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DATA-DRIVEN DECISION-MAKING SYSTEM FOR INJECTION MOLDING PRODUCTION AND MAINTENANCE

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Abstract: A data-driven injection molding production and maintenance decision-making system is designed to address the issues of low efficiency and poor real-time performance in traditional data collection models, meeting the modern industrial needs for high reliability and intelligence. The system adopts a three-layer architecture, including data collection, edge computing, and maintenance decision-making layers. It achieves real-time collection and processing of multi-source heterogeneous data to assess equipment health status dynamically and predict failures. The data collection layer integrates sensor, PLC, and visual device data; the edge computing layer processes key parameters through lightweight models to reduce cloud-side pressure; the maintenance decision-making layer predicts the remaining life of the equipment using the Weibull distribution model and optimizes maintenance strategies. The system proposes a quantitative evaluation index for the health of the injection molding machine and utilizes a weighted fusion algorithm for accurate maintenance decisions, significantly reducing operational costs and improving production efficiency, providing a feasible technical solution for intelligent manufacturing.
Keywords: Injection molding production; Edge computing; Equipment health; Maintenance decision-making

1 INTRODUCTION

To achieve the goal of becoming a manufacturing powerhouse as part of "Made in China 2025", technologies such as Industry 4.0, Internet of Things (IoT), and intelligent manufacturing have rapidly developed. Data collection technology, as a bridge between the physical and digital worlds, provides foundational support for equipment condition monitoring, failure prediction, and maintenance decision-making. However, traditional data collection methods often face issues such as diverse device protocols, reliance on manual integration, low efficiency, high costs, and delayed responses, making it difficult to meet the high reliability and real-time demands of modern industries.

In this context, the operation and maintenance decision-making system, derived from data collection, has emerged. This system builds a closed-loop framework from data to decision-making through real-time collection, edge computing, and intelligent analysis of multi-source heterogeneous data, realizing dynamic assessment of equipment health, early failure prediction, and accurate maintenance strategy recommendations. For example, in an injection molding factory, by monitoring parameters such as vibration and temperature in real-time and combining predictive maintenance algorithms, failure handling can shift from "passive response" to "active prevention", significantly reducing operational costs. This contributes to the large-scale application of data in modern industrial settings and holds significant practical and applied value.

Current technologies primarily focus on overall production line forecasting, resulting in bulky systems with high on-site deployment costs. Many features remain impractical for factory applications, while the integration between real-time data and decision-making loops remains inadequate. Point-to-point equipment maintenance still faces challenges of being undetectable and unpredictable.Taking injection molding machines as an example, existing maintenance systems fail to effectively accommodate the diverse production needs across different factories. Significant disparities exist in equipment intelligence levels, while data monitoring devices remain relatively outdated. Equipment failures consequently cause severe production losses. Given the substantial market demand, there's an urgent need to enhance information-based management and intelligent control of injection molding equipment. This includes real-time monitoring of production data and predictive maintenance scheduling - specifically, establishing a mapping model between multi-source heterogeneous data and equipment health status, validating lightweight deployment of LSTM algorithms on edge computing nodes, and ultimately elevating intelligent operational standards.

2 SYSTEM DESIGN

The system is designed with a three-layer architecture, consisting of the data collection layer, edge computing layer, and maintenance decision-making layer. The data collection layer is responsible for integrating raw data and transmitting it to the edge computing layer. Data collection is distributed across various production processes to enable comprehensive monitoring of the entire production flow. The edge computing layer deploys edge computing devices at key nodes to process data streams. It handles high-feedback real-time parameters, reducing latency and cloud-side computational pressure, while leaving traditional data measurement and control tasks to be processed locally. The maintenance decision-making layer receives standardized data forwarded from the edge computing layer. It provides essential maintenance services, including overall data monitoring, individual equipment health assessment, and an open application programming interface (API) to support the development of customized maintenance services. The overall architecture is shown in Figure 1.

