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An Expert Bayesian Network Solution for Intelligent Machine Fault Diagnosis

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Abstract

Vibration-based fault analysis remains the standard approach to condition monitoring of rotating machines. However, with increasing complexity and volumes of data, condition monitoring engineers are turning to Artificial Intelligence (AI) to improve maintenance productivity and accuracy. This paper describes an engineering solution combining the AI methodologies of Expert Systems and Bayesian Networks, providing close-to real-time on-line machine fault diagnosis. The solution involves capturing machine fault domain knowledge as encoded heuristics rules in an Expert System. A Bayesian Network then permits diagnosis with uncertain machine data, where data anomalies or multiple faults still result in the correct identification of fault(s). The solution has been designed and implemented to operate in a cloud platform and results have been verified using Ailsa Reliability Solutions Limited's (ARSL) Research & Training Skid, where real faults were introduced for system validation. The solution was tested using operational machine data from an industrial site, captured using a variety of technologies: portable vibration analysers, and online fixed-wired vibration sensors. This provides condition monitoring engineers with a rapid means of assimilating large amounts of heterogeneous performance evidence to diagnose machine faults in the field.

1. Introduction

As technology becomes more readily available and the world is more data-driven, Artificial Intelligence (AI) is finding its way into all aspects of life, from medical advancements to brewing coffee. An area where AI has been under assessment for deployment is condition monitoring of industrial plants in manufacturing, power generation and other engineering industries [1] and is expected to provide significant benefits in terms of condition monitoring process automation, and faster and more accurate machine fault diagnoses [2]. AI may have many applications in these industries; however, this paper considers the fault classification of an industry-scale electric motor, belt-driven fan installation through different vibration sensing technologies. An intelligent fault diagnosis model, based on industry expert knowledge, has been created where domain expert knowledge representing predefined fault signatures associated with both the type of machine and the vibration sensor telemetry characteristics, has been codified and automated. This paper utilises an Expert System

software architecture to capture fault characteristics (rules) and compare these with input data (facts), which result in a decision-like output as if the expert were analysing the data themselves. Subsequently, a Bayesian Network (BN) is coupled to the Expert System to provide classification likelihood, in that it no longer relies on the input data being perfectly aligned with the Expert System rules.

When working in a controlled or laboratory environment, data is usually clean and predictable. Industry data, on the other hand, can be more difficult to analyse and can have many anomalies due to, for example, external environmental effects or internal process measurement uncertainties [3]. In this work, the BN allows for these anomalies or data imperfections, even if a section of data does not match the required rule. For instance, if the rest of the Expert System rules have been triggered, then there is still a high probability of the fault being accurately detected, as characterised by the expert who parameterised the model. This real-world industrial scenario is demonstrated in this paper by implementing the Expert Bayesian Network solution on an industrial-scale test rig and utilising real industrial condition monitoring equipment to capture and ingress the associated data into the same Expert Bayesian Network. This experimental set-up is used to demonstrate the effectiveness of the proposed approach against its ability to diagnose a real industrial fault (over-hung fan unbalance) utilising two different monitoring strategies (on-line and ad-hoc).

The remainder of this paper is constructed as follows. Section 2 defines and describes the need for condition monitoring in industrial engineering scenarios. Section 3 describes the state-of-the-art in related fields of AI-based intelligent machine fault diagnosis. Section 4 provides an overview of the novel methodology developed for this work. Section 5 covers the experimental rig set-up and associated technology case-study demonstration. Section 6 provides a short discussion on the results. Section 7 then concludes and proposed future work.

2. Condition Monitoring Industry Need and Problem Statement

When conducting fault diagnosis in many industry domains, condition monitoring engineers generally follow predefined accepted procedures and protocols. These approaches are generally well established and have been developed over many years, as an aggregation of expert engineering domain knowledge, physical laws and based upon domain guidance provided in the form of industry standards. They describe how each process variable (e.g. vibration, flow, temperature etc), as associated with the plant in question, behave and change under different operational and fault scenarios. Based on this understanding, condition monitoring engineers looks for artefacts and trends in the process variable data to determine if these conditions have been met. In the event any of these conditions are met, the condition monitoring engineers are then in an informed position to make operational and/or maintenance decisions in order to improve the efficiency of the plant, or reduce the chance of further damage, and consequently reduce the costs associated with operating and maintaining the process/machine.

