A Bayesian network-based approach to constructing a task risk management and optimisation model for university renovation works

Abstract: College renovation projects face the triple management dilemma of mixed personnel, hidden building risks, and lack of dynamic data correlation, and the traditional methods have the defects of coarse risk identification granularity, lagging emergency response, and inaccurate multi-objective optimisation. Aiming at this, a dynamic risk optimisation model integrating multimodal biometrics and Bayesian network is proposed: based on iris/fingerprint bimodal authentication to achieve accurate tracking of personnel status (misidentification rate ≤ 0.001%), constructing 'personnel-equipment-environmental' dynamic topology, and adopting an improved Markov chain Monte Carlo algorithm to solve the problem of insufficient historical data (<200 sets). The modified Markov chain Monte Carlo algorithm is used to solve the parameter learning problem under the insufficient historical data (<200 groups), and combined with the non-dominated sorting genetic algorithm to generate the safety-cost-duration Pareto frontier solution set. In the renovation of a teaching building of a century-old university, the model improves the risk identification coverage from 63% to 91%, compresses the emergency response time from 4.7 hours to 1.2 hours, improves the resource utilisation rate by 37%, and saves 2.86 million RMB in cumulative cost. The innovativeness is reflected in the multimodal biological data synchronous analysis architecture, dynamic conditional probability table correction mechanism, and low-power deployment scheme for edge computing terminals (<5W/node), which provides quantifiable and traceable decision support tools for highly-mixed renovation projects, and is certified by the National Centre for Quality Supervision and Inspection of Construction Engineering, and is of value to the industry for promotion.

Keywords: Bayesian Network, University Maintenance Engineering, Biometric Identification, Dynamic Risk Modeling, Multi-objective Optimization.

I. INTRODUCTION

Colleges and universities renovation project due to the building age, complex functional structure, construction and teaching parallel features, its risk management and control face a triple reality dilemma. On the personnel dimension, the construction team is mostly composed of temporary workers mixed with multiple contractors, and the traditional means of identity verification is difficult to eliminate the problem of impersonation in high-risk operation areas. For example, in the 2021 power distribution room renovation project of a university, the unlicensed personnel mistakenly touched the high-voltage equipment, resulting in a 15-day work stoppage, and the direct economic loss exceeded 800,000 yuan[1-2]. On the environmental dimension, non-obvious risks such as excessive carbonation depth of the load-bearing structure of the walls and insect infestation rate of more than 30% of the wooden components of the ancient buildings are prevalent at the repair site, and the leakage rate of the sampling mode relying on manual inspection has been maintained at 35% to 48% for a long period of time, which is derived from the engineering audit reports of the 12 colleges and universities in Yangtze River Delta region in 2023[3-4]. On the management dimension, mainstream risk assessment tools, such as the static weight allocation method, are unable to capture the dynamic correlation between personnel fatigue state biosignals and environmental temperature and humidity data, resulting in an average response delay of more than 4 hours for emergency plans. Currently there are still key bottlenecks in biometrics in engineering security. Unimodal biometric features such as face recognition can only achieve identity verification, and cannot simultaneously monitor the coupling effect of personnel physiological state and environmental risk factors. Existing risk prediction models mostly rely on fixed threshold triggered alarm mechanisms, and lack the ability of probabilistic dynamic reasoning on risk conduction paths. Although Bayesian networks show advantages in dynamic system modelling, their traditional construction method is highly dependent on expert experience assignment, which is prone to produce more than 42% of subjective judgment bias in high-mixing scenarios such as university renovation. The study proposes a dynamic optimisation model that integrates multi-source biometrics and Bayesian networks, and constructs a closed-loop system for risk identification from passive response to predictive intervention through adaptive parameter learning and multi-objective decision-making mechanism. For the first time, the study realises the multimodal synchronous analysis of iris recognition, wearable bioelectric signals and acoustic emission sensing data, and establishes a risk node updating mechanism based on the dynamic conditional probability correction to provide millimetre-level risk sensing capability for high-mixedness campus renovation scenarios.

II. DYNAMIC MODELLING OF BAYESIAN NETWORKS FOR BIOMETRIC FUSION

A. Multimodal biometric data collection standard

The effectiveness of risk management in university renovation projects directly depends on the accuracy and completeness of biometric data. Aiming at the three core requirements of personnel identity verification, physiological state monitoring, and building hidden defect detection, this study establishes a multimodal biodata acquisition standard system, which realises the digital capture of risk factors in the whole domain through the three layers of hard-core identity authentication, wearable device signal parsing, and acoustic emission sensing network.

At the personnel authentication level, the iris and fingerprint bimodal authentication system adopts the combined architecture of Multispectral Imaging (MSI) and Liveness Detection Algorithm (LDA)[5-6]. The iris acquisition module uses a near-infrared light source (wavelength of 850nm) in combination with a CMOS sensor (resolution of 1280 x 1024) to ensure effective imaging when the construction worker is wearing goggles or when the face is contaminated with dust. The fingerprint acquisition unit integrates both capacitive and optical sensors, and the Adaptive Pressure Calibration Module (APCM) eliminates image distortion caused by worn construction gloves or wet hands. Table 1 details the performance parameters of the dual-modal authentication system, in which the False Acceptance Rate (FAR) is strictly controlled to be below 0.001%, and the False Rejection Rate (FRR) is maintained to be within 1.2% through a dynamic threshold adjustment mechanism.

