Implementing Automatic Generation of Primary Equipment Status Awareness and Maintenance Priority Using a Hybrid GCN-RNN Architecture

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ABSTRACT To address issues in industrial production, such as low monitoring accuracy of primary equipment, poor adaptability to complex electromagnetic testing and industrial operating environments, and unreasonable maintenance priority allocation, this paper proposes a framework integrating GCN and RNN for intelligent equipment condition awareness and automatic maintenance priority generation. First, multi-source monitoring data, including vibration, temperature, pressure, current, and operating load, from primary equipment are cleaned, standardized, and subjected to feature engineering preprocessing to construct an operational status dataset. Second, a GCN module is designed to extract spatial correlation features among monitoring points, while an RNN subnetwork based on LSTM captures temporal evolution patterns of equipment status. This establishes a hybrid model integrating dual spatial-temporal features, enabling precise identification of equipment health levels, including normal, mild anomaly, moderate anomaly, and severe anomaly. Then, based on the equipment status perception results, an evaluation system for maintenance priority is established by integrating indicators such as equipment importance, fault impact scope, and repair costs. The Entropy Weighting-TOPSIS method is employed to achieve quantitative prioritization, providing technical support for maintenance decision-making in industrial systems involving electromagnetic measurement platforms, antenna testing equipment, and radio-frequency monitoring devices.

INDEX TERMS primary equipment, condition awareness, maintenance priority, graph convolutional network, electromagnetic measurement

I. INTRODUCTION

A. RESEARCH BACKGROUND

DRIVEN by Industry 4.0, process industries such as chemical manufacturing, metallurgy, power equipment, and electronic manufacturing are transforming toward intelligent and flexible operations through the integration of automated monitoring, intelligent control, and digital production systems. This shift enables modern industrial production lines to achieve higher precision and adaptability in response to the increasingly complex demands of modern industrial manufacturing. As the core carriers of production systems, the operational status of main equipment (such as reactors, steam turbines, pump sets, etc.) directly determines production continuity, product quality, and operational safety [1]. Statistics indicate that approximately 70% of production interruptions in industrial sectors stem from primary equipment failures, with 45% resulting from unplanned shutdowns caused by delayed condition detection and suboptimal maintenance decisions [2]. Traditional equipment condition monitoring relies heavily on single-sensor data and manual expertise, which presents several challenges: first, the spatial correlation among multi-source monitoring data (vibration, temperature, pressure, etc.) remains underutilized, leading to low detection accuracy and difficulty in identifying early latent faults. Second, it ignores the temporal evolution characteristics of equipment status, resulting in inadequate predictive capabilities for gradual failures. Third, maintenance priority allocation relies on subjective expert experience, lacking a quantitative evaluation system, which easily leads to resource misallocation issues such as prioritizing secondary equipment over critical equipment [3,4].

B. CURRENT RESEARCH STATUS DOMESTICALLY AND INTERNATIONALLY

1) Research on Equipment Condition Monitoring Technology

Internationally, research in equipment condition monitoring began earlier, resulting in relatively mature technical frameworks [5-7]. Kim et al. [8] proposed a CNN-based bearing fault diagnosis model. By extracting features from two-dimensional spectral maps of vibration signals, they achieved 91.2% accuracy in fault type identification, though spatial correlations between sensor nodes were not considered. Zhang et al. [9] employed LSTM networks for time-series modeling of wind turbine operational data, effectively capturing gradual changes in equipment status. However, neglecting spatial dimensional features resulted in insufficient early-stage fault detection capabilities. Yuan et al. [10] applied GCN to power grid equipment condition monitoring, modeling device topological relationships through graph structures to enhance multi-source data feature fusion. However, this approach did not incorporate dynamic temporal variations.

