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Treatment of Erroneous Interference Effects from Post-processed Planet Gear Vibration Signals

Nader Sawalhi[1], *Wenyi Wang and David Blunt*
Defence Science and Technology Group (DSTG), Melbourne, VIC 3207, Australia
[1]*Correpondance: nader.sawalhi@defence.gov.au;*
wenyi.wang@defence.gov.au; david.blunt@defence.gov.au

Abstract

Occasional sensor signal transients (e.g. spikes, outliers) and anomalies (e.g. biased values) that arise primarily from measurement-related issues, such as poor cable connections, sensor faults, power-line or control system interference, temperature drift etc., may cause false-positive fault detections in, or assessments of, the system being monitored. Detecting these misleading transients and anomalies by visually inspecting the signals can be both time consuming and impractical where large amounts of data are involved. For trending purposes, the use of median average filtration provides a sensible solution to rectify anomalous trending indicators (e.g. kurtosis) and obtain a monotonic trend. However, the signals containing the misleading anomalies cannot be analysed effectively using more-sensitive fault-detection algorithms unless those anomalies are removed. In this paper a post-processing scheme is proposed to remove misleading anomalies from planet gear hunting-tooth synchronous signal averages (H-SSA) that were obtained from an accelerated planet gear rim fatigue crack propagation test conducted in a helicopter gearbox rig. The HSSA signals were post-processed using cepstrum and minimum entropy deconvolution (Cep-MED) to monitor the crack growth through the gear rim. The scheme consists of two stages. The first comprises the calculation of kurtosis for each planet-cycle in the HSSA-Cep-MED filtered signal, and the use of the scaled median absolute deviation (SMAD) as a threshold to identify anomalous planet cycle/s. The second stage involves the removal of the identified anomalous cycle/s and the re-connection of the adjacent normal cycles. A weighted moving-average filter (Savitzky-Golay filter) is proposed to correct the resulting discontinuities at these re-connection points. The use of the proposed algorithm negates the need to use a median filter by providing an authentic monotonic trending and enables the use of treated signals in machine learning algorithms or further processing.

Keywords: Planet gear, hunting-tooth synchronous signal average, cepstrum, minimum entropy deconvolution, scaled median absolute deviation and Savitzky-Golay filter

Introduction, Background and Objectives

Planetary gearboxes are commonly used in transmission systems, such as helicopter main gearboxes and wind turbines, for their compact design and high torque capacity. Monitoring the health of these gearboxes typically involves placing accelerometers radially on the casing outside the ring gear to capture vibration data. These signals contain complex harmonics and sidebands due to multiple vibration sources, particularly from the planet-sun and planet-ring gear meshes, which operate at the same frequency. Detecting failure modes, especially fatigue cracks in gear teeth or the gear rim, is challenging because the cracks produce minimal wear debris, making vibration analysis crucial for early detection and monitoring. Traditionally, planet gear faults have been identified using the planet gear synchronous signal averaging (P-SSA) technique, based on order tracking [1]. A more recent algorithm, which combines cepstrum editing (Cep) and minimum entropy deconvolution (MED), has been applied to hunting-tooth synchronous signal averages (H-SSA) and has shown promise in detecting cracks in helicopter planetary gearboxes earlier [2]. However, while P-SSA effectively removes transient noise through synchronous averaging, the residuals from the H-SSA-Cep-MED algorithm may still contain misleading transient anomalies, leading to false fault indications. Figure 1 compares crack growth trends from kurtosis analysis using both methods, showing that the traditional P-SSA diagnosis does not provide a consistent trend and reports low kurtosis levels. In contrast, the H-SSA-Cep-MED approach detects anomalies at load cycles 49, 50, 57, and others, where elevated kurtosis levels do not accurately reflect the actual crack condition.

