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Integration and Innovation of Cloud Computing and the Internet of Things in Enterprise Production and Operations Management

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Abstract: The collaborative application of cloud computing and the Internet of Things (IoT) in enterprise production and operation management is explored in this study, with the aim of improving the efficiency and security of production data processing. Hierarchical data processing is achieved by the system through the combination of edge computing and cloud computing. The edge layer is responsible for the rapid response to real-time data, whereas large-scale data analysis and prediction are conducted by the cloud. The experimental results show that the time series analysis model Autoregressive Integrated Moving Average (ARIMA) demonstrates accuracy in production prediction, and the random forest model exhibits high accuracy in equipment fault detection. To ensure the security of data transmission and storage, the Advanced Encryption Standard–256 bit (AES-256) and the Transport Layer Security (TLS) protocol is adopted for encryption, and blockchain technology is introduced to achieve data traceability, thereby ensuring data transparency and tamper-proofing. Role-Based Access Control (RBAC), two-factor authentication, and the Open Authorization (OAuth) protocol further enhance access management and privacy protection. Overall, the effectiveness of the edge–cloud collaborative architecture in improving production efficiency, optimizing resource utilization, and strengthening data security is verified in this study, providing a reference scheme for the intelligent production of enterprises.

Keywords: Cloud computing, Internet of Things, edge computing, data security, production management.

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1. Introduction

In the domain of enterprise production and operation management, the integration of digital technologies has become increasingly important. The advent and widespread adoption of cloud computing and the Internet of Things (IoT) have led to innovative technical solutions that enhance operational efficiency, optimize resource allocation, and facilitate intelligent management. Cloud computing, with its high-performance data storage capabilities, computational power, and scalable resources, enables enterprises to handle extensive data demands more effectively in production management.

With the rapid development of e-commerce, enterprises increasingly demand accurate predictions of customers' purchasing behavior. The accurate prediction of user purchasing behavior can not only optimize marketing strategies and improve the user experience but also enhance inventory management, supply chain optimization and dynamic pricing capabilities. However, user data in the e-commerce environment exhibit complex characteristics, such as high dimensionality, time series and nonlinearity, which limit the accuracy and real-time performance of traditional statistical models.

Research on enterprise operations management, predictive models, and artificial intelligence technologies, including supply chain management, production optimization, and data-driven decision-making, is increasing. Longoni et al. (2024) studied the role of social enterprises in the supply chain and emphasized the importance of social influence in promoting system change. Muangmee et al. (2022) analyzed the competitiveness of SMEs in supply chain management and noted that a data-driven optimization strategy aims to enhance market competitiveness. Li et al. (2023) discussed the sustainable development mechanism of high-tech enterprises on the basis of the system dynamics model and highlighted the impact of innovation collaboration on the long-term development of these enterprises. Mathrani (2022) examined the enhancement effect of enterprise systems on production agility, proposing that information technology can optimize the production decisions of enterprises and improve resource allocation efficiency. Wang et al. (2022a) analyzed the influence of policies on industrial symbiosis through simulation research, reporting that the role of policy regulation in optimizing enterprise operations is. Wang et al. (2022b) further discussed the impact of interprovincial power resource allocation on the production behavior of enterprises, finding that reasonable energy resource allocation can enhance production efficiency. Lim et al. (2022) proposed a circular economy model based on the green-lean concept, emphasizing the role of sustainable production and operations in the long-term competitiveness of enterprises. Gao et al. (2023) developed an enterprise digital service platform utilizing IoT technology to provide technical support for the intelligent operation management of enterprises. Al-kuwari et al. (2024) studied the roles of sustainable value chain management and lifecycle management in power production technology, emphasizing the necessity of sustainable operation management. Holgado et al. (2024) discussed the role of supply chain management in building enterprise resilience and proposed that supply chain optimization is a means to achieve sustainable development for enterprises.

