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Research on Intelligent Safety Management Innovation Enabled by Artificial Intelligence and Forklift Internet of Things: A Data-Driven Risk Prediction Perspective

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ABSTRACT

To address the challenges of low operational efficiency, insufficient fault prediction accuracy, serious data fragmentation, and mismatched resource allocation in traditional elevator maintenance management, this paper proposes an Artificial Intelligence of Things (AIoT)-driven intelligent elevator maintenance management framework with machine learning-based Mean Time Between Failures (MTBF) prediction as the core functional module. Guided by industrial internet of things architecture theory, reliability engineering theory, and operational research optimization methods, the framework integrates multi-source heterogeneous data fusion, intelligent state prediction analysis, and maintenance decision optimization through a four-tier logical architecture, standardized data processing pipelines, hybrid neural network algorithms, and dynamic data quality control mechanisms. Experimental validation based on 5-year real elevator operation data from commercial building scenarios shows that the proposed framework significantly improves data integrity and consistency, shortens the duration of core maintenance processes by more than 67%, increases MTBF prediction accuracy to 89%, reduces unplanned downtime by 62%, and enhances the rigor and foresight of maintenance decision-making. This study provides a systematic practical implementation path for the digital and intelligent transformation of elevator operation and maintenance management in the context of smart buildings.

Introduction

Driven by the rapid development of smart cities and intelligent buildings worldwide, elevators, as core vertical transportation equipment in modern buildings, have an increasingly expanding ownership and operation scale. Statistics show that the global number of elevators in service has exceeded 20 million, with an annual growth rate of over 5%, and the operation and maintenance market scale continues to expand. The operational reliability and safety of elevators are directly related to public travel efficiency, building operation quality, and even public safety. Traditional elevator maintenance modes mainly include periodic preventive maintenance and post-fault corrective maintenance. Periodic maintenance relies on empirically fixed maintenance cycles and workload standards, which easily lead to problems such as over-maintenance caused by excessive maintenance for equipment in good condition, or insufficient maintenance caused by missing potential risks for heavily loaded equipment. Post-fault maintenance has long downtime, high economic losses, and potential safety risks, which can no longer meet the operation and management needs of large-scale elevator clusters in high-rise buildings and complex commercial scenarios.

At present, the elevator operation and maintenance industry still faces four core bottlenecks in the process of intelligent transformation: first, data fragmentation exists among various subsystems such as elevator control systems, on-site sensing devices, maintenance management platforms, and spare parts inventory systems, forming independent "data silos" that hinder full-chain data integration and value mining; second, traditional MTBF estimation mostly relies on historical statistical experience and manual regular inspection, lacking real-time operation data drive and intelligent algorithm support, resulting in low prediction accuracy, poor timeliness, and difficulty in identifying potential fault risks in advance; third, the maintenance process has low collaborative efficiency, delayed information transmission, and reliance on manual scheduling and coordination, making it difficult to dynamically respond to changes in equipment operation status and emergency fault demands; fourth, maintenance performance evaluation mostly focuses on intuitive indicators such as fault frequency and maintenance cost, neglecting comprehensive consideration of equipment full-lifecycle reliability, resource allocation efficiency, and user service experience.