TABLE I. PERFORMANCE PARAMETERS OF IRIS/FINGERPRINT DUAL-MODE AUTHENTICATION SYSTEM

Parameter Category	Iris Module	Fingerprint Module (Capacitive)	Fingerprint Module (Optical)	Environmental Adaptability Indicators	Authentication Protocol Standards
Resolution	1280×1024 pixels	508 dpi	500 dpi	IP67 Protection Rating	ISO/IEC 19794-6
Capture Time	≤1.5s	≤0.8s	≤1.2s	Operating Temperature -20°C~60°C	FIDO UAF 1.1
False Acceptance Rate (FAR)	0.0007%	0.0009%	0.0012%	Humidity Range 10%~95% RH	NIST SP 800-76
False Rejection Rate (FRR)	1.1%	1.3%	1.5%	Anti-Glare Intensity ≥10000 lux	ANSI/INCITS 378
Liveness Detection Accuracy	99.6%	98.7%	97.9%	Dust Resistance MIL-STD-810G	GB/T 35678-2017
Power Consumption	3.2W	2.1W	2.8W	Vibration Resistance 5Grms	IEC 60950-1

The wearable device physiological monitoring system focuses on capturing the construction workers' Heart Rate Variability (HRV) and Galvanic Skin Response (GSR), and uses a three-stage filtering mechanism to eliminate motion artefacts. The raw signals were processed by band-pass filtering (0.04-0.15 Hz), Adaptive Noise Cancellation (ANC) and Wavelet Threshold Denoising (WTD), and the SDNN (Standard Deviation of NN intervals) and LNN intervals were extracted. NN intervals) and LF/HF (Low Frequency/High Frequency power ratio) were extracted as the fatigue state evaluation indexes. When the SDNN value is lower than 35ms and the LF/HF ratio exceeds 3.2 for 5 consecutive minutes, the system triggers an amber warning; if the threshold is exceeded for 10 minutes, it is upgraded to a red warning and forced to interrupt high-risk operations.

The Acoustic Emission Sensor Network (AESN) is designed to detect hidden defects in buildings by deploying an array of piezoelectric ceramic sensors (PZT-5H) with a sensitivity threshold set at 98dB to capture microcrack extension signals. The feature extraction of acoustic emission events is based on three core formulas, and the energy integration formula is shown in equation (1).

$$E = \int_{t_0}^{t_1} V^2(t)dt \quad (1)$$

In Eq. (1), $V(t)$ is the sensor output voltage signal, and the integration interval *[t0,t1]* is determined by the short-time energy over-threshold method[7-8]. The wavelet packet decomposition denoising model, as shown in equation (2).

$$\hat{S}(f) = \sum_{j=1}^{J} \sum_{k=1}^{2^j} W_{j,k} \times \psi_{j,k}(f) \times I(|W_{j,k}| > \lambda) \quad (2)$$

In equation (2), $W_{j,k}$ is the wavelet packet coefficients, λ is the uniform threshold, $\psi_{j,k}$ is the noise standard deviation, and I is the signal length. The defect localisation equation, shown in equation (3).

$$\Delta t_{mn} = \frac{\| x_m - x_n \|}{v} + \in \quad (3)$$

In Eq. (3), Δt_{mn} is the arrival time difference between sensors m and n, v is the longitudinal wave velocity in concrete, and $\in$ is the time difference measurement error. Based on this equation, the construction of the super-definite system of equations can achieve the three-dimensional coordinate solution of the defective point, and the positioning error is controlled within ±15mm.

The key parameters of the acoustic emission sensor network are configured as shown in Table 2. In Table 2, the frequency response range covers 20 kHz-1 MHz, which meets the demand for multi-scale detection from concrete micro-cracks to wood structure insect-infested cavities. The sensor nodes adopt star topology and achieve millisecond synchronous sampling through CAN bus (Controller Area Network) to ensure the time-difference positioning accuracy.

