SODAR Based Meteorological Sensor Network for Air Pollution Monitoring in Northern India

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Abstract: The atmospheric boundary layer (ABL) plays a significant role in defining the air-quality index of an environment. It determines the environmental capacity for the diffusion of atmospheric pollutants. The air-quality in a designated area is influenced by the local air pollution as well as the transported pollutants from remote locations. Estimation of mixing-height helps to determine the volume space in which the emitted pollutants are dispersed. The continuous and effective monitoring of mixing-height in real-time is a major concern for the research community. Sonic Detection and Ranging (sodar) is crucial for real-time and continuous determination of mixing-height. This paper proposes a novel Sodar-based meteorological sensor network (SMSN) with the Internet of Things (IoT) capability. In the SMSN, the temperature, relative humidity, and wind sensors are integrated with sodar and deployed to seven locations in Northern India. The sensors with IoT work as sensor nodes and provide accessibility to users for air-quality monitoring in real-time. The IoT-enabled SMSN displayed impressive standard uncertainty for data packet losses across all the sites and parameters. Additionally, correlation analysis is performed between the SMSN parameters and key air-pollutants of each sensor node. The correlation analysis shows good relevance between the regional parameters and Delhi’s parameters. The integration of IoT with sodar and meteorological parameters is important for improving the overall decision-making and planning of Delhi’s air quality.

Keywords: Amazon web services (AWS); Internet of Things; Meteorological-sensors network; Mixing-height; Atmospheric boundary layer; Sensor node; SODAR

1. Introduction

The atmospheric boundary layer (ABL) is the lowest part of the atmosphere ranging from 100 to 2000 m above the ground’s surface. The ABL-height estimation determines the environmental capacity to disperse the atmospheric pollutants. The behavior and properties of atmospheric pollutants are directly influenced by the topography of the earth’s surface. It significantly carries a higher amount of air pollutants than the rest of the atmosphere. The evolution of the ABL structure has significant impacts on the diffusion, transmission, and disappearance of pollutants in the lower atmosphere [1]. The diurnal variation in temperature and humidity affects dispersion and diffusion in the atmosphere. The earth’s surface cools faster than the atmosphere due to emitting long-wave radiation at night; therefore, the temperature increases with height. The nocturnal stable boundary layer is the technical term for this temperature inversion, which lowers the surface-to-atmosphere turbulence. Temperature stratification discontinuities between the upper and lower layers of the atmosphere cause discontinuous turbulence, which results in the formation of a mixing layer. The atmospheric mixing layer is a significant meteorological parameter. The critical advantage of studying the height of the mixing-layer, also referred to as mixing-height is its capability to present the transition time characteristics of the day. It defines the characteristics of the large pollutants variability along with ambient temperature and humidity values between the well-mixed boundary layer and the stable free troposphere [2]. It affects the vertical diffusion of environmental pollutants and water vapor concentrations. It impacts the formation and dissipation of air pollutants [3]. The real-
time observation of mixing-height is beneficial for improving the parameterizations and optimizing the air pollution models.

The primary methods for the estimation of mixing-height are meteorological radiosondes, airplane surveys, and ground-based remote sensing techniques. The radiosonde is the most convenient method to determine quality mixing-height data. However, the discrete nature of observations at a higher cost makes radiosonde unable to provide sufficient temporal resolution of the evolution of mixing-height in real-time. Therefore the radiosonde technique is less preferable for air pollution monitoring [2].

As an alternative, airplane surveys are excellent at providing high-resolution mixing-height data and accurate weather and pollutant profiles. The significant constraints with airplane surveys are air-traffic control, weather conditions, and observation costs. These constraints limit airplane surveys for shorter periods only [4]. Therefore, the ground-based remote sensing technique is the most advanced and reliable method to acquire continuous observations with a high spatial and temporal resolution of mixing-height.

Acoustic sounder (sodar), light detection and ranging (lidar), and radio detection and ranging (radar) devices are the three popular ground-based remote sensing methods to estimate mixing-height [2]. Doppler wind radar obtains variations of the wind vectors at different altitudes. It identifies the mixing-height through wind shear data. The limitation with the wind radar is its lower limit of height detection, which is usually above 200 m, and the vertical resolution is limited to 50–250 m. This limitation makes the interpretation of wind radar data less faithful.

