Towards the use of hybrid models for diagnosis and prognosis in turbomachinery health management

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Abstract
Turbomachinery failures are often caused by the dynamic behaviour of rotating blades. The implications of such failures may be serious and practical blade condition monitoring methodologies are therefore becoming important. In this work the idea of hybrid models that rely partly on data driven blade tip timing and partly on physics based finite element models is explored. The work is founded on a Bayesian linear regression based blade tip timing technique which is combined with a stochastic finite element model. This stochastic hybrid approach is applied for the identification and classification of turbomachine blade damage. For the purposes of demonstration, discrete damage is incrementally introduced to a simplified test blade of an experimental rotor setup. The damage identification and classification processes are further used to determine whether a specified damage threshold has been reached, therefore providing sufficient evidence to schedule maintenance.

1. Introduction

Failures of turbomachinery are often caused by the dynamic behaviour of rotating blades. The financial and production implications of such failures may be very significant and appropriate blade condition monitoring methodologies are therefore of critical importance [1,2]. Blade tip timing (BTT) is a non-intrusive measurement technique for online measurement of turbomachine vibration. Essentially it senses when a blade passes a number of proximity probes distributed circumferentially and mounted radially through the turbomachine casing above the row of rotor blades being measured, to determine the blade tip time of arrival. This can be linked to the blade vibration by employing an accurate measure of the once per revolution reference signal. The technique is non-intrusive and online monitoring is possible.

BTT is therefore often regarded as a feasible technique to track the condition of turbomachine blades and prevent unexpected and catastrophic failures. The processing of BTT data to find the associated vibration characteristics is however not trivial. In addition, these vibration characteristics are difficult to validate, therefore resulting in great uncertainty of the reliability of BTT techniques. To deal with the uncertainties of the method, various new concepts have been introduced [2,3,4]. These ideas deal primarily with diagnosis. Techniques for prognosis to assist with maintenance decision making is however becoming more important. Mishra et al. [5] explored a range of techniques of interest to accomplish this through the use of hybrid models that merge physics based and data driven approaches into a unified approach.

In this work the idea of hybrid models is pursued further in the context of turbomachinery blades, by proposing an approach comprising a stochastic finite element model (FEM) based modal analysis and a Bayesian linear regression (BLR) based BTT technique. The use of this stochastic hybrid approach is demonstrated for the identification and classification of turbomachine blade damage. For the purposes of this demonstration, discrete damage is incrementally introduced to a simplified test blade of an experimental rotor setup. The damage identification and classification processes are further used to determine whether a damage threshold has been reached, therefore providing sufficient evidence to schedule maintenance. It is shown that the proposed stochastic hybrid approach may offer benefits for practical implementation. This paper highlights some aspects from of a comprehensive study by Du Toit, Diamond and Heyns [6] as well as some additional results that further corroborates the approach.

2. Hybrid methodology

Figure 1 outlines the proposed hybrid approach for the identification and classification of damage in a turbomachine blade. The process firstly comprises a data driven blade tip timing analysis to track the relative change in natural frequency of a blade to identify and infer the extent of blade damage at a given time. A blade damage threshold is established through finite element analysis. The BTT analysis is repeated continuously until this threshold is reached. Once this threshold is reached, the operation of the turbomachine should be stopped and relevant maintenance be conducted. Subsequently the blade natural frequency and amplitude determined from the blade tip timing results are clustered using predetermined mean values as initial cluster centres. This clustering then allows the severity of the damage to be classified.

