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Predictive Maintenance of Flexible Pipe Connectors in Parabolic Trough Collectors Using Artificial Neural Networks

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Abstract. In parabolic trough solar power plants, flexible pipe connectors, specifically Rotation and Expansion Performing Assemblies (REPAs), are critical yet failure-prone components due to their exposure to thermal cycling, mechanical stress, and harsh environmental conditions. This study focuses on the Rotary Flex Hose Assembly (RFHA), one common REPA type. Unexpected RFHA malfunctions, such as leaks in swivel joints, can lead to costly downtime and safety hazards. Despite regular preventive maintenance, current strategies often fail to anticipate such failures early enough to prevent disruption. This study investigates whether vibration analysis, combined with machine learning, can provide early warnings of RFHA degradation. A convolutional neural network (CNN) was trained to detect pre-failure conditions using spectrogram comparisons derived from high-frequency vibration data collected during an accelerated life-cycle test campaign. Structural Similarity Index (SSIM) values were used to quantify differences between twin RFHA vibration patterns over time. The model successfully predicted failures up to 1,000 cycles in advance, equivalent to more than two years of lead time in field operation, achieving an overall accuracy of 0.93 and a precision of 1.0, indicating that all predicted failure events were correct and no false positive alarms were generated. These results demonstrate that SSIM-based vibration comparison and CNN classification can provide a robust foundation for predictive maintenance of RFHAs, offering a scalable solution for enhancing the reliability of CSP plant operation.

Keywords: Vibration Analysis, Rotary Flex Hose Assembly, Concentrated Solar Power, Neural Network, Machine Learning, Predictive Maintenance

1. Introduction

The global transition to renewable energy sources is important to mitigate climate change, aiming to reduce greenhouse gas emissions significantly and uphold the goals of the Paris Agreement [1]. Concentrating Solar Power (CSP) systems, particularly Parabolic Trough Collectors (PTC), have emerged as mature and commercially viable technologies, capable of generating electricity sustainably and reliably due to their inherent capability for thermal energy storage [2], [3].

Within the PTC systems, the Rotation and Expansion Performing Assembly (REPA) is identified as a critical and vulnerable component. REPAs connect the stationary field piping to the rotating absorber tubes, enabling rotational and translational movements caused by sun tracking and thermal expansion. Operating continuously under demanding conditions, including high temperatures around 400 ℃, pressures up to 35 bar, and cyclic mechanical loads, REPAs often experience failures, manifesting as leakages of hot heat-transfer fluids (HTF). Such failures can lead to serious operational disruptions, safety hazards such as fires, and considerable financial losses due to unscheduled maintenance and downtime [4]. Two REPA designs are widely used in PTCs: rotary flex hose assemblies (RFHAs) and ball-joint assemblies (BJAs). In this work, primarily RFHAs were studied.

Maintenance strategies for REPAs in current practice are primarily based on preventive maintenance, relying heavily on fixed intervals and routine inspections. However, preventive strategies often lead to unnecessary replacements or overlook early-stage component degradation, thus incurring extra costs and/or reducing operational reliability. Predictive maintenance addresses these shortcomings by continuously monitoring the component conditions and forecasting potential failures before their occurrence [5]. Vibration analysis techniques, such as Fourier Transform and Short-Time Fourier Transform (STFT), have proven effective in identifying early indicators of mechanical degradation in various industrial applications [6], [7].

This paper builds upon previous investigations on vibration-based condition monitoring of REPAs in CSP plants [8], specifically by developing a predictive maintenance framework. An accelerated life-cycle testing methodology was employed using a specially designed REPA test rig, simulating long-term operational conditions within weeks. Vibration signals were continuously recorded, processed into spectrograms via STFT, and analyzed using a convolutional neural network trained to differentiate between normal and pre-failure operational states.

2. Experimental Setup

2.1 REPA Test Rig

In this study, exclusively RFHAs, one of the two main types of REPAs, were studied. To achieve the goal of predictive maintenance through vibration analysis, comprehensive lifecycle vibration data of the RFHAs was required. However, collecting real-time lifecycle data from actual parabolic trough collector (PTC) systems is impractical, given that a typical REPA operational lifetime is expected to be about 25–30 years. Thus, an accelerated lifecycle testing method was implemented using a specially designed REPA test rig at the Plataforma Solar de Almería (PSA).

