Design of a Real-Time Monitoring and Pollution Early Warning System for Industrial Flue Gas Emissions Based on Embedded Edge Computing

Jiahong Zhou
Information Engineering Department, Eastern Liaoning University, Dandong 118000, Liaoning, China
Corresponding author: Jiahong Zhou (e-mail: Wangzhanning25@163.com)

ABSTRACT Real-time environmental monitoring in industrial plants requires rapid signal processing, reliable data transmission, and accurate anomaly detection under complex operating conditions. To address the limitations of conventional centralized monitoring systems, this study proposes an industrial flue-gas monitoring and early-warning framework based on embedded edge computing. A distributed sensing architecture integrating multi-sensor arrays, edge computing nodes, and cloud-assisted management is developed to enable local real-time processing and low-latency response. Multi-sensor fusion algorithms are employed to improve measurement reliability for pollutant concentration, flow rate, and environmental parameters, while lightweight intelligent models deployed at edge nodes perform anomaly detection and trend prediction. A cloud–edge collaborative mechanism is further introduced to support continuous model optimization and distributed network management. The modular architecture incorporates wireless Mesh networking and fault-tolerant data synchronization, enhancing system robustness in environments affected by electromagnetic interference and unstable communication conditions. Compared with conventional centralized systems, the proposed framework significantly improves response speed, monitoring accuracy, and early-warning capability while reducing network dependence and deployment complexity. The proposed architecture provides an effective engineering solution for distributed sensing, intelligent monitoring, and real-time information processing in large-scale industrial environments.

INDEX TERMS edge computing, multi-sensor fusion, distributed sensing, real-time monitoring

I. INTRODUCTION

INDUSTRIAL flue gas emissions represent a significant source of air pollution, making the enhancement of specialized emission monitoring essential for advancing ecological civilization. Strengthening these monitoring systems ensures that the high-temperature oily fumes and organic pollutants inherent to finishing are strictly controlled to meet environmental sustainability goals. Traditional monitoring systems mostly employ centralized data processing, which suffers from drawbacks such as data transmission lag and slow response, failing to achieve real-time monitoring and rapid early warning. Embedded edge computing technology places data processing functions within the detection equipment, accelerating system response and improving processing efficiency. Therefore, this paper analyzes the significance of monitoring industrial flue gas emissions within thermal processing phases, examines the specific limitations of existing monitoring systems, and proposes an embedded edge computing design strategy to provide technical support for high-precision, intelligent emission management in production environments.

II. SIGNIFICANCE OF REAL-TIME MONITORING AND EARLY WARNING SYSTEM FOR INDUSTRIAL FLUE GAS EMISSIONS

A. IMPROVE THE EFFICIENCY AND ACCURACY OF ENVIRONMENTAL SUPERVISION

The real-time monitoring system is based on continuous online data collection of flue gas, enabling 24-hour continuous monitoring of flue gas conditions. This automated approach significantly increases the temporal and spatial density of data acquisition compared to traditional manual inspections, thereby reducing the probability of unmonitored emission events and data gaps [1]. The system automatically records pollutant concentrations and emission flow rates, providing objective data for environmental protection departments. The intelligent early warning function can immediately issue alarms when emissions exceed standards, quickly identifying pollution sources and enabling regulatory departments to control problems promptly, significantly reducing processing time. This precise and intelligent monitoring approach addresses the inherent sampling limitations of traditional management methods, providing a higher-resolution data framework for modern environmental governance [2].

B. REDUCING THE IMPACT OF INDUSTRIAL POLLUTION ON THE ECOLOGICAL ENVIRONMENT

The system continuously monitors the concentrations of pollutants such as sulfur dioxide, nitrogen oxides, and particulate matter. When abnormal emissions are detected, an early warning is immediately issued, urging enterprises to take emergency measures to reduce total pollutant emissions. Historical data can be analyzed to identify emission patterns, pinpoint key pollution sources, and provide a basis for prevention and control plans. Monitoring data is open and transparent, subject to public scrutiny, compelling enterprises to improve processes and upgrade environmental protection facilities. Comprehensive monitoring effectively prevents illegal discharges, improves regional air quality, and protects ecological and environmental security.