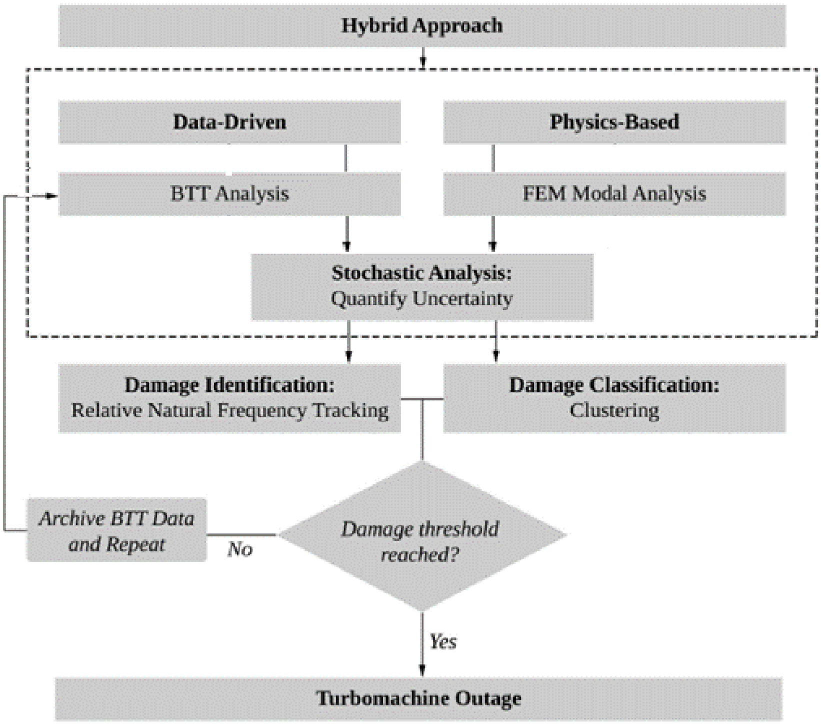


Figure 1: Schematic overview of the proposed hybrid methodology

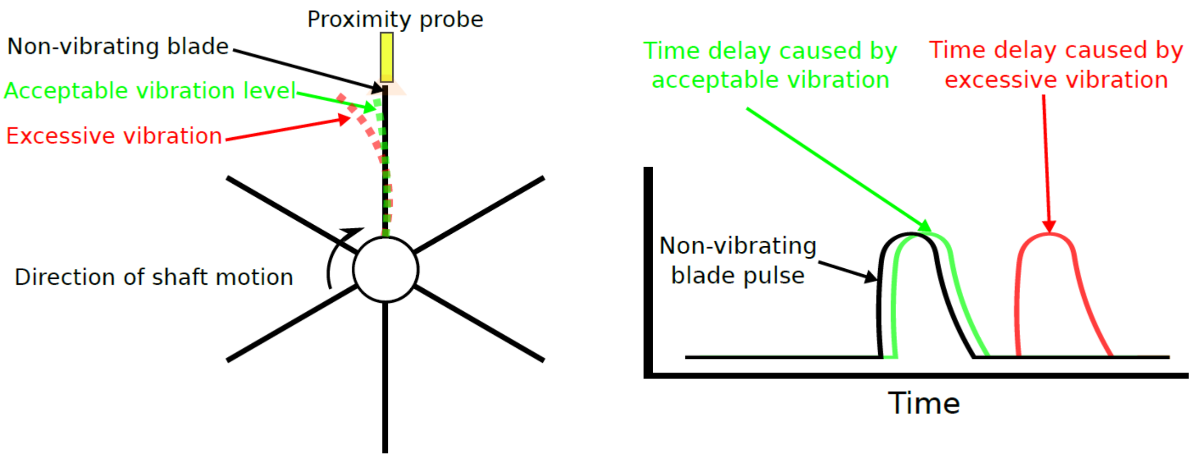
The rationale behind adopting such a hybrid approach is to:

- Use finite element analysis (FEA) to establish a baseline for comparison before BTT tests are performed.
- Project expected blade condition before it becomes possible from the BTT measurements.
- Correct for real blade behaviour and aspects not considered in the FEA.
- Enhance remaining useful life estimation.

The current methodology comprises two analysis types, namely damage identification in which the relative change in natural frequency is tracked to identify and infer the extent of the blade damage, and damage classification in which the natural frequency and blade response amplitudes derived from the BBT results are clustered using predetermined mean values as initial cluster centres to determine the severity of the blade damage. A damage threshold is determined based on FEA.

3. Data-driven investigation

The basic idea behind blade tip timing is to measure the time of arrival (ToA) of blades passing a proximity probe in the casing. This data is then analysed to determine the vibrational state of the blade. The ToA is dependent on the rotational speed of the shaft. However, a vibrating blade will either arrive earlier or later than expected at the proximity probe (see figure 2). Extracting the blade vibration from the ToA measurements can be complex in practice. Many algorithms have been developed for this purpose. Most of these algorithms are based on so-called *indirect* methods in which the maximum amplitude and corresponding frequency at resonance is determined during transient operating conditions and only one or two proximity probes are required, or *direct* methods in which the maximum amplitude at each rotational speed is determined during steady state and at least four probes are normally used.



