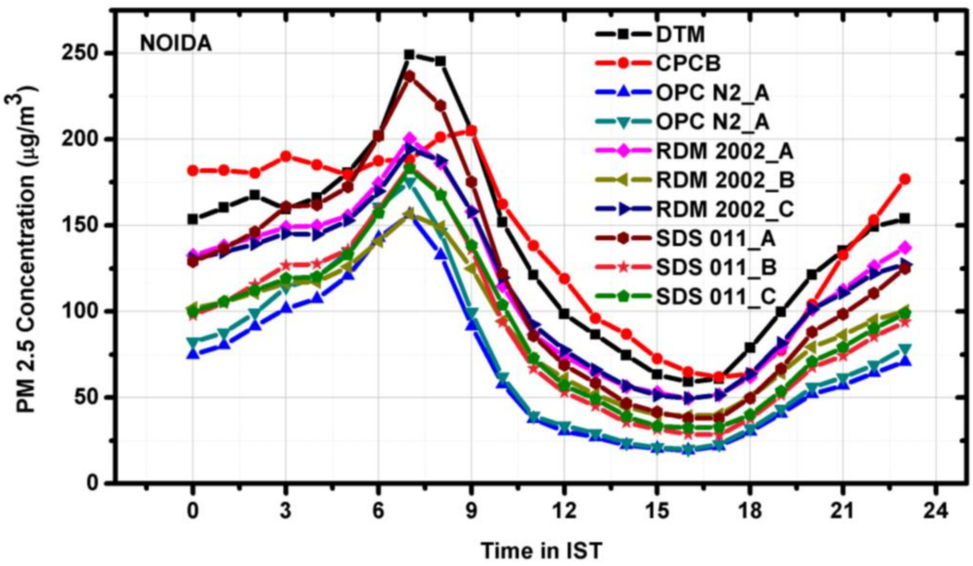

Figure 9: Hourly mean variation of $PM_{2.5}$ at Noida

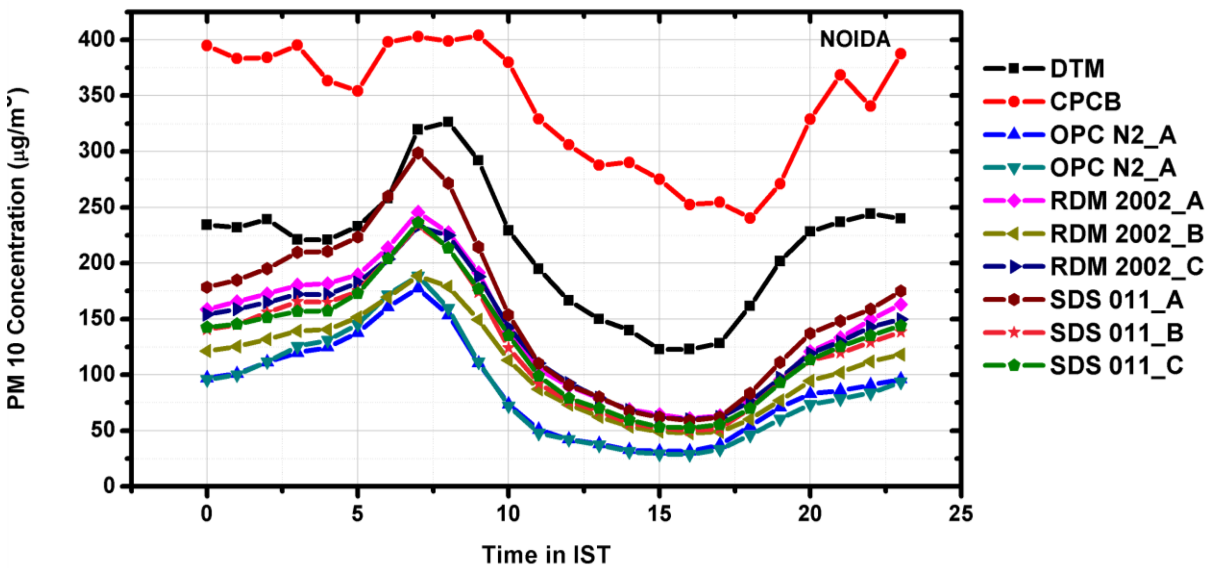

Figure 10: Hourly mean variation of PM_{10} at Noida

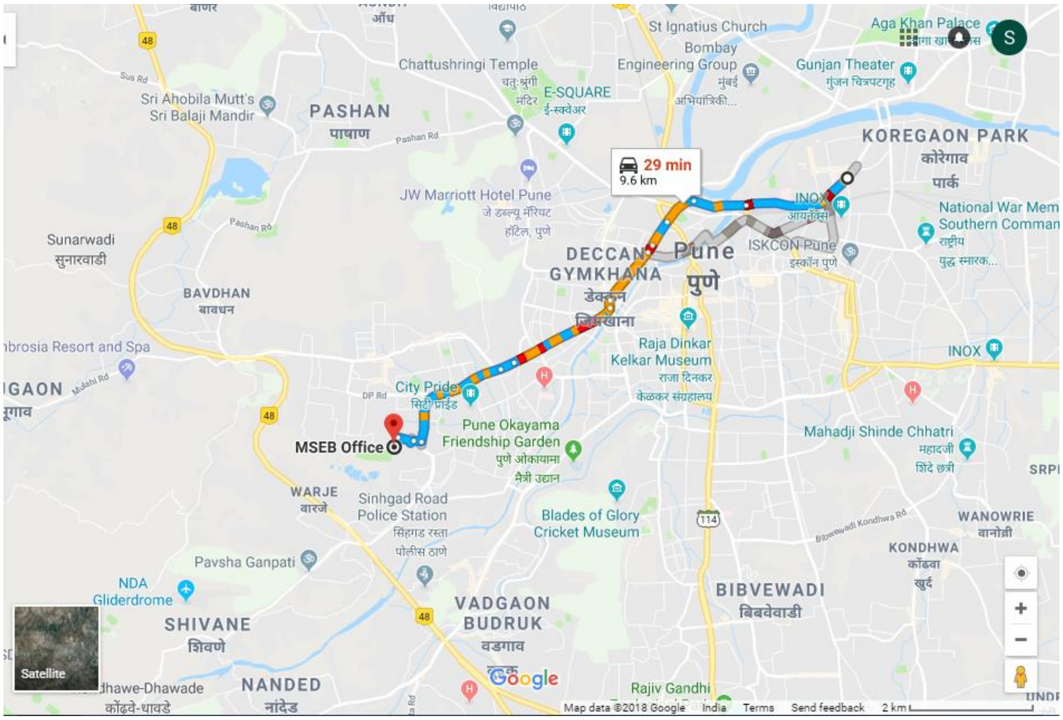

Figure 11: Distance between CPCB monitoring station and Skymet location.

