

# Conductor Aging Monitoring and Intelligent Analysis Strategies for Power Grid Status Visualization

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## Abstract

**INTRODUCTION:** Continuous sensing, unified analysis, and spatial representation of conductor aging remain challenging in power-line monitoring involving computer vision, edge computing, and digital twins.

**OBJECTIVES:** This study develops a cloud-edge collaborative framework for power-grid status visualization to improve conductor defect detection and aging-risk assessment under complex operating conditions.

**METHODS:** The sensing layer collects visible-light, infrared, electrical, vibration, and micrometeorological data; edge nodes perform time alignment, quality assessment, lightweight defect inference, and event filtering; and the cloud establishes conductor digital-twin instances through object-level coding.

**RESULTS:** The proposed lightweight network achieves an mAP@0.5 of 96.05% with a single-frame inference time of 16.3 ms. The aging-state recognition accuracy reaches 95.16%, while the health-index mean absolute error is 0.041, the 7-period forecast RMSE is 0.047, and the risk-classification F1 score is 94.12%.

**CONCLUSION:** Dynamic overlay visualization reduces the anomaly localization time to 34.7 s and increases the task completion rate to 96.5%. Quality-aware fusion and digital-twin object mapping establish a closed-loop connection among multi-source monitoring, state prediction, and 3D interactive decision support.

**Keywords:** Power grid status visualization; Conductor aging monitoring; Cloud-edge-end collaboration; Digital twin; Multi-source data fusion

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## 1. Introduction

Computer vision, edge computing, and digital twin techniques have made it possible for transmission line monitoring to move from manual interpretation to continuous state estimation. Santos et al. [1] Fusion of visible and infrared thermal images from UAVs to detect line targets and thermal anomalies; however, no quantitative relationship has been established between the monitoring characteristics and the extent of conductor aging. Chatzargyros et al. [2] Smart UAV checks are carried out on real transport networks to test the technical feasibility of

artificial intelligence; however, this approach is not able to satisfy real time warning requirements in bad communication conditions. Bellou et al. [3] YOLOv8 is used to identify high voltage line components in real time, increasing detection efficiency; however, thin, broken strands and weak texture are still prone to change in scale and complexity. Singh et al. [4], a pseudo-prototype component network is used to improve the interpretability of detection results, which can be traced back to local classification criteria; however, there is no correlation between thermal, electrical and mechanical degradation. Sharma et al. [5] This paper summarizes the problems of

sample imbalance, small object recognition, and edge deployment, and points out that the simple improvement of detection precision is not enough. Faisal et al. [6] Automatic Power Line Checking Methods have been systematically reviewed and concluded that there is still a lack of a uniform framework for multimodal fusion, low latency reasoning and long-term trend forecasting. Ukiwe et al. [7] Infrared thermal imaging and deep neural networks have been used to detect electrical hotspots, but they have not been able to account for temperature rise bias due to variations in load, wind velocity, and emissivity. Pulcini et al. [8], which combined multi-sensor data into a digital twin for predictive maintenance, has demonstrated the value of real virtual synchronization for degradation tracking. However, their approach lacks spatial topology mapping and component-level mapping. Islam et al. [9]. The importance of synchronising visual characteristics with the status of double objects has been stressed, but there are still differences in quality and reliability of state estimates. Bala et al. [10] Edge computing has shown that it is possible to reduce maintenance latency and cloud side load, but there is still a need for coordinated optimization among tasks deployment, computing resources, and risk prioritization. Existing studies leave three technical gaps in conductor-aging monitoring. First, multimodal information is commonly fused without explicitly adapting its contribution to time-varying data reliability caused by occlusion, thermal reflection, missing samples, or operating-condition changes. Second, heterogeneous monitoring results are seldom organized through a unified object-level spatiotemporal code that binds measurements, quality information, and state evolution to the same conductor or hardware instance. Third, defect recognition and condition assessment are often separated from degradation forecasting and digital-twin interaction, limiting the continuity from sensing evidence to maintenance decisions. To address these gaps, the proposed framework introduces a quality-aware fusion rule that jointly uses feature response, data quality, validity tags, and operating conditions to regulate modal contributions, and an object-level coding scheme that organizes heterogeneous features and their temporal changes within each digital-twin instance. The TCN-GRU module is employed as the temporal predictor rather than claimed as a newly developed sequence architecture; its role is to model the quality-conditioned object-level state sequence and provide future health indices for risk classification. These components are connected through the cloud-edge-digital-twin workflow, so that reliability-aware sensing, state estimation, degradation prediction, spatial mapping, and interactive decision support operate on the same continuously updated object state rather than as isolated processing modules. A concise comparison of representative existing approaches and the proposed framework is provided in Table 1, highlighting the differences in multi-source fusion, object-level state organization, temporal prediction, and digital-twin interaction.

Table 1. Comparison of Representative Existing Approaches and the Proposed Framework

| Approach                | Main capability described in the cited study                                                                       | Limitation relative to conductor-aging monitoring                                      | Relation to the proposed framework                                                                                          |
|-------------------------|--------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------|
| Santos et al. [1]       | Visible-light and infrared UAV inspection                                                                          | Aging degree is not quantitatively linked to multi-source monitoring characteristics   | Multi-source features are further mapped to aging-state assessment                                                          |
| Chatzargyros et al. [2] | AI-assisted UAV inspection                                                                                         | Real-time warning remains limited under poor communication conditions                  | Edge-side preprocessing and event-triggered inference reduce communication dependence                                       |
| Bellou et al. [3]       | YOLOv8-based power-line component detection                                                                        | Thin broken strands and weak-texture defects remain difficult                          | Lightweight multi-scale detection is designed for slender conductor defects                                                 |
| Ukiwe et al. [7]        | Infrared hotspot detection                                                                                         | Load, wind speed, and emissivity effects are insufficiently considered                 | Operating-condition correction is introduced before thermal-feature fusion                                                  |
| Pulcini et al. [8]      | Multi-sensor digital twin for predictive maintenance                                                               | Spatial topology and component-level mapping are limited                               | Object-level coding binds heterogeneous states to conductor and hardware twins                                              |
| Bala et al. [10]        | Edge computing for maintenance                                                                                     | Task deployment, computing resources, and risk priority require coordinated processing | Cloud-edge task allocation combines latency, resource cost, and risk urgency                                                |
| Proposed framework      | Multi-source sensing, quality-aware fusion, object-level coding, temporal prediction, and digital-twin interaction | —                                                                                      | Reliability-aware state estimation, prediction, and visualization are connected through a continuously updated object state |

## 2. Analysis of Power Line Aging Mechanisms and Monitoring Characteristics

As a result, their aging process exhibits the characteristics of multi-field coupling and progressive accumulation. Due to load fluctuations, the increase in metal oxidation and the resistance at the contact point. Continuous mechanical

vibration can easily cause strand wear, strand loosening, and local fractures, while salt mist, moisture, and contamination deposits alter surface texture, cross section area, and electrical conductivity [11]. In order to prevent the effects of operating conditions on individual temperature and/or image characteristics, the monitoring functions should include at the same time surface defects, thermal anomalies, electrical deterioration, mechanical reactions and environmental stresses. Their unified state vector is represented as

$$x_t = \left[ p_t, s_t, \Delta T_t, G_t, \frac{R_t - R_0}{R_0}, a_{rms,t}, f_{dom,t}, h_t, v_t \right] \quad (1)$$

where  $p_t$  and  $s_t$  represent the probability of defect categories and the proportion of defect area, respectively;

$\Delta T_t$  and  $G_t$  represent the relative temperature rise of the conductor relative to the environment and the local temperature gradient, respectively;  $R_t$  and  $R_0$  represent the current resistance and reference resistance, respectively;  $a_{rms,t}$  and  $f_{dom,t}$  represent the root-mean-square (RMS) vibration value and the dominant frequency, respectively; and  $h_t$  and  $v_t$  represent humidity and wind speed, respectively. The mechanism-characteristic correspondence in Table 2 provides the foundation for selecting the type of sensor terminal, configuring the filter parameters of the edge node, and constructing the cloud based aging evaluation input, so as to establish a uniform monitoring chain for identifying the surface damage, extracting the hot spot, characterizing the electric degradation, and correcting the environment.

