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The construction path of information sharing platform in construction project management in the era of big data

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SUMMARY: *The research discusses how an information sharing network is built through construction project management in the age of big data and focuses on power coordination and dynamic adjustment in the process of implementing projects. Through combining multi-source data that include project schedule records, temporary electricity consumption records, electrical installation progress records, equipment operation status records, material circulation records, personnel allocation records, and safety inspection logs, a platform architecture consisting of a data access layer, edge preprocessing layer, cloud sharing center, and collaborative decision layer is developed. Based on this, the platform ensures standardised coding, real-time synchronisation, shared permission, inter-departmental cooperation, and prompt alerts of unusual power-related situations, which enhances the effectiveness of temporary electricity distribution, electrical equipment assignment, and construction power load changes. Experimental application outcomes indicate that the platform has a data synchronization precision of 96.3 percent, an average response time of 0.84 seconds, and a data integrity of 99.1 percent. The paper has demonstrated that the proposed platform can be very useful in addressing information fragmentation when managing construction projects, improving the timeliness of cross-participant collaboration and increasing the ability to make decisions based on digitalized information when managing construction projects related to power.*
Povzetek: The proposed study offers a large-scale solution to information exchange in construction project management with coordination and adjustment of the construction processes related to energy use. The platform supports real-time information delivery, permission-based sharing, and fast reaction to power adjustment tasks through multi-source data integration, edge preprocessing, cloud sharing, and collaborative analysis. The experimental findings show high synchronization accuracy, low response time, and strong integrity of data which means that the platform can be used effectively in enhancing collaborative management and online decision-making within the construction process.

KEYWORDS: *Big data; Construction project management; Information sharing platform; Power adjustment*

1 Introduction

When we talk about big data, it is not as much as a challenge of the construction project management as it is being limited by the inability to provide on-site sensing and other constraints that have been caused by the fragmentation of project information, delays and

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inconsistency of standards among participating units. Particularly in the case where there is a simultaneous presence of temporary usage of electricity, the level of electrical installations, energization of equipment, and inter-team scheduling, managers require one single platform of information sharing to facilitate prompt power shift, resources coordination, and risk management in all the stages of the project cycle. The emergence of IoT, cloud computing, and intelligent terminals has made the implementation of the integrated information sharing platform of construction projects a feasible route to enhance the efficiencies of management and decision-making through digital means.

The information on schedule implementation, current electricity use, condition of electrical devices and installation, material flow, human resources allocation, and safety checks in construction projects is frequently scattered among various departments and systems. In case such data is not gathered, cleaned, coded, and shared in an integrated fashion, power-related decisions are prone to being delayed, duplicated, or out of sync with real-life site conditions. The introduction of edge preprocessing, wireless transmission, cloud sharing, and collaborative analysis mechanisms will lead to a significant enhancement of the timeliness, consistency, and usability of project information on the platform.

Nevertheless, implementation of information sharing platform in the construction project management is still associated with numerous practical challenges: non-homogeneous data sources among different stakeholders such as owners, contractors, subcontractors and supervisors; non-uniform coding of power-related information, including temporary electricity demand, cable distribution, and equipment commissioning; cross-departmental cooperation feedback delays; and the necessity to restrict access and protect data. To address these problems, current practices of platform construction have started to embrace architectures that combine data access, edge preprocessing, cloud sharing, and collaborative decision-making to enhance reliability, efficiency, and coordination ability.

The paper discusses the building approach to an information sharing system in construction project management within a context of big data but gives more attention to the aspect of power adjustment and coordination contributing to the following:

•The multi-layer platform architecture was built, which comprised of a data access layer, an edge preprocessing layer, a cloud sharing center, and a collaborative decision layer;

•Combine integrated project schedule records with equipment operation status, temporary electricity consumption, electrical installation progress, material circulation, personnel deployment and safety inspection logs into one integrated data structure;

•A permission-based sharing mechanism was designed along with a warning response process to facilitate power allocation for the time being, electrical equipment scheduling, and abnormal load adjustments in the course of construction.

•The effectiveness of the proposed platform was established using experimental analysis of the accuracy of data synchronization, response time and data integrity.

The paper structure is as follows: Section 2 will review related research in this field of study; Section 3 will discuss the system architecture, major modules, and data processing workflow; Section 4 will show the experimental findings and analysis; Section 5 will be a summary of research findings and recommendations on future work.

2 Related Research

In the last few years, as the construction industry is digitalized, there has been a gradual shift in construction project management research towards the integration of information sharing and collaborative decision making instead of independent information processing. Big data, cloud computing, IoT and BIM technologies based information platforms have become effective methods of enhancing schedule control, safety management, material delivery, and cooperation related to power in complex projects. Current literature has placed more emphasis on one data access, information flow across departments, and real time support of management decisions on the platform.

IoT technology implementation allows construction sites to have access to real-time data gathering and remote surveillance. According to Rao et al. (2022) [4], an IoT-based real-time monitoring system could be developed to monitor construction sites. In this system, sensors are used to gather environmental information including temperature, humidity and air pressure at a given time, which is transmitted over wireless networks to the cloud where the information is analyzed and processed. The main benefit of this system is that it can get real-time information on the construction site as well as remotely monitor it which will allow identifying the possible safety threats in due time.

Regarding embedded hardware systems, the introduction of edge computing further optimizes intelligent monitoring performance at construction sites. Jiang and Jiang (2022) [5] designed an edge computing-based monitoring system that distributes data processing and computational tasks to embedded devices on-site. This approach reduces reliance on cloud infrastructure, minimizes network latency, and enhances the system's real-time responsiveness. By performing preliminary data analysis on sensors and embedded devices at the construction site, the system enables rapid local decision-making and timely responses to emergencies.

