Architecture of an Intelligent Predictive Analytics System for Gas Environment Monitoring Based on Sensor-Series IoT Devices

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Abstract*—Industrial facilities operating with toxic and explosive gases require continuous monitoring systems capable not only of detecting threshold exceedances but also of anticipating hazardous trends. Conventional IoT-based gas monitoring solutions are primarily limited to real-time data acquisition and alarm triggering, which restricts their ability to prevent incidents proactively. This study presents the architecture of an intelligent predictive analytics system for gas environment monitoring that integrates sensor-series IoT gas analyzers with advanced data analytics. The proposed system is built on domestically developed SENSOR-Mine gas analyzers supporting LoRaWAN and Wi-Fi communication, centralized data storage in MS SQL Server, machine learning–based analytics implemented in Python, and a web-based visualization platform using ASP.NET MVC. Time-series forecasting models and anomaly detection algorithms are jointly employed to analyze gas concentration dynamics and identify potentially dangerous situations at early stages. Experimental validation using carbon monoxide measurements demonstrates the practical applicability of the proposed architecture for industrial safety monitoring. The presented approach provides a scalable foundation for intelligent gas environment monitoring systems aimed at reducing industrial risks and improving worker protection.

***Keywords*—Intelligent system; predictive analytics; IoT; gas analyzer; LoRaWAN; industrial safety; machine learning**

I. Introduction

Ensuring industrial safety remains one of the most critical challenges for modern manufacturing enterprises. At first glance, this may seem like a well-studied issue; yet statistics confirm that it remains highly relevant today. According to the International Labor Organization, more than 2.3 million deaths and over 300 million cases of injuries and occupational diseases are recorded worldwide each year, directly or indirectly linked to unsafe working conditions [1]. In countries with a developed mining industry, such as Kazakhstan, a significant share of incidents is associated with hazardous gas leaks, which often lead to fires and explosions at industrial sites.

The World Health Organization has revised the permissible exposure limits for several hazardous substances, including carbon monoxide, nitrogen dioxide, sulfur dioxide, and particulate matter [2]. This update, introduced only a few years ago, once again emphasizes the need for continuous air quality monitoring, not only in urban environments but also within industrial zones.

Recently, IoT-based intelligent sensor networks have been gaining attention as one of the most effective approaches to industrial monitoring [3, 4]. LoRaWAN, in particular, has shown strong performance, offering long communication range with minimal power consumption [4, 5]. Yet, sensors alone are limited: they primarily gather information, which by itself cannot guarantee safety. To address risks proactively, predictive analytics must be applied, allowing trends within time-series data to be analyzed and potential threats to be forecasted in advance [6].

Machine learning algorithms - such as LSTM, GRU, and autoencoders - have demonstrated strong performance when applied to the task of anomaly detection in streaming data generated by IoT sensors [7, 8].

This study focuses on the architecture of an intelligent predictive analytics system designed for gas environment monitoring. The foundation of the system is built upon domestically developed gas analyzer sensors-SENSOR-Mine 4G1 and SENSOR-Mine 4G2, created by KAB SYSTEMS. The purpose of the research is not limited to presenting the system's architecture; it also aims to demonstrate its practical applicability in ensuring continuous monitoring and the early prediction of potentially hazardous situations.

Recent studies have actively explored IoT-based solutions for air quality and gas monitoring in both indoor and industrial environments. Existing works demonstrate the effectiveness of sensor networks combined with wireless communication technologies, including LoRaWAN, for reliable long-range data transmission and low-power operation. Several approaches focus on real-time monitoring and alarm generation based on predefined thresholds, while others investigate the application of machine learning techniques for forecasting gas concentration dynamics or detecting anomalies in sensor data. However, in most reported solutions, predictive modeling and anomaly detection are addressed separately and are rarely integrated into a unified architecture designed for continuous industrial deployment. Furthermore, many studies remain limited to experimental setups and do not sufficiently consider system scalability, communication redundancy, and integration with enterprise-level information systems. These gaps motivate the development of an integrated architecture that jointly combines IoT sensing, hybrid communication, and intelligent analytics for industrial gas environment monitoring.