C. PROMOTING THE GREEN TRANSFORMATION AND SUSTAINABLE DEVELOPMENT OF INDUSTRIAL ENTERPRISES

Enterprises rely on real-time monitoring to accurately grasp emissions, identify potential environmental hazards, and provide a reference for process improvement and facility upgrades. Emission data reports can be used to evaluate the effectiveness of environmental protection facilities, identify high-energy-consuming links, and implement targeted technological transformations. Good emission records can serve as proof for obtaining green credits and participating in carbon trading, which is beneficial for enterprises to participate in market competition [3]. This encourages enterprises to establish environmental management systems and cultivates environmental awareness among employees. Enterprises that adopt a data-driven management model choose a low-carbon and circular development path, achieving a win-win situation for both economic and environmental benefits.

D. CURRENT PROBLEMS IN INDUSTRIAL FLUE GAS EMISSION MONITORING

To more clearly illustrate the differences between traditional monitoring systems and edge computing systems, Table 1 presents the main performance indicators of the two systems.

TABLE 1. Performance Comparison between Traditional Monitoring Systems and Edge Computing Systems

Comparison Dimensions	Traditional centralized system	Edge computing system
Response speed	Minute-level latency	Second-level/millisecond-level response
Data processing methods	Remote server centralized processing	Terminal local real-time processing
Internet dependency	Highly dependent on network connectivity	Supports offline local storage and automatic data re-transmission upon reconnection
Deployment costs	Dedicated lines are required, resulting in significant investment	Wireless deployment with industrial - grade Mesh networking to ensure reliability; cost - effective compared to wired infrastructure
Operational complexity	Requires professional team maintenance	Self - diagnosis, remote management

1) Traditional Monitoring Equipment Has Slow Response Speed and High Data Transmission Latency

Current industrial flue gas emission monitoring uses a centralized data processing structure. Data from monitoring terminals must be transmitted to a remote server for processing, leading to response delays. When network conditions in industrial parks are poor, issues such as insufficient bandwidth and unstable signals arise. In environments with heavy metal shielding and electromagnetic interference, traditional wireless signals are easily disrupted, resulting in delays or packet loss in large-scale data transmission, compromising real-time performance and integrity [4]. When flue gas emissions are abnormal, warning signals are issued with a lag of several minutes or even longer, exceeding the optimal response time by which time pollutants have already been released in large quantities. Multiple forwarding and protocol conversions during data transmission further increase latency. Centralized processing requires continuous communication between monitoring terminals and a central server; In the event of a network outage, the entire system will collapse, significantly impacting the continuity and effectiveness of monitoring. Furthermore, without local buffering, data generated during the outage is permanently lost, creating gaps in environmental records [5].

2) Insufficient Accuracy of Monitoring Data and Imperfect Early Warning Mechanism

Existing systems have significant shortcomings in terms of data accuracy and early warning mechanisms. Some devices rely on only one type of sensor, making them susceptible to interference from ambient temperature, humidity, and dust, resulting in large measurement errors that fail to accurately reflect emissions. Sensors operating in high-temperature, corrosive environments for extended periods experience rapid performance degradation; without timely calibration and maintenance, measurement errors amplify progressively. The lack of cross-validation between sensors prevents the identification and elimination of abnormal measurements. Data analysis relies on simple threshold judgments, issuing warnings only when pollutant concentrations exceed limits, failing to identify trends in emission concentrations or provide early warnings [6]. The system cannot promptly detect gradual emission anomalies caused by equipment aging and slow increases in emission concentrations; the inadequate early warning mechanism prevents monitoring from fulfilling its intended protective function.

