Urban Air Quality Monitoring System Enhanced by IoT for Comprehensive Deployment, Data Collection, and Environmental Impact Analysis

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Abstract: - In this study, we discuss aspects of success in the implementation and sustainability of an EMS in air pollution monitoring, such as the utilization of Internet of Things technology, location choice, sensor installation, support structures, and the capacity for future addition. It therefore is designed to plot the temporal changes of environmental factors such as contaminants and weather using synthetic data generation and assessments. This paper proves that air pollution is rather variable over the course of the defined time and highly depends on population density, industrial output, and green zone coverage. The paper deals with the quantitative and qualitative sensor deployment as well as sound engineering for data acquisition and transmitting; therefore the issues of scalability, modularity, and low cost are considered relevant to enhance more efficient and inexpensive sensing systems. In fact, data acquisition, as well as data communication and storage qualities, measurements of sensors, and analysis of their specifications such as their accuracy calibration, and coverage are also captured in the study. It complements and imposes the notion of sensitivity, accuracy, and requirement for maintenance during the organization's information exchange, cloud storage and data dependability, and measures of data superiority. It therefore covers source identification of counter various polls through source apportionment and health effects of the resultant pollutants underlining the significance of effective antipollution measures. From policy and regulation impact analysis, a number of suggestions would need to be made regarding fairly balanced policy effort distribution between the policy and compliance, the effectiveness of the interventions, and the number of times the general public is to be made aware. These findings contribute to increasing the available knowledge on environmental monitoring activities and offer delicate recommendations for policymakers and other stakeholders regarding the improvement of the quality of the environment and the population's health.

Key-Words: - Environmental monitoring systems, Air quality, IoT technology, Data analysis, Pollution control, Public health.

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1 Introduction

The introduction brings enlightenment to the area of concern; that is UAQM in view of rising trends in urbanization as well as technological advancement. From the 4IR, it underscores the existing methods that occur in UAQM, they are regulation monitor, data from satellites, IoTs, and AI are embraced. Based on data derived from scientific databases and 'grey literature' encompassing governmental and international sources the paper stresses the role of urban computing for radical innovations in UAQM approaches. The current positive model directly supports integrated technologies in the observed and actual governance actions and in empowering citizens with decision-making tools and information. The proposed MultiTechnology offers the ground to align the services of UAQM against the constantly evolving smart city setting to achieve highly operational solutions for addressing air quality as may be needed, [1].

Why it is impossible not to have dynamic traffic management (DTM) systems to minimize the negative effects of traffic congestion in the urban areas concerning pollution of the air mainly. It exposes the aspect that such systems rely on traffic and environmental monitoring strategies and approaches. This paper provides a new solution to the above challenge through recommending a low-cost IoT system capable of achieving both, traffic movement and AQI. An estimation of traffic flows in real-time is performed and the motion vectors are applied to the video processing at the compressed domain on embedded architectures. Further, it does not require calibration of AQI and the embedded device measurement challenges inherent to AQI estimation for pollutant gases using machine learning regression techniques to predict the AQI. When implementing the planning in various experimental scenarios in different environments of a city environment where different climate systems and Traffic conditions are incorporated the above-mentioned formation imposed works as the effectiveness of the designed architecture proposed. This work evaluates the performances of several regressors adapted from machine learning techniques namely Linear Regression (LR), Gaussian Process Regression (GPR), and Random Forest (RF) through comparatives on average performances of ballparking AQI in terms of Mean Absolute Error (MAE), Root Mean Square Error (RMSE) together with coefficient of determination (R-squared) measurements, [2].

In combination with population growth other human activities within the environment especially in the areas of rapid urbanization have greatly influenced the air quality of the regions. AQI or the Air Quality Index is very vital in providing a barometric of how healthy a certain extent of air pollination is. Citizens are to be informed by public authorities about the state of air quality, however large amount of pollutant information is ambiguous and challenging to act upon. Most of the countries have adopted daily indices which indicate, for minutes, The Air Quality in several large city areas of use to the public. As for the entire Mediterranean, the goal of developing a single indicator for public communication has not been achieved fully. The AQI is used in this study as a basic and real-time method of informing the public on the quality of air being breathed. Based on this, the study evaluates the trends in AQI for the years 2013, 2014 and 2015 in order to forecast the air quality with objectives of preserving human health and ecology. The evidence for this research framework should extend to other countries of the world including municipal regions to enhance the understanding of the populace and enhance the quality of the environment, [3].

The paper begins with a description of the problems occurring when applying the maximum of sub-indexes that represent pollutants; it does not take into account the accumulative effect of several pollutants on human health. The better AQI technique that we proposed in this paper incorporates these additive effects to present a more comprehensive view of air quality and its effects on health. This paper fills the gap in previous literature by developing an enhanced model of the air quality index with PM10, SO2, NO2, and O3, where daily cardiovascular and respiratory admissions in Hong Kong from 2001 to 2012 are used as a dependent variable. This is an index that employs the multiple pollutants expressed in the power function of root-mean-power concentrations to achieve the least of the prediction errors and these have been developed. Comparisons made between the states reveal the new AQI pollution bands align with health consequences and had a constant dose-response relationship as evidenced in this study. Comparison with AQIs from China, the UK, and the US can justify the application of the proposed method. This work presents a proper background for enhancing the computation of AQI to do the needful and enhance the defense of the populations' health and air quality of numerous cities, [4].

Scientific analysis also suggests that IAP has a negative impact on public health and is a cause of factor of thousands of deaths annually. Drawing from the current literature, this paper provides a synthesis of the main sources and indoor pollutants, health consequences, and conditions; SBS and BRI. This effort is applied to determine the diversity of the sources in an attempt to address the strategies toward the reduction of IAPs and an enhancement of the IAQ. The review of pollutants emissions evaluates the several effects of the pollutants on the health of the people and the controversy concerning the relation of illness to IAP. Further, the techniques involved in the control and reduction of each of the different types of pollutants as developed in recent years are explained. In detail, the development of advanced materials for sensors, IAQ control systems, and smart homes is identified as the fourth strategy for controlling IAQ in the future. This paper proves that embracing such new technologies could improve better indoor environment for the wellbeing of humans as such new technologies should be adopted, [5].

Since it defines control strategies, knowledge of the source of pollution is essential in the regulation of air pollution. The current paper can be best described as a literature review of the most commonly utilized source apportionment methods employed in air quality analyses. The study therefore is able to juxtapose theoretical statements with experience findings and thus illustrate how different approaches to a problem lead to different conclusions concurrently the study enhances appreciation of the underlying assumptions of methodologies. These assumptions are crucial in the generality and credibility of the method, hence a threat if applied in other fields. From the review scenario, the incremental approach, which is the least complex, does not afford satisfactory provision of sound air quality planning. However, receptor models and tagging methods within air quality models particularly for specific pollutants are appropriate but limited in this way. The first class of models that can make a direct estimate of the effects of pollution is considered more suitable achieve for achieving integrated air quality planning. However, the efficiency is based on the evaluation in order to check if such trends, for example, correspondingly reflect modern tendencies in chemistry. Therefore, this analysis brings a plea for appropriate selection and application of source-apportionment techniques to improve ultimately air-quality management, [6].

Therefore, the identification of sources of VOCs has an enormous value in confirming the emissions and the impacts of VOCs on the quality of the urban air. In this paper, possible VOC sources in Seoul have involved the use of receptor models, such as PMF and CMB together with the chemical transport model. For this purpose, the data obtained from four sites in Seoul, South Korea between 2013-2015 were adopted to compare the potentials of varying emission sources of VOCs on ambient O3 and PM2.5 and their associated health effects during a photochemically active sampling campaign in June 2015. The CMAQ and BenMAP modeling on the rate of pollution of the selected VOCs reveals that solvent use, and on-road mobile emissions are the major sources of VOCs in Seoul. Therefore, 35% of

VOCs are contributed by other factors apart from Seoul, supporting the idea that regional sources occupy a significant fraction of the VOCs. Solvent use accounted for 3.4% of the increment in daytime O3 formation while the contribution of solvent use for PM2.5 formation was negligible. BVOCs made minimal impacts on the formation of O3 and reasonable impacts on PM2.5. This research paper computes the Recurring high health costs due to VOC-induced O3 and PM2.5 identified major deaths associated with solvent use emissions. This comprehensive review supports the need for designing appropriate strategies to control VOC emissions to mitigate the effects that are brought by air quality and health in enormous cities like Seoul, [7].

In the recent past, severe pollution incidents have been more rampant in India, especially in New Delhi thus the need to identify the sources of the pollutants for parade in their emission. This study uses source-oriented versions of the CMAQ model linked to the EGDAR inventory to apportion eight important source categories: energy, industry, residential, on-road, off-road, agriculture, open burning, dust emissions for PM2.5 and their constituents PPM and SIA with sulfate, nitrate, and ammonium ions. The analysis focuses on Delhi and three surrounding cities: Had for Chandigarh, Lucknow, and Jaipur cities for the year 2015. Based on this analysis, industrial and residential sectors are found to regulate PPM mass meeting more than 60% of the total proportions. That has influenced PPM levels of energy and industry below south Delhi reaching 200 $\mu g/m^3$ in winter seasons. SIA densities are much less diverse and southern Delhi and central Uttar Pradesh show high density of SIA mainly from energy and industrial and residences other than aviation. The agriculture sector has made very exhaustive contributions to SIA as compared to PPM and on-road and open burning sources have influenced SIA more than PPM. Out of all the sectors, the residential sector has the highest percentage of PM2.5 emissions in North India followed by industry, energy, and agriculture. Delhi's 80 % of PM2.5 was from industry and residential activities and hence needs to be addressed in these two sectors to improve air quality, [8].

In this work, the case of PM2.5 pollution is examined in 25 provincial capitals and municipalities in China, and the main emission sources are identified using the source-oriented CMAQ model. By identifying the briefly observed yearly PM2.5 levels, the nine clusters were created through hierarchical clustering analysis, the northern cities had the highest average of annual PM2.5 (range: 81-154), and the southern and the east coastal cities had the minimum annual PM2.5 (range: 27- 57). This was while the seasonal differences indicated moderate to high-levellevels of PM2.5 during the winter season. The highest BC values were recorded in the industrial zones of the cities in groups C, B, and A, whereas the highest OC values were observed in the same groups in an inverse order to the values in Industrial and residential emission sources where the main source of PM2.5 in all the city groups contributing annually between 25.0 and 38.6% and 9.6 to 27%, respectively. Other significant sources inter alia included power plants, agricultural ammonia (NH3), windblown dust, and secondary organics aerosol SOA. More specifically, secondarily generated PM2.5 accounted for 47 – 63% of the yearly PM2.5 emissions and 50 – 70% on high emission days. Even less than 8 % yearly PM2.5 portions originated from transportation, sea salt 2 %, and Open burning 6 %, the open burning, SOA, and wind-blown dust perhaps may play relatively larger roles on high pollution days or during the spring season. The further works built important prerequisite for applying certain steps to reduce the annual concentration of PM2.5 and the number of pollution days taking into consideration features of pollution in every area of China, [9], [10].

Managing the pollution of air in and around structures becomes virtually impossible with increased rates of deaths resulting from diseases caused by outdoor air pollution standing at millions per year. The contributions made by local emissions to direct years of life lost from the damages have been measured by prior studies, but pollution transport and international trade are no longer small additions to impacts that directly affect local people's air quality and health. Exports are also a contributor to emission externalization in that production of products in one country brings about emissions as well as resultant health effects in another country. While there are such regional reviews of these dynamics, a global comparative assessment of the impacts on health resulting from globalization through trade and transboundary transport of air pollution has not been done. Drawing on four global models embedded in this paper, years of life lost due to premature mortality caused by atmospheric transport and production and consumption-based emissions of PM2.5 are evaluated. The observations made in this research indicate that out of the total global premature mortality of 3,450,000 from PM2.5 pollution in 2007, approximately 12 % resulted from pollutants from other zones and 22% from trade. In particular, cross-border PM2.5 pollution decreased the health amps in other regions, including western Europe and the USA, and conversely. These findings describe the main impacts of PM2.5 emission concerning int'l trade across borders compared to atmospheric pollutants' long transport. This is an illustration of the fact that there is a need for international collaboration on air management with a view to abating the numerous health impacts arising from air pollution, [11], [12].

2 Literature Survey

Work on the present time period topay more emphasis on global air pollution and where new monitoring systems are needed. Current approach's drawbacks include low accuracy, and poor sensitivity with the ability to deliver real-time information which needs to be enhanced. In reply, it provided a three-phase air pollution monitoring system on the Internet of Things (IoT) basis as follows: In our proposed design we have used gas sensors, Arduino Integrated Development Environment, and Wi-Fi modules in an IoT plant and travel kit. Gas sensors feed data on the real-time concentration of gases in the atmosphere; these details are transmitted on the Arduino IDE and forwarded to the cloud via Wi-Fi. Moreover, it presents the IoT-Mobair which is an Android application thatlets the users control the air quality remotely. That is why, intending and working like Google's traffic predictive model, IoT-Mobair predicts pollution levels en route and triggers high-level alerts. Besides, the elaborated system allows producing the forecast of future AQI levels for using in environmental and health policy. On this basis, this research work will make a contribution towards a reduction of existing gaps in monitoring of air pollution for improved decision-making and activity, [13].

The paper of Air pollution remains a problem in China with hefty effects on the people of this country and the climate too. Nonetheless, current literature lacks elaborate investigations of regional and temporal distributions of the major air pollutants in the country. Based on the over 300 ground observation stations of air quality across more than 300 cities in China from May 2014 to December 2018, this study attempts to provide systematic and quantitative descriptions of the basic characteristics and temporal variations of the air pollution level in each of the seven regions in China. For example, overall results are marked by reduction of air pollutants from 2014 to 2018 due to emission control and alterations in climate. However, the present work focuses on an ever-increasing trend in O3, which suggests new challenges in the context of air quality control. Spatially even though some pollution is relatively homogenous other of its parts are spread through the different regions in different varieties of hot spots depending on the amount of emissions. Thus, the North China Plain and the central and western Xinjiang Province are outlined as the areas of more pollutive attention. The given research is of great significance to society since the paper offers a broad spectrum of data and findings concerning the actual state of the problem of air pollution in China and helps develop the strategies and policies for the preservation of the environment in the country, [14], [15].

