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ORIGINAL ARTICLE

Techniques of trend analysis in degradation-based prognostics

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Abstract Monotonic fault progression is an important assumption for a number of prognostic models. This assumption can be violated through human intervention and self-healing and result in non-monotonic degradation data which not only increases the uncertainty but also may cause model failure. Methods to analyze and handle non-monotonic degradation in repairable systems are practically nonexistent in the literature. In this research, we intend to consider repairable systems in which self-healing is possible and human interventions are desirable. We presented a novel example of self-healing for fatigue cracks analyzed by acoustic emission. The aim of the present paper is to initiate a new research area on using non-monotonic measures in degradation-based prognostics. However, this research is not a review of trend analysis techniques, and therefore, there are more techniques to be considered or developed in future studies. In effect, trend analysis should be considered as an integral part of prognostics and health management. This study considers trend analysis for three classes of data, (1) prognostic parameters, (2) degradation waveform, and (3) multivariate data. A new form of crest factor is introduced for more effective waveform analysis of non-monotonic data. In addition, two algorithms are introduced to treat non-monotonic trend. The prognostic model used in this research does not produce results without treating non-monotonicity. These kinds of algorithm have promising potential to treat non-monotonicity and deal with arbitrary stationary noise in degradation data.

Keywords Prognostics · Degradation · Monotonicity · General path models · Acoustic emission

1 Introduction

Uncertainty management has been always a key issue in successful applications of prognostics and health management (PHM). Uncertainties in PHM arise from imperfections in predictability of prognostic models. The sources of uncertainties in PHM are classified into three categories, (1) randomness related to future degradations, (2) modeling errors, and (3) inaccuracies in degradation data [1]. The errors in modeling can emerge due to violating fundamental assumptions and excessive simplifications. It is pertinent to mention that monotonic fault progression is an imperative assumption for a great number of prognostic models [2–6]. Hence, there can be no doubt that non-monotonic degradation features intensify uncertainty and may cause model failure. A monotonic trend suggests unidirectional and consistent change in the mean level of degradation data. Therefore, not only monotonic degradation data are more desired, but it is also recommended to quantify and consider monotonicity in systematic construction of PHM models [5, 6]. Monotonicity is a measure of data complexity which deals with subjacent positive or negative trend of parameters based on the assumption that systems do not experience any form of repair. Monotonicity can be quantified as the average difference of the fraction of negative and positive derivatives of degradation measurements [6].

$$\text{Monotonocity} = \left(\left| \frac{\#\,\text{pos}\,\frac{d}{\text{dx}}}{n-1} - \frac{\#\,\text{neg}\,\frac{d}{\text{dx}}}{n-1} \right| \right) \tag{1}$$

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For degradation data, trend can be defined as the pattern of the time-ordered degradation measures. Trend analysis is a prevalent tool in different fields of science to identify significant decreases or increases in the magnitude of a reference variable in time-series data [7]. Moreover, trend analysis has been investigated for aging properties, such as failure rate and mean residual life (MRL) [8, 9]. Researchers have also worked on the trend of failure process in repairable systems based on statistical hypothesis tests [10–12]. This type of trend analysis is mainly helpful for model selection and cannot be part of trend analysis for degradation data. However, the trend analysis of the failure times is a decent candidate to measure prognosability [6] i.e., the variance of the critical failure times.

In essence, degradation data consists of a certain trend and noise (i.e., stochastic variations). The noise is an inherent feature of degradation data which needs to be minimized during the feature extraction phase. For instance, highly loaded bearings and cutting tools require sophisticated feature extraction to display clear degradation trends [13, 14]. Although considerable research has been devoted to feature extraction, rather less attention has been paid to non-monotonic degradation features due to the existence of pre-failure repairs. From a practical point of view, repairs can be in the form of human intervention and/or self-healing. The former refers to all kinds of maintenance activities and alteration of operating conditions e.g., in tool condition monitoring. In effect, repairs can change the degradation trend, and therefore, result in non-monotonic fault progression.

Methods to analyze and handle non-monotonic degradation in repairable systems are practically nonexistent in the PHM literature. In this research, we intend to consider repairable systems in which self-healing and human interventions are desirable. We presented a novel example of self-healing for fatigue cracks analyzed by acoustic emission (AE). The aim of the present paper is to initiate a new research area on using non-monotonic degradation data in PHM modeling. Moreover, there have been few investigations on the application and usefulness of trend analysis methods on degradation measures. This study provides a roadmap in processing non-monotonic degradation data. This work considers the trend analysis for three classes of data, (1) prognostic parameters, (2) degradation waveform, and (3) multivariate data. A new form of crest factor is introduced for more effective waveform analysis of non-monotonic data. In addition, two algorithms to deal with non-monotonic data are introduced with the objective of revealing the possible monotonic components of such data.

The remainder of this paper is organized as follows: Section 2 describes two different sets of data utilized in this study. These data sets provide non-monotonic degradation features because of human intervention and self-healing. Section 3 covers several graphical and analytical trend analysis methods for analyzing degradation data. Section 4 introduces two algorithms for treating a non-monotonic trend, and it is followed by conclusions in Section 5.

2 Description of data and experiment

Two different data sets applied in this research to represent non-monotonic degradation features. The first set relates to bearings degradation. Over recent years, a significant amount of research has been undertaken to develop and apply PHM models for common rotary machinery components, particularly rolling element bearings [15–17]. Nevertheless, little attention has been paid to the performance of PHM models subject to change in operating conditions. For this reason, and also due to technical difficulty, the bearing data set was made through simulation with variable shaft speed. The fault signal of bearings was modeled through the combinations of the following parts: repetitious impulses, load, bearing-induced vibration, and machinery-induced vibration (see [18, 19] for more details). The simulation used the ball pass frequency of outer race as the frequency component of bearing faults. It should be noted that all the bearing's fault frequencies are linear function of shaft speed. Therefore, by changing the shaft speed the rate of degradation will be changed. Figure 1 shows different cases of degradation measures simulated for rolling element bearings. It is evident that the root mean squared (RMS) of the degradation signal is a function of the shaft speed (see case 1–3). Accordingly, changing the shaft speed results in non-monotonic degradation measures (see case 4–6). It is important to emphasize that the simulation results, as shown in Fig. 2, are similar to the experiment results produced by Gebraeel and Pan [20]. Table 1 provides the feature selection metrics, introduced by Coble [6], for the non-monotonic cases (4–6). Each case has a population of 50 samples. As expected, case 4 has the lowest monotonicity metric as well as the high variance of critical failure times.

The second set of data was generated in a fatigue crack growth test for a sample of HAYNES® HR-120™. This material is a heat-resistant alloy that provides excellent strength at elevated temperature. The experiment intends to analyze crack growth using AE for a sample shown in Fig. 3.