7.2 Correlation between Comparison monitor and low-cost sensors

Figures 12, 13, 14 and 15 show correlation plots of low-cost sensor concentrations against the DTM for PM during the study period. Figure 12 indicates hourly correlation of $PM_{2.5}$ between DTM and low-cost sensors, it reveals good agreement of low-cost sensors with comparison monitor DTM. However, better agreement than other sensors have been found between RDM 202_A and DTM with correlation coefficient 0.87 and slope 0.81. Figure 13 portrays hourly correlation of PM_{10} between comparison monitor DTM and low-cost sensors, it also shows better agreement of low-cost sensors with comparison monitor DTM. Figure 14 and 15 represents daily correlation plots of concentration $PM_{2.5}$ and PM_{10}. Daily correlation of $PM_{2.5}$ and PM_{10} also bears good agreement with comparison monito DTM.

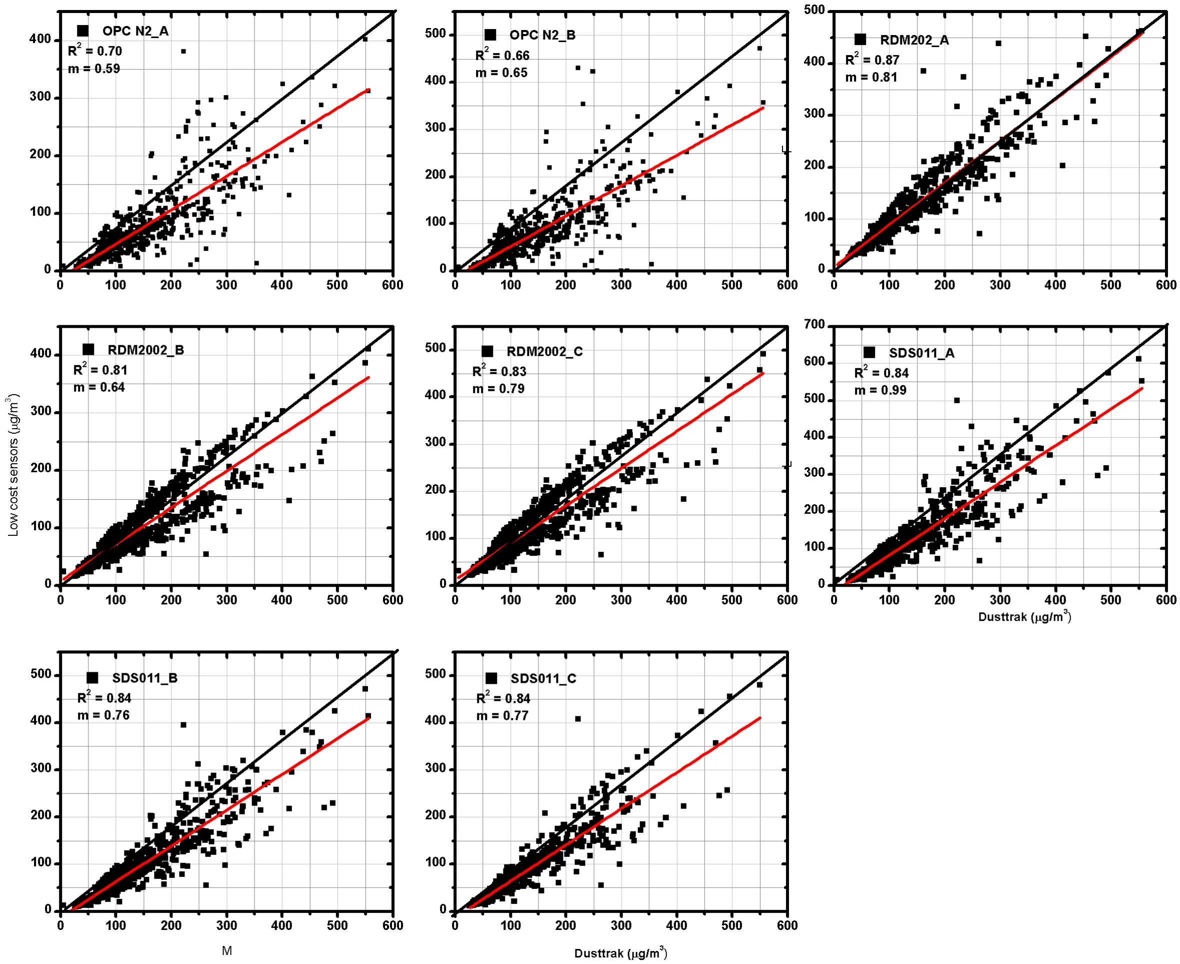

Figure 12: Correlation between comparison monitor and low-cost sensor for hourly $PM_{2.5}$