Table 2. Correspondence between Wire Aging Mechanisms and Multi-Source Monitoring Features

| Aging Mechanism                       | Typical State Characteristics                                                              | Core Monitoring Features                                                        | Data Sources                             | Corresponding Analysis Module                    |
|---------------------------------------|--------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------|------------------------------------------|--------------------------------------------------|
| Thermal Aging and Contact Degradation | Localized overheating, joint oxidation, reduced current-carrying capacity                  | Relative temperature rise, temperature gradient, hotspot area, hotspot duration | Infrared thermal images, current data    | Hotspot Extraction and Temperature Rise Analysis |
| Mechanical Fatigue                    | Wear, loose strands, broken strands, abnormal sag                                          | Defect area, vibration amplitude, dominant vibration frequency, sag deviation   | Visible-light images, vibration sensors  | Surface Defect Detection                         |
| Electrochemical Corrosion             | Surface pitting, loss of cross-sectional area, increased electrical resistance             | Texture changes, corrosion area, relative increase in resistance                | Visible-light images, electrical sensors | Comprehensive Assessment of Aging Condition      |
| Environmental Stress Aging            | Icing, contamination deposits, and damp-heat erosion                                       | Ambient temperature, humidity, wind speed, ice thickness                        | Environmental sensors, image terminals   | Feature Correction and Risk Classification       |
| Multiphysics-Coupled Aging            | Thermal anomaly propagation, decline in mechanical strength, and progressive deterioration | Multi-source feature correlation, rate of change in health index                | Multi-source time-series monitoring data | Trend Prediction and Risk Classification         |

### 3. Architecture and Strategy of the Power Grid Status Visualization Monitoring System

#### 3.1 Overall System Architecture and “Cloud-Edge-End” Collaborative Strategy

In order to satisfy the demands of multiple sources for the defect of the conductor, the IR temperature rise, the electrical parameters, and the environment stress, the system uses three layers of cooperative architecture including the sensing end, the edge, and the cloud. Figure 1, "Conductor Aging Visualization Monitoring System Overall Architecture for Cloud-Edge-End Collaboration", organizes the function modules based on data collection, edge processing, cloud analysis, and digital twin mapping workflow. The sensor layer is made up of a visible light camera, an IR thermal image, a current and a temperature sensor, a vibration sensor, and an environment monitoring unit. It is responsible for the

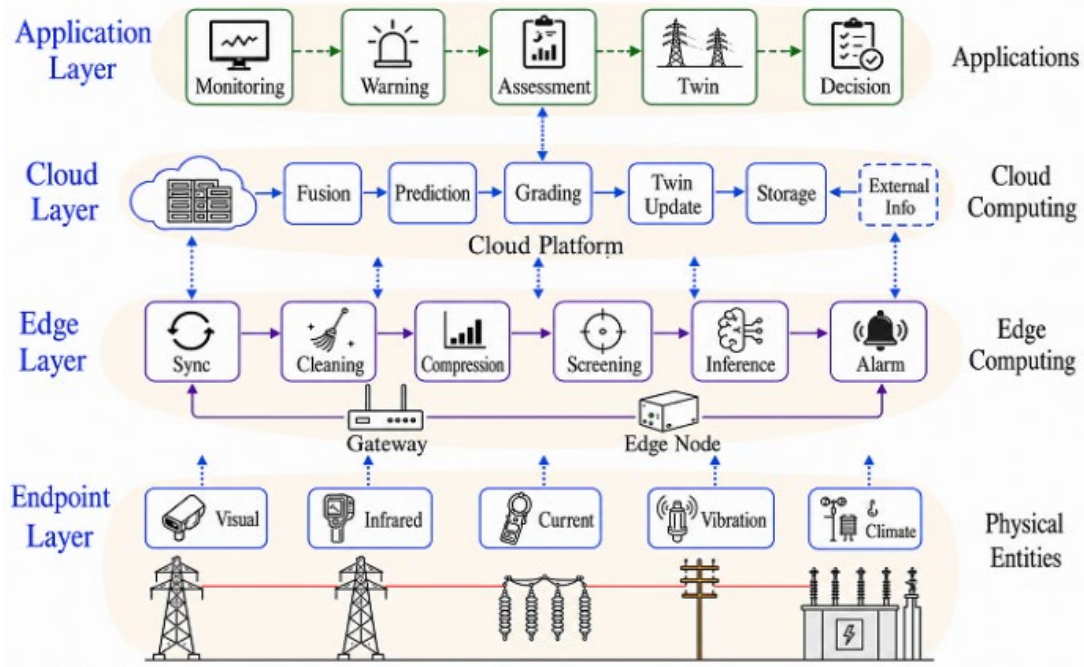
generation of raw data flows, including the device ID, the space coordinates, and the uniform time stamp. The edge layer deals with multi-source time synchronization, outlier removal, image compression, initial hot spot selection, and lightweight defect reasoning, so as to reduce the redundancy of data transfer and alert delay[ 12]. To avoid network congestion caused by the fixed upload of all tasks, the system determines the task deployment location based on computational latency, transmission cost, and risk urgency:

$$j^* = \arg \min_{j \in \{edge, cloud\}} (\alpha D_{i,j} + \beta C_{i,j} + \gamma E_{i,j} - \eta P_i) \quad (2)$$

where  $D_{i,j}$  represents the processing and transmission latency when task  $i$  is deployed at node  $j$ ;  $C_{i,j}$  represents the communication bandwidth consumption;  $E_{i,j}$  represents the computational resource consumption;  $P_i$  represents the risk priority of the anomaly task; and  $\alpha$ ,  $\beta$ ,  $\gamma$ , and  $\eta$  are

set based on line communication quality, node load, and alarm timeliness requirements. Priority is given to high-risk hot spots and suspected strand breaks at the edge, triggering local alarms, and cross section state correlation, long-term

degradation modeling, and 3-D visualization. This creates a system operating mechanism that integrates real-time monitoring, centralized analysis, and dynamic mapping [13].



**Figure 1.** Overall Architecture of the Cloud-Edge-End Collaborative Visualization Monitoring System for Conductor Aging

### 3.2 Design and Deployment Plan for Multi-Source Sensing Terminals

The sensor side uses a three-level space indexing system of "tower — span — hardware", which is configured as a fixed monitoring terminal, with visible, infrared, electric, vibration, and micrometeorological elements as fixed monitoring terminals. Table 3 includes defect discrimination, temperature differential sensitivity, vibration frequency band, and representative local environment. In particular, visible light cameras and infrared thermal imagers have a common field of view, which makes it possible to bind corrosion, broken strands, and hot spots to the same conductor segment; current and temperature sensors are concentrated in areas susceptible to contact degradation, e.g. splice tubes and tension clamps [14]; vibration sensors cover span ends and regions susceptible to microwind vibrations; and micrometeorological units are mounted on unobstructed towers. In order to strike a balance between the cost of risk and the cost of deployment of the terminal, the method of deployment of candidate points is expressed as

$$z^* = \arg \min_z \sum_{m=1}^M c_m z_m, \quad s.t. \quad \sum_{m=1}^M a_{qm} z_m \leq r_q, \quad z_m \in \{0,1\} \quad (3)$$

where  $z_m$  indicates whether a terminal is deployed at candidate location  $m$ ,  $c_m$  represents the combined cost of installation, power supply, and communication,  $a_{qm}$  denotes the effective coverage relationship between location  $m$  and risk unit  $q$ , and  $r_q$  represents the redundancy requirement set based on the aging grade; splice fittings and corrosion-sensitive areas employ dual-source coverage, while standard spans use single-source continuous monitoring. Every terminal records the line number, the phase, the coordinates, and the time stamp synchronized with Beida. The vibration data is subjected to local short window feature extraction, and the image and heat image are uploaded periodically or triggered by an abnormal event; when communication is interrupted, the original recording of the abnormal time period is cached.

