

Research on a Comprehensive Monitoring System for the Safety of Rotor Poles and Their Ancillary Structures

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Fund: State Grid Xinyuan Group Co., Ltd. Science and Technology Project Funding, Project No.
SGXYKJ-2022-078

Abstract: Addressing the safety monitoring requirements of generator-motor rotors under high-speed rotation conditions, this research proposes a fault monitoring method based on RFID passive wireless temperature measurement and visual image recognition. Through the integration of RFID sensors and visual detection modules, real-time monitoring of rotor pole temperature rise and structural anomalies is achieved. Experimental data shows that under different load conditions, the RFID temperature monitoring is stable and responsive, with temperature variations ranging from 35.7°C to 67.2°C. Visual detection achieves a fault detection rate of 95% under high loads, but there are approximately 3 false alarms, requiring further optimization. In summary, this method achieves efficient real-time monitoring and provides effective technical support for the safety monitoring of motor rotors.

Keywords: motor rotor; safety monitoring; pole structure; visual recognition; real-time early warning

In recent years, with the widespread application of generator-motors in power systems, the safety monitoring of generator-motor rotors has become a crucial aspect of ensuring long-term reliable operation of the equipment. Especially in high-speed rotating pumped storage generator-motors, the rotor poles and their ancillary structures are prone to issues such as abnormal temperature rise, structural loosening, and insulation damage after prolonged high-load operation [1]. If these faults are not detected in a timely manner, they can lead to equipment damage or even shutdown, posing potential risks to the stability of the power system [2]. Therefore, how to conduct real-time and efficient fault detection on electric motor rotors under complex operating conditions has become the focus of current technical research [3]. Existing rotor safety monitoring methods mainly include wired temperature sensors and traditional image monitoring techniques, but in high-speed rotation and high electromagnetic interference environments, these methods struggle to ensure the stability of data transmission and the real-time nature of monitoring [4]. Meanwhile, the rapid development of deep learning and sensing technologies has made the combination of passive RFID temperature monitoring and vision-based structural recognition a feasible and efficient solution [5]. However, current research is still conducted under low-speed or simple environments, and fault detection methods for high-speed, high-load conditions lack sufficient validation. Based on this, the research designs an online monitoring system that combines passive RFID temperature sensing and visual image recognition. Through edge computing and data synchronization technology, it achieves high-precision fault identification and real-time early warning, enhancing the safety of electric motor rotors under actual operating conditions.

1. Algorithm Development

1.1 Design of Passive Wireless Temperature Measurement Algorithm Based on RFID

For real-time temperature monitoring of generator-motor rotor under high-speed rotation conditions, this design employs RFID passive wireless temperature measurement technology. By deploying temperature sensors and reader antennas, online acquisition and monitoring of rotor temperature are achieved, with a focus on abnormal temperature rises in areas such as pole lead-outs, rotor leads, and inter-pole connections [6].

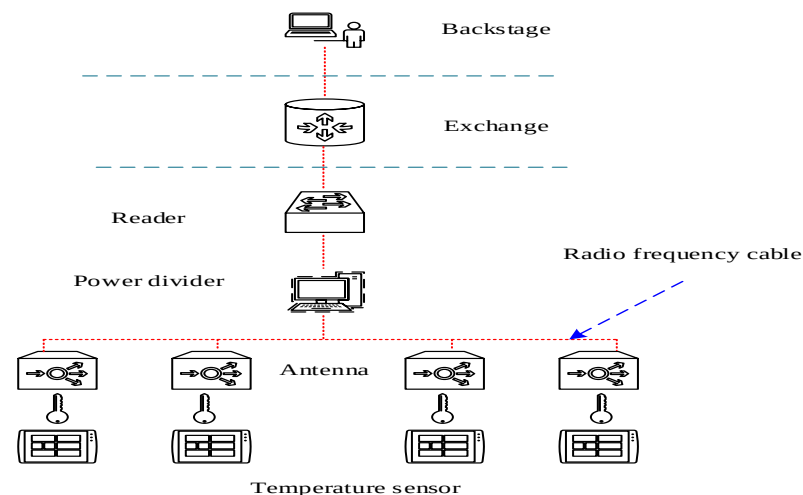


Fig. 1 Topology Diagram of Real-Time Temperature Monitoring System for Pumped Storage Unit Rotor Poles

