

Aligning PHM, SHM and CBM by understanding the physical system failure behaviour

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ABSTRACT

In this work the three disciplines of condition based maintenance (CBM), structural health monitoring (SHM) and prognostics and health management (PHM) are described. Then the characteristics of the disciplines are compared, which leads to a clear insight in the commonalities, but also in the difference in objectives and scope of the three disciplines. The disciplines are then demonstrated using three different case studies on bearing vibration monitoring, composite panel structural health monitoring and helicopter landing gear prognostics, respectively. After a discussion on the benefits of understanding the system physical (failure) behaviour, an integrated approach is proposed in which the three disciplines are aligned. This approach starts from defining an appropriate monitoring strategy (SHM and CM) and eventually ends in supporting the decision making (PHM) that leads to an optimal maintenance process throughout the life cycle of the asset.

1. INTRODUCTION

The disciplines of condition based maintenance (CBM), structural health monitoring (SHM) and prognostics and health management (PHM) have a lot of commonalities. They all aim to improve the maintenance decision making, with the ultimate goal of reducing maintenance costs and increasing system availability. But at the same time they are focusing on different aspects of the field and are being developed in more or less separate communities. Although implicit links between, for example, CBM and PHM are being made in several occasions (Buderath & Adhikari, 2012), the explicit relation between the disciplines has not

often been addressed specifically. In this work we therefore aim to align the three disciplines by identifying the major benefits of the individual approaches and proposing an integrated approach that combines these aspects. Firstly, in section 2 of this paper, we discuss the major differences and commonalities of the three disciplines in a general sense, both in terms of the adopted techniques and methods and underlying philosophy. Secondly, each of the disciplines will be illustrated in section 3 with three (existing) practical cases from our own research in the different disciplines. The CBM illustration case is the rather traditional approach followed in the blind identification of bearing damage. The SHM illustration case concerns the damage assessment in a composite structure using a structural vibration technique, while the PHM illustration case concerns the prognostics of landing gear failure in a helicopter. After that, partly based on the experience from these three cases, the role of understanding the system failure behaviour will be discussed in section 4. It will be demonstrated that knowledge on the physical failure mechanisms, in combination with the monitoring of loads or condition, is a key element in all three disciplines, while this aspect is recognized and covered by only a minority of the cases found in practice. This aspect will thus be taken to align the approaches of CBM, SHM and PHM in section 5. Taking into account the differences in scope and objective of the three disciplines, but fully exploiting their individual strengths, it will be shown that they can be aligned to yield an integral approach for optimizing system life cycle management. The proposed approach will start on the lowest level by monitoring the appropriate parameters and will ultimately provide decision support on the highest level for the optimal life cycle management.

2. DESCRIPTIONS AND COMPARISON OF DISCIPLINES

In this section the authors' view on the basic concepts of the SHM, CBM and PHM disciplines will be presented. Also the differences and commonalities will be discussed.

2.1. Condition Based Maintenance

Condition based maintenance is the oldest discipline of the three. It is closely associated to Condition Monitoring (CM), which is a term covering a range of techniques that have been developed in the past fifty years to assess the condition of systems and components. Well-known condition monitoring techniques are vibration monitoring, oil analysis, acoustic emission and thermography. These methods are widely applied in industry, where the interpretation of measurement data is mainly experience-based and data-driven. Vibration analysis techniques are mostly applied to rotating equipment (e.g. pumps, compressors, gear boxes, bearings). This means that the source of the vibrations is the machine's normal operation, while faults can be detected as a change in that source (either in frequency or amplitude).

When the results of condition monitoring are used to trigger maintenance activities, a condition based maintenance (CBM) policy emerges. The ISO-13374 standard, Condition Monitoring and Diagnostics of Machines (ISO, 2012), defines the functionality in a condition monitoring system in six blocks: data acquisition, data manipulation, state detection, health assessment, prognostics assessment and advisory generation. Further, the Open Systems Architecture for Condition-Based Maintenance (OSA-CBM) (MIMOSA, 2013) provides an implementation of that standard by adding data structures and defining interface methods for the functionality blocks in the ISO standard. Although research on advanced concepts like wireless sensor networks and energy harvesting to power autonomous sensors is ongoing, the data acquisition (sensors) and manipulation are nowadays rather well-established. Therefore, a major portion of the research in this discipline focuses on analyzing the obtained data to retrieve information from it. The methods developed for that are mainly data-driven, e.g. based on trending or on comparing with a baseline measurement, and are seldom based on physical models. Application of the final blocks, the health assessment and prognostics steps, is until now very limited in practice. This discipline is not covered widely in the scientific world, other than the application of CBM policies in maintenance modelling approaches. Also no scientific journals specifically on CM or CBM exist. However, since the field already exists for decades, many books on the topic are available.

