Self-tuning diagnosis of routine alarms in rotating plant items

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Abstract

Condition monitoring of rotating plant items in the energy generation industry is often achieved through examination of vibration signals. Engineers use this data to monitor the operation of turbine generators, gas circulators and other key plant assets. A common approach in such monitoring is to trigger an alarm when a vibration deviates from a predefined envelope of normal operation. This limit-based approach, however, generates a large volume of alarms not indicative of system damage or concern, such as operational transients that result in temporary increases in vibration. In the nuclear generation context, all alarms on rotating plant assets must be analysed and subjected to auditable review. The analysis of these alarms is often undertaken manually, on a case-by-case basis, but recent developments in monitoring research have brought forward the use of intelligent systems techniques to automate parts of this process. A knowledge-based system (KBS) has been developed to automatically analyse routine alarms, where the underlying cause can be attributed to observable operational changes. The initialisation and ongoing calibration of such systems, however, is a problem, as normal machine state is not uniform throughout asset life due to maintenance procedures and the wear of components. In addition, different machines will exhibit differing vibro-acoustic dynamics. This paper proposes a self-tuning knowledge-driven analysis system for routine alarm diagnosis across the key rotating plant items within the nuclear context common to the UK. Such a system has the ability to automatically infer the causes of routine alarms, and provide auditable reports to the engineering staff.

1. Introduction

1.1 Context

Condition-based maintenance (CBM) and monitoring has long been identified as an area of huge importance to the effective management of rotating assets within the energy generation context(1). The avoidance of an unplanned outage is central to any operational strategy. Nuclear generation is no exception, and the industry in the UK has a wide variety of key nuclear power plant components considered for CBM(2)(3), often under strict regulatory requirements. Among the most important of these assets are the turbine generator sets and gas circulators (utilised historically by both Magnox and the current Advanced Gas-cooled Reactor (AGR)). Strategically placed transducers across the components of each of these plant items allow for a rich variety of vibro-acoustic data to be collected, examined and archived. From these datasets, engineers can then make important decisions regarding the health of the machine and take remedial action against any emergent faults.

However, the large volumes of generated data from such a process across a multitude of items (normally two turbine generator units and eight gas circulator units per reactor) is often dealt with by a small team of monitoring experts. To combat onerous levels of analysis, alarm-based processes driven by vibration analysis software provide latched notifications to the engineering team. Alarms fire when vibration levels deviate above pre-defined limits (in accordance with regulatory standards). This generates lists of alarm incidences for closer scrutiny by the engineer, negating the requirement for continuous low-level data analysis. This discrete alarm approach, while reducing the data analysis requirements markedly, is not without its own problems. The nature of the set vibration limits creates incidences of alarms that are not indicative of system damage or anomalous behaviour, and can be explained by changes in the operational behaviour of the asset. For example, during load transients, the vibration signals in a steam turbine react accordingly and are not due to a mechanical fault in the turbine itself. However, the corresponding vibration observables exceeding the alarm limits still trigger the alarm, and the requirement is there for the engineer to make analyses of all the corresponding vibration and operational observables to identify the load transient and rule out any other potential cause. This type of alarm is commonly referred to as a "routine alarm", and high incidence of routine alarms during maintenance and/or transient conditions renders the engineering effort often repetitive and time consuming.

1.2 Related work

Monitoring of rotating plant items is commonplace to a variety of engineering industries, including the aeronautical and non-nuclear generation industries. Gas turbines especially represent a large area of interest for the industry, with a body of work in the areas of machine learning driven anomaly detection(4)(5), and model based condition monitoring(6). Knowledge-based systems (KBS), in application to vibrating machinery, have a long history of success and industrial utilisation. A KBS (also referred to as an 'expert system') can be defined as a system that utilises a knowledge representation in order to come to decisions with clear justification. One example of a successful deployment of such a system is TIGER(7), which utilised a combination of qualitative model-based diagnosis and rule based modules to provide decision support to gas turbine engineers within a software environment. Efforts in applying the expert system paradigm to fault diagnosis in vibrating machinery include the VIBEX(8) project and knowledge bases exploiting both time and frequency domain data(9). These systems are focused on early detection of machinery faults from physics-based or empirical understanding.