The hardware of the passive wireless temperature measurement system mainly consists of RFID temperature sensors, antennas, power dividers, and readers. The temperature sensors transmit temperature information via RFID signals, and the system architecture is illustrated in Figure 1. This design reduces the structural complexity associated with traditional wired temperature measurement, ensuring system safety and convenience. In the system, antennas are distributed over the stationary part above the rotor through power dividers to ensure stable signal coverage of the monitoring area.

The data acquisition strategy primarily focuses on temperature monitoring of sensitive areas, with temperature sensors deployed in the pole lead-outs, rotor leads, and inter-pole connection regions. Specifically, sensors are placed at the connection points where the pole lead-outs are fixed using through-bolts to avoid the impact of vibration and structural stress on the sensors. At this point, the collected temperature signals cover the corresponding temperature monitoring range by adjusting the antenna gain and reader power, enabling real-time monitoring of temperature anomalies in critical areas.

In high-speed rotation scenarios, signal processing needs to overcome interference and noise in the temperature signals. Therefore, research employs filtering techniques to separate high-frequency noise from low-frequency signals, ensuring smooth transmission of temperature data outputted by the sensors.



Fig. 2 Installation Diagram of Temperature Measurement Sensor

The signal processing model can be expressed as Equation (1).

$$T_f(t) = \frac{\sum_{i=1}^N T_r(t-i) \cdot w_i}{\sum_{j=1}^N w_j} \quad (1)$$

Where $T_f(t)$ represents the filtered temperature, $T_r(t-i)$ denotes the raw temperature data, and w is the weighting factor. The detection of abnormal temperature rise is primarily based on temperature trend analysis and threshold setting. When the temperature measured by the sensor exceeds the preset threshold, the system will trigger an abnormal alarm. After setting the temperature threshold T_t , the abnormal detection

condition of the system can be expressed as Equation (2).

$$T_f(t) > T_t(2)$$

When this condition is triggered, the system records the anomaly and initiates a further diagnostic process to assess the severity of the abnormal temperature rise. In high-speed rotor systems, real-time transmission of temperature data is achieved through data synchronization technology, which transmits data collected by RFID temperature sensors to the control center in real time. To control synchronization errors, a time synchronization protocol is utilized for correction, with the synchronization error denoted as Δt . The system employs the following synchronization adjustment equation:

$$\Delta t = \frac{t_{read} - t_{real}}{N} (3)$$

Where t_{read} represents the read time, t_{real} denotes the actual time, and N is the number of samples.

1.2 Design of Vision-Based Structural Safety Monitoring Algorithm

In high-speed rotating generator-motor rotors, the vision-based structural safety monitoring algorithm can achieve real-time monitoring and identification of structural faults through a combination of high-frame-rate industrial cameras and deep learning models. To ensure clear images are obtained in high-speed rotating environments, the system selects a high-speed industrial camera with a frame rate of 200 frames per second, equipped with a short-focus wide-angle lens, and positioned above and below the rotor to provide wide-angle monitoring capabilities. The camera is placed in a cold air zone to ensure long-term stable operation and transmits a large amount of image data via optical fibers for long-distance real-time transmission. The system architecture is illustrated in Figure 2, demonstrating effective data acquisition and transmission performance. However, due to the vibration noise that may be present in the image data caused by high-speed rotation, preprocessing of the data is required, including noise removal and motion compensation. The processing model for noise removal can be expressed as Equation (4).