The test rig realistically simulated the operational conditions encountered by RFHAs in the field, including high temperatures ($\sim$ 390 ℃), pressures of approximately 35 bar, and cyclic mechanical stresses. Two RFHAs were tested simultaneously, mirroring the real-life configuration within a PTC, allowing approximately 570 cycles per day.

The test rig (see Figure 1) was comprised primarily of four components: a hydraulic kinematic unit, a traverse mechanism, the HTF cycle, and two RFHA fixtures. The hydraulic system provided precise rotational and translational movements that replicated daily sun-tracking and thermal-expansion-induced movements typically experienced by RFHAs. Specifically, rotational movements simulated continuous sun-tracking, while translational movements represented thermal expansion cycles ($\sim$ 500 mm) occurring each day.

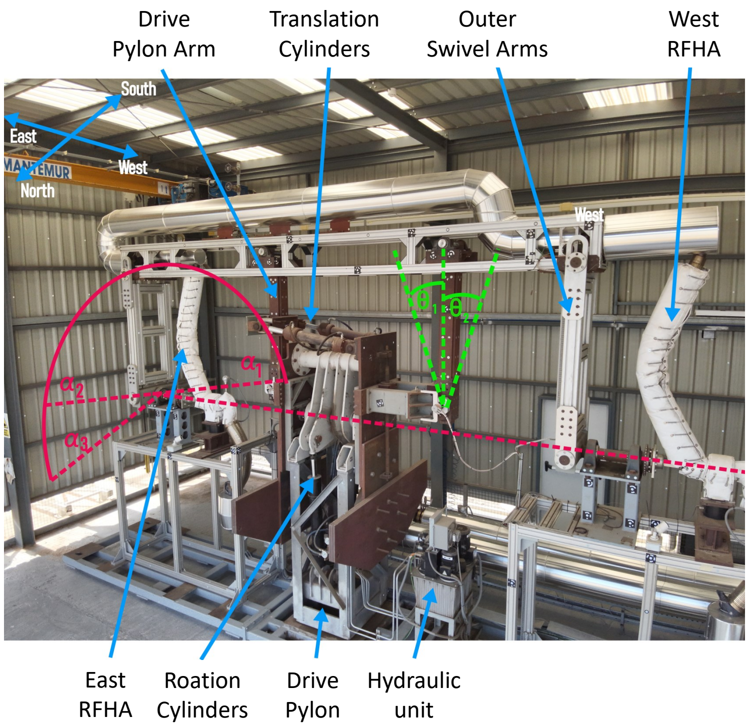

Figure 1. *Overview of the REPA test rig used for accelerated life-cycle testing.*

Each RFHA consisted of three main components: a flexible metal hose, a swivel joint allowing rotation, and a torque sword designed to transmit rotational motion. The swivel joint was installed stationary on the test rig's table, with the flexible metal hose connected to the traverse, enabling precise simulation of real operational stresses.

2.2 Vibration Data Acquisition

Vibration measurements were continuously recorded during the accelerated RFHA test campaign using piezoelectric accelerometers (PCB-(M)320C52, PCB Piezotronics). These sensors provided a sensitivity of 1.02 mV m^{-1} s^{-2} and sampling rates up to 10 kHz.

Vibration sensors were installed on the lower section of each RFHA, between the swivel joint and the flexible metal hose. Thermal insulation surrounding the metal hose was partially removed in the sensor installation region to facilitate direct attachment and accurate vibration capture without sensor overheating. During the campaign, approximately 13,700 accelerated operational cycles were completed. Assuming one cycle per day in real parabolic trough collector operation, this corresponds to roughly 37 years of equivalent service time. This exceeds the typical REPA lifetime of around 10,000 cycles ($\approx$ 25–30 years), ensuring that full life-cycle behavior, including failure events, is captured. Throughout the campaign, vibrations were continuously monitored.

3. Methodology

3.1 Data Processing

Raw vibration data, collected continuously by accelerometers at a sampling rate of 10 kHz, required segmentation into discrete rotational cycles. Cycle boundaries were identified using rotation-angle data recorded by the Supervisory Control and Data Acquisition (SCADA) system of the test rig, with cycles defined between the rotation angle's minimum and maximum positions. Margins were implemented to account for the 5-second measurement resolution of the SCADA system. Only cycles recorded at a stable operating temperature ($\sim$ 390 ℃) were selected for further analysis to ensure consistency in the dataset.