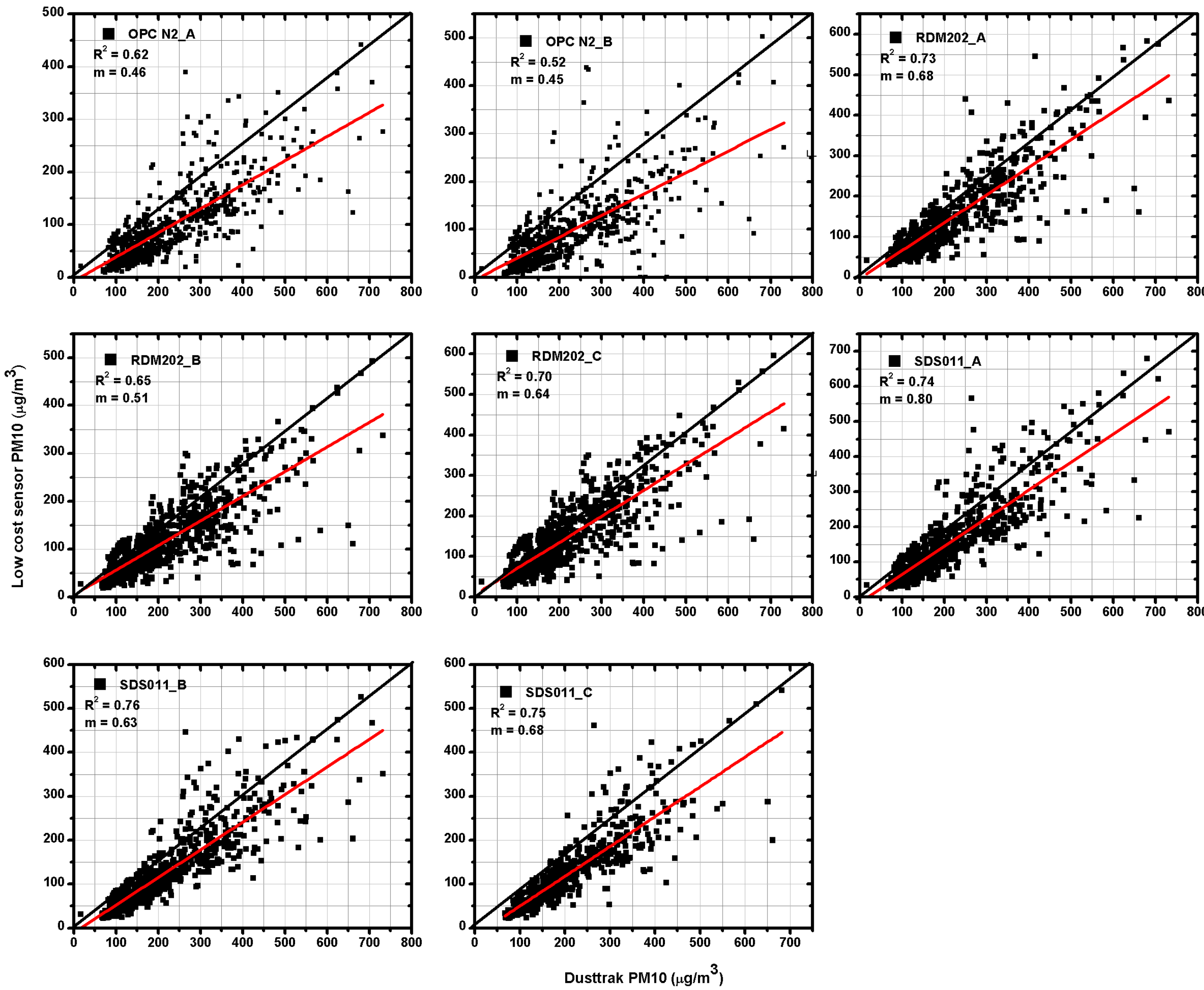

Figure 13:Correlation between comparison monitor and low-cost sensor for hourly PM_{10}