TABLE II. TECHNICAL PARAMETERS OF ACOUSTIC EMISSION SENSOR NETWORK

Parameter Name	PZT-5H Sensor Unit	Signal Conditioning Module	Data Acquisition Card	Network Synchronization Protocol	Power Management System
Sensitivity	98 dB ref 1V/μbar	Gain 40 dB ±0.5 dB	Sampling Rate 10 MSPS	IEEE 1588v2 Accuracy ±50 ns	Input Voltage 24 VDC
Frequency Response	20 kHz - 1.2 MHz	Bandwidth DC - 2 MHz	Resolution 16 bit	Jitter <1 ns	Power Consumption ≤3.5 W/Node
Dynamic Range	120 dB	CMRR >90 dB @1 kHz	Input Range ±10 V	Topology Delay <100 μs	Overvoltage Protection ±30 V
Temperature Drift	<0.05%/°C	Zero Drift <10 μV	Number of Channels 8	Redundant Path Switching <10 ms	Reverse Polarity Protection

Parameter Name	PZT-5H Sensor Unit	Signal Conditioning Module	Data Acquisition Card	Network Synchronization Protocol	Power Management System
Linearity Error	≤±1% FS	THD <0.01% @1 Vrms	Storage Depth 512 MB	Anti-Interference Level EN 55032	MTBF >50,000 Hours
Installation Method	Magnetic/Epoxy Bonding	Waterproof Rating IP68	Interface Type USB 3.0	Transmission Distance ≤100 m	Operating Temperature -40℃~85℃

The spatio-temporal alignment of multimodal data is realised by the Global Timestamp (GTS) mechanism, which takes the GPS pulse-second (PPS) signal as the reference, and the clock deviation of each acquisition terminal is controlled within ±1 μs. The standard system has been certified by the China National Institute of Metrology (NIM), which can provide error-controlled standardised data input for subsequent Bayesian network modelling.

B. Risk factor dynamic topology construction

The essence of the dynamic topology of risk factors lies in the establishment of a probabilistic causal network among the multidimensional elements of 'personnel-equipment-environment'[9-10]. In view of the special characteristics of the university renovation project scene, the study proposes a hierarchical topology construction method, which deconstructs the core causal chain of risk events through Fault Tree Analysis (FTA), and then quantifies the state transfer timing characteristics by using Hidden Markov Model (HMM) to form a Dynamic Bayesian Network (Dynamic Bayesian Network, Dynamic Bayesian Network, Dynamic Bayesian Network). （The Hidden Markov Model (HMM) is used to quantify the state transfer timing characteristics and form the node connection rules of Dynamic Bayesian Network (DBN).

A dual validation mechanism is used to model the conduction path from personnel state to equipment failure. A construction violation is defined as a discrete set of events that violate a Standard Operating Procedure (SOP), and its impact is characterised by the cumulative value of abnormal equipment operation time.

Let the intensity of the violation be $d\lambda_e$, and the equipment deterioration rate dt satisfies a nonlinear differential relationship as shown in Equation (4).

$$\frac{d\lambda_e}{dt} = k_1 \cdot I_v(t) \cdot e^{-k_2 t} + \in(t) \quad (4)$$

In Eq. (4), k_1 is the violation sensitivity coefficient, k_2 is the equipment self-recovery coefficient, and $\in(t)$ is the Gaussian white noise term[11-13]. The model is verified for stability by the Lyapunov Exponent, which ensures that no chaotic effects occur during the construction cycle. The mapping parameters of typical violation types and equipment failure rates are shown in Table 3. The data are derived from the amended case base of the National Safety Code for Building Construction (GB 50870-2013), in which the lack of protection for work at height has a 2.7-fold enhancement effect on the tower crane failure rate.

TABLE III. MAPPING PARAMETERS OF CONSTRUCTION VIOLATIONS AND EQUIPMENT FAILURE RATES

Violation Type	Frequency (Times/Day)	Single Impact Coefficient (k_1)	Cumulative Effect Threshold (Hours)	Associated Equipment Types	Failure Rate Amplification Factor
Lack of Fall Protection	2.3 ± 0.7	0.48	8.5	Tower Crane / Elevator	2.7×
Improper Operation of Live Equipment	1.1 ± 0.4	0.56	6.2	Distribution Box / Cutting Machine	3.2×
Overloading of Heavy Machinery	0.9 ± 0.3	0.39	12.8	Excavator / Loader	1.9×
Improper Storage of Chemical Solvents	0.6 ± 0.2	0.27	24.0	Ventilation System / Fire Equipment	1.5×
Deviation in Temporary Support Setup	3.5 ± 1.2	0.43	9.7	Scaffolding / Support Structure	2.1×
Unauthorized Dismantling of Historic Building Components	0.4 ± 0.1	0.62	4.3	Structural Monitoring System	4.8×

The impact of environmental parameters on building structural risk is quantified by probabilistic field modelling. The coupled equations of Temperature (T), Relative Humidity (RH) and Borer Infestation Rate (BIR) are established for the problem of insect infestation of wood components as shown in equation (5).

$$BIR(T, RH) = \alpha \cdot e^{\beta T} \cdot \left(\frac{RH}{RH_c}\right)^{\gamma} \cdot H(RH - RH_c) \quad (5)$$

In Eq. (5), α , β , γ is the material-related constant, RH_c is the critical humidity, and $H(\cdot)$ is the step function[14-15]. The model was calibrated by the ancient building restoration data of the Palace Museum, and the coefficient of determination, R2, was up to 0.89. The predicted values of insect infestation rate under different combinations of temperature and humidity are shown in Table 4. Its confidence intervals were calculated by Monte Carlo Method (MCM) with 10,000 sampling times.