**Table 3.** Design Parameters and Deployment Criteria for Multi-Source Sensing Terminals

| Terminal Type                 | Key Parameters and Basis for Configuration                                                                                                                                                                            | Priority Locations                                                            | Deployment | Module Function                                                                                        |
|-------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------|------------|--------------------------------------------------------------------------------------------------------|
| Visible Light Terminal        | Spatial resolution is calculated based on the minimum defect size, observation distance, and target pixel coverage; exposure parameters are automatically adjusted according to backlighting and vibration conditions | Unobstructed locations on the sides of transmission towers and span sections  |            | Identification of corrosion, wear, loose strands, and broken strands                                   |
| Infrared Terminal             | Temperature resolution no greater than 50 mK; emissivity is calibrated on-site based on conductor material and surface oxidation level                                                                                | Observation side of splice tubes, tension clamps, and current-carrying plates |            | Extract relative temperature rise, temperature gradients, and hotspot areas                            |
| Electrical Terminals          | The current range is set based on the line's rated current-carrying capacity, with temperature accuracy controlled within $\pm 0.5^\circ\text{C}$                                                                     | Splice tubes, line clamps, and sections with concentrated loads               |            | Characterize changes in current carrying capacity and contact degradation                              |
| Vibration Terminals           | The sampling frequency is 2.5 times higher than the upper limit of the monitoring frequency band; the measurement range is set with a margin based on the peak value of light-wind vibrations                         | Ends of spans and areas near suspension clamps                                |            | Extract the root-mean-square (RMS) value, fundamental frequency, and impact component of the vibration |
| Micro-meteorological Terminal | The data acquisition interval is set based on the rates of change in wind speed and humidity; installation locations should avoid obstruction by the tower structure and local heat sources                           | Areas susceptible to icing, salt fog, and strong winds                        |            | Provide temperature rise correction and environmental stress input                                     |

### 3.3 Edge Computing Node Functions and Data Preprocessing

The edge computing node integrates the visible-light, infrared, electrical, vibration, and micrometeorological data described in Section 3.2 according to the line number, phase, span number, and synchronized BeiDou timestamp, and configures differentiated preprocessing chains for different data modalities. Visible-light images undergo distortion correction, brightness normalization, and mild denoising to preserve corrosion textures and broken-strand edges [15]; infrared thermal images are subjected to nonuniformity correction and environmental temperature compensation; the current and temperature time series are treated by restricting the physical range and separating the operating trend data; the band band range of the vibration signal is set based on the target vibration frequency band, and the sliding window length is jointly determined by the sampling frequency and the minimum frequency to be recognized [16]. Resampling and mapping the multi-source sequence into a uniform time window, and the quality score is computed according to the missing rate, signal to noise ratio, and time deviation:

$$q_{k,t} = w_1(1 - r_{k,t}^{miss}) + w_2 \min\left(\frac{SNR_{k,t}}{SNR_{k,t}^{ref}}, 1\right) + w_3 \exp\left(-\frac{|\Delta\tau_{k,t}|}{\tau_0}\right) \quad (4)$$

where  $q_{k,t}$  represents the quality of data in class  $k$  within the time window  $t$ ;  $r_{k,t}^{miss}$ ,  $SNR_{k,t}$ , and  $\Delta\tau_{k,t}$  represent the missing rate, signal-to-noise ratio, and time deviation, respectively; and  $w_1 + w_2 + w_3 = 1$ . Data of poor quality is marked with a trust flag, and the original segments are kept. Hot spots, suspected strand breaks, and vibration/impact events trigger priority uploads, whereas the rest of the data uploads only compressed features, thus

reducing bandwidth consumption in poor communication conditions and maintaining traceability in abnormal periods.

### 3.4 Construction of the Cloud-Based Digital Twin Platform

The cloud-based digital twin platform is built upon the line asset ledger and geographic information. It establishes twin instances based on a six-level object hierarchy of "line — tower — span — phase — conductor segment — hardware," and records equipment codes, latitude, longitude, elevation, material model, commissioning date, rated current-carrying capacity, reference resistance, and maintenance records for each case [17]. The visible light defect box, the infrared hotspot region, the current temperature sequence, the vibration spectrum characteristic, and the micrometeorological data output from the edge node are bound to the object by the line number, phase, space coordinates, and the uniform time stamp; the spatial connection relation is stored in the topology chart, so that the status propagation path between the conductor, the splice tube, and the tension clamp can be recognized in the same span. The platform consists of a time-series database for continuous monitoring data, a static object database, and a file storage for storing abnormal images, thermal images, and vibration clips; an event bus is responsible for receiving high risk alerts and driving updates to the digital twin status [18]. Object states are propagated recursively based on data quality, sampling interval, and anomaly severity:

$$s_{i,t} = \rho_{i,t} s_{i,t-1} + (1 - \rho_{i,t}) \sum_{k=1}^K \omega_{i,k,t} z_{i,k,t} \quad (5)$$

where  $s_{i,t}$  is the state vector of twin object  $i$  at time  $t$ ,  $z_{i,k,t}$  is the edge feature of class  $k$ ,  $\omega_{i,k,t}$  is determined jointly by the data quality score and feature aging sensitivity, and  $\rho_{i,t}$  is adjusted based on the sampling interval and state change rate. Event-triggered updates are used for strand

breaks, persistent hot spots, and sudden resistance spikes, whereas routine monitoring data is compiled and written in a time window; each update records the data source, model version, prior status value, and cause of change, ensuring a consistent database for subsequent state encoding, aging evaluation, and alarm tracing.

### 3.5 Monitoring Data Organization and Status Coding Strategy

A composite primary key consisting of twin object codes, acquisition timestamps, and data types is used to organize the monitoring data. According to the hierarchical hierarchy of "line-tower — span — phase — conductor cross-section — component", the visible light defect box, the infrared hot spot, the current temperature sequence, the short window vibration characteristic, and the micrometeorological measure are recorded in the same spatiotemporal record. In order to solve the problem of inconsistent sampling periods between terminals, state evaluation times are used as window endpoints. High frequency vibration data are transformed into RMS, peak, basic frequency, and band energy. Image and heat image are transformed into defect area, classification probability, hot spot area, and temperature gradient, and continuous electric and environmental variables are represented by window mean, extreme value, and variation rate. The window length is determined on the basis of the inertia of the temperature rise, the stability of the vibration, and the update cycle of the model, and the overlap rate is used to maintain the continuity of the neighboring states [19]. Features with different units are normalized using object reference values:

$$\tilde{x}_{i,k,t} = m_{i,k,t} q_{i,k,t} \frac{x_{i,k,t} - \mu_{i,k}^b}{\sigma_{i,k}^b + \varepsilon} \quad (6)$$

where  $\mu_{i,k}^b$  and  $\sigma_{i,k}^b$  are the mean and standard deviation, respectively, of the  $k$  th class feature of object  $i$  during the

health baseline phase;  $m_{i,k,t}$  is the validity flag; and  $q_{i,k,t}$  is the edge node quality score. The final state is encoded as

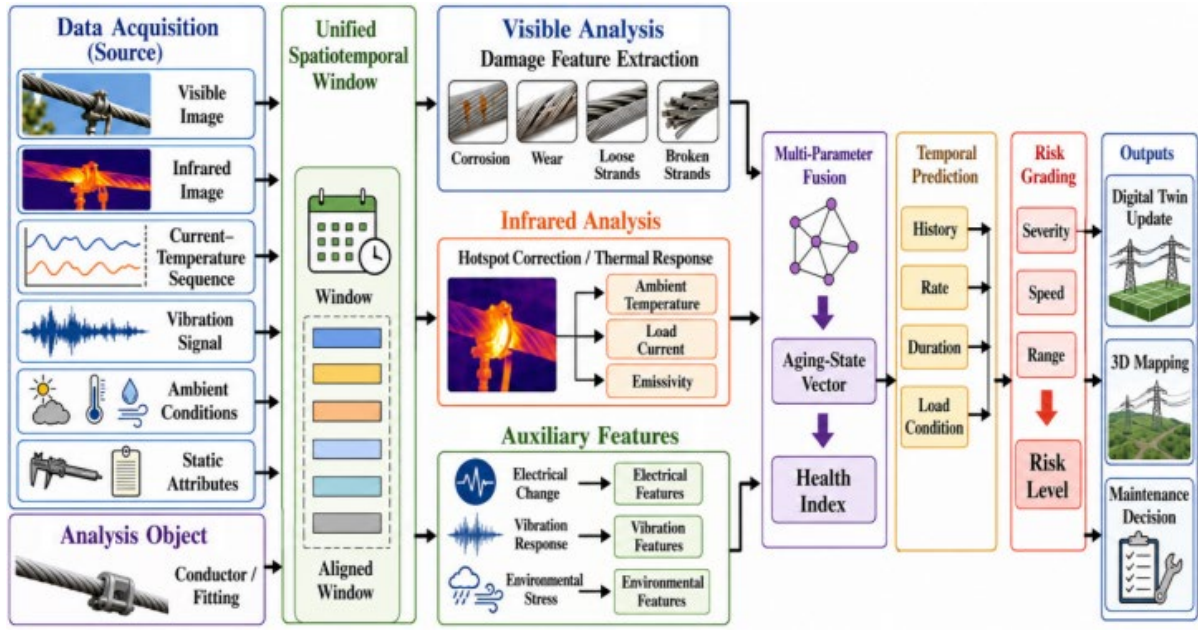
$$X_{i,t} = [\tilde{x}_{i,t-L+1:t}, \Delta\tilde{x}_{i,t}, m_{i,t}, q_{i,t}, a_i] \quad (7)$$

