

Edge Computing Enabled Cyber-Physical Systems for Real-Time Monitoring in Autonomous Industrial Environments

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Abstract: Industrial automation has experienced rapid development with the emergence of cyber-physical systems and intelligent robotics. Autonomous industrial environments require continuous monitoring of equipment, processes, and environmental parameters to ensure operational safety and efficiency. Traditional centralized cloud architectures often introduce latency and bandwidth limitations that restrict real-time responsiveness in industrial applications. Edge computing has emerged as a promising solution by bringing computational capabilities closer to data sources. This research proposes an edge computing enabled cyber-physical system architecture designed to support real-time monitoring in autonomous industrial environments. The proposed framework integrates distributed sensors, embedded edge processing units, and machine learning models capable of performing on-site data analysis. Data streams from industrial sensors are processed locally using edge nodes to detect anomalies and generate alerts without relying solely on centralized cloud servers. A layered architecture consisting of sensing infrastructure, edge computing modules, communication networks, and cloud analytics platforms is introduced. The system incorporates lightweight deep learning models for anomaly detection and predictive analytics. Experimental evaluation was performed using simulated industrial monitoring scenarios involving temperature, vibration, and power consumption datasets. Results demonstrate that the edge computing architecture significantly reduces response latency and network congestion while maintaining high monitoring accuracy. The proposed system achieved a latency reduction of approximately 35 percent and improved anomaly detection accuracy compared with traditional cloud-based monitoring frameworks. The findings highlight the importance of edge-enabled cyber-physical systems for enhancing reliability, safety, and operational efficiency in modern autonomous industrial environments.

Keywords: Cyber-physical Systems, Edge Computing, Industrial Automation, Anomaly Detection, Real-time Monitoring

1. Introduction

The rapid development of Industry 4.0 technologies has transformed traditional manufacturing environments into highly automated and interconnected systems. Autonomous industrial environments rely on the integration of sensors, communication networks, and intelligent control systems to monitor and optimize production processes. Cyber-physical systems have become a foundational component of such environments by enabling close interaction between computational intelligence and physical industrial processes. In industrial monitoring applications, large volumes of data are generated continuously by sensors embedded in machines, assembly lines, and environmental monitoring devices. These data streams contain valuable information regarding machine health, operational efficiency, and environmental safety conditions. Conventional monitoring architectures typically rely on centralized cloud servers for data processing and analysis. While cloud computing provides substantial computational resources, it often introduces delays due to data transmission latency and network congestion. Real-time monitoring is critical in autonomous industrial environments where delays in detecting abnormal system behavior can lead to equipment damage, production losses, or safety hazards. Edge computing has emerged as a viable solution to address these challenges by relocating data processing capabilities closer to the source of data generation. Edge computing enables local processing of sensor data at distributed computing nodes positioned near industrial equipment. This architecture reduces dependency on remote cloud infrastructure and improves system responsiveness. By integrating edge computing with cyber-physical systems, industrial monitoring systems can achieve faster anomaly detection and improved reliability. The purpose of this research

is to design and evaluate an edge computing enabled cyber-physical monitoring framework capable of supporting real-time decision making in autonomous industrial environments.

2. Literature Review

Cyber-physical systems represent a convergence of physical processes, computational algorithms, and communication networks. These systems have been widely adopted in industrial automation due to their ability to support intelligent monitoring and control. Research has shown that real-time monitoring plays a critical role in ensuring safety and operational efficiency within industrial environments. Data collected from sensors can reveal early signs of equipment degradation or abnormal operational conditions. However, traditional monitoring architectures that rely exclusively on centralized cloud computing often encounter limitations associated with latency and network bandwidth. As industrial systems become increasingly connected, the volume of sensor data transmitted to cloud servers grows significantly. Edge computing addresses this challenge by performing data processing at local computing nodes positioned near sensors and industrial devices. These edge nodes can execute machine learning algorithms for anomaly detection and predictive analysis before transmitting summarized information to cloud platforms. Recent studies have also explored the use of deep learning models for industrial anomaly detection. Convolutional neural networks and recurrent neural networks have shown promising results in identifying abnormal patterns in sensor data streams. Despite these advancements, integrating edge computing with cyber-physical systems in large-scale industrial environments remains an ongoing research challenge.

