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Predictive maintenance (PdM) analysis matrix: A tool to determine technical specifications for PdM ready-equipment

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Abstract. Predictive maintenance (PdM) and operations optimisation are expected to generate the highest industrial and societal impact within the oil and gas industry. Such an optimistic expectation requires several changes in asset design and maintenance management. Nowadays, design for maintenance and maintenance support needs are mainly guided by the IEC 60706-2 standard. However, Designing for PdM ready-equipment is not yet part of that standard. To design PdM ready-equipment a specific analysis method shall be performed to evaluate the technical requirements and specifications of designed equipment to be PdM ready. Therefore, the purpose of this paper is to propose and demonstrate a PdM analysis method that helps to specify the technical specifications to monitor and predict the health of a specific physical asset. The proposed matrix is an evolution of further development of failure Mode, effect and criticality analysis (FMECA) and failure mode symptoms analysis (FMSA) rather than a revolutionary analysis. The case study method is used to extract stakeholders needs of what they expect from PdM analysis (PdMA) and how practical such type of analysis shall be. The developed PdMA matrix shows a simple relation between failure (their modes/levels) and measured abnormal symptoms and tracking and prediction indicators. The electric generator is used to demonstrate the use of the matrix. The PdMA matrix can be developed further to be more quantitative by including the probability of detection and probability of prediction.

1. Introduction

Predictive maintenance (PdM) and operations optimisation are expected to generate the highest industrial and societal impact within the oil and gas industry [1]. To gain the potential benefits of predictive maintenance in industry 4.0 era, two aspects shall be considered at the design phase: (1) design a PdM ready-equipment, and (2) develop a robust maintenance management architecture. Designing for PdM ready-equipment is not only to allocate sensors, but all physical and cyber items shall also be allocated to support the planned detection and prediction purposes. Especially, prediction in industry 4.0 context is about system-level prediction where physical components: (1) interact with each other and with the cyber-infrastructure using the Internet of thing technology, and (2) share data coming from several data acquisition systems with clear variety (process parameters, health parameter, i.e. value/waveform, meta-data) that acquired at different velocities and of different levels of veracity (Quality of data). Thus, the technical requirements and specifications that shall be allocated while designing PdM ready-equipment are complicated and require critical evaluation.

Nowadays, design for maintenance and maintenance support needs are mainly guided by the IEC 60706-2 standard [2]. However, Designing for PdM ready-equipment is not yet part of that standard. To design PdM ready-equipment specific analysis shall be performed to evaluate the technical requirements and specifications of the designed equipment to be PdM ready. The general maintenance requirements and specifications are commonly determined by applying reliability centred maintenance (RCM) analysis. RCM determines the specific maintenance policy to prevent specific failures based on the Failure Mode, Effect and Criticality Analysis (FMECA). NORSOKZ-008 Standard [3] defined work-flow for establishing preventive maintenance (PM) program. The FMECA can also be used to determine the most critical components and failures that shall be designed-out, monitored or frequently inspected. For monitoring purpose, Failure Modes and Symptoms Analysis (FMSA) ISO-13379-1 [4], ISO-17359 [5] is used to determine the most effective symptoms to detect abnormalities in the asset health. Gonzlez Nava[6] considered FMSA as core step within the entire work process of PdM evaluation at the design phase. However, the FMSA currently looks like (as shown in figure 1) a matching matrix between faults and their general symptoms. It is not offering any kind of quantification for the symptoms to select the most critical one. Thus, Lemme and Furseth [7] developed a procedure to quantify the symptom effectiveness within FMSA matrix.