(a) (b)

Figure 2: Blade tip timing (a) Rotor blade during operation (b) Proximity probe output

In this work we utilise a direct BTT method based on statistical inference [2]. The technique employs Bayesian linear regression (BLR) which offers a number of practical advantages: The tip displacement amplitude and phase with respect to the angular reference signal may be determined at each measured rotational speed. Firstly, this results in a detailed picture of these parameters and their changes over the operating domain. Secondly the processed data considers the whole range of inferred solutions, therefore resulting in a stochastic solution. Lastly, the stochastic nature of the processed data allows one to establish confidence intervals for amplitude and phase and renders the approach noise tolerant.

The BTT technique employed here assumes a single-degree-of-freedom (SDOF) model for the blade vibration. Equation (1) describes the blade tip displacement x at a specific time t, rotor order EO and circular frequency ω:

$$x_i(t) = A_i \cdot \cos(\omega \cdot t_i) + B_i \cdot \sin(\omega \cdot t_i) + C_i \quad \text{where} \quad \omega = EO \cdot \Omega \tag{1}$$

BLR is used to infer the values of the constants A, B and C as probabilistic quantities. The equations are solved for each revolution i at a corresponding shaft speed Ω, with EO also inferred from a probabilistic approach. The parameter set **x** is solved for each revolution and forms part of a multivariate normal distribution with associated mean μ_i and covariance matrix Σ_i as per equation 2.

$$\mathbf{x}_i = \begin{pmatrix} A_i \\ B_i \\ C_i \end{pmatrix} \quad \boldsymbol{\mu}_i = \begin{pmatrix} \mu_{A_i} \\ \mu_{B_i} \\ \mu_{C_i} \end{pmatrix} \quad \boldsymbol{\Sigma}_i = \begin{pmatrix} \Sigma_{AA_i} & \Sigma_{AB_i} & \Sigma_{AC_i} \\ \Sigma_{BA_i} & \Sigma_{BB_i} & \Sigma_{BC_i} \\ \Sigma_{CA_i} & \Sigma_{CB_i} & \Sigma_{CC_i} \end{pmatrix} \tag{2}$$

These random values are substituted in equations (3) to quantify the amplitude and phase:

$$\widehat{A}_i = \sqrt{A_i^2 + B_i^2}$$
$$\phi_i = \arctan\left(\frac{B_i}{A_i}\right) \tag{3}$$

The maximum amplitude and the associated natural frequency is indicated by equation (4)

$$f_{n_{\widehat{A}}} = f(\vartheta) \quad \text{where} \quad \vartheta = \max_{i \in N} \widehat{A}_i \tag{4}$$

while the natural frequency can also be derived from the phase angle

$$f_{n_{\hat{\phi}}} = f(\varrho) \quad \text{where} \quad \varrho = \frac{f_u + f_l}{2} \quad \text{subject to} \quad \Delta\hat{\phi} \geqslant \pi \tag{5}$$

For this work we used an experimental setup (see figures 3 and 4) comprising a rotor assembly, and excitation mechanism, sensors, a data acquisitioning and signal generation system. Labview was used to generate the signals for controlling the motor speed.