The length of crack for this test is 20 mm. However, there is an unusual difference between this experiment and the regular fatigue crack growth tests. When the crack reached the middle point of the intended crack length (i.e., 10 mm), the test was stopped and a single tensile load (STL) was applied for 300 s. The magnitude of the STL was 150 % of the maximum load applied for crack propagation [21]. The STL creates the chance for a phenomenon known as fatigue crack closure (FCC). First pioneered by Elber [21], FCC is an important phenomenon in evaluating the effective driving force for crack growth. Elber identified that plastically deformed material left in the wake of a propagating crack would result in partial or

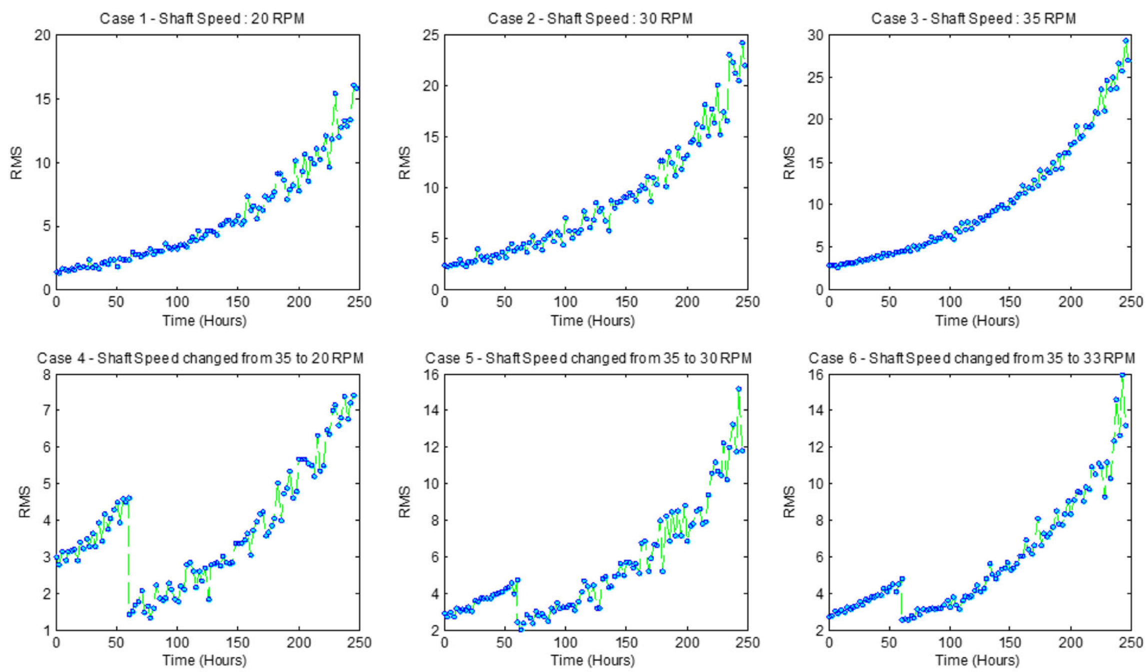

Fig. 1 Different cases of the simulated degradation measures

complete crack closure for a portion of the applied loading range. After applying the STL, we expect to observe non-monotonic change in the AE signals which represents FCC i.e., the period of retardation. The AE data set contains over 27,000 observations and 11 response variables (i.e., signal features) as follows:

- X_1: PAC-energy is derived from the integral of the rectified voltage signal over the duration of AE hit. PAC-energy and AE count are the two discrete variables in this data set.
- X_2: Average frequency (over the entire AE hit = AE count/duration)
- X_3: Initiation frequency, i.e., rise-time based frequency
- X_4: Count is defined as the number of times the signal crosses the threshold in an AE hit. In effect, AE counts imply the existence of a transient wave in the AE waveform.
- X_5: Amplitude or maximum AE signal excursion
- X_6: Absolute signal level (ASL) is the averaged amplitude of the AE signal
- X_7: Reverberation frequency (AE count—count to peak)/(duration—rise-time)
- X_8: Absolute energy is the true energy measure of AE hit.
- X_9: Rise-time is the time from the start of AE hit to the time of the peak amplitude
- X_{10}: RMS of AE signal
- X_{11}: Signal strength which is similar to energy but it is calculated over the entire AE

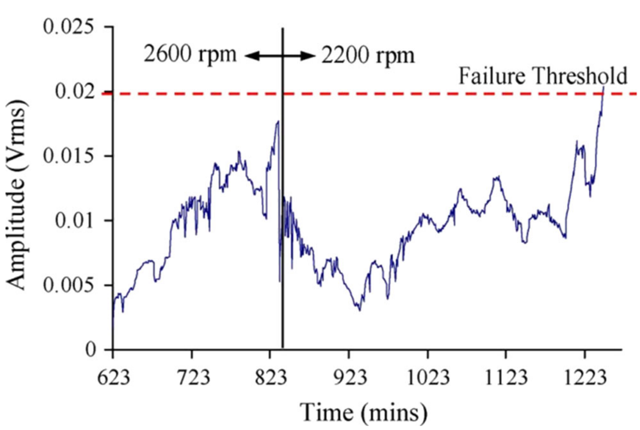

Fig. 2 Result of the change in shaft speed in bearing degradation experiment produced by Gebraeel and Pan [20]

The AE data set is applied in multivariate trend analysis. General information about the AE signal and the details of AE signal features are available in the literature [22–24]. Figure 4 shows an AE feature (PAC-energy) after removing the background noise. The areas shown in the red ellipses represent the periods of retardation i.e., crack closure.

3 Trend Analysis techniques

3.1 Statistical trend analysis

Statistical trend analysis refers to a set of parametric and non-parametric statistical tests to detect the existence of a trend in time series. Hypothesis tests in statistical trend analysis

Table 1 Metrics for the non-monotonic degradations (cases 4–6)

	Case 4—speed change from 35 to 20 RPM	Case 5—speed change from 35 to 30 RPM	Case 6—speed change from 35 to 33 RPM
Monotonicity	0.333	0.75	0.85
Prognosability	0.855	0.855	0.951

usually contemplate the null hypothesis as "no deterministic trend." Each test has a statistical quantity to perceive the existence of a deterministic trend. Parametric tests (e.g., *t* test) are mainly based upon the linear regression coefficients for normally distributed and homoscedastic random variables [25]. Thus, the parametric tests are limited to linear trends. On the other hand, nonparametric tests are not highly affected by outliers and large data gaps. Mann-Kendal (MK) is the most used nonparametric trend test which is based on the relative ranking of data (i.e., a rank-based test). The MK test computes the difference between the sequential data ($x_i - x_j$). Then, it assigns integer values of 1, 0, or −1 to the computed differences:

$$\mathrm{sign}(x_i - x_j) \begin{cases} -1 & \text{for } (x_i - x_j) < 0 \\ 0 & \text{for } (x_i - x_j) = 0 \\ 1 & \text{for } (x_i - x_j) > 0 \end{cases}$$

If n represents the length of the data series, the test statistic, S, is computed using the sum of the integers as:

$$S = \sum_{i=2}^{n} \sum_{j=1}^{i-1} \mathrm{sign}(x_i - x_j) \tag{2}$$

Hence, the MK test is related to the sample size, trend magnitude, and coefficient of variation. It is important to note that failure to reject the alternative means that there is no enough evidence to conclude the existence of a trend in data. Therefore, statistical trend analysis methods might be useful only as a preliminary trend check.