Moreover, edge computing and cloud computing integration is one of the major trends to optimize the existing intelligent monitoring systems. Reaño et al. (2024) [6] has put forward a cloud-edge collaborative computing system whereby computational chores are distributed among both cloud and edge nodes in order to make data transmission and processing more efficient. The hybrid architecture takes advantage of the strong computational abilities of cloud computing and fast decision making and processing of edge devices in construction sites, hence not experiencing the problem of latency associated with conventional cloud-only architectures. Optimization of the interaction between the two components of the cloud and edges will contribute greatly towards enhancing both efficiency and responsiveness of on-site intelligent monitoring systems.

Although the significant advancements have been made in the sphere of enhancing system functioning, there are still some issues, especially with respect to energy use, transmission of data safety, and protection against the invasion of privacy. The concern of data security in intelligent monitoring systems was raised by Chen et al. (2024) [7], who proposed a security model that combines both the IoT technology and cryptography methods to protect construction site data. The sensors and embedded devices that are employed in construction sites typically work in sophisticated network settings, and the issue of ensuring that data privacy and integrity are not compromised by unauthorized access or leakage is one of the paramount issues that arise in the design of intelligent monitoring systems.

Moreover, there are also approaches that use deep learning (DL) and machine learning (ML) which are extensively used in detecting anomalies and predicting analytics of intelligent monitoring systems in construction sites. The safety monitoring strategy proposed by Häikiö et al. (2020) [8] was a deep learning-oriented model of safety monitoring of construction sites, which involved analyzing video surveillance data to detect possible safety risks. The method is trained to teach deep neural networks to learn important features of video streams automatically, which enables it to determine whether workers are wearing safety gear or entering dangerous areas. In a like manner, Xiao et al. (2024) [9] used deep learning algorithms to categorize the behavior of workers on construction sites, enabling them to evaluate the safety status of the construction site. These anomaly detection methods using deep learning have been adopted extensively in smart monitoring and have shown promising outcomes.

In order to improve the predictive ability and stability of the system even more, many researchers have investigated the use of data augmentation and model optimization methods. An optimization-based random forest algorithm has been proposed by Liu et al. (2024) which combines the IoT sensor data with live video data of a construction site to monitor it and allows multi-dimensional, multi-level safety surveillance and prediction of risks. Through this method, the combination of conventional machine learning algorithms and IoT data can be used to achieve a higher level of accuracy in monitoring in a cluttered setting and minimize the rate of false alarms. Summarized in Table 1 are current developments in research on embedded systems and smart monitoring technologies and their features.

Table 1: Comparative Research Progress of Information Sharing Platforms and Collaborative Management Technologies in Construction Project Applications

Study	Methods and Techniques	Advantages	Challenges and Limitations
Rao et al. (2022)	IoT-based real-time monitoring system	Real-time data acquisition and remote monitoring	Limited by network bandwidth and transmission latency
Jiang & Jiang (2022)	Edge-computing-based monitoring system	Reduces network dependency and improves response speed	Requires high-performance embedded hardware
Reaño et al. (2024)	Cloud–edge collaborative computing architecture	Improves computational efficiency and reduces latency	High coordination complexity between cloud and edge devices
Häikiö et al. (2020)	Deep-learning-based safety monitoring	Automated detection and reduced manual intervention	Requires large datasets and computing resources
Liu et al. (2024)	Enhanced random forest integrated with IoT	Improves accuracy of safety monitoring and risk prediction	Requires multi-sensor data fusion

Despite the promising prospects for intelligent monitoring systems in construction sites, ongoing technological advancements necessitate continued research into enhancing system intelligence while addressing robustness and real-time performance challenges in complex environments. The integration of embedded hardware systems and intelligent monitoring technologies will be further optimized in the future, and it is likely to play a substantial part in increasing the number of application scenarios.

3 Materials and Methods

3.1 Overall Architecture of the Information Sharing Platform for Construction Project Management

Due to the growing development of big data, IoT, and cloud collaboration technologies, the project management in construction is shifting towards the sharing of information on the platform and the coordination of it. In order to solve such issues as scattered project data, slow transmission, duplicated reporting and poor linkage in power adjustment, this paper presents the design of a multi-layer information sharing platform architecture. As shown in Figure 1, the platform consists of a data access layer, an edge preprocessing layer, a cloud sharing center, and a collaborative decision layer.

At the data access layer, project schedule records, temporary electricity plans, equipment operation status, electrical installation progress, material circulation records, personnel deployment data, and safety inspection logs are collected from on-site terminals, mobile applications, management systems, and intelligent devices. After unified coding and interface conversion, the data are transmitted to local processing nodes to ensure timely and stable access of multi-source information in complex construction environments.

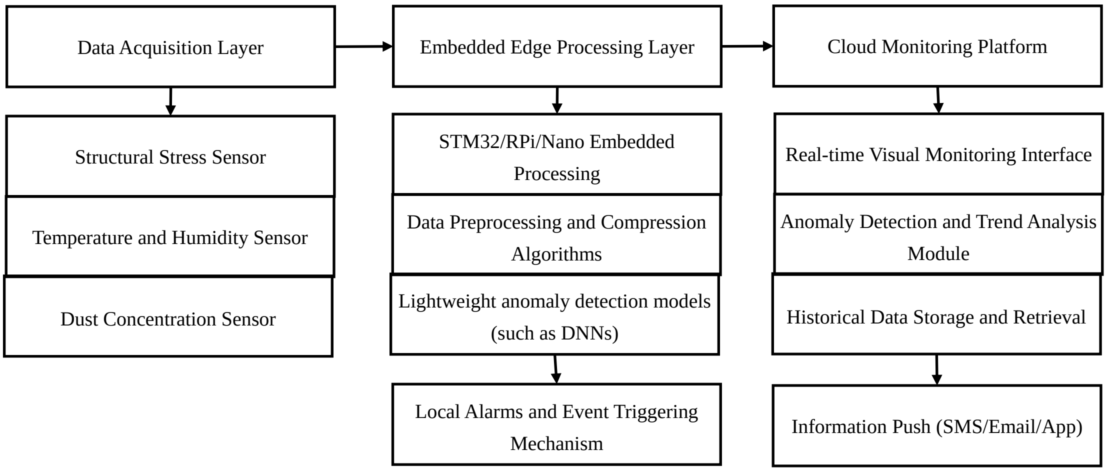

Figure 1: Overall Architecture of the Information Sharing Platform for Construction Project Management

The edge preprocessing layer deploys local computing units and preprocessing modules to complete data cleaning, duplication removal, timestamp alignment, preliminary warning identification, and temporary local caching. This layer mainly handles real-time preprocessing of project information and preliminary judgment of power-related abnormal states, thereby reducing the transmission burden of the cloud center and improving response efficiency for on-site coordination tasks. Some local nodes can also integrate lightweight analysis modules to support rapid recognition of abnormal load fluctuation and delayed electrical progress.

