Advancing Safety in Industry: A Wireless Multisensory Approach to Toxic Gas Detection Enhanced by AI and ML

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ABSTRACT:

In the context of industrial landscape, where the diverse applications of gases range from food preservation to specialized medical treatments, the imperative for advanced safety measures is more pronounced than ever. The extensive deployment of gases, despite their indispensable benefits, introduces the peril of toxic gas leaks, posing a formidable challenge to both human safety and operational integrity within industrial settings. Traditional gas detection systems, often hampered by wired infrastructures, limited reach, and high operational costs, fall short of addressing these challenges effectively. Recognizing these gaps, this paper introduces a pioneering solution: A system for detecting toxic gases wirelessly using multiple sensors. enhanced by Artificial Intelligence (AI) and Machine Learning (ML) methodologies. This system not only aims to revolutionize the remote monitoring and detection of hazardous gases such as Cl2, CO, NO2, and SO2 but also represents a paradigm shift towards leveraging cutting-edge technologies to ensure environmental safety and protect human lives in industrial contexts.

Keywords:Industrial Safety, Wireless Sensory Systems, Toxic Gas Detection, Artificial Intelligence, Machine Learning, Hazardous Gas Monitoring, Environmental Safety, Industrial Risk Management.

INTRODUCTION:

In a dynamic industrial environment where gases find diverse applications ranging from essential tasks like food preservation to intricate medical procedures, the need for advanced safety measures is paramount. Despite the manifold benefits of gases, the persistent threat of toxic gas leaks poses a significant challenge to both human well-being and operational continuity within industrial settings. Traditional gas detection systems, constrained by their reliance on wired infrastructure, limited coverage areas, and prohibitive operational costs, struggle to effectively mitigate these risks. [2,3] Recognizing these shortcomings, this study introduces a revolutionary solution: a wireless multisensory system for toxic gas detection, integrated with Artificial Intelligence (AI) and Machine Learning (ML) methodologies. With a primary aim to revolutionize the monitoring and detection of hazardous gases such as Cl_2, CO, NO_2, and SO_2, [4] this innovative system represents a paradigm shift in industrial safety practices, harnessing cutting-edge technologies to uphold environmental integrity and safeguard human lives. [31,29]

This innovative approach reflects a collaborative endeavor at the intersection of engineering and safety sciences, seeking to address critical gaps in conventional gas detection techniques. Through the integration of wireless sensory systems and the augmentation with AI and ML algorithms, this research strives to improve accuracy, efficiency, and breadth of toxic gas detection within industrial settings.[16] Furthermore, beyond its immediate application in hazard mitigation, this system holds broader implications for industrial risk management and environmental conservation. By embracing state-of-the-art technologies, this study not only proposes a ground-breaking solution to

contemporary challenges but also lays the groundwork for future advancements in industrial safety standards, fostering a safer and more sustainable industrial environment. [9]

RELATED WORK:

Comprehensive System Architecture and Gas Identification

Approach System Design Overview: Detection system comprises testing apparatus, communication nodes, and a centralized control center. Its primary function is to gather information regarding four varieties of hazardous gases (Cl_2, CO, NO_2, and SO_2), along with environmental temperature and humidity, at across manufacturing locations via multisensory modules. This information is then integrated using microprocessor STM32F107VCT6 and transmitted to control center via the wireless ZigBee communication module, while also managing the movement of detection equipment. [24] Movement of this equipment is guided by specific instructions for avoidance of obstacles on the road and detection of gas emissions detection. These instructions are generated by control center, utilizing real-time visual data of industrial site obtained through a multidirectional wireless camera with adjustable orientation. [21,25] Information relay station comprises ZigBee data relay stations and Wi-Fi video relay stations. Former facilitates the transition of data collected from detection equipment to the control center and vice versa, while the latter transmits video captured by camera to control center and conveys rotation instructions from control center to detection equipment. Control center provides an intuitive display of toxic gas information and real-time visual feeds, allowing for precise control of detection equipment based on the camera's movements. Socially-Oriented Emotional Intelligence Constructs. [6]

