# A Novel Implementation of Vibration Signal Decomposition for Estimation of Degradation in Rotating Plant

Blair Brown, Bruce Stephen, Stephen McArthur, Graeme West and Craig Michie
Department of Electronic and Electrical Engineering, University of Strathclyde
Glasgow, G1 1RD, United Kingdom
0141 444 7027
Blair.Brown@strath.ac.uk

**Abstract**

Effective and transparent monitoring of rotating plant assets is essential to the continued reliable operation of power stations. Rotating plant monitoring generally includes analysis of vibration signals, where operations and maintenance engineers use the output from vibration sensors to justify the continued operation of the plant or plan for maintenance interventions where necessary. One common approach to such vibration monitoring is the adoption of alarm driven strategies where certain operational or mechanical interventions are performed when thresholds are triggered due to deviations from a predefined operational envelope. This reactive intervention approach, however, does not provide operators or equipment manufacturers with any insight into the long-term degradation of a rotating plant item, which could be used to mitigate unplanned stoppages. This paper proposes the novel implementation of Empirical Mode Decomposition to boiler feed pump vibration signals, alongside subsequent statistical analysis of the decomposed signals to estimate time-frames associated with alarm violations and entry into predefined zones of operation. Such a technique provides pump operators with information that can be used to plan for future maintenance interventions and pump manufactures with insight into the likely degradation of their product during sustained operation.

## 1. Introduction

### *1.1 Context*

The ability to conduct effective and transparent monitoring of plant items in power generation is essential to continued operation; rotating plant assets make up a significant proportion of the monitoring to ensure the station's safe operation(1)(2). Through implementation of condition-based maintenance the aim is to avoid unplanned outages, which would result in decreased power output and subsequently a decrease in revenue for the operator.

Increases in the data made available to monitoring systems alongside the desire of both plant operators and manufactures to gain greater insight into the health status of plant items has led to the development and introduction of intelligent data-driven techniques and systems. These use modern, advanced algorithms and approaches to extract useful information from the ever increasing volume of on-going and historical operational data related to monitored plant. Rotating plant assets are no exception to this rule with a number of new systems being developing for gas turbines(3), centrifugal pumps (4) and electrical motors(5) amongst others(6).

The power generation industry employs rotating plant in a variety of different roles, including the movement of water in pumps, electrical motors and turbines, and fans or gas circulators. A specific example is the boiler feed pump. Boiler feed pumps move liquid water from a condenser to a boiler. As these pumps are essential to the continued operation of the station they are subjected to a significant number of data-related condition monitoring activities. Also, as there are generally multiple boiler feed pumps on each station the analysis of monitored data represents a significant burden on the analyst responsible for their safe operation[7].

While condition monitoring has mainly focused on diagnosing existing faults or abnormal modes of operation a further goal is to develop the means of predicting the remaining useful life of plant items[8][9]. Such techniques or procedures would be valuable to the power generation industry as plant item failures could be identified earlier and planned for. Moreover, by corroborating the likely degradation of the asset against known operational conditions it may be possible to extend the asset's operational life.

This paper proposes a novel technique to estimate the time-scale associated with degradation of boiler feed pumps. The approach is based upon the deconstruction of a real boiler feed pump's vibration signals by applying Empirical Mode Decomposition (EMD), plus subsequent statistical analysis to determine predictive metrics. These metrics are based upon a boiler feed pump's real operational envelop and associated alarm driven strategy[10], providing real insight for pump operators and manufacturers.

### *2.1 Related Work*

Rotating machinery prognostics is an on-going field of study that is actively pursued by many organisations and industries, with several existing reviews that cover the subject[8][11][12]. Prognosis in this capacity is defined as the prediction of the remaining useful life of an asset (or asset's component) or estimating the probability that an asset can maintain functionality until failure occurs[13]. Prognostic models can be categorised into model-based, data-driven based, and combination models[14]. Data-driven approaches make use of condition monitoring data, instead of building particular physical models based upon predetermined system physics[6]. A data-driven approach is selected for this research, as a substantial quantity of vibration data is available as a matter of operational course. Development of prognostic techniques, which can be applied to non-linear and non-stationary operating conditions, such as those associated with boiler feed pumps, is a non-trivial task[15]. Boiler feed pumps are complex machines and the power stations they are deployed on usually have a range of complex operating conditions requiring similar considerations to be taken into account[7].