In the cloud sharing center, all data processed at the edge are aggregated, stored, analyzed, and shared according to project roles and permission rules. The platform integrates a visual interface, sharing engine, task scheduling mechanism, and collaborative analysis module, supporting remote access, cross-department information circulation, historical record tracing, and trend analysis of key project indicators. When the platform detects power-related warnings such as temporary electricity imbalance, delayed electrical installation, or abnormal load changes, it automatically pushes the information to relevant managers to support coordinated adjustment. Compared with traditional isolated management methods, this architecture emphasizes edge-cloud collaboration, thereby improving sharing efficiency while reducing unnecessary network pressure.

3.2 Data Access Layer

The data access layer forms the foundation of the entire information sharing platform, with its primary task being the continuous and stable acquisition of key management information in construction projects. The accessed data include project schedule updates, temporary electricity consumption, electrical equipment status, electrical installation progress, material entry and dispatch records, personnel attendance, and safety inspection results. The data access layer relies on on-site terminals, smart meters, equipment controllers, mobile reporting devices, and project management subsystems to collect project information. These access units support multi-source data acquisition, interface conversion, and local buffering, and can adapt to complex construction environments. To reduce communication load and redundant reporting, the access layer incorporates preliminary data filtering and coding mechanisms at the local side. Different collection devices can transmit data to edge nodes through wired or wireless communication channels, thereby enabling distributed preliminary screening and stable access of project information. Considering the dynamic variation of reporting frequency at the construction site, the upload period Ts is positively correlated with the total amount of accessed data D. Its estimation model can be expressed as:

$$D = N \cdot f_s T_s B \tag{1}$$

Here, N denotes the number of data sources or access channels, f_s represents the reporting frequency, T_s indicates the data collection duration, and B signifies the average data volume of each record. By dynamically adjusting f_s and T_s, transmission load can be controlled while maintaining accuracy, thereby adapting to the processing capabilities of the edge layer. To enhance transmission efficiency and access stability, the data access module uniformly connects to the local gateway through a standardized communication interface. Combined with an error correction mechanism, this ensures stable uploading and reliable synchronization of collected data in complex construction environments, providing a robust data foundation for subsequent analysis.

3.3 Edge Preprocessing Layer

The edge preprocessing layer serves a dual role of ‘preprocessing + preliminary warning’ within the platform. It primarily receives data streams uploaded from the data access layer and performs real-time cleaning, coding, alignment, and initial recognition of abnormal power-related states. To adapt to temporary construction networks and distributed project nodes, this layer adopts local computing devices and lightweight analysis modules for data filtering, trend analysis, and event determination, thereby improving the practicality of on-site information sharing.

When operating, edge nodes will clean data, eliminate duplication, smooth fluctuations and identify preliminary warnings of power related information. The key to their processing flow is sliding window analysis with threshold function control. Assume that the temporary electricity load or power-related indicator in time t is x(t) and that the length of the window is w. The sliding-average is thus:

$$\bar{x}(t) = \frac{1}{w} \sum_{i=0}^{w-1} x\,(t-i) \tag{2}$$

If the current value x(t) satisfies $|x(t) - \overline{x}(t)| > \delta$, n initial warning is triggered, where δ is the adaptively set power-adjustment threshold. Warning information is generated locally and uploaded to the cloud sharing center through the communication interface. At the same time, all data and preliminary judgment results are cached at the edge to ensure continuity of local coordination under unstable network conditions. The platform also implements permission control to regulate data access, ensuring controlled circulation and compliant use of shared project information within the management team.

3.4 Cloud Sharing Center

Because it is the upper-level decision-making and data management hub of the platform, the Cloud Sharing Center plays a key role in the storage, analysis, sharing and access control management of project information of edge nodes. It has the capacity to support ingesting large quantities of data and distribute storage, which also makes it appropriate when performing an analysis that requires a broad picture of the project, including cross-division coordination of schedules, temporary electricity scheduling, electrical installation alignment and historical analysis of power-related data.

The system is uploading edge data using the HTTPS protocol and uses the RBAC (Role-Based Access Control) model to control user permissions, which facilitates safe and controlled data management in multi-user settings. To process massive amounts of data, the platform has a latency-resilient analysis model that is built on a buffering time window, which is determined as follows:

$$T_{total} = T_{\mathrm{u}pload} + T_{\mathrm{b}uffer} + T_{compare} \tag{3}$$

T_{total} represents the total response time, $T_{\mathrm{u}pload}$ denotes the data upload delay, $T_{\mathrm{b}uffer}$ indicates the platform buffer window duration, and $T_{compare}$ signifies the processing time required for backend analysis. By adjusting $T_{\mathrm{b}uffer}$, a balance can be achieved between system load and response speed. The analysis findings are transferred to project managers via the visual platform which facilitates remote coordination, power adjustment warning, and cross-department collaborative decision-making. It creates a data-based information transfer system of construction project management.

3.5 Data Security and Permission-Controlled Sharing

The general use of information sharing systems in the project management of construction projects requires effective security measures to ensure the protection of the data and access controls especially during sensitive information including project progress, temporary electricity arrangements, equipment operation records, material circulation, and inter-department coordination logs.