In the case of affordable sensors, focus on the prospects associated with enhancing the spatial resolution of air quality sensing in city environments. However, data measured from such sensors is usually deemed imprecise due to internal constraints and the fact that the sensors are seldom deployed at a steady rate in terms of time or spread across space. In response to this challenge, this study recommends a data fusion method grounded in geostatistics that would incorporate data from a network of cheap sensors with spatial data gained from an urban air quality model. Employing Gaussian nitrogen dioxide dispersion data with mean values obtained in January for the city of Oslo, Norway indicates the ability to depict precise hourly concentration fields through aggregating model-generated spatial distribution data with data gathered by the sensor. In the case of the adopted fusion method, the degree of achieved accuracy is a function of an observation quantity, its distribution, as well as the type and magnitude of uncertainty involved along with the capacity or potentiality of representing urban pollution. Regarding the performance of the present system in recreating city averages and daily cycles of nitrogen dioxide, it has been positively compared with data from the certified monitoring stations. When used together with the complete information of various sensors and the static model of the dataset this approach offers a valid method with which information can be mined from unreliable sensor measurements, [16].

Rising consciousness of the deterioration of environments in the global environment and the worsening of ill health through exposure to polluted air within urban centers has challenged innovation, policies, and the people, and researchers. Accurate identification of air quality at the same or near real-time in a relatively smaller area is crucial to minimize the effect of air pollution on health. Conventional methodology for monitoring ambient air quality for instance gaseous pollutants has entailed the use of few fixed air quality stations which are often scarce in the urban setting. However, major advances in micro-scale sensing technology over the last decade had dramatically altered this field by enabling the utilization of transportable sensing equipment on carriage platforms, particularly for traffic-related pollution identification. Therefore, this paper will seek to offer a review of the exposure models that employ data collected from the FMSs but at the same time make a point that the mobile sensing for air pollution lacks evaluation. However, there is a lack of such a recent outlook of air pollution monitoring methods covering both data acquisition and evaluation strategies This article seeks to address this gap. However, the present paper differs from the other papers in the literature since it will apply the traditional models on data obtained from both stationary as well as mobile sensors. Furthermore, it describes the further development of the study concerning the integration of data from static and mobile sensing to enhance pollution area and assessment. Therefore, this paper will seek to elaborate more on the current and probably the progressive course in air pollution monitoring in an effort to extend to the future, [17].

When reviewing the challenges of air quality, water pollution, and radiation pollution it is clear that there is a need to have a relevant monitoring system to enable the provision of a unitary growth of the society. Most environment monitoring has in the last couple of years moved to smart environment monitoring (SEM) due to improvements in IoT and advanced sensors. This manuscript is a review of first-generation studies and contributions in SEM specialty mostly on air quality, water quality, radiation pollution, and agricultural systems. For each of the uses, the review explains the kinds of sensors used, the ML, and the classification techniques used as well. Examining these segments in detail, the authors provide major recommendations and impacts of the points addressed by the focus on the discussion of the research trends and findings. Particular emphasis is given to the evolution that SEM has undergone because of the incorporation of sensor technology, IoT, and ML. Similarly, the manuscript articulates for designing of sound machine learning algorithms, and observed data filtering of WSN accompanied with policies for improving environmental assessment outcomes, [18].

In controlling resource consumption and enhancing the quality of the services offered by smart cities to the citizens, the environmental characteristics such as temperature, humidity, and CO2 have to be observed. This paper thus proposes a new IoT-based environment monitoring system more appropriate for this purpose. The system architecture consists of a transmitter node that sends data to the receiver node and data is stored and observed in a Graphical User Interface programmed in LabVIEW. Importantly, data is also transmitted along with a personal computer (PC) and an Android application for remote monitoring through smart phones. Based on a description of the proposed system, this paper assesses the design, implementation, and performance analysis of the proposed system. Therefore, the research that connects IoT technologies with LabVIEW-based GUI and mobile applications provides a good solution for real-time environmental monitoring in smart cities. This work enriches the understanding of the existing state of knowledge concerning IoT technologies for smart city support and offers direction on how to design and develop today's monitoring systems to enhance post-sustainable characteristics of urban areas and the quality of life of the inhabitants of these cities, [19].

The continuous fight against pollution to argue that the effectiveness of the air quality monitoring systems remains a key to the health and wellbeing of the people as well as the environment. This research aims to react to the issues of greatest concern concerning the accuracy of air quality data and identification of sources of pollution. This paper presents a new approach that is expected to significantly improve the air quality monitoring device placement process and ultimately distribution effectiveness. Its inclusion of spatial distribution patterns reduces the capital costs of monitoring initiatives as well as their operational costs. The algorithm presented in the proposed paper uses a database of 300 days, while the study area covers 80 km^2 of Durgapur city; the algorithm achieves a 90%+ level of accuracy. Careful choices of the spots to install that algorithm guarantee that it captures as much data as possible but costs an arm and a leg. This advancement has potential for enhancing economically sustainable efficient pollution prevention measures and decisions on the distribution of resources within the affected areas experiencing environmental decay, towards shaping a healthier and sustainable population's future, [20]. To meet the vulnerabilities characterized that arose from the current and emerging challenges of urban air pollution, this paper looks at the shortcomings of the traditional monitoring systems and looks for new opportunities offered by the low-cost portable air pollution sensors. As mentioned with the conventional systems, despite the good accuracy they provide, particular lack of extensive spatial density and lower resolutions fail to provide accurate volume of pollutants. Building upon recent developments in low-cost sensor technology, this paper emphasizes the need for sensor calibration to reduce errors incurred by these sensors especially when operating under hostile conditions. Describing major error sources and reviewing the present calibration models and network recalibration approaches specific to various sensor distributions, the paper is based on the literature analysis. The paper provides a review and analysis of the current literature in order to present what has been done with the methods used and what has not been done as well as directions for future research involving the calibration of sensors. The goal of this work is to help improve outcomes for accurate and efficient mechanisms for air pollution monitoring, which are crucial for the protection of the public and cities against the negative impacts of pollution, [21], [22].

They analyzed the outdoor IoT-based air quality monitoring testbed developed in Uppsala, Sweden. Taking advantage of low-cost hardware components and free software, the IoT sensing unit presents a scalable and inexpensive approach for real-time measurements that could be used to supplement the existing tools and increase the extent of monitored settings. The system incorporates specified low-power wireless standards, including IEEE 802.15.4, RPL, and MQTT, to have a very high end-to-end packet delivery rate (above 98%) when tested outdoors. Furthermore, it assesses the continuously network connectivity of the testbed in real time and gives an appropriate overall measurement of testbed characteristics. Toward this end, this research provided the proof of concept of the IoT-based monitoring approach and helped to expand the base of knowledge of the scalable and cost-effective solutions in air quality monitoring that are important to the spheres of environmental management and public health, [23].

The features of available low-cost sensor technology, for IAQ monitoring indoors as they identified this technology as a tool capable of contributing immensely to the understanding of the type of pollutants that may be present in our indoor environment and health risks that are being posed by the pollutants. Although they are portable and offer near real-time measurement, their data has been criticized for reliability because of some design compromises. Besides, the available literature and the increasing number of studies on this subject have contributed to isolated information. To counteract these problems, this research follows a post-positivist framework to comprehensively critically review and synthesize scientifically peer-reviewed articles on IAQmTDs employing low-cost sensors. In the scientific databases, 891 titles were found, published in the period after 2012, 41 of which were research articles. There was a focus on device development factors such as calibration and efficiency of sensory instruments, computational capacity, storage and transmission of information as well as real-time telecommunication access to acquired data from the sensors. Of particular interest, the authors have highlighted that there is quite limited primary research that directly discusses SS PERFORMANCE CALIBRATION & VALIDATION which suggests that such aspects should be of focus for future research efforts to further standardize the way assessment of data from such sensors take place in order to increase reliability and comparability of results, [24].

Who primarily concentrated on air quality analysis with an emphasis on particulate matter, this paper employs a novel approach based on low-cost sensing approaches. However, the authors knew such sensors had drawbacks such as sensitivity to aging and environmental conditions, challenging the research to overcome by proposing low-cost particulate matter monitoring. Used in both fixed and rotating sensor platforms the system is scrutinized with delicate precision to determine different parameters such as calibration methods, concentration range precision, and use of backup sensors. During the winter season roughly about 50GB of data is gathered and analyzed from sensors over six months. The performance of the system is supported by comparative measurements with standard β-radiation sensors and mobile station measurements for assessing the system response to various environmental changes. More significantly, the methods or the approach is well acclaimed for the ease of calibration, high sampling rates, and most importantly the use of more open-source software architecture to make it easier and quite probable to be adopted at large for air quality measurements. The accessibility of the database and the software used in this study as open sources puts the study in a more special place of propelling the area of low-cost sensing in air quality monitoring forward, [25].

The aspects in the evaluation of the indoor environment that cannot be overemphasized if he wants to enhance public health sustainability through the indoor environment monitoring systems.

By observing and analyzing different levels of indoor environments like schools, workplaces, and residences, authorities obtain data that can help them to take action towards improving occupant's indoor environment. Furthermore, such systems also provide the generalized public with information on the quality of indoor air. In an effort to fill this gap, this paper presents the development of an Intelligent Indoor Environment Monitoring System (iDEMS) that utilizes Information Technology, Big data, and Cloud computing. The system uses wireless sensor network technology based on ZigBee for information acquisition and relies on environmental sensors to collect indoor gas information. Lastly, information about the environment is stored and resolved in HBase as the Big Data analysis requires. The proposed intelligent-control socket allows giving alerts when air quality is above the legal standards. Also, the implementation of a web-based Monitoring Platform provides individuals with convenient access to remote monitoring and management of the environment. This paper has presented iDEMS as a systemic integration of these technologies for monitoring the indoor environment with significance for improving population health and quality of life.

In the global study conducted on air pollution, this paper presents a standalone and real-time air quality monitoring system implemented to mitigate the effects of air pollution on human health, climate and systems. Accepting particulate matter as one of the major components of air pollution, the system includes parameters such as PM 2.5, CO, CO 2, T, RH and AP. The system uses IoT in combining cloud computing to enhance the processing of data captured by various sensors. Implemented through a low power, low-cost ARM based minicomputer Raspberry Pi the system provides real-time air quality monitoring at a reasonably low cost. Implementations of the system measured in Delhi are validated against data from environment control agencies in the area, and presented in tabular form. Of special importance, the values of the measured parameters are disclosed on IBM Bluemix Cloud, which illustrates the efficiency of the proposed system as an easily accessible and actionable source of air quality information. As this study advanced the understanding of IoT-driven EMS as an applicable framework in air quality management amidst pandemic disease, the study plays a notable role in the emerging literature in this area.

Air pollution was among the researched domains where S. of Engg letter's proposed the WSN-EPA system based on the wireless sensor network to intervene. Socially, the study identifies the effects of air pollution on health and developmental aspect which in turn identifies the ability of WSNs to monitor the levels of pollution more effectively. WSN nodes are spread throughout the city and the main roads and the system is constantly measuring pollution levels, and it follows the movement of public transport. Information on air pollution particles is obtained by using sensors installed on vehicles and on stationary nodes, which transmit data to the pollution monitoring system. The study proves how the proposed system is efficient for monitoring environmental pollution for designing WSN technology in smart city air quality management. This work contributes to the existing knowledge of environmental monitoring systems and offers a solution to key negative effects of air pollution in cities.

The effectiveness of China's Air Pollution Prevention and Control Action Plan, especially in the decrease of PM2.5 emissions in the Greater Beijing-Tianjin-Hebei (Jing-Jin-Ji) region which is one of the most polluted areas. Based on emission inventories for the years 2012, 2017, and 2020, the WRF-CMAQ model system is used to quantify the effects of phased emission control measures for PM2.5 concentration reduction. Projected emission reductions of SO2, NOX, PM2.5, NMVOC, and NH3 by 2017 and 2020 as compared to the base year of 2012 signify a reduction in elevated ambient PM2.5 concentrations. In particular, the Action Plan is effective in tackling PM2. 5 pollution, but the study finds that stricter emission controls are needed to reduce NMVOC and NH3 concentrations in the future. Furthermore, it highlights the rationale of vertically integrated strategies for emission control focused on multiple pollutants at once because they produce nonlinear effects on PM2.5 and O3 levels. This work aims to add to the existing literature on the impact of policy measures in dealing with air pollution and also highlights the necessity for the integration of policy measures in the campaign against air pollution.

3 Research Gap

The current scientific focus on air pollution is reflected as a complex investigation of various aspects of monitoring, technologies, and policies. Nevertheless, it is also important to mention that certain rather significant gaps in the current range of scholarly studies have continued to exist within this abundance of research focus areas and require a precise, systematic study. Surprisingly, there toappear to be limited studies focusing on the comprehensive assessment of integrated stationary and mobile sensing data for air pollution. Specifically, a literature review highlighted that multiple previous works exist that focus only on the stationary or mobile sensing modality, but rarely, an evaluation that combines the two is performed. Nonetheless, problems associated with sensor reliability, calibration, and validation persist hence the limited application of low-cost sensor technologies. To fill this gap, this research work examines the prospect of merging data from stationary and mobile sensing to understand the working of the two and the constraints of each strategy. To that end, by examining different approaches to sensor calibration, field validation, as well as the integration of stationary and portable monitoring streams, this research aims to bring a step forward to the development of future effective solutions in air pollution monitoring, crucial for decision-making and preventative strategies.

3.1 The Objective of the Work

- ✓ To generate comprehensive synthetic data sets for air quality, environmental conditions, site selection, and infrastructure to simulate real-world scenarios, enhancing environmental assessment reliability.
- ✓ To develop advanced AQI calculation and visualization techniques for insightful representation of air quality conditions and trends.
- ✓ To integrate environmental, sensor, infrastructure, scalability, and data quality factors to optimize monitoring systems.
- ✓ To analyze health impacts and policy effectiveness through synthetic data and to provide evidence-based visions for regulatory interventions.
- ✓ To conduct temporal and spatial pollution analysis to identify variations and develop targeted air quality management strategies.