where  $L$  represents the time window length,  $\Delta\tilde{x}_{i,t}$

denotes the rate of state change, and  $a_i$  includes material, years in service, and rated parameters. This coding preserves current status, evolution trends, data reliability, and equipment changes, and provides a uniform input for the subsequent multiparameter fusion and aging trend modeling.

### 4. Intelligent Analysis Model for Conductor Aging Status

On the basis of organizing multi-source monitoring data, quality marking and two-object state encoding, the intelligent analysis model of conductor aging constructs a hierarchical processing chain to identify the surface damage, the location of thermal anomaly, the comprehensive degradation evaluation, and the risk tendency forecast [20]. As illustrated in Figure 2, the model analyses the section of the cable and the joint, the mapping of the visible light image, the infrared thermal image, the current time sequence, the vibration characteristics, the environment parameters, and the static equipment properties into a unified spatiotemporal window. The visible light branch extracts the local morphological characteristics, such as corrosion, wear, slack, and broken strands, while the infrared branch corrects the hot spot response on the basis of the ambient temperature, the load current, and the emissivity of the material. These two types of local anomalous characteristics, together with variations in resistance, vibration, and environmental stress, are input into a multiparameter fusion module to form an interpretable aging state vector and health index [21]. It then classifies the risk according to the severity, the progression rate, and the extent of the impact, and provides uniform analysis results for the digital twin state update, 3D visualization, and maintenance decision.



**Figure 2.** Overall Framework of the Intelligent Analysis Model for Conductor Aging Status

#### 4.1 Conductor Surface Defect Detection Based on Lightweight Deep Learning

The conductive surface defect detecting module processes the visible light images that have been corrected for distortion, brightness normalization, and quality screening. It crops the conductor and splice hardware regions based on the digital twin's coordinates to minimize interference from tower components, vegetation, and sky backgrounds during feature extraction. The input resolution is determined by the smallest identifiable broken strand size, the terminal viewing distance, and the percentage of valid pixels occupied by the defect [22]. Based on the model, the main network uses an inverse residual structure and deep separable convolutions to reduce the computation load, retain the corrosion spot, wear pattern and strand edge, and extract the semantic characteristics of the loose strand, the broken strand and the deep layer fitting. The feature fusion layer connects features at different scales via a bidirectional pyramid and introduces coordinate attention along the conductor's axial direction, enabling the network to respond to both the continuity and local abrupt changes of the thin target. The detection head uses a decoupled classification and localization architecture that separately outputs the likelihood of corrosion, wear, loose strands, and broken strands, as well as the bounding box and the percentage of defect area. Its training loss is expressed as

$$L_d = \lambda_c L_{focal} + \lambda_b L_{CloU} + \lambda_o L_{BCE} \quad (8)$$

where  $L_{focal}$  reduces the dominant influence of a large number of normal background samples;  $L_{CloU}$  constrains the position, scale, and aspect ratio of slender defects;  $L_{BCE}$  calculates the probability of target presence; and  $\lambda_c$ ,  $\lambda_b$ , and  $\lambda_o$  are set based on the degree of class imbalance and sensitivity to localization errors. The detection results, together with the time stamp, wire segment code, and confidence score, are synchronized to the digital twin, providing the surface damage characteristics for the evaluation of the multiparameter aging condition.

#### 4.2 Infrared Thermal Imaging-Based Conductor Hotspot Extraction and Temperature Rise Analysis

Based on co-field-of-view calibration parameters from the visible and infrared terminals, the infrared thermal imaging module maps the regions of the conductors, the splice tubes, and the tension clamps to the same twin object, while removing the sky, tower, and vegetation from the background [7]. First, the emissivity is determined on the basis of the conductive material and the degree of surface oxidation, and the ambient temperature, the reflection temperature, and the transmittance of the atmosphere are used for radiation correction. Adjacent normal conductor segments in the same phase are used as dynamic references to reduce the effect of seasonal changes in temperature and total load on local anomalies. In order to solve the problem

of blurred boundaries in weak hot spots, an adaptive threshold is constructed using the mean and the absolute median difference:

$$\tau_t = \text{med}(\Delta T_{p,t}) + \kappa \cdot 1.4826 \text{MAD}(\Delta T_{p,t}) \quad (9)$$

where  $\Delta T_{p,t}$  is the temperature difference between pixel  $p$  and the reference region, and  $\kappa$  is determined based on the thermal imager's temperature resolution and the acceptable false alarm rate. Pixels above the threshold and satisfying spatial connectivity criteria form a candidate hot spot, where the minimum area of the area is restricted by the spatial resolution of the thermal imager and the minimum detection scale for contact degradation. In order to eliminate differences due to current and air cooling, the temperature rise of hot spots is normalized according to operating conditions:

$$\Theta_t = \frac{(T_{h,t} - T_{a,t})(1 + \beta v_t)}{(I_t / I_N)^2 + \varepsilon} \quad (10)$$

In the equation,  $T_{h,t}$ ,  $T_{a,t}$ ,  $I_t$ ,  $I_N$ , and  $v_t$  represent the hotspot temperature, ambient temperature, operating current, rated current, and wind speed, respectively;  $\beta$  is determined based on the wire diameter and convective heat transfer relationships. The module extracts the highest, the mean, the temperature gradient, the hotspot region percent, and the duration, and links them to the component codes and quality scores to provide the thermal anomaly characteristics for a comprehensive aging evaluation.

### 4.3 Comprehensive Evaluation of Conductor Aging Status via Multi-Parameter Fusion

The integrated evaluation module takes the time window of the wire segment or the hardware component as the calculation unit. It combines defect category probability, defect area percentage, normalized temperature rise, temperature gradient, relative resistance increment, root mean square (RMS) vibration value, fundamental frequency offset, and environmental stress to form modal features  $z_{i,k,t}$  [23]. Different from direct concatenation or fixed-weight fusion, the contribution of each modality is not predetermined. Reliability variations caused by image occlusion, thermal reflection, and intermittent sensor sampling are explicitly introduced into the fusion process, and the modal weights are jointly determined by feature response, data quality, and validity tags:

$$\alpha_{i,k,t} = \frac{m_{i,k,t} q_{i,k,t} \exp(v^T \tanh(W_k z_{i,k,t} + U c_{i,t} + b))}{\sum_{j=1}^K m_{i,j,t} q_{i,j,t} \exp(v^T \tanh(W_j z_{i,j,t} + U c_{i,t} + b))} \quad (11)$$

where  $m_{i,k,t}$  and  $q_{i,k,t}$  represent the modal validity flag

and quality score, respectively, and  $C_{i,t}$  includes load factor, ambient temperature, wind speed, years in service, and material properties, enabling temperature rise, resistance, and vibration features to contribute to the assessment under corresponding operating conditions. The fusion layer simultaneously encodes coupled relationships such as “hotspot—resistance increase,” “corrosion—cross-sectional area loss,” and “strand loosening—vibration anomaly,” rather than treating heterogeneous features as independent inputs. The resulting state representation is used to calculate the probability of aging levels and the health index:

$$p_{i,t} = \text{soft max}(W_o h_{i,t} + b_o), \quad H_{i,t} = 1 - \sum_{r=1}^R c_r p_{i,t}^{(r)} \quad (12)$$

Here,  $c_r$  represents the graded damage coefficient set based on defect severity, operating procedures, and maintenance criteria. The module outputs the probability, the health index, the dominant anomaly parameter, and the reliability of the data for each grade, so as to prevent the direct determination of the aging status by a single heat or surface defect, and to provide a sequential sequence of states for modeling the degradation trend.