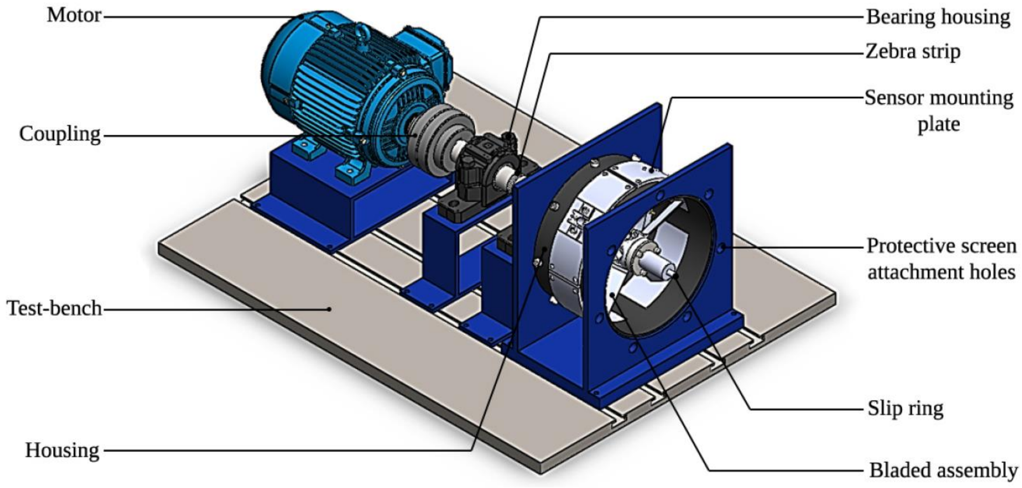


Figure 3: Schematic of the experimental setup

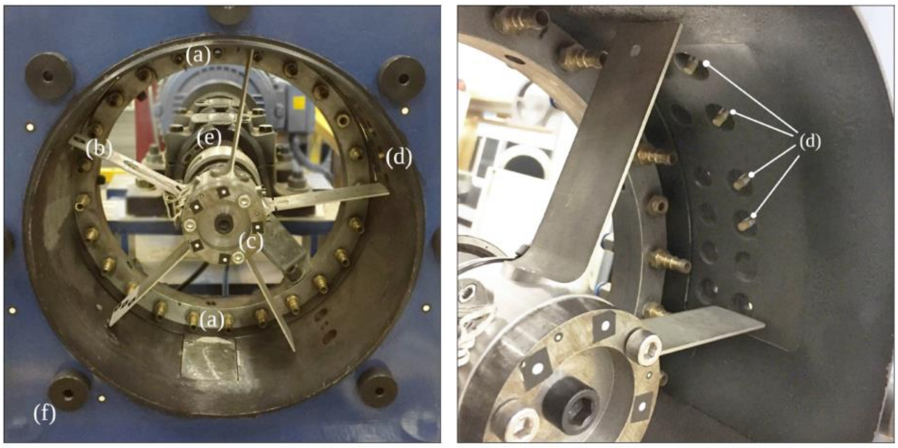


Figure 4: Photos of the rotor and casing

The bladed assembly and casing setup comprises (a) compressed air supply nozzles for blade excitation (b) a bladed assembly with 5 aluminium blades (c) a central hub with a slip ring arrangement for validation measurements using strain gauges (d) four irregularly spaced eddy current probes and (5) a shaft connected to a motor with a variable speed drive.

In this study damage was artificially introduced to a single blade (blade 2) of width 40 mm in twelve discrete steps ranging from 0 mm to 8.61 mm. Damage was classified in three ranges: non-severe (damage increments 1 to 6, ranging from 0 to 1.81 mm), mid-severity (damage increments 7 to 9, ranging from 3.11 mm to 5.60 mm) and severe (damage increments 10 to 12, ranging from 6,97 mm to 8.61 mm).

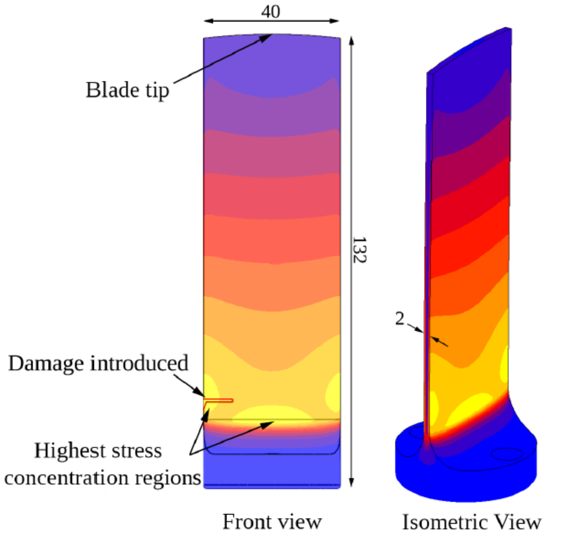


Figure 5: Damage introduced on blade 2, relative to the areas of highest stress concentration for mode 1, as determined from a FEA

The rotor shaft speed was subsequently ramped up from 1195 r/min to 1330 r/min in order to pass through the blade resonant frequencies to allow for the estimation of the amplitude and phase parameters as indicated in equations 4 and 5. BTT tests were repeated six times for each of the 12 damage increments, i.e. a total of 72 tests were conducted. To allow comparison of the extracted blade phase results between the tests, all measurements were synchronised with respect to a specific shaft encoder pulse.