4 Research Methodology

The flowchart presented in Figure 1 from the data presented above expounds a clear approach to the methodological framework amid the faceted approach to air quality including data acquisition, AQI computation, categorization, and other analysis viewpoints. Starting with the generation of artificial air quality data, the process is followed by the calculation of AQI values and plotting them, thus providing the grounding context for data generation. The next nodes include the creation of synthetic environmental data and its visualization that precedes site selection factors and sensor placement data as critical inputs to provide best-suited monitoring strategies. The workflow also aggregates the data related to the infrastructure and scalability assessment; the comments emerging, as a result, consider the ability of the system under construction to handle distinct workloads and sizes of space occupied. Analytical factors related to data acquisition, transmitting mechanisms, and subsequent storage, management, and quality are examined and assessed for the overall assurance of the strength and reliability of data processing systems. The formation of the AQI and the subsequent categorization of the AQI into different air quality categories improves the readability of pollution levels. This data when represented feeds into temporal analysis – this shows short-term fluctuations and long-term time trends, which are crucial in analysis for understanding the temporal fluctuations of pollution. Analysis of spatial pollution is encountered which provides pollution data for various locations and graphs it in order to set out the spatial trends. Hence, the percentage, with the help of pie charts, measures indication of major pollution sources originating from mobile and stationary sources in addition to the natural sources. Next is the health impact data generation followed by the visualization of the impacts and risks resulting from exposure that helps to inform the epidemiological consequences and exposure risks in making decisions for public health. The last area is concerned with the evaluation of the effects of policy and regulation, these will be mapped to illustrate the performance of compliance control, the success of the intervention, and work with the public. Interactions between nodes add challenge, as in reality, most processes are interconnected and illustrate the cyclical methodology of examining environmental information. This methodological consistency leads to a total synthesis of the change in air quality and helps to formulate efficient policies and strategies for environmental management.

The method of data collection for this research incorporates aspects of systematic collection that help in collecting accurate datasets required for air quality assessment. The techniques of synthetic data generation were used to mimic realistic conditions along multiple dimensions of air quality, environment, site, and sensors. For these kinds of data sets synthetic data sets were produced through random sampling algorithms by simulating variability and trends as might exist in real data. For example, air quality data were synthesized by producing plausible pollution values that mimic usual urban and rural deterioration. Environmental data included parameters like temperature, Humidity, and wind speed which were synthesized, and altered to generate more test conditions. The selection data for the sites involved geographical and topographical factors and thus ensured that the sites that had been selected for the emplacement of sensors were different. Data for sensors was assumed to represent placement strategies in both high-risk levels of exposure and low risk of exposure, thus, covering a broad range. Scalability data considers the capability of the infrastructure to respond to a high volume and number of data in the system by measuring the solidity of the system under different operating conditions.

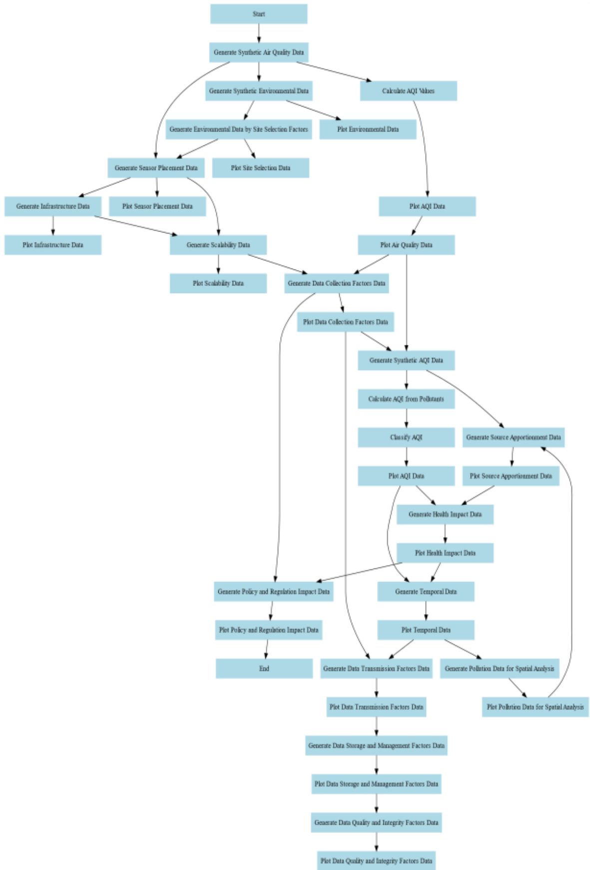

Fig. 1: Flow chart of Research work

Data collection and transmission factors incorporated proxy specifications of data transfer speed, duration, and accuracy necessary for occasioned operational surveillance. Data storage and management factors were examined by constructing datasets with redundancies, Error Detection, and Correction features that would mean that the data was correct and easily retrievable.

Data quality and integrity factors assessed the methods of validation and error correction percentages. The synthesized data used for AQI calculations included PM2.5, PM10, CO, NO2, SO2, and O3, and all of them were captured in their normal range of concentration and fluctuations. Specifically, temporal data collected short-term changes in pollution and experimentally long-term alternations; spatial analysis data offered pollutant concentrations at different territories. The mobile, stationary, and natural type of pollution distribution source apportionment information was used in this study to indicate the relative proportion of pollution-causing factors in Bostan Lake. PREMIS exemplar types of data included health impacts that approximated epidemiologic studies, levels of exposure factors, and risk assessment to get an understanding of health risks caused by air pollution. Finally, the policy or regulation-related factors were analyzed to assess the comprehensiveness of the monitoring of compliance, the effectiveness of the intervention, and the level of awareness of the public with regards to the externally set rules and regulations. Due to the highly detailed synthetic generation of data and a strict validation process, this data collection process serves as the basis for the analytical framework to allow for accurate and application-based insights into air quality as well as other related issues.

5 Result and Discussion

5.1 Current Air Quality Monitoring Systems

Existing air quality indexes tend to be based on static monitoring stations through independent monitoring of PM2.5, PM10, NO2, SO2, CO, and O3. These station costs are high and they are few in number meaning that the data collected is often inadequate in terms of density. The introduced program provides a synthetic dataset containing six types of air quality measurements (PM2.5, PM10, NO2, SO2, CO, O3) at ten-time steps. With numpy and pandas libraries, the data is arranged under the pollutants as columns and its corresponding time stamps when the pollutants were measured as indices. The data obtained is next ordered in the time dimension in order to achieve the correct temporal ordering for plotting. The end product of this mode of data visualization creates a profile that shows how the concentration of pollutants changes over the given period of time. Each pollutant is plotted as a separate line graph to ease comparison and identification of trends as observed in the line plot below. The former is labeled as time with units of hours while the latter represents Pollutant concentrations in micrograms per cubic meter (µg/m³) or parts per million (ppm). With respect to the plot, lurking, variations, and feasible cycles of pollutant intensities are discernible. Concentrations differ from one pollutant to the other and this is likely due to various emission sources, atmospheric processes, and the lifetime of the pollutants. Further, temporal variations can be diurnal or periodic indicating the level of air quality in different periods of the day or week, episodic suggesting short-term events, or secular to describe an increase in air quality over a very long period. In total, the generated plot offers insights into the temporal distribution of air pollutant concentrations that remains critical to assess variations in air quality and develop appropriate measures and policies accordingly.

$$\mathrm{AQI_i} = \frac{(\mathrm{I_{hi}} - \mathrm{I_{lo}})}{(\mathrm{c_{hi}} - \mathrm{c_{lo}})}\,(\mathrm{C_i} - \mathrm{C_{lo}}) + \mathrm{I_{lo}} \quad (1)$$

$$\mathrm{C_i} = P_\mathrm{i} \quad (2)$$

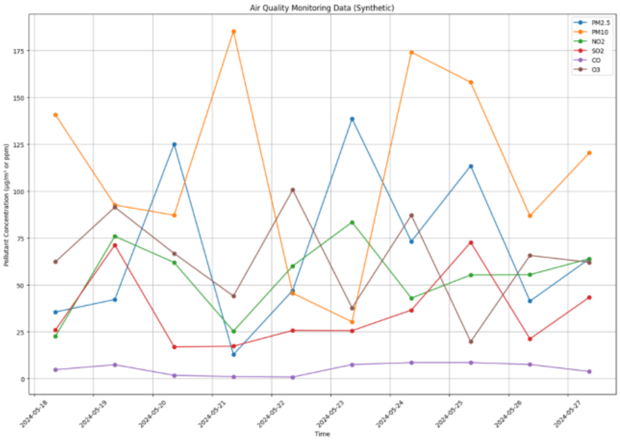

Fig. 2: Air Quality Monitoring Data

From equation 1, where C_iis concentration of pollutant I, c_(hi is upper breakpoint concentration for pollutant I, c is lower breakpoint concentrated) for pollutant I, I_hi is upper breakpoint AQI value (normally the multiple of ten that is least greater than the breakpoint concentration).I_lo is the lower breakpoint AQI value (often 50, 100, and so on) and P_i represents the concentration of the different pollutant ii such as PM2·5, PM10, NO2, SO2, CO or O3.on for pollutant I, I_hi is upper breakpoint AQI value (typically 100, 200, etc.), I_lo is lower breakpoint AQI value (typically 50, 100, etc.) and P_i is the measured concentration of pollutant ii (e.g., PM2.5, PM10, NO2, SO2, CO, O3). From Figure 2 it is evident that over a ten-day period, there is a variation of pollutant quality in the air. They were highest on May 23 at 138.66 µg/m³ and the lowest on May 21 at 12.87 µg/m³. PM10 although followed the same pattern with the highest concentration at 185.31 µg/m³ on May 21 and the lowest concentration at 30.33 µg/m³ on May 23. The minimum NO2 concentration was recorded on 18th May at 22.72 µg/m³ while the maximum NO2 concentration was recorded on 23rd May at 83.51 µg/m³. Average SO2 was found to be 37.11µg/m³ on average with the maximum level recorded on May 25 at 72.77µg/m³ and the minimum on May 20 at 16.96µg/m³. Hence, the CO concentration was highly fluctuating, with the 24-hour average ranging between 8.61 mg/m³ as recorded on May 24 and 0.91 mg/m³ on May 22. The level of ozone varied with the highest of 100.70µg/m³ registered on 22/05/2015 while the lowest 19.75µg/m³ recorded on 25/05/2015. Such data imply that there could be frequent daily fluctuations in air quality due to perhaps climate characteristics, the extent and intensity of industrial activities, and vehicle pollution. These variations clearly point towards the need to constantly survey and control in order to minimize unhealthy effects.

The provided program generates synthetic air quality data and computes the Air Quality Index (AQI) for six major pollutants: This is because the information presented in the model is related to Air pollutants: PM2.5, PM10, NO2, SO2, CO, and O3. When applying breakpoints for AQI, every concentration of a pollutant is assigned an AQI value. The data set obtained exhibits temporal variability of AQI at the selected time points. The obtained plot shows the time dependence of AQI values for the analyzed pollutants.. Every pollution constituent's AQI appears in the form of a line plot over some period of time to understand the fluctuation and the trend in air quality. It suggests changes in AQI value represent changes in the concentration of pollutants and possible effects on the health of the people and the quality of the environment. The horizontal axis defines time while the vertical axis shows AQI, a quantitative indication of air quality. Some changes spotted in the graph may suggest a tendency of pollutant emission, dispersion of pollutants in the atmosphere, or climatological factors that affect the concentration of pollutants. In summary, the AQI variations plotted in this work can be used to analyze spatial and temporal differences in air quality for source identification, assessment of the effectiveness of regulatory mechanisms, and health and policy management. As seen in Figure 3, from the generated air quality data of ten days, there were fluctuations of various types of pollutants. The maximum AQI on May 18, 2024, for PM2.5 was reported and was 198.40 for unhealthy air quality and PM10 at a moderate level of 80.91. Likewise, NO2, SO2, CO, and O3 showed values of 57.56, 25.23, 84.65, 122.38 respectively which revealed a considerably wide range of pollutants. On May 22, both the AQI for PM2.5, 133.27, and for PM10, 36.24 were improved as compared to the previous day. On the other hand, O3 escalated to a dangerous ratio of 215.31. The AQI for SO2 increased to its highest at 95.72 on May 23, with PM2.5 stood at 194.42 and CO at 36.96. On May 26, the amount of PM2.5 was 188.15 with PM10 at 115.69, and SO2 was 99.72 with O3 at 155.88, a critically high level. PM2.5, though slightly declining on the last recorded day, was 171.81 while O3 escalated to 201.72 on May 27. These data highlight a high temporal variation in the levels of the pollutants under consideration; specifically, PM2.5, SO2, and O3 concentrations were of concern and regularly surpassed recommended limits, establishing the need to continue examining their spatial and temporal trends and their potential effects on health.

