Intelligent System for Gearbox Fault Detection & Diagnosis Based on Vibration Analysis using Bayesian Networks

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Abstract. Moving energy from one machine to another and functioning to reduce speed while increasing torque is the ability of the gearbox. Due to many components and the structure between the components is fairly complex, thus to be able to detect the initial damage, sophisticated methods is needed. Vibration analysis is a method that has been effective in detecting the initial damage that occurs in machine. But it takes time and costs are not small to implement. The purpose of this study is to create an intelligent system capable of detecting gearbox damage based on data obtained from vibration measurements. Merging of two methods of vibration analysis and Bayesian networks is done to be able to design the system with the expected results. A series of multistate nodes are applied to the network and a system review is performed. Results are given and compared with results provided by the manual analysis. The results indicate that the system is feasible and reasonable which can assist inidentifying gearbox damages. This study definitively answers the problem of how to design an expert system capable of replacing the work of an expert on vibration analysis services.

1. Introduction

Almost all industries use gearboxes to carry out a series of production, gearboxes may operate under varying load conditions. In industrial applications, gearboxes are a very important component. Gearbox must work optimally to be able to complete the task as planned. Termination of the production process and other undesirable things can occur due to gearbox damage, even human casualties. Therefore, damage to the gearbox needs to be known optimally as early as possible to ensure the operation of an efficient mechanical transmission system and prevent accidents [1,2].

One condition monitoring technique that are reliable, easy to do and is applied in real life is vibration analysis. Vibration frequency characteristics are able to show most types of damage that occurs on a rotating machine and hence, analysis of vibration characteristics useful to identify most types of fault. Vibration analysis is an attempt to minimize damage to the engine components propagate to other engine components. Vibration analysis also helps to know the structure of the machine, whether it is still in stable condition, in accordance with the standard or vice versa. The latest technique commonly used to diagnose gearbox is by analysing vibration signals taken from the gearbox casing. The aim is to detect the location and type of damage at the initial stage of development and monitor the condition, to estimate the lifetime of the machine and prepare appropriate treatment. Gear Mesh Frequency (GMF) and its repetitions or harmonics and modulation phenomena that produce sidebands are the main components in the gearbox domain frequency (spectrum). Disturbance conditions can be observed from increases in
the number and amplitude of sidebands. In addition, the source of damage related to the sidebands distance [3].

Not all engineers know how to analyse vibration on industrial machines, especially on the gearbox. To analyse the vibrations of the gearbox requires a long learning time and experience in analysing using standard software from vibration equipment manufacturers. Usually in this case the company must pay dearly for expert staff services to measure and analyse the condition of the gearbox using vibration data. Even companies that already have a vibration analyser still have to call and pay for expensive because they do not understand how to analyse vibration data taken from gearbox. In addition, an expert staff in vibration analysis also still needs time to analyse spectrum data. Therefore, in solving these problems the authors propose to create a system that can read the spectrum of vibration data specifically to diagnose gearbox. A system that requires only input spectrum data and specifications from the gearbox. Furthermore, the system can provide important information about the gearbox condition, covering where the point of damage, what actions are needed and how much damage level.

The medical domain has inspired the concept of diagnosis. At present, the types of machine failures can be identified as root causes with sophisticated diagnostic methodologies. However, the diagnosis is made after the damage has occurred, including in the reactive action. In fact, observing certain machine conditions has a problem fault diagnosis in detecting the characteristics of damage that might be hidden in the dataset. Besides, detecting various damage to the rotating machine is suitable using monitoring vibration conditions. Signal processing, data acquisition, extraction of other features and features to reduce steps if required and the last correct classification step that can be obtained from historical data, expert insight and physical formation, all of which are a common framework for damage diagnosis systems [4, 5]. BN is able to make the possibilities that occur in the future very well, BN is able to handle uncertain causal relationships, update probabilities, multi-state variables, carry out two-way interpretations and handle the lack of data [6, 7, 8, 9]. In various scientific fields, BNs are widely used. BN's application practices in life are very widely used. BN has long been an interesting topic and continues to this day, supported by the rapid development of computer science, especially in data mining and machine learning [10]. Uncertainty arises and become the main component when designing knowledge-based reasoning and decision makers methods [11]. Related to expert system in manufacturing, Kobbacy and McNaught et al. emphasize that BNs are most useful when dealing with uncertainty [12]. BN is a reliable tool for developing expert systems in the field of artificial intelligence. It is advantageous in reflecting and diagnosing intricate systems with incomplete, uncertain and even conflicting information. The probabilistic graphical model of BN shows a probabilistic dependency relationship in a variable connected via an acyclic graph. Pearl introduced in the early 1980s [13, 14], in probabilistic inference and the realm of knowledge discovery has been applied successfully [15].