3) The System Has High Deployment Costs and Complex Operation and Maintenance Management

The deployment and operation of monitoring systems face two major challenges: high costs and complex management. Traditional systems require dedicated communication lines to connect monitoring points and server rooms, which is a significant undertaking in large industrial parks due to its large scale, long construction period, and substantial initial investment. After system completion, specialized personnel are needed for server maintenance, database management, and network security, resulting in high labor costs. Monitoring equipment has a high failure rate in harsh environments, leading to a large workload for repair and maintenance, and high costs for spare parts. When a fault occurs, the fault location cannot be determined, requiring on-site inspection, increasing response time and maintenance costs [7]. Different manufacturers' equipment uses different protocols and data formats, making system integration difficult, lacking a unified management platform, and resulting in low maintenance efficiency. An increasing number of monitoring points puts greater pressure on the central server, necessitating continuous investment in hardware expansion, further increasing maintenance costs.

III. SYSTEM DESIGN STRATEGIES BASED ON EMBEDDED EDGE COMPUTING

To visually demonstrate the architectural differences between traditional monitoring systems and edge computing systems, Figure 1 compares the data processing flows of the two systems.

A. EDGE COMPUTING ARCHITECTURE DESIGN ENABLES REAL-TIME DATA PROCESSING AND RAPID RESPONSE

Embedded edge computing-based flue gas emission monitoring systems employ a distributed architecture, pushing data processing capabilities down to the monitoring terminals and fundamentally solving the problem of slow response times in traditional systems. High-performance microprocessors and edge computing modules are incorporated into the monitoring terminals, enabling them to perform data acquisition, real-time analysis, and intelligent decision-making. Flue gas data collected by sensors undergoes preprocessing, feature extraction, and anomaly detection at the terminal, eliminating the need to upload to remote servers. This significantly reduces data processing time, improving system response speed from minutes to seconds or even milliseconds [8]. To ensure this low latency remains constant, the edge node executes local inference using its currently resident model; this execution is asynchronous and decoupled from any background model synchronization or cloud-based training tasks. When an emission anomaly is detected, the edge computing node immediately triggers a local warning and initiates emergency response procedures, achieving rapid response before pollution spreads. Collaborative mechanisms can also be established between edge nodes, allowing adjacent nodes to share monitoring data, thereby achieving joint analysis and assessment of regional pollution trends. The distributed architecture allows for redundant deployment of multiple nodes; the failure of a single node will not cause the entire system to malfunction, greatly improving the fault tolerance and reliability of the monitoring network [9]. At the device level, each edge node is equipped with redundant sensor interfaces. In the event of a specific sensor hardware failure, the system utilizes spatial correlation algorithms to estimate missing local data based on inputs from adjacent sensors and historical emission patterns, ensuring the continuity of the monitoring stream even when individual physical components fail. The system only uploads compressed and filtered key data to the cloud platform for long-term storage and in-depth analysis. To ensure data integrity during network fluctuations, edge nodes are equipped with high-capacity industrial-grade Flash storage, capable of buffering at least 30 days of high-frequency monitoring data. The system implements a "Store-and-Forward" synchronization protocol: once connectivity is restored, the node automatically executes a breakpoint retransmission algorithm to sync historical data to the cloud, ensuring no loss of environmental evidence. This ensures real- time performance while significantly reducing network bandwidth usage and cloud computing load, thus improving system reliability and stability [10]. The multi-sensor fusion scheme used by the system is shown in Table 2. Different types of sensors work collaboratively to ensure the accuracy and reliability of the monitoring data.