With large volumes of data now incident from vibrating machinery and the corresponding inference techniques pursued by the applied artificial intelligence research groups, greater academic and industrial interest in the area of machinery *prognosis* has developed. Rotating machinery prognostics can be defined as the forecasting of future operational dynamics and reliability of assets through analysis of historical condition monitoring data. Discussions from Heng[10] and Jardine[11] give an excellent overview of the existing work and potential for the field.

With respect to the existing related work in the field of rotating machinery condition monitoring, the research discussed in this paper seeks to provide a platform for routine alarm analysis, in contrast to the common basis of fault diagnosis. Analysis from an alarm processing perspective allows for the condition of the asset to be benchmarked and potentially mapped to prognostic calculations.

2. Problem definition

2.1 Rotating asset monitoring

There are numerous rotating assets under consideration by engineers in the nuclear condition monitoring context, one of the most prominent of these being the turbine generator. The turbine generator provides the means by which the steam heated in the nuclear secondary cycle generates electricity. There are two turbine generator sets per reactor housed at each of the UK's AGR sites (making a total of four per site). For a turbine generator, there are a multitude of observables that can be obtained through vibration instrumentation. These are used to infer conclusions regarding the short- and long-term condition of the machine. A vibration analysis system commonly provides both time series and Fast Fourier Transform (FFT) visualisation, allowing the fundamental vibro-acoustic components of the machine to be analysed alongside the overall levels. Engineers focus their condition monitoring strategy on the overall levels and FFT components of the signal, including the amplitude and phase measurements. These are analysed alongside operational measurables in order to ascertain the existence of correlations between these machine observables. Differing operational observables apply to other rotating plant items (for example, inlet guide vane angle for gas circulators) and indeed, some more complex alarm anomalous behaviours require more specific operational observables (individual bearing temperatures). This brings the true number of operational observables alone required for consideration to upwards of thirty parameters across the entire vibration monitoring asset family.

In diagnosing routine alarms, the existing manual approach is to identify event correlations between the corresponding vibration and operational signals. This provides the inferential basis for diagnosing the cause behind the alarm notification. Figure 1 gives an illustrative example of a load transient creating a change in vibration behaviour. With respect to Figure 1, an overall level and 1X vector alarm would have been fired at the onset of increased vibration. This directly corresponds to the change from comparatively steady load behaviour to a stepped transient, representing station-side maintenance or operation. Therefore, it can be reasoned that the change in vibration was not due to a mechanical fault in the turbine, but most likely due to the evident change in the load observable. It should be noted at this stage that mechanical damage occurring at the onset of an operational change is a real possibility, and engineers will often carry out post-event analysis across a multitude of channels and correlated observables to safeguard against this.

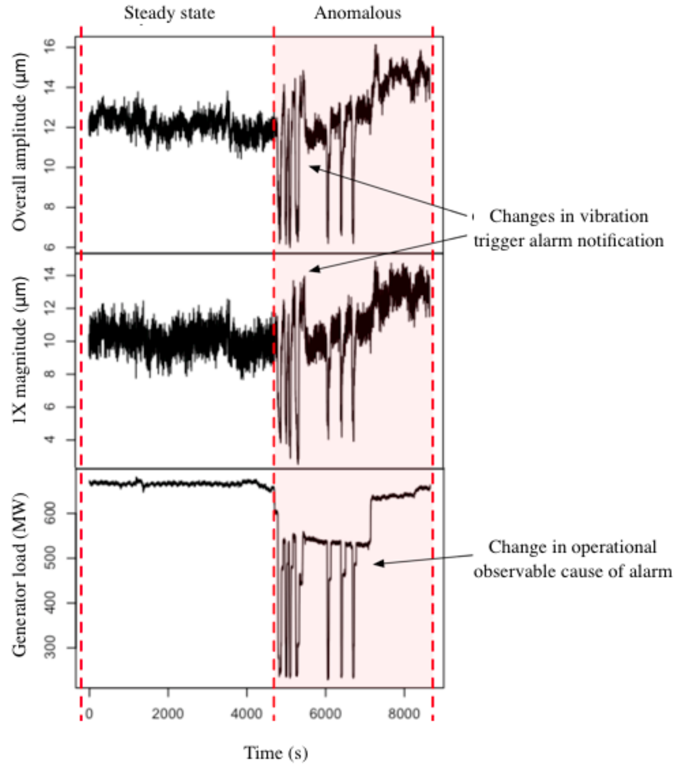

Figure 1. Example routine alarm, in which a transient in generator load has induced a vibration change. This correlation has to be manually identified from a variety of operational observables after the prompting of an alarm.

