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Condition Monitoring for Predictive Maintenance – Towards Systems Prognosis within the Industrial Internet of Things

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Abstract Vibration based condition monitoring (VBCM) is a well-established technique for the application of predictive maintenance to the rotating machinery. The use of this technique for the purpose of machine diagnosis is well researched but there is so far no proven technique for using the same vibration data for systems prognosis. This paper proposes an approach that uses a linear regression technique to derive a mathematical model which is in turn used to predict the future vibration severity of a rotating machine. The frequency peaks of the velocity spectra were used in a real plant case study where the VBCM was applied to the roller element bearing component of a drillship's thruster system. The results obtained were dramatically better than when the overall root-mean-square values of the time waveform were trended over the same period.

Key words Big data, Condition monitoring, IIoT, Industry 4.0, Predictive Maintenance, Prognosis.

1.0 Introduction

As organizations strive to reach their production targets there are assets that are critical to their operations. The reliability and availability of these critical assets directly impact the profit margins of the organizations and by implication their continued existence. Within an organization's maintenance function, predictive maintenance techniques such as condition monitoring and prognosis have today gained an increased attention because they are important to balance the dilemma between maintenance costs and technical acceptability. The level of competence and success recorded with the vibration based condition monitoring techniques means that they have found useful applications within varied industries from aerospace to manufacturing as well as the oil and gas industry in recent times.

However, as the transition is made away from traditional manufacturing and standalone systems, a major concern expressed within the industry is that the current approach presented within Industry 4.0 (the Industrial Internet of Things (IIoT)) [7] for implementing predictive maintenance places too much emphasis on low level data monitoring to a degree that compromises the level of competence already achieved within the industrial application of vibration based condition monitoring and there is so far no proven method to overcome the challenge.

The ultimate goal of any condition monitoring system is to gain the capability to predict the future of the equipment monitored [2]. Such a goal would be hard to reach by simply monitoring low level data such as temperature and pressure as currently suggested in the literatures related to Industry 4.0 although there are still not many publications available in this area. The IIoT is a new and evolving paradigm, therefore research and implementation are still in their formative stages. Previous publications are quick to highlight the strategic importance of big data but fail to demonstrate how it can be organized and analyzed for the purpose of predictive maintenance and for completing the maintenance decision loop. From the perspective of maintenance, the obvious weakness in the present big data exists in the fact that they are collected mainly for operational reasons and only serves maintenance purposes often “accidentally” or as an afterthought at the best.

In this paper, investigations have been carried out and the results reported can bridge some of the existing gaps. Using vibration monitoring of rotating equipment as a case study, it was demonstrated that the next generation of condition monitoring can integrate well into the Industrial Internet beyond low level data monitoring which is currently the case. It was shown that the application of a systematically selected stochastic process to low level data provides the required scaling up of vibration data to produce a more realistic and more practicable solution compared with any existing technique for the implementation of predictive maintenance within the Industry 4.0 environment. Machine generated real data and an industry grade software were deplored to obtain results which are not only compatible with the proposed Industry 4.0 reference architecture but also show a higher level of service when utilizing the proposed condition monitoring technique. Using modern sensors and instrumentation techniques, vibration data is collected in a structured manner for the main purpose of predictive maintenance. The collected data is dimensioned and treated in a form compatible with Industry 4.0 requirement for single value data while retaining the original properties of vibration data. It was proposed to capture multiple snapshots of vibration patterns to which a single average value is assigned to the frequency spikes for every successive and corresponding time horizon. These values are aggregated over time and a regression is run adopting the technique of the autoregressive moving average (ARMA) to predict future failures. This is essentially a machine learning model that follows the propagation of an existing degradation over time and then estimates a future time when the degradation is beyond a predefined threshold. This gives room for planning and arranging for logistics in advance to minimize or totally avoid downtime.

Hence this new approach is expected to radically redefine the use of vibration based condition monitoring techniques within the Industrial Internet of Things without any loss of fidelity in its application to predictive maintenance and thereby ensuring safe cost reduction and the optimal utilization of asset value. It is expected that the proposed solutions are refined further through collaborative efforts of researchers and the end-users in the industry to reach a regulatory level of acceptability.