Various techniques and processes have been developed for the purpose of estimating prognostic metrics on rotating plant based upon vibration data[16][17]. However, to overcome the complexity of the plant and system under investigation a technique based upon EMD[18] has been selected. EMD has mainly been utilised in rotating machine diagnosis tasks[19]. However, an initial study has been conducted to extract data trends in an unsupervised manner[20]. EMD has been used extensively in the fault diagnosis of rotating machine components including rolling element bearings, gears and rotors. Energy operator demodulation[21] and amplitude energy acceleration[22] investigation based upon decomposition outputs have been used as a basis of bearing fault diagnosis. Early fault detection based upon IMF kurtosis'[23] and adaptive angle-domain signals[24] have been proposed for rotating gears. Rotor-to-stator rub and fluid excitation faults have been also been proposed using EMD[25][26]. Alongside the standard EMD technique, improved EMD methods have also been developed to increase the effectiveness of rotating machine fault diagnosis, these include ensemble EMD[27] and b-spline EMD[28].

With respect to the existing related work in the field of rotating machinery prognostics, the research discussed in this paper presents a novel application of EMD to boiler feed pump vibration signals, alongside subsequent statistical analysis of the decomposed signals to estimate time-frames associated with alarm violations and entry into predefined zones of operation. The proposed technique is also transferable to other rotating machine platforms that utilise vibration monitoring.

## 2. Problem Definition

### *2.1 Rotating Plant Monitoring*

Monitoring of rotating machines is often time intensive for analysts to diagnose the state of the machine and vibration analysis is a standard part of the diagnosis process. Generally vibration-based condition monitoring of rotating plant follows a standard process where analysis is performed on the asset's monitored vibration and operational parameters following the triggering of an alarm. Both time-domain features (amplitudes and phases) and frequency-domain features (such as fast Fourier transforms) are widely used in the vibration analysis. These parameters are correlated to operational parameters to determine if the alarm is a consequence of an expected station operation. If the alarm can be attributed to an expected change then it is written off as 'routine'. Alternatively the asset will be subjected to further mechanical inspection to determine the reason for the change in monitored behaviour. This type of reactive maintenance strategy does not permit engineers to proactively plan for interventions that could be identified by deeper analysis of monitored data. Moreover, this process does not provide insight into (or indication of) any longer-term degradation processes. An example of a standard monitored vibration parameter is shown in figure 1. From this figure different modes of operation (on, off, etc.) can be seen alongside the noise and outliers associated with a data capture of approximately two years.

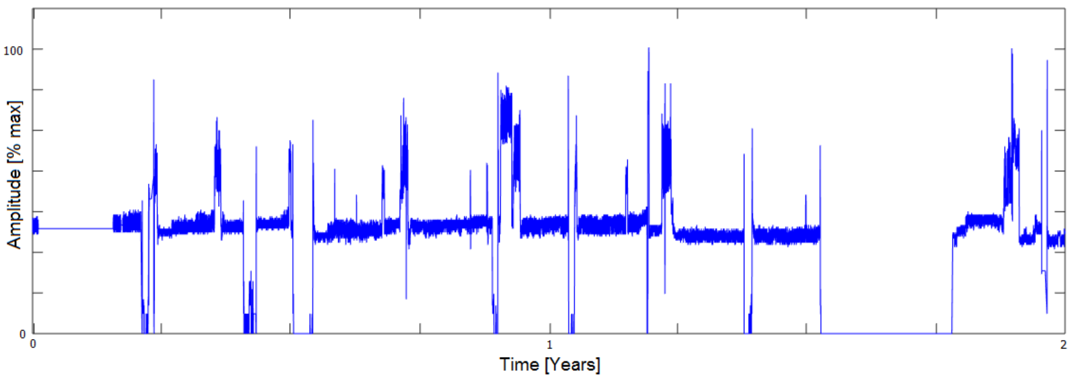


**Figure 1. Example vibration signal**

Boiler feed pumps (BFP) are rotodynamic pumps that are intensively monitored and are responsible for circulating water around the water-steam loop of a power station. Understandably, their health is subject to high levels of scrutiny throughout their entire operational life. Due to the importance of BFP operations on power station availability (and also the trend for power stations life extension programmes[29]) associated condition monitoring has seen a rise in the volume of monitoring data being acquired and stored, alongside an increased analysis of this data for the purpose of diagnosis and prognosis studies.

A problem that arises during the analysis of operational signals is determining an appropriate means of representing and visualising signals such that important characteristics can be identified and assessed in an informative manner. If any BFP vibration level reaches predefined limits it will be taken offline for inspection and refurbishment within a short timescale. The design and maintenance philosophy for BFPs has resulted in very few instances of failures, or maintenance interventions being required. Therefore there is limited failure data for prognostics studies. However, using vibration data related to the limited number of degraded BFP states alongside extensive historical data, long term degradation information may be characterised by features of the component parts of a deconstructed parent signals.