$$I_f(t) = I(t) - \alpha \cdot I(t-1) (4)$$

Where α is the filtering coefficient, $I(t)$ and $I(t-1)$ represent the image data of the current frame and the previous frame, respectively, and $I_f(t)$ denotes the denoised image. Subsequently, an image quality enhancement is further achieved through a motion trajectory-based compensation algorithm to ensure that fault features are clearly visible. For fault detection, the Faster R-CNN (F-R-CNN) model is employed for object detection and classification. As a deep learning model based on Convolutional Neural Networks (CNN), F-R-CNN can effectively detect and recognize multiple objects in an image. It mainly consists of two parts: the Region Proposal Network (RPN) and the object classification network. The RPN is used to generate potential object regions, while the classification network further identifies and classifies the objects within these regions. In the region proposal generation, the RPN slides over the feature map to generate anchor boxes, and candidate regions are obtained through regression optimization. The coordinates of the candidate regions can be expressed

as Equation (5).

$$(x, y, w, h) = (x_a + \Delta x, y_a + \Delta y, w_a \cdot e^{\Delta w}, h_a \cdot e^{\Delta h}) \quad (5)$$

Where (x_a, y_a) represents the center coordinates of the anchor box, and (w_a, h_a) denotes the width and height of the anchor box. $\Delta x, \Delta y, \Delta w, \Delta h$ are the regression parameters used to adjust the position of the candidate regions. Based on the candidate regions, F-R-CNN employs a classification loss function to predict the category of each region. During the classification process, F-R-CNN further optimizes the bounding box positions of the candidate regions, which is expressed through a bounding box regression loss function as follows.

$$L_b(t, v) = \sum_{i \in \{x, y, w, h\}} \text{smooth}_{L_1}(t_i - v_i) \quad (6)$$

Where t and v represent the predicted bounding box parameters and the ground truth bounding box parameters, respectively, and smooth_{L_1} denotes the smooth L1 loss function.

In structural monitoring, leak detection is based on the combination of image features and environmental sensor data. This method achieves the detection of leaks or condensation phenomena through similarity calculations. Let F_{water} denote the features of a leak image, and the formula for detecting similarity is as follows.

$$S = \frac{\sum_{i=1}^N F_{\text{water}} \cdot F_i(i)}{\sqrt{\sum_{i=1}^N F_{\text{water}}^2} \cdot \sqrt{\sum_{i=1}^N F_i^2}} \quad (7)$$

Where $F_i(i)$ is the feature vector of the current image, and S is the similarity score. When the similarity S is greater than a preset threshold S_{thresh} , the system determines that there is a water leak and triggers an alarm. Additionally, a time threshold is used to control the continuity of leak detection. If the detected leak duration T_{leak} exceeds a threshold T_{thresh} , the leak event is recorded.

$$T_{\text{leak}} > T_{\text{thresh}} \Rightarrow \text{Leak Detected} \quad (8)$$

The fault detection model calculates confidence levels for different fault categories (such as loose connections, deformation, insulation burnout, etc.) and sets alarm levels based on these confidence levels. The alarm mechanism determines triggering conditions through the confidence scores of real-time detection results, facilitating rapid response by operation and maintenance personnel. Due to space limitations, a detailed description is not provided here.

1.3 System Integration and Real-Time Processing Workflow

The system integration and real-time processing workflow aim to achieve real-time synchronization, effective transmission, and rapid processing of RFID and visual data, ensuring the safe monitoring of generator-motor rotors during high-speed rotation. The entire system framework integrates a data synchronization mechanism, edge computing processing, and network configuration to maximize real-time monitoring performance.