### 4.4 Conductor Aging Trend Prediction and Risk Classification

The trend forecasting module uses the health index, the aging level probability, the hot spot duration, the defect area variation rate, the resistance increment, and the vibration/impact magnitude output from section 4.3, and the external variables, the environmental temperature, the wind velocity, and the icing conditions are considered as external variables [24]. The input-window length is determined according to the effective correlation time of the load cycle, conductor temperature-rise inertia, and mechanical fatigue characteristics. The TCN component extracts short- and medium-term degradation patterns through causal dilated convolutions with parallel temporal computation, whereas the GRU retains longer-term dependencies associated with persistent temperature rise, corrosion propagation, and vibration accumulation using fewer recurrent gates than an LSTM. This combination is therefore used to balance multi-scale temporal representation and recurrent-state retention without introducing the higher computational cost of a Transformer. Its suitability is further evaluated against ARIMA, LSTM, GRU, Transformer, and TCN under identical input sequences and prediction horizons in Section 6.4. The multi-step prediction process is expressed as

$$g_{i,t} = \text{GRU}(\text{TCN}(u_{i,t-L+1:t}), g_{i,t-1}), \quad \hat{H}_{i,t+\tau} = w_\tau^T g_{i,t} + b_\tau \quad (13)$$

where  $u_{i,t-L+1:t}$  is the dynamic state sequence of the object  $i$  within a window of length  $L$ ,  $g_{i,t}$  is the temporal hidden

state, and  $\hat{H}_{i,t+\tau}$  is the health index at the  $\tau$  th prediction time step. The risk value is calculated by integrating the health level, the serious aging probability, the decline rate, and the forecast uncertainty:

$$R_{i,t+\tau} = \alpha(1 - \hat{H}_{i,t+\tau}) + \beta\hat{p}_{i,t+\tau}^{sev} + \gamma \max(0, -\Delta\hat{H}_{i,t+\tau}) + \delta\xi_{i,t+\tau} \quad (14)$$

where  $\hat{p}_{i,t+\tau}^{sev}$  is the probability of severe aging, and  $\xi_{i,t+\tau}$  is the uncertainty characterized by the prediction interval width; the weights are determined based on failure consequences, the cost of missed detection, and historical validation errors. Table 4 maps continuous risk values in combination with hard constraint events — for example, strand breaks, persistent hot spots, and sudden rise in resistance — to a four-level state classification, with a classification threshold calibrated with maintenance procedures and quantile points from historical failure samples.

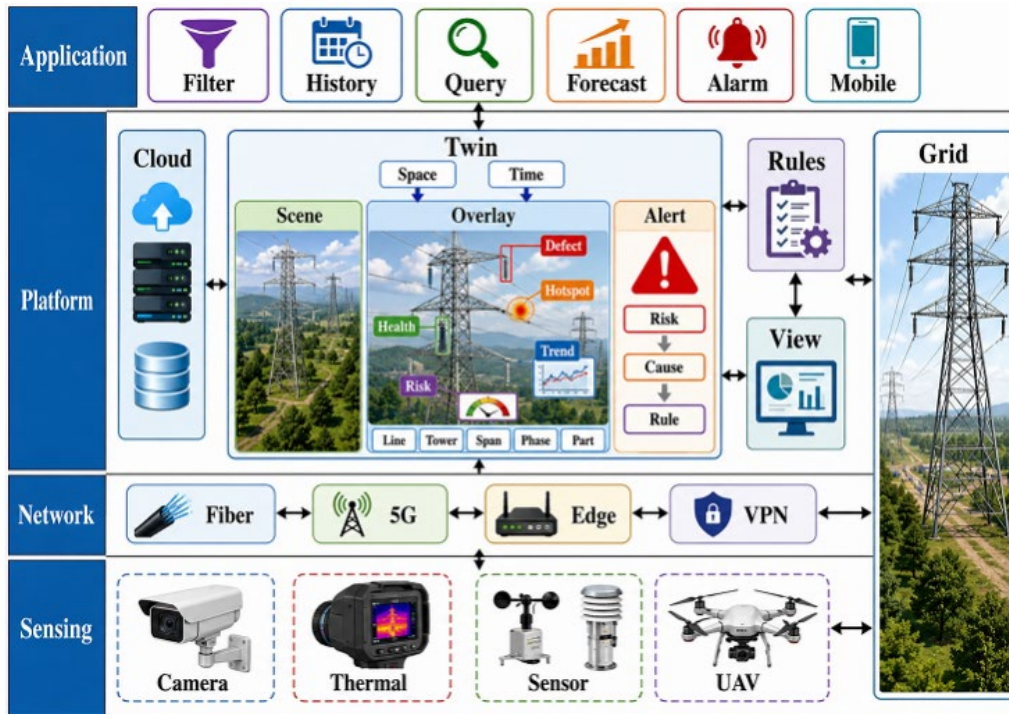
Table 4. Conductor Aging Risk Classification and Response Rules

| Risk Level                  | Determination Criteria                                                 | State Meaning                                                                      | Remediation Requirements                                      |
|-----------------------------|------------------------------------------------------------------------|------------------------------------------------------------------------------------|---------------------------------------------------------------|
| Level I: Normal             | $R < \eta_1$ , no hard-constraint events                               | Stable status; minimal fluctuations in the health index during the forecast period | Monitor according to the established schedule                 |
| Level II: Under Observation | $\eta_1 \leq R < \eta_2$                                               | Slow deterioration or accumulation of localized abnormalities                      | Shorten the monitoring interval and verify the abnormal areas |
| Level III: Alert            | $\eta_2 \leq R < \eta_3$ or persistent hotspots or vibration anomalies | Accelerated aging and reduced operational margin                                   | Schedule special inspections and develop a                    |

|                       |                                                                                                      |                                                            |                                                                                 |
|-----------------------|------------------------------------------------------------------------------------------------------|------------------------------------------------------------|---------------------------------------------------------------------------------|
|                       |                                                                                                      |                                                            | maintenance plan                                                                |
| Level IV<br>Emergency | $R \geq \eta_3$ or triggering hard constraints such as strand breakage or excessive temperature rise | Failure propagation or threats to operational safety exist | Issue an immediate alert and implement load adjustment or power outage measures |

## 5. Implementation of Grid Status Visualization and Intelligent Interaction Strategies

In chapter 4, it is necessary to translate the defect location, hot spot, health index, aging trend, and risk level into visual information that is specific in space, time continuity, and operational interpretation, in order to solve the problem of dispersed multi-source monitoring results, difficulty in locating anomalies, and delayed transfer of risk information. The Visual and Intelligent Interaction Module, as illustrated in Figure 3, is built on a cloud based digital twin object. Based on line, tower, span, phase, and component codes, it binds detection boxes, heat distributions, status curves, and risk tags to corresponding 3D conductors and hardware models; The status mapping layer updates object attributes based on monitoring timestamps and model coordinates, while the multidimensional overlay layer controls information granularity according to the user's viewing distance and risk level, thereby preventing marker occlusion and visual redundancy in high-density line scenarios; the interaction layer supports section filtering, historical review, cross-referencing of abnormal parameters, and switching between prediction time periods, and combines risk levels, primary aging factors, and remediation rules into alarm notifications. Thus, a visual application chain is formed, which is composed of 3D scene reconstruction, monitoring information dynamic overlay, and intelligence early-warning decision.