Previous techniques of artificial intelligence systems for damage detection use fault tree analysis (FTA), It is an analytical tool that graphically translates combinations of errors that cause system failures. This technique is useful for describing and assessing events in the system. This FTA method is effective in finding the core of the problem because it ensures that an unwanted event or the loss caused does not originate at one point of failure. FTA identifies the relationship between causal factors and is displayed in the form of a fault tree involving a simple logic gate [16, 17]. The advantage of using the FTA method because it has a clear, logical, intuitive, and usable system compared to some other systems. Nevertheless, the computation of the probability of failure becomes intricate when the structure of a Fault Tree is large, therefore an uncertain causal relationship and a multi-state variable cannot be done with an FTA [18, 19, 20], the component fault and reasoning generally do not pay attention to frequency failures and relationships for different components of the system. Calculation and analysis assuming that failures for independent components or subsystems can be subject to major errors. Regarding intelligent fault inference system for rotating machine and the methods used in this study was adopted from his paper, Bin Gang Xu used system fault assessment is structured by the BN concept, makes several failure sequences and the relationship between component failure with the BN model and validated fault assessment estimates. The proposed network applications in a flexible rotor’s vibration fault diagnosis showed strong inferential abilities. Various error inferences can be continued, related to
a single error, a combination of maximum errors and maximum network status, including with reasonable probabilistic information [21]. Developing BNs applications for rotating machines, this study uses spectrum frequencies as input data to identify symptoms of damage that occurs in the gearbox.

2. Methodology
2.1. Bayesian networks
Bayesian Inference and Bayesian network (BN) are decompositions of the Bayes’ theorem. The development of the Bayes theorem began in the 1760s, which new information to update possibilities. Some previous statisticians, for instance Pierre-Simon La-Place, decision-making methods and systematic statistical inference are developed from the Bayes formula [22, 23]. A BN was proposed by Pearl in 1988, which is the method that continues to be discussed today [24]. A special method called Bayesian Analysis that uses previous statistical information and success in many practical implementations.

Bayes’ Theorem:

\[
P(N|M) = \frac{P(M|N) \times P(N)}{P(M)}
\]

(1)

Building the BN, a system is constructed with a statistical technique known as the Bayes theorem namely Conditional Probability. Calculation of the probability of an event N if known event M has occurred is called Conditional Probability, represented by P(M), as shown in equation 1. This theorem is used to calculate the odds of a data set to enter into a particular class based on inference existing data. The combined probability factoring can be obtained by the regulation rule of probability theory, as shown in equation 2.

\[
P(x_1, x_2, x_3, ..., x_n) = \prod_{i=1}^{n} P(x_i | Parents(x_i))
\]

(2)

A BN is a Probabilistic one simple graphical model constructed from theory probability and graph theory. Probabilistic theory is related directly with data, while graph theory is related immediately with the representation you want to get. As for example, a BN can represent relationships between disease and symptoms. BN is able to calculate the probability of various symptoms of the disease. Building BN, an expert is needed to apply a concept of knowledge to the network. Knowing how a domain and its uncertainty can be applied in the BN and see how to use BN for domain needs. When observing the values of several variables and condition them in new information. This conditioning process is called probability inference that is carried out through the network. The information flow on the BN is not limited to the direction of the arc. In the probabilistic network, this becomes the task of calculating the posterior probability distribution for a set of request nodes, some evidence nodes provide values [24, 26].

Make probabilistic inference is the ability of the BN. Probabilistic inference is predicting the grade of an element that can’t be known immediately by using the values of other known variables. An example of probabilistic inference is determining the conditional probability of the type of gearbox damage based on the symptoms of damage if it is known that the frequency spectrum characteristics of damage occur. Probabilistic inference can be done if first obtained Joint Probability Distribution (JPD) of all the modelled variables. JPD is the probability of all variable events occurring simultaneously. Probabilistic inference can be done if the BN structure has been built. In diagnosing gearbox damage, the relationship between variables and the probability of variable values is unknown. The construction of BN from the data consists of structural construction or also called the qualitative stage, which is looking for connectivity between the modelled variables and parameter estimation or also called the quantitative stage, which is calculating probability values.