Current research has achieved notable advancements in enterprise operation optimization, data analysis technology, and artificial intelligence prediction models (Xing et al., 2024; Moon et al., 2023). Although existing studies have explored the application of deep learning, cloud computing, supply chain management, and other technologies in enterprise management, research on predicting e-commerce customer purchase behavior still has several shortcomings: a lack of modeling user behavior characteristics in e-commerce environments; a greater emphasis on optimizing enterprise operations with less discussion on the purchasing decision-making processes of individual users; and insufficient depth in the optimization strategies of neural network algorithms (Saratchandra et al., 2022a; Saratchandra et al., 2022b). Currently, most studies focus on traditional machine-learning methods, while the adaptability and optimization of deep learning models in the field of e-commerce have not been thoroughly investigated (Guo et al., 2023). Additionally, the business value assessment of prediction models remains relatively limited, with few studies addressing the impact of prediction results on business applications, such as personalized recommendations, dynamic pricing, and inventory management (Alismaili et al., 2020; Lu et al., 2022).

2. Materials and Methods

2.1. Data Acquisition and System Requirement Analysis

2.1.1. Data sources and acquisition methods

The data sources used in this study are divided into three categories, as shown in Fig. 1.

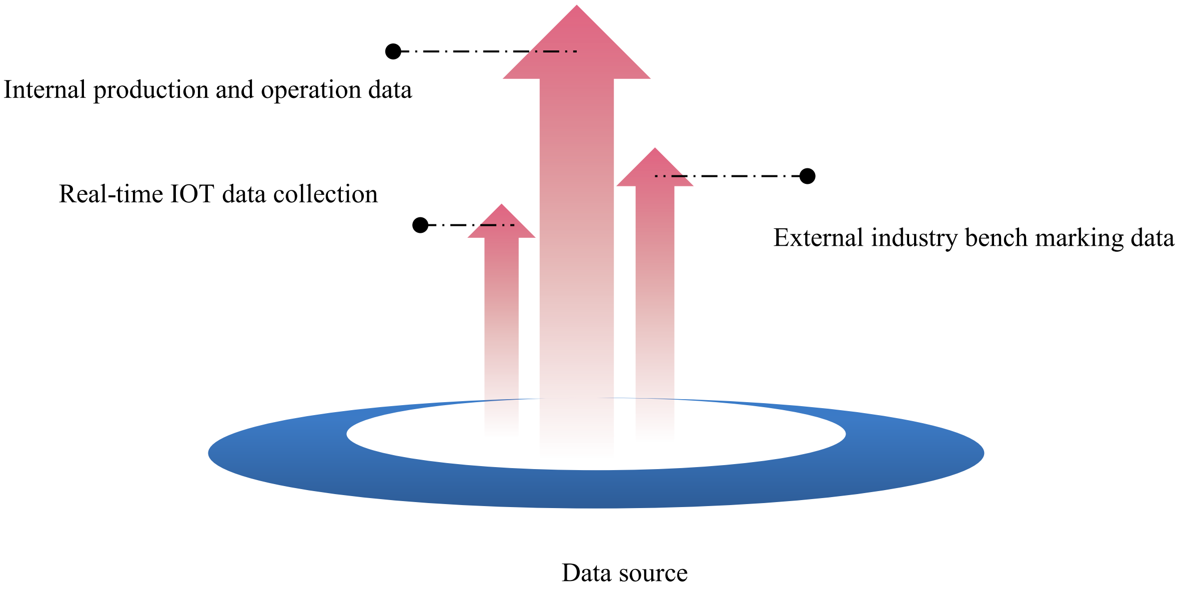

Fig. 1. Data source diagram

IoT data are primarily gathered via sensors embedded in production equipment, capturing metrics such as production rate, operational duration, and energy consumption. To ensure the reliability and consistency of the data, the collection frequency is set at 15-minute intervals. Furthermore, three representative enterprises from China's manufacturing sector are selected as case studies to enhance the breadth and applicability of the dataset. Additionally, external benchmarking data are sourced from publicly available international industry reports, ensuring the dataset's global relevance and comparability, as illustrated in Table 1.