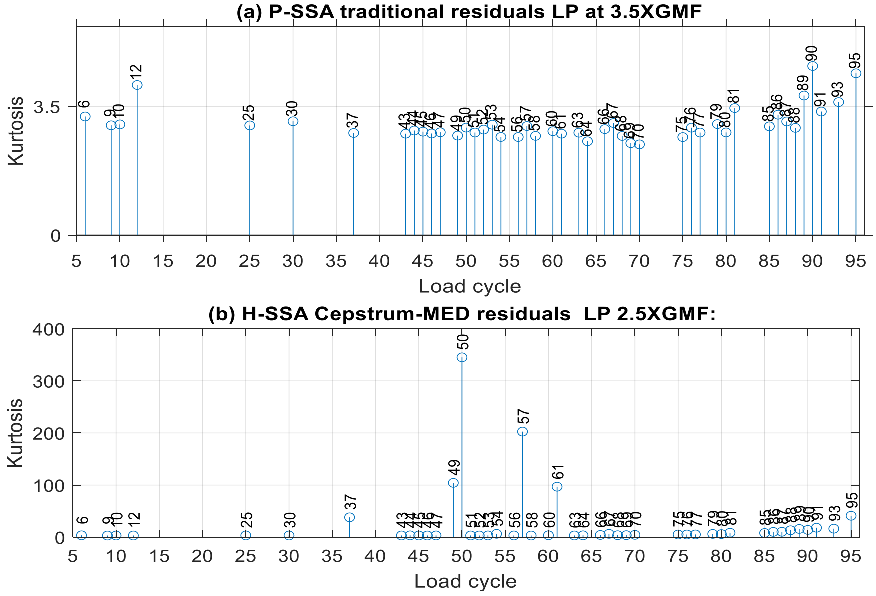

Figure 1 Trending vs load cycle number: (a) kurtosis of P-SSA traditional residual; (b) kurtosis of Cep-MED-H-SSA residual (low-pass filtered (LP) at 2.5x gear mesh frequency (GMF))

Figure 2 shows the H-SSA residuals for load cycles 49, and 57, revealing transient events with significantly high kurtosis values of 104.4 and 202.9 for load cycles 49 and 57 respectively. These transients have been traced back to voltage spikes likely originating in the test rig's electric motor drive system. To address these misleading anomalies, a moving median average filter with a window of 10 samples, as depicted in Figure 3, can be applied. This filtering method efficiently removes the transients and produces a monotonic trend that reflects the progression of crack growth. However, the signals with these anomalies cannot be further analyzed using more sensitive fault-detection algorithms unless the anomalies are removed.

Measurement-related anomalies, including spikes, outliers, and biased values, present significant challenges, as evidenced by the previous analysis. These anomalies may arise from sensor inaccuracies or cable faults, leading to false fault detections and impaired trending analysis, ultimately affecting decision-making and system reliability. Electrical noise and interference, particularly in accelerometer signals used for vibration measurement, exacerbate these issues. Accelerometers may capture not only the intended vibrations but also extraneous noise from nearby electrical sources, resulting in random spikes or data drift, significantly impacting vibration analysis [3]. The repercussions of these measurement anomalies are considerable, particularly regarding false fault detection, which can lead to unnecessary maintenance actions and increased operational costs [3]. Anomalies disrupt trending analysis, a critical component for predictive maintenance and performance monitoring, potentially misleading stakeholders and resulting in poor decision-making [4].

To address outlier detection challenges, various algorithms have been developed, categorized into three main groups: statistical methods, machine learning approaches, and hybrid techniques. Statistical methods, like Z-scores and Grubbs' test, are effective for normally distributed data, but struggle with non-normally distributed datasets. In contrast, machine learning approaches, such as clustering algorithms and supervised techniques, offer adaptability to dynamic environments but often require extensive training data [5]. Additionally, data smoothing techniques are crucial for rectifying anomalies. Common methods, including moving averages, exponential smoothing, and Savitzky-Golay filters [6], aim to reduce noise and enhance trend identification. Combining smoothing techniques with outlier detection can significantly improve data quality, as moving averages help mitigate the impact of extreme values [7]. This paper introduces a post-processing scheme to effectively remove measurement-related anomalies from Cep-MED-H-SSA residual signals derived from an accelerated planet gear fatigue crack fault propagation test in a helicopter gearbox rig. This approach enhances trend analysis accuracy and improves the reliability of data inputs into machine learning algorithms, contributing to more robust predictive maintenance strategies.