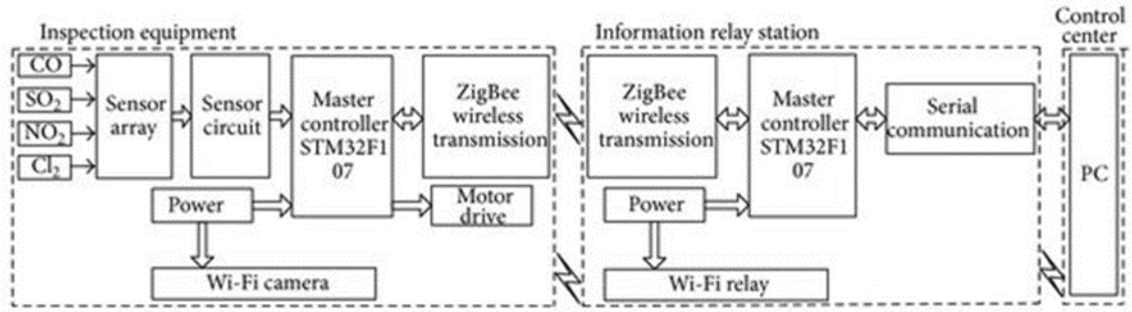

Figure 1: The block diagram of overall system. [31]

Gas Recognition Method: When four-way gas sensor of detection equipment encounters toxic gases in an industrial setting, it initiates a qualitative identification process to determine whether the gas is oxidizing or reducing. If identified as an oxidizing gas, the sensitivity analysis of data collected from the two front oxidizing gas sensors assists in identifying whether the test gas is Cl2 or NO. If the sensitivity analysis indicates that the Cl2 sensor is more responsive, the system proceeds to utilize the present Cl2 quantitative identification model to ascertain the precise gas concentration. Which is depicted in Figure 1.

System Hardware and Software Design: The hardware configuration of the toxic gas detection system encompasses a variety of elements geared towards ensuring efficient and dependable operation. Fundamental to this setup is the circuitry tasked with interfacing with the sensor modules, processing sensor data, and facilitating communication with the control center. Given the operational range of the four toxic gas sensors between 10 K to 300 K Ω, the circuit design must be adaptable to accommodate this variability to ensure precise detection and measurement. This necessitates the implementation of suitable signal conditioning circuits to translate the fluctuating resistances of the sensors into voltage signals compatible with the microcontroller. Moreover, incorporating circuitry for power management, voltage regulation, and noise filtration is crucial to uphold the stability and integrity of the system's performance across diverse industrial environments.

The design of the sensor modules is pivotal in determining the overall efficacy of the toxic gas detection system. These modules are entrusted with capturing data concerning the presence and concentration of toxic gases, alongside environmental factors such as temperature and humidity. Each sensor module integrates four toxic gas sensors, each possessing distinct sensitivities to specific gases. To accommodate the resistive characteristics of these sensors and ensure precise measurement, the module's design incorporates precision voltage dividers and analog-to-digital converters (ADCs) to convert sensor outputs into digital data for subsequent processing. Additionally, robust packaging and environmental sealing are imperative to shield the sensors from harsh industrial conditions, thus guaranteeing prolonged reliability and endurance. Concurrently with hardware development, the software architecture of the toxic gas detection system plays a vital role in its functionality and performance. At the core of this software framework lies the firmware executing on the microcontroller, tasked with sensor data acquisition, processing, and communication with the control center. This firmware integrates algorithms for gas recognition, sensitivity analysis, and decision-making based on pre-established models for each toxic gas. Additionally, software modules for data transmission via ZigBee and Wi-Fi protocols are crafted to establish seamless communication between the detection equipment and the control center. Furthermore, user interface software is implemented to furnish intuitive visualization of toxic gas data and real-time camera feeds, thereby enabling remote monitoring and control of the system. Through meticulous integration of hardware and software components, the toxic gas detection system achieves remarkable accuracy, reliability, and adaptability within industrial settings.