Table 1. Data sources and collection methods

Data Category	Data Source	Data Type	Collection Frequency	Data Volume (in thousands/month)
IoT-Collected Data	Production Equipment Sensors	Temperature, Pressure, Current	Every 15 min	8.67
Internal Enterprise Data	ERP System	Production Volume, Order Completion Rate	Daily	6.73
External Benchmark Data	Public Databases and Industry Reports	Global Production Comparisons	Monthly	2.39

2.1.2. System requirement analysis and function definition

According to the production and operations management needs of enterprises, the system functions primarily cover the following modules:

(1) Real-time monitoring and alarm module: It is essential to analyze equipment operation data in real time and establish an early warning threshold. If the temperature exceeds the set range, the alarm will be triggered automatically. This function requires the system to maintain a response speed of no less than 5 s to ensure the safety and stability of production.

(2) Data storage and call module: The system needs to configure a distributed database with high concurrent processing capabilities to manage massive amounts of data and adopt a *NoSQL* database structure to support the fast storage and access requirements of big data.

(3) Data analysis and visualization module: The system should be able to connect with the big data analysis platform, provide multidimensional analysis, including productivity and equipment utilization, and present the results in charts to facilitate managers' decision-making.

2.1.3. Data cleaning and standardized processing

Due to the wide range of data sources and multiple types of data (such as time series data and classified data), the data need to be cleaned and standardized. The data-cleaning process includes outlier processing, filling in missing values, and removing duplicate data. Outliers are primarily identified by combining the 3σ principle with the boxplot. For missing values, the difference method is used to preserve the authenticity and consistency of the data to the maximum extent. To meet the requirements of data fusion across different dimensions, the Z-score standardization method is applied to transform all data into a distribution with a mean of 0 and a variance of 1, thereby avoiding distortions caused by differences in scale, as shown in Table 2.

Table 2. Data cleaning and standardization processing

Data Variable	Outlier Detection Method	Missing Value Treatment Method	Standardization Method
Production Rate	3σ Principle, Box Plot	Interpolation Method	Z score
Temperature Data	3σ Principle	Interpolation Method	Z score
Order Completion Rate	3σ Principle	Mean Imputation	Z score
Global Production Comparison Data	Box Plot	Previous Value Imputation	Z score

The data-processing methods mentioned above ensure that the data exhibit high consistency and statistical reliability during the analysis process, providing a stable foundation for subsequent model development and application.

Table 3. Specifications and task allocation for the edge and cloud computing layers

Component	Configuration	Specification
Edge Device	8-core Central Processing Unit (CPU), 16 GB RAM	Data processing at source
Cloud Server	16-core CPU, 64 GB RAM, 15 TB storage	High-volume data processing
Latency Requirement	Transmission Delay	<100 ms

2.2. Model Development and Architecture Design

2.2.1. Architecture selection and design principles

In the design principle, the transmission delay is maintained within 100 ms to ensure timely data transmission. The cloud storage capacity is 15 TB, which can meet the long-term historical data storage needs of enterprises and is expected to support data growth over the next five years, as shown in Table 3.

2.2.2. Data processing and analysis model

The ARIMA, with a mean of 0 and a variance of 1, is presented in Eq. (1).

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t+1} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{1}$$

The *ARIMA* model used to forecast production is based on data collected daily over two years, four times a day, resulting in a total of 2,920 records. The model parameters *p, d* and *q* were set to 2, 1 and 2, respectively. This model is used to predict fluctuations in production volume for the upcoming quarter. The actual values of endogenous production for seven days are presented alongside the predicted values, with the gray shaded area indicating the forecast error. The effectiveness of the ARIMA model in production prediction is shown in Fig. 2.