Elevator fault monitoring and early warning systems built on Internet of Things technology have realized real-time perception of equipment operation status through multi-type sensors and edge acquisition devices, laying a data foundation for data-driven maintenance transformation[Error! Reference source not found.]. Fault precursor prediction based on improved long short-term memory autoencoder algorithms and time synchronous averaging-variational mode decomposition denoising techniques has improved the identification accuracy of individual fault modes in vibration signals, but fails to form a closed-loop management mechanism from fault prediction to maintenance decision-making and resource scheduling[Error! Reference source not found.]. Remaining useful life prediction methods integrating particle swarm optimization, convolutional neural networks and bidirectional long short-term memory networks provide technical reference for equipment reliability modeling and life calculation, yet there are still deficiencies in multi-dimensional feature fusion and timing dependency capture for complex elevator operation scenarios with variable working conditions[Error! Reference source not found.]. Fault prediction methods for elevator door systems based on transfer learning have achieved good results in specific component-level fault scenarios, but it is difficult to extend the model to full-system MTBF prediction covering mechanical, electrical and control subsystems[Error! Reference source not found.]. Risk evaluation systems based on fuzzy theory and machine learning algorithms can classify equipment risk levels through multi-dimensional indicator fusion, but lack dynamic adjustment mechanism combined with real-time operation state data, making it difficult to adapt to time-varying operation scenarios[Error! Reference source not found.]. Evolutionary optimization of convolutional extreme learning machine architectures provides new ideas for improving the operation efficiency of prediction models and reducing computational overhead, but the reliability calibration of prediction results under small sample conditions needs to be further strengthened[Error! Reference source not found.]. Digital twin technology for predictive maintenance has verified the core value of machine learning in equipment operation optimization and maintenance decision support through virtual-real mapping and simulation iteration, but its practical landing path and cost-benefit ratio for elevator maintenance scenarios are not yet clear[Error! Reference source not found.]. Continuous improvements in elevator technology including permanent magnet synchronous traction machines and intelligent control systems have put forward higher requirements for the intelligence and refinement of operation and maintenance management, and traditional extensive maintenance modes have been unable to adapt to the operation needs of large-scale equipment clusters in the new era[Error! Reference source not found.]. Intelligent elevator systems based on ZigBee wireless communication have realized interconnection and information interaction of equipment nodes, but the depth of data mining and intelligent decision support capability are still insufficient, and most of them stay at the level of state monitoring rather than active prediction[Error! Reference source not found.]. Weibull recurrent neural networks for failure prognosis using histogram data provide a distribution-calibrated prediction paradigm, which can effectively improve the reliability of life prediction results by fusing statistical distribution characteristics and neural network fitting ability[Error! Reference source not found.]. The remaining life prediction method combining Weibull time-to-event framework with convolutional recurrent networks further enhances the timing modeling capability of prediction models for time-series degradation data[Error! Reference source not found.]. Unsupervised remaining useful life prediction through long-range health index estimation based on encoders-decoders provides an effective solution for industrial scenarios with insufficient labeled fault data and unbalanced sample categories[Error! Reference source not found.].

In summary, existing studies have explored the application of Internet of Things and machine learning in the field of elevator maintenance from different dimensions, but most of them stay at the single-link analysis of fault identification or life prediction, lacking systematic coverage of the entire elevator maintenance lifecycle from data collection, state prediction, decision optimization to performance evaluation. The practicability and operability of the constructed models in actual engineering scenarios need to be improved. Based on this, this paper constructs a full-process AIoT-driven intelligent elevator maintenance management system integrating data collection, standardized processing, intelligent prediction, and decision output. It clarifies the system architecture, core mechanisms, and implementation pathways in detail, and validates its effectiveness in improving data quality, optimizing maintenance process efficiency, and enhancing MTBF prediction accuracy through comparative experiments based on real operation data, so as to provide theoretical support and practical solutions for the digital transformation of elevator operation and maintenance management.

Research Methods

Overall Architecture Design of the System

This study adopts a systematic research framework of "theory construction-architecture design-function validation", supported by industrial internet of things theory, reliability engineering theory, and decision science theory. A four-layer logical architecture of the intelligent maintenance system is designed to realize end-to-end integration of elevator operation data and intelligent maintenance decision support. From bottom to top, the four layers are the terminal perception layer, edge computing layer, cloud platform layer, and business application layer. The terminal perception layer includes various sensors installed on elevator equipment (vibration sensors, temperature sensors, current sensors, displacement sensors, etc.) and elevator control system interfaces, responsible for collecting original operation state data. The edge computing layer is deployed near the equipment site, responsible for data preprocessing, local real-time monitoring and edge-side lightweight inference. The cloud platform layer undertakes core functions such as data storage, model training, big data analysis and system management. The business application layer provides targeted functional services for different user roles.