Symptoms / Faults	Current	Torque	Speed	Vibration	Temperature	Coast down time	Axial flux	Oil debris	Acoustic emission
Eccentric rotor	•			•			•		
Bearing damage	•	•		•	•	•		•	•
Unbalance				•					
Misalignment				•					

Figure 1. Part of FMSA of electric motor faults

The idea is that after preforming FMSA the design process continues with allocating a measurement or monitoring system for each symptom. At this stage, several questions may arise based on FMSA: Are we going to measure all symptoms, do we have measurement/monitoring systems that can measure all symptoms, shall we select the most critical symptoms? How effective the measurement/monitoring systems can detect abnormalities of the measured symptoms, how effective the measurement/monitoring systems can handle fluctuations of the measured symptoms, and how early the measurement/monitoring systems can detect the abnormalities. In fact, these questions point out the detection specifications that shall be determined. Moreover, the FMSA is mainly handling the detection part of predictive maintenance and not the prediction part. To determine the specifications of prediction (How current symptoms will be diagnosed and how future symptoms shall be predicted), a further analysis shall be performed. It is worth to highlight that symptoms might changes over time as the fault is developing. Failures according to NORSOKZ-008 and Offshore and Onshore Reliability Data Handbook (OREDA) [8] are classified into three categories in terms of their evolution (earlier to later): incipient, degraded and critical.

The current prediction requirements are of digital type, i.e. software, cyber-ware, and might not lead to any physical requirements that shall be considered during designing PdM ready equipment. However, some hybrid diagnostic and prognosis techniques might require additional measurements techniques (in physical terms sensors). Thus, selecting some critical symptoms might limit the diagnostic and prognosis process. This means we need to purposefully select the symptoms that will be measured and monitored to support the diagnostic and prognosis process rather than selecting and measuring all symptoms. Moreover, edge computing technology (fog computing) might change the cyber-physical configuration of Predictive maintenance systems. It aims to allow processing and storage to occur at or near edge devices rather than at a centralised cyber infrastructure, e.g. cloud. Svorobej et al., [9] highlighted that edge computing is expected to "reduce latency for time-sensitive applications, support IoT performance in low-bandwidth environments and ease overall network congestion". However, this means also that several physical requirements for prediction shall be designed and allocated at the design phase.

Therefore, the purpose of this paper is to propose and demonstrate a PdM analysis method that helps to specify the technical specifications to monitor and predict the health of a specific physical asset. The case study method is used to extract stakeholders needs of what they expect from PdM analysis and how practical such analysis shall be. The electric generator is used to demonstrate the use of the method. Therefore, in the following sections, the needs for PdM analysis is first extracted and described, followed by the description of the proposed PdM analysis matrix and an illustrative example. Finally, the proposed method is discussed, and some conclusions are drawn up.

2. PdM needs and options

The Predictive maintenance might have several scenarios based on the physical asset needs and expectations of industrial managers. Predictive maintenance scenario is mainly combined of two parts: detection techniques and prediction methods. The Detection part aims to detect fault symptoms before the failure occur so that the failure consequences will be minimal (avoid unplanned stoppage, high downtime and level of repair). Detection is very effective to plan preventive maintenance. However, the maintenance work will be scheduled "when an asset needs" and not "when industrial manager prefers". In other words, detection helps to avoid sudden and sever down-times, but it might not provide flexibility to schedule it during low-production intervals or any opportunistic maintenance interval. In many cases, where the production system has several planned production stoppages, redundancy systems (means maintenance stoppage does not influence production), and maintenance crew are on board; detection is sufficient. However, for production systems that are operated in the unmanned manner (Offshore Wind farms, Offshore Unmanned Oil and Gas platforms), maintenance visits are quite costly and required medium/long time intervals for planning these visits, the detection is not sufficient alone and prediction is required.