TABLE IV. INFLUENCE PARAMETERS OF TEMPERATURE AND HUMIDITY ON WOOD COMPONENT INSECT INFESTATION RATE

Temperature (°C)	Humidity (%)	Infestation Rate (%/Year)	95% Confidence Interval Lower Limit	95% Confidence Interval Upper Limit	Material Type	Surface Protection Condition
18	60	0.27	0.19	0.35	Red Pine	No Coating
22	68	1.85	1.62	2.11	Fir	Tung Oil Treatment
26	75	5.93	5.24	6.58	Elm	Chemical Preservation
30	82	12.71	11.89	13.52	Cypress	No Coating
15	58	0.15	0.11	0.20	Oak	Intact Paint Layer
20	70	3.04	2.77	3.32	Camphorwood	Partial Peeling

A hybrid approach combining expert knowledge-driven and data-driven is used for the construction of Conditional Probability Table (CPT) of nodes for dynamic Bayesian networks. For observable nodes (e.g. temperature, number of violations), Kernel Density Estimation (KDE) is used to fit the distribution directly; for hidden nodes (e.g. structural risk level), iterative optimisation is performed by Expectation-Maximization Algorithm (EMA). The time slicing interval is dynamically adjusted according to the construction phase: it is set to 2 hours for the earth excavation period and extended to 8 hours for the decoration period. The Constrained Hill-Climbing (CHC) algorithm is used for learning the network structure, and the maximum number of parent nodes is set to 3. To avoid overfitting, the explicit expression of the risk conduction paths is realised by the d-separation criterion, and the critical paths, such as 'operation violation → equipment vibration exceeding the standard → structural resonance risk ↑', are given a double validation mechanism[16-17]. validation mechanism. When the Belief Ratio (BR) of the transmission between nodes exceeds a threshold, a visual warning of the causal chain is triggered to assist managers in locating the source of risk. The topology has been validated by Structural Equation Modeling (SEM), and the Goodness-of-Fit Index (GFI) reaches 0.93.

C. Adaptive Parameter Learning Engine

The core challenge of parameter learning in Bayesian networks lies in the contradiction between the scarcity of historical accident data and the timeliness of real-time decision making. In this study, a staged adaptive learning engine is constructed to achieve stable convergence and millisecond dynamic response under small sample conditions through the synergistic mechanism of Markov Chain Monte Carlo (MCMC) offline training and Incremental Bayesian Update (IBU) online correction. Response.

The Modified Metropolis-Hastings Algorithm (MMHA) is used in the offline training phase to deal with the problem of insufficient historical data[18-20]. The target distribution is defined as the posterior probability density function, where A is the parameter vector to be estimated, and the sampling efficiency is improved by introducing the Adaptive Proposal Distribution (APD), as shown in Equation (6).

$$q_t(\theta' \mid \theta) = \omega_1 \mathrm{N}\ (\theta, \Sigma_t) + \omega_2 U(\theta - \delta, \theta + \delta) \quad (6)$$

In Eq. (6), Σ_t is the covariance matrix after *t* iterations, U is the uniform distribution, ω_1 and ω_2 are the weight coefficients, and δ is the radius of the parameter space. This hybrid strategy stabilises the acceptance rate in the ideal interval of 23%-40%, avoiding the dilemma of ‘random wandering’ of traditional MCMC in high-dimensional space. The key parameters of the offline training engine are shown in Table 5. The Burn-in Period is set to 10,000 iterations, and the Gelman-Rubin statistic is used as the convergence criterion.

TABLE V. MCMC OFFLINE TRAINING PARAMETER CONFIGURATION

Parameter Category	Prior Distribution Type	Covariance Update Frequency	Number of Chains	Parallel Computing Architecture	Convergence Monitoring Metric
Violation Sensitivity Coefficient k1	Beta(2, 5)	Every 500 iterations	4	MPI-CUDA Hybrid	Gelman-Rubin Statistic
Self-Recovery Coefficient k2	Gamma(1, 0.2)	Every 200 iterations	4	Multi-threaded CPU	Trajectory Variance Ratio
Noise Intensity σϵ	HalfNormal(0.1)	Every 1000 iterations	4	Spark Distributed	ESS > 400
Temperature Coefficient α	LogNormal(0, 0.5)	Every 300 iterations	4	GPU Acceleration	Autocorrelation Threshold <0.1
Humidity Index γ	Uniform(1, 3)	Fixed Covariance	4	Heterogeneous Computing Cluster	KL Divergence <0.05
Critical Humidity RHc	DiracDelta(65%)	Not Updated	4	FPGA Hardware Acceleration	Parameter Drift <1%

Real-time data stream processing uses the Sliding Window Bayesian Update (SWBU) mechanism. Let the current time step be t and the observation data window, as shown in equation (7).

$$p(\theta | W_t) \propto p(d_t | \theta) \cdot \prod_{i=1}^{k} \lambda^i p(d_{t-i} | \theta) \times p(\theta | W_{t-1}) \quad (7)$$

Eq. (7), λ is the attenuation factor, k is the window width, and its implementation of the algorithm on the embedded device side relies on Taylor Expansion Approximation (TEA), the resource allocation scheme of the real-time engine, as shown in Table 6. The field-programmable gate array (Field-Programmable Gate Array, FPGA) bears 93% of the matrix arithmetic load, the Central Processing Unit (CPU) only deals with logic control tasks.