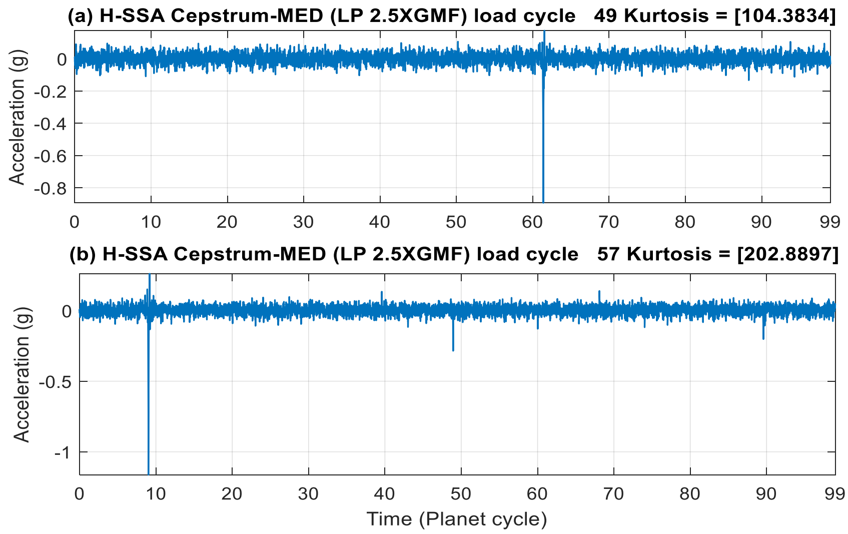

Figure 2 Cep-MED-H-SSA residual signal: (a) Load cycle 49 9; (b) Load cycle 54; (c) Load cycle 57

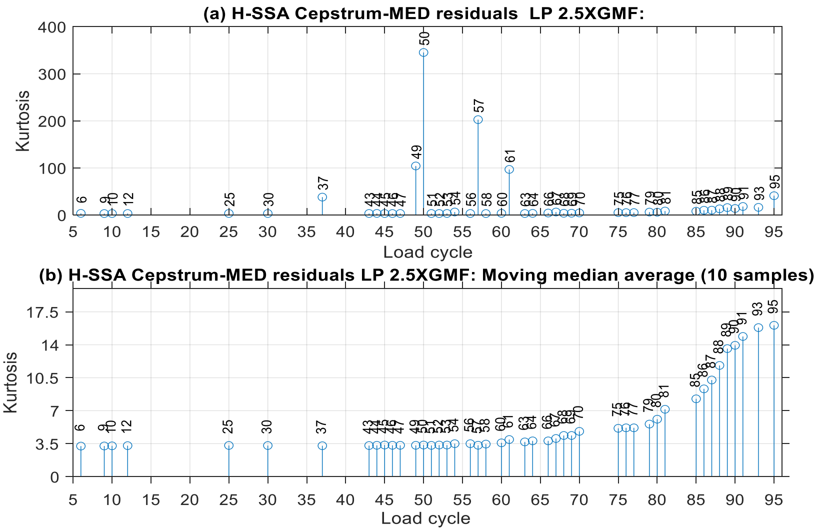

Figure 3 Kurtosis trends of Cep-MED-H-SSA residual signals [LP at 2.5XGMF]: (a) without moving median average filter; (b) with a moving median average filter with 10 samples

Methodology

Measurement error anomalies can be addressed at various stages of signal processing: pre-processing (raw vibration signal), mid-processing (after order tracking and obtaining the H-SSA signal), or post-processing (after applying fault-targeting techniques like Cep-MED). Early treatment of anomalies may complicate signal handling, as adjustments to the raw signal must also be applied to the tachometer signal to ensure effective order tracking. Mid-processing of the H-SSA signal may also be ineffective, as anomalies might not be evident at this stage, risking the removal of critical fault-related features. Consequently, processing the H-SSA-Cep-MED filtered signal (post-processing) is preferable to eliminate affected planet cycles while retaining normal ones. Figure 4 illustrates the proposed scheme for identifying and removing anomalies from the Cep-MED-H-SSA residual signals. This scheme has two stages:

1. **Anomaly Detection**: The first stage calculates kurtosis values for each planet cycle in the H-SSA-Cep-MED filtered signal and establishes a threshold using the scaled median absolute deviation (SMAD) for the identification of anomalies, where SMAD is defined as approximately 1.5 times the median of (x_i − median(x)) [8]. An anomalous cycle is defined as any cycle where the kurtosis exceeds the median of all cycles plus three times the SMAD.
2. **Anomaly Removal**: The second stage involves removing identified anomalous cycles and directly connecting adjacent normal cycles. While this may result in abrupt jumps, it maintains a monotonic trend without requiring median filtering or band-pass filtration on the H-SSA-Cep-MED signals. To smooth abrupt jumps at the endpoints, a Savitzky-Golay filter (order 5 with a 21-sample window) is utilized to mitigate the effects of jumps following the removal of anomalous cycles.