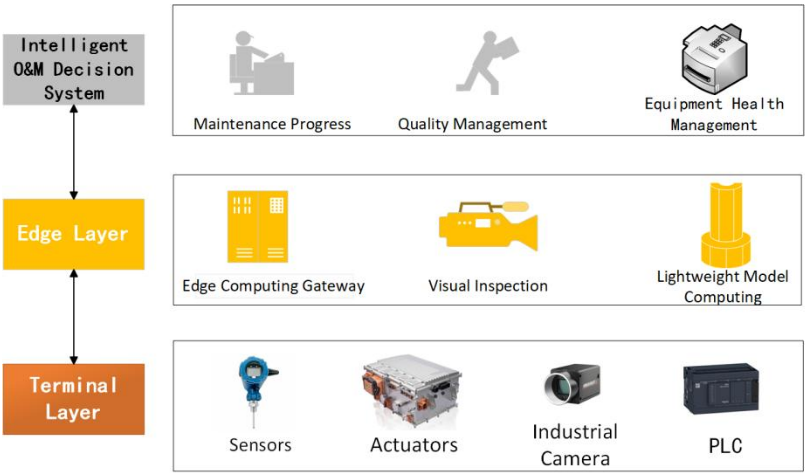

Figure 1 Architecture Design Diagram

The system needs to integrate a large volume of data, with a wide range of sizes, involving multiple process optimizations and complex algorithms. Maintaining high reliability, efficiency, and ease of deployment places high demands on the system design and the related technologies.

3 DATA COLLECTION

3.1 Data Source Analysis

Data collection needs to address the synchronization, integrity, and noise interference of multi-source heterogeneous data. In the injection molding process, a variety of data types need to be reported, covering multiple dimensions such as equipment, processes, and the environment[1]. These include equipment operational data such as real-time monitoring data on voltage, current, temperature, pressure, vibration, etc., as well as status data like on/off states, fault codes, and alarm signals, which are collected from IoT sensors, PLCs (Programmable Logic Controllers), and SCADA (Supervisory Control and Data Acquisition) systems. Production process data includes parameters such as temperature settings, pressure thresholds, and formula ratios, as well as quality control data like product size, weight, and production batch numbers. Environmental and energy consumption data include environmental data like temperature, humidity, and atmospheric pressure, as well as energy usage data such as water and electricity consumption, and emissions data including exhaust, wastewater, and noise levels. Additionally, for product quality inspection, defect detection images and industrial visual data such as barcodes/QR codes are also collected.

3.2 Data Collection Scheme Design

Based on the types of equipment involved in the injection molding process, a targeted data collection plan is designed, as shown in Figure 2. The specific plan is as follows:

Sensor-based Collection: Wireless sensors such as LoRa and Zigbee are used to transmit vibration and temperature data, suitable for mobile devices or long-distance scenarios. Wired sensors with 4-20mA/RS-485 interfaces are used for high-reliability requirements (e.g., high-pressure equipment).

Industrial Equipment Direct Collection: Data is directly collected from PLC/CNC devices by adapting industrial protocols such as OPC UA, Modbus, and Profinet.

Visual Image Collection: Industrial line scan cameras are used to capture equipment monitoring data, and industrial array cameras are used for defect detection in products.

Edge Gateway Collection: Edge computing gateways are deployed to integrate node data, enabling data packaging and uploading, along with local preprocessing of the data.