2) Maintenance Priority Ranking Research

Priority ranking research primarily focuses on constructing evaluation metric systems and optimizing ranking algorithms. Internationally, Smith et al. developed a priority evaluation model based on the risk matrix method, considering both failure probability and impact severity, but metric weights relied on subjective judgment. Jones et al. employed the Analytic Hierarchy Process (AHP) to determine equipment importance weights and quantified priorities based on failure losses, yet failed to account for dynamic metric changes. Domestically, Chen et al. proposed an entropy-weighted TOPSIS-based maintenance priority ranking model, enhancing scientific evaluation through objective weighting, yet failed to dynamically integrate real-time equipment status sensing results. Liu et al. integrated equipment status levels with maintenance costs to construct a priority evaluation system, but lacked quantitative analysis of fault impact scope. Existing studies predominantly address condition monitoring and priority ranking in isolation, failing to establish a closed-loop mechanism linking condition awareness to priority generation. This gap leads to priority assignments that diverge from actual equipment operational states [11-13].

C. RESEARCH SCOPE AND TECHNICAL APPROACH

1) Research Scope

1. Preprocessing of Multi-source Data and Dataset Construction for Primary Equipment: Addressing issues such as heterogeneity and noise interference in multi-source monitoring data (e.g., vibration, temperature, pressure), we design data cleaning, standardization, and feature engineering schemes to construct equipment status datasets incorporating spatial correlation information and time series.

2. Construction of GCN-RNN Hybrid State-Aware Model: Design a GCN module to model spatial correlations among monitoring points, employ an LSTM subnetwork to capture temporal evolution patterns, and build a dual-dimensional feature fusion model for equipment health status classification;

3. Maintenance Priority Evaluation Framework and Quantitative Model Construction: Select indicators including equipment health level, criticality, fault impact scope, and maintenance cost. Determine objective weights using the entropy weight method and implement quantitative priority ranking via the TOPSIS method;

4. Experimental Validation and Performance Analysis: Using main equipment in chemical plants as the research subject, validate the model's state perception accuracy and priority ranking rationality based on public datasets and field-collected data, and conduct comparative analysis with existing methods [14-16].

2) Technical Approach

The proposed framework consists of three stages: the data layer, the model layer, and the decision layer. The data layer collects, preprocesses, and constructs datasets from multi-source monitoring data while defining the graph structure relationships among equipment monitoring points. The model layer constructs a GCN-RNN hybrid perception model, achieving equipment condition level recognition through training optimization; the decision layer establishes a maintenance priority evaluation system, generating maintenance priority rankings based on condition perception results and quantification algorithms, ultimately forming a complete technical chain of "data collection – condition perception – priority generation" [17-19].

The technical approach forms a closed-loop chain:

Data Layer: Collects and preprocesses multi-source monitoring data, constructing graph structures for monitoring points;

Model Layer: Builds a GCN-RNN hybrid model to extract spatio-temporal features and recognize equipment status;

Decision Layer: Integrates status results with multi-dimensional indicators, generating maintenance priorities via Entropy Weighting-TOPSIS.

This framework enables end-to-end intelligent processing from data input to maintenance priority output [17-19].

II. THEORETICAL FOUNDATIONS

A. FUNDAMENTALS OF GRAPH CONVOLUTIONAL NETWORKS

Graph Convolutional Networks (GCNs) are deep learning models adapted for non-Euclidean structured data. Their core advantage lies in precisely extracting associative features between nodes and their neighboring, which matches the distributed characteristics of monitoring points on industrial equipment. In equipment status sensing scenarios, each monitoring point can be regarded as an independent node, while the physical connections and signal transmission associations between monitoring points are treated as edges between nodes, thereby constructing a graph structure describing the equipment monitoring system [20]. When constructing the graph structure, first define the node set—all sensor collection nodes on the equipment, such as vibration, temperature, and pressure sensors. Next, assign edge weights based on the installation distance between monitoring points and the strength of signal influence. For example, adjacent temperature and pressure monitoring points on a reactor vessel receive higher weights, while distant or functionally unrelated monitoring points receive lower weights. Finally, form a node feature matrix where each node's features consist of collected data and extracted characteristics from corresponding monitoring points [21].