The dynamic nature of the generation context creates a wide variety of potential event incidences leading to the firing of routine alarm. The frequency of these routine alarms varies with transient operation, and notably higher magnitudes can be expected during long-term maintenance and dynamic conditions. While Figure 1 represents a fairly simple correlation example, the high frequency of alarms and the volumes of low-level data make this process often onerous for the engineers. Analysis of each alarm across assets is required due to both the nuclear and commercial significance of these events in making decisions regarding condition monitoring and future operation.

2.2 Knowledge-based system

With this problem in focus, research has been ongoing at the University of Strathclyde in developing an automatic decision support solution to the routine alarm analysis process. Previous research efforts have yielded a knowledge-based prototype system[12], with the functionality to diagnose routine alarm conclusions when presented with alarm examples. The prototype is driven by turbine specific knowledge, derived through extensive knowledge elicitation meetings between researchers and vibration engineers. A schematic of the system applied to a turbine generator is shown in Figure 2.

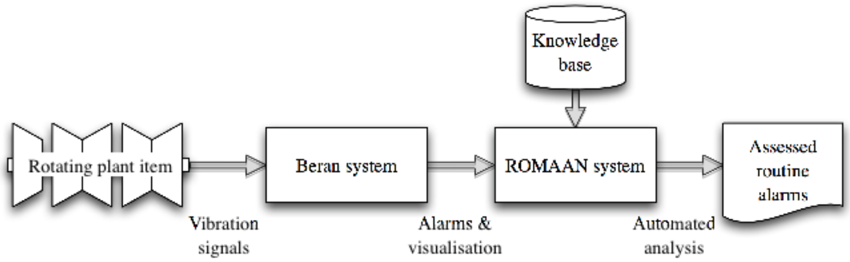

Figure 2. Schematic of the knowledge-based prototype system in use, which provides automatic decision support for turbine generator alarms

Diagnosis is achieved through use of a knowledge base: a crisp inference rule-base which states the requirements for particular alarm conclusions. These rules were derived through an extensive knowledge engineering[13] process, by which the tacit knowledge of the engineers regarding alarm conclusions was recorded through interviews and parsed into a fundamental format readable by the system.

The knowledge base requires symbolic input in order to make alarm conclusions, representing the events of the continuous data as discrete symbols. These fundamental events are the means by which the rules can then chain to come to a corresponding final conclusion.

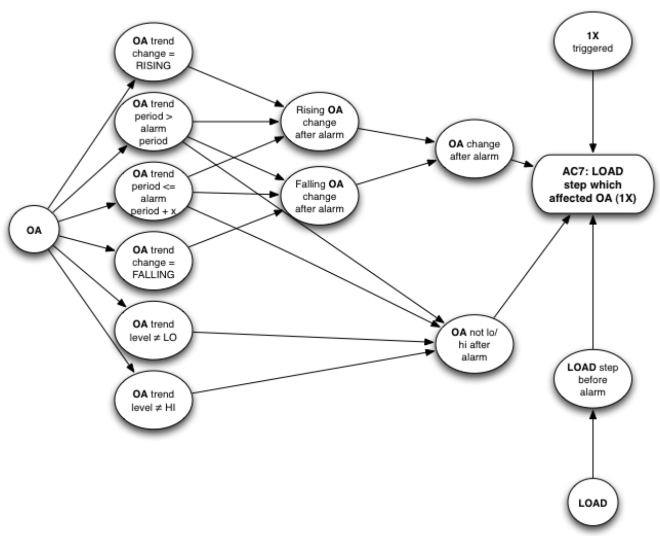

Figure 3. Inference diagram showing the forward chaining nature of the symbolic rules, corresponding to features within the continuous data. This particular example is for a load step change, causing a change in the overall amplitude.