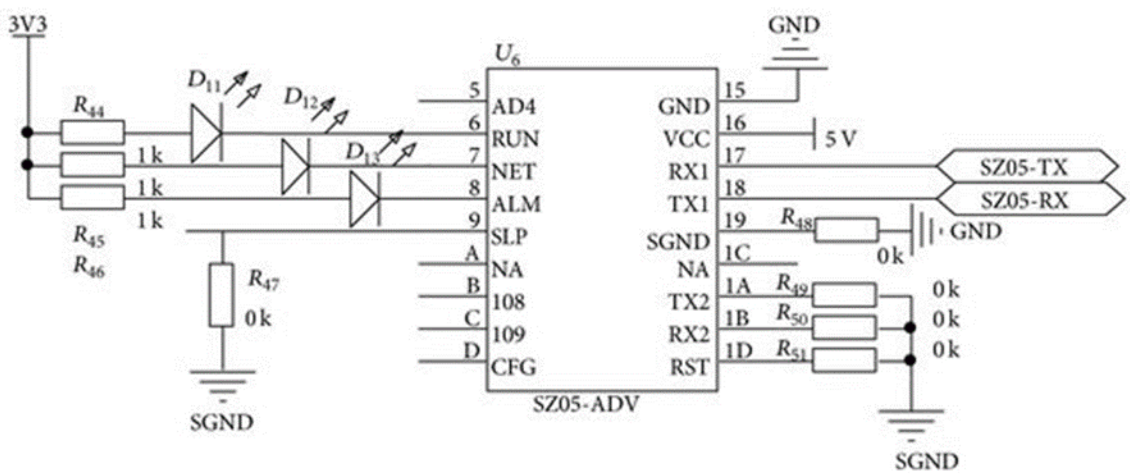

Figure 2: ZigBee communication module circuit diagram. [31]

Communication Module Circuit Design: To mitigate the potential interference between data and video information transmission, the circuit design for the communication module incorporates indicators $D11$, $D12$, and $D13$ to provide operational status feedback. $D11$ indicator flashes during normal operation, $D12$ illuminates in group network states, and $D13$ flashes to signal fault conditions. To ensure seamless

communication, AI and ML techniques are employed to dynamically optimize data transmission parameters, such as frequency hopping and channel selection, based on real-time environmental conditions and network congestion levels.

Wi-Fi Video Transmission Circuit Design: For Wi-Fi video transmission, the Kai Cong

Sip1018 module is selected, powered by three lithium batteries in series. However, due to the high series voltage, a DC/DC voltage conversion circuit is designed to regulate the voltage, ensuring stable operation of the Kai Cong Wi-Fi camera. Advanced AI algorithms are utilized to dynamically adjust power consumption and transmission parameters, optimizing video streaming quality and minimizing latency based on network conditions and camera settings.

Serial Data Transmission Circuit Design: Serial communication is adopted for data transmission between the relay station and the control center due to its simplicity and efficiency. While parallel communication offers higher speed, it requires multiple microcontroller pins. In contrast, serial communication reduces pin usage and simplifies system development. To enhance reliability, AI-driven error correction techniques are implemented to detect and correct data transmission errors in real time, ensuring seamless communication between the relay station and the control center even under challenging environmental conditions.

Motor Drive Circuit Design: The core chip for the motor drive circuit is selected as the L298, which governs various input ports including ENA, ENB, IN1, IN2, IN3, and IN4. ENA and ENB are responsible for activating different motors, while IN1 and IN2 regulate the steering wheel motor and its direction. The output ports OUT1 and OUT2 connect to the steering wheel's positive and negative terminals, whereas OUT3 and OUT4 are linked to the power motor's positive and negative terminals. The control table for the L298 chip, depicted in Table 1, outlines the motor's behaviour under different control states. The system implements AI and ML techniques to optimize motor control parameters dynamically, ensuring efficient operation and enhancing manoeuvrability.