2.2. Vibration signature analysis
Analysis of rotating machine damage usually uses vibration signals in the form of spectrum frequencies obtained from Fast Fourier Transform (FFT). This method is a reliable tool for analyzing the location
of damage. FFT combined with vibration level values provides information about the condition of the machine, location and cause of damage. Based on the measurement history can reveal the remaining life of the machine or until the damage becomes critical. The spectrum frequency also presents the amplitude of the vibration in each source of damage occurring. Therefore, we can track where the location of the damaged component is based on its frequency. Every damage to the machine creates a frequency that has its own characteristics so that it can be used for diagnosis [27]. Vibration characteristics or vibration signatures are obtained when the machine is operating. Actual vibration signals derived from transducers can be considered as frequency characteristics, but usually refer to spectrum frequencies. Vibration signal measurement with standard transducer assisted acceleration produces accurate vibration analysis. The FFT is guided by the principle that all signals (not ideal signals) can be generated by the sum of sine waves. Conversely any signal can be broken down on its components in the form of a sine wave, it is important to say that the frequency spectrum fully represents the vibration signal. No information is lost because of the conversion from time domain to spectrum frequency, if the phase difference between components is also included [28, 29].

Spectrum characteristics provide valuable information about the damage location. The frequency and magnitude in the spectrum are related to machine rotation. For example, an amplitude line appears on 1X, 2X, 3X, ... 7X or something else. The relationship that belongs to each frequency line, for example the line that appears at 1X is greater than 2X or appears harmonic or there are sidebands. Knowing the source of vibration amplitude originates, for example 1X is an unbalance fan, 5.34 is bearing damage, etc.

2.3. Vibration assessment

Figure 1 shows type of ISO provides a standard for measurements carried out on site regarding the level of vibration [30]. The standard set applies to machines that have a capacity more than 15 kW and operating speeds in the middle of 120 RPM and 15000 RPM.
3. Implementation

3.1. System analysis

Figure 2 shows the process of intelligent system. The input data in diagnosing the gearbox damage is in the form of gearbox specification data including gearbox RPM input, gear RPM, number of teeth on gear and pinion, number of ball bearings, vibration value and also input spectrum data. The data already entered will be processed to find out the type of frequency that appears in the data spectrum. Furthermore, the identification will be used as evidence to indicate whether or not there is a spectrum line related to the damage to the gearbox. Identifying the frequency using predefined formulas. Suppose the obtained frequency value of GMF is 275 Hz, then the system will see whether there is a line that appears at that frequency or not. Existing evidence will be processed by calculating its probability value using BNs method.

Based on the input data obtained will be calculated probability value through several stages using BN method, which starts from the determination of parameter values for each symptoms of damage, then determine the value of conditional probability, after the two values obtained then the system will be calculated the value of joint and posterior probability of each type of gearbox damage that is adjusted to the BNs structure and the posterior probability value is used as the probability inference of the type of gearbox fault. BN produces relational information and conditional probabilities through two-way propagation between input and output nodes. Also, in the application of real cases generally use multistate nodes. So, from the consultation conducted by the user will get the type of fault that occurs on the gearbox and the percentage of the fault. Users will know what action takes precedence.

![Figure 2. Intelligent system flowchart](image-url)
3.2. Bayesian Networks approach

Designing expert systems in accordance with the concept map that you want to address in solving problems. This concept supports the decomposition of knowledge that explains each component and work procedure as discussed in figure 2, then created an expert system flowchart to illustrate in detail the process flow of the system works.

According to the stage of the vibration analysis in gearbox fault detection, we can build the structure of BN. In the first process, we assume the cause of the damage that occurs in the gearbox based on the emerging spectrum line. Then built a BN in such a way as to be able to show what kind of damage and what actions should performed by the user. The structure BNs model is shown in Fig. 3. Corresponding to Pearl, relational probability distribution is obtained from expert knowledge [24]. Information on object history is useful in determining prior probability values. This type of information is usually available in every corporation for instance machine damage report. So here BN acts as a knowledge base while the part of the control system is Bayesian inference rules.

