

IoT-based Framework for Real-Time Air Quality Health Index Monitoring using LoRaWAN and Low-cost Sensors: A Proof of Concept for Toronto

MoradiGhiasabadi, B.,¹ Remmel, T. K.^{2*} and Gordon M. D.³

¹Department of Environment, Damavand Branch, Islamic Azad University, Damavand, Iran

ORCID: <https://orcid.org/0000-0001-6241-1356>

²Faculty of Environmental and Urban Change, York University, 4700 Keele Street, Toronto, Ontario, M3J 1P3, Canada, E-mail: remmelt@yorku.ca,* ORCID: <https://orcid.org/0000-0001-6251-876X>

³Department of Earth and Space Science, York University, 4700 Keele Street, Toronto, Ontario, M3J 1P3, Canada, ORCID: <https://orcid.org/0000-0003-4896-4661>

*Corresponding Author

DOI: <https://doi.org/10.52939/ijg.v22i3.4859>

Abstract

It is widely recognized that air quality directly influences human health, which has driven growing research interest in developing real-time index-based systems for air quality monitoring, often leveraging wireless sensor networks. This work presents an Internet-of-Things (IoT) implementation of an Air Quality Health Index (AQHI) framework aimed at assessing environmental conditions at fine spatial scales that leverage low-cost parts, low energy demand, and thus provide cost-effective opportunities for wide-area or dense deployment for monitoring with a network of wirelessly connected sensors. Compared with conventional air quality stations, which are typically bulky, costly, and deliver measurements with low spatial detail, the IoT approach offers inexpensive hardware, a small form factor, straightforward installation, and the ability to build scalable networks that provide fine-grained data for localized analysis. Our system tracks concentrations of key airborne pollutants, such as ozone (O₃), nitrogen dioxide (NO₂), and fine particulate matter (PM_{2.5}), which serve as indicators of overall air quality and are already incorporated into the Canadian reporting system. An exclusive web-based platform was developed to enable live, near real-time monitoring, long-term data archiving, analytical processing, and the visualization of air quality information through an intuitive, user-friendly dashboard. The system computes the AQHI for each sensor deployed which can provide near real time reporting, monitoring, and with known sensor locations, the data could be mapped. Interaction with this scalable platform is through either a computer, tablet, or even smartphone if an Internet connection is available. A single microcontroller enables sensor-derived gas and PM measurements to be transmitted over the Internet to user dashboards. This study outlines the complete hardware configuration and software framework underpinning the proposed system. A case study for multiple sensor deployments to compute AQHI is presented along with an evaluation of cost and energy consumption benefits of using this system.

Keywords: Air Quality, Internet of Things (IoT), Monitoring System, Real-Time Data, Sensors

1. Introduction

Despite the economic gains that urban centers deliver, they often bring about profound environmental drawbacks [1]. Improvements in lifestyle linked to urban expansion often coincide with a decline in environmental integrity and ecological health, with the quality of the air among the most compromised aspects that exert an immediate influence on every living organism [2] and [3]. Given that unpolluted air underpins the survival of all terrestrial life forms, including plants, animals, and humans, the accelerating trend of

pollution and declining air quality imposes direct and urgent threats upon every organism [4]. Although placing an exact monetary value on air pollution is challenging, it remains one of the most pressing environmental issues for all nations, developed and developing alike, further aggravated by the impacts of climate change. Worsening air quality has fueled a steady rise in long-term illnesses, especially in urban areas, where rapid industrial growth and the surge in motor vehicles release vast amounts of gaseous pollutants [5].

Accelerated industrialization and widespread personal vehicle use have intensified air pollution, making it a serious concern in urban areas and drawing increasing attention from both policymakers and the public [6]. In response to these trends, the World Health Organization (WHO) has identified air pollution as a critical global threat to human health.

Several researchers have proposed frameworks and analytical models linking exposure to airborne pollutants with both short-term and long-term health effects. While short-term exposure typically provokes minor allergic responses, such as throat, eye, or nasal irritation, evidence indicates that sustained or high-level exposure substantially increases the risk of serious respiratory and cardiovascular outcomes, including asthma exacerbations, bronchitis, pneumonia, and ischemic heart disease. Observational studies report that air pollution results in approximately 50,000–100,000 premature deaths per year in the United States, around 300,000 in the European Union, and more than 3 million worldwide [7]. Extended exposure to airborne pollutants markedly elevates the risk of developing severe respiratory disorders [8], as a result, conducting systematic local air quality measurements and ongoing monitoring is vital to support mitigation measures grounded in robust data analysis [9]. According to [10], the considerable size, weight, and cost of conventional air-quality monitoring instruments limit their widespread deployment, particularly within urban environments. Their study demonstrated that the high installation and maintenance expenses of fixed monitoring stations hinder their deployment at high spatial density, resulting in limited coverage and delayed data availability. Due to the fact that traditional station-based methods often involve time-consuming procedures that may require offline laboratory analysis, they, despite providing highly precise measurements, may not be able to deliver real-time, spatially dense, air quality data through this approach [11].

Given the well-established significance of air-quality data for environmental assessment and public health, demand for datasets offering both high spatial and temporal resolution continues to intensify [12]. To effectively address this issue, systematic and fine-grained local monitoring is essential for generating the data required for evidence-based mitigation strategies. Conventional air-monitoring stations, though accurate, are typically characterized by high-cost, bulky infrastructure, and sparse deployment, which inherently limits the spatial and temporal resolution of the collected data. This limitation is particularly challenging in dense urban environments

like Toronto, where localized pollution hotspots require fine-scale detection.

This work addresses the deficiencies of traditional monitoring by presenting an Internet-of-Things (IoT) implementation of an Air Quality Health Index (AQHI) framework. The proposed system utilizes low-cost, compact sensors integrated within a scalable IoT architecture to provide highly localized and timely air-quality assessments. The framework tracks concentrations of ozone (O_3), nitrogen dioxide (NO_2), and fine particulate matter ($PM_{2.5}$) and consolidates them into the Canadian-standard AQHI value. A key innovation is the use of a LoRaWAN network for reliable, long-range, and energy-efficient data transmission, coupled with a customized, real-time web-based platform for archiving, processing, and visualizing data. The paper outlines the complete hardware and software framework, demonstrating the feasibility and robustness of expanding AQHI monitoring beyond existing static stations to enhance localized public health protection.

2. Related work

We reviewed a diverse set of scholarly articles on IoT-enabled air-quality monitoring to identify design gaps. With our proposed system, we have attempted to decrease costs while utilizing superior hardware options to provide timely, precise, and accurate environmental readings. Many studies have focused on the development of IoT frameworks for air-quality monitoring and environmental assessment. Several researchers have investigated architectures that combine low-cost sensors with wireless communication technologies such as WiFi, ZigBee, or LoRaWAN to achieve real-time data acquisition and dissemination. Recent works have proposed cloud-and edge-integrated models to improve scalability, data analytics, and decision-support mechanisms for smart-city applications. Collectively, these efforts demonstrate significant progress in leveraging IoT technologies for environmental sensing, yet critical challenges remain regarding cost efficiency, data accuracy, and localized deployment scalability.

The long-term costs of healthcare and environmental restoration are projected to be considerably greater if air quality is allowed to deteriorate unmitigated, as opposed to implementing preventive action promptly [13]. Building on previous findings, recent research has explored the classification and monitoring of air pollutants across multiple environmental domains. Air pollutants encompass various forms, and their monitoring involves measuring environmental variables such as temperature, humidity, and the concentrations of

selected indicator compounds, O₃ (ozone), SO₂ (sulfur dioxide), CO (carbon monoxide), and particulate matter (PM). The PM category is denoted with subscripts to distinguish particle diameters $\leq 10 \mu\text{m}$ (PM₁₀) and $\leq 2.5 \mu\text{m}$ (PM_{2.5}). Given that prompt detection and prediction of these pollutants can improve mitigation strategies, researchers continue to develop methods that operate in, or very close to, real time [14].

According to [10], the considerable size, weight, and cost of conventional air-quality monitoring instruments limit their widespread deployment, particularly within urban environments. Their study demonstrated that the high installation and maintenance expenses of fixed monitoring stations hinder their deployment at high spatial density, resulting in limited coverage and delayed data availability. Due to the fact that traditional station-based methods often involve time-consuming procedures that may require offline laboratory analysis, they, despite providing highly precise measurements, may not be able to deliver real-time air quality data through this approach [11]. Given the well-established significance of air-quality data for environmental assessment and public health, demand for datasets offering both high spatial and temporal resolution continues to intensify [12]. This forms the focus of the present paper, since monitoring urban air quality allows individuals to remain informed about environmental conditions and adapt their behaviour as necessary. Often, however, access to such data proves challenging, even when such information is technically available, as it is typically monitored only through expensive stations installed at specific locations and operated by governments or industry [15]. Policies and standards for measuring, monitoring, and communicating air pollution exist in many countries, and advisories are issued should pollutant levels reach hazardous thresholds (e.g., during summer smog or wildland-fire events) [16]. However, real-time variability in air quality is observed, influenced by pollutant composition, location (indoors versus outdoors), and meteorological variables [17].

The pervasive development of information and communication technology (ICT) across sectors has catalyzed the emergence of the smart city framework [18]. Driven by ICT, smart city initiatives include traditional brick-and-mortar infrastructure, physical (e.g., roads, buildings), technical (e.g., utilities), and environmental (e.g., water, green space), as well as ICT embedded in their operations [19]. According to [20], integrating ICT into urban infrastructures can significantly reduce air pollution expenditures, with projected savings reaching around USD 17 million by 2050. The Lancet Commission on Pollution and

Health and similar reports recommend deploying low-cost sensors (LCS), leveraging satellite observations, applying data-mining techniques, and maintaining open data portals to hasten progress toward meeting air-quality targets [21]. The rapid spread of Information and Communication Technology across municipal services has generated fresh interest in urban computing [22]. As discussed earlier, the considerable size, weight, and cost of conventional monitoring instruments limit their widespread deployment; the system proposed in this study aims to address these limitations.

The placement of air-quality monitoring stations needs careful consideration to ensure measurements capture representative effects of human activity (e.g., construction, transportation). Major road junctions, for example, often record pollutant levels well above normal baselines due to traffic congestion [23]. Over recent years, research interest has shifted toward air-quality monitoring architectures that employ the Internet to unify data from spatially distributed sensors [24]. With advanced instrumentation, these sensor-based platforms can measure O₃, SO₂, CO, and PM in combination, yielding reliable metrics of site-specific pollution levels [25]. Moreover, progress in IoT technologies is expanding remote monitoring capabilities and enabling the seamless integration of numerous spatially distributed air-quality sensors [26]. Driven by advances in IoT technology, cost-effective sensor-based networks are emerging as practical alternatives to conventional air-quality monitoring setups, which have long been characterized by high expense and limited spatial-temporal resolution [27].