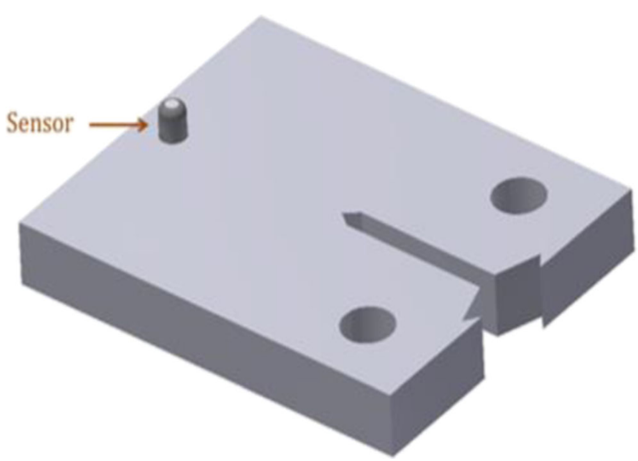

Fig. 3 Sample (according to ASTM E647) and the sensor location

3.2 Graphical methods

Graphical tests do not usually need complicated calculations. Thus, they are simple to perform, and they are powerful in detecting the strong trends. On the other hand, they might not be very useful for data with slight trends, and therefore, they need to be combined with analytical tests. In addition, graphical tests are based upon interpretation which is prone to error. There are a number of graphical methods with respect to trend analysis. Using control charts was even mentioned in the literature as a graphical test. This section covers two graphical tools that were found suitable for degradation data: (1) cumulative plots and (2) temporal shape analysis.

For certain systems, damage is considered to be cumulative. Thus, the decreasing slope of an increasing cumulative degradation can be a sign of improvement in durability. Figure 5 clarifies the change in trends where the shaft speed changes from 35 to 20 RPM (after 60 h). The cumulative plots clearly detect the strong trend in the data due to the variation in shaft speed. Cumulative plots were also produced for the AE signal features. It is interesting to note that only the energy-related features showed considerable change in trend during the retardation period.

The second graphical method known as temporal shape analysis is a qualitative analysis proposed by Konstantinov and Yoshida [26]. This analysis starts by approximating the variable *v* by a polynomial with the order of *m*. Then, the values of the polynomial are evaluated at *v*. Next, the first and the second derivatives of the polynomial are calculated. The sign of difference between every data points and the preceding in the first and the second derivatives should be extracted. The combination of the extracted signs forms the qualitative shape of the variable. The first derivatives show the change in trend, and the second derivatives provide insight about the shape of the variable. It is possible to show the qualitative shape by +1 and −1 which represent + and − signs. Figure 6 shows the qualitative shape for non-monotonic data using a polynomial with the order of 4.

It was realized that with an order of 4 or more, we can obtain the monotonicity of 1 for modest speed changes (i.e., from 35 to 33). High order polynomials take the noise into account and might not be reliable for trend analysis.

3.3 Analysis of waveform

The analysis of waveforms can be performed in time domain or time-frequency domain prior to signal feature extraction.

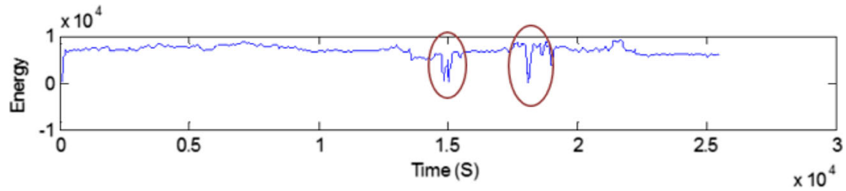

Fig. 4 AE data after smoothing

Time–frequency analysis has gained increasing attention in the field of trend analysis. These techniques analyze nonstationary signals in time and frequency domains simultaneously. Traditional signal analysis relies on the limiting assumption of stationary signals. However, in real physical world, signal features change over time. Wavelet analysis is the most popular time–frequency analysis for detection of meaningful trends [27–29] or finding the turning points [30]. In actual practice, wavelet-based methods are more appropriate for real-time implementation because of better computational efficiency. This section investigates the use of Hilbert-Huang transform (HHT) for trend analysis.

The Hilbert-Huang transform (HHT) is a relatively new time-frequency technique [31]. The HHT method is able to analyze large signals. The empirical mode decomposition (EMD) is the first major operation of the HHT. The details of EMD process can be found in [32, 33]. The EMD relies on the local characteristic time scales of a signal and can decompose the signal into a collection of successive intrinsic mode functions (IMFs). In other words, EMD intends to accurately reveal the signal characteristics. An IMF is a function that reveals a simple oscillatory mode embedded in the signal [32]. After finding the IMFs, Hilbert transform (HT) is applied to produce a full time-frequency-energy distribution of the signal. HT process provides instantaneous frequency and amplitude information for each IMF.