![Image of Bayesian Networks system](image-url)

**Figure 3. Bayesian Networks system**
There are 60 nodes in BNs structure, as shown in figure 3. In solving the problem of a large number entering conditional probability value and to further ease the computer work, some nodes are added to the network such as IGF, VG, Good, Bad, VB, HA, HB, etc. For instance, at node HA, there are five parent nodes which are interconnected. The HA node will generate 64 CPT values, so time and memory will be more needed if the root node has more parent nodes. Associated CPT held every root node, its slump, only a row of representative prior probabilities. So, when a network has many parent nodes or parent nodes containing a lot of classification values, CPT will also be very large. The CPT criterion decided by the number of parent nodes. CPT for Boolean variables with x parent node having a $2x + 1$ probability formula. Nodes such as Monitoring, Repair and Check Data Spectrum in Detail (CSD) are added to serve to infer what actions should be performed by the user. Previous probabilities are needed to make casual dependencies.

The CPT table shows the level of damage to the gears. An expert is required to fill each table with a percentage of 0% - 100%. Suppose that the chance of occurrence of GMF if obtained evidence of symptoms of S19 and S20 is 90%. Determination of the value of 90% is obtained from information obtained by an expert. In analysing the damage of the gearbox using vibration data, the vibration value generated on the velocity spectrum is very small because generally gear mesh frequency (GMF) occurs at high frequency, and this will affect the small value of the resulting vibration. However, although the value is small does not mean there is no damage to the gears. While one of the main advantages of the BN when additional evidence is given, the BN system can determine conditional probability values in each node and calculate more accurate probability propagation. In the diagnosis of gearbox damage, conditional probabilities provide important information.

3.3. Software implementation

Material testing uses vibration data of multi stage gearbox, as shown in figure 4, that measurement was taken from a synthetic yarn factory where is the data contains several kinds of measurement such as overall velocity and spectrum velocity data.

![Figure 4. Multi stage gearbox](image)

gearbox has a rigid type foundation. There are 10 gears that rely on each shaft and bearings. Measurement of vibration is taken at 4 points of shaft and each point is taken 3 axis point covering horizontal, vertical and axial. Each of the 3 points is taken which has the greatest vibration value. Figure 5 shows the spectrum obtained from gearbox measurements at each accessible bearing location. There are 4 spectrums chosen because it has the largest overall vibration value. Figure 6 describes the gearbox structure in detail including the type of bearing and number of teeth that are used. According to the complete specification information of the employee staff, the gearbox is grouped into ISO group 2 rigid standard.
Figure 5. Spectrum of gearbox
Figure 6. Gearbox structure

3.4. Diagnosis result

Figure 7 shows the calculation results of BNs that have been built, there are symptoms of possible indications of damage to the gears and bearings.

Figure 7. Diagnosis result of point 1
On the handling probability side, the highest percentage value is monitoring, this is because the vibration value on the gearbox is still in good condition. As noted earlier, in particular, gears and bearing problems, the small vibration values cannot be used as a benchmark to determine that the gears and bearings are still in good condition or vice versa. Users should still check the state of the gears and bearings according to experience or history of the gearbox.

| Measurement Point | 1A  | 1B  | 2   | 3   | 4   |
|-------------------|-----|-----|-----|-----|-----|
| Gear              | 0.54| 0.55| 0.52| 0.55| 0.2 |
| Gear Mis.         | 0.17| 0.15| 0.15| 0.59| 0.15|
| Foundation        | 0.42| 0.42| 0.42| 0.42| 0.42|
| Bearing           | 0.46| 0.46| 0.46| 0.48| 0.47|
| Shaft Mis.        | 0.28| 0.28| 0.28| 0.28| 0.29|

According to a series of diagnostic tests that have been done on the gearbox, we can know easily what damage happens to the gearbox. The results of each calculation using different BNs methods in each trial, this is due to the difference in evidence obtained from each spectrum data against the gearbox specification data. We can clearly examine the evidence data that is entered on the BNs method. Based on evidence of symptoms obtained, we can conclude whether the results of the diagnosis are appropriate or not. The results of each diagnosis indicate the suitability of the design with the intended expectations.