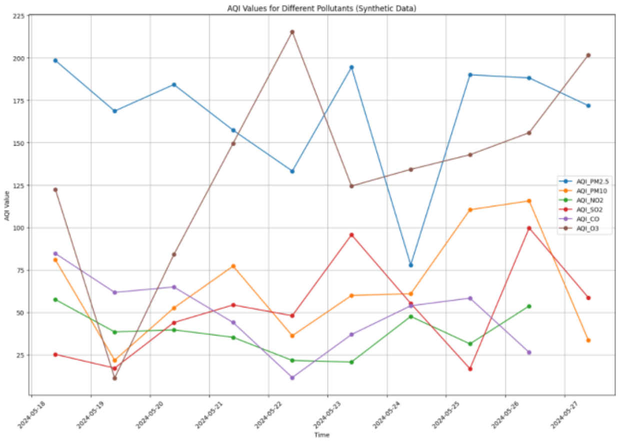

Fig. 3: AQI Values for Different Pollutants

The Air Quality Index (AQI) is adopted as a uniform scale for measuring air pollution contamination levels in relation to existing pollutant concentrations. In our study, we investigate the AQI ranges for six key pollutants: Of all particulate matters, PM2.5, PM10, nitrogen dioxide (NO2), sulfur dioxide (SO2), carbon monoxide (CO), and ozone (O3). Every pollutant has its own AQI breakpoints that divide the concentration of each pollutant and AQI into different levels. These AQI ranges are as important when it comes to explaining the health implications involved with varying degrees of air pollution. For PM2.5 the AQI scale is from 0 to 500 with breakpoints respective to the concent Lionel 0.0-12.0 μg/m ³ for the first range 0-50 AQI and 55.5-150.4 μg/m³ for the last range 151-200 AQI. It shows that even with low concentrations of PM2.5, the air quality is somehow wanting and with high concentrations, people are put at great health risk. Likewise, PM10 has breakpoints within the AQI ranging from 0 to 500 with breakpoints showing concentrations from 0-54μg/m³ to, 505- 604μg /m³. PM10 is more coarse particles and can reach deeper into the lungs therefore, its effects differ by concentration levels. NO2 is an air pollutant generated from combustion activities, and AQI is an index extending between zero and 500 with breakpoints corresponding to concentration levels of 0-53, 54-100…, and 1650-2049 parts per billion (ppb). For NO2, whether permanent or temporary AQI higher reflects the severity of exposure to this pollutant since its exposure causes respiratory problems and worsens conditions of pre-existing health complications. SO2 is a gas emitted from industrial processes and also through the burning of fossil fuels, has AQI ranges from 0 to 500 with breakpoints for SO2 concentration of 0-35(ppb), 805-1004(ppb) covering a broad concentration range. The primary effects include respiratory illnesses and secondary effects involving other pollutants such as particulate matter, CO, and ozone. CO, a colorless and odorless gas which expelled from vehicle exhaust and some industries, has AQI from 0 to 500, breakpoints of which cover concentration range from 0.0-4.4 ppm to 40.5-50.4 ppm. Though it is an odorless gas, exposure to CO may have adverse health effects, particularly at elevated concentrations; the effects include cardiovascular disorders as well as the effects on the neurological system. O3 showing ranges turned out to be from 0 to 300 representing AQI, breakpoints provided concentration range from 0-54 ppb to 106-200 ppb. Ozone may cause respiratory inflammation and aggravate respiratory diseases in particular during high sunlight and high temperature. Such AQI ranges are important in order that policymakers, health and welfare workers, and the public in general can evaluate and minimize health risks from polluted air. Closely observing the concentrations of pollutants and the AQI, it is possible to make reasonable decisions concerning the protection of public health and the enhancement of the air quality in the world's large cities.

5.2 IoT in Environmental Monitoring

IoT technology presents a number of important benefits in environmental monitoring: low cost of sensors, wireless data transmission, and high density of sensing points. As seen from the below code, it creates random environmental data regarding temperature, humidity, and AQI of time duration. In order to identify temporal changes and fluctuations of each environmental parameter, it is graphed against time. The graph derived from analyzing the records showcases how these parameters are reciprocally dynamic at the sampled time points. On the x-axis, there is the differentiation of time and on the y-axis, there is the differentiation of values of the respective environmental parameters. Temperature and humidity are drawn on graphs with a continuous line since such values change continuously. On the other hand, the AQI, which is a discrete index, is illustrated by discrete data points showing the irregularity of the index. Analysis of the data represented on the graph reveals possibilities of the associations or inequalities concerning the environmental factors. That is why, changes in the level of temperature and humidity can affect the AQI by changing air quality. On the same account, fluctuations in AQI could be due to pollution source heterogeneity, weather conditions, or policy changes. The representation assists in identifying trends and variations within the environment making it easier to monitor and manage an entire environment. Techniques used in such analyses are useful in evaluating the quality of the environment, risk evaluation, and in planning ways of dealing with bad effects on human and animal health and safety of ecosystems.

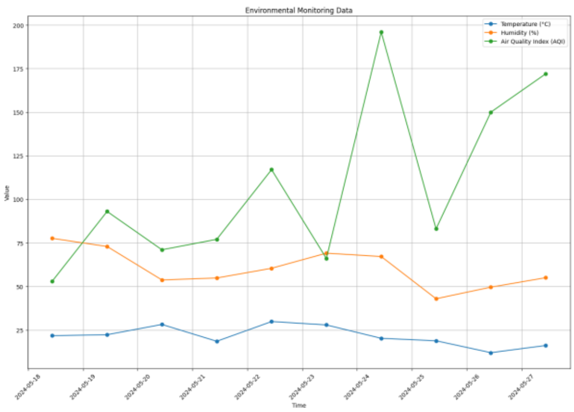

Fig. 4: Environmental Monitoring Data

$$\frac{d[O_3]}{dt} = k_{O_1}[O_1] - k_{O_3}[O_3] \quad (3)$$

From equation 3, [O 3] = [O 1] k (O 1) / k (O 3) On the basis of the same principles as described in gross rate constant determinations, we can determine the net rate constants for the formation of ozone as well as the rate constant for the destruction of ozone. Ground environmental data for the same ten-day period presented in Figure 4 provides information about the concurrent meteorological conditions that may have an effect on air quality. The temperature variation was recorded between 11.93°C on May 26 to 29.79°C on May 22 meaning there were oscillations within the observation time. The same case can apply to the humidity content where fluctuation was great registering the lowest RH of 42.89% on May 25 and the highest of 77.55% on May 18. The AQI varied as overall air quality varied getting as low as 53 on May 18, 2017, to as high as 196 on May 24, 2017. Slightly, hotter mean with low relative humidity like May 22 have signaled high AQI values This rationale indicates that there is a probable relationship between mean climate conditions and quality of air. However, days with low temperatures and high humidity, for example; May 25, had comparatively lower AQI values. These results illustrate the possibility of a climate/air quality interaction and suggest that, in order to adequately address environmental health issues, interdisciplinary approaches are necessary. It is important to have such knowledge to formulate policies in order to prevent risks threatening public health and the environment.

5.3 Deployment Factors

Site Selection:

The generated graph provides a comprehensive visualization of the environmental monitoring data across several critical site selection factors: people density to determine population areas; traffic intensity, locations close to highways and crossing; industrial scale, close to factories and plants and green spaces that are; parks, and urban forests for the reference data set. Data is presented over a time of ten days bringing out striking differences in trends and fluctuations of these factors essential in defining the impacts on the environment in various urban regions. The population density and traffic volume both indicate fluctuation, which has been expected due to the differences in the landscape of cities and ongoing changes. The results also showed that traffic volumes are higher with population density, which suggests that there might be a higher level of pollutants in population-density areas, more particularly in areas with higher volumes of traffic. The industrial activity index between 50 to 100 presents whether the industry is active but the degree of activity is in consideration. The specific separation of this index from the green space area plot of range 5% - 50% shows that industrial zones differ significantly from green spaces in terms of environmental aspects. This differentiation is an important one because it requires a comparison of the negative influence that industrial emission brings to the social setting to the positive impacts that green areas bring to the same society to absorb the pollution. In conclusion, using the data that has been obtained from the IoT-enabled sensors, the graph shows environmental data analysis in the best way. The divergent and complex nature of the observed trends for each of the selected factors enrich our understanding of the state of the urban environment and assist in designing interventions and policies that would help enhance the quality of air in cities as well as the overall quality of living for urban inhabitants. For this reason, this analysis has underlined the need to apply careful site selection in the installation of EMS for the purpose of achieving good granularity and spatial coverage of the data that is being collected.

Linear Regression Model

$$\mathrm{AQI} = \beta_0 + \beta_1 \cdot \mathrm{PD} + \beta_2 \cdot \mathrm{TV} + \beta_3 \cdot \mathrm{IA} - \beta_4 \cdot \mathrm{GS} + \varepsilon \quad (4)$$

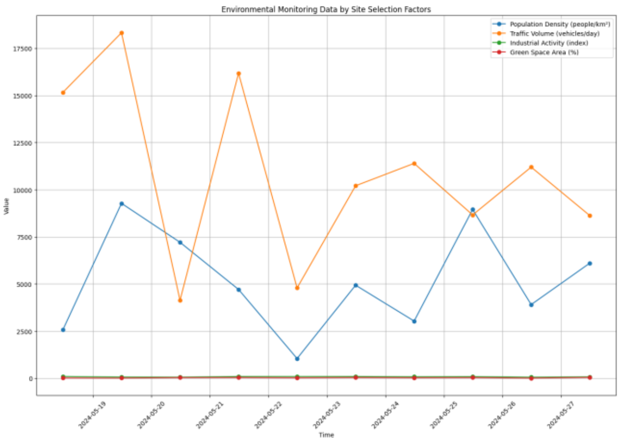

Fig. 5: Environmental Monitoring Data by Site Selection Factors

Here where, AQI is the Air Quality Index, PD is the population density (people/km²), TV is the traffic volume (vehicles/day), IA is the industrial activity index, GS is the green space area percentage (%), ϵ is the error term that accounts for the variance that has not been explained by the model; β0 is the intercept; and β1, β2, β3, β4 are the coefficient that measures the In Figure 5, the outcome of the population density, traffic flow, industrial intensity, and green space size over ten days to the quality of the environment can also be seen. Population density fluctuations were as follows: 1042 people per square kilometer on May 22 and 9275 people per square kilometer on May 19, indicating different patterns of urbanization. Daily average traffic grew to a high of 18,326 vehicles per day on the 19th and low of 4131vehicles per day on the 20th in regard to traffic flow and therefore vehicular pollution emissions. The industrial activity index fell to a low of 54.67 on May 26 and spiked to a high of 95.49 on May 18 in response to changes in industrial production and emissions. The green space area also differed, with the highest percentage being recorded on May 27 at 44.49% and the lowest on May 26 at 6.14%. An increase in population and traffic also affected the AQI values as compared to the days of May 19 and May 24. On the other hand, the percentage of green space had a negative relationship with the AQI levels with the lower AQI values recorded on May 27in areas with a higher green space ratio to the total land area. These results stress the significance of planning cities where population density and traffic can be controlled, and green areas can be rationally distributed for better air quality and health in megacities. These are important aspects that must be taken into consideration for formulation or implementation of necessary policy options for the future sustainable development of most towns and cities across the world with a quality environment.

Sensor Placement:

The presented program provides artificial data as an example of how it is possible to consider factors affecting the location of sensors for environmental control. Three key factors are considered: the height of the sensor above ground which is the appropriate height of the aerological sensor used to sample air quality, its relative position to primary sources of pollution that is how close it is to the immediate sources of emissions, distribution density that is how evenly spaced the sensors should be depending on the area of coverage within the urban city. Each factor is expressed as quantitative measures and then averaged over a set of sample points to address recommendations regarding the best placement of the sensors. The following bar plot shows the averages of these factors as a result. The height of sensors ranging between 10 and 50 meters refers to the level at which the sensors are placed. Distance to emission sources ranging from 10 to 500 meters exemplify the measures of distance of the sensors to the possible sources of pollution. Spatial distribution in the range of 100 - 500 stands for the distribution of the number of sensors in the monitoring region. From the plot, the following are the findings concerning the relevance of each factor in the placement of sensors … Bigger average values indicate higher consideration of such factors as distance to sources of emissions or spatial density. Knowledge of these factors helps to enhance, first of all, approaches to deploying sensors for obtaining maximal, comprehensive information on the state of the environment. The graphical representation proposed helped in the decision-making processes in the analysis of the sensor's placement since it determines areas where sensors should be placed best for better and right data. Such knowledge is important in undertaking environmental surveillance

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and management for purposes of preventing pollution and protecting the populace and the environment.

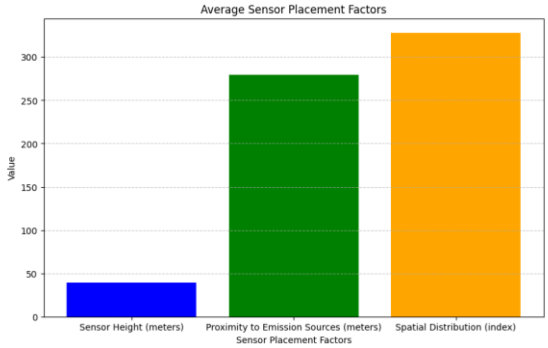

Fig. 6: Average Sensor Placement Factors

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \quad (5)$$

From equation 5, where $\bar{x}$ *is t*he mean value of the sensor placement factor, n is the total number of samples, $\sum_{i=1}^{n} x_i$ the summation of all individual sample values for the factor. From Figure 6, the placement of sensors for environmental monitoring is crucial for accurately capturing pollutant concentrations and assessing air quality. The height of the sensor is ten meters to three hundred and fifty meter The variability in the sensor height is crucial to analyzing the representativeness of the data and the dispersion and diffusion of pollutants in the atmosphere. Distance to emission sources ranges from 143.05 to 446.66 meters, which determines the degree of the sensor's contamination by emissions from industrial enterprises, transport, and other sources. A relatively short traveled distance is met with higher pollutants concentration detected by the sensor, due to proximity to the emission sources. The spatial index of the sensors' dispersion ranges from 113.95 to 491.84 and represents the quantity of monitoring area space. A lower index always means that sensors are clustered and may lead to spatial bias while the higher index means the sensors are distributed evenly over the area of interest. Choosing the positions of sensors requires striking a trade-off between these considerations in order to obtain good coverage of the monitored area, eliminate spatial preferences, and improve the accuracy of the collected data. Where possible, easy access to the emission sources and at different heights will enable us to understand dispersion and areas of high concentration so that interference can be affected. Furthermore, a widely installed sensor network improves the capacity to provide accurate and reliable air quality estimates and provides valuable input for effective decision-making in environmental protection and health care.

Infrastructure Requirements:
The program generates synthetic data to assess infrastructure requirements for environmental monitoring systems, focusing on three critical factors: a reliable source of power, external physical access for UPS systems, quality signals for networks, and last but not least physical access protection against vandals or adverse weather conditions. Since ten samples are collected for each factor, the data enables a calculation of mean values to thereby give a broad viewpoint of average infrastructure conditions. The bar plot generated below presents these mean values making it easier to compare the three factors. The power supply reliability index is from 90 to 100, which may be characterized as high reliability for the constant functioning of the sensor. Network connectivity therefore presents signal strengths within the 70 – 100 % range which is an indication of the security of communication channels that are essential while passing real-time data. Physical security, which ranges from 50 to 100, means that there is a need to protect the sensor equipment from physical threats. Meaning, that though, power supply and network connectivity show an acceptable picture with more than 4.5 on 7 as the mean value, physical security is fluctuating around them with 3.8 on 7 as the median value. This implies that only if security measures could be improved the overall performance of the monitoring could be considered rather critical. These insights are rather valuable for strategic planning and fine-tuning of the further deployment of environmental monitoring systems. Accurate assessment of any threats or vulnerabilities concerning the infrastructure's requirements may lead to efficiency improvement of the monitoring operation and boost the quality of the environmental data for the overall efficiency in the environmental management policies and decisions.