Centrifugal Pump: Edges are defined by "radial distribution + functional correlation" centered on the pump shaft. Vibration and temperature sensors (installation spacing $\leq$ 5cm) are set as strongly correlated edges (weight 0.8-1.0), while vibration and pressure sensors (installation spacing > 15cm) are weakly correlated edges (weight 0.3-0.5);

Reactor: Edges are defined by "cavity area division". Sensors in the same reaction area (e.g., temperature and pressure) are strongly correlated (weight 0.7-0.9), while sensors in different areas are weakly correlated (weight 0.2-0.4).

The edge weight wij is calculated using a two-factor formula: wij = 0.6 $\times$ Distance Attenuation Coefficient + 0.4 $\times$ Pearson Correlation Coefficient. The distance attenuation coefficient is fitted based on the actual installation spacing of sensors, ensuring objective and quantifiable weight allocation.

B. ENTROPY WEIGHTING-TOPSIS PRIORITY RANKING METHOD

1) Entropy Weighting Principle

Entropy weighting is an objective weighting method based on the information entropy of indicators. Its core principle involves determining weights according to the degree of data dispersion. Information entropy reflects indicator uncertainty: higher dispersion yields lower entropy, indicating that the indicator provides more discriminative information and thus warrants a higher weight. Conversely, lower dispersion results in lower weights [22].

In maintenance priority evaluation, the Entropy Weighting Method eliminates subjective expert bias by automatically calculating weights through analysis of raw data such as equipment condition levels and fault impact scope. For instance, when equipment condition levels exhibit significant variation across different assets, higher weights are assigned to ensure objective and scientific weight distribution [23].

2) TOPSIS Ranking Principle

TOPSIS is a multi-criteria decision method based on relative proximity. Its core principle involves calculating the distance between evaluation objects and both positive and negative ideal solutions to determine relative superiority. The positive ideal solution is a hypothetical entity composed of optimal values across all criteria, while the negative ideal solution is a hypothetical entity composed of the worst values across all criteria [24]. In maintenance priority ranking, a standardized indicator matrix is first constructed and combined with entropy weighting to form a weighted standardized matrix. Positive and negative ideal solutions are then defined. The distance between each device and both ideal solutions is calculated. Finally, proximity is determined through distance calculations: greater proximity indicates closer alignment with the negative ideal solution, warranting higher maintenance priority.

C. EQUIPMENT CONDITION-AWARE EVALUATION INDICATORS

The performance of the equipment condition awareness model is evaluated through four core metrics. Accuracy reflects the overall correct recognition rate of all equipment states (normal, mildly abnormal, moderately abnormal, severely abnormal), providing an intuitive measure of overall performance. Precision measures the proportion of samples predicted as a certain state that are actually in that state, avoiding false positive misclassifications. For example, high precision in identifying mildly abnormal conditions indicates that the proportion of genuine mildly abnormal cases in the recognition results is high. Recall reflects the proportion of samples actually in a certain state that are correctly identified, preventing false negative. For example, high recall for severe anomalies prevents overlooking critical failures. The F1 score is the harmonic mean of precision and recall, balancing both metrics to avoid the limitations of single-metric evaluation. It comprehensively measures the model's overall performance across all state classifications, providing a basis for model optimization.

III. DESIGN OF THE MAIN EQUIPMENT CONDITION MONITORING AND MAINTENANCE PRIORITY GENERATION MODEL

A. OVERALL SYSTEM ARCHITECTURE

The system adopts a four-layer architecture: "Data Preprocessing Layer - Feature Fusion Layer - Condition Monitoring Layer - Priority Generation Layer". Each layer collaborates to achieve end-to-end intelligent processing from multi-source data input to maintenance priority output. The Data Preprocessing Layer purifies raw monitoring data and extracts features to deliver high-quality inputs. The Feature Fusion Layer employs GCN and LSTM in tandem to achieve deep integration of spatial and temporal characteristics. The Status Awareness Layer identifies equipment status levels based on fused features. The Priority Generation Layer combines status recognition results with multi-dimensional metrics to output scientifically ranked maintenance priorities, forming a complete technical closed-loop.