To ensure the confidentiality and integrity of data when transmitted, the data acquisition layer and edge computing layer also use the end-to-end encryption technology. All data are encrypted over the TLS 1.2 protocol during data transfers, and therefore, the data can be securely transferred across insecure networks. Moreover, to improve the level of data security, the system uses the 256-bit AES encryption algorithms to store sensitive data in a safe manner, including temporary electricity data, operating conditions of equipment, power adjustment logs, and coordination information on projects. The data transmission encryption algorithm is given below:

$$C = E(K, P) \tag{4}$$

Here, C represents encrypted data, E denotes the encryption operation, K signifies the encryption key, and P stands for plaintext data. Key management employs a dynamic key exchange mechanism, generating a unique key for each data transmission to prevent man-in-the-middle attacks.

The system uses a Role-Based Access Control (RBAC) mechanism to control data access, making sure that no unauthorized people have access to sensitive information. The permissions are explicitly outlined in each operator, monitor, and project manager. Access to the relevant data is only allowed once the identity has been verified successfully. Such as, the temporary electricity plans, equipment energization logs, and adjustment logs must be accessible only to the appointed managers, electrical engineers, or approved supervisors. Multi-factor authentication (MFA) is used in identity verification which combines password, OTPs (one time passwords) and biometric technology to enhance the reliability of user authentication. Lastly, in order to provide long term security of data on the platform, it includes a scheduled data backup system that helps to avoid the loss of data due to the failure of systems. The backup data is encrypted and kept on the cloud storage services that meet ISO/IEC 27001 standards to be able to secure the data and follow the regulations. With such multi-layered security measures in place, the platform provides effective security, integrity, and controllable circulation of information related to projects, and ensures that all shared data stay within a protected domain during the implementation of a project and the adjustment of power.

3.6 Power Adjustment Warning and Collaborative Decision Model

Over the past few years, data-driven approaches have proven to be very useful in determining more complicated management conditions on based on multi-source construction data. Traditional coordination strategies that are based on rules are frequently unable to react appropriately whenever there is a dynamic interplay of temporary electricity demand, device operation, electrical installation processes, and schedule changes. The study proposed and implemented a light-weight deep neural network model to be used to identify warnings and provide collaborative-decision assistance to facilitate power-adjustment operations in the platform by facilitating quick identification of abnormal loads and coordination requirements.

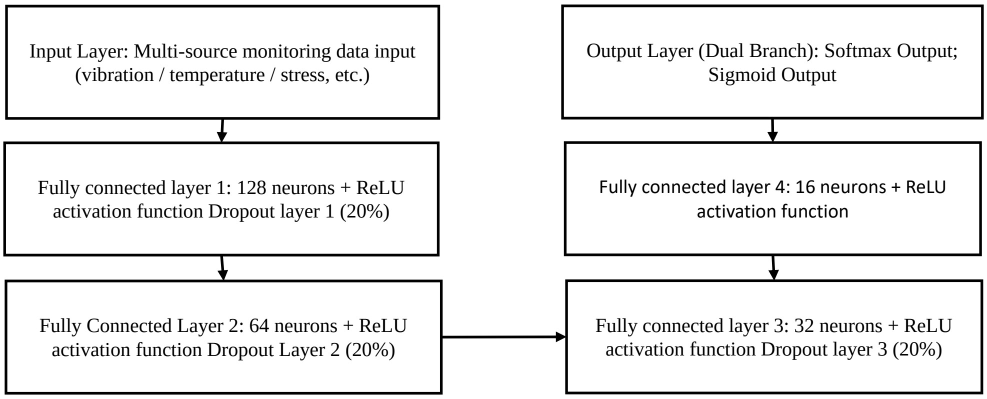

Figure 2: Schematic Diagram of the Power Adjustment Warning Model in the Information Sharing Platform

The constructed model structure, as shown in Figure 2, is a sequence-based dense neural network. It employs a multi-layer fully-connected architecture with regularization strategies to enhance generalization capabilities, suppress overfitting, and adapt to resource-constrained edge computing environments. The network comprises an input layer, four hidden layers, and two output layers. Each layer employs the ReLU activation function, endowing it with nonlinear fitting capabilities suitable for modeling and processing multi-source project information related to power coordination.

The first layer consists of a fully connected layer with 128 units. Weights are initialized using a normal distribution, while an L2 regularization term is introduced to control parameter scale. Its mathematical expression is:

$$L_{reg} = \lambda \sum_{i=1}^{n} w_i^2 \tag{5}$$

Here, w_i^2 represents the i-th weight parameter, and λ denotes the regularization coefficient (set to 0.001 in this experiment). This term functions as an additional penalty in the loss function, helping to suppress the model's tendency toward overfitting. Subsequent hidden layers are configured with 64, 32, and 16 units respectively, each followed by a Dropout layer that randomly discards 20% of neurons to further enhance model robustness. The structure of each layer is as follows:

$$\text{Layer}_i = \text{Dropout}(p)(\text{ReLU}(W_i x + b_i)) \tag{6}$$

The output end is configured with two branches: one is a multi-class output layer (with Softmax activation) for power coordination state classification (e.g., balanced, warning, overloaded); the other is a binary output layer (with Sigmoid activation) for determining whether a power adjustment task should be triggered. The classification loss function employs cross-entropy loss, whose formula is:

$$L_{cross} = -\sum_{i=1}^{c} y_i \log(p_i) \tag{7}$$

Here, C represents the number of categories, y_i denotes the true label, and p_i indicates the predicted probability. The training process employs the Adam optimizer with an initial learning rate of 0.001, a batch size of 16, and 50 training epochs. An early stopping mechanism is incorporated to prevent overfitting. Training is terminated prematurely when the validation set loss shows no significant decrease for five consecutive epochs. Model training employs a collaborative mechanism between edge servers and the cloud. The initial models are trained centrally in the cloud and later weights are sent to edge devices on which they can perform real time inference balancing performance and efficiency.

The model was found to be highly accurate in terms of performance evaluation with an average accuracy of 92.8 percent on the test set and an F1 score of 0.91 which reflects strong recognition of power-related warning states and a low level of misjudgment. In practice, the model reaches an average answer time of 0.12 seconds per query on local computer systems, which satisfies the needs of real-time on-site coordination. In addition to detecting common abnormal events like abrupt increase in load and tardiness in electricity advancement, this model has the ability to identify progressive coordination hazards via time-based input which allows active change.