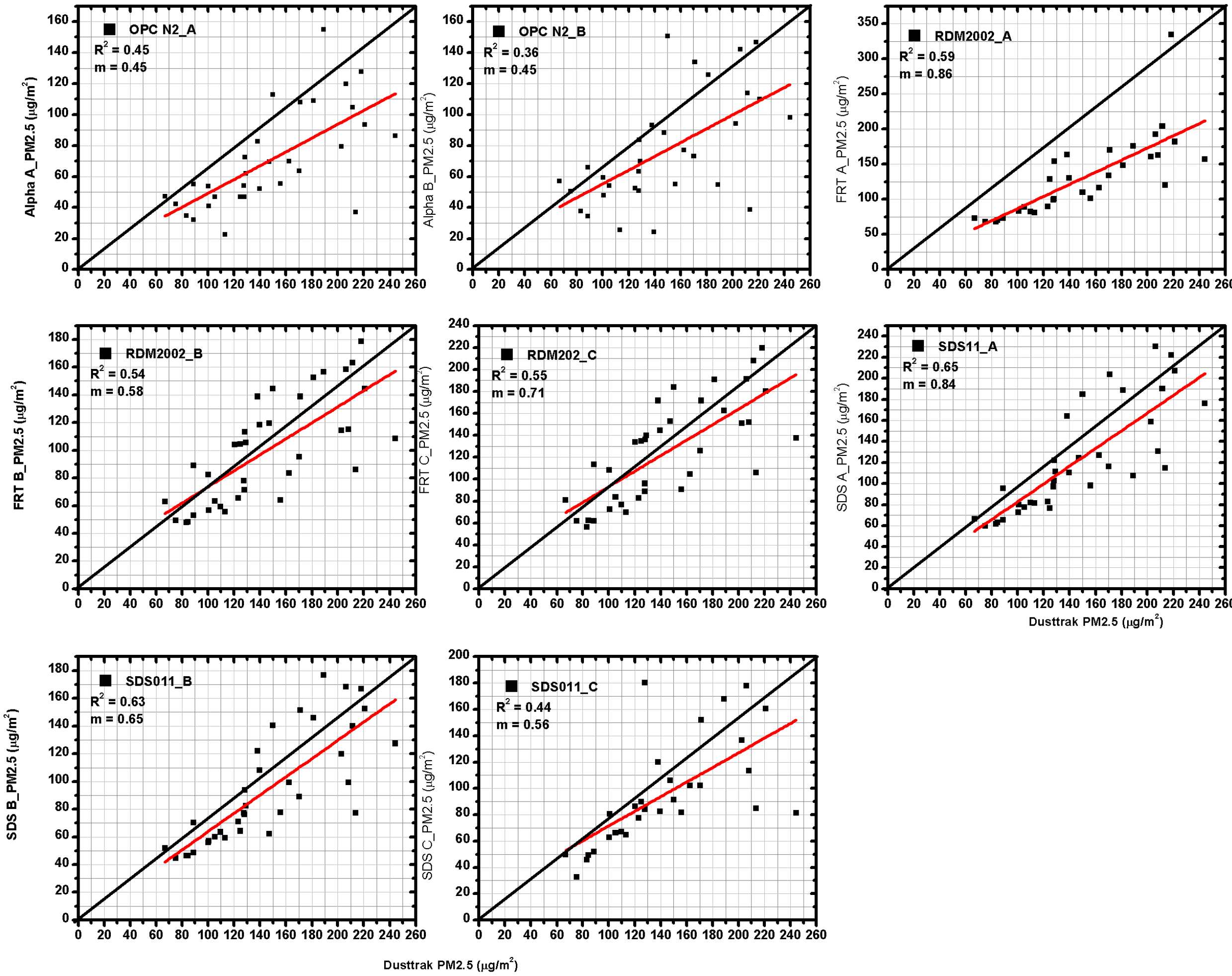

Figure 14:Correlation between comparison monitor and low-cost sensor for daily $PM_{2.5}$

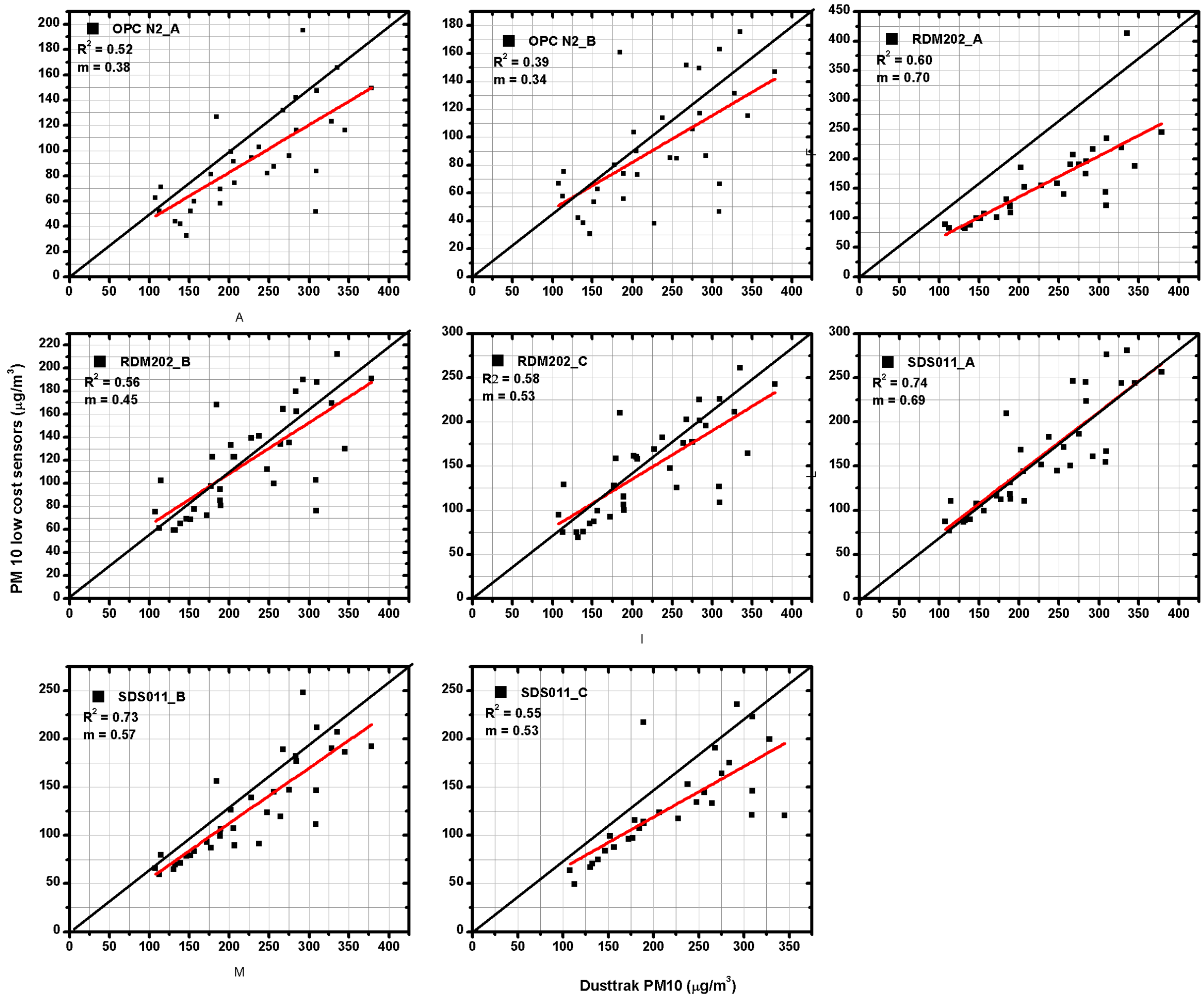

Figure 15:Correlation between comparison monitor and low-cost sensor for daily PM_{10}

7.3 Effect of RH on PM concentration

Humidity is the amount of water vapor present in the atmosphere. Particulate matter is hygroscopic in nature. Therefore, as the relative humidity increase, particles absorb water and appear larger when measured by the light-scattering sensors. This artifact of light scattering sensors results in an over estimate of PM concentrations during high humidity.

The adsorption of water vapour onto the particulate matter may increase their settling rates and deposition (Ediagbonya et al., 2013). Zaharim et al., notes a negative correlation between PM_{10} and relative humidity.

To determine the effect of humidity on PM concentration we created a subset of data to analyse with RH >85% and RH <85%. A simple linear regression technique is used to determine the correlation between relative humidity and PM. Results are presented in Table II. For all the sensors, strong positive correlation was observed between RH and particulate matters. Correlation coefficients were ranging from 0.70 to 0.85 for the subset of data RH<85 % against $PM_{2.5}$. While this range were 0.39 to 0.97 for RH > 85% Vs $PM_{2.5}$. Corresponding slopes were ranging from 0.62 to 0.97 and 0.60 to 1.17 respectively.