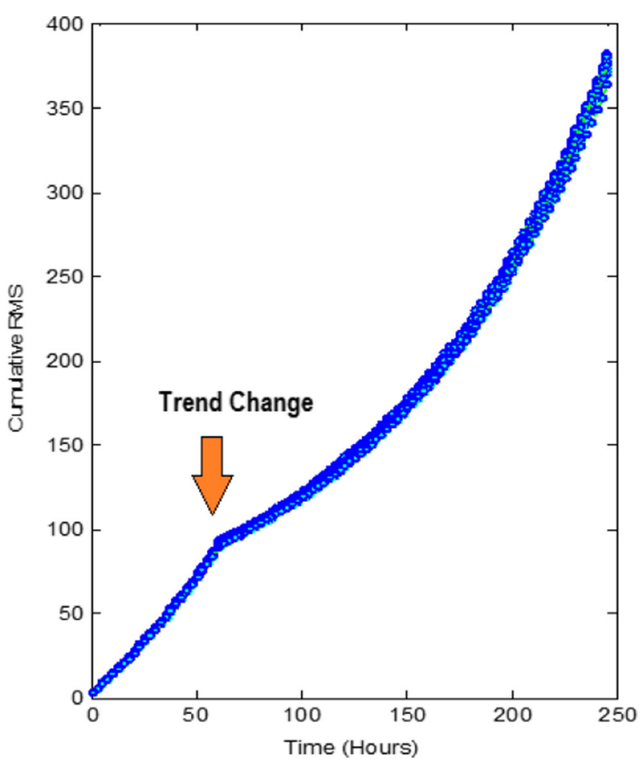

Fig. 5 Cumulative damage (shaft speed changes from 35 to 20 RPM)

In essence, the amplitude of signal waveforms would be a useful feature to display a non-monotonic trend. Nonetheless, the amplitude in a degradation signal might not be a good indicator of the incipient fault, particularly in the absence of certain physical quantities such as impacting. Figure 7 shows a typical waveform which is a combination of small waveform collected periodically. The change in the amplitude of the signal represents the change in the shaft speed. However, thorough analysis is required if there is a slight trend change, or there is a need for comparison of several degradation signal. In this way, HHT is able to decompose the signal to several components and provide the instantaneous amplitude. Accordingly, the important components of signals can be analyzed, and the component associated with noise can be removed [34, 35].

The concept of crest factor is utilized to further improve the waveform analysis. For a waveform, crest factor is the ratio of the peak amplitude to the RMS value. This dimensionless feature is an indication of significant peaks. Here, the instantaneous amplitudes of the main signal components and the RMS for each individual wave were used to provide the crest factor. Figure 8 illustrates the crest factor calculated for the first signal components related to the three non-monotonic cases introduced in Fig. 1. It is evident that the crest factors in Fig. 8 are neither helpful for detecting the trend change nor useful for comparing different cases of speed change.

For these reasons, a new form of crest factor is introduced which can be defined as the ratio of the maximum amplitude up to the time of calculation over the RMS of each waveform. The trend changes using the modified crest factor are illustrated in Fig. 9. A better comparison of the first two signal components is provided in Fig. 9. The trend changes occur after the 24th waveform. Obviously, the first component of the signal has better indication of the trend change. Therefore, HHT along with the modified crest factor has the potential to provide the indication of trend change even for real-time applications.

3.4 Multivariate trend analysis

For some data sets, it might be of interests to analyze the whole complex multivariate data. There are many approaches

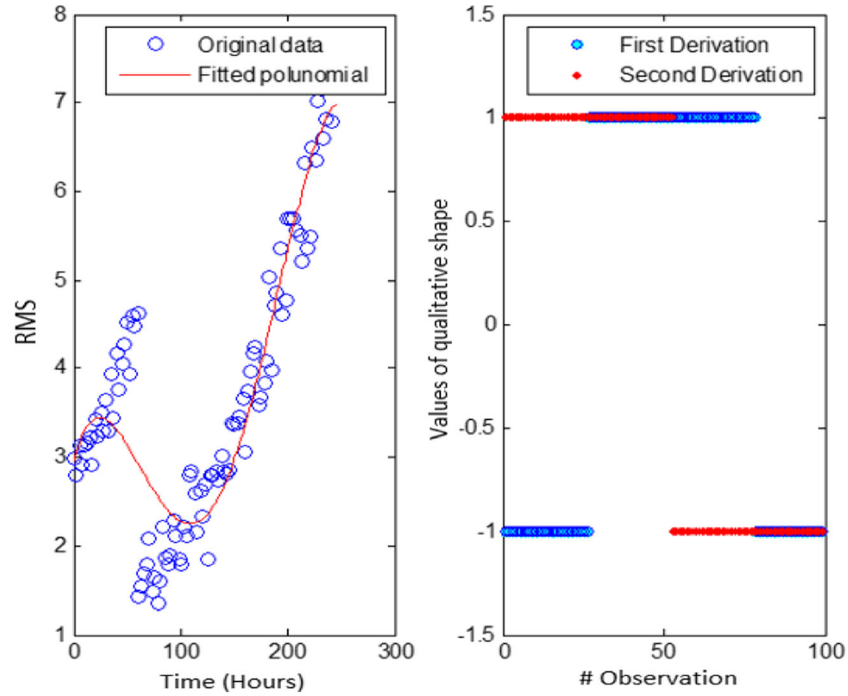

Fig. 6 Qualitative shape (non-monotonic trend for speed changes from 35 to 20 RPM)

to investigate multivariate data sets. Among those methods, independent component analysis (ICA) and principal component analysis (PCA) seem to be good candidates for trend analysis of multivariate degradation signals.

ICA is a popular signal processing method to decompose a multivariate signal into uncorrelated and maximally independent components [36]. This method is also helpful in selecting the proper variables for further analysis. This method was applied on the AE data related to the FCC test. ICA was not able to appropriately handle the retardation period.

PCA is a widely used linear statistical technique for reducing the dimensionality of complex multivariate data. In PCA, the goal is to analyze covariance structure and reduce the complexity of the data by projecting onto a lower dimensional subspace while retaining the variability. Through the PCA, the data will be represented by the products of scores (i.e., mutually orthogonal data) and principal component loadings (i.e., transposed linear transformation matrix) plus the matrix of residuals. PCA has been utilized in the literature to analyze the features and the waveform of AE signal [37–39].

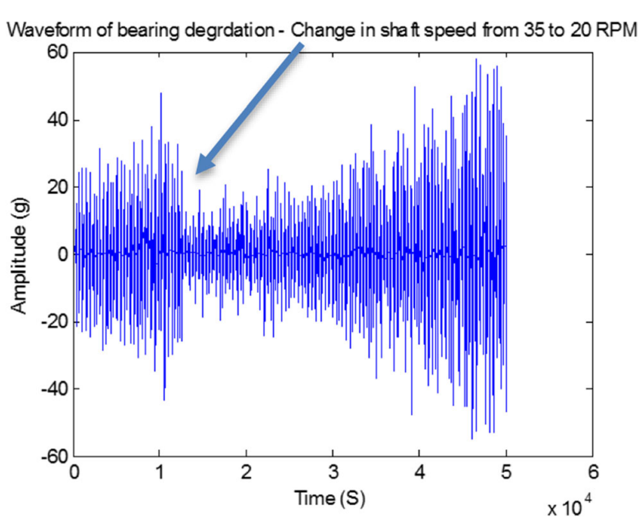

Fig. 7 Typical waveform (non-monotonic signal)

The AE data used in this analysis was introduced in section 2. Using scatter plots and correlation maps, the highly correlated variables were identified. Accordingly, energy (variable 1) is highly correlated with count (variable 4) and absolute energy (variable 11). All these variables are related to the energy of the signal. Also, RMS (variable 10) correlated with ASL (variable 6). In essence, correlated variables increase the contribution of their related principal component. Hence, the highly correlated variables were eliminated, and the data set with seven variables was used for the next phase. PCA was performed for the smoothed AE data that was free of highly correlated variables. Figure 10 shows the bi-plot for all the vectors. The direction and length of the vectors in the bi-plot represent the contribution to the first two principal components. For example, the first PC on the horizontal axis has positive coefficients for all the variables except variable 3.