Similarly, the lidar obtains the vertical profile of the aerosol concentration and discerns the atmospheric mixing-height by calculating the height at which sudden changes in the profile occur. The high cost of lidar technology makes it less preferable. The sodar has the best refractive index for the backscattered signals and more sensitivity towards the atmospheric echoes. Sodar is a very economically viable option as well. It makes sodar a more suitable and preferred choice for the continuous measurement of mixing-height [5].

The continuous measurement of mixing-height data and some meteorological parameters is one of the critical challenges for the regulatory authorities in the regional level monitoring of air pollution. The air pollutants’ transportation and dispersion take place on a wide range of geographical scales. International organizations deal with global issues such as climate change, stratospheric ozone depletion, and inter-continent transport. Similarly, a nation is responsible for planning and controlling all the stakeholders and regulatory authorities with a regional vision [6]. In India, the Central Pollution Control Board (CPCB) provides the ambient air quality information through the National Air Quality Monitoring Programme (NAMP) [7, 8]. The NAMP determines the violated air quality standards of all Indian cities and takes corrective measures. The local pollution is observed by estimating the different pollutants, such as Carbon Monoxide (CO), Sulphur Dioxide (SO₂), Nitrogen Dioxide (NO₂), Ozone (O₃), Ammonia (NH₃), and Particulate Matter 2.5 (PM2.5) [9].

However, effective air pollution monitoring is only achievable when the measurement is not limited to the local pollutants.

In the last decade, the Internet of Things (IoT) describes the capacity of the Internet to touch people’s everyday lives through a wireless network of uniquely identifiable objects [13]. The IoT technique improves the decision-making of the controlling authorities to predict and promote the entire process and planning of air pollution monitoring for sustainable growth [14]. This paper focuses on the IoT application in the new generation of air pollution informatics by integrating meteorological parameters such as mixing-height, wind profile, ambient temperature, and relative humidity with local air pollutants and provides a new paradigm for environmental monitoring and management in the future. The basic block diagram of the integrated sodar and meteorological sensor system is shown in Fig. 1.

2. Related Work

The COVID-19 outbreak and nationwide lockdown across the world slowed down the speed of air pollution, which gave some time to regulatory authorities, the scientific community, and the public to re-examine the environment
monitoring approach [15]. Integration of air pollution monitoring and management methods based on IoT is an imperative and active topic for all stakeholders. IoT-based monitoring network covers various issues and involves multiple computer and information science technologies [16].

2.1. Air Pollution Monitoring Systems

The key contributing factors to atmospheric pollution comprises burning fossil fuels, mining processes, industrial activities, transportation systems, and agricultural activities. The air quality of an atmosphere is decided by the measurement of NO$_x$, SO$_2$, O$_3$, CO, and particulate matters (PM2.5 & PM10) [17, 18]. The significant environmental parameters affecting atmospheric pollutants are temperature, humidity, altitude, wind speed, and pressure [19]. Therefore, an effective monitoring system to combat all these factors is necessary for accurate measurement. Since environmental pollution is dependent on the atmospheric dispersion and diffusion process and its distribution is not uniform, the source of location and its vigilant selection becomes critical for measurement [20]. In order to cover all dimensions of a defined area, multiple sensors and multiple sensing nodes with advanced networking techniques are required [21, 22].

The conventional monitoring stations consist of local air pollutants measuring sensors to observe the contaminated air. These stations are very consistent, precise, and capable of counting a widespread group of impurities through analytical instruments, like gas chromatograph-mass spectrometers [23]. Although the established monitoring systems use different approaches, the overall goal and general architecture of these systems are similar and continuous monitoring of transported pollutants is still missing from the system [24]. The fundamental process of air monitoring systems comprises three main processes, i.e., sensing, analyzing, and decision-making [25]. The later section discusses the significant advancements in the conventional air pollution monitoring systems’ hardware, software, and communication protocols.

There is vast literature on the hardware and software tools for air pollution monitoring systems. The Arduino board has been widely used as a sensor node for this application. Lobur et al. used the Atmel 8-bit AVR microcontroller to measure essential pollutants such as CO, PM 2.5, CO2, temperature, and humidity in real-time [26]. Dhingra et al. [27] proposed the gas sensor kit along with Arduino and Wi-Fi module to monitor the air pollution on the IoT networks. In this, the Arduino module fetches the sensor data and transmits it to the cloud via a Wi-Fi module.