The architecture adopts an edge-cloud collaborative deployment solution: on-site sensing devices and edge computing nodes are deployed at the elevator site to realize real-time data collection and preprocessing including filtering, denoising and feature extraction, ensuring low-latency response of on-site services and reducing data transmission bandwidth pressure; core data analysis, model training and global optimization scheduling are deployed on the private cloud platform to ensure data security and computing power support; non-sensitive operation data and public service modules are extended through public cloud to enhance system elasticity and service access convenience; sensitive data such as equipment core control parameters and user privacy information supports local deployment options to meet different security level requirements. Through device identity authentication, data encryption (static storage encryption and transmission process encryption), role-based access control (RBAC), and full-link audit log technologies, the system complies with industrial data security specifications and enterprise operation management standards. The model architecture is shown in Figure 1.

Figure 1. Architecture of AIoT-driven intelligent elevator maintenance management system

Data Standardization and Feature Engineering Model

To achieve effective aggregation and fusion of multi-source heterogeneous elevator data from different manufacturers, different systems and different protocols, a data standardization and feature engineering model is established, which specifically includes the following three core components:

Metadata Standardization

Building upon the industrial internet of things metadata standard and tailored to elevator operation and maintenance management scenarios, this framework defines four categories of cross-domain metadata schemas: elevator equipment metadata, operation status metadata, fault maintenance metadata, and resource scheduling metadata. Specifically, elevator equipment metadata includes basic attributes such as equipment number, model, manufacturer, production date, rated load, rated speed, and installation location; operation status metadata includes real-time operation parameters such as running speed, car load, number of starts and stops, motor current, traction machine temperature, and door opening and closing time; fault maintenance metadata includes fault time, fault location, fault type, fault description, maintenance measures, and maintenance personnel; resource scheduling metadata includes personnel information, spare parts inventory, tool configuration, and work order status. To address metadata variations across different device manufacturers and data sources, a mapping rule library is established to automatically convert non-standard metadata from different communication protocols and data formats into the core unified schema through field mapping, format conversion and unit unification.

Semantic Conflict Resolution and Numerical Normalization

To address semantic inconsistencies in multi-source data caused by different naming conventions and coding standards, canonical mapping tables and synonym dictionaries are constructed and maintained by dedicated data administrators. For coded data such as fault codes and equipment models, unified national or industry standards are adopted for normalization to ensure consistent semantic expression of the same indicator in different systems. For numerical operation data including vibration amplitude, motor current, temperature and other continuous variables, Z-score normalization is applied to eliminate dimensionality effects and magnitude differences, as illustrated in the following formula:

$$X_{norm}=\frac{X-\mu}{\sigma} \tag{1}$$

Here, X is the original data value, μ is the population mean of the data item calculated from historical data, and σ is the standard deviation of the data item. After normalization, all numerical features are distributed with a mean of 0 and a standard deviation of 1, which improves the convergence speed and stability of subsequent model training.

Feature Extraction and Structuring Conversion

For unstructured data such as maintenance logs, fault description texts and on-site inspection records, natural language processing (NLP) technology is employed to extract key fault feature information including fault location, fault phenomenon, severity level and treatment measures through word segmentation, named entity recognition and keyword matching. For time-series operation data, multi-dimensional feature extraction is carried out: time-domain features including mean value, variance, peak value, root mean square, kurtosis, skewness, peak factor and margin factor are extracted from the original signals; frequency-domain features including main frequency, harmonic component amplitude and frequency band energy ratio are extracted through fast Fourier transform. For categorical discrete variables such as equipment type, fault type and maintenance level, one-hot encoding is applied to transform them into numerical vectors, ensuring model compatibility. The formula is as follows:

$$Code(C_i)=[0,...,1,...,0] \tag{2}$$

where C_i is the i-th category, and the vector has a value of 1 only at the i-th position, with all other positions being 0. This encoding method avoids introducing artificial ordinal relationships between categorical variables.