**Figure 3.** Framework for Visualization and Intelligent Interaction of Power Grid Conductor Aging Status

### 5.1 3D Scene Reconstruction and Conductor Twin Model Mapping

The 3D scene is built on the basis of line geographical information, tower design parameters, UAV imagery, point cloud data, and equipment stock records. It is uniformly converted into the local coordinate system of the line, and the control point is registered with the tower center, the cross-arm end point, and the hardware connections. Terrain, the tower, the conductor, and the hardware are modeled in layers. The center line of the conductor is calculated according to the length of the span, the difference in elevation, the design tension, and the real time temperature. Splice tubes, tension clamps, and suspension clamps are connected to their respective phase and conductor segments. The mapping relationship between model points is expressed as

$$p_{i,t}^w = R_i p_i^l + t_i + d_i(s, T_t, I_t, v_t) \quad (15)$$

where  $p_i^l$  and  $p_{i,t}^w$  represent the object's local coordinates and scene coordinates, respectively;  $R_i$  and  $t_i$  denote the rotation matrix and translation vector; and  $d_i$  is the deformation correction factor determined by the arc length position  $s$ , conductor temperature  $T_t$ , load current  $I_t$ , and wind speed  $v_t$ . The scene model uses multi-level detail

management: at a distance, it keeps the line topology and risk markers; at a distance, it loads the strand texture, the hardware structure, and the defect area. Monitoring results are bound to model surfaces using object codes, timestamps, and spatial bounding boxes to make sure that the defect box, hotspot region, and health state are always consistent with the actual conductor position.

### 5.2 Dynamic Overlay Visualization of Multidimensional Monitoring Information

The multi-dimension monitoring information is overlaid on the double object of the conductor section, the splice tube, and the line clamp established in section 5.1. Surface defect boxes, IR temperature fields, current temperature curves, vibration spectra, health indices, and risk levels are related to these objects based on object codes and uniform timestamps. Spatial overlay uses model surface projection and bounding box constraints to bind corrosion, loose strands, and broken strand markers to actual defect locations. Hot spots are transformed into semi-translucent thermal textures based on thermal image registration matrix, and continuous state variables are represented by object contours, floating information windows, and time curves. In order to control marker occlusion in dense line situations, the display priority of overlay objects is defined as

$$P_{i,t} = \alpha R_{i,t} + \beta |\Delta H_{i,t}| + \gamma C_{i,t} + \delta D_{i,t} \quad (16)$$

where  $R_{i,t}$  represents the risk value,  $\Delta H_{i,t}$  represents the rate of change in the health index,  $C_{i,t}$  represents the confidence level of the analysis results, and  $D_{i,t}$  represents the duration of the anomaly; weights are set based on the impact on operational safety and the timeliness of alerts. System switches display granularity according to the observed distance: the line view maintains the risk profile and anomaly count; the interval-level view extends to display temperature, vibration, and trend information; and the component level view loads defect images and historical records. The timeline will replay the state of affairs from the monitoring window, making sure that the location of the anomaly, its evolution, and the analysis evidence are kept in sync.

### 5.3 Intelligent Early Warning and Interactive Decision Support

Intelligent early-warning module is used as the input of risk grade, forecast health index, dominant anomaly parameter, and data reliability. It defines as immediate trigger conditions, such as broken strands, sustained high temperatures, and sudden increases in resistance, and sets slow corrosion, increased vibration, and constant decrease in health index as trend-based trigger conditions. In order to avoid frequent alarm switching due to load fluctuations or thermal imaging reflections, the system uses the duration assessment, threshold hysteresis, and alarm cooling mechanisms for the same object, and combines events in neighboring segments that occur at similar times and have the same anomaly type into correlated alarms. Alarm priority is represented as

$$A_{i,t} = \alpha R_{i,t} + \beta \max(0, \Delta \hat{H}_{i,t}) + \gamma D_{i,t} + \delta S_i - \mu U_{i,t} \quad (17)$$

In the formula,  $R_{i,t}$  represents the risk value,  $\Delta \hat{H}_{i,t}$  represents the predicted rate of change in the health index,  $D_{i,t}$  represents the duration of the anomaly,  $S_i$  represents the importance of the line section, and  $U_{i,t}$  represents the prediction uncertainty; the weights are set based on the consequences of a fault, the impact on power supply, and the response time. By clicking on the warning object, the operator and the maintenance worker can simultaneously see the defect image, the thermal imaging area, the status curve, the model version, and the history of the service. Based on the level of risk, the platform generates recommendations for re-testing, specialized checks, load adjustments, or power down maintenance; manual confirmation, false alarm mark, and disposition results are simultaneously written into the digital twin object to calibrate the alert threshold and inform subsequent state analysis.

## 6. Experimental Validation and Results Analysis

### 6.1 Experimental Environment and Data Sources

The test data were obtained from fixed monitoring terminals and UAV inspection records of two 110 kV overhead lines and one 220 kV transmission line, covering 21.6 km, 58 towers, 104 spans, and 312 critical components, including splice tubes, tension clamps, and suspension clamps. Data acquisition covers operating conditions ranging from high temperature and humidity to strong winds and low temperatures. After time alignment, duplicate removal, and quality screening, 12,480 visible-light images, 9,720 infrared images, and 8,640 multi-source condition windows were retained. For the main experiments, the samples were divided into training, validation, and test sets at a 7:2:1 ratio by line section to prevent adjacent segments from entering different subsets. To further examine generalization, additional leave-one-line-out and leave-one-season-out evaluations were conducted. In the line-level tests, two lines were used for training and validation, and the remaining line was used only for testing; in the seasonal tests, samples from one season were excluded from training and used as an independent test domain. The labels were separately annotated by two-line maintenance technicians; in the event of a dispute over the category or boundary, a third technician carried out the examination. The model training environment and the edge reasoning environment are shown in Table 5.

Table 5. Experimental Data and Hardware/Software Environment Configuration

| Item                       | Configuration or Quantity                                              | Primary Purpose                                                 |
|----------------------------|------------------------------------------------------------------------|-----------------------------------------------------------------|
| Monitored Lines            | 2 × 110 kV lines, 1 × 220 kV line                                      | Covers different voltage levels and operating conditions        |
| Monitoring Scope           | 21.6 km, 58 towers, 104 spans                                          | Construction of line-level digital twins and spatial indexes    |
| Visible-light data         | 12,480 images, 1920×1080 pixels                                        | Corrosion, wear, loose strands, and broken strands detection    |
| Infrared thermal imagery   | 9,720 images, 640×512 pixels                                           | Hotspot extraction and temperature rise analysis                |
| Multi-source status window | 8,640 sets                                                             | Aging Assessment and Trend Prediction                           |
| Dataset Split              | Training set 70%, validation set 20%, test set 10%                     | Segregated by line section                                      |
| Training Server            | Intel Core i9-13900K, 64 GB RAM, RTX 4090 24 GB                        | Model Training and Parameter Optimization                       |
| Edge node                  | Jetson Orin NX 16 GB                                                   | Lightweight Inference and Anomaly Detection                     |
| Software Environment       | Ubuntu 22.04, Python 3.10, PyTorch 2.2, CUDA 12.1                      | Algorithm Development and Experiment Reproducibility            |
| Optimization Parameters    | AdamW, initial learning rate 0.001, batch size 32, 200 training epochs | Training conditions were kept consistent across all deep models |

## 6.2 Comparison of Defect Detection Algorithm Performance

In order to verify the validity of the lightweight flaw detection network described in section 4.1, we chose MobileNet-SSD, Faster R-CNN, YOLOv5s, and YOLOv8n as comparative models. All of the algorithms were based on the same training data set, augmentation, and the same input size of  $640 \times 640$  pixels. The evaluation measures include precision, recall rate, mAP @ 0.5, mAP @ 0.5: 0.95, parameter size, computation cost, and inference time for each image. Table 6 shows that the Faster R-CNN has strong regional localization capabilities, but it is not suitable for continuous processing at the edge node; MobileNet-SSD has a lower computational cost, but it is difficult to maintain the characteristics of fine strand breakage and weak texture corrosion. The proposed network effectively reduces false detections of small defects against elongated conductor backgrounds. With 2.7 million parameters and 6.9 GFLOPs, the single-frame inference time is 16.3 ms on the Jetson Orin NX, satisfying the computational requirements for periodic image acquisition and edge-side anomaly detection. Compared with YOLOv8n, the proposed network improves mAP@0.5:0.95 by 3.97 percentage points while reducing the parameter count by 15.63%.