Ultimately, prediction aims to estimate whether the faulty asset can survival until the next opportunistic maintenance interval. If prediction achieves this goal, then the unintended maintenance visits can be avoided or at least reduced. The detection and prediction scenarios are illustrated in Figure 2. Figure 2 illustrates four items: (1) the health status (black solid lines) of one physical component over the entire lifetime, (2) Planned intervals for maintenance visit (Yellow columns) and time between planned maintenance visits, (3) several levels of health status (Incipient, degraded, critical and full damage), and (4) detection points (green and yellow circles). In fact, critical faults usually have strong and clear symptoms that most of the condition monitoring instruments and tools are able to detect them. However, the effectiveness and earliness of these instruments and tools may significantly vary in detecting symptoms of degraded and incipient faults. Thus, the detection capabilities differ for each fault level, and they are more complex and demanding for degraded and incipient faults. The component shows healthy status until point 1, after that there are three different fault growth scenarios: scenario 1 (points 1-2-3-D), scenario 2 (points 1-4-6-D), and scenario 3 (points 1-5-7-8-D). It is clear that scenario one was detected by several detection levels and luckily, all before the planned maintenance visit. So, in this case, the condition monitoring system that just capable of detecting critical faults was sufficient for this scenario, even though the degraded and incipient symptoms could provide longer planning interval. However, if the planned maintenance interval was done just before the critical fault was detected, at point 6 in scenario 2, then the critical fault detection will not be effective as in scenario 1. At point 6, the industrial manager had to plan and fix the fault as soon as possible. So, scenario 2 shows that critical fault detection is good to detect and prevent damage/unplanned downtime, however, it could not help to avoid unintended maintenance visit (still we have to visit and fix the fault after point 6). Scenario 3 shows the most unfortunate cases, where both critical and degraded fault detection systems have not detected any fault symptoms before the planned maintenance visit. Based on Figure 2, the yellow points between the two planned maintenance visits means that two unintended maintenance visits are required. The potential solution to avoid the unwanted maintenance visits is to predict them at some points (i.e. points 1, 4 or 5) before the planned maintenance interval. The prediction at point 1 or 5 requires long-term prediction compare to point 4.

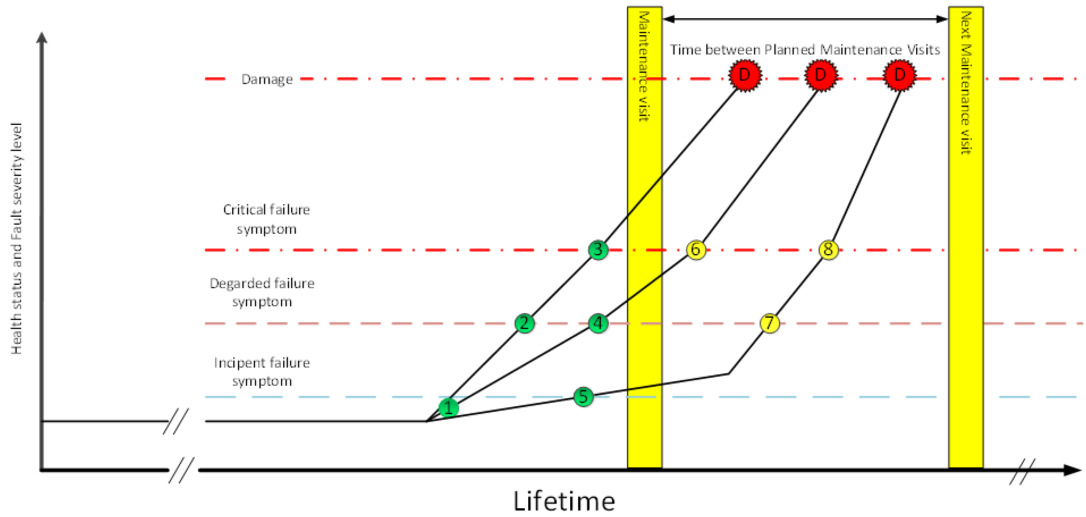

Figure 2. PdM analysis matrix

Prediction can be made in different ways. For example, many managers and engineers who have long experience, they prefer to perform heuristic prediction once the condition monitoring system detects a critical fault. Based on their experience of a specific system, fault type and severity, they might decide to fix right now or within the next few weeks. That might be sufficient for reaching an immediate goal, as in scenario 1 where the planned maintenance visit is quite soon. However, for cases like in scenario 2 and 3, the heuristic uncertainty is quite high. The second prediction way is statistical based, and the ISO 13381-1 (2015) listed two statistical-based prediction methods: extrapolation and projection. Predicting the remaining useful-time using extrapolation means you are going to make a regression fit curve based on the historical measured points (e.g. point 1 and 4). The intersection between the fit curve and what is called a "trip set-point (a little bit before damage/failure value)" defines the end of the remaining useful-time. The drawback for most of the statistical prediction is that you predict the future based on the past. So, in case, the future loading is changing, or the fault growth in the following stage is different than previous stages, such prediction will be misleading.