Using the scree plot, it can be shown that it is possible to represent over 90 % of the variability of the data with the first four PCs. The same analysis was performed for the portion of the data that contains retardation. Interestingly, similar to the bi-plot for the whole data, variable 3 causes the variation on the opposite way comparing to the whole data. It was realized that all the retardation period for the signal features have some

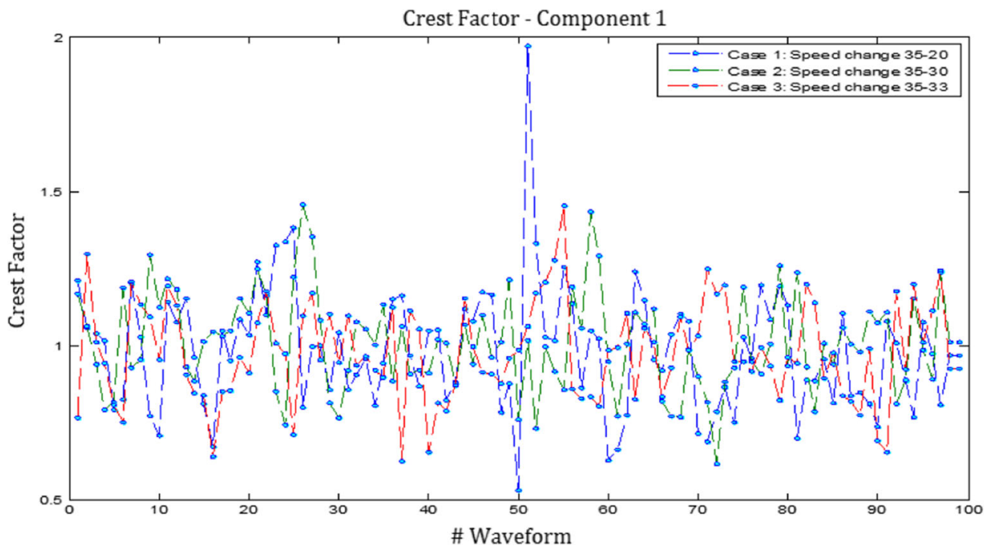

Fig. 8 Crest factor (speed changes from 35 to 20 RPM)

negative values except variable 3. To this end, by eliminating variable 3, improved results were obtained. Furthermore, it is possible to look at the portion of the data that has no retardation. In this respect, the first 14,000 observations were used. Finally, by removing variable 3 and comparing the bi-plots, it is possible to say that the shift in the relationship between PCs can represent the retardation period. Thus, it can be concluded that PCA can display the trends in the data as shown in Fig. 11, where the black circle represents the retardation period. Considering the new scree plot for the modified data, we can conclude that three principal components are appropriate to represent that data even with the retardation period.

There are always two important questions regarding PCA, (1) how many principal components should be retained for the analysis and (2) is there any useful information in the remainder of PCs (i.e., PC4, PC5,

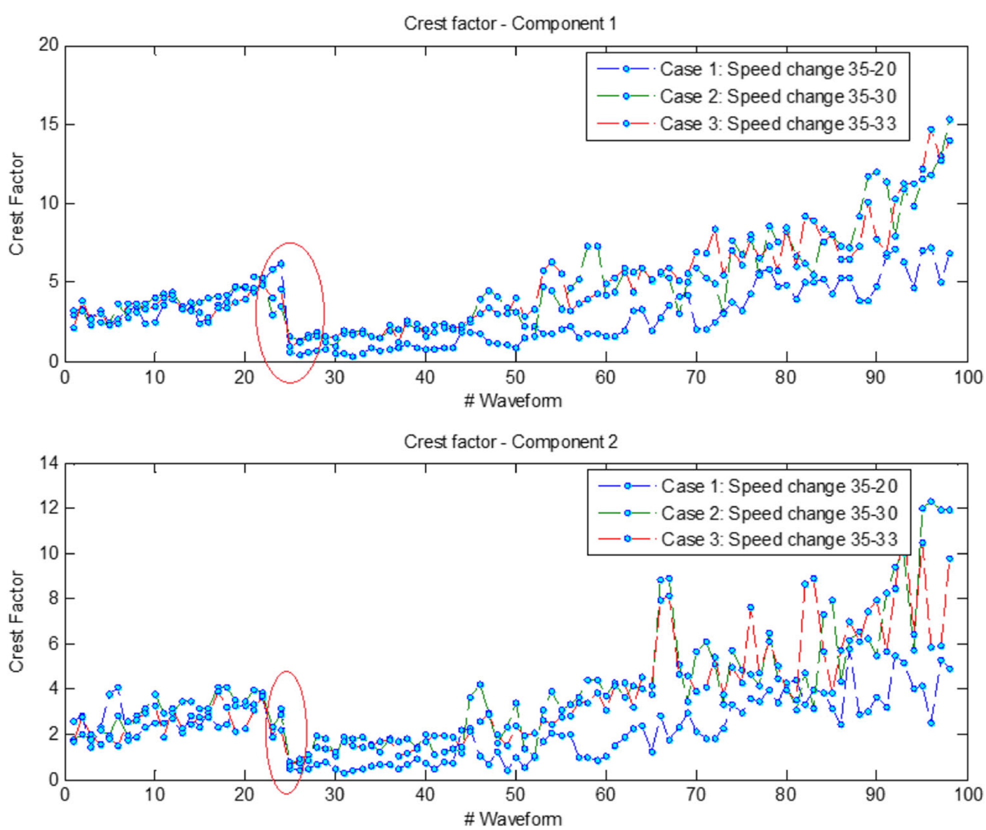

Fig. 9 Waveform analysis with the modified crest factor (speed changes from 35 to 20 RPM)