Through the above standardization process, all data from different sources and formats are integrated into a unified dimensional feature space, providing a high-quality data foundation for subsequent MTBF prediction and decision analysis.

Core Mathematical Modeling and Decision Optimization

MTBF Prediction Model Based on Hybrid Neural Network

Aiming at the demand for full-system reliability prediction of elevators under complex operating conditions, a hybrid neural network MTBF prediction model integrating convolutional neural network (CNN), bidirectional long short-term memory (BiLSTM) and Weibull distribution calibration is constructed. The model adopts a five-layer structure: input layer, CNN local feature extraction layer, BiLSTM timing dependency modeling layer, attention mechanism weighting layer, and Weibull distribution output layer. The model first uses one-dimensional CNN to extract local fault feature patterns from time-series sensing signals such as vibration, current and temperature, capturing subtle changes of equipment degradation characteristics. Then it captures the long-term time dependency and evolution trend of operation data through BiLSTM network, which can simultaneously utilize historical and future context information in the sequence. An attention mechanism is introduced to assign higher weights to key fault-sensitive features and important time nodes, enhancing the model's perception of degradation critical points. Finally, the output layer maps the extracted deep features to the shape parameter and scale parameter of Weibull distribution, and calculates the MTBF value through the reliability function. The calculation formula is as follows:

$$MTBF=\eta\cdot\Gamma\left(1+\frac{1}{\beta}\right) \tag{3}$$

where β is the shape parameter of Weibull distribution reflecting the change trend of failure mode: when β<1, the equipment is in the early failure period with decreasing failure rate; when β=1, it is in the random failure period with constant failure rate; when β>1, it enters the wear-out failure period with increasing failure rate. η is the scale parameter characterizing the characteristic life of equipment, and $\Gamma(\cdot)$ is the gamma function. The model is trained with a joint loss function combining mean square error loss and log-likelihood loss, with weight coefficients adjusted according to data characteristics to balance prediction accuracy and distribution fitting effect.

Maintenance Resource Allocation Optimization Model

A multi-objective optimization model is constructed to solve the problem of rational allocation of maintenance resources including maintenance personnel, spare parts and maintenance tools among multi-station elevator clusters. The model takes three optimization objectives into account: minimize total downtime economic loss, minimize operation and maintenance cost, and maximize comprehensive resource utilization, with constraints including total resource limit, maintenance response time limit, equipment priority constraint and spare parts inventory constraint. The model expression is as follows:

$$\begin{cases} \min\ f_1 = \sum_{i=1}^{n} w_i \cdot T_i(x_i) \\ \min\ f_2 = \sum_{i=1}^{n} c_i \cdot x_i \\ \max\ f_3 = \frac{\sum_{i=1}^{n} u_i \cdot x_i}{X_{total}} \\ s.t. \sum_{i=1}^{n} x_i \le X_{total}, \quad x_i \ge 0 \\ T_i(x_i) \le T_{max}, \quad i = 1,2,\ldots,n \end{cases} \tag{4}$$

Here, n is the number of elevator stations, x_i represents the amount of resources allocated to the i-th station, X_{total} is the total available resource volume, w_i is the downtime loss weight of the i-th station determined by building importance and passenger flow, $T_i(x_i)$ indicates the predicted fault downtime corresponding to the allocated resource amount, c_i denotes the unit resource cost, u_i is the resource utilization efficiency coefficient, and T_{max} is the maximum allowable maintenance response time specified by the service level agreement. The non-dominated sorting genetic algorithm (NSGA-III) is employed to solve this multi-objective optimization problem, with parameter settings of population size 100, iteration number 200, crossover probability 0.8 and mutation probability 0.1, yielding a Pareto optimal solution set for decision-makers to select according to actual needs.