2.2. Structural Health Monitoring

Structural health monitoring is a discipline that is closely related to condition monitoring, but has its origin in the inspection of structures. The methods are based on non-

destructive testing (NDT) techniques. These techniques, like ultrasonic testing, eddy current and acoustic emission, are traditionally applied using hand-held sensors or scanning techniques, and inspections are only performed occasionally or periodically, not bearing any relation with previous inspections. Due to the increased reliability and availability requirements of many assets, research has focused on developing continuous monitoring techniques, which evolved into the structural health monitoring discipline. A lot of scientific work is currently being done in this field, which also has its own scientific journals. The focus has been on the one hand on the development of new sensing techniques, and on the other hand on the development of advanced damage features and classifiers. Development of sensing approaches are based on new technologies using optical fibers and sensors to measure structural vibrations (e.g. piezo patches) and wave propagation (e.g. ultrasonics). The development of new damage features and classifiers follows a data-driven approach, motivated by the "statistical pattern recognition paradigm" (Farrar & Worden, 2010), which is one of the key foundations of SHM. The application of physical models in this discipline is very limited.

Applications are mainly found in aerospace and infrastructures (e.g. bridges). For vibration based methods, the source of vibrations is generally not the system itself, but the environment it is operated in (e.g. wind, waves). Faults or damage can be detected by observing changes in the response of the system to the vibrations. Note that this field has a strong focus on health assessment, but does not provide a clear approach to apply that to maintenance policies (although a link with CBM is rather straightforward). Instead, developments in SHM techniques mainly focus on increasing the probability of detection of faults, which originates from the NDT background of this discipline. Further, the first standard in this field was established only very recently (SAE, 2013), and in addition there is well-defined structure considering the five levels of SHM (Farrar & Worden, 2010). From levels 1 up to 5 more and more information on the damage in the structure is obtained:

- Level 1: damage detection,
- Level 2: damage localization,
- Level 3: damage characterization,
- Level 4: damage quantification,
- Level 5: prognostics.

The first three levels can now be achieved by many methods, while the final two are still quite challenging.

2.3. Prognostics and Health Management

The prognostics and health management discipline is somewhat different from the previous two, and also emerged more recently. Whereas CBM and SHM focus on

the monitoring of the system, PHM is a more integrated approach that aims to provide guidelines for managing the health of the system. In that way, it is a philosophy to perform Life Cycle Management, with a strong focus on the predictability (i.e. prognostics) of failures and maintenance. This is generally achieved by adopting some monitoring strategy, which may be a CM or SHM technique. Also in this field many data-driven approaches emerged to analyze the monitoring data, but in addition to that several physical model based methods have been developed (Orsagh, Roemer, Sheldon, & Klenke, 2004; Roemer, Byington, Kacprzyński, & Vachtsevanos, 2006). As for CM and CBM, this discipline emerged from industry, and has a relatively limited presence in the scientific world. PHM has a background in the military world, especially related to the development of the F-35 fighter aircraft (Brown, McCollom, Moore, & Hess, 2007). Thereafter, PHM approaches have also been developed for other military vehicles, but also for electronics and (civil) aerospace systems.

2.4. Commonalities and differences

Upon analyzing the commonalities and differences between the three disciplines, the following aspects have been found. These aspects are also visualized in Figure 1.