AI can support these processes, and it is also possible that the current increase in AI technology development and deployment may support society's wider net-zero goals [4], with improved machine efficiencies and reduced energy waste being part of the solution. Coupled with modern sensor technology and cloud computing infrastructure, using AI in fault diagnostics may be revolutionary for engineers as AI models can review drastically more data than a human in a significantly shorter time [5]. For engineering teams, this means that reliability engineers can use AI to analyse data and flag any issues that need attention. Introducing AI into industrial condition monitoring will help engineers monitor more of the site and improve reliability figures. This can be greatly beneficial in sites where there are hundreds of machines and limited technicians or for engineers who must cover numerous

sites. Additionally, the deployment of appropriate AI models may also benefit machine condition monitoring analysis by providing early fault detection. Having the power to predict when a machine might fail and what is the cause can help limit downtime and planned maintenance, leading to improved condition-based maintenance strategies.

3. Intelligent Machine Fault Diagnosis

Industrial fault detection identification can be broken down into seven steps [6]: gathering information, verifying the issue, simple issues resolutions, application of diagnostics, split-half search, use additional resources to investigate the issue further, and escalate the issue (if necessary). Generally, the parts of this process that can be automated with AI are related to data gathering (e.g. assessing data quality), data analysis (e.g. identifying trends or correlations) and machine diagnostics (e.g. determining if specific faults are present). Furthermore, the approaches to AI automation can be broken into two different categories: data-driven (e.g. machine-learning) approaches; and, knowledge driven approaches, such as those adopted in this paper.

While not exclusively, the current state-of-the-art in data-driven approaches is predominantly Machine Learning, which rely on large volumes of high-quality, relevantly labelled data. This is an inherent challenge in developing such systems, as there is currently limited availability and access to high-quality data sets. For example, in [7] a convolutional neural network-based approach to fault diagnosis proposed but the authors highlight a limitation of the approach being able to classify common fault conditions with large amount of labelled training data. The authors of [8] hence propose a deep convolutional transfer learning network (DCTLN) method for fault diagnosis of unlabelled data, utilising labelled data from one machine to classify unlabelled data for another mechanically similar machine. More recently, in [9] the authors propose a generative adversarial network-based approach that produces an augmented training dataset.

An alternative class of methods to solve machine fault diagnostic problems involves knowledge-based approaches. Unlike data-driven approaches, knowledge-based approaches do not require a large amount of training data to be available, but instead, encode a significant amount of expert knowledge or human expertise into the system that can be used to perform fault diagnosis. In [10] the authors present an expert system for fault diagnosis of chemical processes, using a pre-existing knowledge base. A vibration-based expert system is presented in [11] and uses a decision tree style approach to perform the analysis. Due to the nature of how rules are formalised and stored in a rule-based expert system, having low generality and low expandability, a task-based diagnostic expert system was proposed in [12]. This allows for the rules to be customised for specific assets and stored as more general rules, however, this also requires a well-structured logic to exist and applies only to similar assets.

3.1. Expert Systems

An official definition of an expert system is a computer program that simulates the thought process of a human expert to solve complex decision problems in a specific domain [13]. This implies that the computer software adopts heuristic knowledge representative of a human expert instead of implementing a predetermined algorithm or mathematical model. Expert systems are a sub-class of AI that are suited to solving problems requiring true understanding of the engineering problem and the finesse of how data is captured and represented in this context. Most expert systems are created by working closely with human domain experts who have this detailed and specific knowledge of the system and associated problem. In a Rule-Based Expert System (RBES) [14], such as implemented in this work, expert knowledge is delineated into a set of rules. Parameterisation of the rules is determined but the number of rules in the system, and each parameter has a predetermined value as

relates to the final decision being made by the system. All this information is supplied and defined by the expert in the development process. Each rule can be simply implemented in its general form as: **IF** *Condition* **THEN** *Action*. A simple example of this being [15]:

IF (*Condition1*) **AND** (*Condition2*) **THEN**

RuleID_Fault = True

ELSE

RuleID_Fault = False

Where *Condition1* = Variable1 > Threshold1 and *Condition2* = Variable2 < Threshold2

The Expert System presented in this paper uses predefined rules to identify vibration characteristics. The system evaluates 'facts' which are data points collected by the data acquisition system during a measurement. These vibration values are assigned an alarm status to help identify elevated vibration with the machine. This is accomplished using the pre-programmed alarms with the acquisition equipment. Based on the alarm statuses, specific 'rules'/vibration characteristics will be triggered. For example, an elevated overall vertical velocity at the motor may look like this:

IF *OVVel_1MTRH = "no alarm"* ***AND*** *OVVel_1MTRV = "alarm"* **AND** *OVVel_2MTRH = "no alarm"* **AND** *OVVel_2MTRV = "alarm"*

R1_OVvelV = True

ELSE

R1_OVvelV = False

The Expert System is created from many of these rules and these rules need to cover a wide enough variety of situations so that a fault defined by the expert can be created when multiple of these are combined.