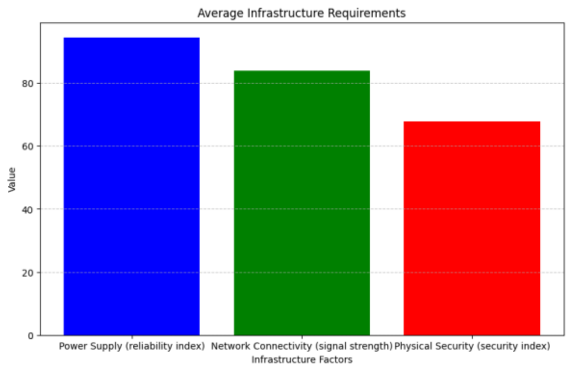

Fig. 7: Average Infrastructure Requirements

Power Supply Reliability Index (RI)

$$\mathrm{RI} = \frac{1-\mathrm{P_f}}{1+\left(\frac{\mathrm{MTTR}}{\mathrm{MTBF}}\right)} \tag{6}$$

Network Connectivity Signal Strength (SS)

$$\mathrm{SS(d)} = \mathrm{P_t} + \mathrm{G_t} + \mathrm{G_r} - 20\log_{10}(\mathrm{d}) - 20\log_{10}(\mathrm{f}) - 20\log_{10}\left(\frac{4\pi}{\mathrm{c}}\right) \tag{7}$$

Physical Security Index (SI)

$$SI = \frac{1}{\mathrm{N}}\sum_{i=1}^{N}\left(\frac{\mathrm{E_i}}{\mathrm{V_i}} + \frac{\mathrm{D_i}}{\mathrm{T_i}}\right) \tag{8}$$

From equation 6, P_f represents the probability of failure, MTTR is the mean time to repair and MTBF is the mean time between failures. From above equation 7, Pt is the transmitted power in dBm, Gt is the transmitter antenna gain in dBi, Gr is the receiver antenna gain in dBi, d is the distance between the transmitter and the receiver in metre, f is the frequency of the signal in Hertz and c is the speed of light in meter per second. From the above equation 8 where N is a number of security factors, Ei is the encryption strength of the i-th factor, Vi is the vulnerability score of threats for the i-th factor, Di is the detection effectiveness of threats for the i-th factor, Ti is the time duration to respond for threats of the ith factor. As given in Figure 7, the infrastructure data analysis provides insights into the operation environment of the monitoring system. The power supply reliability index ranges between a low of 90.09 and a high of 99.24, with a mean of 94.47, which pointed to wholsomely steady and reliable sources of power at the monitoring stations. The possible range for network connectivity, extending signal strength from 76.65 to 93.76 with the average of 83.89 affirms that the network connection necessary for real-time data transfer and low data loss rate has solid connectivity. Physical security measured as a security index, varies from 52.03 to 96.87 with a mean of 67.70 indicating variability in protection of monitoring equipment from vandalism and theft. Values far above 90 like 96.87 show that the network has very strong protective mechanisms in place while values below point to areas of improving security to enhance the integrity of the monitoring system. Functional power reliability along with powerful network connections may therefore be required to enable environmental sensors to run continually and deliver punctual readings without a hitch. This variation in the physical security of the infrastructure needs some level of planning person to make sure that the security of facilities in the respective areas of low-security indices is enhanced. Sustained and stable development of support structures within the context of evaluation of the environmental status is important to facilitate the use of evidence for decision-making with regard to public health and environmental management interventions.

Scalability:

The program provides synthetic data to assess scalability factors relating to modules of the EMS with particular emphasis on modularity and cost. Variations of each of the ten samples are displayed corresponding to the sample index such that temporal trends and relative evaluations could be performed easily. The algorithm generated above shows the period and scope of variability of the two scalability factors. Integrated sensors, which can range from fifty to one hundred, indicate how devised the monitoring system is to add/supplement more sensors. At the same time, cost efficiency percentages that is, cost factors for large-scale implementation, between 70 to 100 percent indicate the economic feasibility of the system, considering results alongside budget constraints. Looking at the plot, one can see certain trends in time and possible relationships between the two types of scalability. Fluctuations in integer points for the modular design could be due to changes in system layout or enhancements, and trends to either cost efficiency percent could be due to changes in purchasing strategies, technological improvements, and other factors. The graphical representation, therefore allows stakeholders to evaluate the manner in which future scalability of environmental monitoring systems will be addressed when it comes to system enhancement, resource allocation, and future planning. With these parameters of scalability within focus, organizations are able to overhaul and alter their monitoring frameworks to suit new trends and improvements in technology to check on their capacity to go on delivering service while staying within their cost benchmark.

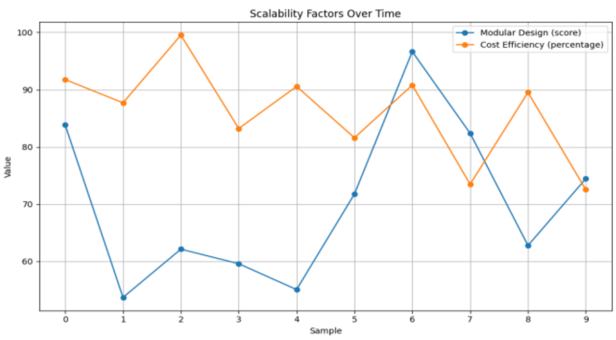

Fig. 8: Scalability Factors over Time

Modular Design (score)

$$\mathrm{MDS} = \frac{\mathrm{N} * \mathrm{C}}{\sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{E_i}} \tag{9}$$

Cost Efficiency (percentage)

$$\mathrm{CEP} = \frac{\text{Net present value of benefits} - \text{Total cost of ownership}}{\text{Total cost of ownership}} * 100 \tag{10}$$

As reflected in equation 9, N represents the number of the modules aimed at developing the system, C represents the complexity of the system; Ei represents the effectiveness of each module. From equation 10, the net present value of benefits is a sum total of all benefits that will be accrued from the system. Total cost is thus the first cost, all operating cost, and such other costs as may be necessary. As seen in Figure 8, from the basic scalability data analysis of the monitoring system, one is able to compare the operation and expansion costs of the system's design. This score evaluates the capability of the system to extend in a single shot through assembling modular units the overall score ranges from 53.71 to 96.63 and the average score is 73.33. A higher Higgs score implies less architectural fragility; thus, it is easily expandable or alterable to meet specific demands for the new system. Lower results may show that it has less potential for expansion because of its less versatile structure. Measuring cost efficiency in percent scale the range is 72.53% to 99.52% having an average of 88.97%. It aims at measuring the capacity of the system in achieving its goals and objectives locally, regionally and internationally more efficiently with lesser resources and expenses. Hearing higher percentages means that is more cost-efficient, meaning that the system provides value while at the same time, controlling spending well. On the other hand, frequencies below the established percentages could imply that resources are poorly utilized, or even that more funds are expended than are desirable. The balance between applying modular design in the monitoring and cost efficiency percentage considered shows a system that could cost-effectively expand or modify in order to meet the requirements of scale. Such scalability is important in order to handle future growth or introduce new environmental issues without chancing for extremely high costs. The flexibility in the modularity level and cost-effectiveness allows the monitoring system to remain efficient in responding to changes in requirements for future endeavors in environmental monitoring and management.

6 Data Collection Factors

6.1 Sensor Specifications

Here, the program creates synthetic data for evaluating factors associated with data collection regarding the sensor characteristics for the EMSs, including types of pollutants being detected, sensitivity and accuracy, and calibration frequency. For convenience in comparing the values and in making decisions, each of them is depicted in a graphical form. The bar plot used in this article represents changes in the sensitivity/accuracy ratios and the number of calibration operations concerning various kinds of pollutants. Sensitivity and accuracy scores change from 70 to 100, representing the sensors SAS capability of detecting the presence of pollutants and accurately measuring the concentration of pollutants. Calibration frequencies expressed in days from 7 to 30 describe how often a sensor needs to be recalibrated to remain accurate. There are points of trade-off analysis from the plot which help the stakeholders to differentiate between factors requiring monitoring. This means that high sensitivity and accuracy mean more effective data collection while low calibration frequencies mean low levels of maintenance. The selected pollutants also determine the layout and efficiency of the system under consideration. A basic understanding of this graphical representation helps in improving sensor specifications when it comes to the provision of credible data that has been designed for the purpose of monitoring the environment. Thus, reflecting on these data collection factors, organizations can improve actual environmental monitoring systems, as well as provide substantial support for decision-making on environmental issues and the subsequent development of corresponding policies.

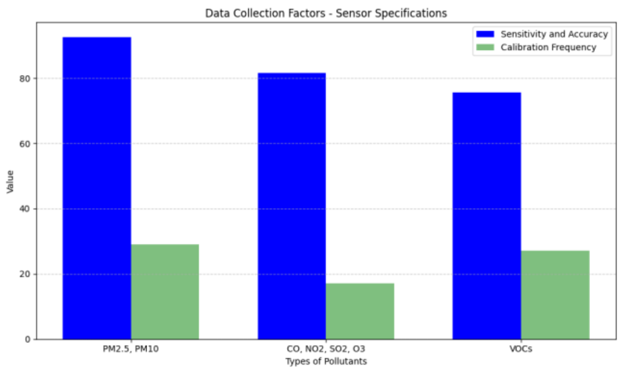

Fig. 9: Sensor Specification

Sensitivity and Accuracy

$$\mathrm{SAS} = \frac{\mathrm{S} * \mathrm{SNR} * \mathrm{CA}}{\mathrm{TV}} \quad (11)$$

Calibration Frequency

$$\mathrm{CF} = \frac{\mathrm{St} * \mathrm{EF}}{\mathrm{RC}} \quad (12)$$

From equation 11, the resolution of the sensor is presented by S, signal-to-noise ratio by SNR, calibration accuracy by CA, and total variability by TV. From equation 12, where St is the stability of the sensor, EF is the environmental factors and RC is the regulatory compliance. The analysis of data collection factors from Figure 9 reveals some distinguishing features that relate to the sensitivity, precision and calibration rates of the environmental sensors as well as the kinds of pollutants to be monitored. These sensitivity and accuracy scores from 75.64 to 92.49 show the ability of sensors to measure specific pollutants in their closeness to real values. Higher values of the parameters represent better sensitivity and selectivity which are essential for measurements of pollutants. The scale of frequency from 17 to 29 represents how often a sensor must be calibrated so that it will still possess high accuracy and reliability even in the future. Fewer calibration cycles imply longer periods between calibration and therefore impact on the quality and accuracy of the data collected. The kinds of pollutants highlighted include airborne particles such as PM2.5, PM10, CO, NO2, SO2, and O3 as well as VOCs reflecting the completeness of the monitoring system in covering key pollutants of environmental interest. Different types of pollutants may need sensors and calibration processes arranged in the particular manner in order to work correctly. For example, while the particulate matter (PM) sensors can be prone to fouling or drifting, these can require frequent calibration; conversely, the gas sensors require calibration to maintain accuracy in tracing the levels of trace gases. The use of sensitivity and accuracy scores, calibration frequency, and range of pollutants measured show that data acquisition in environmental monitoring is complex. All these means that through enhancing the sensitivity of the sensors, calibration techniques adopted, and the expansion of the coverage of pollutants, the monitoring system can capture essential environmental data that enable cause-effect relationships or environment and public health and institute remedial measures.

6.2 Data Transmission

To assess data transmission factors it is necessary for the program to produce synthetic data to test, the application is based on LoRa, NB-IoT, and Zigbee protocol. Three aspects – real-time data acquisition percentage, bandwidth and latency are depicted visually in order to facilitate the comparison of results depending on the used protocol. The bar plot given above shows the relative differences in these transmission factors for the chosen communication protocols. The percentage of real-time data acquisition is between 70 percent and 100 percent thus referring to the protocol's ability to deliver data in real-time. Bandwidth, expressed in megabits per second (Mbps) and from 1 to 100, defines the traffic-carrying capability per protocol. Delay referred to in milliseconds (ms) as well as ranging in numbers between 1 and 100, is the time it takes for an item of data to be transferred. This paper reveals from the plot that different monitoring occasions require different communication protocols where stakeholders can use the identified trade-offs to choose the appropriate communication protocols for a certain monitoring occasion. Higher real-time data acquisition percentages and bandwidth values translate to swifter and more secure data transfer while low latencies point to less delay. This graphical representation assists in achieving the best results in the communication of data to enhance the timely and effective delivery of environmental data. It is therefore through taking into account these transmission factors that organizations can equally improve and ensure the stability in the environmental monitoring system to help in decision-making and efficient environmental management.

Real-time Data Acquisition (Percentage)

$$R = \frac{\int_0^t S(t)\,\mathrm{d}t}{T} \times 100 \quad (13)$$

Bandwidth (Mbps)

$$\mathrm{B} = \frac{\max_{0 \le t < T} \mathrm{D(t)}}{\Delta_{\mathrm{t}}} \times \frac{8}{10^6} \quad (14)$$

Latency (ms)

$$L = \frac{\int_0^t \Delta t(t)\,\mathrm{d}t}{N} \times 10^3 \quad (15)$$

From the assessment in, equation 13 where R signifies the percentage real-time data acquisition. It can be expressed in terms of the success rate of data transmission (S) and the total time duration (T in hourly values). In equation 14 Bandwidth B can be defined as the maximum rate of data transfer Dmax over the entire time interval T in Mbps. From equation 15 we get, Latency L = average of time delay (Δt) per data transfer (N) over the entire time interval (T) in milliseconds.