4. Physics based investigation

A 3D FEA was conducted to determine the likely blade resonances at specific operational speeds. Centrifugal loads were accounted for by applying angular velocities to all elements. Thermal loads were accounted for by varying the material properties. The FEA was intended to supplement the BTT results as outlined in sections 5 and 6.

Marc Mentat was used to perform the FEA with the Lanczos algorithm to compute the natural frequencies and amplitudes for the simplified blade. The damage was again introduced in 12 discrete stages corresponding to the damage in the experimental test blade. Slight variations in angle (approximately 10°) and size (length, width and height – about 12%) were introduced for each discrete stage to account for uncertainties in true crack and crack location measurements as well as material properties and centrifugal loads. 89885 ten-noded tetrahedral finite elements were used for the basic geometry. Samples of these parameters were randomly selected from a uniform distribution within the angle and dimension ranges. Aluminium was selected as material with uncertainty again being introduced by varying the material properties within 12% of the reference values.
Variation in these parameters resulted in variation in the natural frequencies for each test within a particular series of tests. This allowed a mean with its associated confidence intervals around the mean, to be determined for each damage condition.

5. Damage identification

The first part of the proposed hybrid procedure considers the tracking of the relative change in the blade natural frequency (see equation 6) to identify and infer the degree of blade damage. Tracking the relative natural frequency change aims to give a more general indication of the blade condition, due to differences in the responses determined from the BTT results and the FEA results, which might not necessarily capture all the important physics associated with the rotating blade response.

The procedure therefore relies on tracking the relative changes of the derived BTT natural frequency results to infer the extent of the blade damage. The FEA allows one to estimate the expected blade conditions (relative change in natural frequency) corresponding to a particular damage size that is considered critical. This process is illustrated in figure 6.

The change in natural frequency from a reference state Δf_{ni} (undamaged in this case) is first quantified. f_{n0} is the original natural frequency and f_{ni} is the current natural frequency.

$$\Delta f_{n_i} = \frac{f_{n_0} - f_{n_i}}{f_{n_0}} \times 100 \tag{6}$$

The aim is to determine if the blade damage threshold has been reached. The challenge however is of course that the actual crack size of the blades can in practice not be determined while the online BTT measurements are made, and that the extent of blade damage must therefore be inferred from the processed BTT results.

Figure 6 shows two iterations of the proposed identification procedure. The figure shows the results from tracking the BTT relative natural frequency based on amplitude and phase based results.

The process follows the following steps:

- Define a blade damage level that would justify physical inspection. This is calculated from the FEM based on the principles of fracture mechanics or fatigue analysis and leads to the identification of a Level 1 damage threshold as seen ion figure 6.
- The FEM modal analysis is performed stochastically at this discrete crack size in order to quantify uncertainty. The mean μ_{FEM1} and the standard deviation σ_{FEM1} corresponding to this damage increment is subsequently recorded.
- A new variable δ_{damage} is then defined as in equation 7. This parameter represents the difference between the relative change in the natural frequency from the BTT results (for a particular batch of tests) and the relative change in natural frequency of the FEM results at a particular discrete damage size, represented by Level 1:

$$\delta_{damage} = \Delta f_{n_{BTT}} - \Delta f_{n_{FEM}}(K) \tag{7}$$

K corresponds to the predetermined crack size in the FEM modal analysis. δ_{damage} is a normal probability distribution with both Δf_{nBTT} and $\Delta f_{nFEM}(K)$ having associated normal distributions.

- The calculation of the mean and the variance of δ_{damage} requires that a number of repetitive BTT tests must be performed and that the mean μ_{BTT} and the standard deviation σ_{BTT} be determined.
- The probability $P(\delta_{damage} \leq 0)$ is determined for a batch of BTT tests and the chosen Δf_{nFEM} (Level 1 in this case). This probability is found from the cumulative distribution function (CDF) of δ_{damage} with the associated mean and variance as shown below:

$$\delta_{damage} \sim \mathcal{N}\left(\mu_{BTT} - \mu_{FEM}, \sigma_{BTT}^2 + \sigma_{FEM}^2\right) \tag{8}$$