3.2. Bayesian Networks

Knowledge-based tools can provide excellent performance in fault diagnosis where there are clear separable fault scenarios. However, this is frequently not the case and hence 'hybrid' methods have also been proposed to eliminate some of the limitations of knowledge-based approaches. This is paper, the expert system is combined with a Bayesian Network (BN) to distinguish between similar faults and assign a probability to the likelihood of each occurring in a simultaneous manner.

Interest in BN for fault detection and diagnosis has increased in the last 10 years, both to address limitation of knowledge-based approaches but also as an interpretable alternative to purely data-driven methods. BNs are common in the fields of risk analysis, dependability, and maintainability [16]. [17] demonstrated the application of a BN in detecting and diagnosing the faults in the commonly considered Tennessee Eastman (TE) chemical process. Many BNs proposed in existing literature are static in nature. However, [18] proposed a dynamic BN (DBN) for process fault detection, root cause diagnosis and fault propagation pathway identification. Building on the DBM concept, [19] incorporated a Gaussian mixture model with a DBN to detect and isolate the fault.

As defined by [20], a BN is a causal network which belongs to the family of probabilistic graphical models, i.e. represents knowledge in a graphical form. It is a directed acyclic graph, which links up the uncertain observations and helps to reach a certain conclusion. Bayes' theorem is the governing equation of a BN:

$$P(\theta/X) = \frac{P(X/\theta)*P(\theta)}{P(X)} \quad \text{(Equ.1)}$$

Where P(θ) is the prior belief, and P(X) is the probability of an observation or evidence. P(X/θ) is the conditional probability of X given θ – conditional probability. P(θ/X) is the conditional probability of θ given X – posterior probability. For a certain evidence of X, the updating equation can be written as:

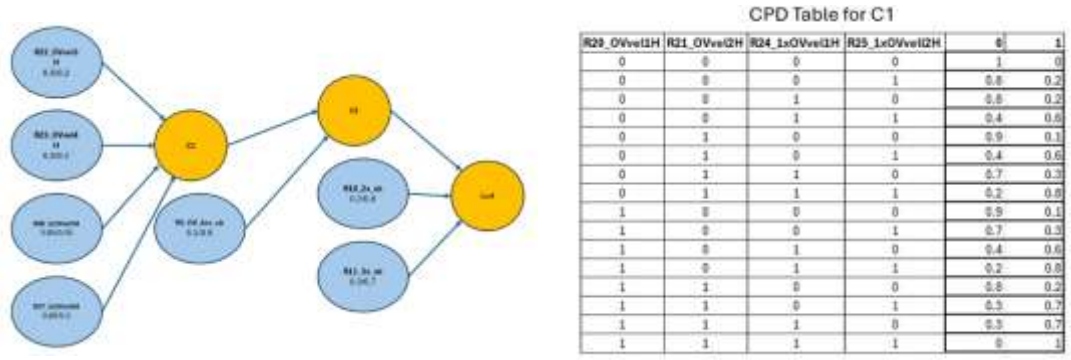
$$P(\theta/X) = P(X/\theta) * P(\theta) \quad \text{(Equ.2)}$$

A BN works by propagating the belief in the entire network. The joint probability distribution (JPD) of the network can be obtained from the product of all likelihood probabilities. Using chain rule, the JPD can be expressed as:

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^{n} P(X_i/Pa(X_i)) \quad \text{(Equ.3)}$$

Where $Pa(X_i)$ is the parent set of any node X_i.

A BN is constructed in three main steps: (1) determining the causal dependency among the variables, (2) estimating the prior probability distribution, and (3) estimating the conditional probability distribution.