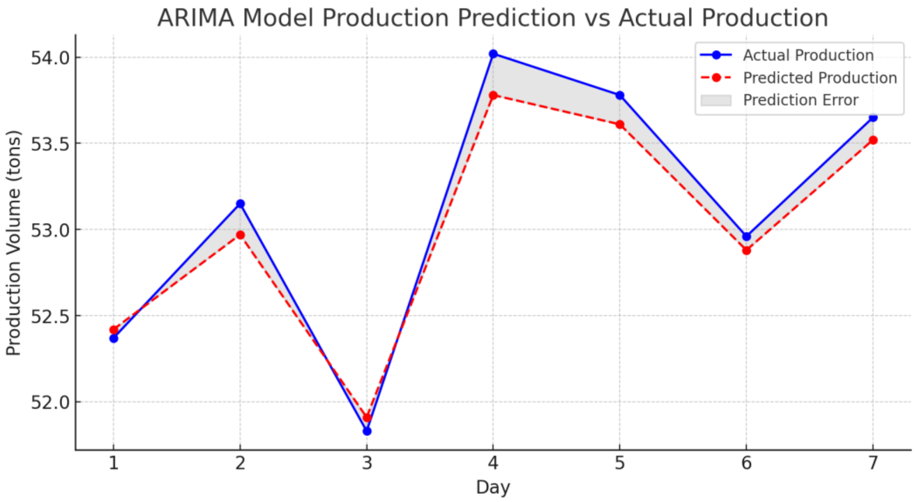

Fig. 2. Effectiveness of the ARIMA model in production predictions

This graph shows the ARIMA production prediction over a seven-day period, comparing the actual production with the model's predictions. The horizontal axis represents time (in days), whereas the vertical axis represents units of production (assumed to be in tons). The blue curve indicates the actual production volume, the red curve indicates the predicted values, and the shaded area between the curves reflects the forecast error.

A total of 3000 sample data points, including the operating temperature, vibration frequency, working time and other characteristics of the production equipment, are used for equipment fault identification in the random forest model. The ratio of the model training set to the test set was 7:3, the number of trees in the model was 73, the minimum sample split was 13, and the prediction accuracy was 92.5%, as shown in Fig. 3.

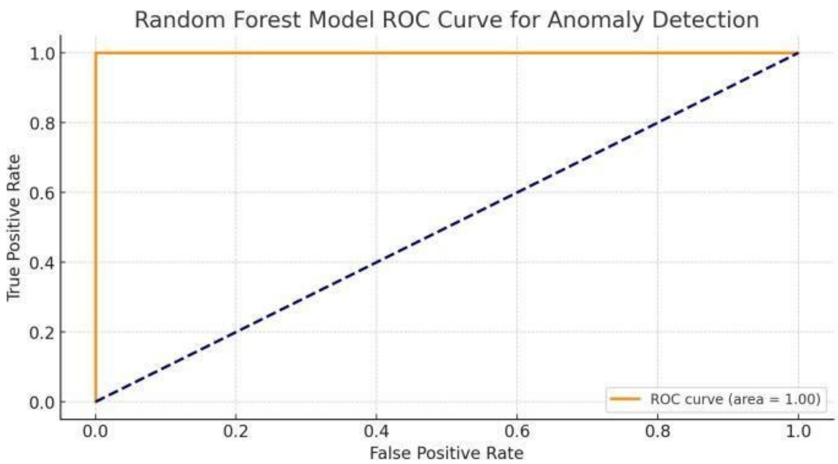

Fig. 3. ROC curve illustrating the anomaly detection performance of the random forest model

The Receiver Operating Characteristic (ROC) curve of the random forest model reflects the performance changes of the model under different thresholds. The AUC value of the curve indicates that the overall performance of the model in anomaly detection is good and provides a direct reference for the accuracy evaluation of the system, as shown in Table 4.

Table 4. Specifications for data processing and analysis models

Model Type	Application Area	Algorithm	Training Data (Samples)	Key Features
Time Series Analysis	Production Forecasting	ARIMA	2920	Production Volume Over Time
Machine Learning	Anomaly Detection	Random Forest	3000	Temperature, Vibration, Working Hours

2.2.3. Parameter setting and model calibration

ARIMA model parameters:

The optimal combination of p, d and q was determined using the *Akaike* Information Criterion (*AIC*), resulting in final settings of p=2, d=1 and q=2. The *AIC* score of the model was 135.7, indicating a satisfactory degree of fit for the prediction model.

Random forest model parameters:

The optimal parameters of the random forest model are determined by cross-validation. The number of trees was set to 73, the minimum number of split samples was 13, the average accuracy of the model on the test set was 92.5%, and the F1 score was 89.3%. as shown in Table 5.