System Software Design: The software architecture of the system encompasses software design for the detecting equipment, information relay station, and the central control center. A key aspect of this software design involves the quantitative recognition of four types of toxic gases. A flow chart illustrating this recognition process is presented in Figure 10. The detecting equipment's software is tasked with integrating data from the toxic gas sensors and temperature/humidity sensors, transmitting it to the control center via ZigBee wireless transmission, and executing obstacle avoidance maneuvers during operation. The software is divided into subroutines for processing toxic gas data, temperature/humidity data, and obstacle avoidance. The toxic gas data processing subroutine employs the bubble sort method to gather and analyse data on Cl2, CO, NO2, and SO2, utilizing the microprocessor's A/D acquisition module and digital filtering for data stability. It is depicted in Figure 3.

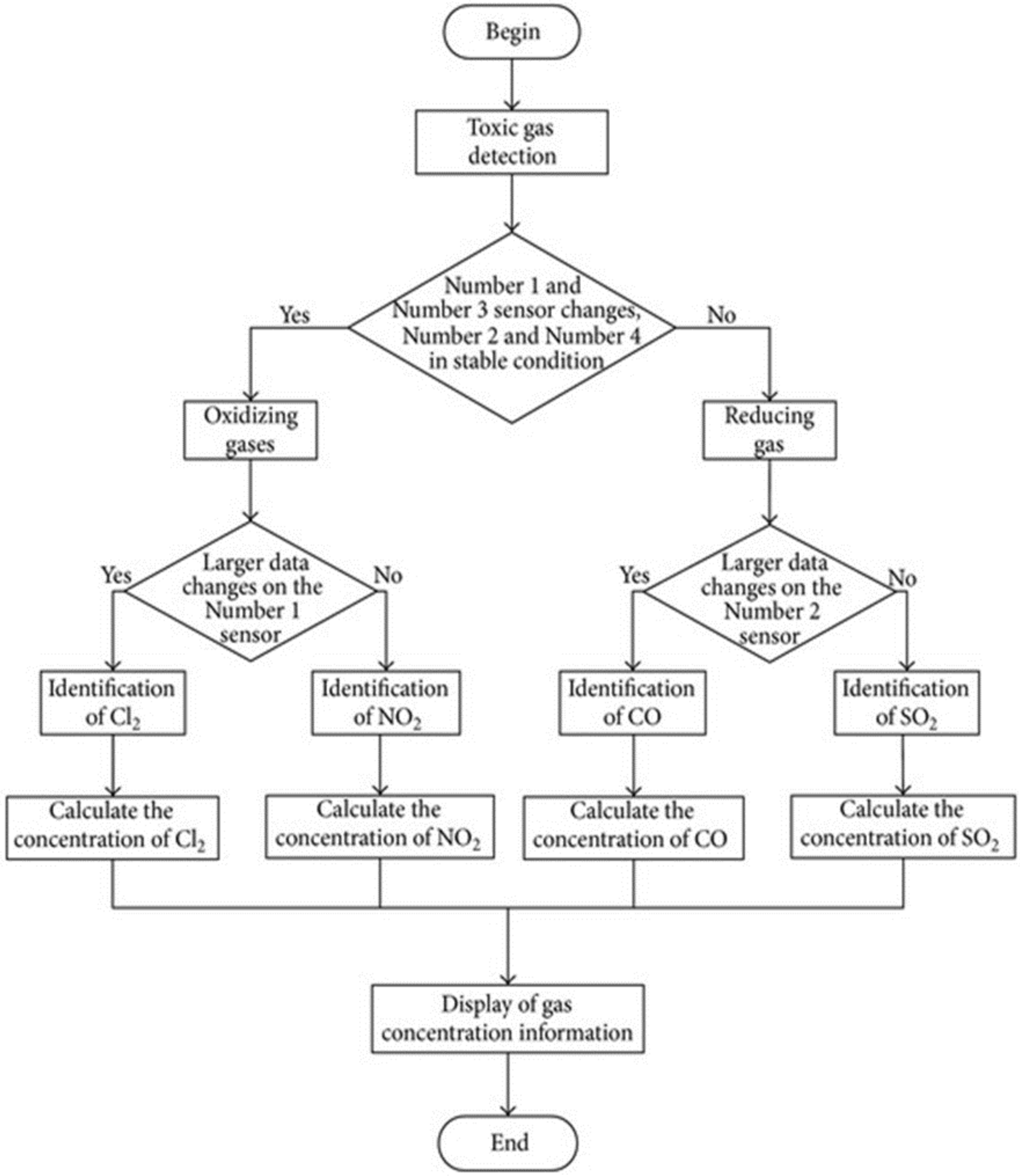

Figure 3: Flow chat of toxic gas identification [31]

processing toxic gas data, temperature/humidity data, and obstacle avoidance. The toxic gas data processing subroutine employs the bubble sort method to gather and analyse data on Cl2, CO, NO2, and SO2, utilizing the microprocessor's A/D acquisition module and digital filtering for data stability. It is depicted in figure 3.

Information Relay Station Software Design: The ZigBee relay station software primarily handles the transmission of data collected by the detecting equipment to the control center, as well as relaying instructions from the control center to the detecting equipment. Control Center Software Design: The host computer software for the control center is tailored to facilitate personnel control over the wireless detection system. The software enables real-time video interfaces, automatic data acquisition for generating real-time data curves, and analysis of gas concentrations using predefined calculation formulas. outlining the steps for data acquisition, analysis, and control interface management. Through the integration of AI and ML techniques, the software optimizes system performance and enhances user experience, ensuring efficient and reliable operation of the toxic gas detection system.