2.0 Rotating Machines Prognostics: The Science & Art of Vibration Technique

Vibration is characterized with frequency (measured in Hertz, CPM or RPM) and amplitude (measured either as peak, peak-to-peak or RMS values). The vibration energy can be described in terms of either the displacement (measured in micrometers), velocity (measured in millimeters per second) or acceleration (measured in meters per square second) caused by its transmission. A vibration signal can be related to another vibration or reference signal in terms of phase. There are several international standards dedicated to best practices in vibration analysis. They are mostly focused on the area of using vibration analysis for the purpose of operational monitoring and acceptance testing of rotating equipment or reciprocating machines. They often generally cover diagnosis but there is so far neither an existing standard nor is there available any proven technique to use vibration analysis to implement system prognosis. This is important because gaining an early awareness about an impending failure provides the opportunity to mitigate surprises and plan maintenance based on a schedule to optimize production time and reduce downtime. This section proposes a technique that provides a basis for using vibration analysis to carry out system prognosis within the framework of a predictive maintenance policy. The discussion begins with an introduction to ISO 10816-1 standard to aid a better understanding of the topic.

2.1 Mechanical Vibration and the ISO 10816

The ISO 10816 is one of the key international standards that set out the procedures and conditions for measurement and evaluation of vibration data. The ISO 10816 specifically focuses on measurements made on non-rotating/nonreciprocating parts of the machine. It stipulates two evaluation criteria. These are the magnitude of vibration and the change of vibration. The vibration signal captured from a machine is specified to be broadband in the sense that the frequency spectrum of the equipment under consideration is reasonably covered. The appropriate frequency range for any given type of machine will depend on its configuration and the previous experience gained with its vibratory behavior.

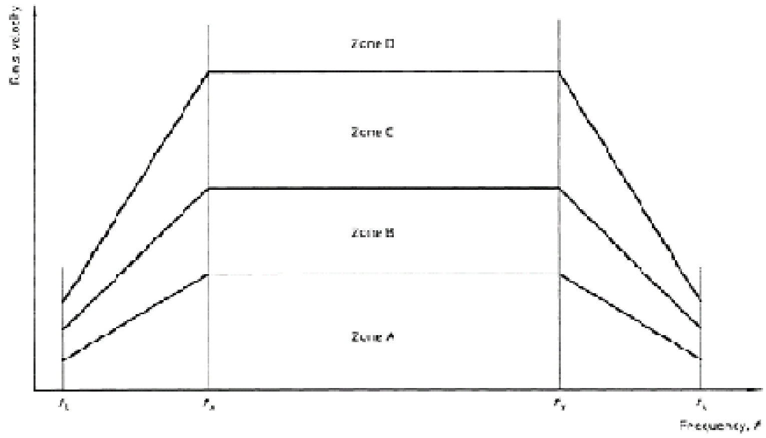

Figure 2.1: ISO 10816 – General form of vibration velocity acceptance criteria

The overarching objective of any vibration analysis system is to determine the vibration severity of a machine and the trend of the vibration over time, increasing or decreasing. In order to meet this objective, measurements are made at carefully selected measurement points and often in two or three different directions which are mutually perpendicular to each other. This results in a set of vibration data representing vibration magnitude. By definition, vibration severity is the *"maximum broadband magnitude value measured under agreed machine support and* operating *conditions"* (ISO 10816-1). In many machines a single vibration severity value is enough to characterize the vibration level however in other cases it will be insufficient and a more accurate representation will depend on a number of severity values from several locations. The vibration severity at each bearing housing or pedestal is compared with the four predetermined evaluation zones (Zones A, B, C and D) stipulated by the ISO 10816-1 and ISO 10816-3 standards to give the indication of normalcy, alarm or trip (ref. Figure 2.1). The measuring positions are marked and subsequent measurements are taken from the same positions with the same transducer orientations and similar operating conditions, otherwise it may produce an erroneous result when trended over time. When these conditions are met, significant changes from the established normal vibration readings must be investigated further to avoid reaching a position which could be dangerous to the continued operation of the machine. It is however important to note that in some cases some deviations cannot be detected unless the frequency components of the vibration signal is analyzed. This is further illustrated with the use of a case study in the following section.

2.2 Case Study: Implementing System Prognosis with the Thruster Gearbox Bearing Velocity Spectra

The vibration data used in this case study were obtained from measurements made on a roller element bearing at one of Company A's machines. The velocity spectrum for a component of the thruster system, that is one of the gearbox bearings was analyzed. The survey periods are assumed to be at six months interval. That is a logical deduction but it was not exactly the case. It is important to assume an equal interval to proceed with the regression analysis. The results of the regression analysis is shown on Figure 2.2. The numbers used for the regression were obtained by taking the average of 5 peaks on a survey period: the maximum peak for the period, two next lower peaks on the left and two next lower peaks on the right. The frequency range of interest was from 250 Hz to 300 Hz (this frequency range is associated with the bearing of interest). The vibration severity or peaks are measured in millimeters per second.