Table 5. Model parameter settings and calibration results

Model	Parameter	Value	Performance Metrics
ARIMA	(p, d, q)	(2, 1, 2)	AIC Score: 135.7
Random Forest	Number of Trees	73	Accuracy: 92.5%, F1 Score: 89.3%

2.2.4. Model verification and performance optimization

ARIMA model validation:

It is used to evaluate the predictive performance of the model, including the Root Mean Square Error (*RMSE*) and the Mean Absolute Percentage Error (*MAPE*). The RMSE is calculated using Eq. (2).

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2} \tag{2}$$

The *MAPE* is shown in Eq. (3).

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \times 100\% \tag{3}$$

The RSME was 8.17, and the *MAPE* was 4.25%. These error values align with the error tolerance of production forecasts for enterprises and enhance reliability for practical applications.

The specific formula for validating the random forest model is expressed as the average of predicted results for each tree in regression or as majority voting in classification, as shown in Eq. (4).

$$\hat{y} = majority\_vote(T_1(x), T_2(x), \ldots, T_n(x)) \tag{4}$$

Through 10 cross-validations, the accuracy rate, recall rate and F1 score of the random forest model for anomaly detection were evaluated. The average accuracy of the model was 92.5%, the recall rate was 87.8%, and the F1 score was 89.3%. To optimize the model's performance, feature selection and hierarchical sampling strategies were adopted to further improve its generalizability, as shown in Table 6.

Table 6. Model performance metrics and optimization techniques

Model	Performance Metric	Value	Optimization Technique
ARIMA	RMSE, MAPE	RMSE: 8.17, MAPE: 4.25%	Feature Scaling
Random Forest	Accuracy, Recall, F1 Score	Accuracy: 92.5%, Recall: 87.8%, F1 Score: 89.3%	Feature Selection, Resampling

2.3. Technical Implementation and System Integration

2.3.1. Collaborative implementation of edge computing and cloud computing

In enterprise production management, the purpose of collaboration between edge computing and cloud computing is to optimize the data-processing speed and reduce the load on the cloud. The delay calculation formula is presented in Eq. (5).

$$Average\,Delay = \frac{\sum_{i=1}^{n} D_i}{n} \tag{5}$$

Edge compute nodes are deployed near production equipment and are responsible for the real-time collection and processing of critical data, including temperature, pressure, and energy consumption. By handling data locally, these nodes help minimize transmission delays. Each edge node is equipped with an 8-core CPU and 16 GB of memory, enabling the efficient processing of substantial volumes of field data within a short timeframe, thereby ensuring a rapid response.

In contrast, the cloud is utilized for long-term trend analysis and large-scale data storage, providing enterprises with the computational capacity required for in-depth data processing. Each cloud server is conFig.d with a 16-core CPU and 64 GB of memory, ensuring that it can accommodate extensive analytical operations, as illustrated in Table 7.

Table 7. Specifications for edge and cloud computing and task allocation

Computing Layer	Primary Function	Hardware Specification	Task Allocation
Edge	Real-time data processing, anomaly detection	8-core CPU, 16 GB RAM	Local preprocessing
Cloud	Large-scale analysis, data storage	Distributed 16-core servers, 64 GB RAM	Predictive analytics, complex computations

In this table, the division of labor between the edge and the cloud is clear: the edge layer is primarily used to process field data in real time, with a relatively low hardware configuration. However, its low latency characteristics make it suitable for quickly detecting anomalies and transmitting early warnings. In contrast, cloud hardware is more powerful, focusing on predictive analytics and deep computing, and can perform a comprehensive assessment of production data across the enterprise. This layered structure effectively reduces overall latency and enhances resource utilization efficiency.

2.3.2. IoT device access and data transmission protocol

Each device is bound to the edge node using a unique device ID for precise point-to-point transmission. Moreover, to ensure that key data is not lost, the transmission is set to the QoS 2 level of Message Queuing Telemetry Transport (MQTT); that is, the receiver must confirm that the sender has accurately transmitted each piece of data. This mechanism is particularly suitable for rapid response to and feedback on abnormal conditions in real-time production environments, as shown in Table 8.