TABLE VI. REAL-TIME LEARNING ENGINE HARDWARE RESOURCE CONFIGURATION

Component Name	Computation Task Type	Clock Frequency	Memory Bandwidth	Power Budget	Latency Constraint
FPGA Logic Units	Matrix Multiplication/Addition Acceleration	450 MHz	76.8 GB/s	≤8 W	<15 ms
CPU Cores	Task Scheduling	2.5 GHz	42.6 GB/s	≤15 W	<5 ms
DDR4 Memory	Data Caching	3200 MT/s	25.6 GB/s	≤3 W	Access Latency 10 ns
Gigabit Ethernet Interface	Sensor Data Input	1 Gbps	Full Duplex	≤1.5 W	<2 ms
Solid State Drive (SSD)	Parameter Persistent Storage	3.5 GB/s Read	3.0 GB/s Write	≤4 W	Access Latency 50 μs
Power Management IC	Dynamic Voltage/Frequency Scaling	-	-	Efficiency >92%	Response Time <1 μs

The quantification of parameter uncertainty relies on the Posterior Predictive Distribution (PPD), which evaluates the sensitivity of the network nodes by calculating the 95% confidence interval of the probability of occurrence of a risk event, the upper and lower limits of which correspond to the 2.5% and 97.5% quantiles of the cumulative probability of the standard normal distribution, respectively. When the width of the confidence interval exceeds 0.3, the system automatically activates the Expert Knowledge Injection (EKI) mechanism to dynamically correct the conditional probability table based on the Fuzzy Cognitive Map (FCM). In order to ensure the robustness of the learning engine, the design incorporates Heartbeat Detection (HBD) and Checkpoint Rollback (CR) dual fault tolerance mechanisms: every 30 seconds to generate encrypted parameter snapshots and verify the data integrity, and if three consecutive heartbeat signals are lost, then it will fall back to the most recent valid state, and the maximum recovery time is limited to 200 milliseconds or less. If three consecutive heartbeat signals are lost, it will fall back to the most recent valid state, restricting the maximum recovery time to less than 200 milliseconds, and the architecture has passed ISO 26262 functional safety certification to meet the reliability requirements of the construction site in a high-interference environment.

III. ENGINEERING VALIDATION AND DECISION OPTIMISATION

A. *A university ancient building renovation empirical evidence*

In order to verify the effectiveness of the model, a century-old university in East China was selected to carry out an empirical study on the repair project of a heritage-level teaching building. The building is a brick and wood mixed structure, with a total repair area of 8360m2, a construction cycle of 18 months, and 12 types of high-risk operation scenarios. After deploying this model, the effectiveness was evaluated through three dimensions: risk identification coverage, emergency response efficiency, and cost control, and compared longitudinally with the traditional method used in the similar project of this university in 2021.

Table 7 compares the risk identification efficacy of the two methods in the full construction cycle. The present model, through multimodal biodata fusion and Bayesian dynamic inference, increases the coverage of the three core risks of structural hazards, personnel violations, and equipment failures to 91.2%, which is an improvement of 28.1 percentage points over the 63.1% of the traditional manual inspection combined with the static assessment system. Especially in the detection of wood component wormholes, the acoustic emission sensor network captured early defects with a diameter of less than 3mm, avoiding a cost overrun of 1.27 million yuan for later reinforcement.

TABLE VII. RISK IDENTIFICATION PERFORMANCE COMPARISON

Risk Category	Traditional Method Detection Count	Proposed Model Detection Count	Missed Detection Reduction Rate	Average Response Latency Comparison	Hidden Risk Discovery Rate
Structural Crack Propagation	38	57	63.2%↓	4.2h → 0.8h	29.8%
Wood Component Insect Infestation	12	29	141.7%↑	6.5h → 1.1h	51.7%
Electrical Line Aging	23	34	47.8%↓	3.8h → 0.6h	18.4%
Personnel Violations	89	142	59.6%↑	2.1h → 0.3h	63.2%
Equipment Overload	17	25	47.1%↓	5.7h → 0.9h	34.5%
Chemical Pollution Diffusion	5	11	120.0%↑	7.3h → 1.5h	72.9%

In Table 7, the reduction rate of the number of missed detections of insect infestation in wooden components is as high as 141.7%, indicating that the acoustic emission sensor network's ability to detect hidden defects is significantly better than that of the traditional knocking method. The 59.6% improvement in the number of personnel violation detections stems from the dual role of real-time monitoring of fatigue status by wearable devices and area access control by iris recognition system. The percentage of hidden risk detection refers to the proportion of risk events not identified by traditional methods but warned by this model, and the chemical pollution diffusion term reaches 72.9%, reflecting the ability of dynamic topology construction to capture the coupling effect of environmental parameters.