Figure 3 shows an example of the inference propagation routes that constitute a load step type alarm affecting the overall amplitude would take in the knowledge base. Under scrutiny in Figure 3 are the observables of overall amplitude (OA) and generator load (LOAD). Each of the nodes in the chain represents a symbolic event occurrence within the corresponding observable, and the structure provides the inference mechanism by which the final conclusion is derived. Note that the '1X triggered' node represents the initial firing of the alarm event by the vibration monitoring latched notification system.

This process provides a clear and analytic means of reaching system conclusions, which are easily communicable to the user. In this sense, examples of KBS have a noted advantage over ‘black-box’ techniques of inductive inference such as neural networks by providing auditable and logical reasoning. This is especially important in safety-centric applications such as rotating plant monitoring, where a fundamental understanding of diagnoses needs to be achieved in order to meet regulatory requirements.

2.3 Signal-to-symbol transformation

In order to utilise the rules within the knowledge base, the continuous observable data from the rotating plant item first needs to be converted to a discrete, event-driven symbolic representation. This issue is common to many examples of KBS, especially those operating with time series data, and is solved through the implementation of a *signal-to-symbol* (STS) transform module. Time series data from the rotating plant item is passed to the STS module, which has the ability to extract discrete event elements for analysis by the knowledge base. The STS module collates all identified events from a particular observable or group of observables into a profile, which then fire the heuristics within the inference base. This allows the system to provide repeatable decision support from the data automatically.

The creation and usage of symbolic inference from continuous time series plant data provides key advantages for the system. It allows for routine alarm conclusions to be easily auditable and reviewed by the rotating plant engineer, as the fired rules provide a clear and explicable chain of reasoning. The discrete nature of the manner in which the knowledge base draws conclusions bears parallel to the diagnosis procedure an expert would take. The process by which the transformation stage operates differs between systems, and is often dependent on the application domain. In the instance of the prototype system, symbols are derived through use of a *limit profile*, which defines the absolute qualifier values for particular features of the continuous data corresponding to that machine component or channel. Each channel on a turbine, for example, will have a corresponding limit profile defining expected levels and the criteria for anomalous envelopes of operation.

Table 1. Fundamental symbol definitions; created by the STS for use by the knowledge base to come to routine alarm conclusions.

Fundamental symbol	Definition
Level	Defines threshold of allowable operation through expected average, upper tolerance and lower tolerance (envelope limits).
Trend	Defines qualifiers for rising and falling trend changes through trend tolerance and period of trend.
Step	Defines qualifiers for rising and falling step changes through step tolerance, period of step and lead/tail tolerances.

The most fundamental of these symbols within the limit profile are *levels*, *trend changes* and *step changes*, which are all parametrically defined by the limit profile for each observable in the machine (shown in Table 1). The system identifies trend transients through two simple algorithms corresponding to trend and step changes. Each example of buffer data is deconstructed into smaller periods from which the transient behaviour can be analysed, recording parameters such the moving average and spread of the period. Instances where the moving average exceeds the trend tolerance without exhibiting high variance and instability typical of a noisy signal create the symbolic trend input to the KBS. Figure 4 illustrates an typical trend example, with the corresponding annotated limits.

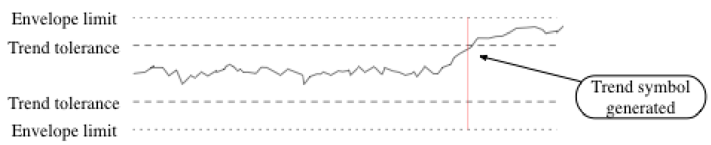

Figure 4. Example time series data illustrating calibrated tolerance and limit settings. The breach of the trend tolerance boundary with continued transient behaviour represents the criteria for generating a trend symbol to the KBS. The envelope limit corresponds to a excessively high/low level within the inference base.

