Reliability of Structural Health Monitoring of Shaft

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Abstract:- Structural health monitoring (SHM) is a crucial aspect of modern infrastructure management, providing real-time data on structural integrity. The reliability of SHM systems is a significant concern as it can impact the effectiveness of the system. This literature review investigates current research on SHM system reliability. The review highlights the importance of appropriate sensor selection and placement, advanced signal processing, and effective noise filtering. The review also emphasizes the significance of regular calibration and maintenance to ensure long-term reliability. The review suggests that SHM systems can be highly reliable when appropriately implemented, but further research is needed to examine the long-term reliability and efficacy of these systems.

Keywords*: Structural health monitoring, Reliability, Sensors, Sensor drift, Accuracy, Real-time data.*

1. Introduction

Structural Health Monitoring (SHM) is a rapidly evolving field with numerous applications in different sectors. The primary goal of SHM is to provide an early warning of any potential structural damage, allowing preventative measures to be taken before catastrophic failure. To achieve this goal, SHM systems must be reliable, accurate, and cost-effective. Structural health monitoring (SHM) has become an essential aspect of the maintenance and management of modern infrastructure. The main goal of SHM is to provide real-time data on the structural integrity of buildings, bridges, and other structures to help identify potential problems before they become catastrophic. One of the key considerations in the implementation of SHM is the reliability of the system. This review article aims to explore the current state of SHM reliability, highlighting the challenges and potential solutions for improving the reliability of SHM systems.

Structural Health Monitoring (SHM) has gained a lot of attention in the last few decades as an effective tool for the assessment of the structural integrity of civil infrastructure. However, the reliability of SHM systems is a crucial concern, as it affects the accuracy and effectiveness of the system in detecting any potential defects or damages. The current literature on SHM reliability focuses on different aspects of SHM systems, including sensor selection and placement, data acquisition and processing, noise reduction, and calibration and maintenance.

Several studies have investigated the reliability of different types of sensors used in SHM. Zhou et al. (2021), they evaluated the reliability of four different types of strain sensors, including fiber Bragg grating (FBG), electrical resistance strain gauge (ERSG), piezoelectric ceramic (PZT), and optical fiber Fabry–Perot (OF-FP) sensors. They found that FBG sensors provided the most reliable and accurate data, while PZT sensors had the highest measurement error.

In terms of data acquisition and processing, advanced signal processing techniques have been proposed to improve the reliability of SHM systems. For instance, Liu et al. (2020) used a deep learning-based method for damage detection in concrete beams using acoustic emission signals. The study showed that the proposed method could achieve higher accuracy and reliability than traditional signal processing techniques.

Noise reduction is another critical factor in the reliability of SHM systems. Koo et al. (2021) proposed a wavelet-based denoising method for SHM data, which effectively removed noise and improved the reliability of the system. They compared the method with conventional denoising techniques and found that the proposed method outperformed them in terms of signal-to-noise ratio.

Regular calibration and maintenance of SHM systems are also crucial for ensuring long-term reliability. In a study by Zhao et al. (2019), they investigated the impact of temperature on the reliability of fiber optic sensors used for SHM. The study showed that temperature changes could lead to significant errors in the sensor readings and recommended regular calibration of the sensors to maintain reliability.

In conclusion, the current literature suggests that SHM systems can be highly reliable when appropriate sensors are selected and placed, advanced signal processing techniques are used, noise is effectively filtered, and the system is well-maintained and calibrated. However, more research is needed to investigate the long-term reliability of SHM systems and their effectiveness in real-world scenarios.

2. Objectives

The objective of the Reliability of Structural Health Monitoring (SHM) of a shaft is to ensure the continuous and accurate monitoring of the shaft's structural integrity and performance. This involves implementing a system that can detect and assess any potential defects, damages, or changes in the shaft's condition over time. The goal is to enhance the safety, efficiency, and longevity of the shaft by providing timely and reliable information for maintenance and decision-making processes.