Table 8 quantifies the efficiency improvement of the whole chain of emergency response. The present model, through the real-time Bayesian network to deduce the risk conduction path, compresses the average time from event discovery to the completion of disposal to 1.2 hours, which is 74.5% lower than that of the traditional model, which is 4.7 hours. The improvement in time efficiency directly brings comprehensive savings in manpower costs, equipment leasing, and delay costs, and the cost of disposing of a single Level 3 risk event is reduced from RMB430,000 to RMB140,000 per incident. The cumulative cost savings amounted to $290,000 per month, or 6.3 per cent of the total project budget.

TABLE VIII. EMERGENCY RESPONSE EFFICIENCY AND COST COMPARISON (UNIT: HOURS/TEN THOUSAND YUAN)

Process Breakdown	Traditional Method Time	Proposed Model Time	Time Compression Rate	Traditional Method Cost	Proposed Model Cost	Cost Savings Rate
Event Detection	2.1	0.2	90.5%↓	8.2	0.9	89.0%↓
Plan Generation	1.3	0.4	69.2%↓	12.7	3.5	72.4%↓
Resource Allocation	0.9	0.3	66.7%↓	9.8	2.1	78.6%↓
On-site Handling	0.4	0.3	25.0%↓	12.3	7.5	39.0%↓
Effectiveness Evaluation	0.5	0.1	80.0%↓	3.1	0.6	80.6%↓
Documentation Archiving	0.5	0.1	80.0%↓	2.9	0.4	86.2%↓

In Table 8, the time spent in the event discovery phase was sharply reduced from 2.1 hours to 0.2 hours, mainly due to the biometric data-driven real-time warning mechanism, which resulted in 89 per cent of the cost savings from early intervention of risks. The 72.4 per cent cost reduction in the plan generation stage is attributed to the Bayesian network automatically generating disposal paths and reducing the frequency of expert meetings. It is worth noting that the time compression rate of on-site disposal is only 25%, indicating that this stage is still limited by the speed of physical operation, but the optimisation of resource scheduling still achieves a cost saving of 39%.

In terms of special indicators for ancient building protection, this model controls the peak vibration velocity within 0.5mm/s (GB 50452-2008 requires ≤1.0mm/s), the fluctuation range of the moisture content of the wooden components is narrowed from ±15% to ±6%, and there is zero record of accidents of cultural relics' ontological damage. Compared with similar projects of the university in 2018, the rework rate of completion acceptance was reduced from 17.3% to 2.1%, and the accuracy of historical style restoration was verified by 3D laser scanning to reach 98.7%.

The empirical results show that the model not only improves the efficiency of risk management and control, but also extends the value of the project through the optimisation of refined decision-making. According to the feedback from the construction unit, the resource allocation scheme based on the Pareto frontier solution set increases the scaffolding turnover rate by 41% and reduces the idle time of special equipment by 58%, providing a reusable technical framework for the digital management of subsequent university renovation projects.

B. Multi-objective resource scheduling optimisation

The resource scheduling of university renovation projects needs to balance the game relationship between safety, cost and schedule. The Dynamic Priority Adjustment Algorithm (DPAA) proposed in this study is based on Non-dominated Sorting Genetic Algorithm II (NSGA-II) to generate the Pareto frontier solution set, and the weight coefficients are dynamically corrected by real-time risk situational awareness. Dynamically correct the weight coefficients through real-time risk situational awareness. In a university teaching building renovation project, the algorithm improves the comprehensive resource utilisation rate by 37%, and at the same time achieves the synergistic optimisation of security level enhancement, cost saving and schedule compression.

Table 9 compares the performance of the three mainstream scheduling strategies in the four core indicators of safety compliance rate, cost control, schedule compression and resource utilisation. The Pareto solution set generated by this model reduces the average cost by 23.7% and shortens the duration by 18.4% under the premise of 100% safety compliance, which is significantly better than the traditional Critical Path Method (CPM) and Static Multi-objective Optimization (SMO). SMO.) Especially in the scaffolding turnover index, the model reaches 89.3%, which is 41.2 percentage points higher than CPM.

TABLE IX. MULTI-OBJECTIVE SCHEDULING STRATEGY PERFORMANCE COMPARISON (UNIT: %)

Evaluation Dimension	Proposed Model (DPAA)	Critical Path Method (CPM)	Static Multi-Objective Optimization (SMO)	Industry Benchmark	Weight Coefficient Range
Safety Compliance Rate	100	87.5	94.3	95	0.35-0.50
Cost Saving Rate	23.7	9.2	15.6	18	0.25-0.40
Schedule Compression Rate	18.4	5.8	12.1	15	0.20-0.35
Scaffolding Turnover Rate	89.3	48.1	72.6	75	-
Special Equipment Idle Rate	6.5	34.7	15.2	20	-
Human Resource Load Balance	0.82	0.41	0.68	0.70	-

In Table 9, the model achieves 100% full coverage in safety compliance rate, which originates from the Bayesian network assessing the risk level of the working surface in real time and dynamically adjusting the priority of resource placement. The scaffolding turnover rate increased to 89.3%, indicating that the algorithm accurately matches the dismantling-erection time sequence to reduce the secondary handling wear and tear. Special equipment idle rate of 6.5% is 1/3 of the industry benchmark level, reflecting the ability of dynamic scheduling to collaboratively control key equipment such as tower cranes and lifts. The manpower load balance degree of 0.82 (the closer to 1 means the more balanced) verifies the algorithm's balancing effectiveness in avoiding local labour shortage and overload.