## 3. Signal Decomposition

Traditional signal processing techniques, including time-domain and frequency-domain analysis, are based on the assumption that the process generating the signals are stationary (i.e. inherent features do not change when shifted in time) and linear (i.e. the vibration signal responds in a linear fashion to any change in operational state). This can result in false information when the technique is applied to signals corresponding to mechanical faults or degradation processes, as these events or processes can be non-stationary and generate transient events. To deal with non-stationary signals, several advanced time-frequency analysis techniques have been introduced and applied to fault diagnosis of rotating machinery. For the purpose of this study, one specific technique has been utilised: EMD, as it is regarded as a robust tool for analysing non-stationary, nonlinear data.

### *3.1 Empirical Mode Decomposition*

EMD is a powerful time-frequency analysis techniques due to being computationally efficient and also conserving the features of the parent signal. It is based on the local characteristic time scales of a signal and can decompose the parent signal into a set of complete and almost orthogonal components signals that are denoted intrinsic mode functions (IMF). The IMFs represent natural oscillatory modes embedded in the parent signal and serve as representative functions, which are determined by the signal itself, rather than predetermined kernels.

The technique is an intuitive means of investigating the underlying structure of an oscillating signal and naturally adapts to the features of the signal under investigation. EMD automatically decomposes the original signal (*x(t)*) into a finite number of band-limited oscillations (IMFs)[18]. The decomposition technique defines each decomposed oscillation as an IMF if it satisfies two conditions:

1. The number of extrema and the number of zero crossings must be equal or differ at most by one;
2. The local average is zero, i.e. the envelop mean of the upper envelop and lower envelop is zero;

Therefore *x(t)* can be represented by the linear sum of the constituent IMFs plus a residual term:

$$x(t) = \sum_{k=1}^{N} IMF_k(t) + r_N(t) \qquad (1)$$

where $IMF_k(t)$ denotes the k*th* IMF and $r_N(t)$ is the residual.
The EMD process can subsequently be defined as:

1. Identify the local extrema of $x(t)$;
2. Determine the two functions defined by the local maxima ($max(t)$) and local minima ($min(t)$);
3. Calculate the average of the two functions defined by the local maxima and local minima, $ave(t) = \frac{(\max(t) - \min(t))}{2}$;
4. Subtract the mean from the signal to form a candidate IMF signal, $c(t) = x(t) - ave(t)$;
5. Determine if the candidate signal is an IMF:
    a. Yes - return to step 1. with the residual deduced from the original signal, $res(t) = x(t) - c(t)$
    b. No – replace $x(t)$ with $c(t)$ and return to step 1.

The IMFs determined from the above process ($IMF_1(t), IMF_2(t), \ldots IMF_n(t)$) are representative of frequency bands of decreasing frequency. The components contained within each frequency band are different and vary with the signal $x(t)$.The final residual term $r_N(t)$ represents the central trend of the signal in general, i.e. increasing or decreasing.

### *3.2 Boiler Feed Pump Vibration Signal Decomposition*

The main benefit of adopting an EMD approach to signal decomposition is that the resultant IMFs preserve the time-variant oscillatory modes that exist in the parent signal. This property of the technique can henceforth be used to determine underlying features present in the signal and also to potentially remove any noise. An example of a real vibration signal decomposed by EMD is shown in Figure 2. The subplot at the top of the figure depicts the parent signal and the subsequent eight subplots correspond to the eight IMFs that result from the decomposition. Comparing the parent signal to the IMFs it is evident that the first two IMFs are representative of signal noise. Features that are more interesting can be identified in the subplots related to IMFs five, six, seven and eight - here it becomes evident that the original signal contains lower frequency features that are more representative of phenomena such as the machine's response to operational changes.

### *3.3 Prognosis: Statistical Analysis, Regression and Extrapolation*

By comparing the statistical features of the lower frequency IMFs during multiple periods of similar BFP operational state it is possible to derive an impression of how the BFP state is changing over time. If linear regression is then applied to the statistical features and this trend is extrapolated in time, it is possible to make an estimate of the longer term degradation trends or when BFPs may potentially require a maintenance intervention, hence producing a prognostic tool.

The first step in this process requires the identification of multiple similar BFP operational states. To achieve this five periods of stable BFP operation have been selected based upon the ground truth of the pump speed. When the pump speed is operating within predefined upper and lower speed limits it can be regarded as being in normal operation. EMD is then applied to each period of normal operation and the IMFs determined. An example of this process is shown in Figure 3. Similar to the data depicted in Figure 2 it can be seen that the parent signal is dominated by the magnitudes in the first two or three IMFs, however there are significant statistical artefacts in the remaining IMFs (four through eight) to permit further analysis.