Projection method to predict the remaining useful-time is also listed in ISO 13381-1, and might be more reliable than extrapolation. It is based on using a ready-made curve of component health evolution (similar to the bathtub curve). The measured fault indicators will be projected on that curve, and the remaining useful-time will be estimated. The health evolution curves of specific physical component/system are usually generated using massive industrial data sets until a robust evolution pattern is extracted. For example, the SKF bearing rating life curve is quite reliable for bearings since it was created based on long-term and huge industrial cases and experimental tests. In fact, SKF extracted a mathematical equation based on these tests that allow us to estimate the bearing rating life with variable operating conditions and loads. However, the question is do other original equipment manufacturers have such models to be used for prediction.

There are other advance data-driven prediction methods, beside physics-based and hybrid methods [10], [11]. Instead of presenting each prediction method and discussing the advantages and drawback, it is better to discuss the main challenges of predicting remaining useful-time for physical components. In fact, these challenges might not be presented in each physical components. So it is more useful to know what are the main challenges of your component and then determine the appropriate prediction method. In Figure 3, four main challenging scenarios are illustrated. It is assumed that a degraded fault is detected at point D, and we are going to predict the health evolution curve. Scenario 1 considers potential overloading and reinforced failure mechanism due to multi-faults (either within the same component or other connected components). The effect of overloading and reinforced failure mechanism can both accelerate the fault evolution and make the remaining useful-time shorter. Scenario 2 represents the case of fault evolution when it influenced by either overloading or reinforced failure mechanism. In this scenario, the fault evolution is accelerated, but not as fast as scenario 1.

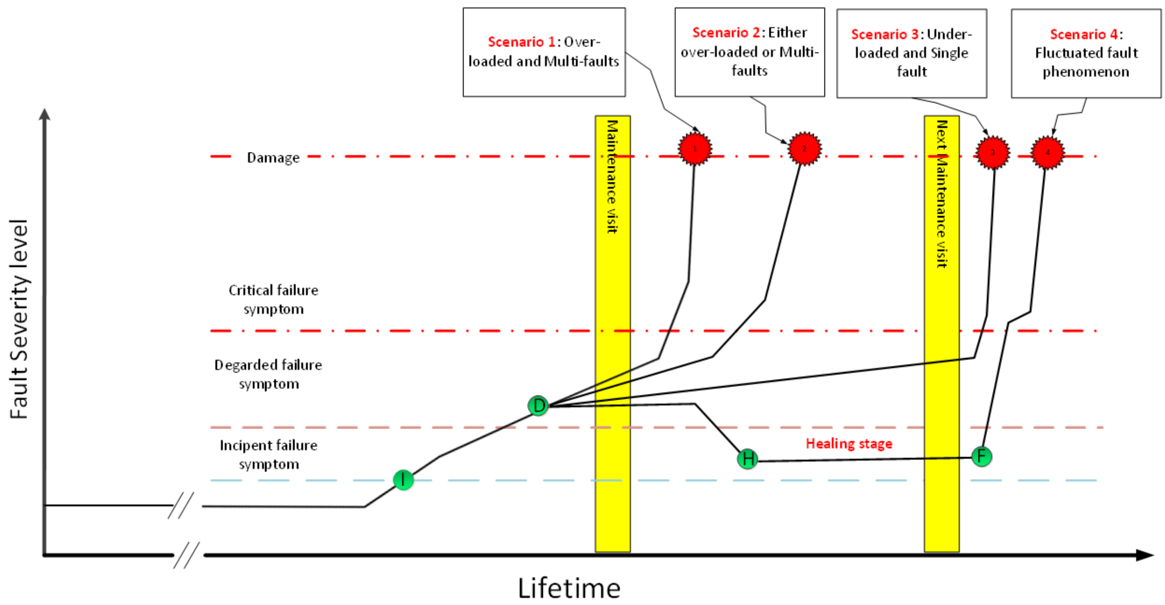

Figure 3. PdM analysis matrix

Scenario 3 represents the mild evolution of the detected fault where the component is going to be either normally loaded or even under-loaded. Moreover, there is only one fault and is not influenced by other faults of other components. Therefore, the fault evolution in this scenario is quite slow. These three scenarios illustrate two challenges of prediction: an estimate of future loading and failure mechanisms interactions among multi-fault situation and at system-level (several faulty components).