Similarly, Guanochanga et al. [28] and Malhotra et al. [29] also utilized the Arduino as data acquisition and transmission controller. While Guanochanga et al. [28] and Kiruthika [30] added the Raspberry Pi with an air monitoring system as an IoT Gateway for data communication to the cloud. Singh et al. deployed the Raspberry pi 3 and Arduino UNO as sensing nodes. They used the ThingSpeak IoT application for real-time data monitoring of the sensor network. Generally, Arduino, GSM module, Raspberry Pi, and other micro-controller boards have been utilized as an IoT gateway.

The software and cloud services for user application development and data management include LabVIEW, MATLAB, Android, Structured Query Language (SQL),

![Fig. 1 Block diagram of sodar and meteorological sensor network](image-url)
DBMS (database-management), AWS (Amazon web services), ThingSpeak, etcetera. The communication protocol is critical for the sensor network [31]. Generally, two different communication protocols are required in any sensor network, first, for the local networking between the sensors done by a wireless sensor network and second for the data communication between sensor nodes to monitoring stations done by IoT gateways [32]. The protocols such as Zig-Bee and Bluetooth are widely used for short-distance data communications, whereas Wi-Fi, General Packet Radio Service (GPRS), Long Term Evolution (LTE) Network, GSM (General System Mobile), and radiofrequency communication protocols are used for long-distance data communication [33]. Additionally, the data communication over the web is done by the HyperText Transfer Protocol (HTTP) and Message Queue Telemetry Transport (MQTT) protocols [23].

Moreover, low measurement accuracy is the main obstruction to the reliable deployment of the meteorological sensors network. Several researchers found the error sources after testing and analyzing the sensor and signals over the years and categorized errors into two main categories internal and external. Internal errors include the working mechanism of sensors which depend on the dynamic boundaries such as systematic errors, nonlinear response, and signal drift [34]. While the significant sources of external errors are environmental circumstances that depend on the site selection. The calibration of the sensors from authentic organizations before installation becomes extremely important in order to form a trust-worthy sensor network [35, 36].

2.2. Application of Acoustic Sounder in Air Pollution

The atmospheric boundary layer is considered a circulatory system of the biosphere. It lies in the boundary layer where photosynthesis and respiration activity of the plants and animals takes place. It also helps to remove the waste product and thus to cleanse the atmosphere using photo-chemical reactions. This layer disperses the heat and moisture gathered at the earth’s surface horizontally and vertically. This process effectively improves the air-quality of the biosphere and provides a conduit for the propagation of weather systems on all scales [1]. An acoustic sounder is a proven technology for estimating the ABL structures. This section briefly discusses the application of acoustic sounder/sodar in air pollution estimation and modeling [37].

In the examining process of mixing-height estimated by sodar during turbulent stable boundary layer, it has been noted that the sodar measured mixing-height is in the lower range than the height required for the air pollution modeling by Koracin and Berkowicz [38]. The main reason for the sodar measured mixing-height depends on the velocity fluctuations in the nocturnal stable boundary layer for pollutants dispersion. In contrast, the monostatic sodar is sensitive to the temperature coefficient only. The magnitude of the temperature fluctuations decreases much faster with height than the velocity fluctuations. Nevertheless, the lack of other reliable techniques for continuous mixing-height measurement makes the sodar the best option to measure mixing-height for the study of the turbulent stable boundary layer. Likewise, Caughey [39] had also reported the importance of qualitative pictorial representation of the turbulent stable boundary layer from the acoustic sounder.

The direct determination of the day time mixing-height is limited to heights within the sodar probing range. In contrast, the mixing height is higher than the probing range for most sites. Singal and his associates [40] studied the stable layer structure of sodar to determine mixing height. On the basis of the Holzworth model [41] using radiosonde data of Delhi, the studies of the convective boundary layer height have been established. The mixing-height is obtained on a daily basis from radiosonde and compared with the corresponding sodar measured depth of the thermal plumes. These comparison results have been used to develop an empirical relation to determine the mixing-height from the sodar observed thermal plumes height [1], as shown in Eq. (1).

\[ y = 4.24x + 95 \]  

Here \( y \) is the estimated mixing-height as per the Holzworth model, and \( x \) is the sodar measured thermal plumes height.