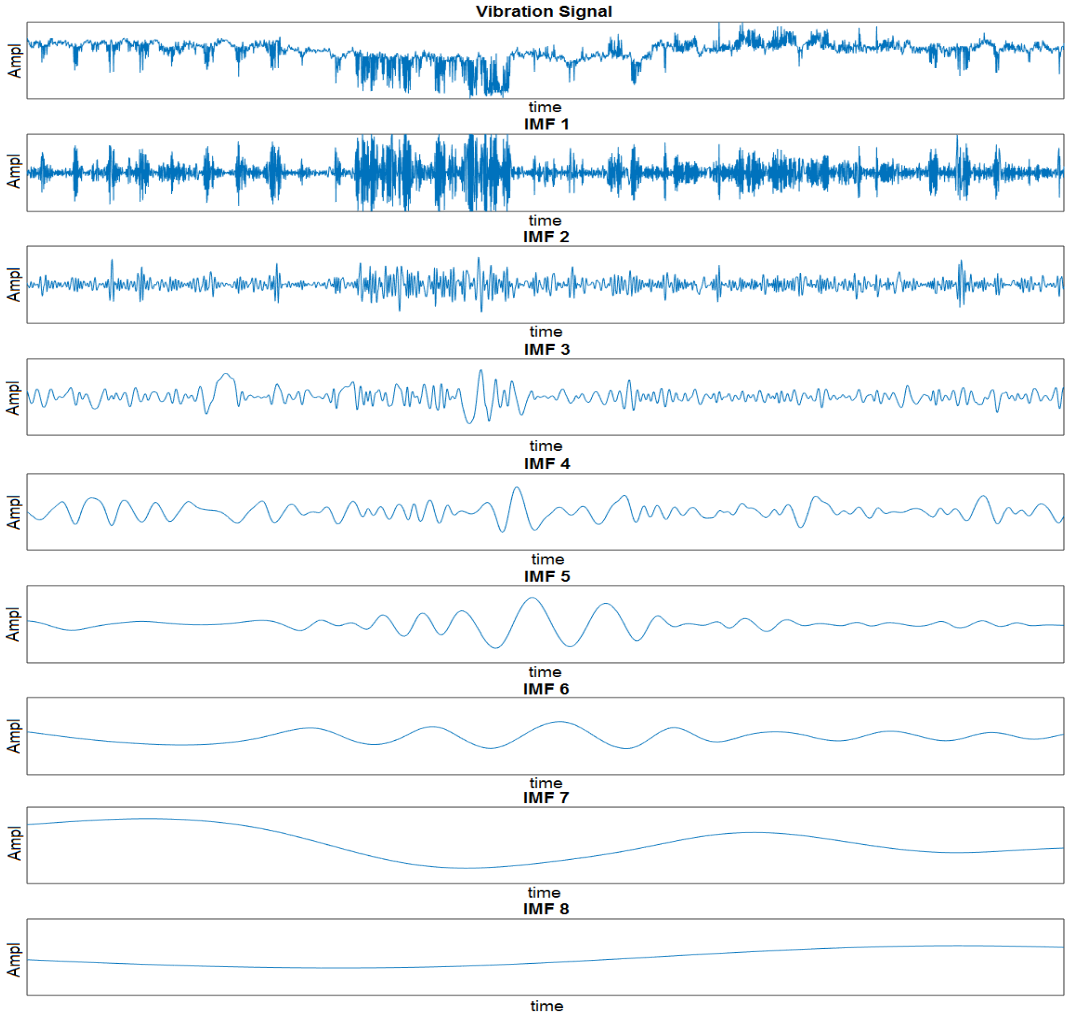


**Figure 2. Vibration signal decomposed by EMD**

A statistical analysis based upon the decomposed signals is now performed on IMFs four through eight at each of the five periods of normal BFP operation. The first step of the statistical analysis is to assess the first four statistical moments associated with each IMF. For the same operational periods considered in Figure 3 the values for each of the first four statistical moments associated with IMFs four through eight are depicted in Figure 4. From Figure 4 it is not easy to interpret any change in the BFP's state due to multiple time series for each IMF being present. However the qualitative similarity across many of the IMFs can be seen, implying underlying trends; the exception being IMF eight, which varies considerably in comparison to the others. This is not surprising as IMF eight represents considerably lower frequency features of the decomposed signals with any non-stationary feature being more prominent. The second step of the statistical analysis is now performed on the second, third and fourth moments of the decomposed signals. The first moment is excluded due to the first condition associated with the EMD process requiring the mean value of IMFs to always be equal (or close to) zero (see section 3.1). To determine any underlying trends associated with the data presented in Figure 4 the mean and standard deviation are calculated based upon the data for IMFs four through eight, again at each of the five periods of normal operation. The results of this second phase of assessment are shown in the six lower plots in Figure 5.