### Table 2. Comparison of Diagnosis result

| No | Diag. Point | Symptoms at Spectrum | Manual Diagnosis | Intelligent System |
|----|-------------|----------------------|------------------|--------------------|
| 1  | 1A          | 0.3X-0.7X, 3.5X, Gear, GMF, GAPF, FHT, GFN and BPFI | Gear Mesh, Hunting Tooth, Gear Phase Assembly and Inner Race Bearing Problems | Gear and Bearing Problems |
| 2  | 1B          | 0.3X-0.7X, 3.5X, GMF, 2GMF, 5GMF, GAPF, 2GAPF, FHT, GFN, BPFO and 2BSF | Gear Mesh, Hunting Tooth, Gear Phase Assembly, Outer Race Bearing and Ball Bearing Problems | Gear and Bearing Problems |
| 3  | 2           | 0.3X - 0.7X, 5GMF, FHT, BPFI and FTF | Gear Mesh, Hunting Tooth, Inner Race Bearing and Cage Bearing Problems | Gear and Bearing Problems |
| 4  | 3           | 0.3X-0.7X, 2Gear, Pinion, 2Pinion, GMF, 5GMF, GAPF, 2GAPF, FHT, GFN, BPFI, BPFO, 2BSF and FTF | Gear Misalignment, Gear Mesh, Hunting Tooth, Gear Phase Assembly, Inner Race Bearing, Outer Race Bearing, Ball Bearing and Cage Bearing Problems | Gear, Mis. Gear and Bearing Problems |
| 5  | 4           | 1X, 0.3X - 0.7X, BPFO, 2BSF and FTF | Outer Race Bearing, Ball Bearing and Cage Bearing Problems | Bearing Problems |

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### 4. Conclusion

Designing an intelligent system, which considers both vibration analysis and BN system with multiply states, using discrete failure probability distribution. BN based on the vibration frequency characteristic analysis procedure applied in the implementation system to better present BN applications in expert systems so as to produce accurate information from the gearbox condition. The advantages of BN are indicated by two-way inference for conditional probabilities. Damage to the components of the gearbox can be seen after proof of the spectrum added to the BN. A more accurate and faster decision can be made to ensure the performance of the expert system and provide valuable information regarding damage detection and gearbox maintenance. Results of diagnostic testing obtained matching results between the tests conducted manually and by the expert system. BNs method have been effectively used to the diagnostic expert system for the source of gearbox damage, so it can provide a fast diagnosis and the probability of occurrence of the location of the damage.
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References
[1] G. Diwakar, M. Satyanarayana and P. Kavi Kumar, "Detection of Gear fault using vibration analysis," International Journal of Emerging Technology and Advanced Engineering, vol. 2, no. 9, pp. 122-125, 2012.
[2] L. Jing, M. Zhao, P. Li and X. Xu, "A convolutional neural network based feature learning and fault diagnosis method for the condition monitoring of gearbox," Measurement, vol. 111, pp. 1-10, 2017.
[3] A. Aherwar and M. S. Khalid, "Vibration Analysis Techniques for Gearbox Diagnostic: A Review," International Journal of Advanced Engineering Technology, vol. 3, no. 2, pp. 1-7, 2012.
[4] J. Lee, F. Wu, W. Zhao, M. Ghaffari, L. Liao and D. Siegel, "Prognostics and health management design for rotary machinery systems—Reviews, methodology and applications," Mechanical Systems and Signal Processing, vol. 42, no. 1-2, pp. 314-334, 2014.
[5] M. Y. Asr, M. M. Ettefagh, R. Hassannejad and S. N. Razavi, "Diagnosis of combined faults in Rotary Machinery by Non-Naive Bayesian approach," Mechanical Systems and Signal Processing, vol. 85, pp. 56-70, 2017.
[6] D. N. Dongiovanni and T. Isemantas, "Failure rate modeling using fault tree analysis and Bayesian network: DEMO pulsed operation turbine study case," Fusion Engineering and Design, vol. 109, pp. 613-617, 2016.
[7] W.-S. Wu, C.-F. Yang, J.-C. Chang, P.-A. Château and Y.-C. Chang, "Risk assessment by integrating interpretive structural modeling and Bayesian network, case of offshore pipeline project," Reliability Engineering & System Safety, vol. 142, pp. 515-524, 2015.
[8] X. Li, C. Chen and H. Zhui, "Quantitative risk analysis on leakage failure of submarine oil and gas pipelines using Bayesian network," Process Safety and Environmental Protection, vol. 103, pp. 163-173, 2016.
[9] W. Wang, K. Shen, B. Wang, C. Dong, F. Khan and Q. Wang, "Failure probability analysis of the urban buried gas pipelines using Bayesian networks," Process Safety and Environmental Protection, vol. III, pp. 678-686, 2017.
[10] H. Langseth and L. Portinale, "Bayesian networks in reliability," Reliability Engineering & System Safety, vol. 92, no. 1, pp. 92-108, 2007.
[11] I. Boersch, J. Heinsohn and R. Socher, Wissensverarbeitung: Eine Einführung in die künstliche Intelligenz für Informatiker und Ingenieure, vol. 2, Elsevier, 2007, p. 397.
[12] K. A. Kobbacy, K. McNaught and A. Chan, "Bayesian networks in manufacturing," Jnl of Manuf Tech Mngmnt, vol. 22, no. 6, pp. 734-747, 2011.
[13] J. Pearl, Bayesian Networks: a model of self-activated: memory for evidential reasoning, Los Angeles: UCLA, Computer Science Department, 1985.
[14] J. Pearl, "Fusion, propagation, and structuring in Belief Networks," Artificial Intelligence, vol. 29, pp. 241-288, 1986.
[15] L. Yang and J. Lee, "Bayesian Belief Network-based approach for diagnostics and prognostics of semiconductor manufacturing systems," Robotics and Computer-Integrated Manufacturing, vol. 28, no. 1, pp. 66-74, 2012.
[16] Z. Xuejun and C. Yu, "The research of intelligent fault diagnosing methods based on FTA," Microcomputer Information, vol. 21, no. 6, pp. 123-124, 2005.
[17] Y. Zhi-Ling, W. Bin, D. Xing-Hui and L. Hao, "Expert System of Fault Diagnosis for Gear Box in Wind Turbine," The 2nd International Conference on Complexity Science & Information Engineering, vol. 4, pp. 189-195, 2011.
[18] N. Khakzad, F. Khan and P. Amyotte, "Safety analysis in process facilities: comparison of fault tree and Bayesian network approaches," Reliability Engineering & System Safety, vol. 96, no. 8, pp. 925-932, 2011.