Similarly, for the subset of data for RH < 85% and RH> 85% against PM_{10}; the correlation coefficient of all the sensors were observed in the range of 0.53 to 0.77 and 0.38 to 0.75 respectively. While corresponding slopes were ranging from 0.43 to 0.79 and 0.47 to 0.90. Though correlation coefficient was different for different sensors, it clearly indicate impact of RH on PM concentration.

Table II: Correlation coefficient between $PM_{2.5}$ and RH < 85% and corresponding mean bias of the sensor.

Sr. No	Sensor	RH< 85% Vs $PM_{2.5}$			
		R^2	M	Bias	Relative Mean Bias
1	OPC N2_A	0.70	0.64	-72.64	-0.50
2	OPC N2_B	0.70	0.70	-64.36	-0.45
3	RDM202_A	0.85	0.91	-19.03	-0.13
4	RDM202_B	0.82	0.62	-42.99	-0.30
5	RDM202_C	0.82	0.77	-17.99	-0.12
6	SDS011_A	0.84	0.97	-11.27	-0.08
7	SDS011_B	0.84	0.74	-32.60	-0.22
8	SDS011_C	0.83	0.76	-29.25	-0.21

Table III: Correlation coefficient between PM2.5 and RH > 85% and corresponding mean bias of the sensor.

Sr. No	Sensor	RH > 85% Vs $PM_{2.5}$			
		R^2	M	Bias	Relative Mean Bias

1	OPC N2_A	0.73	0.65	-39.42	-0.19
2	OPC N2_B	0.39	0.60	-12.06	-0.06
3	RDM202_A	0.88	0.77	-35.92	-0.19
4	RDM202_B	0.80	0.71	-38.33	-0.21
5	RDM202_C	0.80	0.85	-1.72	-0.01
6	SDS011_A	0.84	1.17	25.49	0.14
7	SDS011_B	0.87	0.86	-37.05	-0.20
8	SDS011_C	0.97	0.96	-39.40	-0.25

Table IV: Correlation coefficient between PM_{10} and RH < 85% and corresponding mean bias of the sensor.

Sr. No	Sensor	RH < 85% Vs PM_{10}			
		R^2	M	Bias	Relative Mean Bias
1	OPC N2_A	0.64	0.45	-73.34	-0.33
2	OPC N2_B	0.53	0.43	-133.29	-0.59
3	RDM202_A	0.72	0.67	-11.73	-0.05
4	RDM202_B	0.69	0.51	-33.41	-0.15
5	RDM202_C	0.70	0.68	-19.00	-0.09
6	SDS011_A	0.75	0.79	-61.06	-0.28
7	SDS011_B	0.77	0.63	-29.37	-0.13
8	SDS011_C	0.75	0.68	-18.79	-0.09

Table V: Correlation coefficient between PM_{10} and RH > 85% and corresponding mean bias of the sensor.

Sr. No	Sensor	RH > 85% Vs PM_{10}			
		R^2	M	Bias	Relative Mean Bias
1	OPC N2_A	0.63	0.49	-82.40	-0.31
2	OPC N2_B	0.38	0.47	-50.45	-0.19
3	RDM202_A	0.91	0.87	-73.70	-0.29
4	RDM202_B	0.72	0.62	-70.02	-0.29
5	RDM202_C	0.72	0.76	-29.55	-0.12

6	SDS011_A	0.71	0.90	-2.81	-0.01
7	SDS011_B	0.75	0.66	-63.52	-0.28
8	SDS011_C	0.73	0.77	-73.59	-0.34

7.4 Simulation Study

Laboratory simulations have been performed to evaluate performance of the low-cost sensors during high concentrations of smoke. Figures 16 and 17 represent hourly variation of $PM_{2.5}$ and PM_{10} concentrations respectively. Figures 18 and 19, show hourly variation of $PM_{2.5}$ and PM_{10} on 26th April while Figures 20 and 21 reveals hourly variation of $PM_{2.5}$ and PM_{10} on 2nd and 3rd May 2018. Table III shows bias and correlation of low-cost sensors with comparison monitor DTM during the simulation period. Data from the simulation study were further divided into two categories such as i) PM concentration less than 300 μg/m_3 and ii) PM concentration greater than 300 μg/m_3. Correlation coefficient and bias have been calculated for these two categories and results are presented in Tables IV and V.

While reviewing the literature, we have found that Plantower's PMS 7003 technical architecture was like RDM202. Therefore, In the simulation study we had additionally deployed Plantower's two more sensors namely PMS7003_A and PMS7003_B.

Hourly variation (figures 18, 19, 20, 21) and correlation statistics and bias calculation (table III, IV, v) depicts that, PMS 7003_A and PMS 7003_B follow similar trend as like DTM. Correlation coefficient of PMS 7003_A for $PM_{2.5}$ was 0.94, corresponding slope and relative mean bias were 1.02 and -0.10. Whereas for PM_{10} correlation coefficient, slope and relative mean bias were 0.95, 1.29 and 0.07 respectively. Similarly, correlation coefficient, slope and relative mean bias of PMS 7003_B for PM2.5 were 0.90, 1.03 and -0.12 respectively and corresponding values for PM_{10} were 0.91, 1.29 and -0.04. Higher correlation coefficients, lesser relative mean bias and closeness of slope to the unity of sensor PMS 7003 indicate its extent of performance. In general, even though all the low-cost sensors showing better agreement with comparison monitor DTM, but PMS 7003 performs best than other low-cost sensors.