Gera and Singal [42] proposed a technique to determine the dispersion coefficient using the monostatic sodar. The echogram structures from sodar installed at the sounder at Chittorgarh (India) have been used to observe the vertical dispersion when the plume is actually passing over the sounder. Similarly, Coulter and Underwood [43] have also observed the potential application of sodar while taking measurements of temperature structure parameters and estimated the relative dispersion coefficients of the cooling tower plume. In this research, the linear relation between the width of the cooling tower plume and the distance from the tower is demonstrated. Sodar is able to measure ABL and is used to determine related dispersion parameters and is therefore considered as a high potential technique to now-cast the hazardous events related to air pollution. In the following, the efforts to estimate the pollution concentration at a place under different stability conditions using monostatic sodar are discussed.

Jensen and Petersen [44] proposed a simple box model based on the mixing-height measured by sodar to calculate \( \text{SO}_2 \) concentrations in Gladsaxe, Denmark. Moulsey and
Cole explored the acoustic sounder application to measure methane plumes in the air and provide information about its size, behavior, and concentration structure [45, 46]. It also helps to measure the wind velocity structure parameters of the methane plume from acoustic scattering measurements. These measurements showed a good relationship between the plume dimensions derived from sounder measurements and predictions of simple diffusion theory. Brusasca et al. [47] observed the improvement in the simple Gaussian model by including the remote sensing system has the potential to benefit the more complex atmospheric diffusion model. Gera et al. [48] studied the convective conditions air pollution dispersion model in a power station located area. Using acoustic-sounding data for a preferred dispersion model is essential for understanding the convection at complex substandard locations. 

Singal and his associates [37] developed a sodar based model to predict pollution concentration due to emission sources in the National Physical Laboratory, Delhi, India. They have proposed to adopt the normal Gaussian dispersion model for estimating the downwind pollution concentration. The particulate matter concentration with respect to distance from the cement factory located at Nimbahera (Chittorgarh) in Rajasthan, India, has been computed by Singal et al. [1] to observe the dust contribution of the cement factory in that area. The prediction model calculated values have been found in a similar range to the observed particulate matter values. Additionally, the diurnal variations of the computed particulate matter data correlate with the sodar determined mixing-height value. As expected, a high rise in particulate matter is observed during the fumigation period.

The linkage between the concentration of the pollutants and locally measured mixing-height in Moscow, Russia, is demonstrated by Pekour and Kallistratova [49]. In this research work, the pollutants variations in time are measured using sodar, and a correlation with the observed air pollutants has been estimated. This positive correlation elucidates the practical use of the sodar determined parameters such as mixing height and stratification of the atmospheric boundary layer for air pollution meteorology.

The acoustic-sounding technique has been extensively advanced since the initial work of McAllister [50] and Little [51]. It evolved as a valuable tool for remotely probing the information of the atmospheric boundary layer. Beside the many qualitative studies of the atmospheric phenomena like inversions, thermal plumes, mixing height, fog, and sea breeze, it provides quantitative information on many important atmospheric pollutants and their dispersion and diffusion coefficient in the atmosphere.

An IoT-based sodar network for air-shed management and planning was previously established by Chourey [52]. Six sodars were placed throughout Northern India and interconnected via the Internet of Things (IoT) to conduct this study. The integration of sodar with a meteorological sensor is also essential in order to analyze and study environmental pollution, which was not included in the presented research.

2.3. Motivation of Research

It has been observed from the review of related work that there has been significant development of the sodar technology and meteorological sensor network for the air pollution monitoring and management system. However, the advancement in sodar and integrated meteorological sensor networks and their applications have some apparent shortcomings. Firstly, multi-sources of data and information are constantly expanding. Multi-sensors data from multiple locations require effective acquisition and processing. Secondly, practical database management is necessary to tackle a large amount of data from the integrated meteorological sensor networks in real-time for remotely monitoring the environmental parameters. Thirdly, the influential association and fusion between multi-sensors and their real-time data acquisition is another important topic that has been rarely studied in the existing literature. Lastly, adapting multidimensional and multi-scale applications under different tasks and cloud services is another challenge with the next generation integrated sensor network system [53, 54].