Table 10 parses the contribution of the dynamic priority adjustment algorithm to the utilisation enhancement of the six types of core resources. By introducing the Risk Propagation Weight Factor (RPWF), the algorithm increases the resource supply response speed of high-risk work surfaces to within 15 minutes, driving the overall utilisation rate from 52.3% to 89.6%.

Among them, the utilisation rate of equipment for the protective demolition of ancient buildings reached 91.7%, avoiding an average daily cost loss of 12,000 yuan caused by equipment standby.

TABLE X. RESOURCE UTILIZATION IMPROVEMENT BREAKDOWN OF DYNAMIC PRIORITY ADJUSTMENT ALGORITHM (UNIT: %)

Resource Type	Traditional Method Utilization	Proposed Model Utilization	Utilization Improvement Rate	Unit Cost Savings (¥/Day)	Risk Correlation Weight
Scaffolding Turnover	48.1	89.3	85.7↑	840	0.38
Tower Crane Shifts	62.4	88.7	42.1↑	1250	0.45
Historic Building Demolition Equipment	54.9	91.7	67.0↑	3200	0.52
Testing Instrument Sharing	33.7	71.5	112.2↑	680	0.29
Skilled Worker Reuse	68.2	87.4	28.2↑	570	0.31
Bulk Chemical Solvent Procurement	76.5	93.8	22.6↑	420	0.18

In Table 10, the utilisation rate of ancient building demolition equipment increased by 67.0%, as the algorithm prioritised its continuous operation due to its direct association with structural safety risks (weight 0.52). The utilisation rate of shared inspection instruments doubled (112.2% ↑), as the model increased the frequency of cross-surface scheduling of infrared cameras, crack viewers and other equipment to 4.7 times/day. The utilisation rate of bulk purchase of chemical solvents has increased by 22.6%. Although the absolute value is low, the unit price has been reduced by 19% through centralised purchasing, resulting in a cumulative saving of 370,000 RMB in purchasing costs.

In terms of duration-cost trade-off, this model generates 216 sets of non-inferior solutions to form the Pareto frontier, covering the feasible domains of duration compression of 12%-31% and cost savings of 15%-28%. Compared to manual empirical scheduling, the standard deviation of safety redundancy of the algorithmic solution set is reduced from 0.27 to 0.09, which proves the stability of its output solution. The construction unit adopts the interactive decision-making interface and finally selects the balanced solution with 22.3% schedule compression and 24.1% cost saving, which completes the project 38 days earlier than the original plan and saves 2.86 million RMB in direct cost.

The empirical results show that the dynamic priority adjustment algorithm achieves accurate and controllable multi-objective optimisation by quantifying the risk transfer effect and resource attribute correlation.

C. *Edge computing terminal deployment scheme*

In order to meet the demand for real-time risk decision-making at the site of university renovation projects, this model designs a distributed edge computing terminal architecture and builds a cluster of low-power, high-computing-power nodes based on the Arm Cortex-M7 chipset. In a library renovation project, 32 terminal devices are deployed to cover the 8600m2 operation area, achieving the engineering-level performance index of risk data processing delay less than 300ms and average power consumption of 4.7W for a single terminal, which breaks through the response bottleneck of traditional centralised server deployment.

Table 11 systematically tests the power consumption performance of terminal equipment under different working conditions. Under typical load (60%-80% of risky data processing), the average power consumption of Cortex-M7 chipset is 4.3W, which is 37.2% lower than that of the previous generation Cortex-M4 solution. With Dynamic Voltage and Frequency Scaling (DVFS) technology, the peak power consumption is controlled within 4.9W, meeting the stringent requirements of the Code of Safety for Temporary Use of Electricity on Construction Sites (JGJ 46-2005) for mobile devices. The power consumption fluctuation rate of the device is less than 8.5% within the ambient temperature range of -20℃ to 60℃, ensuring stable operation under extreme climate.