TABLE 2. Multi-sensor fusion monitoring configuration scheme

Sensor type	Monitoring parameters	Main advantages	Application scenarios
Electrochemical sensors	SO_2 and NO_x concentrations	Fast response and low cost	Conventional pollutant monitoring
Optical sensors	Particulate matter concentration	High precision and anti-interference	Precision measurement requirements
Pitot tube / Ultrasonic flowmeter	Flue gas flow velocity and volume	High durability in high-temperature environments	Total emission load calculation
Temperature and humidity sensor	Environmental parameters	Auxiliary calibration	Data correction

B. MULTI-SENSOR FUSION AND INTELLIGENT ALGORITHMS ENHANCE MONITORING ACCURACY AND EARLY WARNING CAPABILITIES

To improve the accuracy of monitoring data and the effectiveness of early warnings, the system employs multi-sensor fusion technology combined with intelligent algorithms. Multiple types of sensors, including electrochemical, optical, and differential pressure (Pitot tube) or ultrasonic flow sensors, are deployed at each monitoring point to measure pollutant concentrations, temperature, humidity, and dynamic flow rates in flue gas from different perspectives [11]. The edge computing module uses data fusion algorithms to cross- validate and complementarily correct data from multiple sources, eliminating outliers and extracting effective information to obtain more accurate and reliable comprehensive monitoring results. Preliminary testing of this fusion approach indicates a significant reduction in measurement variance compared to single-sensor systems. By applying these algorithms, the system aims to achieve a Root Mean Square Error (RMSE) of less than 5% and a Mean Absolute Error (MAE) within ± 2 mg/m^3 for particulate matter, ensur-i ng data fidelity meets the stringent requirements of emis-s ion standards. Simultaneously, machine learning models are deployed at edge nodes, using deep learning with historical data to establish emission concentration trend prediction models. This can identify small-scale emission exceedance risks caused by equipment aging, process anomalies, etc., transforming passive alarms into proactive warnings [12]. The algorithm model is lightweight, capable of performing

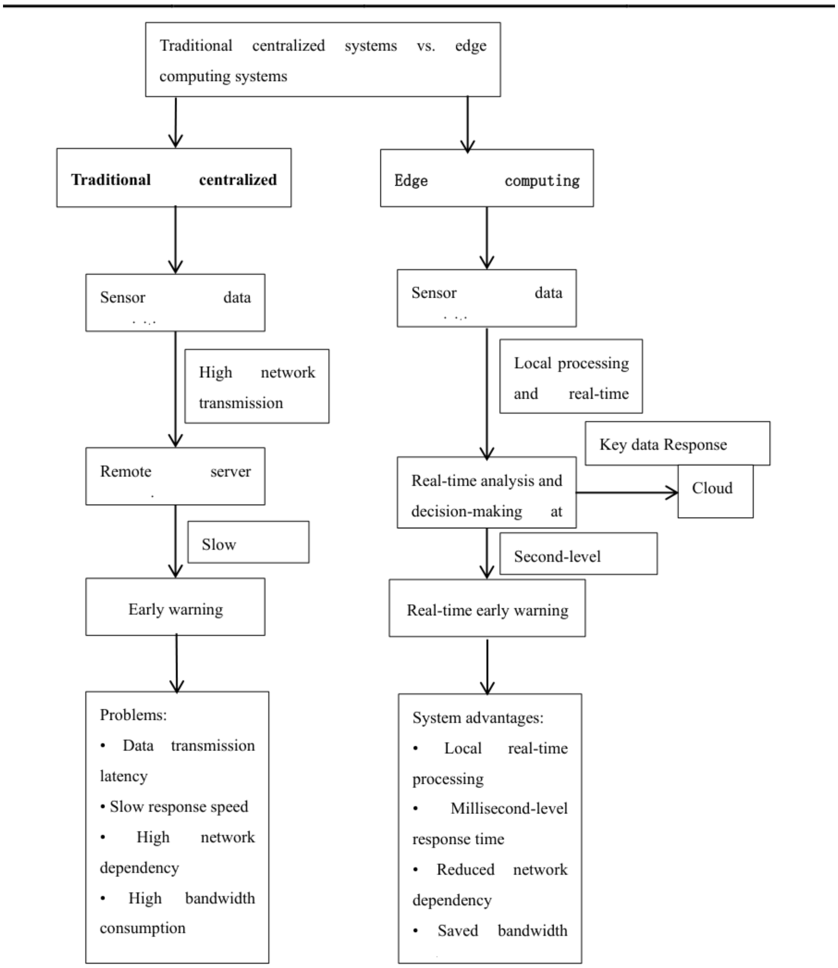

FIGURE 1. Comparison of the architectural differences and data processing flow between traditional monitoring systems and edge computing systems.