Elevator Fault Risk Grading Model

The fault risk of elevator equipment is influenced by multiple factors including operation status, service age, environmental condition, and maintenance history. A multi-dimensional fault risk grading model covering four categories of risk factors is established. The four categories are technical risk (component wear degree, performance attenuation rate, control system stability), environmental risk (ambient temperature and humidity, dust concentration, power supply quality), operation risk (daily operating times, average load, overload frequency), and maintenance risk (maintenance quality, spare parts quality, maintenance timeliness). The Analytic Hierarchy Process (AHP) is employed to determine the weights of each risk factor by constructing a pairwise comparison judgment matrix and passing consistency test (consistency ratio CR<0.1), followed by a fuzzy comprehensive evaluation method to calculate the comprehensive risk level, as shown in the formula below:

$$R = \sum_{j=1}^{m} w_j \times r_j \tag{5}$$

The comprehensive risk value R of the equipment ranges from 0 to 1, with higher values indicating greater risk. The evaluation score r_j for the j-th risk factor is determined through expert scoring and data-driven quantitative assessment. According to the risk value, equipment is divided into three risk levels: low risk ($0 \leq R < 0.3$), medium risk ($0.3 \leq R < 0.7$) and high risk ($0.7 \leq R \leq 1$), corresponding to differentiated maintenance strategies of routine maintenance, enhanced inspection and predictive maintenance respectively.

Comprehensive Maintenance Performance Evaluation Model

To overcome the limitations of single indicator evaluation and one-sided assessment, a four-dimensional performance evaluation model integrating reliability, economy, efficiency, and safety is constructed. The standardized comprehensive performance index is defined as follows:

$$P_{total} = \sum_{k=1}^{4} w_k \times P_k \quad (6)$$

Here, w_k represents the weight of the k-th dimension calculated by the entropy weight method, which determines the weight according to the information content contained in each indicator data, avoiding subjective deviation. P_k denotes the standardized score of each dimension:

Reliability dimension: the standardized mean of indicators such as MTBF, failure rate, average downtime, and fault recurrence rate;

Economic dimension: the standardized mean of indicators such as unit maintenance cost, spare parts inventory cost, downtime loss cost, and personnel cost;

Efficiency dimension: the standardized mean of indicators such as fault response time, maintenance completion rate, work order processing efficiency, and resource utilization rate;

Safety dimension: the standardized mean of indicators such as safety accident rate, hidden danger rectification rate, safety inspection pass rate, and emergency rescue response time.

The standardized scores of each dimension are processed using the extreme value method, where the original indicator value is linearly mapped to the [0,1] interval based on the maximum and minimum values of the indicator in the statistical cycle, facilitating horizontal comparison between different dimensions and vertical comparison across different cycles.

Dynamic Data Quality Assessment Model

Data quality is the foundation of effective maintenance decision-making. A four-dimensional dynamic evaluation model of completeness, consistency, accuracy, and timeliness is established to regularly calculate data quality metrics, drive automatic data cleaning and missing supplementation, and form a closed-loop data quality management mechanism.

Completeness Assessment

Define the integrity score for data entities to measure the missing degree of required fields. The formula is as follows:

$$Score_{comp} = \frac{\sum_{f \in F_{required}} I(\text{not null}(e,f))}{|F_{required}|} \quad (7)$$

Here, e is the data entity such as equipment record, fault work order or operation log, $F_{required}$ is the set of required fields for this entity specified by the data standard, $I(\cdot)$ is the indicator function (returns 1 if the field is not empty, otherwise returns 0), and $|F_{required}|$ is the total number of required fields. The completeness score ranges from 0 to 1, with higher values indicating better data integrity.

Consistency Assessment

To address discrepancies in records of the same indicator across different business systems, the consistency error is defined to measure the degree of data inconsistency between multiple sources. The formula is as follows:

$$Err_{cons}=\sum_{i=1}^{m}\ \sum_{j=i+1}^{m}\ |v_i\text{-}v_j|\times w_{ij} \quad (8)$$

Here, v_i and v_j represent the recorded values of the same indicator across different data sources such as elevator control system, maintenance management system and IoT platform, while m is the number of data sources, and w_{ij} is the weight coefficient for the data source pair determined by the source's credibility and data accuracy. Smaller consistency error indicates higher data consistency.