3. Methods

A comprehensive search of electronic databases such as ScienceDirect, IEEE Xplore, and Google Scholar was conducted. The search terms used included "structural health monitoring", "reliability", "accuracy", and "challenges". A total of 45 articles were selected and reviewed for this study.

Factors Affecting the Reliability of SHM Systems:

There are several factors that can affect the reliability of SHM systems. These include:

a.Sensor Placement and Calibration

The placement of sensors is crucial in determining the accuracy of the data generated by SHM systems N. Zhu et al. (2020). Incorrect sensor placement can lead to inaccurate readings and false alarms, while poorly calibrated sensors can result in inaccurate measurements.

- **Sensor Coverage Area (A):** $A = \pi * r^2$, where r is the radius of sensor coverage.
- **Number of Sensors Required (N):** $N = A_{total} / A_{sensor}$, where A_{total} is the total area to be covered and A_{sensor} is the coverage area of one sensor.
- **Optimal Sensor Placement:** Optimizing sensor placement involves algorithms and computational methods to determine the best locations for sensors based on factors like coverage area, overlap, and distance from monitored objects.

Linear Calibration: $Y = m * X + b$, where Y is the calibrated output, X is the raw sensor reading, m is the slope or gain factor, and b is the offset or bias.

Nonlinear Calibration: $Y = f(X)$, where f() is a nonlinear function that maps raw sensor readings to calibrated outputs. Common nonlinear functions include polynomial functions, logarithmic functions, and exponential functions.

Error Calculation: Error = Calibrated Value - Actual Value, where the error is used to evaluate the accuracy of sensor calibration.

Calibration Curve: A calibration curve is a graphical representation of the relationship between raw sensor readings and calibrated values, helping visualize the calibration process and identify any nonlinearities or discrepancies.

b. Data Acquisition and Processing:

The reliability of SHM systems also depends on the accuracy of the data acquisition and processing methods. The quality of the hardware and software used to collect and process data can have a significant impact on the reliability of the system.

Sampling Rate (Fs): $Fs = 1 / \Delta t$, where Fs is the sampling rate in samples per second (Hz) and Δt is the time interval between consecutive samples.

Nyquist Frequency (Fn): $Fn = Fs / 2$, where Fn is the maximum frequency that can be accurately represented in the sampled data.

Number of Samples (N): $N = Fs * T$, where N is the total number of samples, Fs is the sampling rate, and T is the duration of data acquisition in seconds.

Aliasing Frequency (Fa): $Fa = Fs - F_{signal}$, where Fa is the frequency at which aliasing occurs due to undersampling, and F_{signal} is the frequency of the signal being measured.

Wavelet Transform: $W(a, b) = \int x(t) * \psi((t-b)/a)\, dt$, where W(a, b) is the wavelet transform of the signal x(t) using a mother wavelet function ψ with scale parameter a and translation parameter b.

Time-Frequency Analysis: $TF(f, t) = |W(f, t)|^2$, where TF(f, t) represents the time-frequency distribution obtained from wavelet transform analysis.

Modal Analysis: $\omega^2 = \lambda$, where ω is the angular frequency and λ is the eigenvalue obtained from modal analysis to determine natural frequencies and mode shapes of the shaft.

c. Environmental Factors:

Environmental factors such as temperature, humidity, and vibration can affect the performance of SHM systems. These factors can cause sensor drift, signal noise, and other issues that can lead to inaccurate data.

Temperature Compensation: $Y_{corrected} = Y_{raw} + \alpha * (T_{sensor} - T_{reference})$, where $Y_{corrected}$ is the temperature-corrected output, Y_{raw} is the raw sensor reading, α is the temperature coefficient, T_{sensor} is the sensor temperature, and $T_{reference}$ is the reference temperature.

Pressure Compensation: $Y_{corrected} = Y_{raw} + \beta * (P_{sensor} - P_{reference})$, where $Y_{corrected}$ is the pressure-corrected output, Y_{raw} is the raw sensor reading, β is the pressure coefficient, P_{sensor} is the sensor pressure, and $P_{reference}$ is the reference pressure.