The third challenge of prediction is the fluctuation phenomenon, as illustrated in scenario 4 in figure 3. Scenario 4 starts at point "I" and getting higher until point "D" where it stabilises and goes down for a while (between points "H" and "F") before it goes rapidly at point "F" to the damage level. This phenomenon that is shown between points "H" and "F", is named as "Healing phenomenon" and was explained in a great deal of literature [12]. In fact, there is no physical healing, rather than the symptoms disappear due to an interaction between several failure mechanisms and they cancel the symptoms of each other. However, the fault growth is continuing and therefore it is rapidly accelerated at the end. To understand how symptom might be cancelled or disappeared, let us take the symptoms of localised defect inside a bearing. When the defect is initiated, the rolling element in the bearing will repetitively hit that defect (especially its asperity) and generate impact signals (as a symptom). Since this is a repetitive process, the defect after a while will be smoothened (asperity is getting lower and less sharp) due to abrasive wear. Therefore, the impact of the hits is getting smaller and hence, the symptom as well. However, the failure growth process is progressing where cracks are propagating and branching until the larger amount of material is detached and more prominent defect(s) with sharper asperities are created. Therefore, at that stage, the symptom is very evident and high. Thus, a symptom is an output of a specific physical phenomenon. However, it is hard to separate or isolated that specific phenomenon from its context (physically connected with other components) while we are taken measurements. Therefore, the measured symptom is a collective measurement at a specific location, not an individual and insulated measurement.

The main risk of healing phenomenon is to believe that the component is healing by itself and take no action toward that. Moreover, the development of failure (at the end of the healing stage, point "F") toward the damage state is very fast (almost sudden) and leave very short or even no time to act. In terms of prediction, this scenario is a nightmare. Several prediction models, especially statistical ones, when they try to predict at point "D", they end up with too early remaining useful time (almost like scenario 1 or 2). Getting earlier prediction or shorter remaining useful time than the real values are not acceptable as we might loss useful-time if we follow such prediction (and fix the component before it is required). Being early in fault detection is something to look for, but predicting and fixing the damage earlier than needed is something to be avoided, it shall be precise. Other group of prediction models estimate the precise useful-time at point "F", however, at that stage, such prediction has very little advantage for planning, since the situation needs very fast action. The best case is to predict at "D" or "H" a precise remaining useful-time. It is worth to mention that such a scenario is the most common scenario for several mechanical components as industrial and experimental cases have indicated [12],[13].

The fourth challenge of prediction is related to the diagnostic and tracking performance. As you might notice that all predictions are based on the diagnosed indicators of current health status as points "I" and "D". However, it is significantly vital to understand what is diagnosed and tracked. We don't track the symptom rather than its indicator "Symptom indicator". To illustrate that, let us have one example. Most of health monitoring symptoms are measured as waveform i.e. signals, for example, vibrations, acoustic emission, ultrasonic. Therefore, diagnostic engineers try to extract a clear and relevant indicator to track the symptom evolution, for example, Root mean square (RMS) value in time-domain or the peak-amplitude value at a specific frequency in the frequency domain. For each measurement data set, these value (indicators) will be estimated and tracked over time. So, the values of points "I" and "D" are in fact values of one selected fault indicator such as RMS, Kurtosis, Crest factor, Peak-to-Peak, or peak-amplitude value at the natural frequency, etc. The challenge is that the performance of almost all time-domain and frequency domain indicators varies over time due to the involvement of several physical failure phenomenon and limitation in their mathematical structure. For example, if you use Kurtosis for single fault case might show a clear indication of the fault. However, for a multi-faults case, it might indicate that everything is normal (it lose it's effectiveness) and mislead your detection and further prediction.