Despite the significant progress in IoT-based gas monitoring systems, most existing solutions primarily focus on real-time data acquisition and threshold-based alarming, offering limited capabilities for proactive risk prevention. Many approaches lack integrated predictive analytics and are not designed to jointly address long-term trend forecasting and rare-event detection in industrial environments. Moreover, a substantial portion of reported solutions remains at the experimental or laboratory level and does not sufficiently consider deployment constraints such as communication reliability, scalability, and integration with industrial IT infrastructures. In this context, the present study proposes an architecture that combines distributed IoT gas analyzers with a hybrid LoRaWAN/Wi-Fi communication layer and intelligent data analytics. By integrating time-series forecasting models with anomaly detection methods within a unified system, the proposed approach extends conventional monitoring by enabling early identification of hazardous trends. The architecture is specifically designed for industrial deployment and is validated using data obtained from SENSOR–Mine gas analyzers, positioning this work as a practical and scalable solution for intelligent gas environment monitoring.

II. Methods and Materials

The hardware backbone of the gas monitoring system is formed by the SENSOR series gas analyzers, developed as part of a domestic project. These devices are designed to measure the concentrations of various gases (CO, CH_4, NO_2, H_2S, and others), with detection ranges spanning from 0.1 ppm to 1000 ppm, depending on the sensor module used. The measurement accuracy reaches ±2%, while the minimum detection threshold does not exceed ±2 ppm.

The SENSOR-Mine 4GN gas analyzer is designed for continuous monitoring of harmful and hazardous gases in the air of both underground and surface industrial facilities. The device serves as a tool for ensuring industrial safety, protecting workers' health, preventing accidents, and monitoring compliance with permissible exposure limits (PEL) in production and technological environments.

The 4GN model is configured to monitor up to four different gases, where N denotes the specific gas set. Table I presents the available models, each equipped with a defined combination of sensors tailored to the particular needs of industrial enterprises.

The gas analyzer is suitable for use in a wide variety of facilities, including mining operations, tunnels, underground storage units, ventilation shafts, as well as laboratory and industrial settings. The detection range specifications of the built-in sensors integrated into the SENSOR gas analyzer are provided in Tables II and III.

The key features of the developed gas analyzer include modular sensor replacement, an integrated microcontroller for primary data filtering, and support for wireless communication via LoRa and Wi-Fi. The device is designed for low power consumption, reaching up to 200 mW in transmission mode, while maintaining ease of use in industrial environments.

Similar solutions are already being applied in LoRaWAN-based research systems for air quality monitoring [9].

Communication layer: LoRaWAN and Wi-Fi. Two technologies were employed for transmitting data from the sensors to the server. LoRaWAN provides a communication range of up to 10 km with very low power consumption, making it an optimal choice for distributed systems [10]. Wi-Fi, in turn, is used as a backup channel and for local debugging. This combination was selected as the primary solution for mines, quarries, and industrial sites where large-area coverage is essential.

In the present implementation, a significant advantage lies in the networking capability between gas analyzers. Data packets are transmitted based on the measurements obtained, first exchanged among neighboring analyzers and then forwarded to the central database server, where the aggregated dataset undergoes further processing through predictive analytics.

TABLE I. CONFIGURATIONS OF SENSOR-MINE 4GN

Configuration Number	Model Designation	Measured Gases
1	SENSOR – Mine 4G1	SO_2, NO_2, CO, O_2
2	SENSOR – Mine 4G2	H_2S, CH_4, CO, O_2

TABLE II. SPECIFICATIONS OF SENSOR–MINE 4G1

Gas	Measurement Range	Accuracy	MAC RK (ppm)	Alarm Threshold (ppm)
SO_2	0–20 ppm	±2 ppm	3.4	3
NO_2	0–20 ppm	±2 ppm	1.0	1
CO	0–200 ppm	+20 ppm	17.4	20
O_2	0–25%	±4 % of the measured value	<18%	18% ↓

TABLE III. SPECIFICATIONS OF SENSOR–MINE 4G2

Gas	Measurement Range	Accuracy	MAC RK (ppm)	Alarm Threshold (ppm)
H_2S	0–100 ppm	±10 ppm	10	10 ppm
CH_4	0–100% LEL	±3 % of the measured value	5% LEL	10% LEL
CO	0–200 ppm	±20 ppm	17.4	20 ppm
O_2	0–25%	±4 % of the measured value	<18%	18% ↓

Wi-Fi is primarily applied in local industrial facilities and laboratories, where high data transfer rates are critical. However, its use in confined environments such as mines or underground tunnels proves to be ineffective. Wi-Fi requires a constant network connection, and in harsh conditions, physical cables can easily be damaged by passing machinery or rockfalls. For this reason, Wi-Fi is most effective in surface applications, such as open industrial sites and quarries.