Figure 5 depicts the original vibration signature (upper) and the results from the two step statistical analysis. By including a first order linear regression for each of the six statistical measures it can be seen that there is a tendency for each of the measures to increase. It is noted that the positive gradient for the mean of the skewness indicator is based upon negative numbers approaching zero. This implies that the data is becoming less negatively skewed over the time periods analysed. By comparing the original vibration signal with the six outputs from statistical analysis it can be seen that there are underlying trends in the data that cannot be easily assessed manually. This analysis hence forms the basis of the process for estimating a long term state change in BFPs.

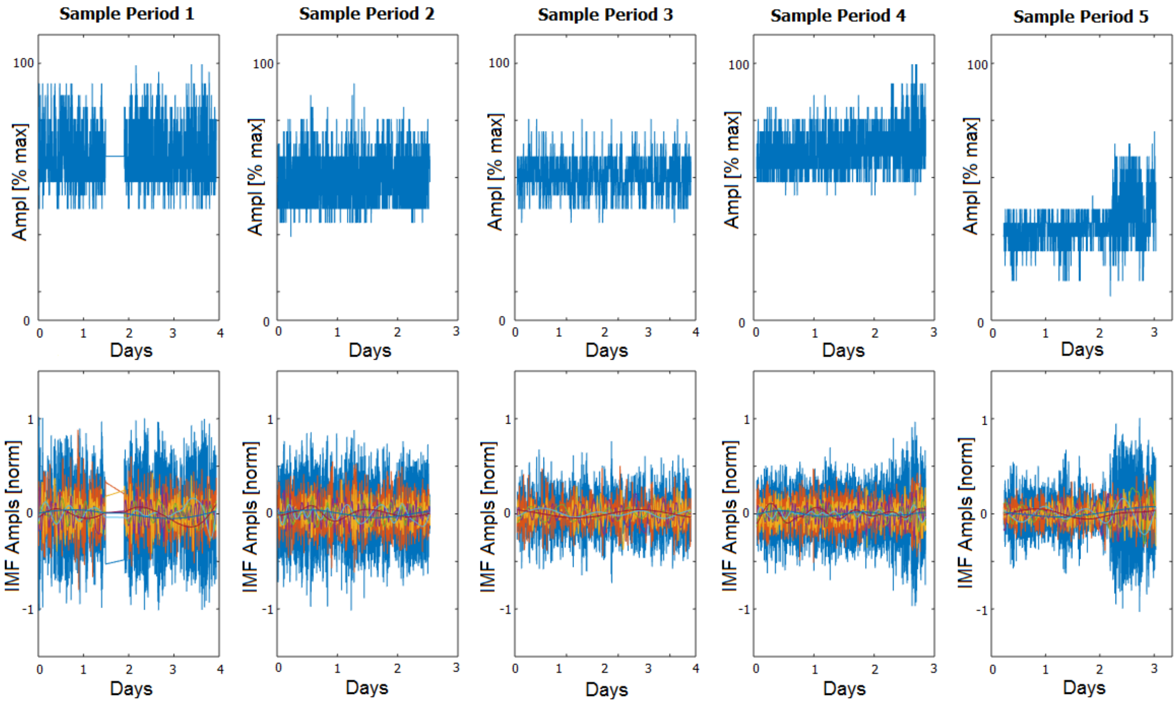


**Figure 3. Five Successive EMDs on one vibration signal**

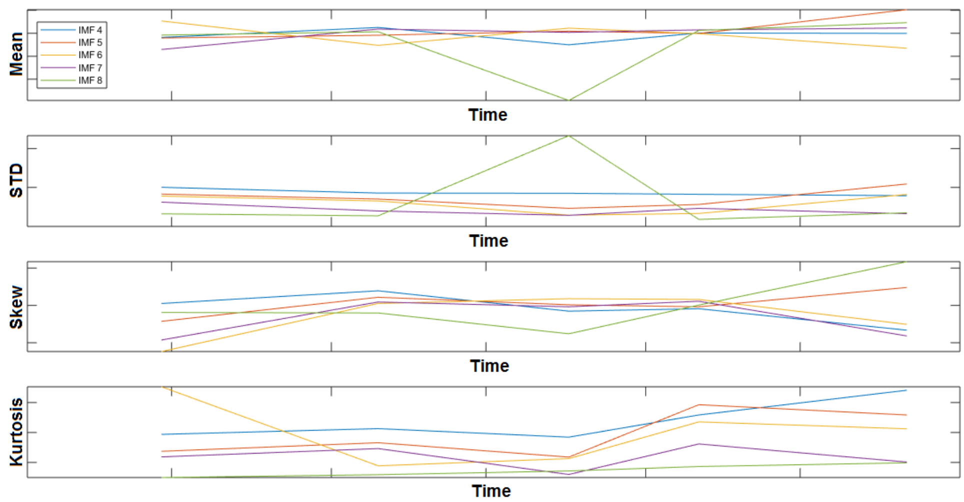


**Figure 4. Statistical moments for IMF four through eight**

To provide a bench mark for when the BFP is approaching undesirable levels of vibration it is necessary to conduct the same analysis described above on a case study where the same BFP is known to have degraded. For the BFP in question there is one instance where vibration levels exceeded acceptable operational levels (as defined by BS ISO standard 10816-7 2009) and required a maintenance intervention. This case study is depicted in Figure 6, with the vertical red lines indicating the time when the maintenance intervention occurred, both in terms of the original vibration signature and the six prognostic indicators. It is noted that the signal decomposition and subsequent analysis were performed on five time periods prior to the maintenance intervention.