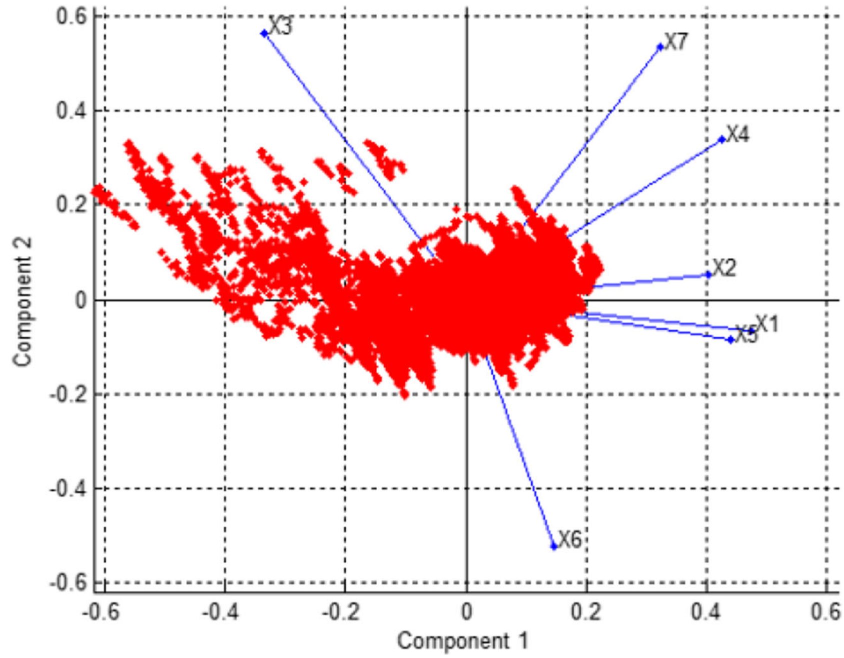

Fig. 10 Bi-plot for all the vectors

and PC6) which were not selected. To address the second question, the information complexity criteria was used [40]. The results show that one PC would be enough to cover the remainder of information that was not covered in the selected PCs. It seems variable 6 may contain significant information. It is clear from Fig. 11 that variable 6 has different direction, and it should contain some information that is not appeared in the first three principal components. Variable 6 is RMS which is basically different from other signal features.

4 Treatment of non-monotonic trends

4.1 Trend-based segmentation

Trend-based segmentation methods are able to locate the turning points in time series data. These methods are popular in financial time series to locate a set of trading [30, 41, 42]. The most common segmentation methods include piecewise linear representation (PLR) [41], Fourier transform, and wavelets. Figure 12 illustrates the results of trend-based segmentation for the non-monotonic-bearing degradation data which

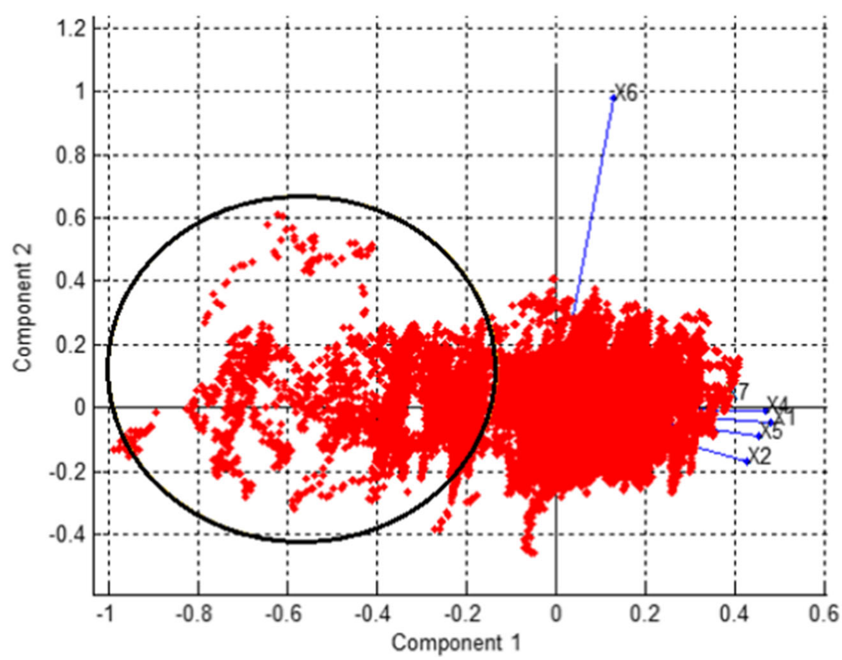

Fig. 11 Trend analysis by PCA

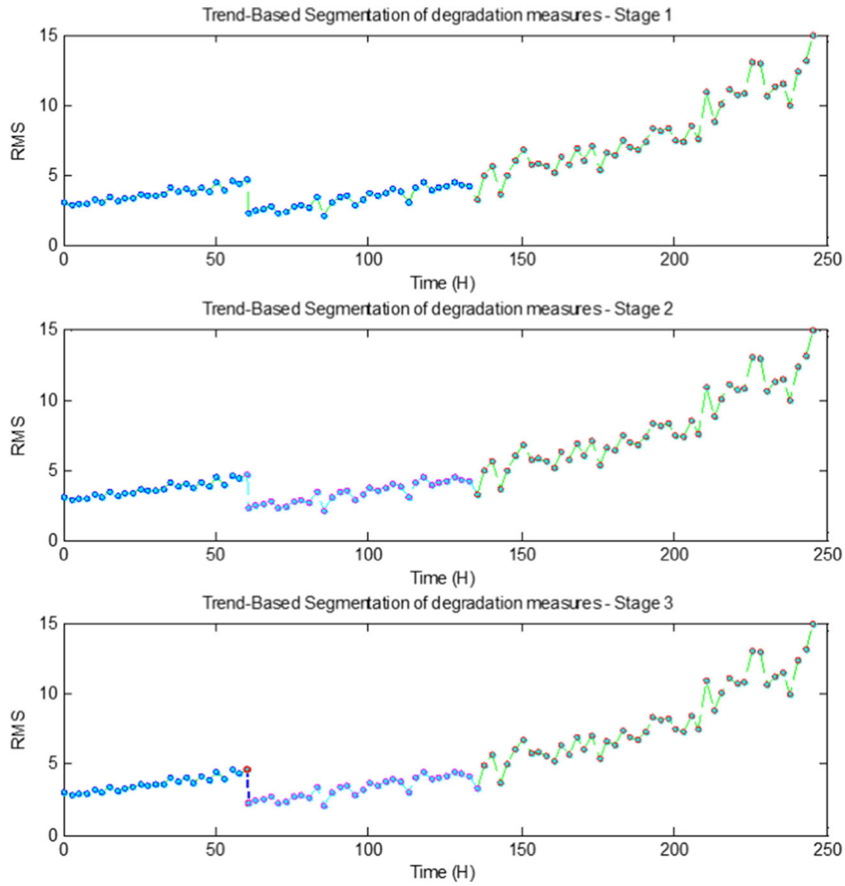

Fig. 12 Trend-based segmentation for the non-monotonic-bearing degradation data. *Various colors* represent different segments of the data

presented in section 2. In this example, three stages of segmentation using the PLR method were enough to group the data into four segments. The first segment represents the degradation with high speed, and the second segment represents the speed reduction (i.e., change in operating condition). Segments 3 and 4 belong to the degradation measures after the speed reduction.