Timeliness Assessment

Define the data timeliness score to measure whether the data update frequency meets the business requirements. The formula is as follows:

$$Score_{timely}=\begin{cases}1, & t\le t_0\\ 1-\frac{t-t_0}{t_{max}-t_0}, & t_0<t<t_{max}\\ 0, & t\ge t_{max}\end{cases} \quad (9)$$

where t is the interval between the data update time and the current time, t_0 is the data update threshold representing the acceptable normal delay, and t_{max} is the data expiration threshold beyond which the data loses reference value. Different thresholds are set for different types of data: for real-time operation data, t_0 is 5 minutes and t_{max} is 30 minutes; for maintenance work order data, t_0 is 24 hours and t_{max} is 7 days.

The system automatically calculates the above data quality metrics every 24 hours. If the comprehensive data quality score falls below the preset threshold (e.g., 0.8), it triggers an automatic alert and automatically initiates the data cleaning process including missing value filling, duplicate data removal and error data correction, forming a continuous optimization mechanism of data quality.

Experimental Results and Analysis

Experimental Setup

To validate the feasibility and effectiveness of the proposed model, we analyzed elevator operation and maintenance data from 2019 to 2023 of a large commercial complex in a domestic first-tier city, which manages 126 elevators of different brands and types covering passenger elevators, freight elevators and escalators. The dataset includes 18 types of sensing data such as vibration, temperature, current and displacement collected at 1Hz frequency, 2,147 formal fault records, 8,936 maintenance work order records, and 3.6TB of multi-source heterogeneous data encompassing both internal system records and external industry benchmark data.

Data Preprocessing

According to the standardization model in Section 2.2, the original multi-source data was cleaned, transformed, and integrated: 1,562 duplicate records caused by multi-system synchronization were eliminated, 4,289 missing data entries were filled through interpolation and similar device matching, and 1,024 semantic conflict entries were resolved through mapping rules, ultimately forming a unified elevator operation and maintenance data resource pool. The dataset is divided into training set, validation set and test set according to the ratio of 7:2:1 in chronological order to ensure the authenticity of simulation prediction effect.

System Development

The backend service is developed using the Java Spring Boot framework, with the frontend operation interface built with Vue.js. It employs a hybrid database architecture combining time-series database InfluxDB for storing massive operation data and relational database MySQL for storing service data, deployed on an edge-cloud collaborative platform. The cloud server is configured with 32-core CPU, 128GB memory and 10TB storage, and each edge computing node is configured with 8-core CPU and 16GB memory. The system supports concurrent access of over 500 elevator devices and 200 online users.

Evaluation Indicators

The evaluation method combining quantitative and qualitative analysis was adopted, covering four dimensions:

Data quality: field completion rate, data inconsistency error rate, and duplicate record count;

Process efficiency: processing time of core maintenance links and manual workload per task;

Prediction performance: MTBF prediction accuracy, root mean square error (RMSE), mean absolute error (MAE); prediction accuracy is defined as the proportion of samples whose relative error between predicted value and actual value is within ±10%;

User satisfaction: 5-point Likert scale was used to survey the user satisfaction (1=very dissatisfied, 5=very satisfied).

Comparative Analysis of Data Integration Quality

Table 1 presents the data quality metrics before and after implementing the proposed model. The results demonstrate that the model significantly enhanced data quality through standardization and integration: field completion rates for all data types exceeded 98%, while the equipment-operation association data completion rate rose from 56.2% in the traditional mode to 98.1%, showing the largest improvement. This is because such cross-system association data was the most affected by data silos in the traditional mode, and the unified standard and associated primary key mechanism effectively solved this problem. The data inconsistency error rate was substantially reduced, with fault maintenance data error rates decreasing from 16.7% to 1.2%. Duplicate records were eliminated by 99.3%, effectively resolving information redundancy caused by multi-system data repetition. The overall improvement of data quality provides a reliable foundation for subsequent prediction models and decision analysis.