CPD Table for C1

R20_OVvel1H	R21_OVvel2H	R24_1xOVvel1H	R25_1xOVvel2H	0	1
0	0	0	0	1	0
0	0	0	1	0.8	0.2
0	0	1	0	0.8	0.2
0	0	1	1	0.4	0.6
0	1	0	0	0.9	0.1
0	1	0	1	0.4	0.6
0	1	1	0	0.7	0.3
0	1	1	1	0.2	0.8
1	0	0	0	0.9	0.1
1	0	0	1	0.7	0.3
1	0	1	0	0.4	0.6
1	0	1	1	0.2	0.8
1	1	0	0	0.8	0.2
1	1	0	1	0.3	0.7
1	1	1	0	0.3	0.7
1	1	1	1	0	1

Figure 1 – BN for structural looseness in the horizontal direction: a) directed acyclic graph for the fault, b) the CPD table for the first child node (C1)

An example of a BN used to classify a fault in this work is presented in Figure 1. The example used is the horizontal structural looseness fault at the driven component from the spot-tester's model. This network is created with a combination of rules relating to overall velocity and 1x velocity at the driven part of the machine in the horizontal direction being causing an alarm. The overall velocity and 1x velocity are important characteristics that create a structural fault; therefore, they have the highest impact on the final probability. Having an overall acceleration, 2x and 3x in a non-alarm state have also been added but do not carry much weight. This is so that when the machine is running well, these nodes can be triggered but the probability of the fault being true will be low.

3.3 An Expert Bayesian Network for Intelligent Machine Fault Diagnosis

The model used in this experiment consists of an Expert System to identify specific vibration fault characteristics in the data and multiple BN's to determine the probability of a fault(s) being present in the system. The knowledge base for the Expert System was created using a table where different fault characteristics were developed using alarm statuses for different vibration points. This table was designed by a vibration expert based upon what the alarm statuses are likely to display if a certain vibration fault is present. The telemetry signals used in a vibration measurement are as follows: overall velocity, overall acceleration, 1x velocity, 2x velocity, 3x velocity, 3-8x velocity, low-frequency

acceleration, medium-frequency acceleration, high-frequency acceleration, peak-to-peak acceleration and envelope energy.

Two different data acquisition technologies/methods are assessed for use with the Expert Bayesian Network. First, for a 'spot-test', the data was taken as an export from a sensor's Graphical User Interface (GUI) and entered into the model manually. The code for the model is executed on a local machine, whereas the online system has a more complex data pipeline. The online system uses an API to access data, which is then stored in a cloud database before being passed onto the model. The model for the online system is also deployed on a cloud application and stores the results in a cloud database, which feeds data to a GUI for engineers to view. The data taken from the vibration source/database is fed into the inference engine of the Expert System as 'facts' and when compared against the knowledge base, certain 'rules' may be triggered regarding what facts were true or not. The rules are the fault characteristics created by the expert, and the facts are the vibration data.

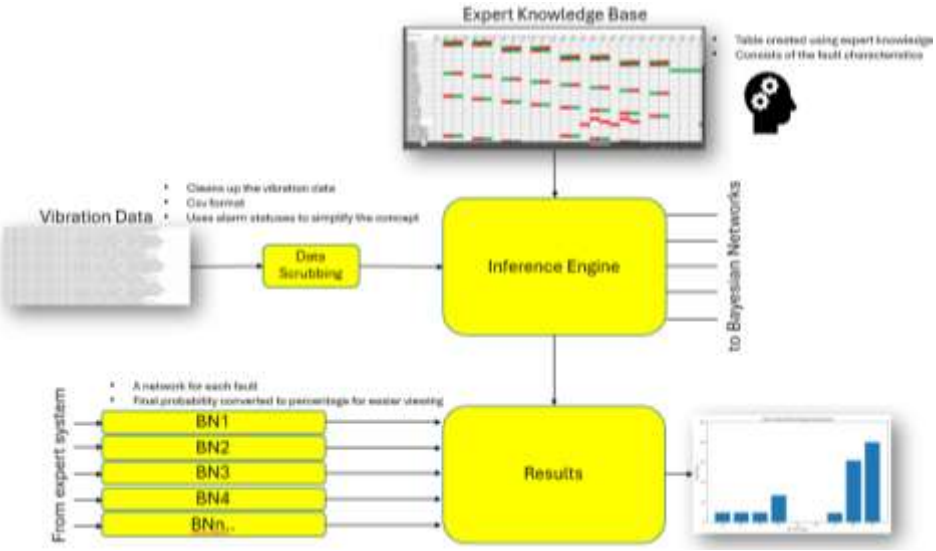


Figure 2 - Simplified flow diagram of the spot-tester model

These rules/fault characteristics that have been triggered by the vibration data are then passed downstream to the BNs. These rules are used as input data for these networks to allow a classification of how likely a certain fault is. These networks have again been constructed using expert knowledge to ensure that the correct BN will produce a high probability if the data matches the expert's fault table. Each fault has its own BN, and the BN provides a final probability of how likely that fault is to be present in the system. The probability of the final node being true is then converted to a percentage to allow easier understanding of the data. An overview of the full Expert Bayesian Network methodology is shown in Figure 2.