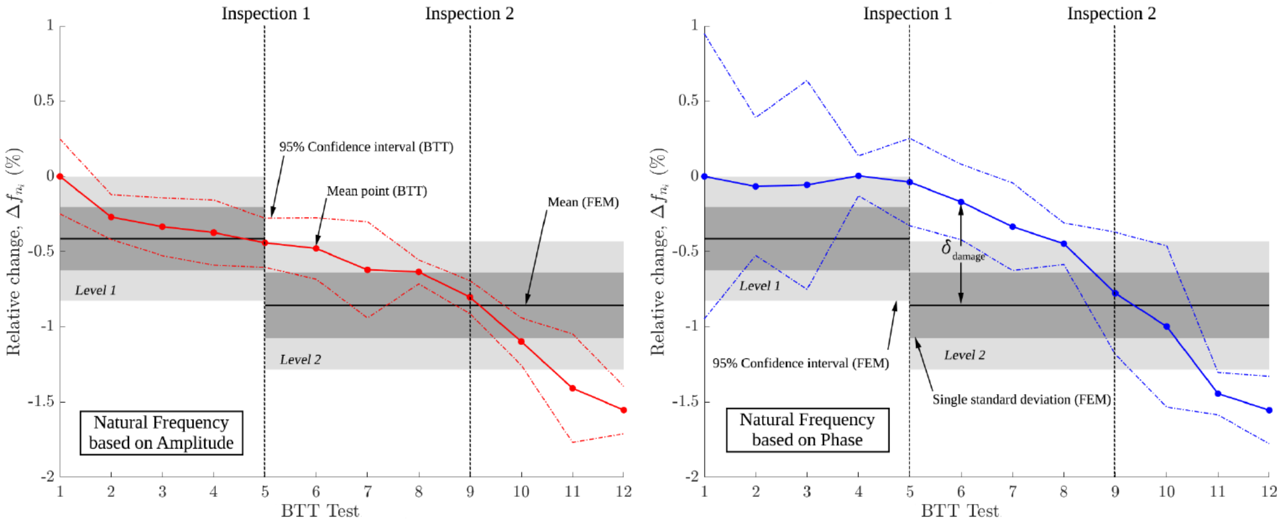


Figure 6: Damage identification at ambient temperature of 22°C

$P(\delta_{damage} \leq 0)$ is the probability that the relative change in natural frequency derived from the BTT measurements Δf_{nBTT} equals or exceeds the permissible relative change in natural frequency derived from the FEA, $\Delta f_{nFEM}(K)$. The damage threshold X_{dt} is based on a selected probability $P(\delta_{damage} \leq 0) > X_{dt}$

The user must decide what an acceptable probability would be to justify maintenance. Repetitive BTT tests are conducted until this probability value (damage threshold) is reached. It is important to note that the damage threshold X_{dt} may be selected to be conservative.

The above steps are repeated after every inspection or maintenance until a blade needs to be replaced. After each inspection a new damage level, based on the FEM results may be prescribed to determine a new blade damage threshold.

Figure 6 demonstrates two iterations of the damage identification process. In this diagram Level 1 corresponds to a relative discrete crack size of 3.95% and Level 2 corresponds to a relative discrete crack size of 9.675%. Both Levels 1 and 2 are arbitrarily selected here for demonstration purposes, but would in practice be based on physical evidence.

A very comprehensive set of experiments were also done at elevated temperatures of 41° and 98°C, using two 2 kW commercial heaters to heat the air stream through the machine. As a further example of the application of the procedure typical results for 98°C are also shown in figure 7. This figure confirms the general behaviour observed at ambient temperature (figure 6) and at 41°C (not shown here).

6. Damage classification

The damage identification process presented in section 5 relies on repetitive measurements to be available. The damage classification process described here however aims to allow the use of a single set of BTT measurements to determine the blade condition. A high level of confidence must therefore be attached to this measurement. To accomplish this a damage classification procedure that is based on the clustering of BTT natural frequency and amplitude values is investigated. Here we use the well-known K-means clustering technique, which assigns the observations with the nearest means to a certain cluster of data points. Physically this means that the vibrational characteristics of the blade from a specific BTT measurement, are assigned to an existing cluster of vibrational characteristics with the nearest mean. The aim of this cluster is to classify the severity of the blade damage according to which group the vibrational characteristics are assigned to. This means that the damage severity may be established from these clusters.