B. MULTI-SOURCE DATA PREPROCESSING AND DATASET CONSTRUCTION

1) Data Preprocessing Workflow

Data standardization eliminates dimensional differences across monitoring data types (e.g., vibration, temperature, pressure with varying units). Z-score normalization transforms all data into standardized values with mean 0 and standard deviation 1, ensuring comparable scales and unbiased feature treatment by the model.

Feature engineering constructs high-dimensional feature vectors by extracting meaningful information. For the time-domain characteristics of monitoring data, features such as mean, variance, and peak values are extracted. For the frequency-domain characteristics, features like spectral peak values and dominant frequencies are extracted. Additionally, statistical features such as coefficient of variation and trend components are extracted. Ultimately, a 24-dimensional feature vector is constructed to provide rich input information for the model.

Graph structure construction adapts to the GCN module, building an adjacency matrix based on the physical characteristics and signal correlations of equipment monitoring points. The spatial distribution and functional types of monitoring points are analyzed, with association weights set according to physical distance, signal transmission paths, and functional interdependencies to accurately model the spatial relationships within the equipment monitoring system.

2) Dataset Construction

A hybrid approach combining "public datasets + field-collected data" is adopted for dataset construction. Public datasets include the PHM2015 bearing fault dataset and the CWRU motor fault dataset, encompassing diverse typical states to provide varied foundational samples for model training.

Field data was collected from primary equipment such as reactors and centrifugal pumps at a chemical plant.

Sensors were scientifically deployed: vibration sensors sampled at 10 kHz, temperature sensors measured -40 °C to 200 °C, and pressure sensors measured 0 to 10 MPa. Data collection spanned six months, covering four typical states: normal, mildly abnormal, moderately abnormal, and severely abnormal.

The dataset was partitioned into training, validation, and test sets at a 7:2:1 ratio. The training set optimized model parameters, the validation set monitored overfitting, and the test set independently evaluated model generalization performance.

Training set: First 70% of the six-month data (4.2 months), used for model parameter optimization;

Validation set: Middle 20% of the data (1.2 months), used for overfitting monitoring;

Test set: Last 10% of the data (0.6 months), used for independent generalization performance evaluation. This chronological partitioning ensures no temporal overlap between training and test sets, avoiding data leakage. The partitioning ratio refers to industry standards for industrial time-series data, combined with the average equipment fault evolution cycle (15-30 days), ensuring the test set contains complete fault evolution samples.

C. DESIGN OF THE GCN-RNN HYBRID CONDITION-AWARE MODEL

1) Model Architecture

The GCN spatial feature extraction module employs a two-layer network structure. Input consists of graph-structured data (adjacency matrix and node feature matrix). The first layer maps the 24-dimensional feature vector to a 64-dimensional feature, enhancing nonlinear expressive capability to preliminarily extract local spatial correlation features. The second layer compresses the feature dimension to 32 dimensions, expanding the feature receptive field to achieve global spatial correlation feature extraction and capture the collaborative variation patterns of monitoring points across different regions of the equipment. The LSTM temporal feature extraction module employs a two-layer architecture. It arranges the spatial features output by GCN in temporal order to form time-series data (with a time step of 20). The first hidden layer has a dimension of 64, capturing rapid trend changes within short time intervals. The second layer deepens feature learning to capture long-term evolutionary patterns. A dropout layer (dropout rate 0.2) is inserted between the two layers to prevent overfitting.

The fusion classification module employs an attention mechanism to weight and integrate spatial and temporal features, training to adaptively learn the weight distribution between the two feature types. The fused 128-dimensional features are fed into a fully connected layer for classification. The softmax activation function outputs a probability distribution across four device states, with the state exhibiting the highest probability serving as the final classification result.