In the emerging IoT paradigm, networks of devices and sensors leverage Internet connectivity to support the distributed operation of comparatively intelligent, autonomous systems. With reliable Internet access, IoT enables remote monitoring, control, updates, and integration of sensors, devices, appliances, and other connected entities. Closely intertwined with key smart-city domains, such as traffic optimization, security, and healthcare deployment, it is increasingly attracting research interest as a means to monitor and address urban air-quality issues [28]. By enabling dense deployment of compact, low-cost sensors across an urban landscape, the latest wave of IoT innovation is transforming how cities approach air-pollution challenges. Instead of relying solely on a few static monitoring stations, diverse neighbourhoods can now be equipped with measurement devices whose readings are gathered through wireless sensor networks (WSN) and delivered to central servers for analysis and strategic response [29].

Among the key indicators of deteriorating air quality are not only gaseous pollutants but also microscopic particles like PM_{2.5}. Once inhaled, these fine particulates, which readily attach to hazardous chemical compounds, can transport them deep into the lungs, creating serious health risks and underscoring the need for precise monitoring to assess their combined impacts in urban environments [2]. Therefore, integrating a PM sensor into monitoring networks is crucial, as it enables the accurate detection of airborne dust particles, a capability that directly supports precise assessments of overall urban air quality [30]. In conventional approaches, measuring gas concentrations and particulate matter involved demanding field sampling campaigns, with subsequent analysis carried out in laboratories. Although these methods provided reliable scientific outputs, they were burdened by considerable expenses, operational complexity, and long delays before results could be put to practical use. The integration of spatially distributed sensors into IoT framework has removed the need for manual field sampling and subsequent lab work, as continuous streams of environmental data are now generated and delivered instantly [31]. Within seconds, sensors are able to capture specific air-quality parameters and relay the information to central servers, which then distribute it at scheduled intervals to support near real time monitoring and assessment [32]. Although sensor readings may not attain laboratory-grade precision, these frequent measurements and real-time tracking of temporal changes enhance the quality of air-quality assessments, and it is IoT technology that provides the connectivity to sustain these spatially distributed sensor networks [33].

Due to the unpredictable fluctuations of hazardous atmospheric gases and particulate matter across an urban area, deploying multiple spatially distributed sensors enables the continuous detection of these pollutants, resulting in a more complete and real-time understanding of air-quality conditions. By leveraging IoT technology, cities can establish extensive networks of sensors that operate continuously, as noted by [9], measuring ambient air quality parameters and transmitting the data to centralized servers for integrated analysis.

Because exposure to peaks of toxic gases can severely impair immune, reproductive, and other vital human systems, sensor-driven platforms can automatically detect deteriorating local air quality and promptly issue alerts, giving communities the opportunity to take protective action before harmful concentrations are reached [4]. Emissions from fossil-fuel combustion in transportation, industry, manufacturing, and other urban activities release

high concentrations of carbon oxides, a variety of toxic gases, and particulate matter into the atmosphere. Initially, such pollutants can provoke mild allergic responses, irritation of the throat, eyes, or nasal passages, but continued exposure may escalate to bronchitis, cardiovascular disease, pneumonia, and even lung or skin cancers. Beyond direct health impacts, these emissions intensify the greenhouse effect, deplete protective stratospheric ozone, and generate cascading environmental and climatic consequences [10].

Given the health risks posed by elevated concentrations of harmful gases and particulate matter specifically O₃, NO₂, and PM, we designed a cost-efficient IoT-based framework that deploys spatially distributed sensors to capture high-temporal-resolution air-quality data. This information is transmitted to a connected web server, where automated algorithms compare measurements against predefined safety thresholds and trigger immediate alerts when exceedances occur. We have developed a web-based dashboard that displays the concentrations of individual pollutants and consolidates these measurements into the scaled index used in Canada to quantify the health impacts of air quality, the Air Quality Health Index (AQHI). Through this IoT-enabled implementation, distributed pollution levels can be monitored flexibly from any location via computer, tablet, or mobile device, and the resulting information can be readily shared with others.

Analysis of monitoring data allows us to assess air pollution levels nearly continuously through time without having to physically visit multiple locations to manually take measurements and then analyze them in a laboratory. The reliance on IoT facilitates distributed data collection in near real-time on a regular and repeated interval [34] and [35]. We propose an air-quality monitoring system capable of assessing the AQHI in real time, thereby enabling immediate warnings and allowing individuals to take protective action. Integration with IoT technology ensures that data management and sensor control can be performed remotely within a secure environment. Key innovations of our work include (1) the incorporation and integration of PM measurements into an IoT-based system for AQHI computation, (2) the delivery of highly localized air quality measurements, and (3) a scalable framework for distributed IoT data collection and management via a user friendly dashboard, all at lower cost than traditional monitoring stations and consuming less power. The lightweight, low-cost implementation further increases public access to high-quality air-quality data. These technical advantages, combined with their capacity to enhance

decision-making for the protection of human health, render this IoT-enabled air-quality-monitoring system both timely and broadly applicable, not only for residents of Toronto but also for populations in other urban centres.

3. Methods

An IoT-driven monitoring framework was designed and implemented to address the need for tracking air pollutants across extensive urban and peri-urban regions while ensuring timely public alerts. Within this framework, sensor nodes transmit measurements through a web-server infrastructure using standardized low-power wireless communication protocols (e.g., Wi-Fi, LoRa, ZigBee).

Automated algorithms compare the measurements with predefined thresholds set for individual pollutants as well as for composite air-quality indices (AQHI), enabling continuous surveillance of harmful gases such as NO₂ and O₃ alongside PM metrics. This architecture supports prompt interventions and informed management of urban air quality. The system employs specialized air sensors to detect pollutants in the ambient atmosphere and transmit measurement data to a microcontroller, which subsequently forwards and stores the information on a web server for public dissemination. By strategically deploying IoT devices within a dense wireless sensor network, both toxic gases and airborne particulates can be monitored with near real-time resolution. This data infrastructure enhances continuous urban air-quality surveillance, accelerates reporting, and supports effective responses to

emerging pollution events. In Ontario, existing air quality monitoring stations are sparsely distributed over a large territory, and only twelve operate within Toronto, the most populous city in Canada (over 3M people and over 5M people within the surrounding region). This limited density constrains both spatial coverage and temporal resolution. The availability of numerous low-cost air sensors now enables dense deployment across the highly urbanized and populous Greater Toronto Area (GTA), where integration through an IoT-based infrastructure provides a cost-effective, scalable, and readily deployable solution for continuous air-quality surveillance. Such an IoT network substantially enhances spatial granularity, ensures timely data accessibility, and supports more informed decision-making to safeguard public health (Figure 1).

The Internet of Things refers to an architecture of uniquely identifiable computing devices, mechanical components, digital objects, and other interconnected elements that communicate and exchange data autonomously without requiring direct human-to-human or human-to-computer interaction. Emerging from the convergence of remote local area networks (LANs), wide area networks (WANs), micro-electromechanical systems (MEMS), and web-based services, IoT has effectively bridged the historic divide between Operational Technology (OT) and Information Technology (IT). This integration enables the analysis of unstructured, machine-generated data to derive actionable insights, ultimately informing adaptive feedback systems and enhancing operational performance [36].

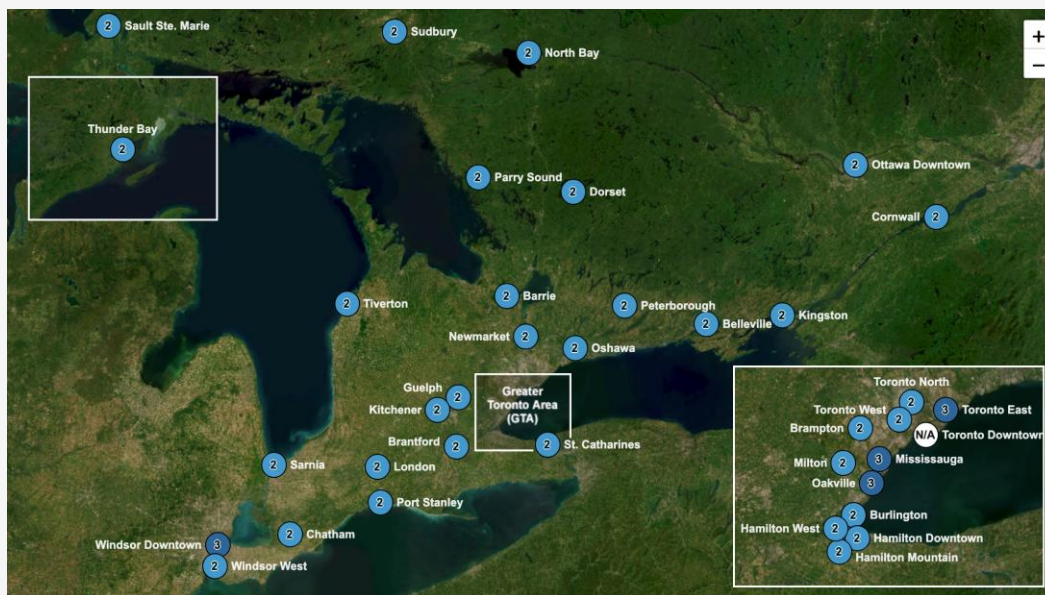


Figure 1: Existing Air Quality Health Index stations in Ontario.

Source: <https://www.airqualityontario.com/aqhi/locations.php>

3.1 Canadian Air Quality Health Index (AQHI)

The AQHI is a health-based index developed in Canada to communicate the health impacts of air quality. It serves as a health-protection tool enabling individuals to make informed decisions to reduce short-term exposure to air pollution by adjusting activity levels during periods of elevated pollutant concentrations. Beyond immediate exposure reduction, the AQHI can encourage behavioural changes aimed at lowering one's environmental footprint, ultimately contributing to improved air quality. This index is particularly valuable for individuals sensitive to air pollution, as it provides timely guidance across conditions categorized as low, moderate, high, or very high health risks. The formulation of the national AQHI is grounded in the observed relationship between nitrogen dioxide (NO₂), ozone (O₃), particulate matter (PM_{2.5}), and mortality data collected from Canadian cities. Importantly, each of these three pollutants can adversely affect health even at low exposure levels, particularly among individuals with pre-existing health conditions. During the AQHI's development, Health Canada's initial analysis considered five major air pollutants PM_{2.5}, O₃, NO₂, Sulfur dioxide (SO₂), and carbon monoxide (CO). However, as SO₂ and CO contributed minimally to predicting health effects, they were ultimately excluded from the index formulation [37]. The national AQHI is derived from three-hour average concentrations of the three identified atmospheric constituents. O₃ and NO₂ are measured in parts per billion (ppb), while PM_{2.5} is measured in µg·m⁻³.