Data Analysis and Processing of Toxic Gas: In the wireless detection system's toxic gas sensors, resistance variations occur when exposed to oxidizing or reducing gases. Exploiting this property, the detection targets of each sensor are confirmed via data analysis. The data undergoes quadratic fitting to ascertain the quantitative identification function for gases.

Data Analysis and Processing of Oxidizing Toxic Gas Cl2: Exposing sensors to varying Cl2 concentrations reveals an increase in resistance for Number 1 and Number 3 sensors, with a corresponding gradient decrease as gas concentration diminishes. Sensitivity analyses, depicted in Table 1, illustrate this trend. Notably, Number 1 sensor exhibits a higher gradient than Number 3 sensor across all gas concentrations, positioning it as the primary Cl2 recognition front-end. Leveraging MATLAB, a curve fitting process correlates Cl2 concentration changes with resistance gradients, yielding a quantitative identification function for Number 1 sensor. The resulting equation, $y = 8.0362 \times x^2 + 0.943 \times x - 0.676$, underscores the sensor's sensitivity to Cl2 concentration changes. Response and recovery times for Cl2 detection by Number 1 sensor are indicated as 20s and 35s

Table 1: Analysis of varying sensitivities among sensors towards Cl2

Concentration of gas	No.1 sensor variance resistance	No.3 sensor variance resistance
40	220.2	139.2
20	142.6	117.1
10	114.1	96.8
5	85.5	75.0
2.5	67.3	49.2

Data Analysis and Processing of Oxidizing Toxic Gas NO2: Similar analyses are conducted for NO2 exposure, revealing resistance increases in Number 1 and Number 3 sensors with diminishing gas concentrations. The sensitivity analysis in Table 1 corroborates this trend, with Number 3 sensor exhibiting a higher gradient than Number 1 sensor across all gas concentrations, designating it as the primary NO2 recognition front-end. MATLAB-based curve fitting confirms the quantitative identification function for NO2 of Number 3 sensor, yielding the equation

$y = 18.801 \times x^2 + 11.656 \times x + 0.437$.