Table 1: Comparison of Key Indicators for Data Integration Quality.

Data category	Field completion rate (Traditional mode)	Field completion rate (Proposed model)	Data inconsistency error rate (Traditional mode)	Data inconsistency error rate (Proposed model)	Duplicate records (Traditional mode)	Duplicate records (Proposed model)
Elevator basic information	83.5%	99.2%	4.1%	0.5%	312 items	3 items
Operation status data	72.8%	98.5%	10.6%	0.8%	486 items	4 items
Fault maintenance records	77.3%	99.0%	16.7%	1.2%	364 items	3 items

Equipment-operation association data	56.2%	98.1%	19.2%	1.4%	200 items	2 items

Maintenance Process Efficiency Assessment

The study identified four core operational processes in elevator maintenance management, comparing processing times and manual workloads before and after implementing the model, as shown in Table 2. Through process automation and data integration, the model significantly reduced processing times: fault work order dispatch time decreased from 2.3 days to 0.4 days, realizing automatic matching of fault type, personnel skills and geographic location; predictive maintenance scheduling time dropped from 5.8 days to 1.1 days, achieving near-real-time dynamic adjustment based on equipment risk status; emergency fault response time shortened from 1.5 days to 0.3 days through automatic alarm and nearest dispatch; and annual performance evaluation time decreased from 8.5 days to 1.2 days with automatic data aggregation and report generation. Concurrently, manual workload was substantially reduced, with annual report preparation hours decreasing from 96 hours per person to 7 hours per person, and data verification workload decreasing by over 90%, effectively alleviating administrative burdens for maintenance managers.

Table 2: Comparison of Core Maintenance Process Efficiency.

Maintenance process step	Average duration of traditional mode (days)	Average duration of proposed model (days)	Time reduction rate	Traditional mode man-hour (hours/task)	Proposed model man-hour (hours/task)	Man-hour reduction rate
Fault work order dispatch	2.3	0.4	82.6%	8.5	1.0	88.2%
Predictive maintenance scheduling	5.8	1.1	81.0%	22.0	2.4	89.1%
Emergency fault response	1.5	0.3	80.0%	12.5	1.6	87.2%
Annual maintenance performance appraisal	8.5	1.2	85.9%	56.0	6.8	87.9%

Validation of MTBF Prediction and Decision Support Effect

Three representative maintenance decision-making scenarios were selected to compare traditional manual decision-making with model-supported decision-making, as shown in Table 3. The model achieved dual improvements in decision-making efficiency and scientific rigor: the annual maintenance plan formulation process was shortened from 7 working days to less than 2 hours, and through data-driven industry trend analysis and resource optimization, the implementation success rate of plans increased from 63% to 89%. The fault risk warning accuracy for elevator equipment rose from 56% in the traditional mode to 87%, identifying 32 high-risk elevators in advance and avoiding approximately 8.6 million yuan in downtime losses including passenger flow loss and emergency maintenance cost. Multi-station maintenance resource scheduling shifted from experience-based judgment to data-driven optimization, with resource utilization rate increased from 62% to 83%, generating an annual cost saving of about 3.2 million yuan.

In terms of MTBF prediction accuracy, comparative experiments were carried out with the traditional statistical method, single LSTM model and the proposed hybrid model. The results show that the RMSE of the traditional statistical method is 12.5 days, the MAE is 9.7 days, and the prediction accuracy is 52%; the RMSE of the single LSTM model is 8.3 days, the MAE is 6.5 days, and the prediction accuracy is 71%; while the RMSE of the proposed model is 4.2 days, the MAE is 3.1 days, and the prediction accuracy reaches 89%, verifying the superiority of the hybrid model integrating CNN, BiLSTM and Weibull distribution in MTBF prediction.

Table 3: Comparison of Support Effect in Typical Decision-Making Scenarios.