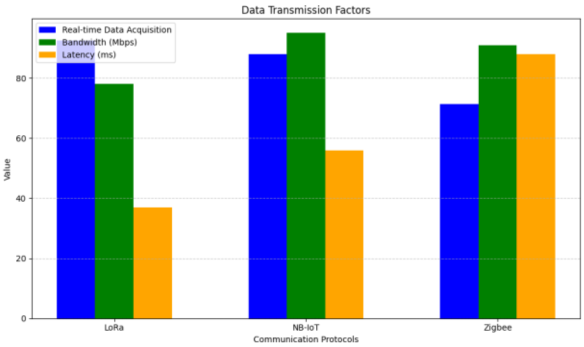

Fig. 10: Data Transmission Factors

Specifically from Figure 10 the data transmission factors explained under different communication protocols will reveal significant information on their applicability in real-time data collection in IoT systems. Comparing all the protocols, LoLo achieved a real-time data collection efficacy of 92.43% and is the least time-consuming to collect data from the IoT devices. Additionally, LoRa was able to handle an acceptable bandwidth of 78 Mbps which enables it to transfer large amounts of data in a shorter amount of time. Also, The low latency of 37 ms shows that its response time is fairly efficient for the delivery of data. Again, NB-IoT and Zigbee offer slightly lower real-time data acquisition percentages of 87.97% and 71.37% respectively. However both protocols still displayed good efficiency in collecting real-time data from IoT devices. NB-IoT had a specified bandwidth of 95 Mbps which is much higher than that of LoRa, which indicates the capacity of NB-IoT to handle big data loads effectively. Nevertheless, its latency of 56 ‘ms proves that it takes a bit longer to transmit data compared to LoRa. On the other hand, Zigbee had a lower bandwidth of only 91 Mbps and a higher latency of about 88mS which means that the data transmission and the response times of Zigbee are quite slow. However, the real-time data acquisition percentage of Zigbee is still high, although not as high as LoRa and NB-IoT. In conclusion, the information presented in this paper is quite useful for evaluating the fitness of various communication protocols for real-time data acquisition in IoT systems with an aim to enhance the performance or make informed decisions on the protocol to be used according to the system specifications in terms of defined performance indicators.

6.3 Data Storage and Management

It uses synthetic datasets to evaluate aspects critical for storing and handling data in environmental remote sensing applications. The assessed parameters are: cloud storage growth rates, data protection, and data compatibility based on ten objects to assess time series and comparative characteristics. The graph obtained reveals the fluctuation and effectiveness of such factors in time. The cloud storage is proposed to have an index, known as the storage scalability index, normalized between 70 and 100 to measure the capacity of a system to scale up storage capacity to cater to growing storage demands. Data security indices ranging from 80 to 100 are predictors conveying the level of implementation of protective measures for data data security and privacy. Data integration scores are in the range of 60-100 and provide the systems ability to easily integrate various data sources for analysis. Hence from the plot, it can be seen that all three factors have high mean indicating their importance in making sure that the management of data is efficient. Nonetheless, this investigation indicates a relatively higher variability when it comes to data integration than when data storage, security in the cloud, and security are considered. Indeed, this graph serves as one of the valuable tools to the stakeholders in a bid to enhance the data storage and management solutions. Due to these factors, organizations can improve the values of scalability, security, and integration of data management systems so as to facilitate good handling of environmental data. This optimization enhances the effective and efficient collection of data, and SMEs can gather pertinent environmental data and apply the knowledge to improve their efficiency.

System Efficiency

$$\mathrm{SE} = \propto \left(\frac{\text{Cloud Storage (Scalability index)}}{1+e^{-\beta(\text{Data security (Security Index)} - \gamma)}}\right) + \delta\,.\,\text{Data Integration (integration score)}^2 \quad (16)$$

From equation 16, where α, β, γ, and δ are constants that need to be determined based on the specific system and requirements, the term $\left(\frac{\text{Cloud Storage (Scalability index)}}{1+e^{-\beta(\text{Data security (Security Index)} - \gamma)}}\right)$ represents a sigmoid function that models the effect of data security on the utilization of cloud storage scalability and the term $\text{Data Integration (integration score)}^2$ represents the quadratic influence of data integration on the overall system efficiency.

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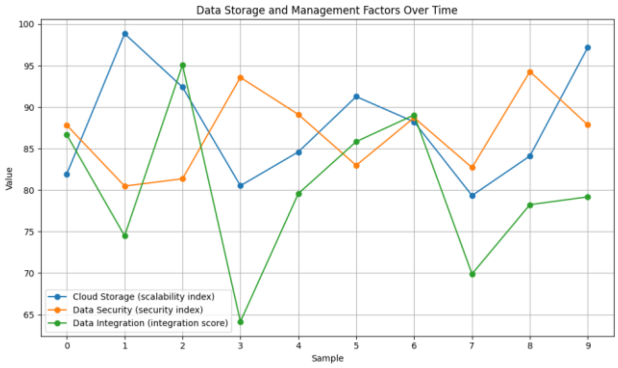

Fig. 11: Data Storage and Management Factors over Time

From Figure 11, the evaluation of cloud storage solutions shows significant difference in scalability, security and data integration. The values of scalability indices vary from 79.34 up to 98.84, and the greatest level of scalability was identified for the second solution (98.84) while the least level is in the seventh solution offering 79.34. This means that these solutions have a different ability to scale for increasing amounts of data and users. The fourth solution has the lowest scalability index of 80.53; however, it owns the highest security index, scoring 93.58 among all the components. This makes security indices vary from wide-ranging, that is between 80.48 and 94.28. The ninth solution has the highest security score of 94.28 proving that all solutions address information security and confidentiality thoroughly. The first solution also scores highly on the security index with a score of 87.83 besides scoring a high scalability index of 81.92. Similar to the positive outcomes identified in objective seven, the assessment of data integration scores produces an additionally differentiated range of 64.15 to 95.08 revealing the broad versatility of these cloud solutions. The second procedure is considered to be maximally compatible as the integration value that has been estimated equals 95,08. However, the third solution thatsubmit to one of the lower integration scores (64.15) provides a high security score (93.58) of its rising question of the tendency of improving flexibility of integration with the potential cost of security. Thus, the evaluation of the cloud storage based on concrete parameters, to which the organization puts emphasis, such as scalability, increased security, and integration options, is crucial for the enhancement of the application performance and data management.

6.4 Data Quality and Integrity

To assess factors considered critical in maintaining data quality and integrity in environmental monitoring systems, the program produces synthetic data. Some of these are validation techniques' accuracy score, redundancy score, and the efficiency of error detecting and correcting score. To enable easy comparison, the variation of each factor in ten samples is illustrated graphically as barplots. The graph that follows helps to compare and show how these factors are performing and varying in different samples. Numbers assigned to ‘‘validation techniques’’ represent the percentage, pegged at 80-100 percent, of methods used in validation of data accuracy and believability. Redundancy scores range from 70 to 100, which represent the extent, to which redundancy has been applied to minimize data loss or corruption. The error detection and correction utilises efficiency scores ranging from 60 to 100 to measure the speed and accuracy inwhich the system identifies and fixes errors. Assumptions from the plot help stakeholders to determine adequacy of measures performed towards ensuring high data quality and data integrity in environmental monitoring systems. In other words, higher scores mean that validation, redundancy, and error detection and correction provision are stronger or more efficient so that users have greater confidence in data on the environment. Figure 12 representation helps in the selection of data quality and its strategy to work in a much better way for improving the reliability and accuracy of the environmental monitoring systems. Through managing some of these factors organizations can be confident in the accuracy of the information that they are collecting to measure environmental quality as well as make sound decisions and formulate policies.

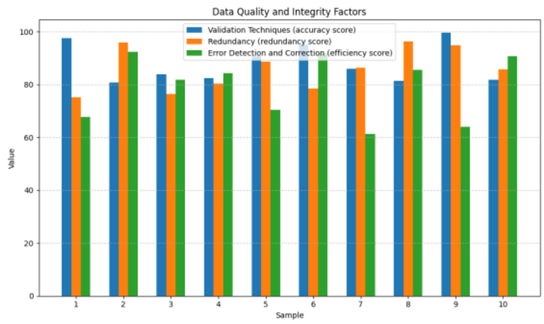

Fig. 12: Data Quality and Integrity Factors

$$E_{efficiency} = \frac{E_{detected\_corrected}}{E_{total}} \times 100 \qquad (17)$$

From equation 17, where, E_total is the total number of errors present in the data and E_(detected_corrected) is the number of errors successfully detected and corrected. To assess factors considered critical in maintaining data quality and integrity in environmental monitoring systems, the program produces synthetic data. Some of these are validation techniques' accuracy score, redundancy score, the efficiency of error detecting and correcting score. To enable easy comparison, the variation of each factor in ten samples is illustrated graphically as barplots. The graph that follows helps to compare and show how these factors are performing and varying in different samples. Numbers assigned to ''validation techniques'' represent the percentage, pegged at 80-100 percent, of methods used in the validation of data accuracy and believability. Redundancy scores range from 70 to 100, which represent the extent, to which redundancy has been applied to minimize data loss or corruption. The error detection and correction utilizes efficiency scores ranging from 60 to 100 to measure the speed and accuracy in which the system identifies and fixes errors. Assumptions from the plot help stakeholders to determine the adequacy of measures performed towards ensuring high data quality and data integrity in environmental monitoring systems. In other words, higher scores mean that validation, redundancy, and error detection and correction provision are stronger or more efficient so that users have greater confidence in data on the environment. This graphical representation helps in the selection of data quality and its strategy to work in a much better way for improving the reliability and accuracy of the environmental monitoring systems. Through managing some of these factors organizations can be confident in the accuracy of the information that they are collecting to measure environmental quality as well as make sound decisions and formulate policies.

7 Environmental Impact Analysis Factors

7.1 Air Quality Index (AQI)

Thus, trends and correlations between the generated synthetic data for AQI parameters, including PM2.5, PM10, CO, NO2, SO2, and O3, are displayed. In this case, accounted AQI values obtained from the simplified approach illustrate the Airliner source potential with regard to contributing pollutants towards general air quality degradation. The maximum AQI values among the pollutants are plotted with pulsating thresholds, which makes the analysis more realistically exclude fixed lineaments to emphasize fluctuation. This is as a result of including noise in ten samples of AQI in the graph below in order to show the real situation in regards to sample inaccuracy and natural variations. Labels for separate types of AQI, representing Good, Moderate, Unhealthy for Sensitive Groups, Unhealthy, and Very categories are shown With slight changes in the threshold boundaries owing to environmental and observational errors. Using the plotted AQI values, this means there is a change of the category of air quality lifting the focus of polluted air risk at various times. These variations afford information on the influences of the ambient air quality thereby facilitating the assessment of the pollinating consequences on the population's health. The graph helps in the indicators of special times when the pollution situation is worse and helps in policy-making to minimize negative impacts on special groups of people. This analysis therefore serves to highlight the need for strong AQI monitoring and the use of synthetic data in analysing air quality trends and results. These studies have highlighted the fact that in a given environment, several pollutants are often present simultaneously and therefore their interaction with other pollutants can reveal a lot about pollution trends and policy making in improving air quality management.

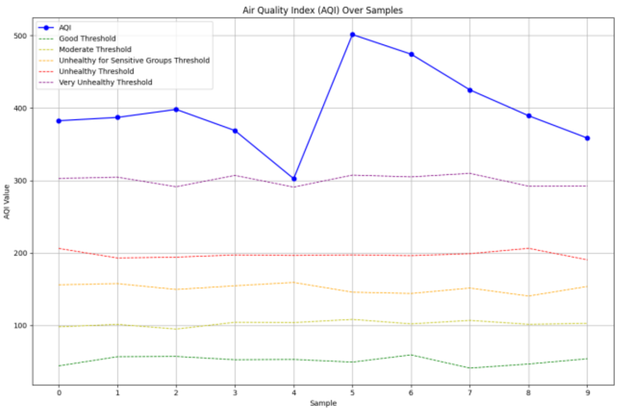

Fig. 13: Air Quality Index over Samples

$$\mathrm{AQI_{pollutant}} = \frac{\mathrm{C_{pollutant}}}{\mathrm{C_{max}}} \times 500 \tag{18}$$

$$\mathrm{AQI} = \max\left(\mathrm{AQI_{PM2.5}}, \mathrm{AQI_{PM10}}, \mathrm{AQI_{CO}}, \mathrm{AQI_{NO2}}, \mathrm{AQI_{SO2}}, \mathrm{AQI_{O3}}\right) \tag{19}$$

For the hazardous category,

$$\mathrm{AQI} > 300 \tag{20}$$

The level of air pollution obtained and presented in the obtained Figure 13 by obtaining AQI from raw concentrations of pollutants using standardized methods strongly indicates a persistently high level of air pollution across all the parameters measured.

The pollution level varies from 43.26 μg/m³ to 398.63 μg/m³ of PM2.5 with an AQI value which defines the hazardous level of pollution. In the same manner, the concentration of the PM10 ranges between 85.34 μg/m³ and 514.56 μg/m³ and has also contributed to the AQI calculation. The results indicate that concentrations of Carbon monoxide (CO) are as low as 0.11 ppm whilst at other times as high as 49.98 ppm these higher values contribute to air quality complications. NO2 percentage was recorded to be between 11.84 ppb and 267.51 ppb while the SO2 percentage recorded was between 26.06 ppb and 859.06 ppb which also confirms the air pollution levels. For the same stations and days, Ozone (O3) concentrations rage from 7.65 ppb to 290.46 ppb also contributes to high AQI readings. From these concentrations, the AQI calculated are in the hazardous range surpassing 300 at every instance. The maximum AQI was 501.42, which showed an extremely hazardous standard while the minimum AQI was 302.51 which also illustrated a hazardous standard. These values conform to the official health-related AQI ranges that subclassify air quality as dangerous if AQI is over 300, indicating health risks for all population groups. It is for this reason that there must be a call for an urgent need to address issues of air pollution and enhance the health standards across the nation since the scores arrived at through AQI were all high due to high concentrations of pollutants.