The AQHI is calculated on a community basis, with each community potentially having one or more monitoring stations. For each station within a community, the average concentration of the three pollutants over the preceding three hours is first determined. This calculation is considered valid only if data are available for at least 2 of the 3 hours. If data for more than one of the preceding three hours are missing, the station average is assigned a "Not Available" status. This stage of the process yields three "station parameter averages" for each monitoring station. In the second step, the three-hour "community average" for each parameter is calculated from the corresponding three-hour substance averages at all available stations. If no stations report data for a particular parameter, that parameter is designated as "Not Available". As a result, this step produces three "community parameter averages." In the third step, if all three community parameter averages are available, the

community's AQHI value is computed using Equation 1 [38].

$$AQHI = \frac{10}{10.4} \times 100 \times (e^{0.000537 \cdot O_3} - 1) + (e^{0.000871 \cdot NO_2} - 1) + (e^{0.000487 \cdot PM_{2.5}} - 1)$$

Equation 1

3.2 System Architecture and Operation

A general overview of our system design is illustrated in the IoT architecture diagram. The architecture comprises three main components: (1) hardware, (2) network, and (3) software. The hardware component consists of the air pollution sensors and the platform controlling them. In any IoT system, sensors form the primary layer – directly interfacing with and influenced by the monitored environment. Their essential role is to capture environmental data and transmit these measurements for further processing. As the origin of all incoming information, sensors are arguably the most critical element of any environmental monitoring system. Depending on the pollutant's physical state (e.g., gas, solid), different sensor types are employed to measure relevant aspects of air quality, with their design tailored to the specific target pollutant (Figure 2).

Many substances classified as hazardous to human health appear in the atmosphere in gaseous states, where their inhalation poses significant physiological risks. To detect and quantify such pollutants, modern ambient-air monitoring relies on an assortment of compact and low-cost devices, including: (a) particulate matter sensors for aerosols (b) electrochemical modules for targeted gas species, and (c) solid-state units that exploit variations in the conductivity of metal-oxide films as they interact with the molecules of interest. This diversity of sensing hardware not only broadens the range of pollutants that can be tracked continuously but also enables scalable deployments in urban and industrial settings where early detection is critical. Atmospheric gases, once ionized to yield free electrons and charged ions, can interact with metal-oxide surfaces through ionic bonding with the constituent metal atoms, forming surface-bound ligand complexes. This interaction alters the electronic structure of the oxide layer, generating a measurable change in electrical conductivity that is used to determine the atmospheric concentration of the gases [39].

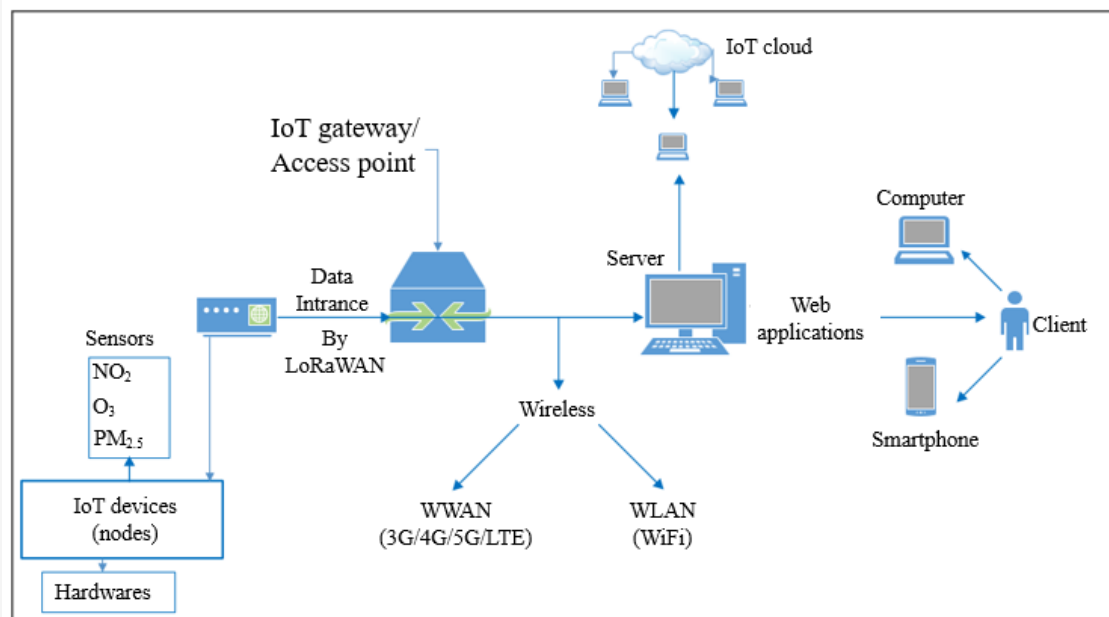


Figure 2: Block diagram of the AQHI system

The server-side data-quality and QA/QC framework has been implemented: automated preprocessing (range checks, temporal-consistency filters, and outlier removal), real-time stream validation, and logging/flagging of suspect records. Unit and integration tests verified processing logic and API stability. The processing pipeline and dashboard were validated using real station measurements: the application reproduces the measured concentrations for the three target pollutants (O₃, NO₂, PM_{2.5}), and – importantly – computes the community AQHI from these quantities using the established AQHI algorithm; these AQHI values were verified against the real-data-derived reference and displayed on the web dashboard, with anomalous readings flagged for further review. Model-based correction modules (calibration/bias adjustment) are ready for deployment pending field co-location datasets. To enhance gas–sensor responsiveness and maintain optimal operating conditions, certain designs incorporate a heating element to both accelerate surface reactions and stabilize sensor temperature [40]. Despite being compact, highly sensitive, and relatively inexpensive, these sensors often exhibit limited measurement accuracy, prolonged warm-up periods, and gradual performance degradation over extended use [41]. Electrochemical sensors, as another widely used category, detect target gases through oxidation–reduction processes occurring between ambient gas molecules and their electrodes, generating an electrical current proportional to the gas concentration [42]. Beyond gaseous pollutants, growing concerns over the health impacts of

atmospheric particulate matter have driven the development of diverse, low-cost optical or gravimetric particle sensors capable of quantifying micro particle concentrations in ambient air [43]. The hardware layer comprises the controllers responsible for acquiring sensor data and coordinating its transmission over the network to a destination for storage or further processing. Fundamentally, this hardware consists of electronic circuit boards that both manage sensor operations and supply the required power. Such boards are generally categorized into two main types: single-board computers and microcontroller boards, each offering distinct advantages depending on the specific application requirements.

A single-board computer is a compact system integrating a powerful microprocessor and substantial memory. It typically operates a lightweight operating system, enabling the execution of complex applications and supporting a wide range of network-communication protocols. These boards are equipped with integrated power-management modules that minimize energy usage, thereby extending their operational lifespan. While they are capable of directly controlling sensors, they are more often employed as compact servers, to coordinate sensor networks or function as gateways for delivering collected measurements to central servers or cloud platforms [44]. A range of capable boards are available for computation, communication, and the control of sensors and actuators. Among them, Raspberry Pi and PINE boards are particularly popular due to their affordability and broad adoption

[45]. A microcontroller board is a compact computing platform characterized by limited processing power and modest memory capacity, typically designed for dedicated control tasks in embedded systems. Compared to single-board computers, these boards generally provide similar types of input-output interfaces but offer lower computing performance, reduced memory capacity, and more limited wireless-communication capabilities. Among them, NodeMCU boards (based on ESP8266 and ESP32 chips) integrate relatively powerful processors, sufficient memory, and built-in wireless modules, making them well-suited for IoT-based air-quality-monitoring systems. Their main limitation is the smaller number of general-purpose input/output pins compared to other board types [46] and [16].

A LoRaWAN (long-range wide-area) network [47], built upon the IEEE 802 standard, connects the monitoring nodes to an access point (AP). The network's primary elements are (1) sensor nodes and (2) an AP node that employs a wireless link to a broader network. The AP collects near-real-time air-quality data from each monitoring node, verifies the data source and validity, and forwards the information through the network [48]. We have designed and implemented a fully customized, in-house web application that systematically collects, stores, organizes, processes, and displays environmental sensing data. Through an application programming interface (API), users on computers, tablets, or smartphones can access sensor data from an IoT cloud database and view numerical, graphical, and near-real-time information from widely distributed IoT sensors.

3.3 System Implementation

3.3.1 Hardware and network

The Monitoring Section and the Access Point are the primary components of this subsystem. In the proposed system, the AP functions as a dedicated wireless-communication bridge, continuously acquiring real-time air-quality measurements from the Monitoring Section. The Monitoring Section integrates four essential subsystems: the power module, the sensor module, the controller module, and the network module. The power module delivers a stable and uninterrupted energy supply to all components, forming a fundamental operational requirement for any smart IoT device. A diverse range of power-supply solutions, such as battery-based, solar-assisted, and hybrid configurations, can be adopted, depending on factors like deployment environment, energy availability, and device duty

cycle. The network module establishes the link between local sensing and long-range data transmission, enabling seamless integration with LoRaWAN infrastructure. This architecture supports efficient, low-power, and wide-area connectivity, ensuring that environmental data is reliably delivered to cloud-based processing and visualization services in near real-time [49].

Air-quality data is transmitted from the IoT device to the gateway via a LoRaWAN network module, providing fast, reliable, and energy-efficient access to the Internet. This link enables the continuous delivery of real-time measurements to the IoT cloud for further processing. Leveraging the capabilities of high-performance modules, the system encapsulates the data into structured packets and transmits them in accordance with standardized communication protocols, ensuring interoperability and secure delivery. At the network layer, the Access Point is implemented using an open-source Software-Defined Radio (SDR) framework running on a general-purpose processor (GPP) in conjunction with a Universal Software Radio Peripheral (USRP). To accommodate all operational frequency bands defined by the IEEE 802.15.4k standard, spanning 70 MHz to 6 GHz, the Ettus USRP B210 is selected as the core RF front-end. Leveraging its high-speed USB 3.0 interface, the USRP B210 delivers the down-converted and digitized baseband signal to the GPP for subsequent processing, enabling flexible, software-controlled wireless communication [50]. While these are not most inexpensive radios, they were available for the testing phase of our work. Even at their current price point however, they remain significantly cheaper than installing a traditional air quality monitoring station. The GNU Radio framework is employed to implement the receiver's baseband signal-processing chain, providing a flexible and software-defined environment for algorithm development [50]. At the receiver, image demodulation commences with non-coherent detection, mitigating the impact of carrier frequency and phase offsets. Subsequently, a parallel preamble-detection scheme is applied, enabling the reliable handling of concurrent data transmissions from multiple monitoring nodes [50][51] and [52]. Utilizing a Fast Fourier Transform (FFT) in conjunction with an energy-based timing-adjustment module, each processing thread performs the correlation procedure required for preamble detection. This approach enhances synchronization accuracy and robustness in the presence of noise and channel impairments [43] and [53].