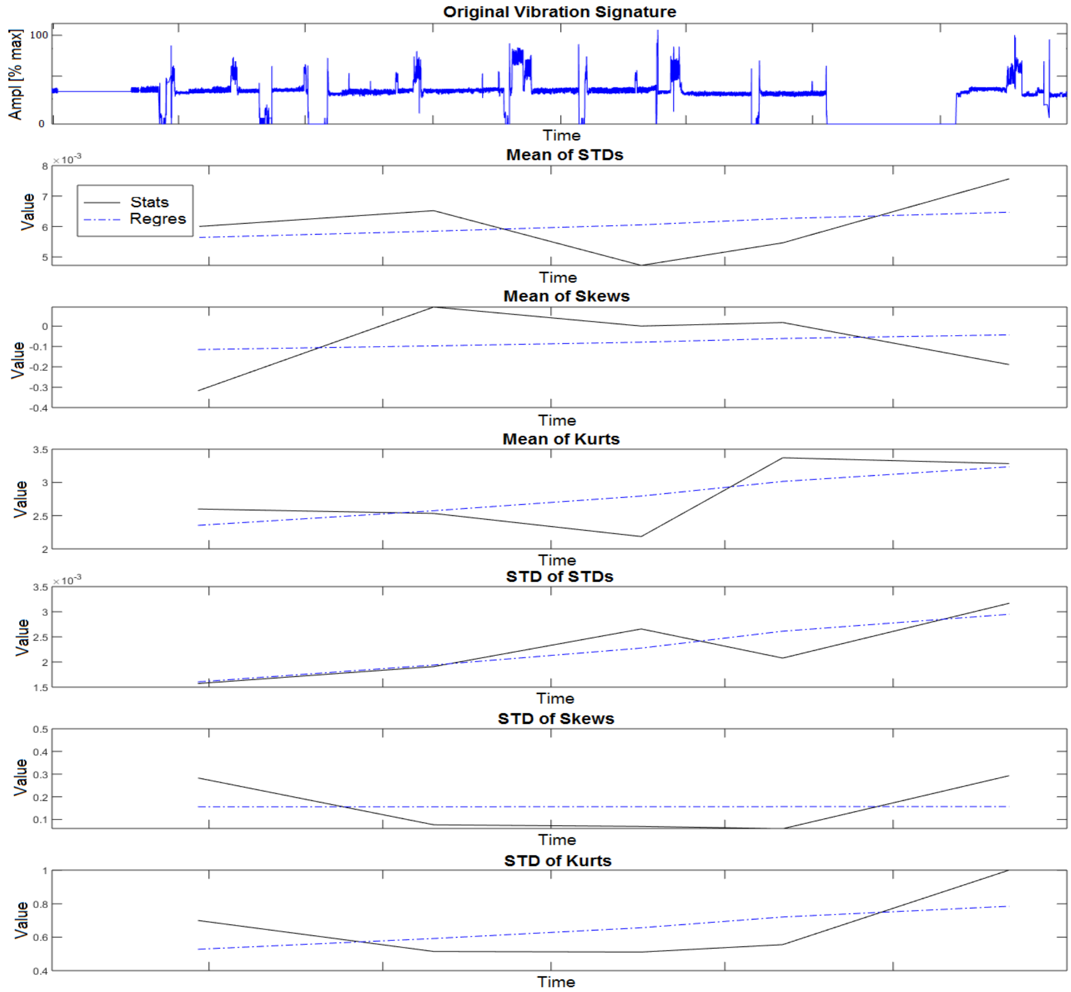


**Figure 5. Two step statistical analysis and 1st order regression**

From Figure 6 the regression lines associated with the six prognostic indicators show a clear positive gradient in five of the six indicators. The sixth indicator, associated with the standard deviation of the IMFs' skew values, indicates a negative gradient. This result is not unexpected as the individual IMF skew values are both positive and negative across the five different time periods. However, the magnitudes of the remaining five positive gradients associated with this data are larger than the gradients of the previous case. This implies that any underlying trend in state change is greater in the degraded case study than in the previous case where no degradation is known to be present. On each plot, from the position where the blue dashed regression lines intersects the red maintenance intervention date lines, the associated magnitude of the statistical indicators can be interpreted as an approximate threshold, representative of the magnitude each statistical parameter may reach when a maintenance intervention is required. The thresholds for each statistical indicator threshold are depicted by the horizontal green lines in Figure 6. Translating the thresholds determined from the analysis containing the maintenance intervention to the previous data set it is possible to gauge the time at which a likely intervention may be required by extrapolating the relevant regression lines until they pass their associated threshold. Extrapolated statistic indicators for the five prognostic indicators that follow a positive gradient are shown in Figure 7. In this figure, it can be seen that each of the five indicators exceed their associated thresholds at a range of projected future times. The indicators associated with skewness and kurtosis pass their thresholds first, with the indicators associated with standard deviation taking significantly longer.