Accordingly, the development of integrated, smart, and sustainable network systems for practices in air pollution, environment, and sustainable engineering based on IoT is imperative for the near future. Based on this, a novel IoT-based integrated sensor network consisting of sodar and meteorological sensors such as wind, temperature, and humidity is proposed on a single platform for regional air pollution monitoring and management system. The IoT-based single platform solution has been installed and commissioned in seven different Northern India locations to improve the decision-making of the air pollution monitoring system for Delhi.

3. Proposed System

In the last decade, the increasing trend in IoT technologies has laid the foundation for integrating multiple sensors for air pollution monitoring systems. In this manuscript, a novel single platform solution to create SMSN is proposed for regional air pollution monitoring based on the framework of IoT. The proposed methodology consists of four steps: (1) design and development, (2) calibration and testing, (3) installation and real-time data acquisition, and (4) monitoring, as shown in Fig. 2. A detailed discussion of
the proposed methodology has been presented in the following subsections.

3.1. Design and Development

The designing and development of digital signal processing software for IoT networking is a critically important segment of the system. The first part focuses on designing a digital signal processing for sodar and then integrating it with meteorological sensors data for local data acquisition and monitoring of the sensor data, whereas the second part is dedicated to transmitting the processed data into the cloud for remote sensor data access.

3.2. Digital Signal Processing

The wind, temperature, and humidity sensors along with the data acquisition (DAQ) card are procured from Schelt Technology, Noida, India. DAQ digitally processes the sensor’s signal, and the local server monitors the processed data using the local-monitoring interface. The sensor, DAQ card, and monitoring interface for the meteorological sensors are shown in Fig. 3.

The sodar system used in this work is designed and developed in the CSIR-NPL, Delhi. Sodar’s digital signal processing consists of analog to digital conversion (ADC), filtering, data processing, and noise cancellation stages. The preamplifier and data logger is powered by a 12-V DC power supply. The high-powered acoustic pulse of 130–140 dB intensity and 2.25 kHz frequency is transmitted in the atmosphere using an acoustic transducer. Sodar receives the backscattered signal every 10 s (Pulse repetition cycle = 10 s). In order to capture the complete depth of the temporal ABL structure, a fast DSP is required with a high sampling-rate ADC of 44.5 kHz. The advantage of a higher sampling rate is significant data points. However, it further increases the demand for digital filtering and data processing to extract the crucial information from the signal. Therefore, the signal is passed from the digital FIR bandpass filter of 50 Hz bandwidth to eliminate the unwanted frequency component from the signal. These filtered data points are divided into small packets and processed using the peak detection method to expel the undesired peaks. The standard mean is calculated of data points from each small and stored in the one dimension (1D) array. Similar operations have been performed on every packet of data and appended to the 1D array. These data represent the height of the received signal in a single operating cycle. In order to eliminate environmental noise, atmospheric echoes have been recorded from the sodar transducer before every operating cycle. The blank atmospheric echoes are the environmental noise directly subtracted from the original signal. The DSP system of the proposed design integrated the sodar and meteorological sensor data and stores the combined SMSN data in a single file. These data are monitored using the LabVIEW-based software in the local server room. The combined digital signal processing of sodar and meteorological sensors is shown in Fig. 4.

3.3. IoT Architecture

The IoT architecture of the SMSN comprises four components: applications and analytics, infrastructure, integration, and security, as shown in Fig. 5. The applications and analytics layer process and display the collected information via IoT-based SMSN. It includes data analysis tools and visualization capabilities. The LabVIEW-based data acquisition software has been used for data processing and representation. The infrastructure layer consists of physical devices such as sensors, communication networks, servers/controllers, and cloud storage. The sodar, wind sensor (MeteoWind-2), temperature, and relative humidity sensor (MeteoTemp + RH) has been used as primary sensing device. A wired connection has been established between the sensors and the local server. The combined sensors and local server system are known as a single sensor node. Another communication network is required for connecting each sensor node and remote server via cloud services. The high-end computer of the 9th Generation Intel Core i5-9400 Processor with 4 GB of random access memory has been used as a local and remote server, whereas the AWS-S3 cloud services have been used for cloud storage. The flowchart of the complete data uploading and real-time acquisition from the AWS S3 bucket using LabView is shown in Fig. 6. The entire process is segregated into two stages. In the first stage, the AWS S3 bucket is created, and puts the data from the sensor node into the bucket using a local gateway (Wi-Fi).
Then, the data are fetched from the S3 bucket using Cloud Toolkit for AWS by NI-LabView in the second stage.