Predicting remaining useful time based on a detected incipient fault is further challenging. Incipient failure is defined in ISO 14224 [14] as "imperfection in the state or condition of an item so that a degraded or critical failure might (or might not) eventually be the expected result if corrective actions are not taken". Therefore, it is more complicated and uncertain process to predict the fault initiation and evolution over a long time interval. In fact, The prediction of critical and degraded faults was mainly based on modelling a specific failure mechanism(s). However, prediction of incipient faults deals with failure causes and vast potential combinations of failure mechanisms. Physics-based prediction is quite challenging as the physics of such a situation is unknown or highly uncertain. In this context, the data-driven prediction is commonly used to correlate and recognise a pattern in the fault causes (inputs) and the evolution value (measured outputs), where the fault mechanisms and their physics considered as a black box. It is worth to mention that most of the causes are related to the operating and loading parameters that are measured using process parameters instruments, e.g. SCADA, while the fault evolution is mainly based on health parameters measured by condition monitoring instruments. Therefore, it requires integrated data analytics.

3. PdM Matrix and Illustrative example

In the previous section, the author tried to describe three detection and four prediction challenges that were extracted from industrial practitioners at the Norwegian Continental Shelf and discussed them inline with the academic literature. These extracted challenges are going to formulate the basic needs for development PdM analysis method. In other words, the proposed PdM analysis method shall enable the PdM designer to identify these challenges for their physical system and determine the related requirements.

First, the detection requirements shall be determined to design PdM ready equipment. The detection requirements can be extracted from the previously illustrated scenarios (in figure 2), and summarized as follows: (1) the abnormal symptoms related to critical faults shall be detected before damage occur and spread/affect other systems, (2) The abnormal symptoms related to degraded and incipient faults should be early detected, i.e. detection earliness, (3) The detection technique (symptom measurement) shall be highly effective i.e. clear that show abnormality value, (4) The detection technique shall be highly dependable, that is not influenced by other sources of abnormalities within the monitored system (5) The detection technique shall be highly dependable to track the symptoms evolution (i.e. fluctuation in the appearance of the symptoms) and (6) The detection technique shall be compatible with the environmental conditions, loading patterns and equipment characteristics, e.g. high/low-speed equipment.

Second, the prediction requirements shall be determined in order to design PdM ready equipment. The prediction requirements can be extracted from the previously illustrated scenarios (in figure 3) and are summarised as follows: (1) The tracking indicators for critical, degraded and incipient faults shall be defined, (2) The diagnostic technique shall be effective to extract clear indicators for tracking purposes, (3) The diagnostic technique shall be effective to extract indicators as early as possible, (4) The diagnostic technique shall be reliable to extract effective and early indicators over the entire fault evolution process i.e. fluctuations in fault symptoms or loading patterns, (5) The prognostic (Prediction) indicators for specific faults shall be defined, (6) The prognostic technique shall be effective to predict future fault evolution and remaining useful-time related to the determined prognostic indicator (or a combination), (7) The prognostic technique shall be precise in predicting future fault evolution and remaining useful-time under fluctuated symptoms situations, (8) The prognostic technique shall be be precise in predicting future fault evolution and remaining useful-time under different future loading patterns, (9) The prognostic technique shall be be precise in predicting future fault evolution and remaining useful-time under multi-fault situation or fault-interactions or both., and (10) the prediction scope (interval) and sensitivity shall be as high as possible.