3.3.2 Software

The effective operation of the IoT processing system requires a wide range of software applications deployed on both the cloud and user sides. The IoT cloud functions as a large-scale distributed network that supports the integration, management, and operation of IoT devices and applications [54]. This encompasses the underlying infrastructure, servers, storage systems, and supporting resources, required for real-time operations and data processing. IoT cloud platforms provide on-demand, cost-efficient hyper-scaling, and enabling organizations to harness the full potential of IoT without investing in the development of physical infrastructure or foundational services. Within such platforms, three primary server types fulfill distinct roles: the Data Processing Server, which handles computation and analytics; the Storage Server, responsible for secure and scalable data retention; and the Proxy Server, which manages intermediary communication and network routing [55].

3.3.3 Data processing server

Measured air-quality data from IoT devices is first transmitted to the IoT cloud. Direct use of raw data is avoided because of potential transmission errors, sensor noise, or equipment malfunctions. To ensure data integrity and analytical reliability, a preprocessing stage is applied, correcting anomalies, filtering out noise, and standardizing formats. The data processing server then analyzes this refined dataset to extract meaningful insights and identify air-quality trends over time.

3.3.4 Storage server

The storage server maintains a database containing pre-processed (modified) raw data received from the data processing server. Upon completion of analysis,

clients are notified via the Web Socket protocol, enabling low-latency, bidirectional communication between the server and end-user applications. This architecture ensures a highly reliable, efficient, and persistent link for data delivery. In continuous operation, datasets are cyclically acquired, processed, and archived in the storage server for future retrieval and long-term analysis. Proxy Server: The proxy server is implemented using Servlet and Java Server Pages (JSP) to deliver services to end-users via the HTTP protocol. By optimizing request handling and data delivery, it significantly reduces the latency of air-quality updates reaching the client. This real-time responsiveness is achieved while implementing load-management mechanisms that prevent excessive concurrent requests, ensuring both service stability and efficient resource utilization [56]. Customers may also access air-quality data through APIs, using a web browser or mobile application.

3.3.5 Display Applications

As previously noted, end-users can access air-quality information via a website or mobile application. The web application, developed in C# and illustrated in Figure 3, provides an interactive interface for visualizing pollutant levels. C# is a general-purpose, high-level programming language that supports multiple paradigms, including static and strong typing, lexical scoping, imperative and declarative programming, functional constructs, generics, object-oriented (class-based) design, and component-oriented development. Through the display modules, users can monitor the AQHI in real-time for the current day, as well as review historical trends for the preceding week and month (see Figure 3).



Figure 3: The air quality monitoring system application

To summarize, the end-to-end data flow of the IoT-based air-quality-monitoring system involves several key stages: gas sensors measure ambient conditions, the LoRaWAN network module transmits these measurements to the AP, and the AP, leveraging its software-defined radio platform, forwards the information to the IoT cloud. Within the cloud platform, the incoming data undergoes preprocessing to remove noise, correct anomalies, and ensure integrity. The processed datasets are then stored, analyzed, and made accessible through dedicated data-processing, storage, and proxy servers. Finally, standardized APIs enable dissemination to end-users via web-based dashboards or mobile applications, allowing real-time visualization and historical trend analysis of local air-quality indices.

3.4 Energy consumption modeling

Energy consumption for each node was estimated using the standard LoRaWAN power-consumption model, which accounts for the transmitter, receiver, and sleep states of the end device. The node-level energy usage is expressed as Equation 2.

$$E_{node} = P_{tx}T_{tx} + P_{rx}T_{rx} + P_{sleep}T_{sleep}$$

Equation 2

Where P_{tx} , P_{rx} and P_{sleep} represent the power consumption in transmission, reception, and sleep modes, respectively; and T_{tx} , T_{rx} and T_{sleep} denote the corresponding time durations of those states. For the data-driven simulation, only logical communication cycles were modeled, excluding physical sensor circuitry. During typical operation, the on-air time

primarily depends on spreading factor, bandwidth, and payload size. Therefore, the energy required for a single uplink transmission can be simplified as Equation 3.

$$E_{tx} = P_{tx}T_{on-air} + P_{sleep}T_{sleep}$$

Equation 3

This term forms the transmission component within the total node-level energy model. Variability in pollutant concentration influenced the adaptive control scheme by dynamically adjusting the transmission interval (Δt) and transmit power (P_{tx}). The outcomes of this simulation-based model are analyzed and discussed in Section 4. This simulation-based modeling provided the foundation for subsequent analysis of energy efficiency within the adaptive IoT framework. The primary objective of this modeling was to quantify the energy savings achieved by the adaptive control mechanism. This mechanism dynamically adjusts the transmission interval and transmit power based on the real-time pollutant concentrations ($O_3, NO_2, PM_{2.5}$), thereby creating a novel energy-aware LoRaWAN strategy. The low energy consumption by LoRAWAN is supported by [57] and thus supports our implementation.

4. Results and discussion

The IoT-based air-quality monitoring system can be divided into three main components, as illustrated in Figure 4 and Figure 5: (1) gas-sensor design, (2) sensor calibration, network, and system architecture, and (3) web application.

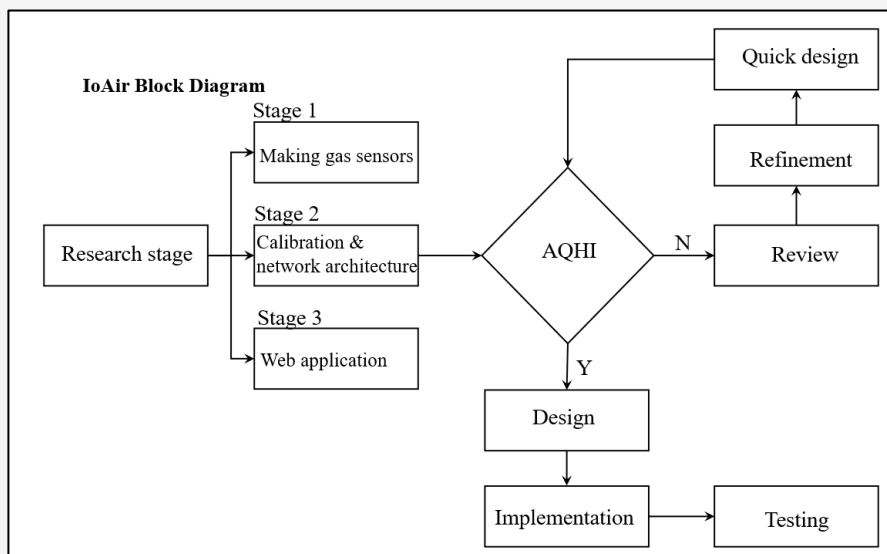


Figure 4: IoA block diagram

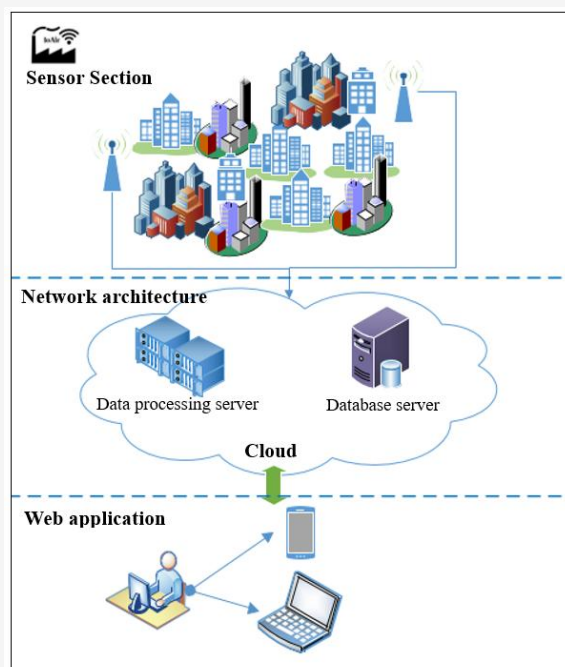


Figure 5: Architecture of the air quality monitoring system based on IoT

The application component processes sensor data and delivers interactive services to users and is itself divided into two parts: the IoT cloud and client applications. Once the AP receives air-quality data from sensor nodes, it stores the information in the IoT cloud database. The cloud environment then aggregates, processes, and analyzes these datasets, supporting both real-time monitoring and historical analysis. In addition, standardized application programming interfaces (APIs) enable the IoT cloud to disseminate information to client applications, whether through a computer-based dashboard or a smartphone application [58]. This setup allows users to easily access accurate air-quality information for the City of Toronto. To this end, dedicated software was developed to transform raw measurement data into reliable references, presenting results through curve-based charts and interactive dashboards. In the subsequent subsections, results from both the system implementation and the quantitative evaluation of node-level energy efficiency are presented and discussed.

4.1 Configuration

Testing activities were planned to be conducted under typical urban-environment conditions. Prior to deployment, a comprehensive software architecture was developed using Microsoft Visio, explicitly

aligned with Ontario's Air Quality Standards. The finalized system design comprises forty detailed pages structured into the following sections: Web Staff, Introduction, Dashboard, Zones, Stations, Reports, Online Data, Charts, Lab Staff, Profile, Contacts, and Login / Sign Out. This structured layout served as the blueprint for both system implementation and operational evaluation.

4.2 Locations of Sensor Nodes, Zones and Stations

For this project, two primary monitoring zones were established within the City of Toronto: (1) Yorkdale Zone ($43^{\circ}43'29.5''$ N, $79^{\circ}26'49.1''$ W) and (2) York University Zone ($43^{\circ}46'37.7''$ N, $79^{\circ}29'52.8''$ W). Each zone hosts two monitoring stations. In the Yorkdale Zone, the stations are Sterling Hall ($43^{\circ}43'23.7''$ N, $79^{\circ}27'36.0''$ W) and Jane Osler ($43^{\circ}44'10.5''$ N, $79^{\circ}28'25.0''$ W). In the York University Zone, the stations are Pioneer Village ($43^{\circ}46'01.9''$ N, $79^{\circ}30'23.3''$ W) and York Regional Road 6 ($43^{\circ}50'19.8''$ N, $79^{\circ}31'54.7''$ W). In total, four sensor nodes are strategically distributed across the project area. The air-quality-monitoring network is deployed following a cluster/tree topology, rather than a star or mesh configuration as illustrated in Figure 6. This topology was selected to optimize communication efficiency and scalability in a geographically dispersed urban environment. By grouping nodes hierarchically, data from local stations can be aggregated at zone-level hubs before being transmitted to the central Access Point, thereby reducing network congestion, improving energy efficiency, and enhancing system reliability.