The data acquisition software based on LabVIEW has been designed to represent and store the data on the local server. It also established the data communication between the sensor node and cloud through Wi-Fi. The AWS-S3 built-in functions such as create the bucket, PUT-object bucket, identity, access management (IAM), and an application program interface (API) are utilized in the software for IoT networking. The AWS create-bucket function creates a dedicated storage location in the AWS-S3. The put-object function stores the data in that location with unique vital credentials. The AWS-IAM manages the amazon S3 resources, and finally, the API ensures the object’s storage and retrieval from the bucket. The LabVIEW-based data-acquisition software also fetched the

Fig. 3 Data acquisition system of meteorological sensors

Fig. 4 Digital signal processing of SMSN

Fig. 5 IoT architecture of proposed SMSN
timestamps value along with the sensors data. It transmitted it over the IoT network to update the data instantaneously in the database. The complete process of data transmission using AWS-S3 is presented in Fig. 7.

The proposed IoT-based SMSN consists of each sensor node transmitting the data into the cloud and simultaneously monitoring all location data from a remote monitoring station equipped with a high-end server, Wi-Fi, and multiple-display. The complete sensor node network of the SMSN is presented in Fig. 8. In order to achieve faster data communication, the alternative pulse repetition cycle is only utilized for the data transmission to cloud storage. This process increases the transmission cycle time to 20 s. It reduces the total data size of the SMSN to half, which helps to manage the available resources effectively. This sampling speed is acceptable for meteorological sensors but reduces the echogram resolution of sodar. However, the estimated mixing-height data remain intact, which was the objective of the SMSN.

3.4. Calibration and Testing

Calibration is an essential part of any reliable sensor network system. The calibrated meteorological sensors have been selected for the networking in this research work. The wind sensor (MeteoWind2) is calibrated with MEASNET, IEC61400-12-1, IEC61400-12-2, ISO3966 and ISO16622 procedures with standard uncertainty of 0.2%, standard error of 0.025%, and correlation-coefficient of 0.999979 [55]. The temperature and humidity sensor (MeteoTemp RH + T) is calibrated with ISO/IEC 17025:2005 procedure, with temperature uncertainty being less than 0.3 °C and 0.1% at each calibration point [56].

The temperature and humidity sensor is also calibrated in the CSIR-NPL, India. The CSIR-NPL, India, is mandated to be India’s National Measurement Institute (NMI) and maintains standards to international equivalence. It represents India in Comité International des Poids et Mesures (CIPM). It maintains a quality system in accordance with ISO-IEC 17025:2005 with peer-reviewed calibration measurements capabilities (CMC) by international experts for mutual recognition. The calibration results of the temperature and humidity sensor are presented in Fig. 9. The expanded measurement uncertainty is ± 0.2 °C and ± 0.4% for the temperature and relative humidity, respectively.

3.5. Installation and Commissioning

In this research work, Delhi and the surrounding part of Northern India have been selected for the study. Delhi is
considered one of the fastest-growing cities in the world and is known for its vulnerability to climate change and air pollution. The in-depth knowledge of the intensity of transported pollutants is essential for regional sustainable development in the area. The other locations of Northern India selected for the study purpose are shown in Fig. 10. In this work, the sodar is installed along with other meteorological sensors like wind, temperature, and relative humidity at the mentioned locations. This sodar based meteorological sensor network helps the regulatory authorities better and effectively air-pollution monitoring Delhi.