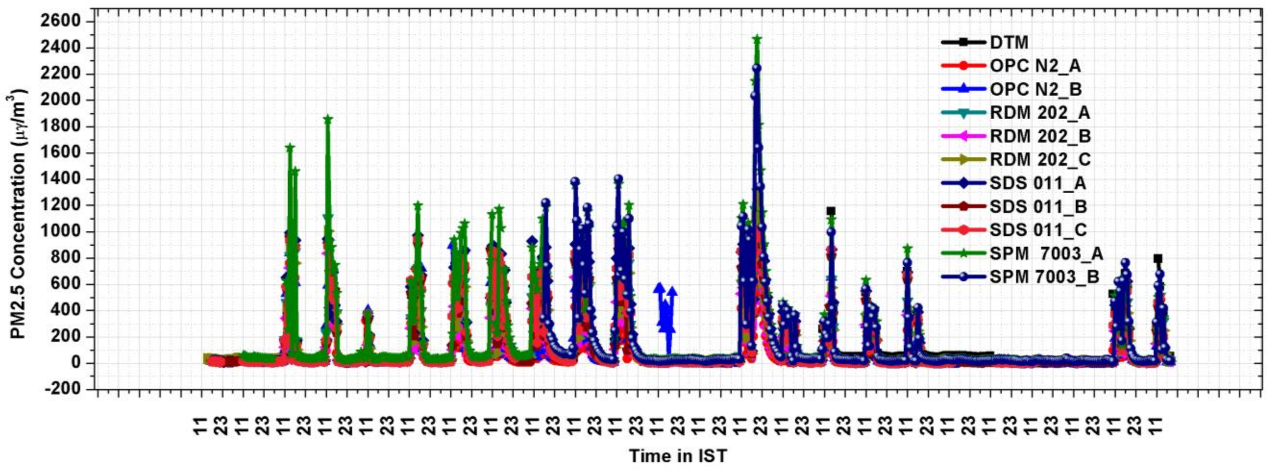

Figure 16:Hourly variation of $PM_{2.5}$ during the simulation study

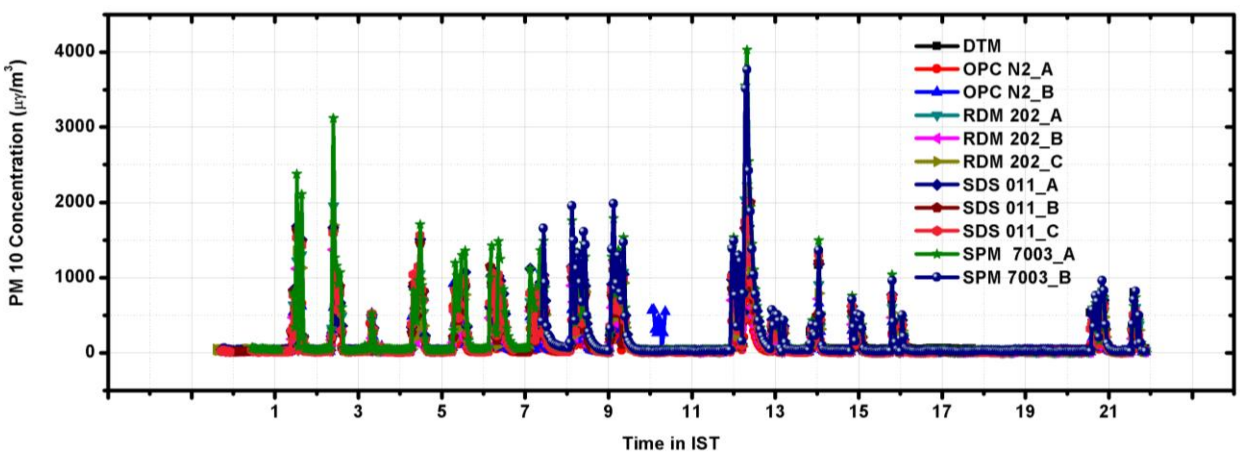

Figure 17:Hourly variation of PM_{10} during the simulation study

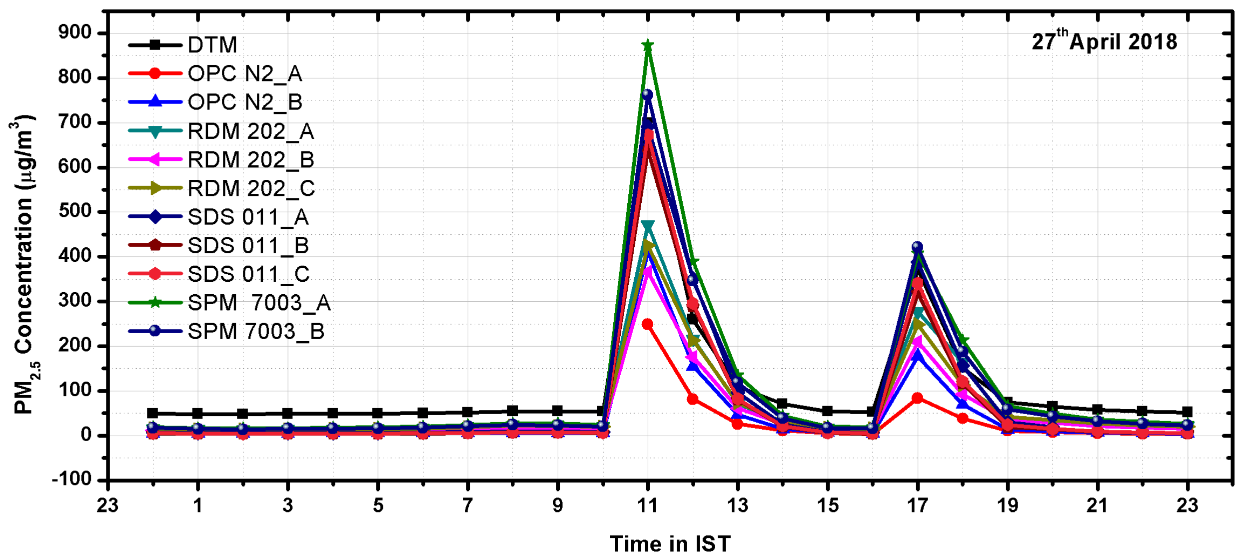

Figure18 :Hourly variation of $PM_{2.5}$ on 27th April 2018.