Survey Period	Peaks: Y,X	
1	0.65	
2	2.29	0.65
3	2.55	2.29
4	2.34	2.55
5	2.42	2.34
6	2.84	2.42
7	3.86	2.84
8	4.86	3.86

Survey Period	Peaks, Y,X	
2	2.29	0.65
3	2.55	2.29
4	2.34	2.55
5	2.42	2.34
6	2.84	2.42
7	3.86	2.84
8	4.86	3.86
Model Prediction for: 9	4.96	

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	3.4336	3.4336	7.575866	0.040194
Residual	5	2.266143	0.453229		
Total	6	5.699743			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.096117	0.744827	1.471639	0.201092	-0.81852	3.010756	-0.81852	3.010756
X	0.795704	0.289092	2.752429	0.040194	0.05257	1.538838	0.05257	1.538838

Figure 2.2: First Order Linear Regression of Vibration Severity/Peaks

From the regression analysis, the model for predicting the next period's expected vibration severity was derived as 1.096117 + 0.795704 Y_t (where Y_t is the vibration severity of the most recent survey period.) The model predicted the vibration severity for period 9 to be 4.96 millimeters per second. Having a systematic way to carry out such predictions has many benefits. In the current case study, surveys were repeated at six months interval. At the end of each survey, it is possible to predict what we expect the vibration severity to be six months from the most recent survey campaign. Should the predicted vibration severity be significantly higher than the predetermined acceptable levels, the asset managers have the benefit of initiating the plan to carry out maintenance long before the possible failure of the component. While working in partnership with the industry for this paper it was observed that maintenance engineering service providers may have reason to authorize the continued use of an equipment even when a trend that could lead to failure has been observed. The main reason for not carrying out maintenance as soon as the first sign of possible failure is known was found to be predicated upon considerations for production interruption. In such situations where it was necessary to escalate the maintenance requirements, the engineering company was observed to have offered the equipment utilization extension based on "expert judgement and best guesses or honest estimates." The systematic approach proposed in this paper offers a more scientific and objective technique for reaching such decisions. Another question that is necessary to address is what the appropriate survey interval should be. This is a difficult question as it will generally involve commercial and contractual considerations. The accessibility of the equipment or its known reliability performance and the cost to personnel or in extreme cases interruption to production flow are among important factors to consider before the survey interval is selected. Due to random events, it might sometimes be necessary to embark on vibration data collection at a time that is off the agreed interval. In such cases, the asset managers have to document and implement the additional survey campaigns without distorting the planned survey periods.

2.2.1 The model has the following limitations:

- Only a few data points (7 observations) were used to train the model.
- The recorded readings were made at different machine revolutions. It was only after July 3rd 2013 that measurements were made consistently at 680 RPM. Between December 12, 2011 and February 01, 2013 the range of RPM where vibration readings were taken varied from 583 to 710. This is contrary to the recommendations made in [4], [5], [6] and certainly has an influence on the derived model.
- Frequency peaks were measured without linking them with their corresponding phase angles. Treating frequency as a vector quantity rather than as a scalar produces better results as shown in the standards referenced in the above bullet point.

- The interval between the survey periods were not equal. In some cases it was approximately six months but it was not generally true.
- The regression analysis has been carried out using the data analysis function in Microsoft Excel. It was sufficient to demonstrate the result but a commercial application would require a more advanced software perhaps application tailored computing.

In order to overcome the aforementioned limitations, the pursuit of predictive maintenance and prognostic techniques need be a rigorously implemented policy. Lots of data are now being generated within industrial applications [3], [7] and with the continued improvements in sensor technology, data mining will witness an upward trend [8], [9]. It is necessary to look into the generated data, structure and analyze it to help in maintenance decision support as well as other value added services. Data scientists will play an increasingly important role in the future of maintenance practice. Analyzing a sufficient amount of data from the same or similar machines with some statistical techniques such as the lifetime models which have been rigorously treated in standard statistical literatures will improve asset reliability and availability. The application of the Nelson-Aalen estimator and the Kaplan-Meier estimator techniques, for example, to the relevant data sets can aid better understanding of components' failure trajectories and a more accurate estimation of the machine's mean time to failure (MTTF) or other important system structures and parameters. The big data is important but the systematic analysis of the big data provides the value adding perspective that would help organizations to realize their overarching business functions to maximize stakeholders' value.