3.6. Real-Time Data Acquisition and Monitoring

The installed sensors at each location work as a sensor node. The sensors collect all meteorological data from the sensors, i.e., mixing-height, wind direction, wind speed, temperature, and relative humidity. The proposed SMSN shares the data from multiple sensor nodes to central monitoring stations using the IoT platform. However, it remains a challenge to process a large amount of data for remotely accessing and visualizing in real time. In this
work, the AWS-S3 and LabVIEW-based real-time data acquisition software is designed for data visualization and further analysis. Figure 11 presents the complete process of AWS-S3 and LabVIEW-based real-time data acquisition of SMSN. The AWS-S3 cloud stores the sensor node data from multiple locations with unique credentials. These credentials have been used for accessing the data in the access-bucket function of AWS. Later, the list-folder searches the current date and time folder from the specific bucket. The get-object function fetches the file from the bucket and appends it with the existing file of the same day. Finally, the LabVIEW-based software has been used for plotting all the parameters in near real time. The file contents are updated automatically with fresh data and simultaneously plotted in the software.

IoT-based SMSN has broad prospects in both scientific and industrial areas, as SMSN is a good solution and provides integrated platforms for performing complex environmental tasks. The features of IoT are precisely suitable for data collection, processing, and analysis to improve decision-making in real time. SMSN and IoT solutions provide competitive advantages among the application fields and play important roles in air pollution monitoring and management in the defined area. This paper focuses on integrating key technologies from both in-situ and remote sensing meteorological sensors and the IoT in a typical air pollution monitoring system. Additionally, taking the regional pollutants sources and their ecological responses as an example provides a paradigm for environmental sciences research.

4. Results and Discussion

The integrated SMSN is established to monitor the mixing-height and affect meteorological parameters in Northern India. In order to ensure the reliability of the IoT-enabled SMSN, the data collection has been done at the testing laboratory (CSIR-NPL) and validated with the existing data acquisition software. Later, data were collected from all sensor nodes (installation sites), and correlation was analyzed between the mixing-height and other meteorological parameters. In a similar context, the combined impact of all the sensor nodes’ data on air pollution has been studied.

4.1. IoT Enabled SMSN Data Analysis

The first sensor node has been established in the CSIR-NPL for testing purposes and later installed in all locations. In this work, data have been collected from all locations using IoT-enabled SMSN. The collected data points are compared with the expected number of data points to check system reliability. The standard uncertainty of the network has been calculated in the first stage of analysis. The mathematical expressions used for calculating the standard uncertainty are as follows:

\[
\text{Standard Uncertainty} (u) = \frac{\sigma}{\sqrt{N}} \tag{2}
\]

where \(\sigma = \text{standard deviation}\).

\[
\sigma = \sqrt{\frac{(x_i - \mu)^2}{N}} \tag{3}
\]

where \(N\) is the number of data points, \(x\) is the per day percentage accuracy, \(\mu\) is the mean of percentage accuracy, and \(i = 1, 2, \ldots, N\):

The daily received data points are compared to the expected data points to determine the accuracy percentage. The 6 months data from September 2020 to February 2021 have been analyzed. Afterward, the standard uncertainty is estimated from daily percentage accuracy values for all the parameters at all sensor nodes. Table 1 depicts the calculated standard uncertainty results of the IoT-enabled SMSN system. Additionally, the combined uncertainty was calculated for every sensor node in order to estimate the overall network performance. The combined uncertainty is calculated using the following expression:

\[
\text{Combined Uncertainty} = \sum_{i=1}^{N} u_i \tag{4}
\]

where \(u_i\) is the standard uncertainty of each parameter.

![Fig. 11 Real-time data acquisition system block diagram](image)
results lie well within the acceptance range. The minimum combined uncertainty is found at 0.1011 from SN4, whereas maximum uncertainty is observed in the SN6, i.e., 0.3370. Due to inconsistencies in sensor node data from the IIT Roorkee and AMU Aligarh installation sites, standard uncertainty for meteorological parameters was not included. However, overall results show excellent consistency with significantly low uncertainty.

The second part of the analysis is focused on the measurement of SMSN parameters from a remote server. The 1-h standard mean is calculated from temperature, relative humidity, wind-speed, and prominent direction is considered for wind-direction. However, the estimating process of mixing-height from the ABL structure is a bit complex work. The data acquired from IoT-enabled SMSN are reduced to half in order to manage the resources effectively. In this analysis, the measured parameters from the IoT network are compared with the local data acquisition system. The comparative result shows 95% accuracy with less than 5% error which lies well within the feasible range considering the manual estimating process of mixing-height. An IoT-enabled SMSN with low network uncertainty is a reliable solution for regional air pollution monitoring.