Table 8. IoT device connectivity and data transmission protocols

Connection Layer	Protocol	Data Type	Frequency	Security Layer
Edge Gateway	MQTT	Production rate, energy consumption, temperature	Every 10 s	TLS encryption
Cloud	HTTPS	Aggregated analytics data	As required	AES-256 encryption

(1) Edge gateway layer: The lightweight MQTT protocol is used to transmit device data to edge nodes and is suitable for low-bandwidth environments. The device's production data, including the production rate and energy consumption, are transmitted every 10 s, and the Transport Layer Security (TLS) encryption protocol is used to ensure transmission security.

(2) Cloud layer: The summary data processed by edge nodes are uploaded to the cloud through HTTPS, and the AES-256 encryption standard is used for data storage to ensure the security of data transmission and storage.

2.4. Security and Privacy Protection Mechanism

The system uses AES-256 and TLS protocols to double-encrypt data, ensuring the security of data transmission and storage. Data traceability through blockchain technology enhances the transparency and credibility of the data. In addition, RBAC permission control, two-factor authentication and the OAuth protocol improve user access management and further enhance the security and privacy protection level of the system, as shown in Fig. 4.

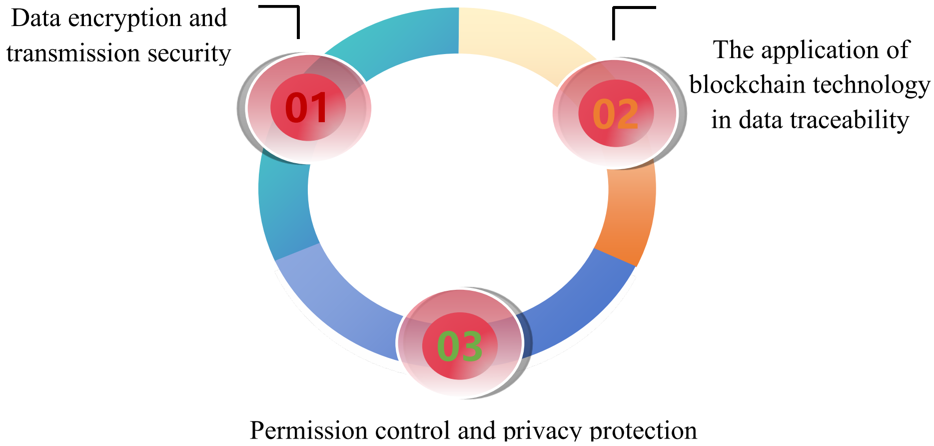

Fig. 4. Diagram of the security guarantee and privacy protection mechanism

2.4.1. Data encryption and transmission security

In the process of transmission, TLS is used to protect the data. The TLS protocol encrypts the data flow at the network transport layer, making it difficult for third parties to intercept or tamper with the data in the transmission path. The workflow of the TLS includes two phases, key negotiation and authentication, ensuring the integrity and privacy of the data as they are transmitted between the client and the server. In addition, to prevent data from being intercepted and tampered with by attackers during transmission, each data transmission is accompanied by a hash check value for data integrity verification. If the data are tampered with during transmission, the receiver can immediately detect the anomaly through hash comparison, ensuring the authenticity of the data.

2.4.2. Application of blockchain technology in data traceability

For example, when it is necessary to trace a production batch of data, information such as the generation time and source device can be found through the hash value in the blockchain, providing full traceability. The application of blockchain also helps enterprises build trust in cross-department or cross-enterprise collaboration, thereby reducing the security risks associated with data sharing. In the alliance chain mode, blockchain nodes are jointly maintained by multiple departments and partners within the enterprise, with controllable participation rights. Each party can read and view only the data relevant to them, while the data are authenticated by consensus mechanisms (such as the PBFT protocol) when written to the blockchain, preventing unauthorized operations from entering the chain. This method enhances the security of data sharing and ensures the authenticity and reliability of the data. Ultimately, blockchain not only provides the traceability of production data but also facilitates the transparent management of multiparty data, thereby eliminating the trust issues caused by data asymmetry.