2) Model Training Parameters

Model training employs the Adam optimizer with a learning rate of 0.001, batch size of 32, and 100 training epochs. The cross-entropy loss function measures the discrepancy between predicted probability distributions and actual label distributions. Training loss values for both training and validation sets are monitored. When the validation loss fails to decrease for 10 consecutive epochs, early stopping is applied to prevent overfitting.

D. MAINTENANCE PRIORITY GENERATION MODEL DESIGN

1) Evaluation Metric System Construction

Following principles of scientific rigor, practicality, and quantifiability, a maintenance priority evaluation system comprising 4 primary metrics and 8 secondary metrics was established.

Equipment Status Level (35% weight) is determined by the hybrid model and categorized into four levels: Normal (1 point), Mild Abnormality (3 points), Moderate Abnormality (5 points), and Severe Abnormality (7 points). Higher levels indicate greater maintenance urgency.

Equipment Importance (25% weight) incorporates Production Impact and Safety Weight. Production Impact is quantified by downtime-induced production delays and capacity loss ratios, while Safety Weight is assigned based on fault safety risk levels.

Failure Impact Scope (20% weight) comprises Production Capacity Loss Rate and Number of Affected Associated Equipment. Production Capacity Loss Rate is calculated as the percentage reduction in production capacity per unit time. Number of Affected Associated Equipment counts the number of related equipment forced to shut down or reduce load due to the failure of the subject equipment.

Maintenance Cost (20% weight) includes Spare Parts Cost and Maintenance Labor Hours, comprehensively reflecting the economic and time costs of repairs.

2) Priority Quantification Process

First, standardize indicator data by converting all metrics to normalized values between 0 and 1. Positive indicators undergo forward standardization, while negative indicators use inverse standardization to ensure alignment between metric trends and priority ranking logic.

Next, determine objective weights for secondary indicators using the Entropy Weighting Method. Weights are allocated based on information entropy calculations—lower entropy values yield higher weights. Weighted summation yields the comprehensive weight for primary indicators.

Finally, the TOPSIS method is applied for ranking. A weighted standardized matrix is constructed to identify positive and negative ideal solutions. The Euclidean distance between each device and both ideal solutions is calculated to determine proximity. Devices are then ranked based on proximity to generate a maintenance priority list.

Calculate objective weights for 8 secondary indicators using the Entropy Weighting Method. Weights are allocated based on information entropy—lower entropy indicates more discriminative information and higher weight;

Obtain comprehensive weights for 4 primary indicators via weighted summation. The "35%/25%/20%/20%" annotated in Section Evaluation Metric System Construction is the calculation result for the experimental dataset, not fixed values.

IV. EXPERIMENTAL VALIDATION AND RESULTS ANALYSIS

A. EXPERIMENTAL ENVIRONMENT

1) Hardware Environment

CPU: Intel Xeon Gold 6330, Memory: 128GB, GPU: NVIDIA A100 40GB, Storage: 2TB SSD;

2) Software Environment

Operating System: Ubuntu 20.04 LTS; Programming Language: Python 3.9; Deep Learning Framework:

PyTorch 2.0; Data Processing Library: Pandas 1.5; Scientific Computing Library: NumPy 1.24.

B. EXPERIMENTAL DATA AND COMPARISON MODELS

1) Experimental Data

Experimental data encompasses two primary equipment types: reactors (12 monitoring points, 8,000 samples) and centrifugal pumps (8 monitoring points, 6,000 samples). Data includes four anomaly labels: Normal (40%), Mild Anomaly (25%), Moderate Anomaly (20%), and Severe Anomaly (15%).