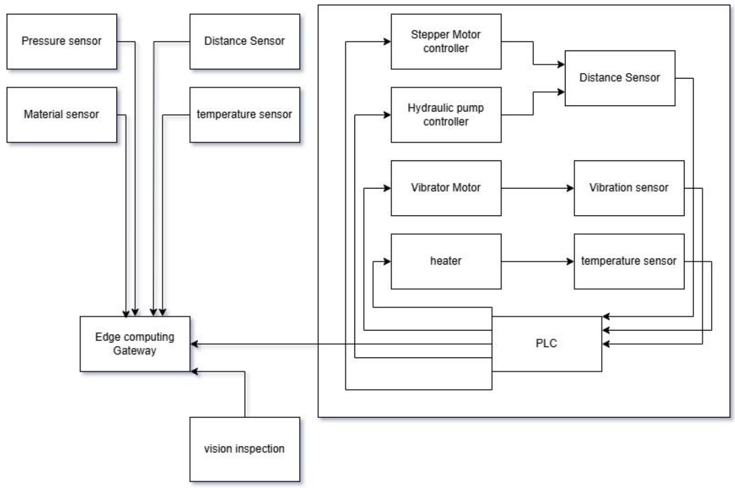

Figure 2 Data Collection Scheme Design Diagram

3.3 Data Collection Technology Implementation

The new sensor network, as an essential component of the modern Internet of Things (IoT), reflects the development trend of sensors in factory environmental monitoring through higher sensitivity, broader applicability, and lower environmental impact. The complementary use of wired and wireless sensors demonstrates broader application prospects. Wired sensors, with their high reliability, frequency, and precision in data collection, hold an irreplaceable position in collecting critical data, while wireless sensors strike the optimal balance between expanding the scope of collection and reducing collection costs.

The data collection module of this system is designed based on advanced Wireless Sensor Networks solutions (WSNs) in the industry[2], incorporating a wired sensor application environment model. This provides a reliable overall collection framework, ensuring data accuracy and transmissibility. Additionally, it integrates automatic control nodes such as PLCs, microcontrollers, and industrial PCs, combining the data collection capabilities of these controllers to offer a more flexible data node configuration for the collection framework.

3.4 Edge Computing Design

With the development of the Internet of Things (IoT), the number of edge devices has rapidly increased, and the amount of data generated has reached the zettabyte (ZB) level[3]. The centralized big data processing model, based on cloud computing, is no longer efficient enough to handle the data generated by edge devices, which has led to the emergence of edge computing technology. Compared to traditional data transmission gateways, edge computing gateways are more expensive, but the technological advantages they bring are significant. By reasonably designing edge nodes for device deployment, it is possible to balance the allocation of computing resources between the edge and the cloud, while also enhancing the speed of massive data processing. Therefore, we have introduced edge node design evaluation standards, using node reliability and performance requirements as criteria to ensure efficient data processing on edge devices.

For special assessments based on the characteristics of the injection molding environment, continuous operation tests were conducted at 85℃, and accelerated aging experiments were used to estimate whether the equipment's mean time between failures exceeds the 50,000-hour industrial requirement. Temperature and humidity range tests (-10℃ to 85℃ for thermal cycling) were performed to verify the stability of components under extreme environmental conditions. Basic performance evaluations, including LINPACK for floating-point operations, Dhrystone for integer operations, and quantifying computational power, were conducted to meet the real-time processing demands of equipment health algorithms. Memory bandwidth was evaluated using the Stream testing tool, and local storage IOPS were tested using the Fio tool for simulating random read/write operations to ensure efficient processing of high-frequency sensor data. Network throughput was measured using the iPerf3 tool, and end-to-end latency was tested with precise timestamp ping tests.

3.5 Edge Defect Detection

Existing industrial camera systems typically record image data and then transmit it to a cloud computing center after direct or simple image processing. However, as video data continues to grow in volume, applications in the injection molding field require defect detection systems to provide real-time and efficient image data processing. To address this, an edge computing model integrates computationally capable hardware units into the existing defect detection system hardware platform, supported by corresponding software technologies, creating a new type of defect detection system with edge computing capabilities[4].

In the edge computing model, computation typically occurs near the data source, i.e., image data processing takes place at the edge where the data is collected. To achieve this, a preprocessing function module based on intelligent algorithms is used to perform partial or full computational tasks on the real-time collected image data, while ensuring data reliability. This enables timely responses to applications with high real-time requirements, while also reducing the computational and bandwidth load on the cloud computing center.