Before spectral analysis, the raw acceleration signals underwent noise reduction to enhance the visibility of relevant vibration patterns. A Wiener filter was applied to eliminate high-frequency noise and aliasing artifacts resulting from sampling limitations, thereby isolating meaningful signal components from background disturbances.

Each filtered vibration signal was transformed into the frequency domain using the Short-Time Fourier Transform (STFT). The STFT provides a time-frequency representation of signals, enabling clear identification of vibration frequency content throughout each operational cycle. The STFT parameters selected for the analysis were:

- Window type: Hann window
- Window length: 1 s (10,000 data points)
- Window overlap: 0.5 s (50 % overlap)
- Frequency resolution: 1 Hz
- Frequency range: 0 Hz to 5000 Hz

This yielded one spectrogram image per RFHA for each cycle, displaying vibration intensity (power spectral density) as a function of both time and frequency.

Due to variations in cycle durations, spectrograms varied in length and needed dimensionality reduction for standardized analysis. Thus, each spectrogram underwent average pooling, resizing to uniform dimensions of 256×256 pixels. This approach maintained essential vibration pattern information while reducing computational complexity for subsequent Convolutional Neural Network (CNN) processing.

3.2 Dataset Preparation for CNN Training

To ensure that detected variations in vibration patterns were genuinely indicative of RFHA degradation rather than external environmental influences (e.g., wind or ambient temperature fluctuations), each pair of simultaneous spectrograms (from the two RFHAs) was quantitatively compared using the Structural Similarity Index (SSIM) metric proposed by Wang et al. [9]. The SSIM provides a numerical measure of similarity between two images, ranging from 0 (completely dissimilar) to 1 (identical), effectively highlighting cycles with significant differences indicative of impending failures. The SSIM between two spectrograms x and y is defined as follows:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \tag{1}$$

where μ_x and μ_y are the average pixel intensities of images x and y, σ_x^2 and σ_y^2 are the variances of pixel intensities in images x and y, σ_{xy} is the covariance between pixel intensities of images x and y, c_1 and c_2 are stabilizing constants to prevent division by zero.

To even out the variance occurring in singular cycles, sequences of 64 consecutive SSIM comparison images (representing approximately two months of real-world operational cycles) were stacked, creating 3-dimensional arrays (64 × 256 × 256 pixels) as input data for CNN training.

A CNN was implemented to classify stacked SSIM spectrogram images into two distinct classes: (0) normal RFHA operational condition, and (1) pre-failure condition. The CNN was specifically designed for time-frequency image recognition, including multiple convolutional layers followed by max-pooling operations. To improve training stability and avoid overfitting, dropout (rate = 0.3) and batch normalization were implemented after each convolution layer. The binary cross-entropy loss function (weighted to mitigate class imbalance) combined with the Adam optimizer (learning rate = 0.00001) facilitated effective training.

The model was validated using standard metrics: accuracy, precision, recall, and F1-score, along with a detailed confusion matrix. Given the higher cost associated with failing to detect impending RFHA malfunctions (false negatives), recall was prioritized during CNN optimization, ensuring good reliability in predicting potential failures.

4. Results

4.1 Vibration Analysis

During the RFHA test campaign, a total of 13,723 cycles were completed under controlled thermal conditions at a cycling temperature of 389 °C. Over the campaign, three key incidents were recorded:

- After 4,381 cycles: A mechanical problem in the traverse movement of the test rig occurred (not RFHA-related but affecting vibration signals).
- At cycle 11,700: A small oil leakage was detected in the west swivel.
- At cycle 13,681: A second leakage in the west swivel was observed, accompanied by visible smoke.

No vibration data was recorded between cycles 500 and 2,204 due to system unavailability.

To track changes in vibration behavior, spectrograms from the two RFHAs were computed for each cycle using STFT and then compared using the Structural Similarity Index (SSIM). Figure 2 illustrates the SSIM score per cycle. Under normal operation, spectrograms from both RFHAs are highly similar (SSIM $\approx$ 1), but as failure approaches, the similarity decreases.

Three patterns emerge:

1. Before 4,381 cycles, the SSIM score remained consistently low (indicating dissimilar patterns), but due to the traverse malfunction, this variance cannot be attributed to RFHA degradation.
2. Before both west swivel failures (11,700 and 13,681), the SSIM score gradually decreased over a period of roughly 1,000 cycles, then returned briefly to high similarity before dropping again. This fluctuation reflects complex degradation behavior.
3. In periods of no degradation, SSIM values remained stable near 1.