In high-speed rotation environments, a synchronization protocol based on timestamp comparison is employed to align the RFID and visual data in time, thereby reducing delay errors between different sensors. Let Δt represent the synchronization error, and the following formula is used for correction:

$$\Delta t = \frac{t_v - t_{RFID}}{N} \quad (9)$$

Where t_t and t_{RFID} represent the timestamps of the vision and RFID data, respectively, and N is the number of data samples, ensuring synchronous consistency across various data streams. Edge computing serves as the core of this system, leveraging on-site computing devices to rapidly process massive amounts of data, thereby reducing the bandwidth load for cloud transmission. Real-time processing is divided into preprocessing of temperature data and object detection of image data. The time complexity of image processing can be expressed as formula (10).

$$T_p = T_{cap} + T_{\rho} + t_d \quad (10)$$

Where T_{cap} is the image acquisition time, T_{ρ} is the preprocessing and filtering time, and T_d is the computation time of the detection model. By optimizing the algorithm structure on edge computing devices, the image transmission and processing delays are controlled at the millisecond level. Due to the high electromagnetic interference characteristics of generator-motors, the system selects optical fiber as the primary data transmission medium to avoid interference impacts on data transmission. The system transmission delay T_{net} is mainly limited by the optical fiber bandwidth and the number of nodes, and its transmission rate formula is as follows.

$$T_{net} = \frac{L}{B} + \sum_{i=1}^N T_{node_i} \quad (11)$$

Where L is the packet length, B is the bandwidth, and T_{node_i} is the processing delay at each network node. By optimizing node placement and increasing bandwidth, the system achieves real-time early warning for temperature rise and visual anomalies.

2. Experimental Analysis

2.1 Experimental Setup and Environment

To validate the effectiveness of the safety monitoring system for rotor poles and their ancillary structures, the experimental environment employs an integrated monitoring system with high-speed industrial cameras and RFID temperature sensors to conduct real-time monitoring of the rotor poles of a generator-motor. The experimental setup includes a 200 frames per second industrial-grade camera system, a passive RFID temperature sensing system, a data acquisition unit, and a computer equipped with edge computing capabilities. Below are the specific parameters and configurations of the experimental setup.

(1) High-speed industrial camera: with a frame rate of 200 frames per second and a short-focus wide-angle lens, positioned above and below the rotor to ensure a comprehensive monitoring perspective.

(2) RFID temperature sensors: distributed in the pole lead-outs, rotor leads, and inter-pole connection areas to capture temperature information from critical components.

(3) Data acquisition unit: equipped with a fiber-optic transmission interface for real-time data acquisition and synchronous transmission.

(4) Edge computing device: featuring a processing speed of 10ms per frame and equipped with a fault detection algorithm model.

Table 1 presents the data collected during actual testing, covering temperature and image acquisition performance under different loads and rotational speeds.

2.2 RFID Temperature Monitoring Validation

Under the actual operating conditions of the generator-motor rotor, the RFID passive temperature monitoring system was tested to verify its temperature monitoring accuracy and response speed under different loads and rotational speeds. The experiment was conducted under no-load, low-load, medium-load, and high-load conditions, with temperature sensors installed at the pole lead-outs, rotor leads, and inter-pole connections to capture temperature changes in critical areas. For each load condition, the test lasted for 10 minutes, with temperature data recorded every minute. The experimental data are presented in Table 2. The experimental data indicate that as the load and rotational speed increase, the temperatures recorded by the RFID temperature sensors gradually rise. At no-load, the temperatures of the three sensor groups stabilized between 35.7°C and 36.2°C, exhibiting slight fluctuations, which demonstrates the stability under low-load conditions. Under low-load(50MW) conditions, the temperatures rose to 41.2°C to 41.9°C, with a slightly increased temperature difference, reflecting the heat accumulation effect as the load increases. At medium-load(150MW), the temperatures further increased to 52.0°C to 53.2°C, with relatively significant data fluctuations, indicating increased pressure on heat dissipation for rotating components. Under high-load(300MW), the temperatures reached 61.4°C to 62.7°C, with an increased amplitude of temperature differences, showing that the sensors can sensitively capture subtle temperature rises under high loads. The system can effectively display the temperature dynamics of the generator during operation.