The research involves the use of sliding-window reconstruction and data standardization preprocessing to make it adaptable to different conditions of construction. Temporal learning abilities are improved by dividing continuous monitoring data prior to model input. At the same time, an anomaly score mechanism in inference is used to improve the interpretability of the results which is determined by the next formula:

$$\text{Anomaly Score} = 1 - \max(p_1, p_2, \dots, p_c) \tag{8}$$

In the case where the maximum predicted probability is much lower than the limit (e.g., 0.6) the system will automatically initiate a secondary confirmation or manual review process to indicate an ambiguous state. On the whole, the model ensures that edge deployment is practical and it provides high recognition accuracy and constancy. It boosts the responsiveness and intelligence of the information sharing platform significantly, which offers valuable support to digital construction management and coordination that has to do with power.

3.7 Multi-source Construction Project Information Dataset Construction

In order to test the viability and strength of the proposed information sharing system in practical engineering settings, this paper developed a multi-source construction project information data set. The process of collecting data was carried out over the period of six weeks through three conventional construction stages, namely foundation excavation, main structure construction, and installation operations. The dataset included records of project schedule, consumption of temporary electricity, equipment operation state, electrical installation progress, material circulation information, personnel deployment and safety inspection logs. Fixed interval data collection was conducted using on-site terminals and management subsystems to produce a raw data exceeding 1.2 million records.

The data structure focuses on typical management and coordination issues in construction projects, which are mostly in terms of information on project progress, power-related information, and information on collaborative operations. All these variables are indicative of the dynamic operation state of the project and can be used as the model inputs to the subsequent warning identification and decision support. Every element of the dataset has a timestamp, project area, information type and manually labeled warnings, which forms the foundation of supervised learning. This distribution of various power-related warning events in Figure 3 shows the distribution of various powers-related warning events throughout the monitoring period, such as temporary electricity overload, delayed electrical installation, and abnormal equipment load fluctuation, which helps explain the main states that the platform should recognize.

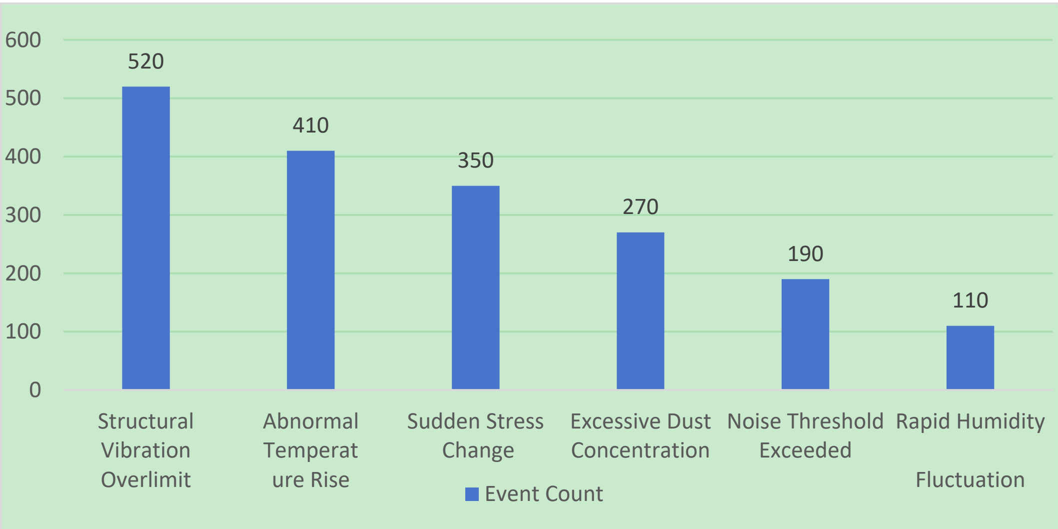

Figure 3: Distribution of Power-related Warning Event Counts Across Different Construction Stages

As the basis of improving the ability to generalize data, the standardization and cleaning of the dataset was done to eliminate missing values and outliers, and the data was sliced through the sliding window approach. The descriptions and units of important fields in the dataset are explained in detail in table 2 which makes the model input structure and physical meanings clear.

Table 2: Field Descriptions for Construction Project Information Sharing Dataset

Field Name	Unit	Type	Description
Timestamp	s	Time	Records the collection time
Project_Area	—	Identifier	Identifies the construction area or work section
Temp_Power_Load	kW	Numeric	Temporary electricity load of the site
Equipment_Status	0/1/2	Categorical	Running state of electrical equipment
Electrical_Progress	%	Numeric	Completion rate of electrical installation tasks
Material_Flow	—	Categorical	Material delivery and circulation status
Personnel_Assignment	persons	Numeric	Number of assigned personnel
Safety_Check	0/1	Categorical	Safety inspection or rectification result
Warning_Label	0/1/2	Categorical	Normal / coordination warning / adjustment required

3.8 Data Preprocessing Methods

Raw data in the information sharing platform is directly collected at on-site terminals, intelligent meters, equipment controllers, and project management sub-systems. Owing to variations in frequency in collections, reporting requirements, and transmission rates, challenges like missing values, late uploads, repetitive entries, and non-uniform codes are common. Standardized processing on the edge or in the cloud must hence be implemented to enhance the precision and consistency of the future information exchange, warning detection, and collaborative decision-making.

3.8.1 Data Cleaning and Imputation

The initial phase of preprocessing is to eliminate invalid data. Timestamp consistency tests and field integrity validation are used to eliminate records with inconsistent timestamps or missing fields. The sliding interpolation method is applied to interpolate small gaps in the data. In cases where a certain variable was not measured at any point in time within a specific time window, its value can be estimated as the mean of the most recent previous and the most recent subsequent sampling instance:

$$x_t^* = \frac{x_{t-1} + x_{t+1}}{2} \tag{9}$$

The extended continuous missing segments (more than three cycles) are coded as "unavailable" to avoid misinterpretation.