Next, it is reasonable to apply a prognostic model to test the treatment of non-monotonic trends. To this aim, General Path Model (GPM) with Bayesian updating was applied [6, 43]. GPM is an important class of degradation models [44] and has been extensively applied in the PHM literature [45–47]. This model was developed based on the famous article by Lu and Meeker [48] in which the authors considered reliability prediction based on degradation measurements where the time-to-failure data is not sufficient to estimate failure distributions.

GPM requires a population of the degradation paths for a specific fault mode. Degradation measurements (i.e., prognostic parameters) show the degradation paths to the end of life under the assumption that there is a unique degradation path for each individual component. The degradation path y for unit i at time t can be expressed as:

$$y_i = \eta(\mathrm{t}, \varphi, \Theta_i) + \varepsilon \tag{3}$$

where ε represents the error, φ is a vector that represents fixed effects, and Θ_i is a vector that represents individual effects for the i^th^ component. End of life is usually indicated by passing over a pre-defined critical threshold. To estimate the remaining useful life (RUL) of an individual component through GPM, the fitted model needs to be extrapolated to the failure threshold. It implies that the model parameters are constantly used for all RUL estimation regardless of the actual trend of degradation measures. It is worth noting that monotonic degradation paths are a key assumption of GPM. Not surprisingly, GPM failed in using non-monotonic-bearing degradation data. The prognostic model works properly if only monotonic segments of the data are taken into consideration. In other words, using the bearing data, we only take segments 3 and 4 into account for successful RUL estimation.

4.2 Average conditional displacement

This section considers the application of an algorithm known as average conditional displacement (ACD) for automatic estimation of monotonic trends. ACD describes data trends using piecewise linear curves. This approximation algorithm was first introduced by Vamoş [49]. It must be emphasized that ACD is based upon the signal values interval not the time interval. In this algorithm, the slope of each estimated linear segment is proportional to the average of the time series values in the corresponding interval [49, 50]. The advantage of the

ACD algorithm is twofold: (1) no need for initial assumptions such as functional form of the trend and (2) the development of an automatic algorithm. The accuracy of ACD is comparable with well-tested methods such as polynomial fitting and moving average particularly for the signals with stationary noise. The ACD works well in estimating the monotonic trend for time series data with arbitrary stationary noise. More importantly, ACD reveals one of the possible monotonic components of a non-monotonic trend. Suppose that a time series $\{x_n\}$, with $1 \leq n \leq N$, can be generated by a discrete stochastic process Z_n and the values of the trend $f(t)$ as

$$X_n = f_n + Z_n \tag{4}$$

Considering δt as the sampling interval, f_n represents the value of $f(t)$ at the moment and we have

$$t_n = (n-1)\,\delta t \tag{5}$$

Instead of the unknown initial and final values (i.e., f_1 and f_N), the ACD algorithm uses the extreme values of time series. In addition, it should be assumed that Z_n does not depend on f_n. Furthermore, it should be assumed that Z_n is stationary, and X_n is a nonstationary process. Figure 13 shows the one-step variation of the time series $\{x_n\}$ for the interval $(\xi_j, \xi_{j+1}]$.

There are J disjoint intervals that embrace all the values of x_n. Therefore, N_j is the number of x_n values in the interval $I_j = (\xi_j, \xi_{j+1}]$, for $j = 1, 2, \ldots, J$. An increase in N results in improved accuracy of the trend estimation. However, the ratio between the noise fluctuation and the amplitudes of the trend variation is the major contributor to the accuracy of the ACD algorithm. In essence, when homogeneous intervals are used, the difference between the values of N_j should not exceed a unit at the most. The one-step variation of the time series can be defined as

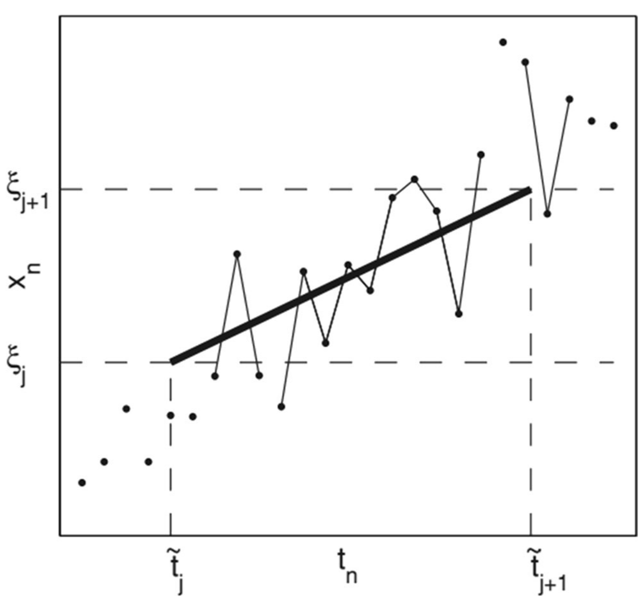

Fig. 13 The one-step variation of the time series in which the *thick straight line* represents the ACD approximation [50]

$$\delta x_n = x_{n+1} - x_n \tag{6}$$

The sample average of δx_n (i.e., the average variation of $\{x_n\}$ within I_j) is computed as follows

$$\hat{g}_j = \frac{1}{2N_j}\left(\sum_{x_n \in I_j} \delta x_n + \sum_{x_{n+1} \in I_j} \delta x_n\right) \tag{7}$$

It should be noted that the interval I_j should contain the initial or final values. Moreover, the values of $\hat{g}_j$ should have similar sign in order to be used in the numerical approximation of the monotonic trend. Otherwise, the monotonic trend cannot be determined. If the values of $\hat{g}_j$ have different signs, repeated central moving average (RCMA) can be utilized to smooth the fluctuation of the time series. RCMA provides a gradual smoothing of the time series based upon two parameters: (1) length of the averaging window and (2) the number of averaging.