Table 6. Comparison of Performance among Different Wire Surface Defect Detection Algorithms

| Detection Algorithm | Precision/% | Recall/% | mAP @0.5/% | mAP@0.5:0.95/% | Number of Parameters/M | Computational Load/GFLOPs | Inference Time/ms |
|---------------------|-------------|----------|------------|----------------|------------------------|---------------------------|-------------------|
| MobileNet-SSD       | 88.21       | 82.47    | 86.35      | 52.48          | 5.6                    | 2.8                       | 18.7              |
| Faster R-CNN        | 92.84       | 88.73    | 91.56      | 60.47          | 41.3                   | 180.2                     | 96.4              |
| YOLOv5s             | 94.12       | 90.65    | 93.18      | 63.54          | 7.2                    | 16.5                      | 24.6              |
| YOLOv8n             | 94.46       | 91.38    | 94.02      | 65.87          | 3.2                    | 8.7                       | 20.8              |

|                              |       |       |       |       |     |     |      |
|------------------------------|-------|-------|-------|-------|-----|-----|------|
| Proposed lightweight network | 96.18 | 94.27 | 96.05 | 69.84 | 2.7 | 6.9 | 16.3 |
|------------------------------|-------|-------|-------|-------|-----|-----|------|

## 6.3 Validation of the Aging Condition Assessment Model

The aging condition evaluation was performed with 8 640 object level windows as samples. On the basis of power failure maintenance records, component replacement records, infrared retest results, and resistance test results, it is divided into four categories: normal, moderate, medium, and serious. Among them are the visible light monomodal model, the visible light – IR bimodal fusion, the fixed weight fusion, the XGBoost multiparameter evaluation, and the quality awareness dynamic fusion model presented in section 4.3. In order to ensure a fair comparison, all methods use the same data division and condition label, and the trend forecast components are uniformly connected to the TCN-GRU prediction heads of the same architecture. Table 7 shows that the visible light monomodal model is struggling to recognize the contact heating and resistance degradation with no apparent external damage, and the Macro-F1 score is only 82.63%; after the introduction of the thermal imaging features, the precision of the condition recognition has increased to 88.95%. Fixed weight fusion is able to utilize electric, vibration, and environment parameters, but unreliable observations caused by thermal reflection, image occlusion, or partial sensor failure retain the same preset contribution to the fused representation. The quality-aware dynamic fusion model instead reduces the contribution of low-quality or invalid modalities according to the quality score and validity tag, achieving a condition recognition accuracy of 95.16%, a health-index MAE of 0.041, a 7-period prediction RMSE of 0.047, and a risk-classification F1 score of 94.12%. Compared with fixed-weight fusion, the accuracy increases from 91.38% to 95.16% and the health-index MAE decreases from 0.068 to 0.041, indicating that the gain is associated with reliability-conditioned fusion rather than the simple addition of multi-source features.

Table 7. Validation Results of Different Aging Condition Assessment Methods

| Evaluation Method                           | Accuracy/% | Macro-F1/% | Kappa | Health Index MAE | 7-Period Forecast RMSE | Risk Classification F1/% |
|---------------------------------------------|------------|------------|-------|------------------|------------------------|--------------------------|
| Visible Light Monomodal Model               | 84.72      | 82.63      | 0.781 | 0.112            | 0.098                  | 81.26                    |
| Visible-Infrared Feature Fusion             | 88.95      | 87.46      | 0.846 | 0.087            | 0.081                  | 86.73                    |
| Fixed-Weight Multi-Parameter Fusion         | 91.38      | 90.21      | 0.884 | 0.068            | 0.069                  | 89.42                    |
| XGBoost Multi-Parameter Evaluation          | 92.47      | 91.36      | 0.899 | 0.059            | 0.061                  | 91.08                    |
| Dynamic Fusion Model for Quality Perception | 95.16      | 94.38      | 0.935 | 0.041            | 0.047                  | 94.12                    |

## 6.4 Cross-Line and Seasonal Generalization Validation

To evaluate the sensitivity of the proposed model to line- and climate-related domain shifts, leave-one-line-out and leave-one-season-out tests were conducted without mixing samples from the target domain into the training set. The model structure and hyperparameters were kept unchanged, and only the training domain was varied. As shown in Table 8, the mean aging-state recognition accuracy across the three line-level holdout tests was 93.06%, with a health-index MAE of 0.054 and a risk-classification F1 score of 91.81%. When the 220 kV line was used as the unseen test domain, the accuracy decreased to 91.96% and the 7-period RMSE increased to 0.066, indicating that differences in voltage level, load characteristics, and equipment configuration introduce a measurable domain shift. Seasonal holdout tests produced a mean accuracy of 93.80%. The largest degradation occurred in the winter subset, where stronger wind and low-temperature conditions increased the health-index MAE to 0.056 and the forecast RMSE to 0.063. These results indicate that the model retains reasonable cross-domain stability but does not eliminate the influence of operating-domain changes. Since the present dataset does not contain sufficiently diverse conductor-material domains, transfer across substantially different conductor materials cannot yet be established. Future extensions will incorporate material and rated-parameter-conditioned normalization, domain-alignment learning, and few-shot fine-tuning of the fusion and prediction layers so that previously learned degradation representations can be transferred to new voltage levels, climatic regions, and conductor types with limited labeled data.

Table 8. Cross-Line and Cross-Season Generalization Results

| Test Domain           | Accuracy/% | Health Index MAE | 7-Period RMSE | Risk F1/% |
|-----------------------|------------|------------------|---------------|-----------|
| 110 kV Line A Holdout | 93.82      | 0.049            | 0.055         | 92.74     |
| 110 kV Line B Holdout | 93.41      | 0.052            | 0.058         | 92.21     |
| 220 kV Line Holdout   | 91.96      | 0.060            | 0.066         | 90.48     |
| Mean of Line Holdout  | 93.06      | 0.054            | 0.060         | 91.81     |
| Spring Holdout        | 94.21      | 0.047            | 0.053         | 93.26     |
| Summer Holdout        | 93.62      | 0.051            | 0.057         | 92.68     |
| Autumn Holdout        | 94.47      | 0.046            | 0.052         | 93.54     |
| Winter Holdout        | 92.88      | 0.056            | 0.063         | 91.72     |

|                          |       |       |       |       |
|--------------------------|-------|-------|-------|-------|
| Mean of Seasonal Holdout | 93.80 | 0.050 | 0.056 | 92.80 |
|--------------------------|-------|-------|-------|-------|

## 6.5 Ablation and Temporal Model Comparison

Ablation experiments were conducted under the same data split, training parameters, and edge hardware configuration to quantify the contribution of the principal components in the lightweight defect detection network and the quality-aware fusion strategy. For defect detection, the bidirectional feature pyramid, coordinate attention, and decoupled detection head were removed separately while the remaining settings were unchanged. As shown in Table 9, removing the bidirectional pyramid reduced mAP@0.5 from 96.05% to 93.88% and mAP@0.5:0.95 from 69.84% to 66.10%, indicating that cross-scale feature interaction is important for small corrosion areas and thin broken strands. Removing coordinate attention reduced the two metrics to 94.62% and 67.21%, respectively, while replacing the decoupled head with a coupled head resulted in 95.03% and 68.12%. The complete network retained an inference time of 16.3 ms, showing that these modules improve detection accuracy with limited additional edge-computing cost.

For the quality-aware fusion strategy, the quality score, validity tag, operating-condition adjustment, and coupled-relation encoding were disabled individually. Table 10 shows that removing the quality score caused the largest deterioration, reducing aging-state accuracy from 95.16% to 92.84% and increasing health-index MAE from 0.041 to 0.058. Without validity tags, the accuracy decreased to 93.27%, indicating that explicit suppression of invalid observations is necessary under intermittent sensing. Removing operating-condition adjustment or coupled-relation encoding also produced consistent degradation in state assessment and risk classification. The complete strategy achieved the best overall results, demonstrating that data reliability regulation, operating-condition adaptation, and cross-modal degradation association provide complementary contributions rather than relying on a single fusion factor.