3.8.2 Noise Filtering and Signal Smoothing

The high rate of change in load, the time taken to upload the meter and the fact that manual reporting was done repeatedly during the construction process may cause the sequence and logs that are related to power to seem unstable over the short term. It is a platform that employs the use of a first order low pass filter to remove temporary electricity load data and the corresponding warning sequences. The discrete filtering model is this:

$$y_t = \alpha \cdot x_{\mathrm{t}} + (1 - \alpha) \cdot y_{t-1} \tag{10}$$

Among these, y_t represents the filtered output, x_t denotes the current input, and $\alpha \in [0,1]$ is the smoothing coefficient. In experiments, selecting α=0.3 effectively preserves trend information while suppressing high-frequency interference.

3.8.3 Feature Construction and Unit Standardization

Different access devices and management subsystems can be reported with other reporting times, coding instructions, and measurement units. As an example, some of the temporary electricity records, equipment operation logs, and schedule progress data can be produced at various intervals and stored in non-uniform formats. Thus, standardization of units, conversion of codes, and time-series alignment are needed prior to uploading and sharing. Time stamp resampling algorithm is used to align the data to a 5-seconds base line and creates a standardized data structure table.

Additionally, multiple derived features are constructed at edge nodes to enhance model input information, such as load change rate (ΔL), electrical progress increment (ΔP), and temporary electricity fluctuation slope, in order to capture potential dynamic warning signals related to power adjustment. For example, the vibration change rate is defined as:

$$\Delta V_t = \frac{V_t - V_{t-1}}{\Delta t} \tag{11}$$

If ΔV exceeds the threshold for multiple consecutive cycles, it is flagged as "sudden vibration change" for retrieval by the anomaly detection module. In summary, the data preprocessing workflow plays a critical role in the system's actual deployment. It not only enhances the quality of raw data but also establishes a reliable foundation for rule-based decision-making and model inference. This ensures the embedded monitoring system operates stably and responds promptly in complex field environments.

4 Experimental Results and Discussion

4.1 Platform performance evaluation

To verify the effectiveness of the proposed information sharing platform in an actual construction environment, this study conducted a two-week on-site deployment test in three typical project scenarios, namely foundation construction, main structure construction, and installation operation. The platform operated through the coordination of the data access layer, edge preprocessing layer, and cloud sharing center, achieving continuous processing and sharing of six key categories of project information, including schedule progress, temporary electricity load, equipment status, electrical installation progress, material circulation, and safety inspection records. Platform performance evaluation was mainly conducted from four dimensions: data synchronization accuracy, warning misjudgment rate, average response latency, and data integrity A total of 107 abnormal events were triggered during the test, among which 103 were successfully identified by the system, 4 were missed, and no false alarms occurred. According to the formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{12}$$

Among them, TP represents the number of correct identification times of real anomalies, and FN represents the number of unidentified anomalies. The overall data synchronization accuracy rate of the platform reaches 96.26%. In addition, the average response latency from edge preprocessing to cloud-side warning push is 0.84 seconds, which meets the real-time coordination requirements of project management. In terms of data integrity, after packet verification and retransmission, the overall effective data reception rate reached 99.1%, indicating that the platform can maintain stable information circulation under complex construction conditions.

Figure 4 shows the changes in recognition accuracy and response delay of the system during five consecutive days of operation under different construction site scenarios. It can be seen that, whether in the underground hot and humid environment or in the high-level interference area, the system performance remains at a relatively high level, with a small fluctuation range and good scene adaptability.

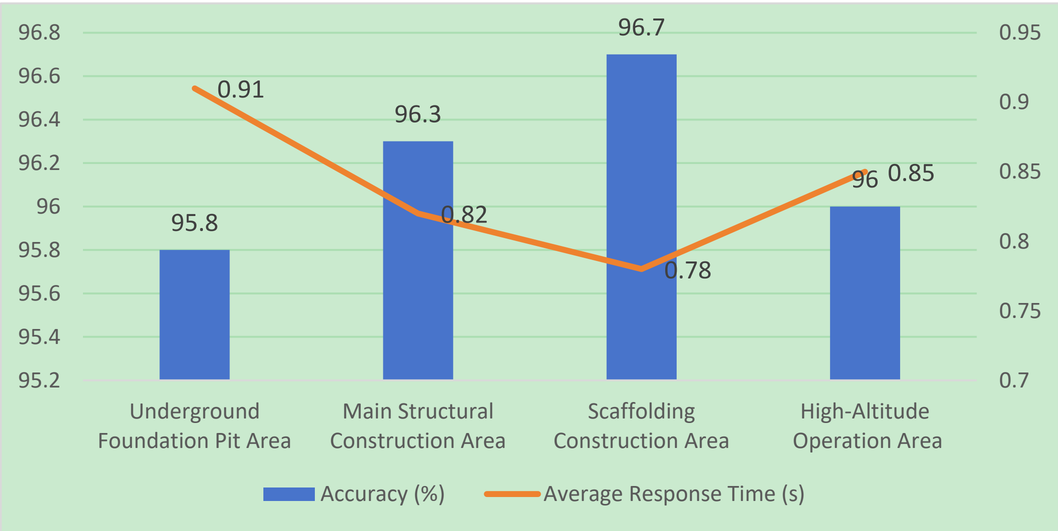

Figure 4: Data synchronization accuracy and average response latency of the platform in different project environments

The results of this performance evaluation show that the proposed information sharing platform not only maintains high data synchronization accuracy and stable warning response, but also achieves low-latency and high-reliability information processing under on-site deployment conditions, demonstrating good engineering feasibility.

4.2 Comparative Analysis

To verify the comprehensive performance of the information sharing platform proposed in this study in actual engineering scenarios, this section conducts a comparative analysis with current mainstream management schemes from multiple dimensions, focusing on data synchronization accuracy, response latency, warning misjudgment rate, data integrity, and resource consumption. The comparison objects selected for the experiment include a traditional manual coordination method, an isolated information management system, a cloud-centralized sharing scheme, and the proposed edge-cloud collaborative platform.