2.5. Experimental Design and Evaluation Methods

2.5.1. Experimental scheme design and variable control

The experimental scheme is designed to verify the effectiveness of cloud computing and IoT systems in enterprise production and operation management. The experimental variables are categorized into independent variables, dependent variables and control variables. The independent variables include the edge computing processing rate, data transmission frequency and equipment failure rate, while the dependent variables consist of production efficiency, equipment health state and energy consumption level. The control variables are the equipment type and experimental environment temperature, which ensure consistency in the experimental conditions.

In the experiment, the operational data acquisition frequency of the equipment was set to every 15 s, and data was collected for 7 days, generating approximately 40,320 records, as shown in Table 9.

2.5.2. Definition and selection of evaluation indicators

Device usage: Calculate the load on edge devices and cloud servers to measure resource utilization. The equipment utilization rate ranged from 73.19% to 84.62%.

Productivity: Evaluate the productivity improvements of cloud computing and IoT systems in terms of output per unit time. The average production efficiency in the experiment ranged from 87.63% to 93.21%, as shown in Table 10.

Table 9. Value of each variable

Variable	Type	Value Range
Edge-Processing Rate	Independent	0.12–0.74 ms
Data Transmission Frequency	Independent	8.47–13.93 s
Equipment Failure Rate	Independent	0.032–0.091%
Production Efficiency	Dependent	87.63–93.21%
Energy Consumption	Dependent	47.78–69.83 kWh
Device Type	Controlled	Fixed Model
Environmental Temperature	Controlled	21.67–23.34 °C

Table 10. Evaluation metrics and definitions

Evaluation Metric	Definition	Range
Device Utilization	Ratio of active to total device capacity	73.19%–84.62%
Data Transmission Delay	Time for data transfer from edge to cloud	57.39–86.13 ms
Energy Consumption	Energy used per unit time	47.78–69.83 kWh
Production Efficiency	Output per unit time	87.63%–93.21%

2.5.3. Data analysis method and result interpretation

The results show that the edge computing processing rate and equipment utilization significantly affect production efficiency (correlation coefficient: 0.763), whereas data transmission delay has little effect on energy consumption. There was no significant difference in energy consumption between the edge and cloud load peaks ($t=1.482$, $p=0.138$), indicating high system stability, as shown in Table 11.

Table 11. Data analysis methods and result interpretations

Analysis Method	Metric	Result
Descriptive Statistics	Mean, Standard Deviation	Varies by Variable
Pearson Correlation	Edge-Processing Rate vs. Production Efficiency	0.763
Independent t Test	Energy Consumption	t=1.482, p=0.138
Chi-Square Test	Equipment Failure Rate	Significant

3. Results and Discussion

3.1. Results Analysis

The collaborative architecture effectively reduces data-processing delays, improves resource utilization efficiency, enables real-time response and predictive maintenance functions, and provides technical support for optimizing enterprise operational efficiency, as shown in Fig. 5.

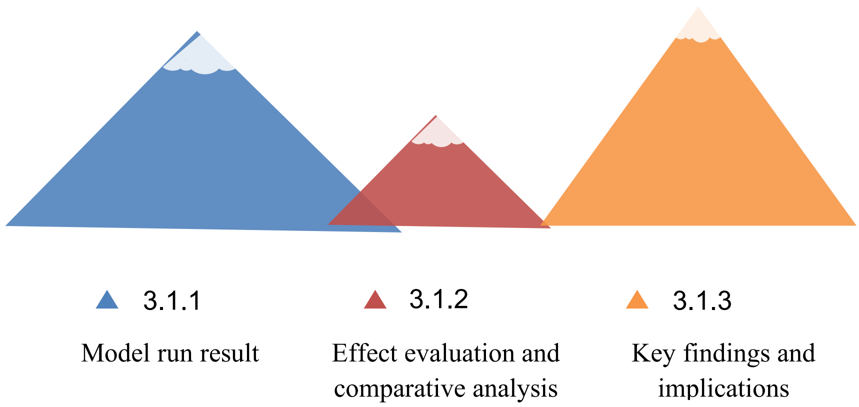

Fig. 5. Results analysis diagram

3.1.1. Model operation results

Under the collaborative architecture of edge computing and cloud computing, the results of model operation confirm that the system demonstrates high accuracy and response efficiency when processing real-time data in production operation management. *The ARIMA model performed well in predicting changes in production volume. During the seven-day experimental period, the average daily RMSE was approximately 8.17, and the MAPE* was 4.25%, which aligns with the error tolerance range for production volume prediction. The selected *ARIMA* model parameters (p=2, d=1, and q=2) effectively capture short-term fluctuations and exhibit strong trend recognition ability.