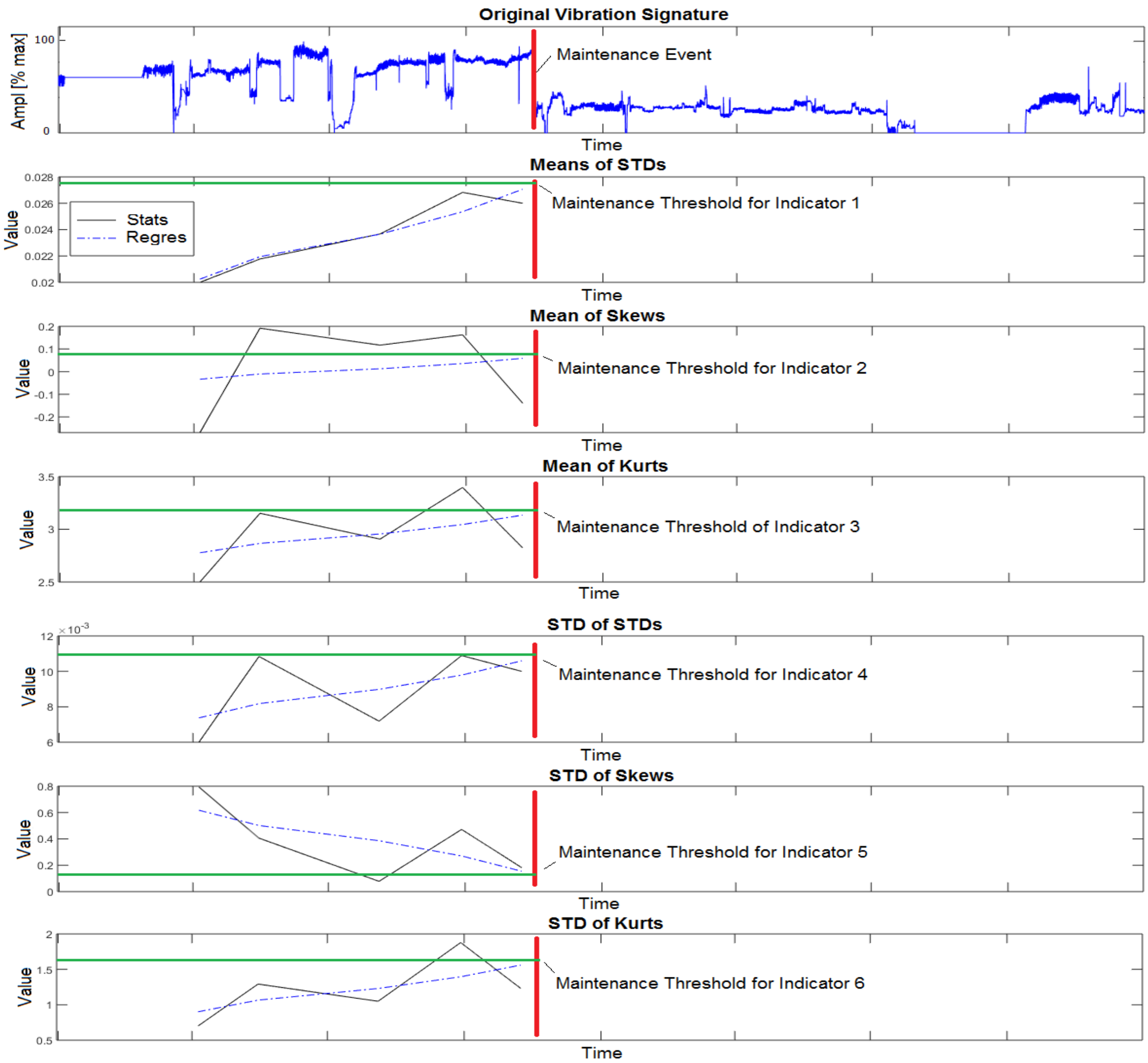


**Figure 6. Statistical trends with event and thresholds**

## 4. Discussion and Future Work

Assessing the outputs from the proposed produces some interesting results. Firstly, although monitored vibration data may not seem to be varying from the perspective of a manual observer, it is possible to gain insight into underlying trends that exist within the data by decomposing the signal and conducting statistical analysis on the resulting components. By interpreting the relevant decomposed signals that are of statistical significance it may be possible to extract information regarding the health of the asset. Extrapolation methods then provide a means of estimating the potential degradation of the asset.

However, the decomposition method does have limitations, as the decomposed signals are not easily associated with real physical phenomenon; hence requiring a statistical analysis to determine features of interest. It is noted that the statistical approach does not always produce an output that can be related to the asset's degraded state. For example, the decomposed skewness values do not evolve over time in a manner that readily lends itself to a long term trend. Also the kurtosis values do not change sufficiently to be interpreted as a significant degradation. These characteristics of the analysis result in a wide variation in prediction metrics.