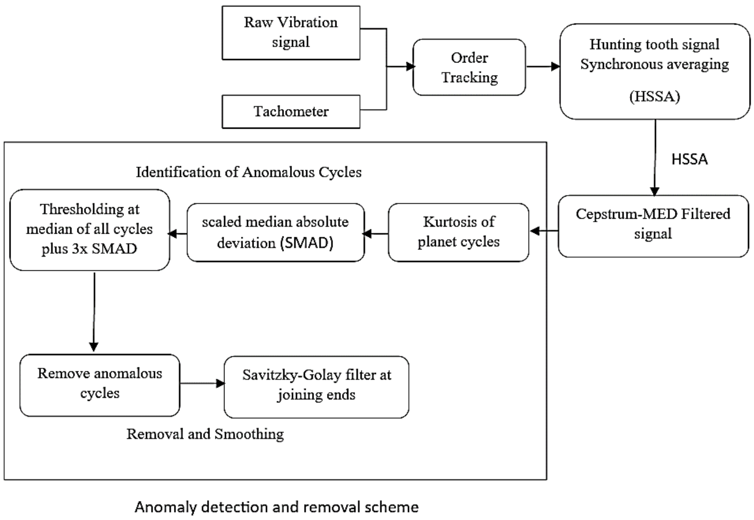

Figure 4 Post-processing Cep-MED-H-SSA residual anomaly detection and removal scheme with smoothing

Results and Discussion

Anomaly Detection Performance

Figure 5 illustrates the first stage of processing, focusing on the identification of anomalies in load cycle 57, which was previously flagged as anomalous. In Figure 5.b, nine planet cycles are marked as anomalous, determined by kurtosis levels exceeding the threshold of 4.29. This threshold is derived by adding three times the scaled median absolute deviation (SMAD) of 0.45 to the median kurtosis value of 2.94. The specific cycles identified as anomalous are highlighted in Figure 5.a, facilitating easy visual recognition. This systematic approach effectively quantifies deviations from normal behavior, providing a reliable foundation for further analysis and corrective actions.

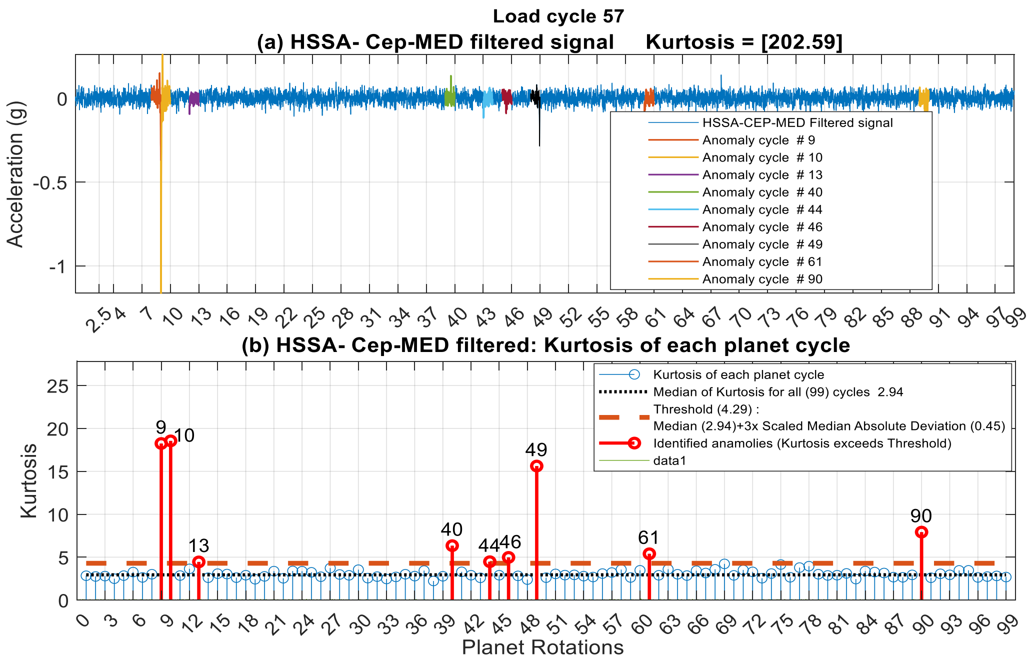

Figure 5 Identifying planet cycles with anomalies for load cycle 56: (a) HSSA-Cep-MED Filtered signal; (b) kurtosis of each planet cycle showing median, threshold (median +3xSMAD) and planet cycles exceeding the threshold