4.3 System and Sensor Parameter

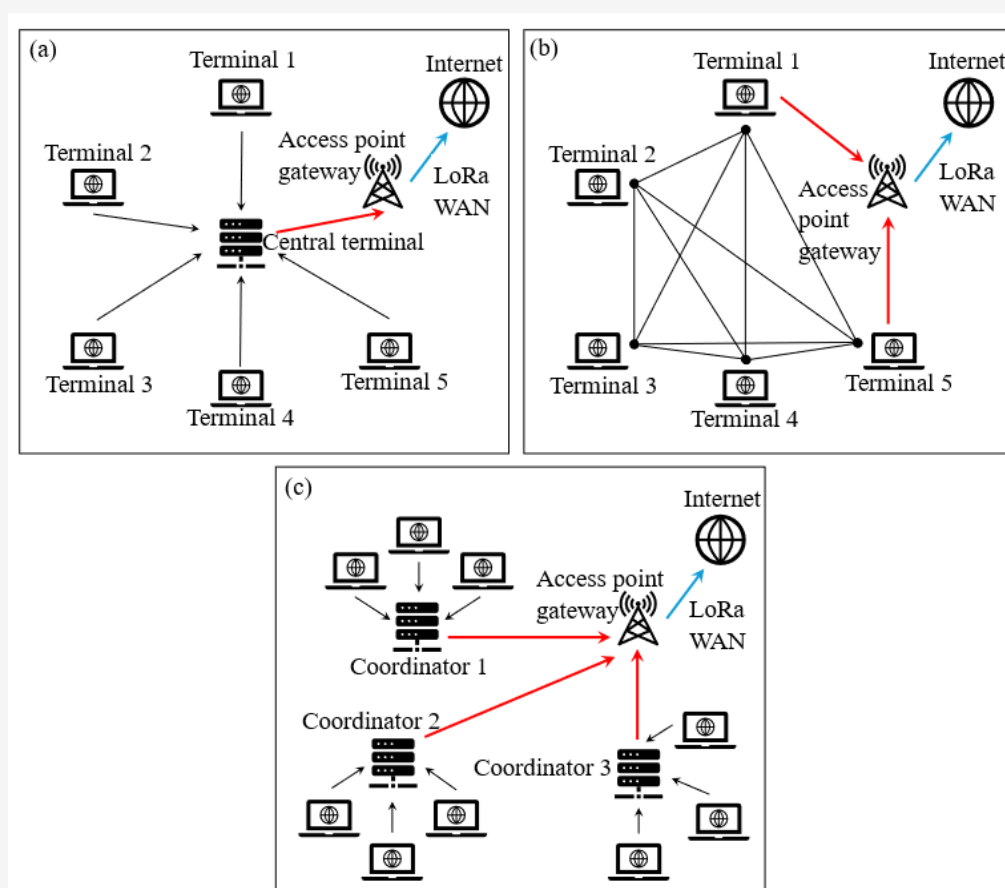
It is assumed that the sensor nodes are also equipped with GPS capability to enhance spatial referencing and improve the contextual interpretation of measurement data [59]. GPS integration enables precise geolocation tagging for every recorded dataset, which is essential for correlating air-quality variations with specific urban locations, validating deployment accuracy, and supporting spatial trend analysis in post-processing. Table 1 summarizes the key field-testing system parameters, including hardware and communication settings, and Table 2 presents the principal field-testing sensor parameters, detailing calibration, sensitivity, and measurement ranges. The parameters in both tables are completed individually for each monitoring station, ensuring that performance variations across locations are explicitly documented for a robust and reproducible evaluation.

Table 1: Parameters of the field – testing

Zone Name	Location	Station Name	Address	Height of Air Intake (m)
Yorkdale	43°43'29.5" N 79°26'49.1" W	Sterling Hall	99 Cartwright Ave, North York, ON M6A 1V4	2
		Jane Osler Park	Cartwright Ave, Toronto, ON	2
York University	43°46'37.7" N 79°29'52.8" W	Pioneer Village	Toronto, ON M7A 2C5	2
		York Regional Rd 6	2901 Steeles Ave W, North York, ON M3J 3B2	2

Table 2: Parameters of the field testing sensors

Sensor	Serial	Alias Name	Lower Limit	Upper Limit
NO ₂	NO2_111	YD_ST_Hall_NO2_1	0	120
O ₃	O3_111	YD_ST_Hall_O3_1	0	80
PM _{2.5}	PM_111	YD_ST_Hall_PM_1	0	40

**Figure 6:** System architecture: (a) star topology, (b) mesh topology, and (c) cluster top

4.4 Dashboard

The dashboard is organized into three primary components: (1) AQHI Categories, (2) Zone-specific AQHI, and (3) Gas and Particulate Matter Pollutant Concentration Display for each station, presented in real-time using (a) a circular diagram, (b) a data

table, and (c) a point-curve chart as shown in Figure 7, Figure 8, Figure 9, and Figure 10. Each dashboard also includes an interactive icon that displays the sensor's location on a map, along with the station and zone names.

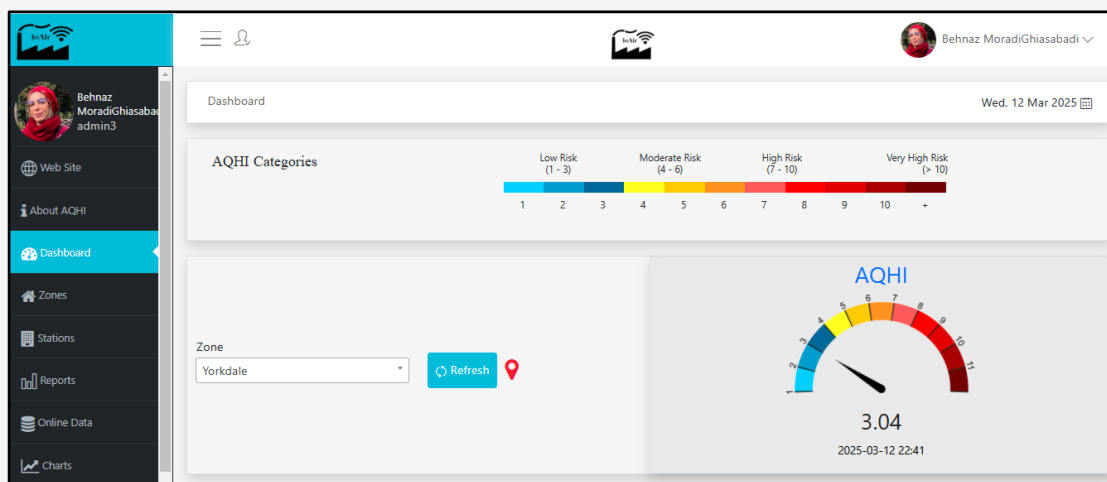


Figure 7: Dashboard display: (a) AQHI Categories, (b) Dashboard Zone

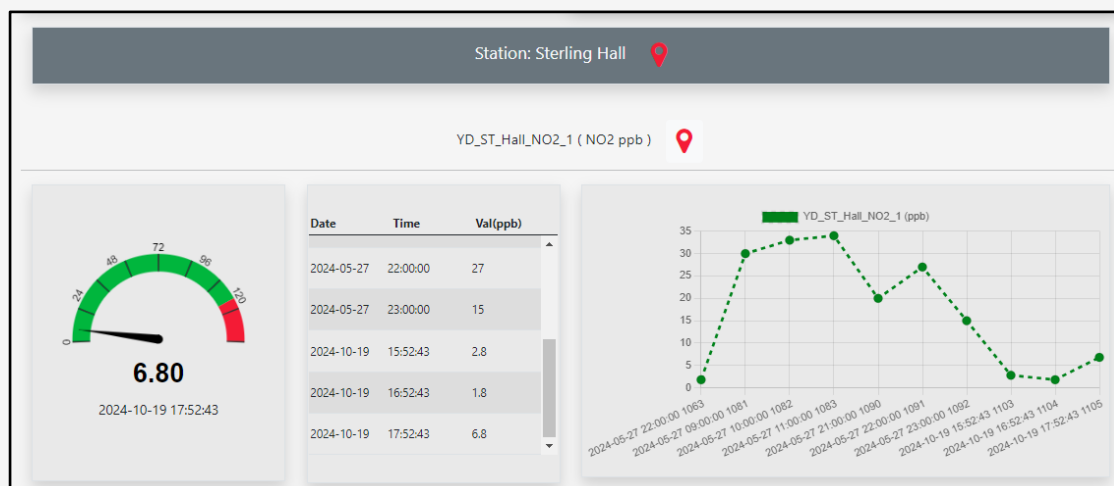


Figure 8: Dashboard display for NO₂ concentration: circular diagram: (a), table (b), and curve (c)

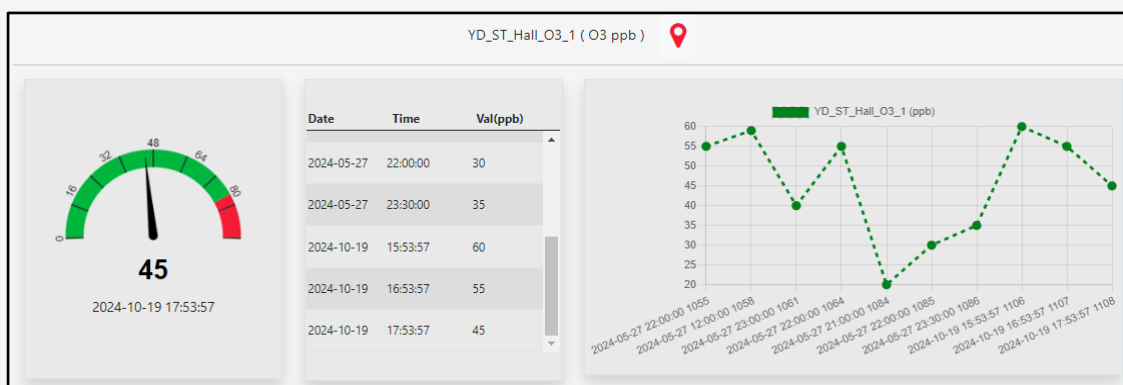


Figure 9: Dashboard display for O₃ concentration: circular diagram: (a), table (b), and curve (c)

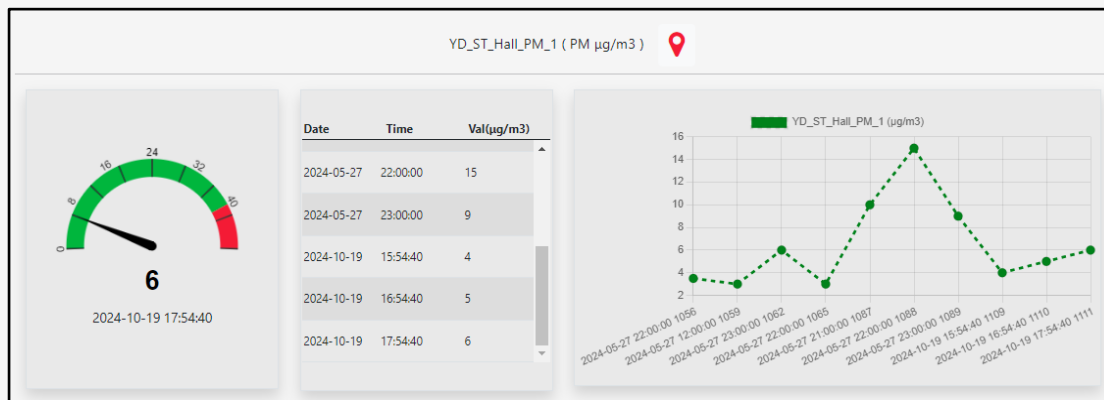


Figure 10: Dashboard display for PM_{2.5}: circular diagram: (a), table (b), and curve (c)

4.5 Analysis

As described earlier, three key air pollutants are used in calculating the AQHI. Unlike general air-quality indices, the AQHI was specifically developed in Canada to communicate the short-term health risks of exposure to air pollution, with the aim of providing timely public-health guidance. To support this purpose, the Canadian Ambient Air Quality Standards (CAAQS – <https://ccme.ca/en/air-quality-report>) define limit values for these pollutants: 200 $\mu\text{g}\cdot\text{m}^{-3}$ for NO₂, 80 $\mu\text{g}\cdot\text{m}^{-3}$ for O₃, and 40 $\mu\text{g}\cdot\text{m}^{-3}$ for PM_{2.5}. In our air-quality-monitoring system, these thresholds serve as critical reference benchmarks for interpreting sensor measurements. Table 3 presents examples of these thresholds alongside actual measured values recorded by the system. By comparing pollutant concentrations to their respective limits, the system can automatically detect exceedance events. This detection process directly informs AQHI scoring, which translates measured conditions into health-risk categories for public use.