4 OPERATION AND MAINTENANCE DECISION MAKING

4.1 Operation and Maintenance Decision Making Design Approach

In injection molding production, continuous monitoring and assessment of the injection molding machine's health status is crucial for ensuring the safe operation of the factory. By establishing a quantitative relationship between monitoring data and equipment status, this system introduces the concept of injection molding machine health. It also incorporates machine health into the maintenance decision-making process, aiming to avoid both excessive maintenance and insufficient maintenance.

4.2 Injection Molding Machine Health Assessment

The core concept of injection molding machine health is to accurately calculate the equipment's operating status using data, with identifying key parameters being crucial. By referring to relevant Chinese national standards, data layering and linear normalization are applied to convert raw values such as vibration, temperature, and pressure into a range of [0, 1]. The general normalization method is as follows:

$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

Where x represents the raw data.
A lightweight model is deployed at the edge layer to calculate the feature health (single-parameter level), and the weighted fusion algorithm used is expressed mathematically as follows:

$$\theta = w_a \times \theta_a + w_b \times \theta_b + w_c \times \theta_c + w_d \times \theta_d \tag{2}$$

Where w represents the weight, the sum of w equals 1, and θ represents the normalized key parameter value[5].
The processed data is forwarded to the cloud for subsequent subsystem health fusion calculations and global health calculations (at the equipment level)[6].

4.3 Predictive Maintenance Decision Design

The system predicts the failure downtime through equipment failure prediction, allowing for proactive maintenance scheduling to avoid production interruptions, reduce downtime, and lower maintenance costs. At the same time, combined with the injection molding machine health assessment, it provides optimal maintenance recommendations.
This system uses a Weibull distribution-based degradation model to fit the equipment performance degradation curve[7]. The Weibull distribution is a commonly used life distribution model that effectively describes the equipment failure process. Its probability density function is as follows:

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}} \tag{3}$$

Where β is the shape parameter and η is the scale parameter.
The parameters of the Weibull distribution are estimated using the maximum likelihood estimation method. Given a set of equipment failure time data t1, t2,..., tn, the estimated values for the shape parameter β and the scale parameter η are:

$$\hat{\beta} = \frac{n}{\sum_{i=1}^{n}\left(\ln\frac{t_i}{\bar{t}}\right)^2} \sum_{i=1}^{n}\left(\ln\frac{t_i}{\bar{t}}\right)\left(\frac{t_i}{\bar{t}}\right)^{\hat{\beta}} \tag{4}$$

$$\hat{\eta} = t^{-}\left(\Gamma\left(1 + \frac{1}{\hat{\beta}}\right)\right)^{-1} \tag{5}$$

Where t ¯ is the sample mean, and Γ is the Gamma function. 3. Remaining useful life prediction.
Based on the estimated Weibull distribution parameters, the remaining useful life (RUL) of the equipment can be predicted. Given the current time t0, the remaining useful life of the equipment is:

$$RUL(t_0) = \eta\left(-\ln(1 - F(t_0))\right)^{1/\beta} - t_0 \tag{6}$$

F (t0) represents the cumulative failure probability of the equipment at time t0[8].

5 CONCLUSION

This paper presents a data-driven injection molding production operation and maintenance decision system, which integrates multi-source heterogeneous data collection, edge computing, and intelligent analysis technologies. It enables dynamic monitoring of equipment health status and predictive maintenance, effectively addressing the inefficiencies and delayed responses inherent in traditional operation and maintenance models. The system adopts a three-layer architecture design, combining lightweight models and Weibull distribution algorithms, which significantly enhance the real-time processing of data and the accuracy of maintenance decisions. This solution is not only suitable for large intelligent factories but also adaptable to the production environments of small and medium-sized enterprises, offering high flexibility and scalability. In the future, with the further development of the industrial Internet of Things and artificial intelligence technologies, the system can further enhance its intelligence level through optimization algorithms and strengthened edge computing capabilities, providing strong support for the digital transformation of the manufacturing industry.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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