7.2 Temporal Analysis

The generated temporal patterns represent variable oscillations characteristic of short-term and long-term variability in understanding environmental change. Short-term variability refers to daily fluctuations where all the variability observed is random and is approximated by a normal distribution with standard error=5. On the other hand, yearly trends show the general trend over days-as-years and are represented by a linear increasing or decreasing pattern with slight fluctuations created by applying a linear interpolation of 50 to 100 and adding Gaussian noise. The graph illustrates daily oscillations as well as overall changes during one year of observation. This is shown by the up and down pattern of the blue line, which represents daily changes in intensity of the disease, or short-term variability. By comparison, the red curve displays general yearly trends and provides the overall, flattened arc showing gradual growths and sharp sudden fluctuations. In evaluation of this aspect, this analysis helps in distinguishing patterns and trends in environmental information very crucial in environmental monitoring and management. This way any deviation from the norm proves easy to point out, as does any anomaly and any periodic features such as trends within specific seasons, helping in timely interventions or strategic resource direction. Further, it helps design models and strategies with predictable patterns and responses regarding environmental risks and resource usage.

$$y(t) = \sum_{n=1}^{N} A_n \sin(2\pi f_n t + \phi n) + C \quad (21)$$

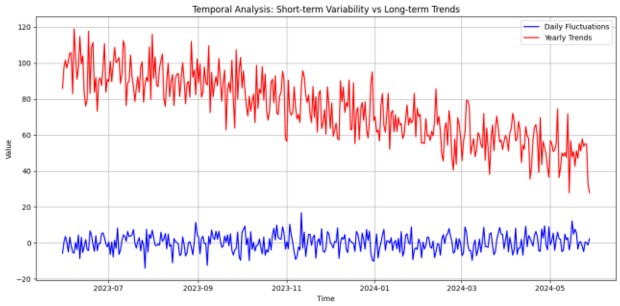

Fig. 14: Temporal Analysis of Short-term and Long term Variability

From equation 21, where A_n represents the amplitude of the n-th harmonic, for the n th harmonic is n f, ϕn is the phase shift of the n-th harmonic and C is a constant offset. As evidenced by Figure 14, a simple analysis of temporal data is useful to highlight that the observed quantities behave with high variance during a day and demonstrate certain yearly patterns. The deviations found with an average of 0 yield daily variations ranging from -5.74 to 3.62. These oscillations are generally attributed to short-term changes in the measured parameter suggestive of prevailing and transient environmental conditions at the time of sampling. I also use the terms negative fluctuation to mean times the response value has been below the mean values and positive fluctuation to mean the times when the response value has been above the mean values. On the other hand, yearly trends, which depict values invariant over a one-year horizon, have average ratios of between 27.82 and 101.58 only. Such trends show the gen or cyclical behaviour of the trends noticed in the given data set. The bar at the right side of the equation shows the units of this stock and a higher number indicates an upward increase over the year while a lower number shows a downward trend. It includes trends which may be influenced by factors like changes in seasons, human activities or the like, or natural processes. Both daily variation and annual changes serve as important sources of information about the temporal patterns in the observed phenomena. Such temporal patterns are important for prediction, resource allocation and decision-making within fields pertinent to temporal distribution such as ecology and environmental science, climatology, or economics. Further, the use of temporal data helps in detecting non-stationarities, in monitoring the impact of interventions, and in shaping related policies, whether in the scope of dealing with permanently emerging trends or in order to avoid or adequately cope with short-term fluctuations.

7.3 Spatial Analysis

The research on pollution levels in twenty geographical locations shows a great variance in environmental quality. The artificial data produced here are pollutant densities ranging from 0 to 100 and each location is numbered from 1 to 20. These variations can be clearly seen in the bar chart provided below, where we compare the level of pollution in different areas. This spatial distribution is very important in tracing areas suspected to be affected by pollution among others. Several points go far above the other points on the entire chart which signifies that concentrated places might be emitting a lot of pollutants or the control measures are not well implemented. On the other hand, there are other areas that experience less pollution mainly due to successful environmental standards, geographical characteristics, or reduced emission activities. Knowledge of such spatial heterogeneity is critical in environmental assessment and management. In this manner, it helps policymakers direct resources to various areas, which can mean emission control regulation enforcement, or community health. In addition, the use of this analysis will help the government and policymakers make adequate decisions on issues regarding urban planning of industrial areas and zoning. It is therefore logical that variability as seen in the data necessitates localized environmental strategies.

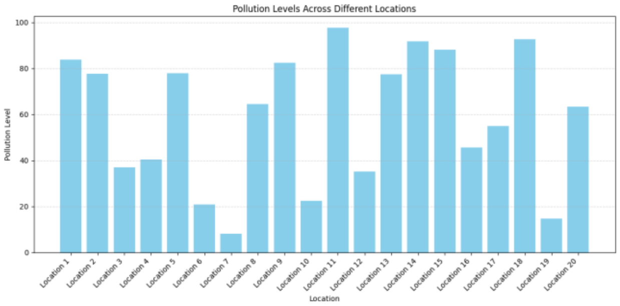

Fig. 15: Pollution Levels Across Different Locations

This indicates that the average rate for a country or even a region may differ from average rates found for localities, and therefore, local conditions require treatment individually. Such a spatial analysis framework can thus offer a fundamental starting point in identifying and designing policy- and intervention- based environmental measures based on existing information.

Pollution Level P(x)

$$P(x) = \frac{\sum_{i=1}^{n} \frac{P_i}{d_i^p}}{\sum_{i=1}^{n} \frac{1}{d_i^p}} \tag{22}$$

From equation 22 post above, Pi is the pollution level at location Li, di is the distance from point x to location Li, ‘p’ is a power parameter that determines the weighting of this measure, where usually p=2. From Figure 15 it is clearly seen that pollution data analysis by 20 sites shows varying spatial distribution of pollution. The highest pollution score is observed the Location 11 with the value 97.73, which shows very bad air quality that requires an urgent intervention. On the other hand, minimum pollution or better ambient air quality was recorded at Location 7 having the pollution index of 7: 97. Similarly, there were relatively high pollution scores in Location 1, Location 9, and Location 14, which were equal to 83,78, 82,51, and 91,80, respectively. These high readings show the areas of interest where the concentration of pollutants is very high in critical levels. On the other hand, a few sitting spots, including Location 6 which is 20.86, Location 10 with 22.50, and Location 19 with 14.70, experience low pollution levels, which corresponds to good air quality. Low-level pollution was recorded at spot five (50.08) and the lowest level was noted at spot 21 (50.03); moderate pollution level which may contain a health hazard was noted in location 8(64.51) and location 20 (63.46). This clearly indicates the variability which exists as far as the pollution levels are concerned where they range from 7.97 to 97.73. It is apparent that this spatial inequality can be explained by factors such as closeness to emission sources, population density, traffic density, and industrial strength. According to the findings, it is now clear that special measures aimed at local conditions must be taken to change the adverse situation and decrease the level of air pollution to prevent future adverse health effects in the population.

7.4 Source Apportionment

The pie charts illustrating the source apportionment display the contribution of mobile, stationary and natural pollutants for six samples in detail. Mobile sources account for between 20 and 50 percent while stationary sources are between 30 and 60

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percent; natural sources are adjusted to give a total of 100 percent. This visualization explains how various types of pollution have different effects depending on different situations. This is evident in the source contributions for different samples as mobile and stationary sources dominate the pollution, but their contributions vary. Natural sources are always there, though they are a diminished and steady part of the pollution. That much of a breakdown is necessary for designing specific individual measures. For example, regions with high contributions from mobile sources may require better standards of emission from vehicles and sound public transport options. On the other hand, relative contributions of stationary sources may call for more stringent industrial measures and cleaner energy production. Identification of distribution in pollution sources helps in prioritization in addition to the use of available resources in addressing the problem. It is in this way that policymakers can utilize this data to bring in appropriate approaches that target the most unmistakable wellspring of air tainting in certain conditions. Thus, this approach helps to minimize the possibilities of pollution control measures and improve the consequent impact of the environment and health. Also, the source information required to value and prioritize the impacts of air pollution needs updated continuously because pollution changes due to the city expansion, industries, and updating environmental policies. Therefore, this analysis offers a rich synthesis to proceed with the evaluation as well as the development of strategies in environmental management.

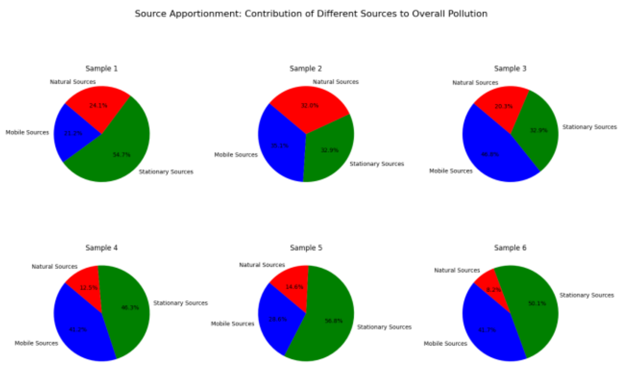

Fig. 16: Source Appointment

From Figure 16 the bar chart shows the source apportionment, the distribution of pollutants due to mobile emission sources, stationary emission sources, and the natural emission sources. Transportation which includes vehicles and other means of transport contributes to up to 46.83% of emissions to up to 21.18%. The mobile sources have the highest percentage in the second dataset with an overall 46.83 % and the lowest in the first dataset with 21.18%. While transportation sources have lower variations: ranging from 43.22% to 67.14%, the stationary sources including industries and power stations have much greater variations of between 32.86% and 56.78%. From the fourth data set, the stationary source contribution is the highest at 56.78-prescribing to industrial impact on emissions. On the other hand, the second dataset indicates the minimum contribution of stationary sources at 32.86%. Natural sources which include those arising from natural processes like wildfire and vegetation stand between 8.19% and 31.97%. The second set of data shows the highest contribution of natural source at 31.97 % indicating strong natural process bias. However, the fifth set of results reveals the smallest likelihood of natural source exposure at 8.19%. This approach forms a basis for allocating emissions among various sources in a way that reflects their overall contribution to air quality degrade. Very high contribution from stationary sources in some datasets underscore the importance of maximum control on industrial emissions. Likewise, high emissions originating from mobile sources suggest the possible gains of improving automobile exhaust emissions and improving environmentally-friendly transportation systems. It is also important when quantifying contributions from natural sources so as to come up with comprehensive air quality management measures that factor anthropogenic and natural factors.

7.5 Health Impact Assessment

Using the three subplots of health impact assessment, the current paper shows the changes in health impact and exposure and risk levels in ten samples. Every subplot reflects a different aspect of the overall assessment offering different perspectives regarding the impact of environmental factors on people's health. To visually depict the first subplot the health outcome in terms of percentage over samples has been plotted and the figure highlights varying trends observed in health impacts across samples. The changes in health outcomes shed light on how conditions of the environment can affect the health of people and identify periods of increased and reduced risks. The second subplot is associated with the changes in exposure levels for the population (µg/m³ on samples) and shows the fluctuations in the level of pollutants. This graph demonstrates why there is a need to consider exposure patterns in order to proportion the possible health hazards of pollutants in the environment. Last but not least, the third拔, lower pane shows the common risk levels (%) based on samples, which gives the risk derived from the defined exposure levels. Integrating exposure data with published risk assessment protocols, this analysis affords a numerical assessment of the potential health risks posed by polluting agents in the environment. Both of these subplots provide a thorough immersion in various aspects of HIA and allow the viewer to more fully appreciate how environmental stressors combine – and interact – to affect health. Such analyses are quite helpful in informing policymakers and public health practitioners on the best strategies for addressing the negative impact of environmental pollution on human health.

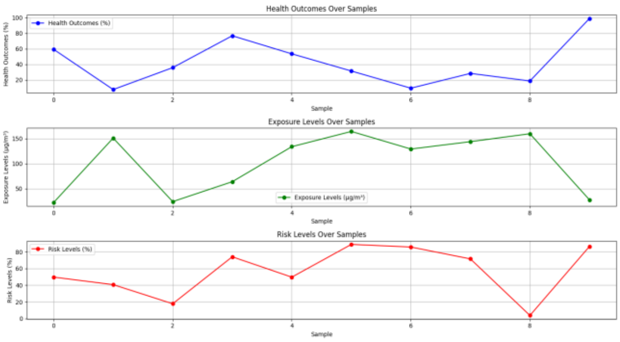

Fig. 17: Health Outcomes Over Samples

Pollutant Exposure and Health Impact

$$\frac{dH\,(t)}{dt} = \beta \cdot E\,(t) - \alpha \cdot H(t) \tag{23}$$

Risk Assessment Model using Logistic Regression

$$P(Y = 1|X) = \frac{1}{1+e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots + \beta_n X_n)}} \tag{24}$$

Exposure Response Function

$$ER = \int_0^{\infty} E(t)\,.\,R(E(t))\,dt \tag{25}$$

Combined Model with Time-Dependent Risk Factors

$$H(t) = \int_0^t (\beta_1 E_1(\tau) + \beta_2 E_2(\tau) + \ldots.. + \beta_n E_n(\tau) \cdot e^{-\alpha(t-\tau)}\,d\tau \tag{26}$$

From eqn 23, H(t) = incidence of a particular disease at time t, E(t) = exposure level to a pollutant at time t, β is the rate at which exposure affects health impact and α is the decay rate representing healing/other related factors. In equation 24, P(Y=1|X) represents the probability that an adverse health outcome Y occurs given predictor variables X, X1,X2, …., Xn; where X1,X2,.,Xn is the level of pollutants to which the subject could have been exposed, his demographic data and other relevant variables: whilst Y is 1 if the subject has an adverse health outcome, otherwise Y = 0; β From equation 25, =ER = E(t) response Since, R(E(t)) quantifies the health impact faced given a level of exposure at time t, can be used to measure the impact of exposure on health. The health impact at time t will be given as: H(t) = E1(τ) β1 + E2(τ) β2 + … + En(τ) βn where τ < t αE1(τ) β1 + αE2(τ))/ β2 ++ αEn(τ) βn/ βn

From Figure 17, a clear understanding of Health Impact Assessment showcases the actual and potential effects of exposure levels of the various pollutants on health as well as the probable risk factors. Showing the degree of health impact due to pollutant exposure as health outcomes in percentage the diverse is between 7.53 % – 98.98%. The figures farther indicate that the extent of adverse health influence remains higher within the population group under investigation. Concentrations of pollutants are in µg/m³, ranging from 22.38µg/m³ to 164.42µg/m³, which gives the idea the widest possible data and maximum variety of pollution levels people come across. High exposure levels increase the health risks explained by the risk ranking, which lie between 3.79% and 88.87%. When individuals operate at higher risk levels then it means that they are prone to health adversities as a result of pollutant exposure. The results presented in the paper support the need to reduce levels of polluters to address adverse effects on population health as well as promote the improvement of health and wellbeing. The relationships between exposure levels, health effects, and risk levels are important to assess the effects that exposure to pollution has on the health of the population and in the development of measures to protect the population from adverse health effects that are associated with pollution exposure.