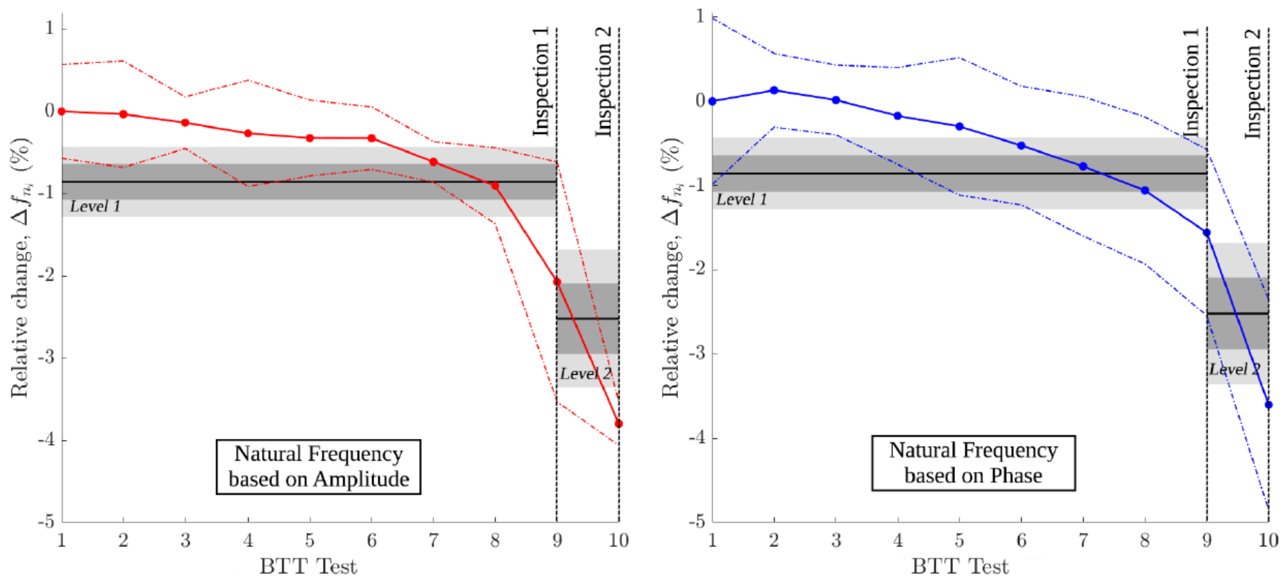


Figure 7: Damage identification at 98°C

The process follows the following steps:

- The amplitude and associated natural frequency of a specific blade are extracted from the BTT measurements.
- We propose clustering of the natural frequency and amplitude results using predetermined mean values. The predetermined values correspond to the natural frequency results from the FEA for mode 1. The blade amplitudes are however not computed from the FEA since this would require a computational fluid dynamic analysis. This is however a complex process and infeasible in practice, and is avoided here by simply assigning zero amplitudes to the initial clusters.
- In this work the data is partitioned in three clusters, namely non-severe damage, mid-severity damage and severe damage (see section 3). These partitions are not enforced on the BTT data before the K-means clustering commences. However after clustering is completed the individual natural frequency points and associated amplitudes are used to determine the accuracy of the final classification.
- The initial cluster centres correspond to zero amplitude values and the mean natural frequency values of the FEA results partitioned using the scheme mentioned above. This results in three amplitude and natural frequency combinations to be used as starting points for the centroids. These initial cluster centres enable individual BTT measurements to be classified to the closest partition.
- The BTT amplitude and natural frequency values are both normalised over the range 0 to 1 for use in the K-means clustering. The initial cluster centroids based on the FEA are also scaled using this scheme.
- The point-to-cluster-centroid distances are computed for all of the individual BTT points. These points are considered with no indication of which damage increment the points belong to. The overall averages of the points are calculated and the new centroid locations are allocated. As a result the BTT points are classified into the associated group of most likely Range of Damage (RoD) that the amplitude and natural frequency would represent. In figure 8 RoD I, RoD II and RoD III represent the new averaged clusters for the undamaged, middle damaged and largest damage increments respectively. The incorrectly classified points are also shown in figure 8.

Figure 8 shows the results of the K-means clustering implementation as part of the damage identification process. RoD I, RoD II and RoD III represent the new averaged clusters for the non-severe, mid-severity and severe damage classes respectively. Incorrectly classified points are indicated by a Roman numeral above the marker.