2) Comparison Models

1. Single Deep Learning Models: GCN, LSTM, CNN;

2. Traditional Machine Learning Models: Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting Tree (XGBoost);

3. Priority Ranking Methods: Single TOPSIS, AHP-TOPSIS, Entropy Weighting.

C. ANALYSIS OF EQUIPMENT STATUS SENSING RESULTS

1) Comparison of Model Performance Metrics

The equipment status sensing performance of different models is compared in Table 1. As shown in Table 1, the proposed GCN-RNN hybrid model achieves an accuracy of 95.3%, with precision, recall, and F1 score at 94.8%, 95.1%, and 94.9%, respectively. This represents a 4.8% improvement over the standalone GCN model, a 6.2% improvement over the LSTM model, and a 12.6% improvement over traditional machine learning models (e.g., RF). This improvement stems from the hybrid model's ability to simultaneously capture spatial correlations and temporal evolution characteristics of equipment states. This effectively enhances state recognition capabilities under complex operating conditions, particularly demonstrating a more significant improvement in the detection rate of early-stage mild anomalies compared to single models (from 82.3% to 91.7%).

Data Leakage Verification: The Pearson correlation coefficient between training and test sets was calculated to verify temporal independence. After chronological partitioning, the correlation coefficient decreased from 0.68 (random partitioning) to 0.12, confirming the elimination of temporal correlation interference. Comparative experiments show that the test set accuracy of chronological partitioning (95.3%) is 3.2% higher than that of random partitioning (92.1%), validating its alignment with practical prediction scenarios.

Sensitivity Analysis of Adjacency Matrix: To verify the robustness of graph structure construction, sensitivity tests were conducted by adjusting weight coefficients (± 20%) and edge connection thresholds (0.3-0.7). The results show that the model's accuracy fluctuates only within 1.2%-2.3% (from 94.1% to 96.5%), confirming that the GCN module captures stable spatial dependencies rather than introducing redundant computational complexity.

2) Model Convergence Analysis

After 30 training iterations, the proposed model converged, with the final loss value decreasing to 0.087. This value

TABLE 1. Comparison of State Awareness Performance Across Different Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Mild Anomaly Recognition Rate (%)
SVM	82.7	81.5	82.3	81.9	70.5
Random Forest	84.5	83.8	84.1	83.9	72.8
XGBoost	86.2	85.7	86.0	85.8	75.2
CNN	88.1	87.6	87.9	87.7	78.4
GCN	90.5	90.1	90.3	90.2	83.6
LSTM	89.1	88.7	88.9	88.8	82.3
Proposed Model	95.3	94.8	95.1	94.9	91.7

is lower than that of the GCN model (loss value 0.156) and the LSTM model (loss value 0.172), indicating that the hybrid model exhibits superior training stability and faster convergence speed. This advantage stems from the feature fusion approach enabled by the attention mechanism, which effectively reduces the model's training complexity and enhances convergence efficiency.

D. ANALYSIS OF MAINTENANCE PRIORITY GENERATION RESULTS

1) Consistency Validation of Priority Ranking

Ten main pieces of equipment (5 reactors and 5 centrifugal pumps) from a chemical plant were selected to validate the maintenance priority ranking. The proposed method was compared with expert assessments, using Kendall's harmony coefficient for consistency analysis.

2) Comparison of Different Priority Methods

Performance comparisons of various priority ranking methods are shown in Table 2. As indicated, the proposed method completed ranking in 0.8 seconds, outperforming the AHP-TOPSIS method (1.5 seconds) in efficiency. Its correlation with actual equipment failure losses reached 0.89, surpassing both the single TOPSIS method (0.76) and the entropy weight method (0.72), indicating that the proposed method's ranking results better align with engineering realities. Additionally, the proposed method considers real-time equipment status levels, enabling dynamic priority adjustments, whereas traditional methods primarily rely on static indicators and struggle to adapt to dynamic changes in equipment status.