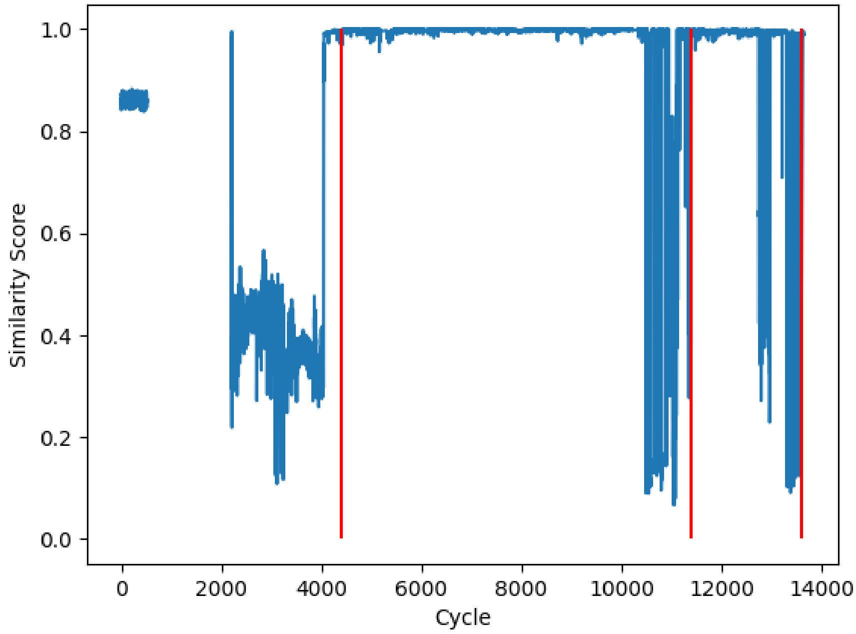

Figure 2. *SSIM score comparing spectrograms from both RFHAs for each cycle. Red vertical lines indicate the three test campaign incidents.*

In real-world terms, a 1,000-cycle window corresponds to roughly 2.5 years of operation (assuming one cycle per day in a real PTC), providing substantial predictive lead time.

4.2 CNN-Based Failure Prediction

A Convolutional Neural Network (CNN) was trained using sequences of 64 consecutive SSIM comparison images as input. These 3D inputs (64x256x256) allow the model to capture temporal and spectral trends in RFHA behavior.
The model was trained on data up to the second failure and evaluated on the remaining life-cycle data. Figure 3 shows the predicted failure probability for each cycle.

The key findings are:

- The failure probability began to increase approximately 1,000 cycles before each leakage incident.
- Although the model sometimes dropped the probability back to zero temporarily, the general trend correctly indicated impending failures.
- In stable periods (i.e., no degradation), the failure probability consistently remained at or near zero.

This behavior matches the SSIM trends in Figure 2. The CNN's use of stacked input mitigated some of the noise and cycle-to-cycle variance.

4.3 Model Performance Metrics

The trained model's classification performance was evaluated using standard metrics, with results shown in Table 1:

The perfect precision score (1.00) confirms that the model generated no false alarms. However, the recall score (0.82) indicates that a few true failure cycles were missed, typically during short-lived probability drops before the second and third incidents.