In Fig. 13, the thin straight segments denote the pieces of $[x_n]$ that enter into the computation of the sample average. The thick continuous line denotes the ACD approximation of the monotonic variation of $[x_n]$ for the interval $(\xi_j, \xi_{j+1}]$. Thus, the points $(\tilde{t}_j, \xi_j)$ and $(\tilde{t}_{j+1}, \xi_{j+1})$ demarcate the j^{th} straight segment which has the slope of $\hat{g}_j$. Hence

$$\tilde{t}_{j+1} = \tilde{t}_j + \frac{\xi_{j+1} - \xi_j}{\hat{g}_j} \tag{8}$$

Therefore, for $t \in (\tilde{t}_j, \tilde{t}_{j+1})$ the estimated monotonic trend (i.e., piecewise linear curve) is

$$\tilde{f}(t) = \xi_j + (t - \tilde{t}_j)\hat{g}_j \tag{9}$$

Furthermore, $\hat{g}_j$ are negative for decreasing trend. Thus the points $(\tilde{t}_j, \xi_{J-j+2})$ and $(\tilde{t}_{j+1}, \xi_{J-j+1})$ demarcate the j^{th} straight segment which has the slope of $\hat{g}_{J-j+2}$. Hence

$$\tilde{t}_{j+1} = \tilde{t}_j + \frac{\xi_{J-j+1} - \xi_{J-j+2}}{\hat{g}_{J-j+2}} \tag{10}$$

Thus, we have

$$\tilde{f}(t) = \xi_j + (t - \tilde{t}_j)\hat{g}_{J-j+2} \tag{11}$$

The theoretical background of the ACD is elaborately explained by Vamoş [49, 50]. Here, we intend to present the numerical quantities of the ACD. Figure 14 shows the application of the ACD for treating the non-monotonicity in the bearing degradation measures. Not surprisingly, the prognostic model, i.e., GPM, only worked after applying the ACD and

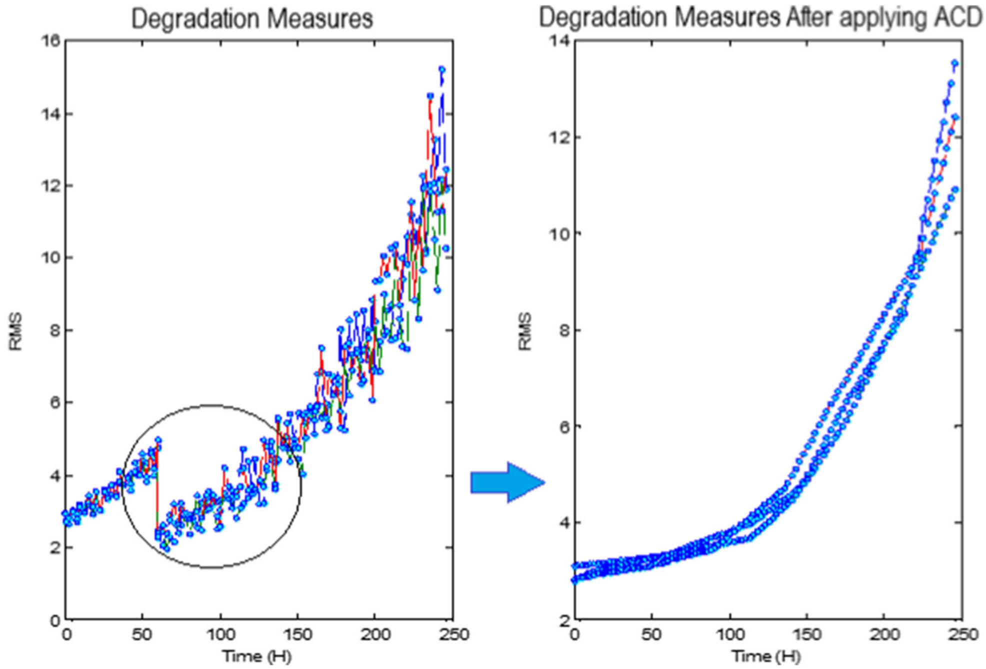

Fig. 14 Applying ACD for treating the non-monotonicity for three bearing degradation signals (speed changes from 35 to 20 RPM)

transforming the non-monotonic data to monotonic. Accordingly, it is worthwhile to consider the potential benefits of ACD for treating non-monotonicity and stationary noise in PHM applications.

5 Conclusion

Monotonic fault progression is an important assumption for a number of prognostic systems. This assumption can be violated through human intervention and self-healing. Non-monotonic degradation data not only increase the uncertainty but also may cause model failure in PHM. The existence of non-monotonic degradation paths among the population of the degradation data would also impact the trendability which indicates the level that data can be described by the same functional form. Methods to analyze and handle non-monotonic degradation in repairable systems are practically nonexistent in the PHM literature. In this research, we intend to consider repairable systems in which self-healing and human interventions are desirable. We presented a novel example of self-healing for fatigue cracks analyzed by acoustic emission (AE). The aim of the present paper is to initiate a new research area on using non-monotonic data in degradation-based prognostics. In essence, efficient trend detection is also critical in early discovery of an impending failure. A fruitful trend analysis requires proper sampling frequency and continuous recording of degradation measures.

Statistical trend analysis methods might be useful only as a preliminary trend check. Graphical methods are appropriate for trend detection of signal features. Particularly, cumulative plots are useful for certain features, e.g., energy-related features. The decreasing slope of an increasing cumulative degradation can be a sign of improvement in durability. Generally speaking, graphical methods are not useful for data with slight trends, and therefore they need to be combined with analytical methods. In addition, graphical tests are based upon interpretation which is prone to error.

Analyzing the waveform might be a better option before doing any feature extraction. HHT is very useful in noise removal and extracting the main components of degradation signals. Those components can be used for trend analysis and feature extraction. Obviously, the first component of the signal has better indication of the trend change. Therefore, HHT along with the modified crest factor has the potential to provide the indication of trend change even for real-time applications. The modified crest factor worked appropriately in analyzing and comparing the waveforms. Nevertheless, the waveform analysis needs to be supported by quantitate measures rather than relying on graphical examination.

For multivariate data, it was realized that PCA is able to indicate the trends in the data providing its perfect performance. Preliminary analysis of the data including smoothing, filtering, and eliminating the correlated variables were very helpful in proper implementation of PCA.

The methods for treating non-monotonicity can be applied in empirical degradation-based prognostic which takes into account the measured or inferred conditions of a specific unit under study. In this paper, two algorithms to deal with non-monotonic trend are introduced: trend-based segmentation and ACD. The ACD works well in estimating the monotonic trend for time series data with arbitrary stationary noise. More importantly, ACD reveals one of the possible monotonic components of a non-monotonic trend. It is important to note that Bayesian GPM applied for the non-monotonic-bearing degradation data. This prognostic model failed to provide any RUL estimation due to high level of non-monotonicity. However, the prognostic model worked properly after applying the ACD and transforming the non-monotonic data to monotonic. It seems, both algorithms have the potential to treat the non-monotonicity in degradation data even for real-time applications.

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