TABLE 2. Comparison of Different Priority Ranking Methods

Method	Sorting Time (s)	Consistency with Expert Evaluation (τ)	Correlation with Failure Loss	Dynamic Adaptability
Single TOPSIS	0.6	0.785	0.76	Poor
Entropy Weight Method	0.5	0.752	0.72	Poor
AHP-TOPSIS	1.5	0.863	0.82	Fair
Proposed Method	0.8	0.921	0.89	Good

Dynamic Adaptability Verification of Weights: Using another chemical enterprise dataset (different equipment types and fault distributions), weights were recalculated. The primary indicator weights changed to Equipment Status Level (32%), Equipment Importance (28%), Failure Impact Scope (21%), Maintenance Cost (19%). The consistency of priority ranking remained 89.7%, verifying that weights dynamically adjust with datasets, meeting the goal of eliminating subjective expert bias.

E. ANALYSIS OF ENGINEERING APPLICATION OUTCOMES

The proposed methodology was applied to the operational maintenance management of primary equipment at a chemical enterprise. A comparison of maintenance metrics before and after implementation is presented in Table 3. As shown, the application of this approach reduced average equipment downtime from 48.2 hours to 39.2 hours—a decrease of 18.7%. Unplanned maintenance costs decreased from 2.36 million CNY/year to 1.81 million CNY/year, a reduction of 23.4%; and the failure recurrence rate dropped from 15.3% to 8.7%. This effectively enhanced production continuity and operational efficiency. These findings demonstrate that the proposed integrated "condition-aware priority generation" technical framework provides robust support for intelligent maintenance of industrial main equipment.

TABLE 3. Comparison of Engineering Application Effects

Indicator	Before Application	After Application	Change Rate
Average Downtime (h)	48.2	39.2	-18.7%
Unplanned Maintenance Cost (10,000 CNY/Year)	236	181	-23.4%
Failure Recurrence Rate (%)	15.3	8.7	-43.1%
Maintenance Personnel Efficiency (Units/Per Person·Month)	8.5	11.2	+31.8%

V. CONCLUSIONS AND OUTLOOK

A. RESEARCH FINDINGS

This study addresses issues such as low accuracy in the condition awareness of primary equipment and unreasonable maintenance priority allocation by proposing a condition awareness and maintenance priority generation method based on a GCN-RNN hybrid structure tailored for complex industrial equipment systems. This framework optimizes the operational reliability of automated industrial production lines by accurately identifying equipment degradation and prioritizing repairs for critical manufacturing nodes. The primary research conclusions are as follows:

1. A multi-source data preprocessing and dataset construction scheme was established. Through data cleaning, standardization, and feature engineering, combined with

graph structure modeling of equipment monitoring point relationships, high-quality data support for condition awareness was provided.

2. A GCN-RNN hybrid state perception model was designed, integrating spatial correlation features with temporal evolution characteristics. This achieved a device state perception accuracy of 95.3%, significantly outperforming single models and traditional machine learning approaches, enabling precise identification of early latent faults;

3. A maintenance priority evaluation system was established, incorporating equipment status levels, criticality, fault impact scope, and repair costs. The Entropy Weight-TOPSIS method achieved quantitative priority ranking with 92.1% consistency against expert assessments;

4. Engineering validation demonstrates that this method effectively reduces average equipment downtime by 18.7% and lowers unplanned maintenance costs by 23.4%, providing a new technical pathway for intelligent operation and maintenance of industrial equipment.

B. RESEARCH OUTLOOK

Future research can be deepened and expanded in the following three aspects: First, introduce attention mechanisms to optimize the feature fusion approach of the GCN-RNN model, enhancing feature extraction capabilities for critical monitoring points and important time nodes; Second, digital twin technology can be integrated to construct virtual simulation models of equipment, enabling visualization and dynamic updates for condition awareness and priority prediction. Third, addressing multi-objective optimization to balance maintenance costs, production benefits, and safety risks in maintenance priority scheduling, thereby enhancing the scientific rigor and comprehensiveness of operational decisions.

AUTHOR CONTRIBUTIONS

Conceptualization –Mingang Bai, Jianmin Zheng and Junji Ma; methodology – Mingang Bai, Jianmin Zheng and Junji Ma; investigation – Mingang Bai and Junji Ma; writing-original draft preparation – Mingang Bai, Jianmin Zheng and Junji Ma. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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