3. Architecture of Edge-Enabled Cyber-Physical Monitoring System

The proposed monitoring architecture consists of four primary components that operate in coordination to enable real-time industrial monitoring. The sensing layer contains industrial sensors installed on machinery and production equipment. These sensors measure parameters such as vibration, temperature, pressure, and electrical current. The edge computing layer consists of embedded computing devices that perform data preprocessing, feature extraction, and anomaly detection. These devices are installed near production equipment and operate with minimal latency. The communication layer facilitates secure data exchange between edge nodes and centralized cloud platforms. Industrial communication protocols such as MQTT and OPC-UA are used to ensure reliable data transmission. The cloud analytics layer performs long-term data analysis and machine learning model training. Insights generated at this level support strategic decision making and predictive maintenance planning.



Fig. 1 Cyber Physical Monitoring System

4. Mathematical Modeling of Monitoring System

Real-time monitoring systems must evaluate sensor data streams to detect abnormal behavior in industrial equipment. Let $S(t)$ represent the sensor signal observed at time t .

An anomaly detection function $A(t)$ can be defined as

$$A(t) = |S(t) - \mu| / \sigma$$

where μ represents the mean value of the signal and σ represents the standard deviation.

If $A(t)$ exceeds a predefined threshold value, the system identifies the observation as an anomaly and generates an alert.

The response latency of the monitoring system can be expressed as

$$L = T_t + T_p$$

where T_t represents transmission time and T_p represents processing time.

Edge computing reduces latency by minimizing transmission time because data processing occurs near the data source.

5. Machine Learning Model for Anomaly Detection

The anomaly detection module in the proposed system utilizes a lightweight deep neural network designed for deployment on edge computing devices. The neural network receives feature vectors extracted from sensor signals and performs classification to determine whether the equipment state is normal or abnormal.

The network training process minimizes a loss function defined as

$$Loss = \sum (y_i - \hat{y}_i)^2$$

where y_i represents the actual label and \hat{y}_i represents the predicted label.

Training was conducted using historical industrial sensor datasets containing both normal and fault conditions.

6. Experimental Setup

To evaluate the effectiveness of the proposed architecture, a simulated industrial environment was developed. The simulation included multiple machines equipped with sensors generating real-time data streams. Edge nodes were implemented using embedded computing devices capable of executing machine learning algorithms. Three monitoring architectures were compared during experimentation: traditional cloud-based monitoring, hybrid cloud-edge monitoring, and fully edge-enabled monitoring. Performance metrics included response latency, anomaly detection accuracy, and network bandwidth utilization.

7. Results and Performance Evaluation

The experimental results demonstrated that the edge-enabled cyber-physical monitoring system significantly improved response time compared with traditional monitoring approaches. Average latency decreased by approximately 35 percent due to reduced data transmission requirements. Network bandwidth usage was also reduced because only processed data and alerts were transmitted to the cloud. The anomaly detection model achieved an accuracy of approximately 91 percent when evaluated on industrial sensor datasets. These results indicate that edge computing can effectively enhance the performance and reliability of cyber-physical monitoring systems.

8. Discussion

The integration of edge computing with cyber-physical systems provides several advantages for industrial monitoring applications. By processing data locally, edge nodes enable rapid detection of abnormal system behavior. The architecture also supports scalability because additional edge nodes can be deployed as industrial systems expand. Furthermore, the hybrid edge-cloud model allows long-term analytics and machine learning model updates to be performed in centralized computing environments. Nevertheless, several challenges remain. Edge computing devices typically have limited computational resources compared with cloud servers. Efficient model design and resource management are therefore essential. Future research should explore distributed intelligence frameworks where multiple edge nodes collaborate to improve monitoring accuracy and system resilience.

9. Conclusion

This study presented an edge computing enabled cyber-physical system architecture designed for real-time monitoring in autonomous industrial environments. The framework integrates distributed sensors, edge processing units, and machine learning algorithms to analyze industrial data streams with minimal latency. Experimental results demonstrated that the proposed architecture improves monitoring responsiveness while maintaining high anomaly detection accuracy. The system effectively reduces network bandwidth usage and

enhances operational reliability. The findings suggest that edge computing will play a critical role in the development of next-generation autonomous industrial systems. Future work will focus on integrating advanced deep learning models and security mechanisms to strengthen the resilience of industrial cyber-physical systems.

References

1. E. A. Lee, "Cyber physical systems: Design challenges," IEEE International Symposium on Object Oriented Real-Time Distributed Computing, 2008.
2. W. Shi and S. Dustdar, "The promise of edge computing," Computer, vol. 49, no. 5, pp. 78-81, 2016.
3. J. Wan, M. Yi, D. Li, C. Zhang, and S. Wang, "Mobile services for cyber-physical systems in Industry 4.0," IEEE Access, vol. 4, pp. 7234-7244, 2016.
4. F. Tao and Q. Qi, "Make more digital twins," Nature, vol. 573, pp. 490-491, 2019.



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