3.1.2. Effect evaluation and comparative analysis

The performance evaluation compares traditional single-cloud computing architectures with edge–cloud collaborative architectures, focusing on differences in data-processing latency, resource utilization, and prediction accuracy, as shown in Fig. 6.

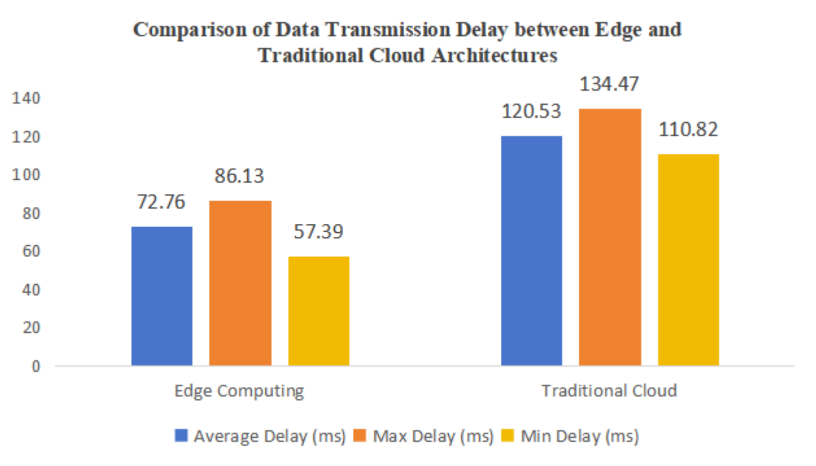

Fig. 6. Comparison of data transmission delays between edge and traditional cloud architectures

Experimental data show that edge–cloud collaborative architectures have significantly lower processing latency than traditional architectures. In the traditional architecture, the average data-processing delay is approximately 120 ms, whereas the edge–cloud collaborative architecture reduces the overall delay to 57.39–86.13 ms by conducting preliminary processing at the edge nodes, resulting in a delay reduction of approximately 45%. This makes the architecture more suitable for production monitoring tasks with high real-time requirements (Khayer et al., 2020; Yaseen et al., 2023).

4. Conclusion

On the basis of the collaborative application of cloud computing and the Internet of Things, a real-time and efficient data processing and analysis system for enterprise production and operation management is developed in this study through the integration of edge computing and cloud computing. Research indicates that the real-time processing capabilities of edge computing effectively reduce data latency, whereas the efficient data storage and analysis provided by cloud computing enhance the accuracy and depth of large-scale data processing. The *ARIMA* model and random forest model are used for production volume prediction and equipment anomaly detection, respectively, demonstrating excellent performance in forecasting accuracy and processing speed. Through experiments, the advantages of the edge–cloud collaborative architecture in multisource data fusion and high-frequency data processing, particularly in improving production efficiency and optimizing resource utilization, are verified. To address data security and privacy protection, AES-256 and TLS protocols are implemented to encrypt data transmission and storage, ensuring the security of the system. At the same time, data traceability is realized through blockchain technology, which enhances data transparency and traceability. The application of *RBAC* model, two-factor authentication and OAuth protocol improves the permission control and privacy protection measures, and further ensures the stable operation of the system and data security. Overall, the research results provide an effective technical framework and method support for enterprises to apply cloud computing and Internet of Things technology in production management, and verify the practical value of cloud computing and Internet of Things collaborative applications.

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Author Contributions

Fangyuan Luo contributes to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, and manuscript editing. Zhiyuan Li contributes to conceptualization, methodology, supervision, and project administration. All authors have read and agreed with the manuscript before its submission and publication.

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Institutional Review Board Statement

Not applicable.

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