For the temporal prediction comparison, the upstream quality-aware fusion module, object-level state encoding, input-window length, training/test split, and 7-period prediction horizon were kept unchanged, and only the temporal prediction model was replaced. ARIMA, LSTM, GRU, Transformer, TCN, and TCN-GRU were evaluated using the same health-state sequences. As shown in Table 11, ARIMA produced the largest prediction error because the nonlinear coupling among temperature rise, resistance variation, vibration accumulation, and environmental stress cannot be sufficiently represented by a linear autoregressive structure. LSTM and GRU reduced the 7-period RMSE to 0.061 and 0.057, respectively, while TCN achieved 0.054 by capturing multi-scale local temporal patterns. Transformer further reduced RMSE to 0.052 but required 2.86 M parameters and 8.7 ms per sequence. The TCN-GRU model

obtained the lowest MAE and RMSE of 0.038 and 0.047 with 1.38 M parameters and a 5.4 ms inference time. Compared with standalone TCN and GRU, the combined model improves long-horizon prediction while maintaining moderate computational cost, supporting its use as the temporal prediction component of the proposed framework.

Table 9. Lightweight defect detection network

| Configuration                    | Recall/% | mAP@0.5/% | mAP@0.5:0.95/% | Parameters/M | Inference Time/ms |
|----------------------------------|----------|-----------|----------------|--------------|-------------------|
| Without Bidirectional Pyramid    | 91.42    | 93.88     | 66.10          | 2.5          | 15.4              |
| Without Coordinate Attention     | 92.13    | 94.62     | 67.21          | 2.6          | 15.8              |
| Without Decoupled Detection Head | 93.01    | 95.03     | 68.12          | 2.7          | 15.9              |
| Complete Lightweight Network     | 94.27    | 96.05     | 69.84          | 2.7          | 16.3              |

Table 10. Quality-aware dynamic fusion strategy

| Configuration                          | Accuracy/% | Macro-F1/% | Health Index MAE | 7-Period RMSE | Risk F1/% |
|----------------------------------------|------------|------------|------------------|---------------|-----------|
| Without Quality Score                  | 92.84      | 91.76      | 0.058            | 0.061         | 91.34     |
| Without Validity Tag                   | 93.27      | 92.15      | 0.053            | 0.058         | 91.92     |
| Without Operating-Condition Adjustment | 93.61      | 92.57      | 0.050            | 0.055         | 92.30     |
| Without Coupled-Relation Encoding      | 94.02      | 93.21      | 0.047            | 0.052         | 92.88     |
| Complete Quality-Aware Fusion          | 95.16      | 94.38      | 0.041            | 0.047         | 94.12     |

Table 11. Comparison of Different Temporal Prediction Models

| Temporal Model | 7-Period MAE | 7-Period RMSE | Parameters/M | Inference Time/ms |
|----------------|--------------|---------------|--------------|-------------------|
| ARIMA          | 0.063        | 0.076         | —            | 1.8               |
| LSTM           | 0.050        | 0.061         | 1.21         | 4.8               |
| GRU            | 0.047        | 0.057         | 0.94         | 4.2               |
| Transformer    | 0.043        | 0.052         | 2.86         | 8.7               |
| TCN            | 0.044        | 0.054         | 0.72         | 3.6               |
| TCN-GRU        | 0.038        | 0.047         | 1.38         | 5.4               |

## 6.6 Validation of Visualization Strategy Effectiveness

To evaluate the effectiveness of 3D twin mapping, multidimensional information overlay, and intelligent warning interaction, 24 participants with transmission-line operation and inspection experience were recruited. The group consisted of 15 field inspection technicians and 9 operation-and-maintenance engineers, with an average professional experience of  $6.9 \pm 3.2$  years. All participants had previously used conventional 2D monitoring interfaces, 10 had experience with 3D/GIS-based equipment visualization, and none had used the proposed dynamic overlay interface before the experiment. Five task categories were considered: defect localization, hotspot tracking, historical-state retrieval, risk assessment, and maintenance recommendation selection. For each category, six-line scenarios were balanced in anomaly number, risk-level composition, monitoring-data volume, and evidence complexity. Three senior inspection engineers independently rated scenario difficulty on a five-point scale; no significant difference was found among the scenario sets ( $p=0.78$ ). Interface order was counterbalanced to reduce learning and sequence effects.

The evaluation indicators included anomaly localization time, parameter retrieval time, decision response time, task completion rate, error rate, and NASA Task Load Index (NASA-TLX). Because observations were repeated across participants and scenarios, interface effects on continuous indicators were examined using mixed-effects models with interface condition as a fixed effect and participant and scenario as random effects; pairwise comparisons used Holm-adjusted p-values and 95% confidence intervals. Binary completion and error outcomes were evaluated using corresponding repeated-measure comparisons. As shown in Table 12, compared with the traditional 2D interface, the dynamic overlay strategy reduced anomaly localization time by 57.7 s (95% CI: 50.5–64.9 s,  $p<0.001$ ), parameter retrieval time by 43.8 s (95% CI: 37.9–49.7 s,  $p<0.001$ ), and decision response time by 73.7 s (95% CI: 62.9–84.5 s,  $p<0.001$ ). Task completion increased from 83.3% to 96.5% ( $p=0.004$ ), while the error rate decreased from 9.7% to 2.8% ( $p=0.006$ ). NASA-TLX decreased from 63.4 to 36.2, corresponding to a 42.9% workload reduction (95% CI for the paired difference: 22.0–32.4 points,  $p<0.001$ ). Since NASA-TLX has no universally accepted categorical cutoffs, these scores are interpreted descriptively as a shift from

relatively high workload toward relatively low workload rather than as fixed diagnostic categories. Compared with the static 3D model, the dynamic interface also significantly reduced the three time-based indicators and NASA-TLX ( $p < 0.001$ ), indicating that the observed improvements are not explained solely by introducing a 3D representation. Compared with the static 3D circuit model, the dynamic strategy further reduced the three time-based indicators by 43.9%, 44.9%, and 36.3%, respectively, while increasing the

task completion rate by 6.4 percentage points and decreasing the error rate by 3.3 percentage points. These descriptive differences are consistent with the object-level binding of defect boxes, infrared thermal fields, health indices, and risk trends, which reduces cross-page information retrieval and allows operation and maintenance personnel to locate, compare, and interpret abnormal states through a unified digital-twin object entry.

Table 12. Comparison of the Effectiveness of Different Power Grid Status Visualization Strategies

| Visualization Strategy               | Anomaly Localization Time (s) | Parameter Retrieval Time (s) | Decision Response Time (s) | Task Completion Rate (%) | Error Rate /% | NASA-TLX Load |
|--------------------------------------|-------------------------------|------------------------------|----------------------------|--------------------------|---------------|---------------|
| Traditional 2D Monitoring Interface  | 92.4                          | 68.7                         | 136.5                      | 83.3                     | 9.7           | 63.4          |
| Static 3D circuit model              | 61.8                          | 45.2                         | 98.6                       | 90.1                     | 6.1           | 49.7          |
| Dynamic Overlay Interaction Strategy | 34.7                          | 24.9                         | 62.8                       | 96.5                     | 2.8           | 36.2          |

## 7. Conclusions

In order to meet the challenges of continuously monitoring, evaluating, and visually presenting the aging state of the overhead power line conductors, the built cloud-edge cooperative monitoring system achieves a unified organization of visible, infrared, electric, vibration, and environmental data. The quality-aware dynamic fusion mechanism reduces the influence of occlusion, thermal

reflection, and sensor-data loss on condition assessment, while lightweight defect detection, hotspot extraction, and TCN-GRU trend prediction improve the consistency of defect recognition, health-index estimation, and risk classification. Digital-twin object mapping and layered information overlay reduce anomaly localization, information retrieval, and decision-response time, forming a closed-loop process from multi-source sensing and edge inference to 3D interactive decision support. The line- and season-level holdout evaluations indicate that the framework retains stable performance under moderate domain shifts, although reduced accuracy on the unseen 220 kV line and under winter conditions shows that voltage characteristics and climatic variation still affect generalization. The current dataset remains limited in geographic coverage, extreme-weather samples, long-term degradation labels, and conductor-material diversity; therefore, performance on substantially different materials or regions cannot yet be assumed. Future work will consider domain-aligned representation learning, material- and rated-parameter-conditioned normalization, and few-shot transfer of the fusion and temporal prediction layers, together with

incremental learning and uncertainty calibration, to improve adaptation to new voltage levels, climatic regions, and conductor types.

### Informed Consent

All participants in Section 6.6 are fully aware of the research objectives, procedures, and the right to withdraw at any time. Written informed consent has been obtained from each participant.

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