Decision support scenario	Traditional manual decision-making mode	Proposed model decision support mode
Annual maintenance plan formulation	Requires coordination with 4 departments, takes 7 working days, with data lagging 1-2 months, and has a 63% success rate for plan implementation	Generates plan automatically, takes less than 2 hours, with real-time data updates and an 89% success rate
Equipment fault risk early warning	Relies on expert experience for judgment, with 56% early warning accuracy and strong lag, which may easily lead to unplanned downtime	Based on multi-dimensional risk model, provides real-time alerts with 87% accuracy rate, enabling risk identification 2-5 months in advance
Multi-station maintenance resource scheduling	Lacks data support and relies on manual coordination, making it difficult to optimize resource allocation and achieve 62% resource utilization	Automatically recommends optimal allocation scheme based on multi-objective optimization algorithm, achieving 83% resource utilization rate

User Satisfaction Survey Results

After six months of trial operation, a satisfaction survey combining online questionnaires and offline interviews was conducted among four core user groups (maintenance technicians, station managers, operation decision-makers, and IT operation staff), with 287 valid responses collected, including 128 maintenance technicians, 65 station managers, 32 operation decision-makers and 62 IT operation staff. As shown in Table 4, all user groups achieved overall satisfaction scores exceeding 4.4 out of 5. Station managers demonstrated the highest satisfaction with "process efficiency" (4.8), as the system significantly shortened the work order processing cycle and reduced management pressure. Operation decision-makers prioritized "decision support value" (4.7), as data-based quantitative decision-making improved the scientificity of resource allocation. Maintenance technicians showed strong approval for "functional practicality" (4.6), and IT operation staff rated "system stability" at 4.6, confirming the model's technical feasibility and stability. However, maintenance technicians gave relatively lower scores to "personalized analytical tools" (4.2), mainly because the current system provides more general analysis functions, and the customized analysis tools for different types of maintenance work and different technical positions are insufficient, indicating key directions for future optimization.

Table 4: Satisfaction scores of different user groups (5-point scale)

User Group	Ease of use	Functional practicality	Process efficiency	Decision support value	System stability	Overall satisfaction
Maintenance technicians	4.4	4.6	4.5	4.2	4.5	4.5
Station managers	4.5	4.7	4.8	4.6	4.6	4.7
Operation decision-makers	4.3	4.5	4.4	4.7	4.4	4.6
IT operation staff	4.6	4.4	4.3	4.2	4.6	4.5

Conclusion

This AIoT-driven intelligent elevator maintenance management system employs a four-tier edge-cloud collaborative architecture for multi-source heterogeneous data integration. Via standardized data processing pipelines, hybrid neural network MTBF prediction, multi-objective maintenance resource optimization, and dynamic data quality assessment mechanism, it enables reliable intelligent quantitative maintenance decision-making covering the whole lifecycle. Experimental validation based on real commercial complex elevator data shows it effectively addresses traditional challenges in elevator maintenance management, significantly improving data quality, cutting core process time by over 67%, boosting fault risk warning accuracy to 87%, and gaining high user recognition from all roles.

The innovations of this study lie in three aspects: first, an end-to-end full-lifecycle closed-loop management system for AIoT elevator maintenance is constructed, realizing full-link integration from terminal data collection, state analysis and prediction, decision optimization to performance evaluation; second, the MTBF prediction model integrating CNN-BiLSTM and Weibull distribution calibration takes into account both local fault feature extraction capability and long-term time series evolution modeling capability, and improves the reliability and interpretability of prediction results through distribution calibration; third, the edge-cloud collaborative deployment architecture and multi-level security protection mechanism balance data real-time processing performance, system flexibility and data security, adapting to different scale application scenarios.

This study still has certain limitations: the current experimental verification is only carried out in commercial building scenarios, and the generalization performance of the model in other scenarios such as residential buildings, hospitals and rail transit hubs needs to be further verified. Future iterations will focus on industry-adaptive lightweight models that can be deployed on edge nodes, deep learning algorithms for unstructured maintenance text data and long-term trend prediction, "collection-transmission-storage-application" full-process data security system, and customized role-based analytical tools for frontline maintenance needs to further enhance practical engineering application value.

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