Exceedance analysis supports the generation of alerts and recommendations that can be disseminated through the IoT cloud to user applications. For instance, if PM_{2.5} levels surpass the 40 $\mu\text{g}\cdot\text{m}^{-3}$ limit, a notification can advise sensitive groups, such as children, the elderly, or individuals with respiratory conditions, to reduce outdoor activity. Through this integrated approach, the analysis module transforms raw environmental data into actionable insights, enabling both situational awareness and timely risk-mitigation measures for the City of Toronto. Table 3 visually illustrates pollutant concentrations over selected monitoring intervals. Peaks that exceed the reference thresholds are clearly identifiable, indicating potential high-risk periods. Trend lines show how pollutant levels vary across time and geographic zones, which aids in detecting recurring patterns such as rush-hour traffic effects (for NO₂) or seasonal ozone increases. Color-coded AQHI categories embedded in the charts provide an

immediate visual link between numerical values and public-health implications, allowing users to interpret air quality trends quickly. This combined visual and numerical representation enhances situational awareness and supports both real-time decision-making and long-term environmental planning.

Table 3: Concentration points for PM_{2.5}

AQHI	PM _{2.5} ($\mu\text{m}\cdot\text{m}^{-3}$)
0	0
1-3	1-10
4-6	10-20
7-10	20-40
>10	>40

Based on the completed system design, a field trial was conducted for the developed IoT-based air-quality monitoring platform, using the AQHI methodology adopted in Ontario, Canada. The trial collected real-time measurements of key air pollutants across predefined zones, each equipped with dedicated sampling stations. Given the system's low cost, a virtually unlimited number of monitoring stations can be deployed, enabling extensive spatial coverage and high-resolution data acquisition. This scalability supports statistically robust generalization of results within acceptable confidence ranges and facilitates near-real-time AQHI computation. In Canadian practice, the AQHI assigns a numerical value from 1 to +10 to indicate the health-risk level associated with local air quality. For this project, the standard 10-point scale was supplemented by a four-category descriptor, Low, Moderate, High, and Very High, to improve interpretability for non-specialist users. Under severe pollution conditions, AQHI values may exceed 10. Importantly, as even low pollutant concentrations can trigger adverse effects in sensitive populations, the index is defined as a

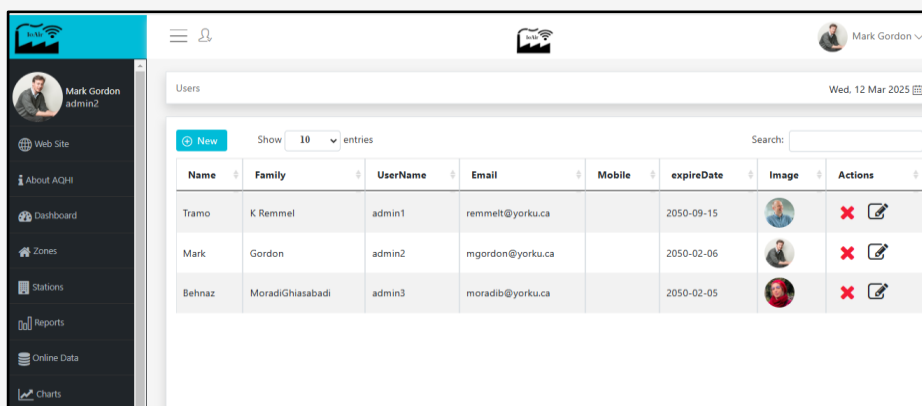
continuum: higher values correspond to greater health risk and a stronger need for precautionary measures.

Sensor readings at each station were first processed to determine pollutant levels and presented via tables, dot/column charts, and circular charts, where critical thresholds are highlighted in red. Subsequently, the zone-level AQHI values were computed by averaging station readings and applying the designated AQHI algorithm and formula. The calculated values were then visualized in circular diagrams within the system's dashboard interface. In addition to reporting current local air-quality conditions, the AQHI module provides a three-hourly forecast of expected maximum values, along with associated health recommendations. The processed monitoring data is displayed in interactive graphical formats through the system's web application, accessible to users via the Internet (Figure 11). Furthermore, results can be exported to tabular format in Excel for offline analysis and reporting. Examples of exported data tables are provided in Table 4.

4.6 Quantitative Analysis of Node-Level Energy Efficiency

Building upon the simulation-based modeling described, this subsection quantitatively analyzes the node-level power performance under the adaptive control mechanism. The analysis aims to demonstrate the explicit impact of pollutant-aware transmission scheduling on energy consumption across individual LoRaWAN end nodes. Based on the simulation outcomes derived from real air-quality datasets for the York District (Toronto), the average node-level energy consumption decreased from 0.93 Wh to 0.71 Wh, representing an observed 23% improvement in energy efficiency. This reduction resulted from adaptive adjustments of the transmission interval (Δt) and transmit power (P_{tx}) in response to real-time variations in the pollutant

concentrations of O_3 , NO_2 , and $PM_{2.5}$. The results highlight that dynamic control of data rate and transmit power, integrated through the Adaptive Data Rate (ADR) – the only mode, can minimize redundant transmissions while retaining communication reliability within the LoRa WAN framework. These findings validate the effectiveness of the simulation-based model developed in Section 3.4 and provide strong practical evidence of its scalability for implementation across Ontario. Consequently, the observed reduction from 0.93 Wh to 0.71 Wh per node indicates that the proposed adaptive control achieved an average energy saving of 0.22 Wh per transmission cycle. When expressed according to the International System of Units (SI), 0.22 Wh corresponds to 0.00022 kWh per cycle. For typical LoRaWAN air quality monitoring that transmits four data packets per hour (96 per day), the total annual number of uplinks per node is approximately 35 040. Thus, the total yearly energy saved per node equal $0.00022 \text{ kWh} \times 35\,040 \approx 7.7 \text{ kWh}$. Using the average electricity cost in Ontario ($\approx 0.20 \text{ USD per kWh}$), this translates into $7.7 \times 0.20 = 1.54 \text{ USD}$ saved per node each year. Assuming a moderate province-wide deployment of one million active nodes over a 25 year time span (2025-2050), the cumulative energy saving is approximately $1\,000\,000 \times 1.54 \times 25 \approx 38.5$ million USD. Even under conservative projection scenarios (with lower power costs or reduced transmission frequencies), the net saving would remain within the 15-20 million USD range by 2050. The demonstrated 23% efficiency gain therefore reinforces both the theoretical foundation and the long-term environmental and economic relevance of the proposed framework within the Ontario context. Thus, the ability to acquire fine-grained AQHI data in near real-time, at low energy cost, is attractive from an adoption and roll-out perspective for any government or organization.



The screenshot shows a web application interface. On the left is a dark sidebar with navigation options: Web Site, About AQHI, Dashboard, Zones, Stations, Reports, Online Data, and Charts. The main content area is titled 'Users' and shows a table with columns: Name, Family, UserName, Email, Mobile, expireDate, Image, and Actions. The table contains three rows of user data.

Name	Family	UserName	Email	Mobile	expireDate	Image	Actions
Tramo	K Rimmel	admin1	remmelt@yorku.ca		2050-09-15		
Mark	Gordon	admin2	mgordon@yorku.ca		2050-02-06		
Behnaz	MoradiGhasabadi	admin3	moradilib@yorku.ca		2050-02-05		

Figure 11: Web application display

Table 4: Sample monitoring data

Zone	Station	Sensor Name	Sensor	Date	Time	Value
York U	Pioneer Village	Y.U_Pioneer_NO ₂ _1	NO ₂	2024-10-13	16:37:42	1.8
					15:37:32	3.6
					14:37:33	2.8
		Y.U_Pioneer_O ₃ _1	O ₃	2024-10-13	16:37:42	55.0
	15:37:32				45.0	
	14:37:33				60.0	
		Y.U_Pioneer_PM_1	PM	2024-10-13	16:37:42	6.0
	15:37:21				5.0	
	14:37:53				4.0	

5. Conclusions

This study introduced an IoT-based AQHI monitoring system, leveraging LoRaWAN communication technology, designed to provide reliable, localized, and real-time assessment of air quality conditions. The system incorporates a tailored web application that separately displays the real-time measurements of O₃, NO₂, and PM_{2.5}, and computes and presents the integrated AQHI value using the official Canadian AQHI algorithm, alongside historical data storage and analytical features within a user-friendly dashboard. By combining low-cost sensors, modular hardware, LoRa WAN wireless connectivity, and scalable architecture, the proposed design addresses the high cost, large size, and limited spatial coverage of conventional air monitoring stations. The deployment results confirm that the IoT-enabled approach with LoRaWAN enhances both temporal and spatial resolution of air quality data while remaining cost-effective, compact, and scalable. The inclusion of PM_{2.5}, a pollutant whose continuous, accurate measurement is technically challenging, marks a scientific and practical advantage, broadening the applicability of this system in urban environments globally. Nonetheless, while the system achieves high granularity, portability, and accessibility, it shares common limitations of low-cost sensors, including sensitivity drift, calibration dependency, and susceptibility to extreme meteorological conditions. Such challenges can be mitigated through periodic calibration, algorithmic correction, and sensor fusion techniques. Future enhancements include deploying denser LoRaWAN-based sensor networks in metropolitan areas, integrating machine learning models for short-term pollutant concentration prediction, and aligning system outputs with public health advisory platforms. With these improvements, the proposed system can serve as a scalable model for policymakers, urban planners, and environmental health agencies aiming to safeguard public well-being in rapidly urbanizing regions.