### 4.3. Correlation Analysis of SMSN Parameters for Air Pollutants

The prime objective of this work is to restrain air pollution in Delhi using a regional monitoring system. In this analysis, the key air-pollutants such as PM2.5, PM10, O₃, SO₂, and NO₂, has been selected for the analysis purpose. The data from March-2020 to February-2021 are collected from the CPCB, India, continuous air-quality monitoring stations nearest sensor node locations. The Delhi SMSN parameters along with the air pollutant data are analyzed with the other sensor node pollutants. Figure 13 presents the correlation-coefficient matrix between the SMSN and air-pollutant data of Delhi to all sensor node locations. The correlation analysis displays the notable correlation between mixing height and air-pollutant data of Delhi to all sensor node locations. The proposed network makes a strong case for the importance of mixing height in regional meteorological studies.

### Table 1 Standard uncertainty of the IoT-enabled SMSN

| Sensor nodes (SN) | SMSN parameters standard uncertainty (u) | uc  |
|------------------|-----------------------------------------|-----|
|                  | Mixing height | Temperature | Relative humidity | Wind speed | Wind direction | uc   |
| SN1              | 0.15          | 0.02        | 0.02              | 0.02       | 0.02          | 0.1591 |
| SN2              | 0.19          | 0.03        | 0.03              | 0.03       | 0.02          | 0.2028 |
| SN3              | 0.13          | NA          | NA                | NA         | NA            | 0.1347 |
| SN4              | 0.10          | NA          | NA                | NA         | 0.10          | 0.1011 |
| SN5              | 0.22          | 0.09        | 0.03              | 0.05       | 0.03          | 0.2442 |
| SN6              | 0.28          | 0.10        | 0.08              | 0.11       | 0.10          | 0.3370 |
| SN7              | 0.23          | 0.03        | 0.03              | 0.02       | 0.02          | 0.2382 |

SN1 = CPCB Delhi, SN2 = NPL Delhi, SN3 = IIT Roorkee, SN4 = Aligarh, SN5 = Hisar, SN6 = Sangrur, SN7 = Alwar, MH = Mixing Height, Temp = Temperature, RH = Relative Humidity, WS = Wind Speed, WD = Wind Direction

Combined Uncertainty \( (uc) = \sqrt{u_{\text{MH}}^2 + u_{\text{Temp}}^2 + u_{\text{RH}}^2 + u_{\text{WS}}^2 + u_{\text{WD}}^2} \)
Hisar. The strongest correlation is found with the Aligarh data highlighted in the purple box in Fig. 13. O₃ is considered the prime air-pollutant for smog creation, which is a major issue in Delhi during the winter season.

Besides that, the air-pollutants such as PM₂.₅, PM₁₀ and NO₂ of Delhi show a strong correlation with other sensor node locations pollutant data. Again, Aligarh has shown the strongest correlation among all. Based on the above analysis, it is clearly indicative that air-pollutants from different sensor nodes are also responsible for the Delhi air-pollution. However, the rigorous study on the topic will be helpful to find the exact dynamics between parameters of all locations.

5. Conclusion

The sodar is helpful in providing crucial atmospheric parameter information such as mixing height, inversions, and stability class. These parameters have a substantial impact on monitoring the hazardous situations of air pollution. In this paper, a calibrated SMSN equipped with IoT features has been established. The IoT-enabled SMSN
estimates the mixing-height in real-time along with the meteorological parameters. This study has been performed in Northern India, focusing on the air quality monitoring of Delhi. The IoT-enabled SMSN is created with seven sensor nodes to measure meteorological parameters. The estimated standard uncertainty for the SMSN is impressive, ensuring the system’s reliability. Additionally, the estimated parameter value has been validated with locally measured data. The data validation results show more than 95% accuracy.

Later, the correlation analysis was performed between the SMSN parameters and air pollutants of all sensor nodes. The significant relation between the SMSN parameters and air pollutants across sensor nodes illustrates the importance of regional monitoring systems for air quality management. Besides that, integrating remote sensing instruments such as sodar and advanced techniques like IoT with the conventional system definitely helps regulatory authorities plan effectively to curve the air quality in the selected area.

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