4. Experimental Rig Validation

The Research & Training Rig used for experimental validation of the Expert Bayesian Network methodology is a Halifax Fan skid consisting of a 22kW 2-pole motor powering a belt-driven overhung fan. This fan skid was developed as a research and training tool to allow testing of new sensor technologies such as vibration, electrical signature and lubrication. These technologies can be installed onto the skid and compared and validated against current technologies in a controlled environment.

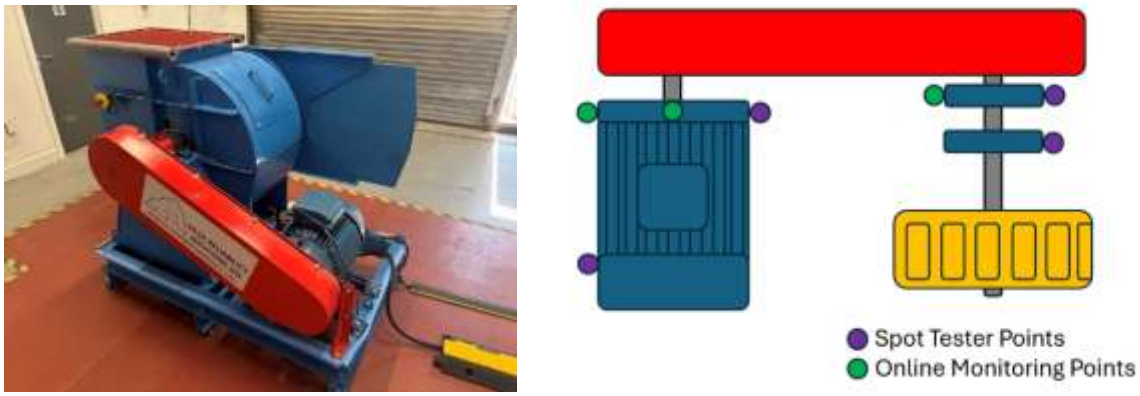
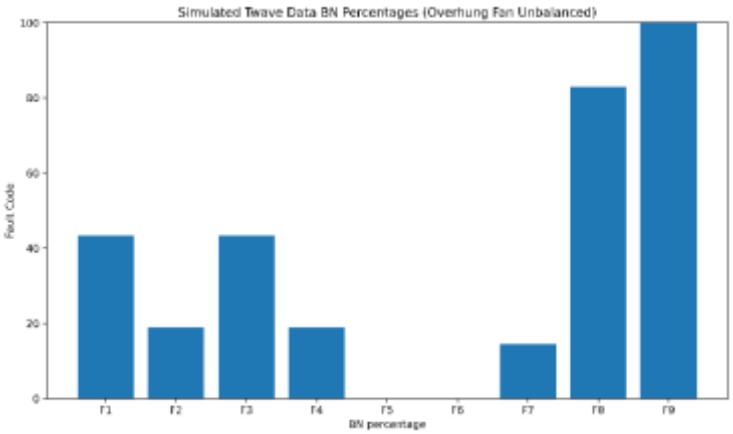


Figure 3 - Research & Training Rig at the DPMC: a) image of the fan skid, b)diagram of the test points used to capture the vibration measurements

The BN's created for the spot-tester and online system vary slightly due to the required hardware setup. The spot-tester uses a tri-axial magnet-mounted sensor, and each test was taken at four points: motor NDE, motor DE, drive DE and drive NDE. The online system has fixed-screwed wired sensors with two single sensors at the motor DE for the horizontal axis and vertical axis, and then a tri-axial sensor on the fan DE as shown in Figure 3.