5.1 Future Work

In the next phase, the research will advance into a fully practical implementation stage, emphasizing the in-house design, development, and fabrication of air-quality sensors by the research team itself. Building upon the current phase, where the data-processing algorithms and software architecture were entirely defined and implemented by our team, the upcoming stage aims to engineer customized sensing units capable of real-time pollutant sampling and measurement at designated monitoring stations. Part of the future work will also require the testing of sensor stability and cross-referencing with calibrated sensors to assess windows and timelines for sensor calibration, cleaning, and maintenance. We expect that statistical analyses of sensitivity to specific inputs will further allow us to identify when sensor readings become suspect. By developing hardware ourselves, we strengthen the project's research autonomy and promote technological self-sufficiency, reducing dependence on commercial sensor modules. Ultimately, the system's integrated software-hardware framework will establish a sustainable and scalable model for long-term, high spatial and temporal resolution measurement of AQHI in urban environments. Once densely distributed sensors begin delivering spatio-temporal data, the subsequent spatial analysis (e.g., cluster detection, trends) becomes possible and further elevates the potential benefits that would stem from the current work.

References

- [1] Fransen, J., Van Dijk, M. P. and Edelenbos, J., (2021). *Urban Paradigm Shifts in Emerging Economies*. In: *Urban Planning, Management and Governance in Emerging Economies*. Edward Elgar Publishing, Massachusetts. 1-19. <https://doi.org/10.4337/9781800883840.00007>

- [2] Ma, Y., Yang, S., Huang, Z., Hou, Y., Cui, L. and Yang, D., (2014). Hierarchical Air Quality Monitoring System Design. *International Symposium on Integrated Circuits (ISIC)*, IEEE, Singapore, 284–287. <http://doi.org/10.1109/ISICIR.2014.7029544>.
- [3] Moursi, A. S., El-Fishawy, N., Djahel, S. and Shouman, M. A., (2021). An IoT Enabled System for Enhanced Air Quality Monitoring and Prediction on the Edge. *Complex Intelligent Systems*, Vol. 7(6); 2923–2947. <http://doi.org/10.1007/s40747-021-00476-w>.
- [4] Dhingra, S., Madda, R. B., Gandomi, A. H., Patan, R. and Daneshmand, M., (2019). Internet of Things Mobile–Air Pollution Monitoring System (IoT-Mobair). *IEEE Internet of Things Journal*, Vol. 6(3); 5577–5584. <http://doi.org/10.1109/JIOT.2019.2903821>.
- [5] Shah, H. N., Khan, Z., Merchant, A. A., Moghal, M., Shaikh, A. and Rane, P., (2018). IOT Based Air Pollution Monitoring System. *International Journal of Scientific & Engineering Research*, Vol. 9(2); 62–66.
- [6] Zheng, K., Zhao, S., Yang, Z., Xiong, X. and Xiang, W., (2016). Design and Implementation of LPWA-Based Air Quality Monitoring System. *IEEE Access*, Vol. 4; 3238–3245. <http://doi.org/10.1109/ACCESS.2016.2582153>
- [7] Adebisi, F. M., (2022). Air Quality and Management in Petroleum Refining Industry: A Review. *Environmental Chemistry and Ecotoxicology*, Vol. 4; 89–96. <http://doi.org/10.1016/j.enceco.2022.02.001>.
- [8] Cheng, G., Lin, Y., Abur, A., Gómez-Expósito, A. and Wu, W., (2024). A Survey of Power System State Estimation Using Multiple Data Sources: PMUs, SCADA, AMI, and Beyond. *IEEE Transactions on Smart Grid*, Vol. 15(1); 1129–1151. <http://doi.org/10.1109/TSG.2023.3286401>.
- [9] Shukri, S., Asmat, A., Rahiman, M., Japeiri, A., and Sahwee, Z. (2024). Real-time Vertical Air Quality Monitoring System Development for Urban Scale. *International Journal of Geoinformatics*, Vol. 20(8). <https://doi.org/10.52939/ijg.v20i8.3463>.
- [10] Shaban, K. B., Kadri, A. and Rezk, E., (2016). Urban Air Pollution Monitoring System with Forecasting Models. *IEEE Sensors Journal*, Vol. 16(8); 2598–2606. <http://doi.org/10.1109/JSEN.2016.2514378>.
- [11] Paithankar, D. N., Pabale, A. R., Kolhe, R. V., William, P. and Yawalkar, P. M., (2023). Framework for Implementing Air Quality Monitoring System using LPWA-based IoT technique. *Measurement: Sensors*, Vol. 26. <http://doi.org/10.1016/j.measen.2023.100709>.
- [12] Ye Y. and Geng, P., (2023). A Review of Air Pollution Monitoring Technology for Ports. *Applied Science*, Vol. 13(8). <http://doi.org/10.3390/app13085049>.
- [13] Kumar, P., Singh, A. B., Arora, T., Singh, S. and Singh, R., (2023). Critical Review on Emerging Health Effects Associated with the Indoor Air Quality and its Sustainable Management. *Science of the Total Environment*, Vol. 872. <http://doi.org/10.1016/j.scitotenv.2023.162163>.
- [14] Ni, Q., Wang, Y. and Yuan, J., (2023). Adaptive Scalable Spatio-temporal Graph Convolutional Network for PM2.5 Prediction. *Engineering Applications of Artificial Intelligence*, Vol. 126. <http://doi.org/10.1016/j.engappai.2023.107080>
- [15] Kuncoro, A. H., Mellyanawaty, M., Sambas, A., Maulana, D. S., Subiyanto, and Mamat, M., (2020). Air Quality Monitoring System in the City of Tasikmalaya Based on the Internet of Things (IoT). *Journal of Advanced Research in Dynamical & Control Systems*, Vol. 12(2); 2473–2479. <https://www.jardcs.org/abstract.php?id=4464>.
- [16] Lounas, R., Salhi, D. E., Mokrani, H., Djerbi, R. and Bennai, M. T., (2019). Towards a Smart Data Transmission Strategy for IoT Monitoring Systems: Application to Air Quality Monitoring. *IEEE International Conference on Theoretical and Applicative Aspects of Computer Science (ICTAACS)*, Skikda, Algeria, 1–7. <http://doi.org/10.1109/ICTAACS48474.2019.8988119>.
- [17] Brijesh, S. A., Jha, S., Dinkar, S. A., Zuber, M. U. and Rajesh, S. A., (2023). A Review on Various Methods Employed to Measure Air Quality in the Vicinity Using Internet of Things. *IEEE 5th Biennial International Conference on Nascent Technologies in Engineering (ICNTE)*, Navi Mumbai, India, 1–6. <http://doi.org/10.1109/ICNTE56631.2023.10146634>.
- [18] Lai, C. S., Jia, Y., Dong, Z., Wang, D., Tao, Y., Wong, R. T. K., Zobia, A. F., Wu, R. and Lai, L. L., (2020). A Review of Technical Standards for Smart Cities. *Clean Technology*, Vol. 2(3); 290–310. <http://doi.org/10.3390/cleantechnol2030019>.

- [19] Chourabi, H., Nam, T., Walkder, S., Gil-Garcia, J. R., Mellouli, S., Nahon, K., Pardo, T. A. and Scholl, H. J., (2012). Understanding Smart Cities: An Integrative Framework. *IEEE 45th Hawaii International Conference on System Sciences*, Maui, HI, USA, 2289–2297. <http://doi.org/10.1109/HICSS.2012.615>.
- [20] Gouldson, A., Kerr, N., Millward-Hopkins, J., Freeman, M. C., Topi, C. and Sullivan, R., (2015). Innovative Financing Models for Low Carbon Transitions: Exploring the Case for Revolving Funds for Domestic Energy Efficiency Programmes. *Energy Policy*, Vol. 86; 739–748. <http://doi.org/10.1016/j.enpol.2015.08.012>.
- [21] Landrigan, P. J., Fuller, R., Acosta, N. J. R., Adeyi, O., Arnold, R., Basu, N. N., Baldé, A. B., Bertollini, R., Bose-O'Reilly, S., Boufford, J. I., Breyse, P. N., Chiles, T., Mahidol, C., Coll-Seck, A. M., Cropper, M. L., Fobil, J., Fuster, V., Greenstone, M., Haines, A., Hanrahan, D., Hunter, D., Khare, M., Krupnick, A., Lanphear, B., Lohani, B., Martin, K., Mathiasen, K. V., McTeer, M. A., Murray, C. J. L., Ndahimananjara, J. D., Perera, F., Potočnik, J., Preker, A. S., Ramesh, J., Rockström, J., Salinas, C., Samson, L. D., Sandilya, K., Sly, P. D., Smith, K. R., Steiner, A., Stewart, R. B., Suk, W. A., van Schayck, O. C. P., Yadama, G. N., Yumkella, K. and Zhong, M., (2018). The Lancet Commission on Pollution and Health. *The Lancet*, Vol. 391(10119); 462–512. [http://doi.org/10.1016/S0140-6736\(17\)32345-0](http://doi.org/10.1016/S0140-6736(17)32345-0).
- [22] Serban, A. C. and Lytras, M. D., (2020). Artificial Intelligence for Smart Renewable Energy Sector in Europe Smart Energy Infrastructures for Next Generation Smart Cities. *IEEE Access*, Vol. 8; 77364–77377. <http://doi.org/10.1109/ACCESS.2020.2990123>
- [23] Asha, P., Natayan, L., Geetha, B. T., Beulah, J. R., Sumathy, R., Varalakshmi, G. and Neelakandan, S., (2022). IoT Enabled Environmental Toxicology for Air Pollution Monitoring Using AI Techniques. *Environmental Research*, Vol. 205. <http://doi.org/10.1016/j.envres.2021.112574>.
- [24] Senthilkumar, R., Venkatakrishnan, P. and Balaji, N., (2020). Intelligent Based Novel Embedded System Based IoT Enabled Air Pollution Monitoring System. *Microprocessors and Microsystems*, Vol. 77. <http://doi.org/10.1016/j.micpro.2020.103172>.
- [25] Clements, A., Duvall, R. Greene, D. and Dye, T., (2022). The Enhanced Air Sensor Guidebook. *United States Environmental Protection Agency, EPA/600/R-22/213* [Online]. Available: <https://globaldesigningcities.org/resource/eap-the-enhanced-air-sensor-guidebook/> [Accessed: Jan. 16, 2026].
- [26] Malleswari S. M. S. D. and Mohana, T. K., (2022). Air Pollution Monitoring System Using IoT Devices: Review. *Materials Today: Proceedings*, Vol. 51; 1147–1150. <http://doi.org/10.1016/j.matpr.2021.07.114>.
- [27] Martín-Baos, J. Á., Rodríguez-Benitez, L. García-Ródenas, R. and Liu, J., (2022). IoT Based Monitoring of Air Quality and Traffic Using Regression Analysis. *Applied Soft Computing*, Vol. 115. <http://doi.org/10.1016/j.asoc.2021.108282>.
- [28] He, Y., Guo, X., Zheng, X., Yu, Z., Zhang, J. Jiang, H. Na, X. and Zhang, J. (2023). Cross-Technology Communication for the Internet of Things: A Survey. *ACM Computing Surveys*, Vol. 55(5); 1–29. <http://doi.org/10.1145/3530049>.
- [29] Peng, C., Qian, K. and Wang, C., (2015). Design and Application of a VOC-Monitoring System Based on a ZigBee Wireless Sensor Network. *IEEE Sensors Journal*, Vol. 15(4); 2255–2268. <http://doi.org/10.1109/JSEN.2014.2374156>.
- [30] Yang Y. and Li, L., (2015). A Smart Sensor System for Air Quality Monitoring and Massive Data Collection. *IEEE International Conference on Information and Communication Technology Convergence (ICTC)*, Jeju Island, South Korea, 147–152. <http://doi.org/10.1109/ICTC.2015.7354515>.
- [31] Siddiqui, S. A., Fatima, N. and Ahmad, A., (2021). Smart Air Pollution Monitoring System with Smog Prediction Model using Machine Learning. *International Journal of Advanced Computer Science and Applications*, Vol. 12(8); 401–409. <http://doi.org/10.14569/IJACS.A.2021.0120846>.
- [32] Ramadan, M. N. A., Ali, M. A. H., Khoo, S. Y., Alkhedher, M. and Alherbawi, M., (2024). Real-time IoT-Powered AI System for Monitoring and Forecasting of Air Pollution in Industrial Environment. *Ecotoxicology and Environmental Safety*, Vol. 283. <http://doi.org/10.1016/j.ecoenv.2024.116856>.