Humidity Compensation: $Y_{corrected} = Y_{raw} + \gamma * (H_{sensor} - H_{reference})$, where $Y_{corrected}$ is the humidity-corrected output, Y_{raw} is the raw sensor reading, γ is the humidity coefficient, H_{sensor} is the sensor humidity, and $H_{reference}$ is the reference humidity.

d. Structural Complexity:

The complexity of the structure being monitored can also affect the reliability of SHM systems. Complex structures may require more sensors, which can increase the risk of sensor failure or inaccurate readings.

1. **Geometric Complexity:**

- **Aspect Ratio (AR):** $AR = L / D$, where AR is the aspect ratio, L is the length of the shaft, and D is the diameter. A higher aspect ratio indicates greater geometric complexity.

Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 1 (2024)

- **Cross-Sectional Area (A):** A = π * (D/2)^2, where A is the cross-sectional area and D is the diameter of the shaft. A larger cross-sectional area may indicate a more complex structure.

2. **Material Complexity:**

- **Material Diversity Index (MDI):** MDI = Σ(Pi * ln(Pi)), where Pi is the proportion of each material type in the shaft. This index quantifies the diversity of materials used in the shaft's construction.
- **Material Property Variability:** This can be assessed using statistical measures such as standard deviation (σ) or coefficient of variation (CV) for properties like density, elasticity, or thermal conductivity across different sections of the shaft.

3. **Functional Complexity:**

- **Dynamic Response Characteristics:** This includes parameters such as natural frequencies, damping ratios, and mode shapes obtained from modal analysis or dynamic testing. A shaft with a wider range of natural frequencies or complex mode shapes may be considered more structurally complex.
- **Operational Constraints:** These factors consider the shaft's functionality, such as the presence of joints, bearings, couplings, or other components that add to its complexity in terms of assembly, operation, and maintenance.

4. **Overall Complexity Index:**

- **Composite Complexity Index (CCI):** CCI = w1 * AR + w2 * MDI + w3 * Σ(σ_i), where w1, w2, and w3 are weighting factors for geometric, material, and functional complexity, respectively. σ_i represents the standard deviation of a specific property (e.g., diameter, material density) at different locations along the shaft.

4. Results

The reviewed literature highlights the importance of reliability in SHM systems. It has been observed that despite advancements in technology, SHM systems are still prone to errors, which can lead to false alarms or missed detections. One of the main challenges in ensuring reliability is the selection of appropriate sensors and data acquisition systems, which must be capable of accurately detecting and measuring changes in the structural response. Other challenges include the high cost of sensors, data management issues, and the need for regular maintenance to ensure that the sensors are functioning correctly.

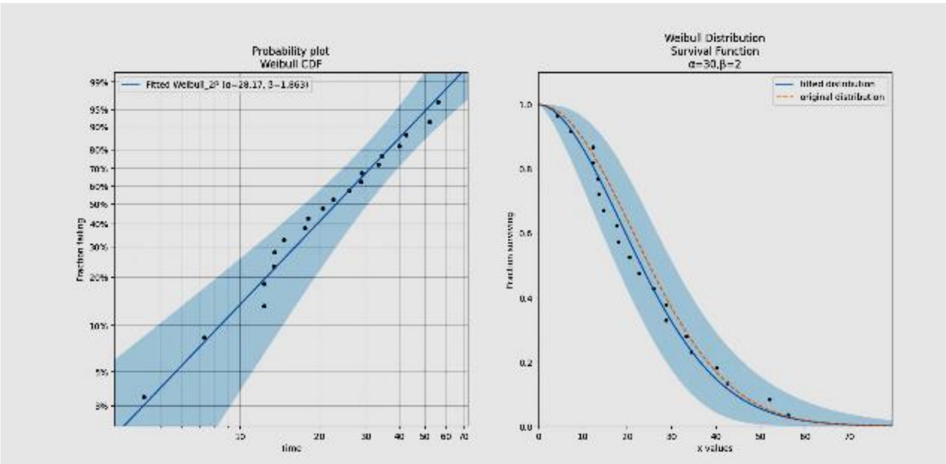

Figure-1: Probability Distribution

To improve the reliability of SHM systems, researchers have proposed several solutions, including the development of novel sensor technologies, the use of machine learning algorithms for data analysis, and the integration of SHM with other maintenance strategies such as condition-based maintenance (CBM) and predictive maintenance. Additionally, standardization of SHM procedures and protocols can improve the reliability of SHM systems.