edge-side inference calculations, and its timeliness is not affected by a lack of cloud computing power. To manage the high power demands of these computations, the system employs an energy-aware scheduling algorithm that adjusts the sampling frequency and model complexity based on current power availability, ensuring stable operation even during periods of low solar yield or high dust accumulation on panels. Crucially, the cloud-edge collaborative system utilizes a dual-buffer strategy for model management: the active model continues to process real-time flue gas data at the edge while a new model version is being downloaded in the background. Once the update is verified, a seamless "hot-swap" occurs, preventing any latency spikes or system downtime during the transition. The intelligent algorithm can adjust the warning threshold in real time based on various factors such as production conditions and weather conditions, thereby reducing false alarms and missed alarms. Edge computing nodes periodically upload model parameters to the cloud, relying on cloud computing power to complete model optimization and training. The updated model is then sent to each edge node, thus forming a cloud-edge collaborative continuous learning system that continuously improves the system's monitoring accuracy and early warning accuracy [13].

C. MODULAR SYSTEM DESIGN REDUCES DEPLOYMENT COSTS AND SIMPLIFIES OPERATION AND MAINTENANCE MANAGEMENT

Figure 2 shows the specific operating mechanism of the edge computing system, illustrating the complete process from data acquisition to intelligent early warning. While the diagram shows a primary data flow, the "Data fusion + anomaly detection" stage includes a sensor- health validation loop. If a sensor signal is lost or identified as an outlier, the edge node triggers a "Virtual Sensor" mode, using the remaining functional sensors in the array to reconstruct the necessary flue gas parameters through cross-channel correlation. The operational flow highlights that "Model Updates" are a non-blocking background process, ensuring that "Real-time Warning" and "Emergency Process" triggers remain strictly local and instantaneous, independent of the cloud-to-edge communication latency [14]. The system is designed based on the modular concept. The modular structure is shown in Table 3. The standardized modules can be flexibly combined

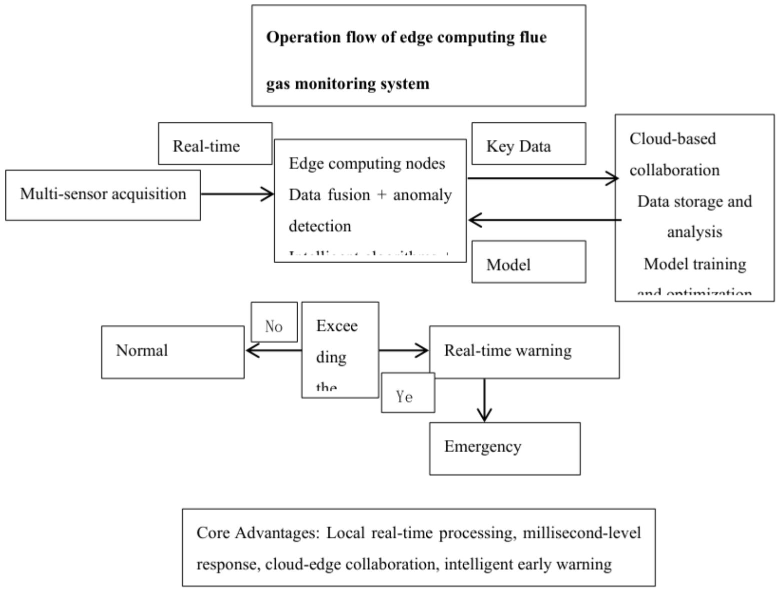

FIGURE 2. illustrates the specific operational mechanism of the edge computing system

to meet the deployment needs of different scenarios.