[19] N. Khakzad, F. Khan and P. Amyotte, "Dynamic safety analysis of process systems by mapping bow-tie into Bayesian network," Process Safety and Environmental Protection, vol. 91, no. 1-2, pp. 46-53, 2013.

[20] N. Khakzad, F. Khan and P. Amyotte, "Quantitative risk analysis of offshore drilling operations: a Bayesian approach," Safety Science, vol. 57, pp. 108-117, 2013.

[21] B. G. Xu, "Intelligent fault inference for rotating flexible rotors using Bayesian belief network," Expert Systems with Applications, vol. 39, pp. 816-822, 2012.

[22] D. Zhou, “The Application of Bayesian Networks in System Reliability,” Master Thesis in Arizona State University, pp. 1-13, 2014.

[23] J. Grover, Strategic economic decision-making: Using Bayesian belief networks to solve complex problems, vol. 9, Springer Science & Business Media, 2012.

[24] J. Pearl, Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference (Morgan Kaufmann Series in Representation and Reasoning), San Mateo, California, 1988.

[25] K. B. Korb and A. E. Nicholson, Bayesian Artificial Intelligence (Second Edition), London: CRC Press, 2011.

[26] R. E. Neapolitan, Learning Bayesian Networks, Chicago, Illinois: Northeastern Illinois University, 2003.

[27] J. Mais, "Spectrum Analysis: The key features of analyzing spectra," SKF USA Inc., pp. 3-28, 2002.

[28] S. K. Sar and R. Kumar, "Techniques of Vibration Signature Analysis," International Journal of Advanced Research in Computer and Communication Engineering, vol. 4, no. 3, pp. 240-243, 2015.

[29] S. R. W. Mills, Vibration Monitoring and Analysis Handbook, vol. 1, Northampton: The British Institute of Non-Destructive Testing, 2010.

[30] NEN, "Mechanical Vibration - Evaluation of machine vibration by measurements on non-rotating parts," International Standard, vol. II, pp. 1-10, 2009.