The overall classification accuracy is 78%. If only the RoD III case is considered, the accuracy would be 94%. However in one case an actual RoD III was incorrectly classified as a RoD I point. This is obviously dangerous and points to further research being required.

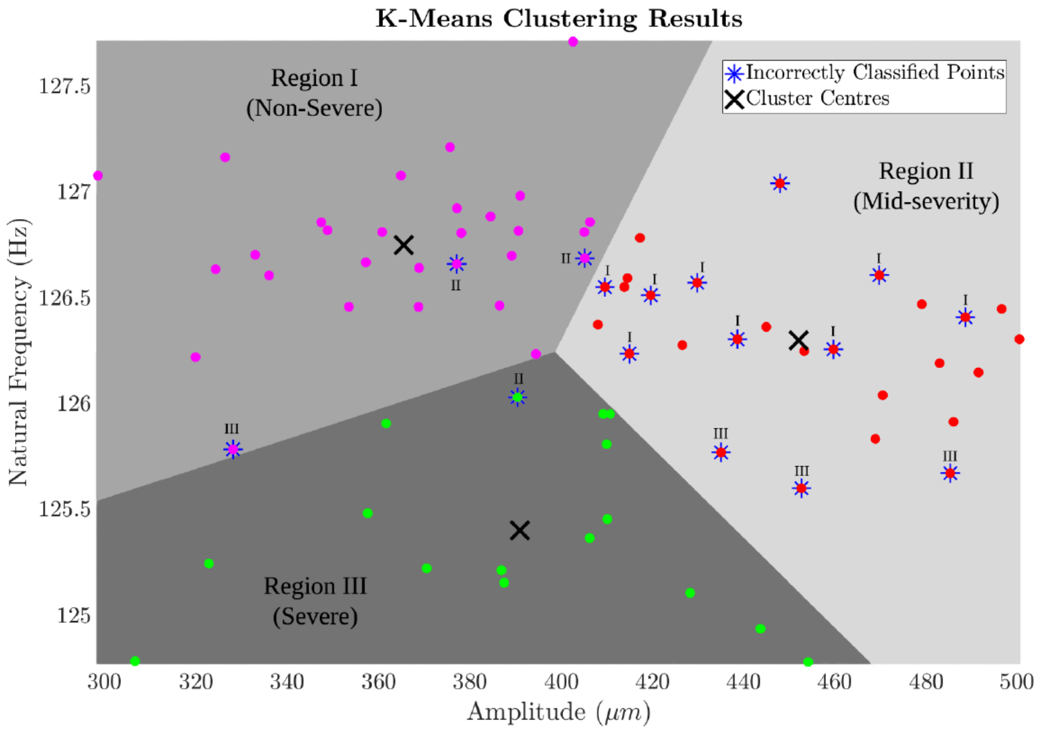


Figure 8: K-means clustering results

7. Conclusion

This work represents a first attempt to develop a hybrid methodology encompassing data-driven BTT and physics based finite element analysis for turbomachinery blade diagnostics and prognostics. This hybrid method uses the outputs of a BTT technique that is based on Bayesian linear regression and stochastic finite element analysis.

An experimental study was conducted on a simplified test rotor, with discretely introduced damage on a test blade.

The work led to a damage identification procedure based on the probability that the relative change in natural frequency of the BTT results is as large as that determined by the finite element modal analysis (at a chosen discrete damage size) projects it to be. This probabilistic damage identification process demonstrates the ability to infer the extent of blade damage.

A damage classification process is introduced to determine the blade condition using a single set of BTT measurements. To simplify the process, K-means clustering is used to classify the derived BTT amplitude and natural frequency values. The predetermined finite element analysis natural frequency results are used to initiate clusters and cluster centroids. The clustering of the derived BTT vibrational characteristics to the nearest cluster centroid enables the severity of the blade damage to be classified. While 78% classification is achieved, it is however shown that the possibility exists of classifying a severely damaged blade as non-severely damaged. This is of course potentially dangerous in practice. Future research into the performance of alternative classification procedures is therefore required.

We do however believe that a useful step has been taken towards the use of hybrid models for diagnosis and prognosis in turbomachinery health management.

Acknowledgments

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