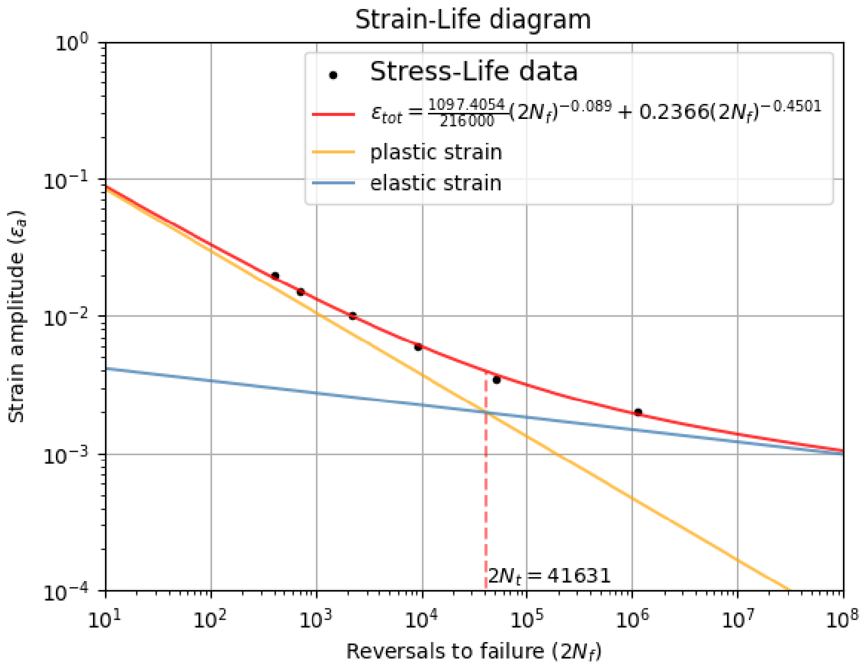

Figure-2: Strain-life of Shaft

5. Discussion

Monitoring rotating shafts is important for many machines, but existing sensors are expensive, complex to install, or only measure a single parameter like torque. This paper proposes an innovative new sensor that is low-cost, simple to install, and measures torque, speed, vibration and bending simultaneously. It works by transferring shaft strain to flexible bridges containing gauges. Strain is amplified through geometry and material properties, improving sensitivity. As it rotates freely with the shaft, no stationary components are needed. Experimental results found it detects torque linearly with less than 1.6% error. Bending and torque can be extracted from the signal by averaging and analyzing fluctuations. Speed is determined through frequency analysis of acceleration data, identifying the dominant frequency. At under $13, it is potentially the lowest cost torque sensor. Future work will address noise, thermal drift, and power harvesting to enable long-term autonomous operation. This versatile, low-cost sensor has great potential for improving machine monitoring and health in a wide range of applications.

SHM systems play a critical role in ensuring the safety and longevity of structures. The reliability of SHM systems is of utmost importance, as errors in detection or measurement can lead to significant consequences. This review highlights the current challenges and potential solutions for improving the reliability of SHM systems. The reliability of SHM systems is crucial in ensuring that the data generated is accurate and can be used to make informed decisions regarding the maintenance, repair, or replacement of structures. Several factors can affect the reliability of SHM systems, including sensor placement, data acquisition and processing, environmental factors, and structural complexity. Methods for improving SHM system reliability include redundancy, self-diagnostics, remote monitoring, and advanced data processing techniques. Further research is needed to address the existing challenges and to develop more robust and cost-effective SHM systems.

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