TABLE 3. Modular Composition of Edge Computing Monitoring System

Functional modules	Core components	Main functions	Design Features
Data acquisition module	Multi-type sensor array (including Pitot tube/ultrasonic flowmeters)	Real-time acquisition of flue gas parameters	Plug and play, scalable
Edge computing module	High-performance microprocessors	Local data analysis and processing	Low power consumption, high computing power
Communication module	Wireless communication unit	Data transmission, command reception, and automatic breakpoint synchronization	Multi-protocol compatibility
Power module	Hybrid Power System (Industrial AC + Solar/Battery Backup)	Redundant power supply for high-load edge nodes	Resilient and energy-optimized
Early warning module	Intelligent Algorithm Engine	Anomaly detection and alarm	Self-learning optimization

The monitoring terminals, edge computing units, communication modules, and power modules are designed as standardized components, facilitating rapid assembly and flexible deployment, significantly reducing system construction costs. The monitoring terminals connect to the edge computing nodes wirelessly, eliminating the need for dedicated lines and reducing construction work. To ensure transmission reliability amidst the electromagnetic interference and metal shielding typical of industrial plants, the system utilizes industrial-grade Mesh networking. While this requires more robust hardware than consumer-grade wireless solutions, it remains a cost-effective alternative to the high labor and material expenses of extensive dedicated cabling. The edge computing nodes feature a low-power design. While solar energy is utilized as a supplemental or backup source to enhance sustainability, the system primarily relies on a stable industrial AC power interface to support the high-performance microprocessors required for real-time multi-sensor fusion. This hybrid approach mitigates the risk of power instability caused by particulate matter accumulation on solar panels or the high energy consumption peaks of complex edge analytics [15]. The system has developed a unified data interface standard and communication protocol, enabling compatibility between devices from various manufacturers, eliminating barriers between devices, and enhancing the system's openness and scalability. The modular design supports on-demand configuration and functional expansion, allowing enterprises to select and combine different modules according to their monitoring needs, avoiding resource waste. In terms of operation and maintenance management, the edge computing nodes have self-diagnostic and self-recovery functions, automatically detecting sensor status, identifying fault types, and troubleshooting through remote upgrades and parameter adjustments, reducing on-site maintenance workload. The system has a unified cloud management platform, allowing maintenance personnel to remotely monitor the operating status of all monitoring points, receive fault alarms, and view historical data through a visual interface, simplifying the operation and maintenance process, reducing the need for specialized technicians, and achieving intelligent and convenient system operation.

IV. CONCLUSION

The industrial flue gas emission real-time monitoring and pollution early warning system based on embedded edge computing, utilizing edge computing architecture, multi-sensor fusion technology, and modular system construction, demonstrates high potential to mitigate the problems of slow response, data inaccuracies (through error margin optimization), and high deployment costs of traditional monitoring systems, providing an advanced technical means for industrial flue gas emission supervision. Initial simulation data suggests that the edge-based deep learning models can predict emission trends with over 90% accuracy, significantly lowering the False Discovery Rate (FDR) compared to traditional threshold-based systems. The system achieves advantages such as local real-time data processing, rapid early warning response to anomalies, significantly improved monitoring accuracy, and efficient and convenient deployment and maintenance, which is of great significance for improving environmental supervision, protecting the ecological environment, and promoting the green transformation of enterprises. With the development of technologies such as the Internet of Things and artificial intelligence, flue gas emission monitoring systems will develop towards greater intelligence and networking, playing an increasingly important role in environmental protection. Environmental science and technology workers must innovate courageously to tackle the specific challenges of emission governance, with a focus on rigorous empirical validation, including long-term field testing to provide comprehensive RMSE and MAE analysis across diverse finishing stages. This will ensure continuous optimization of system performance and expansion of application scenarios to contribute their wisdom toward a greener industry and the harmonious coexistence of humanity and nature.

AUTHOR CONTRIBUTIONS

Jia Hong Zhou designed, collected and analyzed the data, and drafted the manuscript. Jia Hong Zhou conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Jia Hong Zhou participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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