The STS module for the system prototype is, at present, reliant on the manual calibration of these fundamental symbol parameters for each observable on each channel. With around 15-20 parameters requiring initialisation for each of the channel for each turbine, this is an unreasonably long and inaccurate overhead process. This presents the primary problem with the prototype, and potential solutions are addressed through creation of a tuning module.

3. Self-tuning module

In order to best calibrate each limit profile for effective use of the system, it is proposed that a self-tuning, statistical approach to learning modes of operation should be adopted. Such data-driven algorithms have the ability to infer the normal levels and fundamental symbolic parameters from historical and current data, and potentially offer a long-term solution to tuning the KBS to operate correctly. This will give the software the ability to be used by the engineers across a wide variety of rotating machinery through automatic calibration. The new and future versions of prototype modules and software come under the project title ROMAAN (**R**otating **M**achinery **A**larm **AN**alyst). The major goal at this stage of the project is to provide automated initialisation of the limit profile on a previously unseen rotating plant asset, utilising only historical data of machine steady state and step events. This section discusses the algorithms used to infer the limit profile parameters and how tuning to an asset would be achieved.

3.1 Machine learning approaches to initialisation

Each fundamental symbol, as identified in Table 1, has associated parameters that determine its inception, which are to be inferred from the machine data through a variety of methods. Due to the nature of the data that is being tuned to (often subject to stochastic mechanical processes and electrical interference), there is an element of noise and outlier instances that require to be considered in auditing of the tuned parameters. With this in mind, a statistical procedure in defining envelopes of normal operation has been employed. For level symbols, the requirement of the limit profile is to define absolute values such as the *expected average*, *upper tolerance* and *lower tolerance* in order to define an allowable envelope of normal operation. The data to be tuned from in this process is required to be predominantly steady state, as this will provide the benchmark from which normal operation is defined.

Visualisation of the observable distribution and its behaviour achieved through use of Gaussian kernel estimation[15] (also known as 'Parzen windows'), a statistical technique by which the probability distribution of an observable is calculated through the application of a standard Gaussian kernel to each of the observed data instances. This provides the distribution of the historical data in probability space, from which properties of the observable can be ascertained, as shown in Figure 4. The expected average (in the example of a steady state unimodal distribution) is analogous to the peak probability value on the kernel estimation distribution.

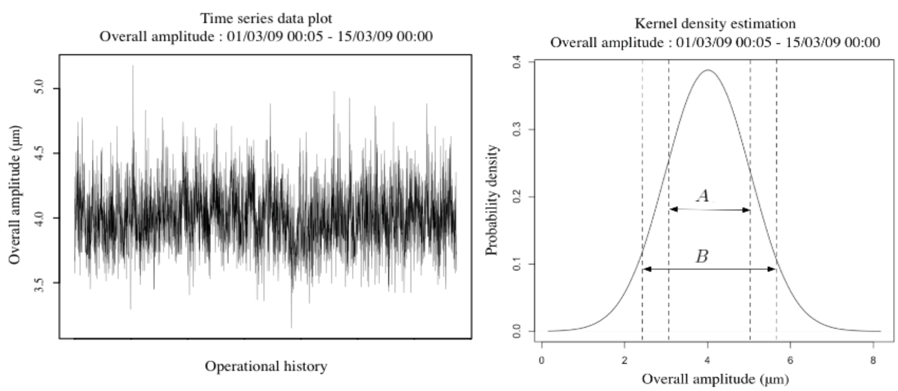

Figure 5. Steady-state overall amplitude data (left), with corresponding kernel estimation (right). From the resulting unimodal distribution, the envelopes of normal operation and trend tolerances can be defined for the limit profile.

The envelopes of normal operation and trend tolerances for the limit profile can then be ascertained through calculation of the standard deviation σ of the data. The σ parameter is scaled through use of two parameters scaled to best describe trend tolerances (*A* parameter) and the envelope (*B* parameter). These parameters are subject to continual testing and are currently set as A=2 and B=2.75 within the tuning module. These values were selected as they best represent previous manually initialised limit profiles on turbine generator channels from the knowledge engineering process. The trend tolerance envelope is used by the trend fundamental symbol to detect trends in the time series data, while the normal operation envelope sets the extreme limits of non-transient behaviour. It should be noted that kernel regression itself is not required for the example illustrated in Figure 4; the technique is used primarily at this stage as a visualisation tool. The use of probability density functions, however, has the potential to be used in the identification of behaviour transients typical of subtler trend changes.