Response and recovery times for NO2 detection by Number 3 sensor are observed as 15 s and 20 s, respectively.

Data Analysis and Processing of Reducing Toxic Gas CO: Exposing sensors to various CO concentrations showcases resistance decreases in Number 2 and Number 4 sensors, accompanied by a gradient reduction with declining gas concentrations. Sensitivity analyses in Table 3 highlight this trend., illustrating its response to varying CO concentrations.

Based on the sensitivity analyses depicted in Table 3, it's evident that the resistance gradient decreases with the gas concentration reduction. Notably, Number 2 sensor exhibits a higher gradient than Number 4 sensor across all gas concentrations, positioning it as the primary CO recognition front-end. Leveraging MATLAB, a curve fitting process correlates CO concentration changes with resistance gradients, yielding a quantitative identification function for Number 2 sensor. The resulting equation,

$y = 169.51 \times x^2 - 75.055 \times x + 1.499$,

underscores the sensor's sensitivity to CO concentration changes. Response and recovery times for CO detection by Number 2 sensor are indicated as 16 s and 25 s, respectively.

Table 2 Analysis of varying sensitivities among sensors towards on NO_2

Concentration of gas	No.1 sensor variance resistance	No.3 sensor variance resistance
25	61.2	85.8
20	46.8	72.9
15	339	64.7
10	19.2	45.1
5	8.1	21.9

Table 3 Analysis of varying sensitivities among sensors towards on CO

Concentration of gas	No.2 sensor variance resistance	No.4 sensor variance resistance
100	98.9	54.4
50	81.8	45.1
25	67.8	35.9
10	50.4	24.1
5	41.9	18.8

Table 4 Analysis of varying sensitivities among sensors towards on SO2

Concentration of gas	No.2 sensor variance resistance	No.4 sensor variance resistance
40	32.1	45.9
20	22.9	34.8
10	19.0	24.6
5	15.8	17.3
2.5	1.2	1.2

Data Analysis and Processing of the Reducing Toxic Gas SO2: Similar analyses are conducted for SO2 exposure, revealing resistance decreases in Number 2 and Number 4 sensors with diminishing gas concentrations. The sensitivity analysis in Table 4 corroborates this trend, with Number 4 sensor exhibiting a higher gradient than Number 2 sensor across all gas concentrations, designating it as the primary SO2 recognition front-end. MATLAB-based curve fitting confirms the quantitative identification function for SO2 of Number 4 sensor, yielding the equation

$y = 231.44 \times x\verb|^|2 - 24.576 \times x + 1.488$.

Response and recovery times for SO2 detection by Number 4 sensor are observed as 10 s and 12 s, respectively.

System Testing: The paper outlines the system testing process, showcasing the inspection equipment and information relay station. The inspection equipment is situated within an industrial environment, featuring labelled bottles simulating gas sources. During testing, the equipment detects toxic gas leaks via the sensors, and the collected information is relayed to the control center through the information relay station. Real-time control center interface displays indicate the specific circumstances of the leaked toxic gas. The figures demonstrate the practical testing scenario, highlighting the system's efficacy in detecting and analysing toxic gas leaks in real-world industrial settings.

Conclusion: In conclusion, our study introduces a cutting-edge toxic gas detection system featuring multisensor recognition, amalgamating advanced toxic gas detection, communication, and data analysis technologies. Through our efforts, we've successfully enabled remote wireless real-time monitoring of diverse gas information within industrial environments. This system not only fulfills the stringent demands of industrial production but also addresses the shortcomings of conventional monitoring approaches. With its wide-ranging applicability and potential for technical advancements, our system presents a promising trajectory for further development and deployment across various industrial sectors.

Author Contributions

Dr.S. Anuradha, Dr.G. Raghu Ram - Conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing— original draft preparation;

A. Pradeep Kumar Yadav and G.Vivekananda Reddy- writing— review , editing, and supervision.

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