It can be seen from Table 3 that the embedded system outperforms other schemes in terms of anomaly recognition accuracy (96.3%) and average response delay (0.84 seconds). Compared with video recognition systems, it has a lower false alarm rate under environmental interference and is suitable for actual construction site conditions with dust and unstable lighting. In contrast to conventional cloud services, the present system uses local preprocessing and event identification systems, which have a significant impact on mitigating the effects of network dependence and data congestion on latency.

Table 3: Comparative Analysis of Platform Performance

Metric	Proposed System	Video Recognition System	Cloud-Centralized System	Manual Inspection
Anomaly Detection Accuracy	96.3%	91.5%	93.8%	78.2%
Average Response Latency (s)	0.84	1.62	2.95	>3600
False Alarm Rate	1.4%	4.9%	3.6%	—
Data Integrity (Reception Rate)	99.1%	93.7%	95.4%	—

Meanwhile, to examine the operational efficiency of the platform under resource-constrained conditions, Table 4 presents the resource consumption of each scheme at local processing nodes. The results show that the edge-enabled sharing platform used in this study has significant advantages in processing power consumption, memory usage, and operational stability. The average CPU usage rate of the platform is less than 35%, and the memory usage does not exceed 800 MB. It is suitable for deployment in on-site temporary management stations or equipment cabinets to achieve low-cost and highly reliable long-term information sharing.

Table 4: Comparison of Resource Consumption on the Edge Side of Each Information Sharing Scheme

Solution Type	Average CPU Usage	Memory Usage (MB)	Peak Power Consumption (W)	Stable Runtime (hours)
Proposed Embedded System	34.7%	786	8.2	>72
Video Recognition System	68.5%	2054	18.5	36
Hybrid Edge–Cloud System	49.3%	1150	10.7	48

In summary, the embedded intelligent monitoring system constructed in this study demonstrates superior comprehensive performance in terms of accuracy, timeliness, and resource efficiency compared to existing mainstream technologies. It is particularly suitable for deployment in application scenarios such as construction sites where response speed and resource constraints are highly demanding, providing practical technical support for the intelligent and digital transformation of the construction industry.

4.3 Comparison of Platform Processing Efficiency

To verify the operational efficiency of the platform in the actual construction environment, this study tested the processing capacity of local preprocessing nodes and compared it with common information management schemes. The test mainly focuses on the time consumption of single data processing, daily data throughput, CPU utilization, and energy consumption. The experimental platform includes the local processing node used in this study and two comparison schemes: a traditional manual reporting plus server summary architecture, and a centralized cloud processing solution.

The outcome indicates that this system can provide an average event response time of 0.84 seconds at the edge, and each node has an average daily data processing capability of about 123 000 items. In comparison, despite the fact that centralized processing solutions have powerful computing capabilities, they are restricted by transmission delays and have poor real-time capabilities. Nevertheless, conventional architecture has disadvantages like excessive use of the CPU and instability of the systems.

Table 5: Comparison of Processing Efficiency among Various Information Sharing Schemes

Metric	Proposed System	Cloud Centralized Processing	PLC + Server
Average Response Time (s)	0.84	2.47	1.36
Average Daily Data Volume (records)	123,000	115,000	88,000
Average CPU Utilization (%)	34.7	65.2	78.5
Power Consumption per Node (W)	8.2	18.5	15.3

4.4 Advantages of Edge-Cloud Collaborative Sharing Architecture

The traditional cloud-centralized processing mode in the field of construction project information sharing is prone to bottlenecks including slow response, high network dependency, and too much raw data transfer, thus cannot satisfy the actual requirements of the time coordination and power adjustment. In order to overcome this problem, the edge-cloud collaborative sharing structure developed in this paper relocates the preprocessing, coding and preliminary warning detection of important project information to the local node, which greatly decreases the remote transmission dependence of the platform.This architecture has the advantages of local processing, low operating cost, and strong adaptability to complex site conditions. It can maintain stable operation under conditions such as temporary network fluctuation and high-frequency reporting, while keeping the warning response delay within one second. Compared with the traditional centralized mode, local nodes shorten the information processing chain and reduce the load on the cloud center, thereby improving the robustness and flexibility of the sharing platform.

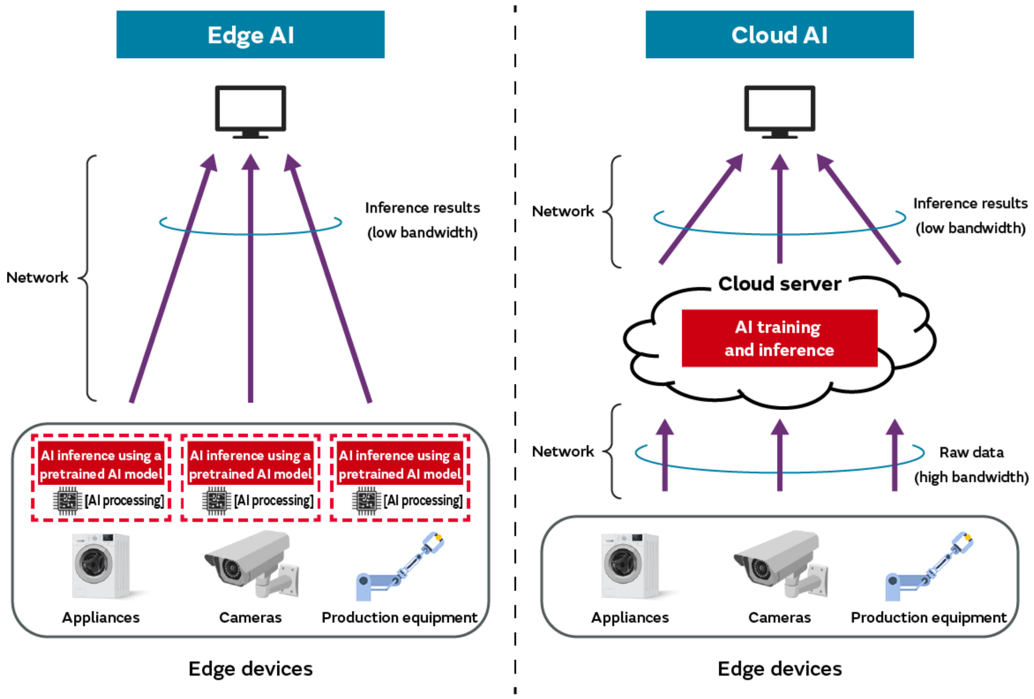

Figure 5: Schematic Diagram of the Difference Between Edge-Cloud Collaborative Sharing and Traditional Centralized Sharing