In initialising step change parameters for a particular channel, the general form of the feature is considered as two separate behaviours: *before* and *after* the transient. For the fundamental step symbols in the limit profile, we seek to extract the parameters of *step magnitude*, *lead tolerance* and *tail tolerance* (used in ascertaining the stability of the signal prior to and after the event). Figure 5(a) across the page provides a time series step change example, with Figure 5(b) showing the corresponding kernel density estimation with the required symbolic parameters (Δ represents the step magnitude, while ε_1 and ε_2 are the tolerance envelopes for before and after the transient, respectively). These parameters are extracted from each example (tolerances are defined in the same manner as envelopes for level tuning examples) of step change for a particular machine channel.

The aim in initialising the limit profile with these step symbol parameters is to discern a representation of a step change transient for each of the observables. This analysis does not primarily concern the incidence of anomalous step changes associated with system damage, but those commonly seen in routine alarm events. It is suggested that the best way to approach this is to initialise the step limit profile parameters through a multitude of initial ‘seed data’ examples from previous routine alarm examples.

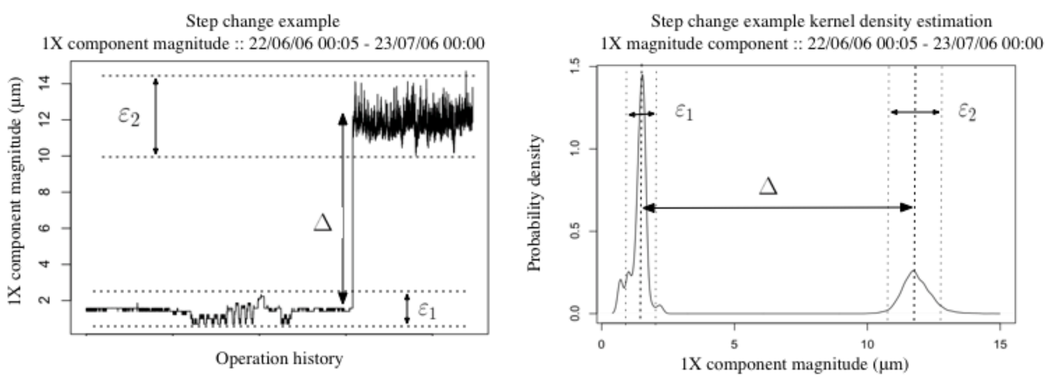

Figure 6. Example step change in vibration observable (left), with corresponding kernel estimation visualisation (right). Limit profile parameters annotated.

At this stage, the volume of step changes required to create the optimal volume of seed data for efficient training remains unclear, and will be a key subject of the ongoing research and development work. It should be noted that in the first instance the KBS simply requires the information that a step event has occurred, rather than the relative magnitude or severity of the transient. Analysis of step severity has been identified as a later research area for the ROMAAN project, with the potential to derive more information on machine condition through transient severity and evolution analysis.

3.2 Tuning to a specific machine

The first step in launching the system for use on a previously unseen rotating plant item is to initialise the limit profile, in order to provide the basis for accurate routine alarm conclusions. The techniques discussed in Section 3.1 provide the mechanisms by which this initialisation process can be achieved from historical data. Within the KBS, the limit profiles are represented by multiple absolute value heuristics (dictated to the KBS in XML files) corresponding to each machine observable. At the conclusion of the initialisation process, the ROMAAN system updates the absolute values within the limit profile files to correspond with the new tuned values.