3.0 Smart Maintenance: The Discussion Continues

Condition monitoring is intended to measure the current status of an operational item but it does not automatically imply that a predictive maintenance policy is in place [2]. There has to be a system that receives the parameter values measured by the condition monitoring technique and utilise these values as an input to the predictive maintenance strategy. A condition monitoring programme is an irreducible minimum for the predictive maintenance strategy to hold but a successful predictive maintenance concept is a consciously applied policy. The evolving paradigms of the Industrial Internet of Things (IIoT) gives credence to the prediction of the 4th industrial revolution which was first identified in Germany as Industry 4.0. The disruptive nature of an industrial revolution means that there will be a shift in the general ways of doing things and there has been discussions in the maintenance engineering communities as per the impacts of these shifts in practice. The relevance of this paper and the results obtained from the investigations are grounded in the reach to provide some basic proposals on how to structure and analyse vibration data for the purpose of predictive maintenance and systems prognosis. It is expected to be a means to bridge the state-of-the-art in maintenance and the future maintenance practice which is smart by its perspective and data driven by application. It was established that the frequency spectrum correctly captures the vibration energy in the rotating machinery when subjected to vibration analysis. The use of frequency peaks in spectral analysis for trending provided better results than conventional trended overall values. Spectral analysis provides a means to separate a complex vibration time waveform into its component frequency spectra which in turn offer the benefit to identify and isolate specific frequencies resulting from each and every component in a complex rotating machine. This was traditionally used for troubleshooting and diagnosis. The investigations conducted for this paper revealed that these frequency peaks can also be used to predict the future behavioural patterns of the rotating machinery and estimate its future vibration severity based on ordinary linear regression.

The particular data-set used for the case study came from a roller bearing which formed part of a thruster assembly on a drill ship. The relevant data used for the regression analysis had a span of eight periods. The interval between two successive periods was approximately six months. When a first order linear regression analysis was conducted based on the data from the eight periods (that is only 8 observations), a prediction model was established. From the regression analysis, the model for predicting the next period's expected vibration severity was derived as 1.096117 + 0.795704 Y_t (where Y_t is the vibration severity of the most recent survey period.) The model predicted the vibration severity for period 9 as 4.96 millimetres per second. If this mathematical model is validated to hold true in similar operating conditions it becomes easy to write an algorithm that is capable of implementing system prognosis. The derived model has the limitation that it was based only on 8 observations which is grossly insufficient. The framework nonetheless provides a basis for further investigations as more data become available. With only a few data points, it was only reasonable to run a linear regression. However, in another report [1] it was suggested that the quadratic model offered better results than linear ones. This report lacked sufficient data to either confirm or refute the claim that quadratic models are better than linear models. The strength of this investigation is that it has provided a proposal which can be easily adapted to create models which can be used for predictive maintenance and prognosis as the sensor technology continues to revolutionise condition monitoring whilst also driving both the big data and big data analytics for the smart maintenance applications.

The rotating machinery form an integral part of most production assets. Pumps, compressors, electrical motors and generators, separators, and gas turbines are common examples of rotating machinery used in industries. The use of vibration analysis for purposes of condition monitoring and diagnostics has been very successful within standalone systems in conventional applications. However, the concept of smart maintenance based on Industry 4.0 requires an extensive use of data [7]. The challenge is to present the data in a format that is compatible with the design philosophies and the reference architecture for the Industrial Internet of Things (IIoT) [3]. This report has provided an initial proposal for tackling the stated challenge. It further shows a technique that makes use of structured data to implement systems prognosis based on the frequency spectrum of vibration data. The procedure outlined for implementing predictive maintenance was simple but a limited amount of data was used. That limitation makes it difficult to argue that the results obtained would be valid in all circumstances. The next phase of improvement must utilise a more extensive data coverage that would help determine the degree of accuracy of the results of the prognosis. In addition to expanding the data coverage, there is a need to calculate and provide the confidence intervals associated with every prediction. The gradual progression from condition monitoring to condition based maintenance and predictive maintenance up to prescriptive maintenance is both worthy and realisable within the sphere of smart maintenance. In order for the idea to reach a proven technology and a regulatory level of service there has to be a consciously targeted effort by all sectors to improve the techniques for measuring parameters and running the analysis. A further refinement of the ideas proposed in this paper to a point of commercial viability is recommended along with the inclusion of those partner companies who are willing to set up pilot services to validate the proposed ideas.

4.0 Conclusion

The derived mathematical model for predicting the future vibration severity was based on single values which are compliant with the proposed Industry 4.0 reference architecture. The vibration data stored, processed and analyzed in the compliant format helps to populate the big data which in turn is used for the data driven smart maintenance which has a great descriptive accuracy, predictive powers and prescriptive capabilities. Condition monitoring was shown to be a safe cost cutting mechanism to the benefit of operators and asset managers because it provides a mechanism to avoid or mitigate surprises. Having an advance awareness about the degraded state of a production asset offers the valuable advantage of synchronizing maintenance needs and operational demands.

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