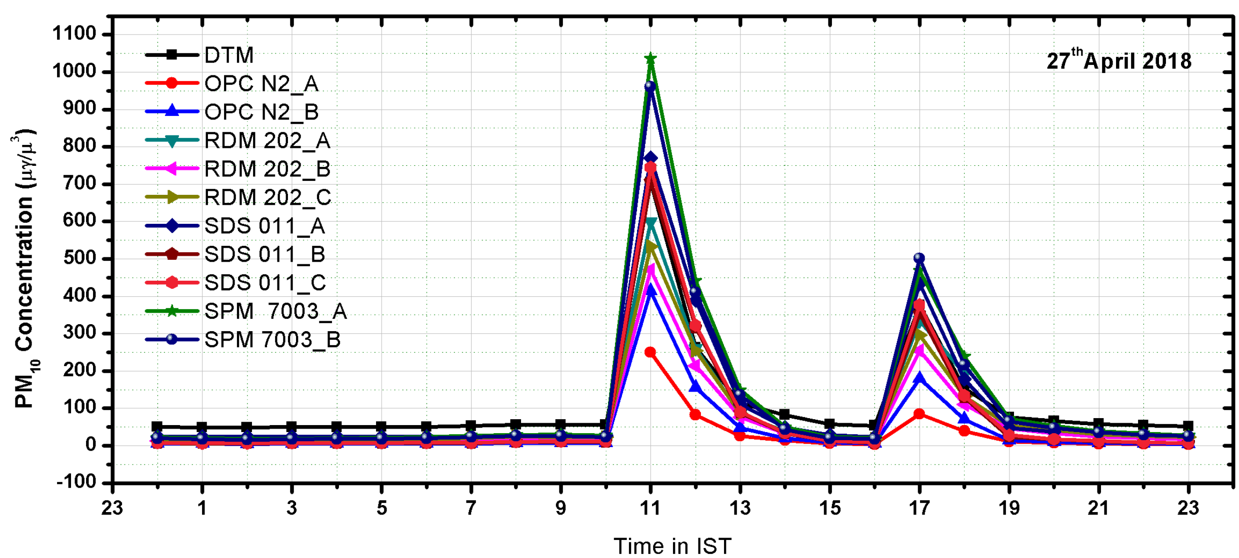

Figure 19: Hourly variation of PM_{10} on 27th April 2018.

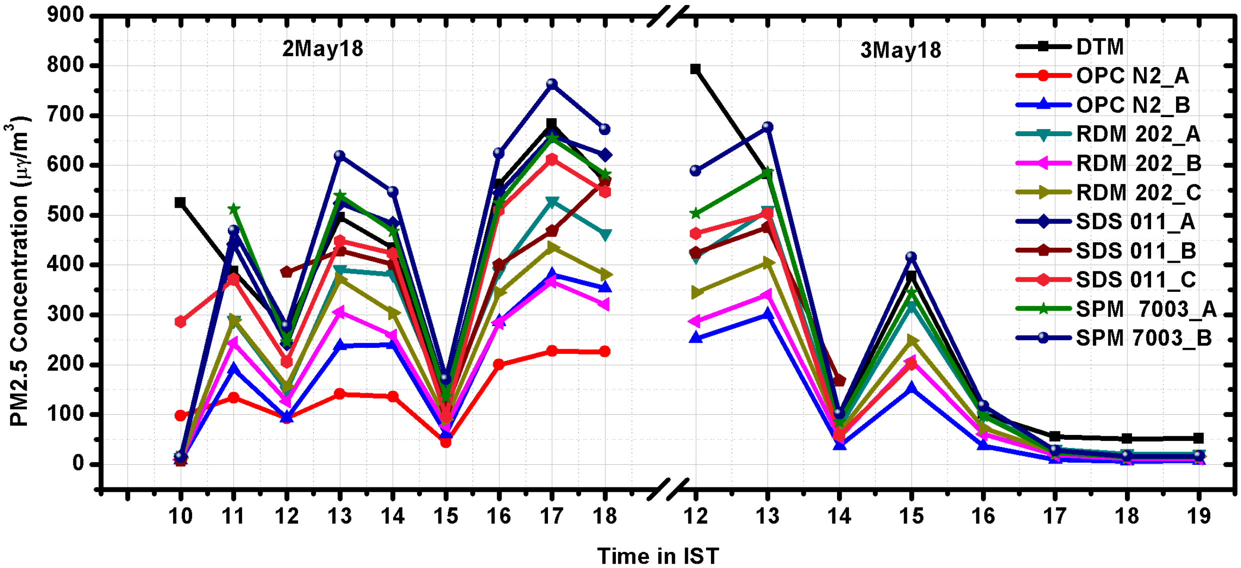

Figure 20:Hourly variation of $PM_{2.5}$ on 2nd and 3rd May 2018.