Figure 6.a illustrates the results of stage 2 processing, utilizing a smoothing Savitzky-Golay filter to connect normal cycles after the removal of anomalous ones. When the smoothed version is compared to the directly connected one, the signals appear to be similar. However, when the acceleration signal is differentiated with respect to the planet rotation (i.e. jerk in units of g/rotation), Figure 6.b clearly reveals abrupt jumps resulting from direct connections without smoothing. A close-up of planet cycle 81 (previously labeled as cycle 89), after removing planet cycle 90, is shown in Figure 7, demonstrating the effects of direct connections at the ends. This filtered signal is now suitable for reliable trending analysis and can be more effectively utilized in machine learning algorithms.

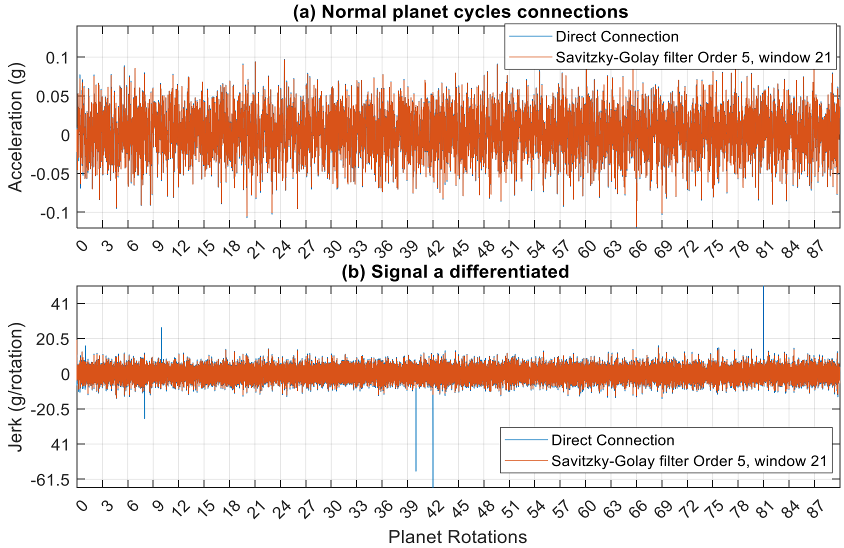

Figure 6 Direct and smoothened connections after the removal of anomalous planet cycles: (a) acceleration signal; (b) jerk signal

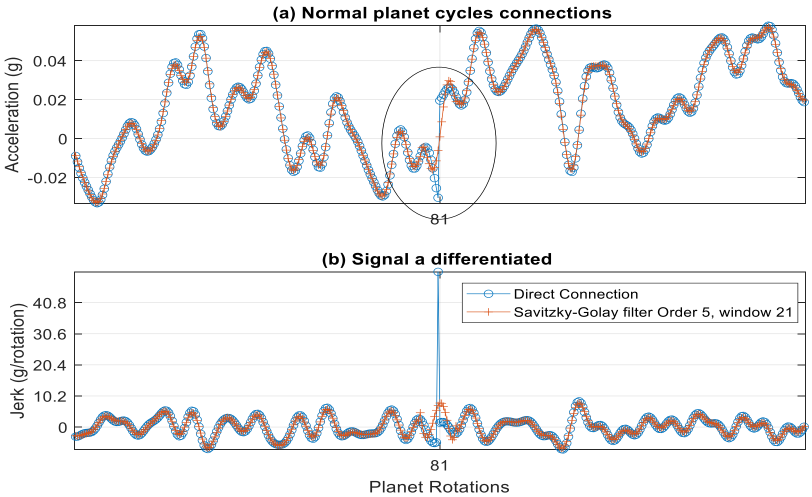

Figure 7 Example of a discontinuity at a direct connection: (a) acceleration signal before smoothing; (b) jerk signal with and without smoothing with a Savitzky-Golay filter

Comparison with Median Filtering

The comparison of trends produced by the moving median average approach and the anomaly removal and Savitzky-Golay smoothing filter approach is shown in Figure 8. It can be seen that the new method reveals a nearly monotonic trend that accurately captures crack progression. This highlights the algorithm's effectiveness in improving data quality for predictive analysis. In contrast to the median filter approach, the post-filtered approach produces a kurtosis trend that more accurately reflects the actual crack propagation shown in Figure 9; specifically, there is a significant increase between load cycles 93 and 95, undetected by median filtering, that is now apparent.