7.6 Policy and Regulation Impact

The stacked bar chart presents a comprehensive analysis of the impact of policy and regulation on three key areas over a twelve-month period: such as; compliance monitoring, effectiveness of interventions, and awareness/education. Each category is painted in separate colors for comprehensible differentiation in cases of cumulatively evaluating many students. Percent compliance monitoring depicted in sky blue always shows high percentages ranging from 70 % to 100 % across the months. This implies a good compliance to legal requirements and this is accompanied by good oversight tools. The high values here show that continuous compliance measures are still essential in supporting regulatory requirements. Shown in light green, the outcome of implemented interventions varies to a moderate degree, with effective scores ranging from 50% to 90%. The observed variations could be due inter alia to the fact that interventions featured in the study are heterogeneous and may be studied at different phases of implementation. Notably, further, the fluctuations may relate to the adoption of new strategies or seasonal impacts on interference effectiveness. The results call for subsequent assessment and modification of the interventions in order to maintain and enhance their application. The awareness and education as personified by salmon in this study are slightly higher and range from 30 percent to 80 percent. The lower initial values also point to initial difficulties of public outreach and awareness in the early years of programmers. However the rise in the case identification through the months can be attributed to sustained efforts in cases of social marketing and health promotion. The fact that it moves upward indicates that long-term commitment to the improvement and management of public education is key to obtaining lasting behavioral and attitudinal change. In general, the stacked bar chart sums up the effects associated with policy and regulation efforts. These findings underscore the need for and logistically integrated approaches to compliance, intervention efficacy, and public awareness in order to meet broad-ranging environmental and public health objectives. The use of the map makes it easier to gain an integrated view of the policy implications, for purposes of effective planning, and policy development.

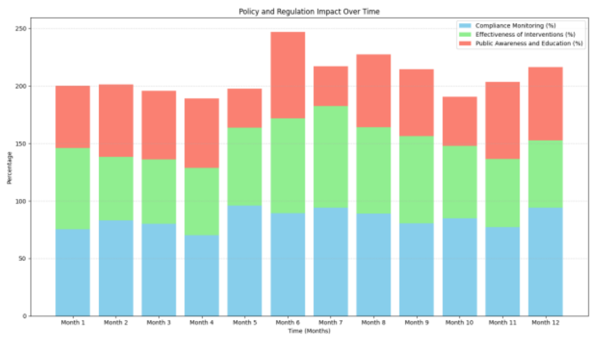

Fig. 18: Policy and Regulation Impact Over Time

$$\text{Impact}(t) = \sum_{i=1}^{t} (\alpha \cdot C_i + \beta . E_i + \gamma . P_i) \quad (27)$$

Drawing from equation 27 above with t signifying number of time periods (months in this case),Ci, which is the compliance monitoring percentage at time I, Ei which is the effectiveness of interventions percentage at time I, Pi which is the public awareness and education percentage at time I and α ,β ,γ which are weighting factors signifying the relative importance towards each component. From Figure 18, the policy and regulation impact data gives information on the success of the various policies that are laid down by the government, through the level of compliance, the outcome of various interventions, and the measure of awareness or sensitization of the public. The compliance monitoring percentages therefore vary between 70.22% and 96.11% which reveals that the organizations have different levels of compliance with the set standard in the regions/sectors. This is pegged on a 96.11% compliance monitoring score which clearly points towards the sound legal enforcement of policies to do with the environment. On the other hand, the lowest percentage of 70.22% is in some of these areas which reveals that the current regulatory enforcement may not be very strict. The extent of application of interventions is calculated in terms of the efficiency of policy measures to mitigate pollution, which varies between 55.04% and 88.46%. While the coach is as high as 88.46 % this shows that reduction of pollution has been achievable through specific approaches, whereas the low cost of 55.04 % shows the need for re-strategizing by improving on implemented measures. Education and awareness results range from 33.84 percent to 75.18 percent which shows the level of community literacy and participation on environmental concerns. The first average of 75.18% shows that the public has adequate understanding and practice on environmental conservation while 33.84% indicate that the public has a poor understanding of the environment and that more effort especially in sensitization should be made. The outcome of this research underlines the need for good compliance monitoring and efficiency of interventions as sound approaches to environmental goals. Lastly, raising public consciousness and cultivating an environment-conscious population is the key to maintaining improvement of pollution rates and increased community participation in pollution cessation. Following a comprehensive assessment, it provides lawmakers with information on the strengths and limitations of existing approaches in order to design and effectively execute policy that seeks to improve environmental quality and population health.

8 Conclusion

Therefore, this study highlights the importance of further development of air quality monitoring systems that use synthetic data generation and IoT. Cleaned daily time series for ambient concentrations of PM2.5, PM10, NO2, SO2, CO, and O3 exhibit strong diurnal patterns dependent on meteorological factors and anthropogenic emissions . A temporal variation in AQI-calculated trends is necessary to track and monitor consistently to assist in effective health and policy-making decisions. When the IoT-based sensors are inserted strategically taking into account factors such as the population and the flow of traffic then the granularity as well as the coverage that is offered is enhanced. The key insights identified focus on the height of sensors, their distance to the sources of emissions, and concerns related to structural aspects such as power supply, communication network, and physical protection. This paper provides a rationale that the idea of scalability factors can contribute to the architectural design of modular, economic, and effective environmental monitoring systems. In light of the options of data collection, transmission, storage, management, quality, discretion, precision, frequency, real-time, bandwidth, latency, scalability, security, and data replication, improvements are pinpointed. In this way, the balance is achieved to have strong data collection and data management. Investigation of the EIFF and, particularly, AQI, temporal variability and spatial distribution of pollutants, source apportionment, effects on human health, and policy/regulation implications all point to the need for preventive measures against pollution. Knowing which areas are most affected and from what or whom remedial measures can be taken affects pollution control processes. The conclusion stresses the importance of pollution prevention and control, as well as the role of compliance enforcement and public awareness programs in goal achievement where the concentration of pollutants is clearly related to adverse health effects.

References:

[1] Kaginalkar, A., Kumar, S., Gargava, P., & Niyogi, D. (2021). Review of urban computing in air quality management as smart city service: An integrated IoT, AI, and cloud technology perspective. *Urban Climate,* 39, 100972. https://doi.org/10.1016/j.uclim.2021.100972.

[2] Mihăiţă, A. S., Dupont, L., Chery, O., Camargo, M., & Cai, C. (2019). Evaluating air quality by combining stationary, smart mobile pollution monitoring and data-driven modeling. *Journal of cleaner production,* 221, 398-418. https://doi.org/10.1016/j.jclepro.2019.02.179.

[3] Monforte, P., & Ragusa, M. A. (2018). Evaluation of the air pollution in a Mediterranean region by the air quality index. *Environmental monitoring and assessment,* 190(11), 625. https://doi.org/10.1007/s10661-018-7006-7.

[4] Thach, T. Q., Tsang, H., Cao, P., & Ho, L. M. (2018). A novel method to construct an air quality index based on air pollution profiles. *International Journal of Hygiene and Environmental Health,* 221(1), 17-26. https://doi.org/10.1016/j.ijheh.2017.09.012.

[5] Tran, V. V., Park, D., & Lee, Y. C. (2020). Indoor air pollution, related human diseases, and recent trends in the control and improvement of indoor air quality. *International Journal of Environmental Research and Public Health,* 17(8), 2927. https://doi.org/10.3390/ijerph17082927.

[6] Thunis, P., Clappier, A., Tarrasón, L., Cuvelier, C., Monteiro, A., Pisoni, E., & Peduzzi, E. (2019). Source apportionment to support air quality planning: Strengths and weaknesses of existing approaches. *Environment International,* 130, 104825. https://doi.org/10.1016/j.envint.2019.05.019.

[7] Song, S. K., Shon, Z. H., Kang, Y. H., Kim, K. H., Han, S. B., Kang, M., ... & Oh, I. (2019). Source apportionment of VOCs and their impact on air quality and health in the megacity of Seoul. *Environmental Pollution,* 247, 763-774. https://doi.org/10.1016/j.envpol.2019.01.102.

[8] Guo, H., Kota, S. H., Sahu, S. K., Hu, J., Ying, Q., Gao, A., & Zhang, H. (2017). Source apportionment of PM2. 5 in North India using source-oriented air quality models. *Environmental Pollution,* 231, 426-436. https://doi.org/10.1016/j.envpol.2017.08.016.

[9] Qiao, X., Ying, Q., Li, X., Zhang, H., Hu, J., Tang, Y., & Chen, X. (2018). Source apportionment of PM2. 5 for 25 Chinese provincial capitals and municipalities using a source-oriented Community Multiscale Air Quality model. *Science of the Total Environment,* 612, 462-471. https://doi.org/10.1016/j.scitotenv.2017.08.272.

[10] Zhang, Q., Jiang, X., Tong, D., Davis, S. J., Zhao, H., Geng, G., & Guan, D. (2017). Transboundary health impacts of transported global air pollution and international trade.

Nature, 543(7647), 705-709. https://doi.org/10.1038/nature21712.

[11] Dhingra, S., Madda, R. B., Gandomi, A. H., Patan, R., & Daneshmand, M. (2019). Internet of Things mobile–air pollution monitoring system (IoT-Mobair). *IEEE Internet of Things Journal,* 6(3), 5577-5584. https://doi.org/10.1109/JIOT.2019.2903821.

[12] Fan, H., Zhao, C., & Yang, Y. (2020). A comprehensive analysis of the spatio-temporal variation of urban air pollution in China during 2014–2018. *Atmospheric Environment,* 220, 117066. https://doi.org/10.1016/j.atmosenv.2019.117066.

[13] Schneider, P., Castell, N., Vogt, M., Dauge, F. R., Lahoz, W. A., & Bartonova, A. (2017). Mapping urban air quality in near real-time using observations from low-cost sensors and model information. *Environment International,* 106, 234-247. https://doi.org/10.1016/j.envint.2017.05.005.

[14] Xie, X., Semanjski, I., Gautama, S., Tsiligianni, E., Deligiannis, N., Rajan, R. T., & Philips, W. (2017). A review of urban air pollution monitoring and exposure assessment methods. *ISPRS International Journal of Geo-Information,* 6(12), 389. https://doi.org/10.3390/ijgi6120389.

[15] Ullo, S. L., & Sinha, G. R. (2020). Advances in smart environment monitoring systems using IoT and sensors. Sensors, 20(11), 3113.

[16] Shah, J., & Mishra, B. (2016, *January). IoT enabled environmental monitoring system for smart cities. In 2016 international conference on internet of things and applications (IOTA)* (pp. 383-388). IEEE. https://doi.org/10.3390/s20113113.

[17] Sarkar, P., & Saha, M. (2024). Optimizing air quality monitoring device deployment: a strategy to enhance distribution efficiency. *International Journal of Information Technology,* 1-5. https://doi.org/10.1007/s41870-024-01893-z.

[18] Maag, B., Zhou, Z., & Thiele, L. (2018). A survey on sensor calibration in air pollution monitoring deployments. *IEEE Internet of Things Journal,* 5(6), 4857-4870. https://doi.org/10.1109/JIOT.2018.2853660.

[19] Tanyingyong, V., Olsson, R., Hidell, M., Sjödin, P., & Ahlgren, B. (2018, December). Implementation and deployment of an outdoor IoT-based air quality monitoring testbed. *In 2018 IEEE Global Communications Conference (GLOBECOM)* (pp. 206-212). IEEE. https://doi.org/10.1109/GLOCOM.2018.8647287.

[20] Chojer, H., Branco, P. T. B. S., Martins, F. G., Alvim-Ferraz, M. C. M., & Sousa, S. I. V. (2020). Development of low-cost indoor air quality monitoring devices: Recent advancements. *Science of The Total Environment,* 727, 138385. https://doi.org/10.1016/j.scitotenv.2020.138385.

[21] Montrucchio, B., Giusto, E., Vakili, M. G., Quer, S., Ferrero, R., & Fornaro, C. (2020). A densely-deployed, high sampling rate, open-source air pollution monitoring WSN. *IEEE Transactions on Vehicular Technology,* 69(12), 15786-15799. https://doi.org/10.1109/TVT.2020.3035554.

[22] Yang, C. T., Chen, S. T., Den, W., Wang, Y. T., & Kristiani, E. (2019). Implementation of an intelligent indoor environmental monitoring and management system in cloud. *Future Generation Computer Systems,* 96, 731-749. https://doi.org/10.1016/j.future.2018.02.041.

[23] Kumar, S., & Jasuja, A. (2017, May). Air quality monitoring system based on IoT using Raspberry Pi. *In 2017 International conference on computing, communication and automation (ICCCA)* (pp. 1341-1346). IEEE. https://doi.org/10.1109/CCAA.2017.8230005.

[24] Zhang, Q. S. (2023). Environment pollution analysis on smart cities using wireless sensor networks. *Strategic Planning for Energy and the Environment,* 239-262. https://doi.org/10.13052/spee1048-5236.42112.

[25] Cai, S., Wang, Y., Zhao, B., Wang, S., Chang, X., & Hao, J. (2017). The impact of the "air pollution prevention and control action plan" on PM2. 5 concentrations in Jing-Jin-Ji region during 2012–2020. *Science of the Total Environment,* 580, 197-209. https://doi.org/10.1016/j.scitotenv.2016.11.188.

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