Acquisition and processing settings were matched where possible; however, due to the nature of the online system, smaller data packets were used to achieve a quick repetition of acquisition. As a result of the differences in the number of hardware points, the knowledge base for the two technologies used in the Expert System does not match fully. The online system uses lower alarm thresholds for the axial readings compared to the spot-tester by a factor of 0.7. To account for these slight differences, first, the spot-tester knowledge base was created, and then the online systems knowledge base was created using the spot-tester as a template.

Initial testing of the Expert System model used simulated values to ensure that the model operated as expected before using real machine data. This allowed certain rules to be triggered and create an ideal situation, increasing the likelihood of a target fault being present. In Figure 4, the input data has been set to simulate an over-hung fan unbalanced fault. F9 is the BN created to classify this imbalance. Shown in Figure 4, the model has identified that this has an extremely high likelihood. This chart also visualises the idea behind the BN methodology as F1, F3 and F8 also have higher likelihoods than the other faults. F8 is a more generic drive unbalanced and F1 and F3 are BN's designed to classify a driven structural looseness horizontal and driven structural looseness vertical which have similar fault characteristics to a driven unbalance, such as elevated 1x velocity at the drive. This is a fault characteristic that is weighted highly, and as the remaining faults do not have this characteristic, their probability remains low.



F1 – Structural Looseness Drive Hor
F2 – Structural Looseness Motor Hor
F3 – Structural Looseness Drive Ver
F4 – Structural Looseness Motor Ver
F5 – Misalignment Hor
F6 – Misalignment Ver
F7 – Motor Unbalanced
F8 – Drive Unbalanced
F9 – Over-hung Fan Unbalanced

Figure 4 - A bar chart showing the results of a simulated Over-hung fan unbalanced fault using the online systems model

To test the model on real machine data, an imbalance was induced on the fan skid by adding 35g to propeller 3 and 50g to propeller 4. These weights are enough to cause a strong imbalance at 30 Hz and validate the proposed methodology, without damaging the rig or exceeding environmental noise constraints. The experiment was conducted in four consecutive speeds: 10 Hz, 20 Hz, 30 Hz and 10 Hz. The online system has the capabilities of recording the vibration data and computing the model results over the period where the testing took place. The speed changes are noted in the graphic, and the shaded areas determine the motor speed for that partition. Blue partition is 10 Hz, yellow partition is 20 Hz and the red partition is 30 Hz.

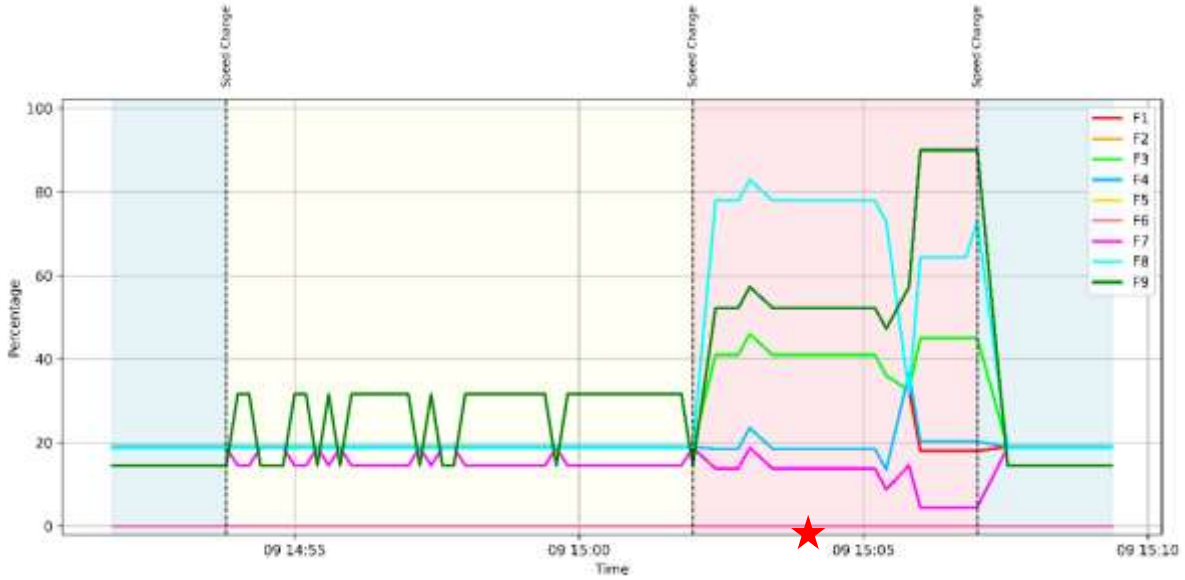


Figure 5- A trend graph of the various BN likelihood percentages as the motor changes through the speed states