The key advantage of the hybrid communication model is its ability to combine the energy efficiency of LoRaWAN with the high bandwidth of Wi-Fi, enabling reliable data transmission under a variety of conditions. Considering these parameters, together with the devices' moisture, explosion, and dust protection, the system is well-suited for deployment in virtually any industrial environment.

Fig. 1 illustrates the alarm triggering algorithm in the gas analyzer: once a hazardous concentration is detected, the data are transmitted to the central database server, and an alarm notification is displayed in the user interface. At the same time, all analyzers located near the unit that raised the alarm automatically receive the signal and activate their own warning alerts, ensuring distributed safety awareness within the network.

A. Data Storage and Processing System

The data collected by the gas analyzer in real-time is transmitted to the server, where it is stored and further processed in a SQL Server database. The data storage structure is based on a relational model and contains fields for a unique sensor identifier, gas type (CO, NO_2, SO_2, CH_4, etc.), timestamp of data acquisition, measured concentration value expressed in ppm or mg/m^3, and a status attribute indicating the measurement level (normal, warning, or alarm).

This organization of data enables the formation of time series, which are then used as the basis for machine learning and predictive analytics algorithms. Fig. 1 shows the architecture of the developed intelligent system, including sensors, server infrastructure, and the user interface.

This data storage structure enables the generation of time-series datasets, which can then be applied for training and operating machine learning algorithms. Fig. 1 presents the architectural diagram of the intelligent system.

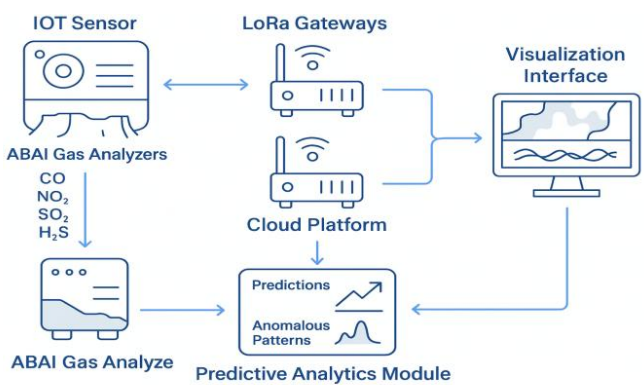

Fig. 1. Architecture of the intelligent system.

Machine learning algorithms are employed to analyze time-series data.

Specifically, Long Short-Term Memory (LSTM) networks are used to predict gas concentrations based on historical measurements, while Gated Recurrent Unit (GRU) models provide a computationally efficient alternative to LSTM.

Isolation Forest is applied for detecting anomalies and sudden spikes in gas concentrations, whereas One-Class SVM is suitable for identifying rare and potentially hazardous events in scenarios where most observations correspond to normal operating conditions.

These methods are widely adopted in predictive monitoring tasks [6], [11].

B. Visualization and User Interface

The data are visualized using an ASP.NET MVC–based platform. The user interface enables real-time visualization of current gas concentrations on the facility map, time-series representation with predictive trends, and dynamic highlighting of detected anomalies. In addition, the system supports automated reporting on the overall condition of the facility.

During the experiments conducted in the chemical laboratory, data were collected using the SENSOR-Mine 4G2 gas analyzer, which measures carbon monoxide (CO) concentrations in the range of 0-200 ppm. As reference values, the regulatory limits of the Republic of Kazakhstan were applied, as previously shown in Table III – SENSOR-Mine 4G2.

Fig. 2 illustrates the dynamics of CO concentration changes over time [12]. It can be observed that within the interval of 120-130 minutes, concentration exceeded the permissible exposure limit (PEL) and reached the alarm threshold.