As can be seen from Figure 5, edge computing reduces the amount of raw data uploaded through local inference, and has obvious advantages in bandwidth occupation and response delay compared with centralized processing in the cloud. This further verifies the real-time performance and energy efficiency advantages of the architecture in this study in on-site monitoring. Meanwhile, the system supports modular deployment and edge-cloud collaboration strategies, which can flexibly adapt to construction scenarios of different scales and types, and achieve on-demand expansion. Practice has shown that this architecture, while ensuring monitoring accuracy, optimizes resource allocation and is an effective path to promote intelligent management at engineering sites.

4.5 Robustness Testing of the Power Adjustment Warning Module

To verify the adaptability and robustness of the proposed platform under multiple scenarios and conditions, this study adopts the 10-Fold Cross-Validation method to evaluate the power adjustment warning module. The original multi-source project dataset is segmented by time dimension to ensure that each segment contains different construction stages and typical power-related variables, thereby testing the generalization ability of the module under different project conditions.

During the cross-validation process, 90% of the data is selected as the training set in each round, and the remaining 10% is used for validation. This process is repeated for 10 rounds of training and testing. The warning recognition performance of the module is comprehensively evaluated by calculating Accuracy, Precision, Recall, and F1-score.

The results of each round of cross-validation show that the overall recognition accuracy of the system remains above 94.2%, with the highest F1 value reaching 97.1% and the lowest 92.6%. The range of fluctuations is low, which indicates a high level of stability. Table 6 represents the exact indicators of mean and standard deviation of 10 repetitions of the cross-validation:

Table 6: Cross-validation Results of the 10-fold Power Adjustment Warning Module

Metric	Mean (%)	Standard Deviation (%)	95% Confidence Interval
Accuracy	95.68	1.23	94.53 – 96.83
Precision	94.82	1.47	93.35 – 96.29
Recall	96.10	1.19	94.98 – 97.22
F1-score	95.45	1.35	94.13 – 96.77

Judging from the standard deviation results, the fluctuations of all indicators are within an acceptable range, especially the fluctuation of the recall rate is the smallest, indicating that the system has good stability in detecting real anomalies. It is especially important when it comes to uses in dynamic setting like construction sites where a consistent high recognition performance and response accuracy are required at different time intervals and with varying operating conditions.

The closer examination of each round shows that even when the percentage of abnormal data was small or there was a heavy signal disturbance, the recognition rate of the system and the F1 score did not experience a considerable decrease, which indicates a high level of robustness to the change of inputs. Overall, the anomaly detection system of this embedded architecture ensures a constant functioning and can be adapted to be promoted, which is why it is applicable in different construction conditions.

5 Conclusion

The current research has proposed an information sharing system of construction project management in the age of big data that incorporates data access, edge preprocessing, cloud sharing, and collaborative decision making mechanisms, particularly focusing on power adjustment and coordination. Platform architecture is based on four layers including a data access layer, an edge preprocessing layer, a cloud sharing center, and a collaborative decision layer. Together, all the layers serve to facilitate the integration of codes, real time integration, permissions based sharing, and dynamic alerts of multi source information on projects, including scheduling progress, temporary electricity usage, state of equipment operation, electrical installation progress, circulation of materials, deployment of people, and safety inspection logs. Experimental findings indicate that the platform has a high degree of data synchronization precision (96.3 percent) and a low latency rate (0.84 seconds) and high data integrity (99.1 percent) in a construction setting, which is significantly higher than traditional isolated management practices.

When implemented in a standard construction environment, the platform proved to be quite robust and flexible, as it was able to ensure steady flow of information and response to warnings in the face of sophisticated conditions at a construction site. At the same time, the lightweight warning model was successfully used to enable real-time inference on local processing nodes with an average processing delay of 0.12 seconds and the ability to support event-level adjustment thus greatly improving the intellectuality of project coordination. By using 10-fold cross-validation, the model also had an F1 score exceeding 0.95 in multi-scenario settings which implies that it has great generalization performance and can be applied to various situations.

However, as it is stated in this article, the current platform also has some drawbacks. The paradigm of warnings may not necessarily be applied to non-standard instances of adjusting the power control; the overhead of communication encryption at high-frequency reporting rates remains suboptimal; additional engineering tests could verify the stability of the local processing nodes over time. To enhance further usage and implementation of the platform, it will focus on the following areas in the future:

• Conduct long-term stability tests in more realistic building projects and optimize the operating and maintenance system of local preprocessing nodes;

• Introduction of privacy-preserving learning techniques that can enhance the flexibility of the warning model when using multi-source heterogeneous project data;

• Enhance the data mining performance of the cloud sharing hub to facilitate trend analysis and smart recommendations on temporary electricity distribution and electrical program.

• Facilitate close integration of BIM systems, dispatching platforms of projects, and digital monitoring systems to create a smart collaborative management system.

Due to the constant advancement of edge computing, cloud collaboration and digital management technologies, information sharing platforms have been taking over an even more significant place in the construction project management sphere. Not only will they enhance the effectiveness of information flow and the promptness of management choices, but will be the main technical tool of the temporary electricity cooperation, electrical planning, and electronic construction control. The platform construction path and optimization strategy introduced in this paper can serve as a reasonable foundation of the further evolution of data-driven, collaborative, and power-oriented management platforms in complex construction environments.

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