To develop this method further there exists a number of avenues for future work. First, there are other signal decomposition methods that should be assessed. These techniques each have their own benefits and drawbacks but may ultimately provide more insight into the decomposed signals interpretation. There also exists analysis techniques that can be used to combine the multiple predictive indicators into a single indicator representative of all the individual parts. Finally, it is suggested that the technique can be extended to multi-dimensional form, where multiple data signals are assessed simultaneously in order to determine a more holistic understanding of the asset under investigation.

## 5. Conclusions

This paper has presented a new approach to predicting the health of BFPs using EMD and statistical analysis. The method moves away from standard methods of health prediction to determine underlying features which are not evident to a manual observer. In the case study discussed it has been shown that the original data stream does contain longer period trends that may be interpreted as asset degradation. It has also been shown that it is possible to make predictions about the future state of the asset even when there is relatively little data available.

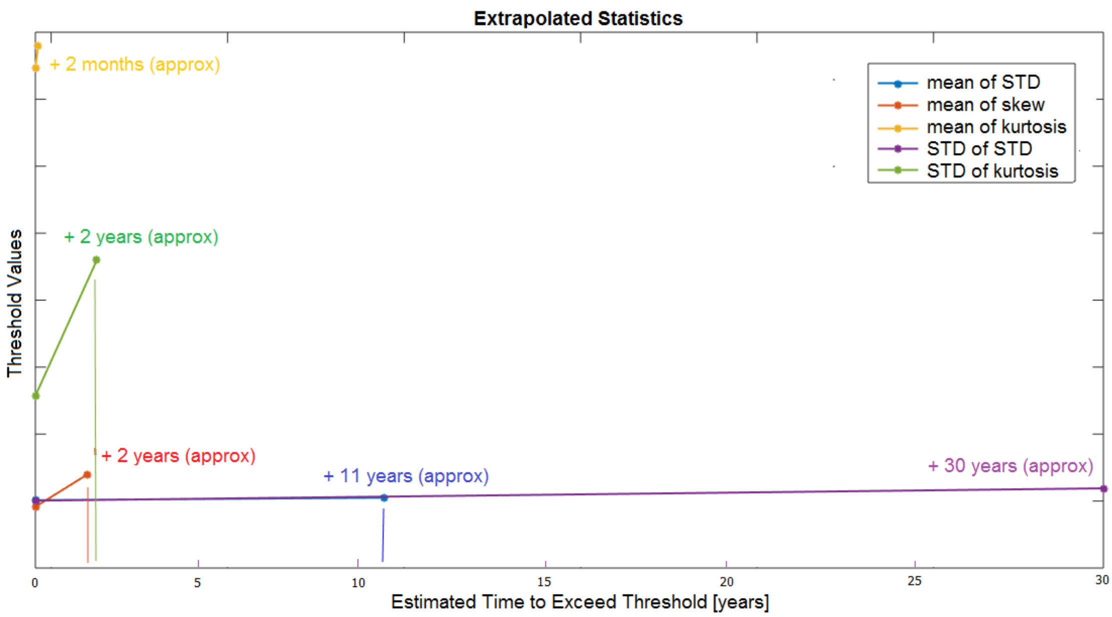


**Figure 7. Extrapolation of statistical trends**

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