The Matrix in Figure 4 is based on the six detection and ten prediction requirements. The sequence of PdM analysis matrix is based on traditional predictive maintenance procedures (described in ISO 13374-1). It links failure modes and mechanisms, with fault symptoms (detection), fault indicators (diagnosis) and prediction indicators (prognosis). The Matrix in Figure 4 helps to roughly map specific physical assets and determine what are required to detect, diagnosis, and predict their faults. Moreover, the PdM analysis as highlighted by industrial practitioners, shall provide a kind of ranking procedure to prioritise the critical faults, critical symptoms, and critical (essential) indicators for diagnoses and prognosis. Such ranking might help in decision making to determine the optimal level of PdM implementation. Therefore, the matrix has three additional columns to facilitate such ranking: detection criticality, tracking (diagnosis) criticality and prediction criticality. At this stage of development, it is not recommended to screen out some component or symptoms from design consideration rather than prioritise the implementation. So the criticality factor might not be a multiplication of several critical factors as it was done for Risk priority index (RPI) in FMECA. Moreover, it is preferred to use a qualitative scale for this matrix instead of quantitative at the moment, since it might be hard for the original equipment manufacturer to provide that. However, this is something good to push toward it. In this regards, a simple scale (High, medium and low) is used to evaluate the criteria in this matrix. The illustrative example is an electric generator, and for simplicity, only some components are selected to illustrate the PdM analysis.

4. Conclusion

The paper shows how the requirements for developing predictive maintenance analysis can be inductively extracted from industrial practitioners and their challenges. These challenges were illustrated and discussed in details to determine the scope, expectations, capabilities and limitations of predictive maintenance (detection and prediction). The PdM analysis matrix built with the aim to help the industrial practitioners to determine or map the requirements to monitor and manage the health of their physical assets. The matrix covers the entire predictive maintenance process, i.e. detection, diagnosis and prediction. However, it is up to the analysts to determine how detailed analysis they would like to perform based on customer needs, operating scenarios, requirements of the physical asset, design opportunities and limitations. In general, the specifications for PdM ready equipment depend on: (1) whether you are going to detect or also predict, (2) how early to detect, (3) how early to predict and (4) time between planned maintenance visits, e.g. short or long, wind farm, and um-manned.

It is worth to highlight that the purpose of this paper is to show how the proposed matrix is developed. Thus, it is hard to claim how effective it is, at this stage of development. It can be mentioned that the matrix is simple and considered as an extension to well-known methods like FMECA and FMSA. However, the scales for criticality determination might need further development. Moreover, the level of implementation for such matrix highly depends on the business model and how detailed the designer would like to go during the design process.

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PdM Analysis (PdMA)

System ______
Subsystem ______
Component ______
Design Lead ______ Key Date ______
Core Team ______

FMEA Number
Prepared By
Date
Revision Date
Page

Scale
H High
M Medium
L Low

System	Maintainable Item	Potential Failure Mode(s)	Probability of Occurrence	Severity of Consequences	Criticality rank	Failure symptoms	Detection Earliness: Detectability of Critical failure (Completion)	Detection Earliness: Detectability of Degraded failure (Propagation)	Detection Earliness: Detectability of Incipient failure (Initiation)	Effectiviness (Clarity)	Dependability (Fluctuation)	Detection Criticality	Tracking Indicators	Tracking Clarity	Tracking Earliness	Tracking reliability	Tracking Criticality	Prediction Indicators	Precision (Future loading	Scope (how far)	Sensitivity (Fluctuation)	Prediction Criticality
Electric Generator	Rotor	Eccentric rotor				Current	H	M	L	M	L											
						Vibration	H	M	H	H	H	Required	RMS	H	M	L	sufficient	Extrapolated RMS	L	L	L	sufficient
		Unbalance				Vibration	H	H	H	H	H	Required	FFT, Peak at 1X	H	H	H	Sufficient	Extrapolated Peak-Value (FFT)	M	M	M	sufficient
		Misalignment				Vibration	H	H	H	H	H	Required	FFT, Peak at 1X, 2X,3X	H	H	H	sufficient	Extrapolated Peak-Value (FFT)	M	M	M	sufficient
	Bearing	Bearing fault				Current	H	M	L													
						Torque	H	M	L													
						Vibration	H	H	M	M	M	Required	FFT, Peak at Natural Frequency	H	H	M	sufficient	Projected Peak-Value (FFT)	M	M	M	sufficient
						Temperature	H	L	L	L	L											
						Oil-debris	H	M	M	M	M											
						Accoustic emission	M	H	H	M	M											
	Other components																					
Other systems																						

Figure 4. PdM analysis matrix

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