To analyze the data and uncover hidden patterns, advanced intelligent processing methods were applied, including the Isolation Forest (IF) algorithm for anomaly detection and the One-Class SVM method for identifying rare events and outliers.

Fig. 3 demonstrates the application of the Isolation Forest method. The red points highlight anomalous values corresponding to a sharp increase in CO concentration, which aligns with the incident detected by the gas analyzer.

Fig. 4 illustrates the identification of rare events with the One-Class SVM algorithm. The orange markers indicate points flagged as potentially hazardous. It is worth noting that this method can capture outliers even with minor deviations from the norm, which makes it valuable for early warning.

The effectiveness of different approaches was evaluated, and the results are summarized in Table IV. The analysis shows that recurrent neural networks such as LSTM and GRU provide the most accurate results in forecasting CO concentration dynamics. However, these models require significantly higher computational resources, which may be a limiting factor for industrial applications that have not yet reached full digital maturity.

While Table IV summarizes qualitative trade-offs, a full quantitative evaluation of anomaly detection performance (e.g., Precision, Recall, and F1-score) requires labeled ground truth for abnormal events. In the current laboratory validation, anomalies were identified based on threshold exceedance and expert inspection; therefore, we report comparative behavior of the methods and include quantitative benchmarking with labeled data as a planned extension of this work.

TABLE IV. COMPARISON OF MACHINE LEARNING ALGORITHMS APPLIED TO GAS ANALYZER (CO) DATA

Method	Task	Advantages	Limitations	Industrial Applicability
LSTM	Forecasting concentrations using time series	High accuracy; captures long-term dependencies	Requires large datasets and high computational resources	Suitable for long-term leak prediction
GRU	Similar to LSTM	Faster and lighter to train; fewer parameters	Slightly lower accuracy compared to LSTM	Suitable for real-time systems
Isolation Forest	Detecting anomalies and sudden spikes	Performs well with outliers; does not require large datasets	Does not forecast, only detects anomalies	Effective for instant accident detection
One-Class SVM	Identifying rare events in normal data	Capable of detecting unusual situations with limited data	Sensitive to parameter selection	Useful for early warning of accidents

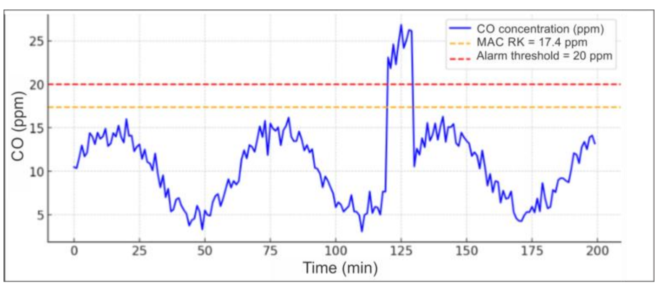

Fig. 2. Dynamics of CO concentration over time.

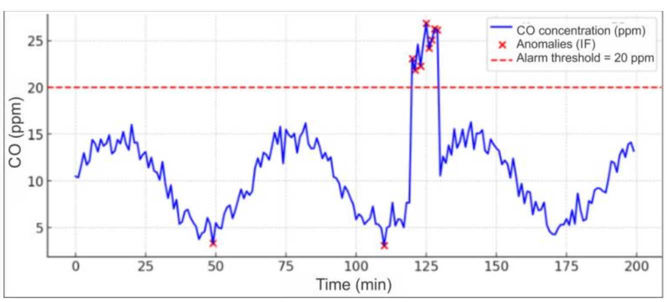

Fig. 3. CO anomaly detection using the Isolation Forest method.

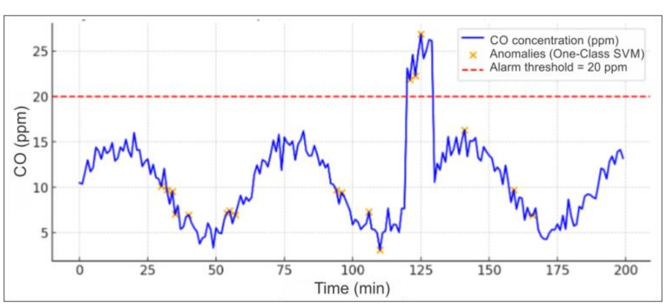

Fig. 4. Detection of rare CO events using the One-Class SVM method.