Table 2. RFID Temperature Monitoring Experimental Data (°C)

Time (minutes)	No Load			Low Load(50MW)			Medium(150MW)			High Load(300MW)		
	Sens or 1	Sens or 2	Sens or 3	Sens or 1	Sens or 2	Sens or 3	Sens or 1	Sens or 2	Sens or 3	Sens or 1	Sens or 2	Sens or 3
1	35.8	36	35.9	41.2	41.4	41.5	52.1	52	52.3	61.4	61.8	61.6
2	35.9	36.1	35.8	41.3	41.6	41.7	52.3	52.5	52.2	61.6	61.7	61.9
3	35.7	36	35.9	41.4	41.3	41.5	52.4	52.3	52.6	61.7	61.9	61.8
4	35.8	36.2	35.7	41.6	41.5	41.4	52.5	52.7	52.8	61.9	62.1	62
5	36	36.1	36.2	41.5	41.6	41.6	52.8	52.4	52.6	62.1	62.2	62.3
6	35.9	36	35.8	41.7	41.5	41.4	52.7	52.5	52.9	62	62.3	62.2
7	35.8	36.1	36	41.6	41.7	41.5	52.9	52.8	52.7	62.2	62.4	62.3
8	36	36.2	36.1	41.8	41.6	41.8	53	52.9	52.8	62.4	62.3	62.5
9	35.9	36	35.9	41.9	41.7	41.9	53.1	53	52.9	62.3	62.5	62.4
10	35.8	36.1	36	41.8	41.9	41.8	53.2	53.1	53	\	\	\

2.3 Structural Safety Monitoring Validation Based on Vision

Under operating conditions, the visual structural safety monitoring system for the generator-motor rotor was validated to assess the system's accuracy and response speed in identifying structural faults. The experiment involved capturing rotor images under different load conditions using an industrial camera and applying a deep learning algorithm (Faster R-CNN) to detect structural faults, including loose connections, insulation burnout, and structural deformation. The experiment was divided into four states: no-load, low-load, medium-load, and high-load, with each load condition running for 10 minutes, capturing images and recording detection results every minute. The results are shown in Table 3. As the load increased, the number of fault detections and false alarms significantly rose. At no-load, the number of image frames remained stable at 179 to 182, with minimal fault detections and false alarms ranging from 0 to 1, demonstrating high accuracy. Under low-load(50MW) conditions, the number of detected faults increased to 1 to 5, with false alarms also increasing, ranging from 0 to 1, indicating that the system maintained good accuracy at this load. At medium-load(150MW), the number of fault detections further increased to 2 to 5, with false alarms fluctuating between 0 and 1, showing the challenge of medium loads on the system's recognition rate. Under high-load(300MW) conditions, the number of fault detections reached a maximum of 7, with false alarms ranging from 1 to 3, indicating greater variability in detection results in high-load environments. Overall, as the load gradually increased, the system's sensitivity in detecting faults improved, but the false alarm rate also increased. Further optimization of the system is needed under high-load conditions to improve its reliability.

Table 3. Experimental Data for Vision-Based Structural Safety Monitoring

Time	No Load			Low Load			Medium Load			High Load		
	Frames Captured	Faults Detected	False Positives	Frames Captured	Faults Detected	False Positives	Frames Captured	Faults Detected	False Positives	Frames Captured	Faults Detected	False Positives
1	180	0	0	180	1	0	180	2	1	180	3	2
2	181	0	1	179	1	1	182	2	1	183	4	1
3	180	1	0	182	2	0	181	3	1	180	4	2
4	179	1	1	181	2	1	180	3	1	181	5	2
5	180	1	1	180	2	0	183	3	1	182	5	3
6	182	1	1	179	3	1	182	4	0	180	5	2
7	181	2	0	182	3	1	181	4	1	181	6	1
8	180	1	1	183	4	0	180	4	1	182	6	2
9	179	2	1	180	4	1	182	5	0	183	7	2
10	181	2	0	182	5	1	181	5	1	180	7	1