The outcome of an improperly calibrated limit profile through manual trial-and-error calibration would be misdiagnosed alarm instances, consisting of both false positives and overlooked alarms. As with all inductive machine learning problems, we seek to infer the values within the limit profile from a domain of training examples[14]. In this manner, the machine itself dictates normal operation through the vibration dynamics displayed in its historical steady-state behaviour. There are two training example approaches worth consideration with regard to this: *learning from historical data*; and *learning from current data from the launch of the system*. Historical data represents a sample of system data over a period of normal operational, preferably as close to the present operation time as feasible. This would provide a default tuned system with the ability to potentially diagnose routine alarms from launch. Problems associated with this, however, including the subjective definition of 'normal' and the debatable amount of data required in order to provide the best calibration to the turbine generator *as-is*. Alternatively, it could be possible to launch the system without a calibrated limit profile, and allow the machine learning algorithms naturally tune to the observed turbine data. This is potentially advantageous as it removes the engineering subjectivity of normal historical data, as the limit profile would converge on the closest steady-state representation of the rotating asset as the data became available. However, questions remain regarding the measurability of *best-fit* in tuning to a particular asset and the period of learning required in order to sufficiently calibrate an accurate system.

In the process of testing the knowledge base in the earlier stages of the research, manually calibrated limit profiles were utilised in a variety of case studies. This process was undertaken on a case-by-case basis to illustrate the validity of the knowledge base. Table 2 shows manually initialised values from the front IP bearing of a turbine used in these previous case studies with automatically initialised steady-state values from the front IP bearing of a previously unseen turbine. The difference in the values and envelopes between the machines illustrates the individual dynamics of each asset. Using the IP bearing case study limit profile on this new machine would set the nominal envelopes at a value unsuitable for that turbine, resulting in incorrect alarm conclusions. This shows the importance of following a data-driven approach to tuning, allowing for the software to infer the best limit profile settings.

Table 2. IP bearing manually initialised limit profile values compared with new steady-state IP bearing automatically inferred values from a different turbine.

	Manually set		**Automatically inferred**	
	Exp. Average	*Tolerance*	*Exp. Average*	*Tolerance*
Overall Amplitude	12.00	±2.40	7.58	±1.04
1X Magnitude	8.00	±1.60	4.04	±0.67
2X Magnitude	1.50	±0.30	2.51	±0.41

An optimally tuned limit profile represents a data-driven representation of normal operation for the corresponding asset. With the ongoing operation of a machine, it is suggested that continual re-tuning over a defined window space will allow for the evolution of the limit profile as the vibro-acoustics of the plant item changes with condition. This will maintain the optimal limit profile representation to allow for continued use of ROMAAN system.

4. Discussion and conclusions

The presented initialisation techniques provide a novel means of utilising time series data to automatically calibrate key symbolic feature parameters for the rotating plant routine alarm KBS. This research in the ROMAAN project was prompted when it became clear that the tuning procedure across a multitude of assets would be very onerous to achieve manually. The limit profile of each asset, once successfully tuned to the characteristics of the machine, is a representation of its vibration characteristics under normal operating conditions at the time of tuning. Using this profile to examine simple alarms through the KBS will provide useful decision support to the vibration engineers and reduce the lead-time in the analysis of rotating assets by identifying routine alarms with justification. Using the parameter extraction techniques outlined in this paper, the ROMAAN system can be deployed across a wide variety of different rotating machines and rotating machine classes. The system uses the machine itself to define the bounds of normal operation and from there utilises this asset-view to identify anomalies in vibration behaviour. This approach provides a potentially powerful platform to build an advanced decision support condition monitoring system, with the ability to tune to a wide variety of machine behaviours over a large number of machines.

In Section 3.2, the concept of continual tuning of the limit profile was introduced. As an effectively calibrated limit profile provides a view of normal operation at that point in machine life, it is potentially beneficial to window this tuning process, with successive re-tunes as operational life progresses. Considering a tuned limit profile orientation for a rotating asset at t_1 evolving through use to a later t_2, it is postulated that there is the potential to map machine condition to these evolving parameters. Information regarding the changing limit profile (and inherently, condition) of a given plant item could then be incorporated into the decision support delivered by the software. Potentially, future versions of the system with continual tuning functionality could offer prognostic calculations based on the evolution of what the machine defines as normal within the limit profile. The development of continual tuning features and their implications for condition monitoring represents the next stage in the research of this project.

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