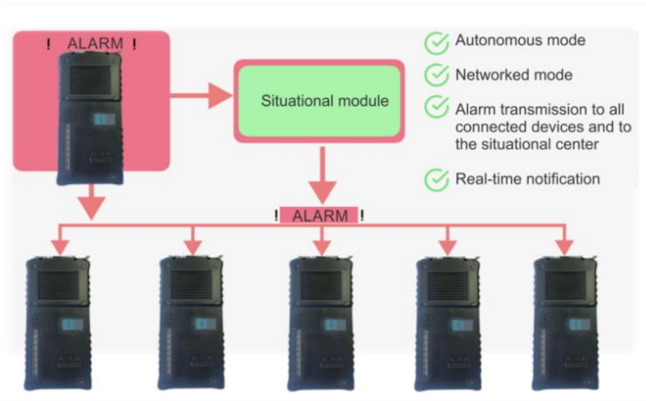

Fig. 5. The main functional components of the system.

On the other hand, anomaly detection methods such as Isolation Forest and One-Class SVM performed better in identifying hazardous episodes. This capability is particularly important for real-time monitoring systems, where timely detection of abnormal events is often more critical than precise long-term trend prediction. Fig. 5 illustrates the main functional components of the system and the alarm-triggering process when either maximum permissible concentrations of harmful substances or anomalies are detected.

Thus, the combination of forecasting models such as LSTM and GRU with anomaly detection methods like Isolation Forest and One-Class SVM provides a more comprehensive approach to intelligent monitoring of the gas environment. This integrated methodology not only records actual exceedances of maximum allowable concentrations but also predicts the development of hazardous trends. As a result, the overall level of industrial safety can be significantly improved.

The relevance of this study is largely driven by the urgent need to implement intelligent predictive analytics systems in industrial enterprises of the Republic of Kazakhstan. In environments where toxic and explosive gases are used, the risks of emergencies remain objectively high, making such solutions particularly valuable.

The scientific novelty of the work lies in the proposed integration of time-series forecasting methods with algorithms for detecting rare and anomalous events, based on data obtained directly from SENSOR - Mine 4G2 gas analyzers equipped with LoRa and Wi-Fi data transmission. This combined approach is introduced in the context of industrial safety tasks. Its application enhances the accuracy of analysis, reliability of the system, and timeliness of detecting potentially dangerous situations.

III. RESULTS

The developed architecture of the intelligent system consists of five core layers. At the sensor level, SENSOR-series gas analyzers provide continuous data collection. The communication layer employs LoRaWAN and Wi-Fi technologies for data transmission. On the server side, the information is accumulated and stored in SQL Server before being processed by the analytical module, implemented in Python with machine learning methods. The final layer is the user level, represented by a web interface built on ASP.NET

MVC, which provides access to monitoring results and analytics.

The proposed approach, tested through the analysis of CO concentrations, can be adapted to other industrial environments and facilities where the risk of hazardous gas accumulation exists. Below are typical scenarios where the system may prove especially useful.

For monitoring air quality in urban infrastructure, a distributed network of sensors can be deployed, focusing on the control of nitrogen dioxide (NO_2) and fine particulate matter (PM2.5). Integrating predictive model outputs with existing environmental monitoring systems makes it possible not only to record regulatory exceedances but also to provide early warnings to the population about potential air quality deterioration.

Fig. 6 illustrates air quality monitoring using SENSOR gas analyzers, with a modeled scenario of hazardous substance dispersion following an alarm event. The SENSOR devices are positioned at specific coordinates and measure data in real-time, transmitting results to a central control center. Based on sensor readings and detected anomalies, information on potential leakage sources is forwarded to local authorized bodies, including the Department of Emergency Situations and the Department of Industrial Safety. Subsequently, notifications are issued to residents within the affected zone through instant alerts delivered to their mobile devices. This example demonstrates the applicability of the intelligent predictive analytics system in an urban context.