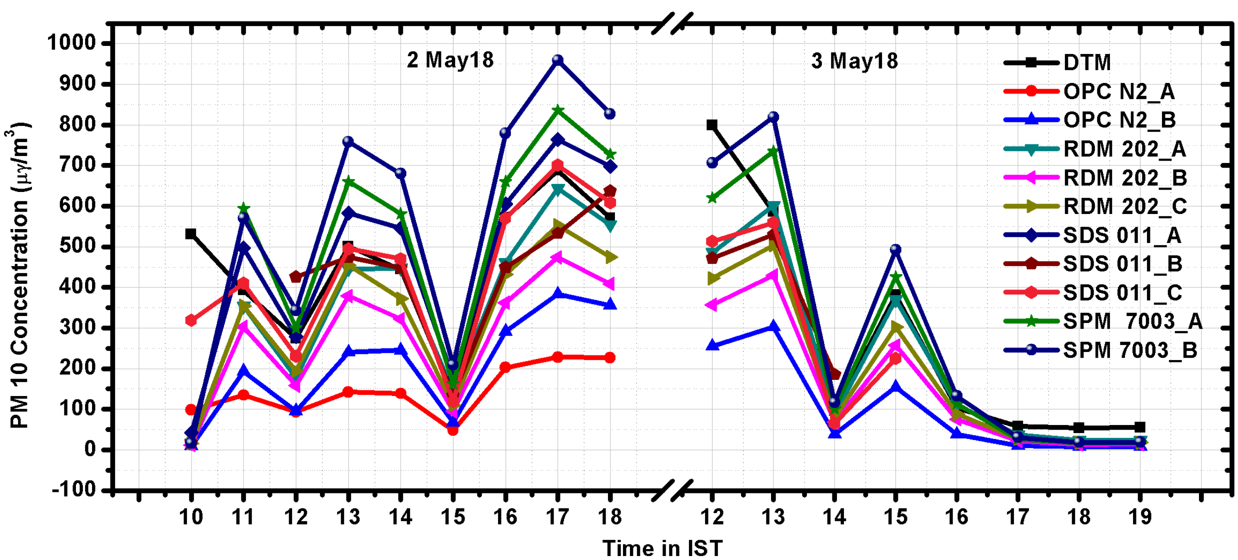

Figure 21:Hourly variation of PM_{10} on 2nd and 3rd May 2018.

Table VI: Correlation and bias values of PM concentration during simulation period.

Sr No	Monitor	R^2		Slope		Relative Mean Bias	
		$PM_{2.5}$	PM_{10}	$PM_{2.5}$	PM_{10}	$PM_{2.5}$	PM_{10}
1	OPC N2_A	0.92	0.92	0.41	0.40	0.67	0.67
2	OPC N2_B	0.95	0.95	0.53	0.53	-0.60	-0.60
3	RDM202_A	0.89	0.91	0.67	0.83	-0.39	-0.28
4	RDM202_B	0.90	0.91	0.50	0.65	-0.54	-0.44
5	RDM202_C	0.89	0.90	0.59	0.76	-0.44	-0.33
6	SDS011_A	0.85	0.88	0.94	1.08	-0.21	-0.05
7	SDS011_B	0.86	0.88	0.80	0.95	-0.37	-0.28
8	SDS011_C	0.93	0.95	0.80	1.06	-0.28	-0.18
9	PMS 7003_A	0.94	0.95	1.02	1.29	-0.10	0.07
10	PMS 7003_B	0.90	0.91	1.03	1.29	-0.12	-0.04

Table VII: Correlation and bias values for the PM concentration less than 300 μg/m^3 during simulation period.

Sr No	Monitor	R^2		Slope		Relative Mean Bias	
		$PM_{2.5}$	PM_{10}	$PM_{2.5}$	PM_{10}	$PM_{2.5}$	PM_{10}
1	OPC N2_A	0.89	0.90	0.53	0.52	-0.71	-0.71
2	OPC N2_B	0.89	0.89	0.58	0.58	-0.72	-0.72
3	RDM202_A	0.90	0.90	0.79	0.93	-0.46	-0.38
4	RDM202_B	0.91	0.90	0.65	0.77	-0.59	-0.52
5	RDM202_C	0.91	0.90	0.77	0.91	-0.48	-0.41
6	SDS011_A	0.91	0.91	1.30	1.34	-0.35	-0.14
7	SDS011_B	0.84	0.83	1.20	1.28	-0.52	-0.46
8	SDS011_C	0.92	0.92	1.13	1.21	-0.47	-0.41
9	PMS 7003_A	0.87	0.87	1.31	1.47	-0.25	-0.17
10	PMS 7003_B	0.91	0.90	1.30	1.50	-0.28	-0.19

Table VIII:Correlation and bias values for the PM concentration greater than 300 µg/m³ during simulation period.

Sr No	Monitor	R^2		Slope		Relative Mean Bias	
		$PM_{2.5}$	PM_{10}	$PM_{2.5}$	PM_{10}	$PM_{2.5}$	PM_{10}
1	OPC N2_A	0.87	0.87	0.49	0.49	-0.65	-0.65
2	OPC N2_B	0.64	0.64	0.52	0.52	-0.51	-0.51
3	RDM202_A	0.49	0.58	0.48	0.69	-0.33	-0.19
4	RDM202_B	0.53	0.58	0.36	0.53	-0.50	-0.37
5	RDM202_C	0.49	0.55	0.40	0.57	-0.41	-0.27
6	SDS011_A	0.46	0.61	0.72	1.02	-0.11	0.03
7	SDS011_B	0.50	0.63	0.60	0.94	-0.25	-0.14
8	SDS011_C	0.72	0.80	0.67	1.04	-0.15	-0.03
9	PMS 7003_A	0.75	0.80	0.77	1.10	0.01	0.25
10	PMS 7003_B	0.51	0.57	0.73	1.03	0.01	0.24

8. Conclusion and recommendation

The study shows that performance of low-cost sensor is different for different ambient conditions and sensors. Trend analysis, regression analysis, and bias calculation shows that some sensors correlate well with the comparison monitor but may have higher bias values.

This study reveals that performance of low-cost monitors varies spatially and temporally and depends on the atmospheric composition and meteorological conditions.

From this study, better agreement of particulate matter at lower concentrations was observed than at higher concentrations.

Simulation study shows that for lower concentrations (< 300 µg/m³) of the particles all the low-cost sensors tend to underestimate whereas for higher concentrations (> 300 µg/m³) particles sensors are underestimating or overestimating.

A positive correlation was observed between relative humidity and PM concentrations during this study period.

In general, this study showed that low-cost sensors have the capability to be usefully deployed in the field to capture real-time PM measurements. Based on findings in this evaluation study, we recommend '**Plantower's PMS 7003**' sensors for field deployment.

Recommendation of PMS 7003 is based on the following parameters.

- Higher correlation coefficients (R^2): 0.94 and 0.95 for $PM_{2.5}$ and PM_{10} respectively.
- Closeness of slopes (m) to the unity: 1.02 and 1.29 for $PM_{2.5}$ and PM_{10} respectively.
- Lesser relative mean biases: -0.10 and 0.07 $PM_{2.5}$ and PM_{10} respectively.
- Comparison of hourly variation with comparison monitor DTM.
- .Price: Price of PMS 7003 is lowest of all the sensors tested.

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