- [33] Gryech, I., Asaad, C., Ghogho, M. and Kobbane, A., (2024). Applications of Machine Learning & Internet of Things for Outdoor Air Pollution Monitoring and Prediction: A Systematic Literature Review. *Engineering Applications of Artificial Intelligence*, Vol. 137. <http://doi.org/10.1016/j.engappai.2024.109182>
- [34] Pal, P., Gupta, R., Tiwari, S. and Sharma, A. (2017). IoT Based Air Pollution Monitoring System Using Arduino. *International Research Journal of Engineering and Technology (IRJET)*, Vol. 4(10); 1137–1140.
- [35] Mamun, M. A. A. and Yuce, M. R., (2019). Sensors and Systems for Wearable Environmental Monitoring Toward IoT-Enabled Applications: A Review. *IEEE Sensors Journal*, Vol. 19(18); 7771–7788. <http://doi.org/10.1109/JSEN.2019.2919352>.
- [36] Koyana, N., Markus, E. D. and Abu-Mahfouz, A. M., (2019). A Survey of Network and Intelligent air pollution monitoring in South Africa. *IEEE International Multidisciplinary Information Technology and Engineering Conference (IMITEC)*, Vanderbijlpark, South Africa, 1–7. <http://doi.org/10.1109/IMITEC45504.2019.9015916>.
- [37] Hawari, H. F., Zainal, A. A. and Ahmad, M. R., (2019). Development of Real Time Internet of Things (IoT) Based Air Quality Monitoring System. *Indonesian Journal of Electrical Engineering and Computer Science*, Vol. 13(3). <http://doi.org/10.11591/ijeecs.v13.i3.pp1039-1047>.
- [38] Stieb, D. M., Burnett, R. T., Smith-Doiron, M., Brion, O., Shin, H. H. and Economou, V. (2008). A New Multipollutant, No-Threshold Air Quality Health Index Based on Short-Term Associations Observed in Daily Time-Series Analyses. *Journal of the Air & Waste Management Association*, Vol. 58(3); 435–450. <http://doi.org/10.3155/1047-3289.58.3.435>.
- [39] Rosli, M. I. and Ahmad, M. R., (2021). Internet of Things Monitoring System of a Modeled Cleanroom. *ELEKTRIKA – Journal of Electrical Engineering*, Vol. 20(3); 7–14. <http://doi.org/10.11113/elektrika.v20n3.283>.
- [40] Yi, W., Lo, K., Mak, T., Leung, K., Leung, Y. and Meng, M., (2015). A Survey of Wireless Sensor Network Based Air Pollution Monitoring Systems. *Sensors*, Vol. 15(12); 31392–31427. <http://doi.org/10.3390/s151229859>.
- [41] Mena, C. C., Macias, J. A. S., Huerta, L. C., Ochoa, J. A. R., Calleros, S. J. and Sánchez-Pérez, A., (2025). Design and Implementation of a Distributed IoT System for Monitoring of Gases Emitted by Vehicles That Use Biofuels. *Sustainability*, Vol. 17(3); 1153. <http://doi.org/10.3390/su17031153>.
- [42] Phasinam, T., Phasinam, K., U-kaew, A., Piyathamrongchai, K., Hataitara, R., Raghavan, V., Nemoto, T., and Choosumrong, S. (2024). Real-Time Monitoring and Positioning of Agricultural Tractors Using a Low-Cost GPS and IoT Device. *International Journal of Geoinformatics*, Vol. 21(1), 111–120. <https://doi.org/10.52939/ijg.v21i1.3799>.
- [43] Collado, E., Calderón, S., Cedeño, B., De León, O., Centella, M., García, A. and Sáez, Y., (2024). Open-Source Internet of Things (IoT)-Based Air Pollution Monitoring System with Protective Case for Tropical Environments. *HardwareX*, Vol. 19. <http://doi.org/10.1016/j.ohx.2024.e00560>.
- [44] Hassan, A. K., Saraya, M. S., Ali-Eldin, A. M. T. and Abdelsalam, M. M., (2024). Low-Cost IoT Air Quality Monitoring Station Using Cloud Platform and Blockchain Technology. *Applied Sciences*, Vol. 14(13). <http://doi.org/10.3390/app14135774>.
- [45] Sabado, W., (2024). The Use of Microcontrollers in Air Quality Monitoring: A Systematic Literature Review. *International Journal of Computing Sciences Research*, Vol. 8; 3298–3327. <http://doi.org/10.25147/ijcsr.2017.001.1.219>.
- [46] Hahm, O., Baccelli, E., Petersen, H. and Tsiftes, N., (2016). Operating Systems for Low-End Devices in the Internet of Things: A Survey. *IEEE Internet of Things Journal*, Vol. 3(5); 720–734. <http://doi.org/10.1109/JIOT.2015.2505901>.
- [47] Maurya, P., Hazra, A., Kumari, P., Sørensen, T. B. and Das, S. K., (2025). A Comprehensive Survey of Data-Driven Solutions for LoRaWAN: Challenges and Future Directions. *ACM Transactions on Internet of Things*, Vol. 6(1); 1–36. <http://doi.org/10.1145/3711953>.
- [48] Almajed, R., Abedallah, Z., Almazaydeh, L. and Ghwanmeh, S. (2023). The Role of Internet of Things in Smart City Environmental Monitoring: A Pollution Detection System. *Journal of Intelligent Systems and Internet of Things*, Vol. 9(2); 239–248. <http://doi.org/10.54216/JISIoT.090218>.

- [49] William, P., Kiran, Y. V. U., Rana, A., Gangodkar, D., Khan, I. and Ashutosh, K., (2022). Design and Implementation of IoT based Framework for Air Quality Sensing and Monitoring. *IEEE 2nd International Conference on Technological Advancements in Computational Sciences (ICTACS)*, Tashkent, Uzbekistan, 197–200. <http://doi.org/10.1109/ICTACS56270.2022.9988646>.
- [50] Prajitha, C., Sridhar, K. P., Deepa, S., Baskar, S. and Abubeker, K. M., (2023). Air Pollution Detection and Monitoring with the Smart Sensor Interface on the IoT Platform. *IEEE Annual International Conference on Emerging Research Areas: International Conference on Intelligent Systems (AICERA/ICIS)*, Kanjirapally, India, 1–7. <http://doi.org/10.1109/AICERA/ICIS59538.2023.10420141>.
- [51] Li, X., Iervolino, E., Santagata, F., Wei, J., Yuan, C. A., Sarro, P. M. and Zhang, G. Q., (2014). Miniaturized Particulate Matter Sensor for Portable Air Quality Monitoring Devices. *IEEE SENSORS Proceedings*, Valencia, Spain, 2151–2154. <http://doi.org/10.1109/ICSENS.2014.6985464>.
- [52] Xiong, X., Wu, T., Long, H. and Zheng, K., (2014). Implementation and Performance Evaluation of LECIM for 5G M2M Applications with SDR. *IEEE Globecom Workshops (GC Wkshps)*, Austin, TX, USA, 612–617. <http://doi.org/10.1109/GLOCOMW.2014.7063500>.
- [53] Alam, M. Islam, Md. M., Nayan, N. M. and Uddin, J., (2024). An IoT Based Real-Time Environmental Monitoring System for Developing Areas. *Journal of Advanced Research in Applied Sciences and Engineering Technology*, Vol. 52(1); 106–121. <http://doi.org/10.37934/araset.52.1.106121>.
- [54] Gondkar, S. S., William, P. and Pardeshi, D. B., (2022). Design of a Novel IoT Framework for Home Automation using Google Assistant. *IEEE 6th International Conference on Intelligent Computing and Control Systems (ICICCS)*, Madurai, India, 451–454. <http://doi.org/10.1109/ICICCS53718.2022.9788284>.
- [55] Mahetaliya, S., Makwana, D., Pujara, A. and Hanumante, S., (2021). IoT Based Air Quality Index Monitoring Using ESP32. *International Research Journal of Engineering and Technology (IRJET)*, Vol. 8(4); 5186–5191.
- [56] Morchid, A., El Alami, R., Raezah, A. A. and Sabbar, Y., (2024). Applications of Internet of Things (IoT) and Sensors Technology to Increase Food Security and Agricultural Sustainability: Benefits and Challenges. *Ain Shams Engineering Journal*, Vol. 15(3). <http://doi.org/10.1016/j.asej.2023.102509>.
- [57] Jafari, S. N. and Silva, B. M. C., (2025). A Survey on Real-Time Data Transfer and Energy Consumption Strategies for Rural and Remote IoT Technologies. *IEEE Open Journal of the Computer Society*, Vol. 6; 1686–1702. <http://doi.org/10.1109/OJCS.2025.3619210>.
- [58] Leal, S. V. A., Nelson, J., Asmare, L., Mahmood, A., Mitchell, G., Tenkorang, K., Todd, C., Campbell, B. and Goodall, J. L., (2023). A Cloud-Based Data Storage and Visualization Tool for Smart City IoT: Flood Warning as an Example Application. *Smart Cities*, Vol. 6(3); 1416–1434. <http://doi.org/10.3390/smartcities6030068>.
- [59] Taj, S., Imran, A. S., Kastrati, Z., Daudpota, S. M., Memon, R. A. and Ahmed, J., (2023). IoT-Based Supply Chain Management: A Systematic Literature Review. *Internet of Things*, Vol. 24. <http://doi.org/10.1016/j.iot.2023.100982>.