In mines and quarries, monitoring methane (CH_4) and hydrogen sulfide (H_2S) concentrations remains one of the most critical tasks in underground operations. The use of LSTM models enables forecasting of methane buildup 5-10 minutes before reaching explosive thresholds. The Isolation Forest algorithm demonstrates high sensitivity to sudden spikes in hydrogen sulfide levels, which is crucial for preventing unexpected emergencies.

In metallurgical production, the main parameters of concern are carbon monoxide (CO) and sulfur dioxide (SO_2) concentrations. Recurrent neural networks, such as GRU, provide rapid and reasonably accurate predictions of CO dynamics in workshops, while the One-Class SVM method makes it possible to timely detect rare SO_2 emissions that often go unnoticed with conventional monitoring tools.

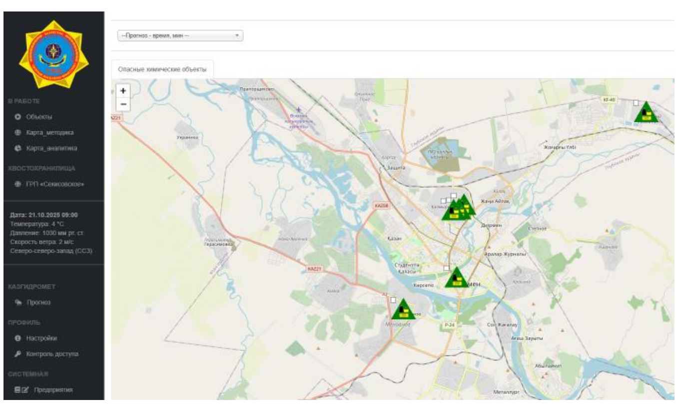

Fig. 6. Simulation of hazardous substance dispersion.

IV. Discussion

A comparison with existing monitoring systems [3, 5, 9] shows that the proposed architecture offers several advantages. Unlike most solutions that primarily focus on data collection, our system integrates LoRaWAN-based communication with predictive analytics methods, enabling not only real-time measurement but also forward-looking prediction. An additional advantage is the use of Python-based modules, which provide flexibility in applying different forecasting algorithms. Moreover, the inclusion of a backup communication channel via Wi-Fi enhances the system's reliability under conditions of primary channel instability.

Despite its advantages, any technical solution or system has certain limitations. For machine learning models to function correctly, a significant amount of data must be accumulated, which may reduce prediction accuracy at the initial stages of implementation. For laboratory validation, the dataset was collected using the SENSOR–Mine 4G2 gas analyzer with a sampling interval of 2 seconds. Measurements were performed at three controlled concentration levels (10 ppm, 100 ppm, and 190 ppm), resulting in a time-series dataset consisting of approximately 1,000–2,000 data points. Another challenge lies in the proper calibration of sensors, especially in harsh industrial environments. The sensitivity of algorithms to input data quality also requires attention: noise or incomplete measurements may lead to false alarms.

Nevertheless, the prospects for system development appear highly promising. One potential direction is integration with digital twins of industrial enterprises, enabling simulation of asset behavior under various scenarios. Another opportunity is the implementation of automated responses, such as automatic activation of ventilation systems or emergency notifications when maximum permissible concentrations are exceeded. In the long term, it is advisable to enable data transmission to state monitoring systems - including the Ministry of Emergency Situations and the Ministry of Ecology - to establish a unified infrastructure for industrial and environmental safety.

V. Conclusion

This study presents the architecture of an intelligent predictive analytics system for gas environment monitoring. The system is based on SENSOR-series IoT sensors, with data transmission via LoRa and Wi-Fi protocols, storage in SQL Server, analysis using Python, and visualization in an ASP.NET MVC web environment.

The developed solution enables early detection of potentially hazardous situations and can be integrated into the industrial infrastructure of enterprises in the Republic of Kazakhstan.

Future research directions include expanding and comparing various predictive analytics algorithms; developing a digital twin of technological processes for integration with safety management systems; and conducting pilot implementations in the mining industry and territorial state agencies.

Thus, the proposed architecture lays the foundation for establishing a national industrial safety system focused on preventing emergencies and enhancing worker protection.

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