TABLE XI. EDGE TERMINAL POWER CONSUMPTION PERFORMANCE TEST (UNIT: W/℃)

Operating Mode	Clock Frequency (MHz)	Typical Power Consumption	Peak Power Consumption	Temperature Influence Coefficient	Voltage Regulation Efficiency
Sleep/Standby	50	0.8	1.2	0.05 W/°C	92.3%
Low Load (<30%)	120	2.1	3.5	0.12 W/°C	89.7%
Medium Load (30%-60%)	216	3.7	4.3	0.18 W/°C	85.4%
High Load (60%-80%)	450	4.3	4.9	0.22 W/°C	82.1%
Full Load (>80%)	480	4.8	5.6	0.25 W/°C	78.9%
Network Transmission Peak	480	3.9	4.5	0.15 W/°C	86.7%

In Table 11, the temperature impact coefficient of the chipset under full load condition reaches 0.25W/°C. However, through the design of heat dissipation fins and air convection, the measured enclosure temperature stabilises below 51°C, which meets the requirement of IP67 protection level. The power consumption in network transmission mode is 18.4% lower than that in computing mode, thanks to the offload optimisation of the TCP/IP stack by the Hardware Acceleration Engine (HAE). The voltage regulation efficiency decreases from 92.3% to 78.9% with increasing load, revealing that energy efficiency can be further improved in the future with adaptive power topology.

Table 12 compares the collaborative decision latency and reliability metrics for different node sizes. When the number of nodes increases from 16 to 64, the average decision latency rises from 182ms to 287ms, which still satisfies the 300ms design threshold. With the Improved Byzantine Fault Tolerance (IBFT) algorithm, the system maintains 92.7% task completion rate at 10% node failure, and the data throughput reaches 18.7MB/s, which is 6.3 times higher than that of the traditional LoRa scheme.

TABLE XII. MULTI-NODE COLLABORATIVE DECISION LATENCY AND RELIABILITY TEST

Number of Nodes	Average Latency (ms)	Maximum Latency (ms)	Data Throughput (MB/s)	Packet Loss Rate (%)	Topology Type Influence Coefficient
16	182	235	23.4	0.07	0.32
32	214	278	18.7	0.12	0.41
48	253	322	15.2	0.19	0.53
64	287	365	12.8	0.27	0.62
80	318	407	10.5	0.35	0.71
96	352	458	8.9	0.43	0.79

In Table 12, the average delay of 214ms at 32-node deployment is 11.2% lower than the theoretical prediction, attributed to the 17.3% reduction in routing hops by the dynamic topology optimisation algorithm. The packet loss rate increases from 0.07% for 16 nodes to 0.43% for 96 nodes, which is still significantly below the 1% tolerance threshold of the IEEE 802.15.4 standard. The topology type influences the system to quantify the delay difference between star, mesh, and hybrid topology, and the measured hybrid topology (star + cluster tree) has the best efficiency, and the standard deviation of delay fluctuation is controlled within 18ms.

In the engineering reliability verification, the Mean Time Between Failures (MTBF) of the terminal equipment for 180 days of continuous operation reaches 8,760 hours, far exceeding the standard of 5,000 hours for industrial-grade equipment. The accuracy of multi-node time synchronisation is improved to ±28ns by IEEE 1588v2 protocol, which ensures that the time difference positioning error of the acoustic emission sensing network is less than 1.5mm. on-site measurements show that the deployment of edge terminals reduces the wireless communication traffic by 73%, and reduces the load of the central server by 68%, which meets the requirements of the third-level index of 'Evaluation Standard for Smart Site Construction' (T/CECS 886-2021). .

IV. DISCUSSION AND OUTLOOK

Due to the complexity of the building structure, multiple cross-work, and high requirements for heritage protection, the risk management of the university renovation project has long been limited by the static assessment system and manual experience decision-making, resulting in the hidden risk leakage rate of more than 35%, and the delay of the emergency response of more than 4 hours. In order to achieve the paradigm shift of risk identification from passive disposal to predictive intervention, a dynamic optimisation model based on Bayesian network is proposed to construct an intelligent decision-making framework covering the whole cycle of the project through the innovation of the three-level method of biometric data fusion, quantification of the risk conduction paths, and multi-objective resource scheduling.

The model adopts the improved Markov chain Monte Carlo algorithm to solve the small-sample training problem, and combines with the non-dominated sorting genetic algorithm to generate 216 sets of non-inferior solutions to support the dynamic equilibrium decision-making of safety-cost-duration. Empirical evidence shows that the identification rate of wood component insect risk is improved by 141.7%, the scaffolding turnover rate is increased from 48.1% to 89.3%, and the edge computing terminal latency is controlled within 300ms. The core contributions are to establish the quantitative mapping relationship between multimodal biological data and engineering risks, to propose an adaptive inference mechanism based on the dynamic correction of conditional probability table, and to develop a low-power terminal device (4.7W/node) to realise millimetre-level risk sensing.

The current study is limited by the size of historical accident data (<200 groups), and the generalisation ability for extreme working conditions needs to be verified; the stability of the dynamic priority adjustment algorithm under ultra-large-scale nodes (>100 units) needs to be further optimised. In the future, it is proposed to combine building information modelling (BIM) and digital twin technology to build a virtual-realistic risk deduction platform, explore the multi-project data sharing mechanism under the federal learning framework, and promote the management of repair works to evolve towards the intelligent stage of 'perception-prediction-self-healing'.

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