From Figure 5, it can be observed that at 10 Hz, there is next to no vibration and all BNs are in their 'healthy' state. As the frequency is increased to 20Hz, F9 (Over-hung Fan Unbalanced) begins to have more of its nodes triggered; however, it does dip between states, indicating that vibration measurements must be around the threshold of the alarm. All other faults remain relatively steady. As the maximum frequency of 30 Hz is reached, some overall velocity readings increase dramatically with the vertical reading increasing from 0.99 mm/s to 8.00 mm/s. The BN for F8 (Drive Unbalance) initially responds well, which is expected following the modification to the fan blades. F9 has enough

nodes triggered to differentiate it from the remaining BN's however it is not as prominent as F8. These BN's are extremely similar and the difference between the two are fault characteristics related to the axial points. As time progressed at 30 Hz, there was a shift of the most likely fault between F8 and F9. From further analysis of the associated telemetry data for the 30 Hz segment, the horizontal accelerometer reading for overall velocity starts just above the alarm threshold and slowly decreases through the threshold. The axial reading for 1X velocity does the opposite and rises above the alarm threshold during the 30 Hz session as shown in Figure 6. This explains the change in result. F3 (Structural Looseness Drive Vertical) is another fault that can be distinguished above the remaining faults, as like an unbalanced fault, the main characteristics of this fault are an elevated overall velocity and an elevated 1X velocity. As the machine is slowed down to 10 Hz, the fault percentages fall back to their 'healthy' machine state.

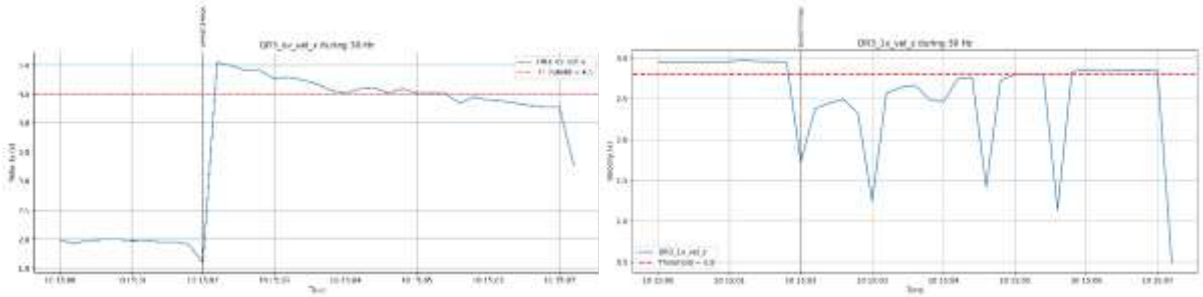


Figure 6 - Telemetry data from the 30 Hz run: a) Drive overall horizontal velocity trend, b) Drive 1X axial velocity trend

During the same experimental session at 10 Hz, 20 Hz and 30Hz, single spot-tester measurements were taken at each frequency. No alarms were triggered during 10 Hz and 20 Hz, hence no results are presented here. The 30 Hz spot-tester measurement was taken at the timestamp noted by a red star on Figure 5. The results from the spot-tester model were less convincing as F9 failed to be registered with a high probability, as shown in Figure 7. F3 and F8 were the standout results, mainly due to elevated vertical velocity measurements being present. The 1X axial measurement for the fan failed to alarm, which is a key characteristic of this difference. Also, as noted above, at the time instance in question, certain alarms were not in their final evolving state.

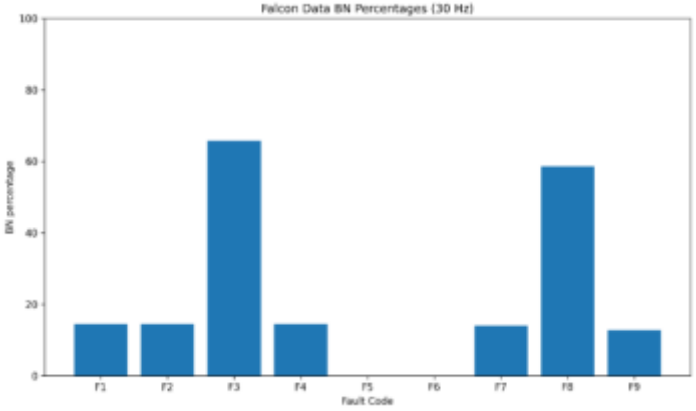


Figure 7 – Spot-tester model results at 30Hz motor speed

ARSL engineers previously worked on a customer skid at a manufacturing site that was a similar design to the fan skid at the DPMC. This machine is also an over-hung fan and was previously out of balance. This machine was balanced by the engineers on site and the unbalanced fault removed. In Figure 8, a comparison of the results is presented from the spot-tester model while the imbalance was present and then once it was rectified.