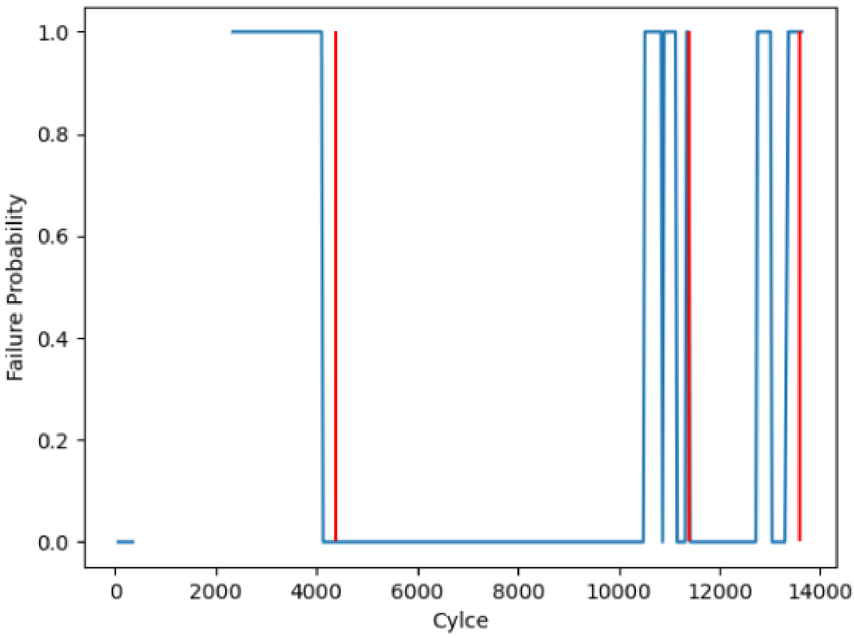

Figure 3. *CNN-predicted failure probability across the RFHA life cycle. Red lines denote recorded failure events.*

Table 1. *CNN Classification Performance for RFHA Failure Prediction*

Metric	Value
Accuracy	0.93
Precision	1.00
Recall (True Positive Rate)	0.82
F1 Score	0.90
True Negative Rate	1.00
False Negative Rate	0.18
False Positive Rate	0.00

5. Discussion

The presented results demonstrate that RFHA degradation is associated with measurable changes in vibration signatures, as captured through the STFT-based spectrograms and SSIM analysis. The CNN model leveraged these differences, predicting impending RFHA failures ahead of actual incidents.

Regarding model performance, the achieved precision of 1.0 indicates that no false positive failure predictions were generated, which is particularly advantageous for industrial applications where unnecessary maintenance actions should be avoided. However, the recall of 0.82 shows that a small number of failure events were not detected. In the context of predictive maintenance, such false negatives are critical, as missed failure predictions may lead to unplanned downtime or safety risks. This highlights a trade-off between conservative failure prediction (high precision) and comprehensive detection of degradation (high recall).

The observed behavior suggests that the current model is tuned towards avoiding false alarms, potentially at the expense of missing some early-stage degradation signals. From an application perspective, this trade-off may be adjusted depending on operational priorities, for example by modifying the classification threshold or introducing cost-sensitive learning approaches to further penalize false negatives.

While these findings validate the potential of vibration analysis combined with machine learning as an effective predictive maintenance tool, several aspects warrant further exploration:

- The CNN's generalizability to different RFHA designs and operating environments.
- Long-term operational reliability and potential improvements in model sensitivity and specificity through advanced architectures or training approaches.
- Real-time implementation considerations, such as computational efficiency and integration within existing SCADA systems.

Overall, this approach offers a promising pathway for improving maintenance practices in CSP plants, ensuring safer and more cost-effective operation.

6. Conclusion and Outlook

This work demonstrates the feasibility of a vibration-based predictive maintenance approach for RFHAs in parabolic trough collector systems. By combining high-frequency vibration monitoring, spectrogram analysis via STFT, and SSIM comparison, a clear pattern emerged: RFHA malfunctions were consistently preceded by a gradual divergence in vibration characteristics between the two assemblies.

A CNN trained on SSIM comparison spectrograms was able to predict failures with a lead time of approximately 1,000 cycles—equivalent to more than 2.5 years in typical plant operation. The model achieved high classification performance, particularly in precision (1.00) and overall accuracy (0.93), while maintaining a low false positive rate. However, the recall of 0.82 indicates that not all failure events were detected. In predictive maintenance applications, such missed detections represent a limitation, as they may result in unanticipated component failures. These results suggest that integrating such a system into real-world CSP plants could significantly enhance operational reliability and reduce unplanned downtime.

While the results are promising, several aspects merit further investigation:

- Future work should address the implementation of this method in live systems, including automated cycle segmentation and continuous model inference on edge or SCADA-connected hardware.
- The current model was trained and tested on a single test campaign. Additional campaigns with other RFHA types and varying operational conditions are required to improve model robustness and generalizability.
- Incorporating additional sensor modalities such as strain, temperature gradients, or acoustic emissions could enrich the input feature space and enhance predictive performance.

Data availability statement

The data supporting the findings of this study are available upon request.

Author contributions

Irene Biermann: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft. **Benedikt Kölsch**: Conceptualization, Methodology, Supervision, Writing – original draft. **Sonja Kallio**: Conceptualization, Investigation, Methodology, Project administration, Supervision, Writing – review & editing. **Rafael López-Martin**: Investigation, Writing – review & editing. **Eckhard Lüpfert**: Funding acquisition, Project administration, Writing – review & editing

Competing interests

The authors declare that they have no competing interests.

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