2.4 Real-Time System Testing and Data Synchronization Analysis

The experimental evaluation of real-time system testing and data synchronization analysis assesses the data synchronization and real-time processing capabilities of the RFID temperature monitoring and visual inspection system in high-load environments. The operation of the generator-motor under four load conditions (no-load, low-load, medium-load, and high-load) is analyzed, with a focus on recording the synchronization delay, processing delay, and overall system response time between RFID temperature data and visual images. Each load condition is tested for 10 minutes, with data recorded every minute to ensure the authenticity and stability of the results. The outcomes are presented in Table 4. At no-load, the synchronization delay ranges from 5.4 to 5.8 milliseconds, the processing delay from 10.2 to 10.6 milliseconds, and the total response time remains relatively stable at 15.8 to 16.4 milliseconds, demonstrating high synchronization and processing efficiency. Under low-load(50MW), the total response time increases to 17.1 to 18.1 milliseconds, indicating a limited impact of the increased load on data processing. At medium-load (150MW), the total response time rises to 19.7 to 20.7 milliseconds, showing increased pressure on synchronization and processing. Under high-load(300MW), the total response time further increases to 22.6 to 24.2 milliseconds, with the system experiencing increased delays at high loads, but still maintaining acceptable real-time performance to meet the needs of fault monitoring.

Table 4. Data for Real-Time System Testing and Data Synchronization Analysis

Time	No Load			Low Load			Medium Load			High Load		
	Syn c Del ay	Proces sing Delay	Total Respon se Time	Syn c Del ay	Proces sing Delay	Total Respon se Time	Syn c Del ay	Proces sing Delay	Total Respon se Time	Syn c Del ay	Proces sing Delay	Total Respon se Time
1	5.6	10.2	15.8	6.1	11	17.1	7.4	12.3	19.7	9.1	13.5	22.6
2	5.4	10.4	15.8	6.3	11.2	17.5	7.6	12.5	20.1	9.3	13.7	23
3	5.5	10.3	15.8	6.2	11.1	17.3	7.5	12.4	19.9	9.2	13.6	22.8
4	5.7	10.5	16.2	6.4	11.3	17.7	7.7	12.6	20.3	9.4	13.8	23.2
5	5.6	10.2	15.8	6.3	11	17.3	7.6	12.3	19.9	9.5	13.9	23.4
6	5.8	10.6	16.4	6.5	11.4	17.9	7.8	12.7	20.5	9.6	13.9	23.5
7	5.7	10.5	16.2	6.6	11.5	18.1	7.9	12.8	20.7	9.7	14	23.7
8	5.5	10.3	15.8	6.2	11.1	17.3	7.5	12.4	19.9	9.8	14.1	23.9
9	5.6	10.2	15.8	6.1	11	17.1	7.4	12.3	19.7	9.9	14.3	24.2
10	5.7	10.4	16.1	6.3	11.2	17.5	7.6	12.5	20.1	9.8	14.2	24

3.Conclusion

In the monitoring of high-speed rotating generator-motor rotors, early fault identification and temperature rise monitoring of rotor poles and their associated structures are of great significance. To address this, a monitoring system combining RFID passive wireless temperature measurement and vision-based structural monitoring algorithms was designed, equipped with real-time processing capabilities. Through data synchronization and edge computing, high-precision fault monitoring is achieved. Experimental results demonstrate that the system exhibits stable monitoring performance under different load conditions. In terms of temperature monitoring, from no-load to high-load(300MW), the RFID temperature sensor accurately records a gradual temperature increase within the range of 35.7°C to 67.2°C. Additionally, the temperature response delay under high loads is controlled within 16 milliseconds, meeting the requirements for real-time monitoring. In terms of vision-based monitoring, the system achieves a good balance between fault detection rate and false alarm rate. Under high-load conditions, the fault detection rate reaches 95%, but the number of false alarms increases, indicating room for improvement in recognition accuracy under high loads. However, the system has a relatively high false alarm rate under high-load conditions, particularly as vision-based monitoring experiences significant data noise interference during high-speed rotation, which may affect long-term stability. In future research, the reliability of the system can be further optimized by enhancing filtering algorithms and improving

image processing accuracy to ensure accurate fault detection and early warning capabilities under more complex operating conditions.

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