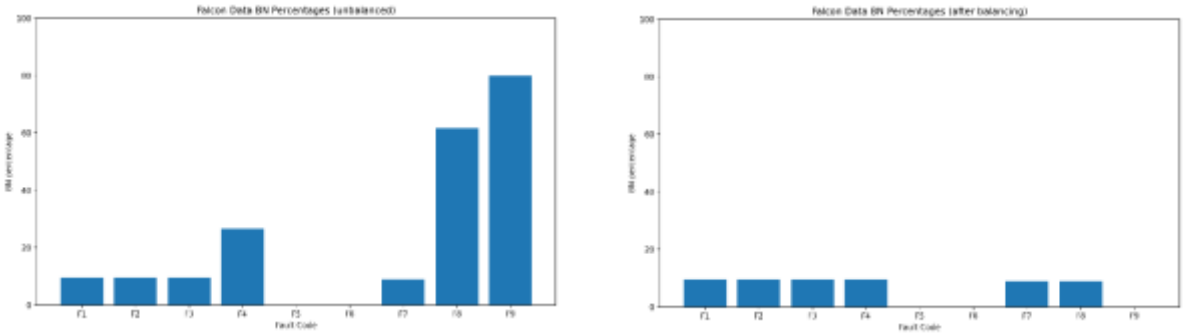


Figure 8 – Spot-tester results from customer machine: a) results while the fan was out of balance, b) results once the fan was balanced

Overall, the modelling approach proposed in this work provides promising results. This final real industrial example clearly captures the known issue (unbalanced) and provides confidence that the fault has been removed, with the BN fault percentages down to their 'healthy' level following subsequent analysis.

5. Discussion and Future Work

This work was a proof-of-concept to test the concept of an Expert Bayesian System to automate the diagnosis of fault on industry-scale plant using real vibration data acquired using industry equipment. The results provided in this paper are promising and hence further development of the approach is on-going. It is noted that the model presented in this work adopts a rudimentary approach to data processing, essentially using binary states that represent vibration alarm thresholds. The model could hence be made more sophisticated by implementing multiple states (no-alarm, pre-alarm, warning, and alarm), or symbolic representations of numeric values and their associated trends. However, such an approach would require additional thought and development/implementation considerations, including how to construct much larger, complex CPD tables. The advantage could be an increase the diagnostic accuracy of the approach and permit a fault tiered system (i.e. an indication of what stage the fault is at).

To ensure the approach can be used by engineers remotely assisting with the labour-intensive task of analysing vibration data, it is a requirement to deploy the spot-tester model to a cloud platform. Once this model is available on-line and the results can be displayed on an easy-to-use GUI, engineers can upload their vibration test data and permit the model to diagnose many machine issues faster than the existing diagnosis process. There will most likely be machines where the model struggles to provide a clear diagnostic result; however, the time savings made by the model when diagnosing routine faults will allow scarce engineering resources to focus on the more difficult problems.

This paper describes preliminary progress associated with the development of an intelligent automated fault diagnosis methodology. The experimental results presented only describe one fault being induced on the system. Work is ongoing to scale the complexity and expand the number and type of faults the system will simultaneously diagnose in a synchronous manner. Future work will also include validating the intelligent approach against the same complex distributed-fault scenarios on both the experimental rig and on client data.

6. Conclusions

Automating the diagnosis of faults routinely found on industrial machines is an on-going challenge and goal in the field of condition monitoring. The paper lays out the theory and describes some preliminary results for an automated Expert Bayesian Network approach that: leverages domain expert knowledge; adopts accepted sensing and data acquisition systems; and is deployed on modern cloud-platform infrastructure. Results are promising and a clear path for future development is intended. This highlights the strategic direction ARSL is moving towards and showcases the potential for modernised condition monitoring solutions.

Acknowledgements

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