Conclusions

This paper highlights the importance of addressing measurement-related anomalies in sensor signals for effective health monitoring. Transient signals, such as spikes and outliers, can compromise fault detection systems, leading to erroneous assessments and significant operational consequences. The proposed post-processing scheme features a two-stage approach to identify and mitigate anomalies. Stage 1 focuses on anomaly identification using kurtosis levels and the scaled median absolute deviation (SMAD) as a threshold to assess deviations from normal behavior, establishing a foundation for further analysis. Stage 2 enhances data reliability by removing identified anomalies and reconnecting adjacent unaffected cycles with a Savitzky-Golay filter. This process improves data quality, resulting in a clean signal suitable for trending analyses. The results indicate that the filtered signal exhibits a clear monotonic trend, essential for accurately tracking crack growth. This enhancement supports predictive maintenance and prepares the data for advanced machine learning algorithms, which require high-quality input for reliable outcomes.

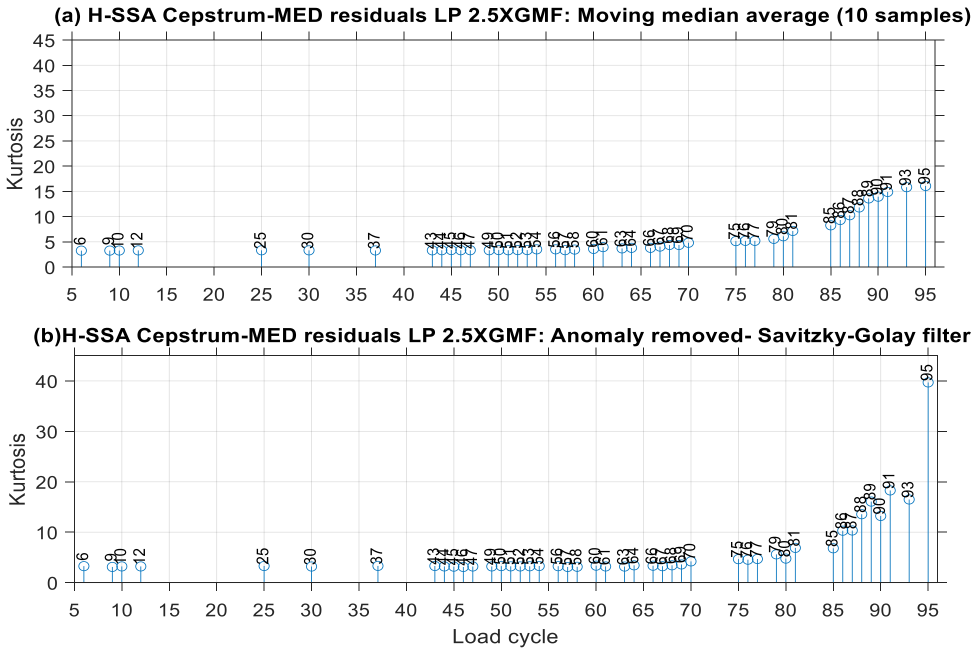

Figure 8 Kurtosis trends of Cep-MED-H-SSA residual signals [LP at 2.5XGMF]: (a) using the moving median average filter; (b) using the anomaly removal and Savitzky-Golay smoothing filter

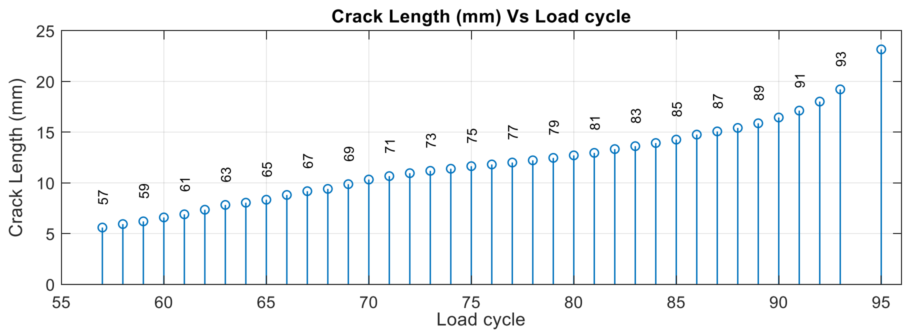

Figure 9 Actual crack length evolution with load cycles

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