(i) the approaches for condition monitoring and structural health monitoring are very similar, since both disciplines

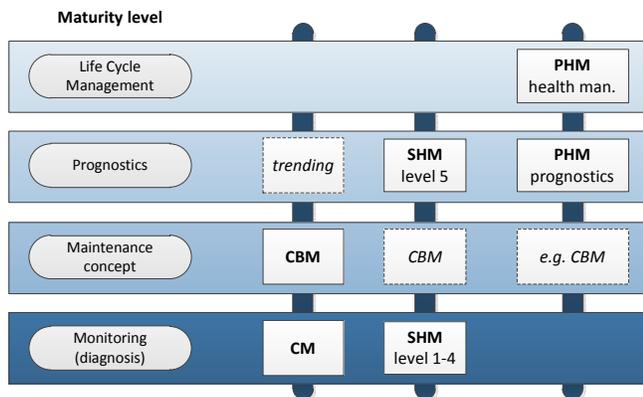


Figure 1. Relation between CBM, SHM and PHM.

look for features that are representative for damage or degradation of the system. However, there are some differences:

- CM is closely related to the CBM policy, which means that the monitoring results are directly applied to guide the maintenance activities. In SHM the focus is completely on the monitoring and no explicit relation to a specific maintenance policy is made. However, linking SHM techniques to CBM seems straightforward.

- In both fields, one of the commonly applied techniques is vibration monitoring, but the approaches are different in the following ways:
 - CM is mostly applied to rotating or reciprocating systems, where the primary vibration source is the system itself. Damage or degradation is diagnosed by detecting changes in that source, e.g. bearing faults that introduce additional vibrations.
 - SHM is mostly applied to load carrying or transferring structures, which are only actuated by their environment (wind, waves). The SHM techniques focus on measuring (changes in) the response of the system or structure and relating those to the presence of damage.
 - The locations of the vibration sensors also vary. In CM the sensor is typically outside the part, whereas in SHM the sensors are commonly on (or even integrated in) the monitored part.

(ii) both SHM and PHM include a prognostic capability, while CBM is mainly diagnostic. However, the differences between CBM and SHM in this respect are not that large, since in the SHM field the prognostics is only at level 5, which is not achieved in many cases. At the same time, CM data is often trended in time, which also provides a limited prognostic capability (which is also mentioned in the CBM ISO standard).

(iii) PHM is acting on a somewhat higher level than CBM and SHM, since it has a clear ambition to enable health management. The latter is an activity related to Life Cycle Management (LCM), which means that an approach is followed to optimize all (maintenance) activities during the complete life cycle of the asset. This includes the selection of an appropriate maintenance policy, defining the maintenance interval length and deciding on the moment an asset should be discarded. CBM, and SHM to an even lesser extent, do not provide that extensive LCM support.

(iv) the PHM field prescribes neither a specific maintenance concept nor a monitoring strategy. However, in typical PHM studies, CBM or other maintenance policies are adopted, and in many cases CM techniques are applied.

3. PRACTICAL CASES

In this section three practical cases will be presented, demonstrating the specific aspects of the three disciplines.

3.1. CBM – bearing blind identification

The field of condition monitoring has matured especially in its application to bearings (Rao, 1996). Since in industry so many bearings are used, a huge amount of experience has been gained on these type of systems. Moreover, the complexity of bearings is rather limited, which makes understanding the failure behaviour feasible in many cases.

For these reasons, condition monitoring data, which for bearings most of the time is vibration data, can in many cases be translated into information on the failure mode or the state / condition of the bearing.

This will be demonstrated using the following case study. Vibration data on four different bearings is available: one undamaged (pristine) bearing and three with an artificial damage on the outer race, inner race and rolling element, respectively. In practice, the location and type of damage is unknown, and a so-called blind identification must be performed. However, since a considerable range of failure mechanisms can occur in the different bearing components (inner / outer race, rolling element), identification is quite challenging. Moreover, a recent development is to apply wireless sensor networks for vibration monitoring. Although this development reduces the wiring and installation efforts considerably, it simultaneously introduces additional boundary conditions due to the limits in data transmission bandwidth, power and local (on the sensor node) processing capacity. A generic approach is developed (Sanchez Ramirez, Loendersloot, & Tinga, 2014) to assess the damage.

The vibration patterns observed will have to be matched with the most likely failure modes and failure mechanisms for bearings. Examples of failure modes are cracking, dry rolling, and heating, where the deterioration or failure of the bearing material is caused by mechanisms like fatigue, static overloading, wear, corrosion, etc. Additionally lubricant deterioration is also a key limiting factor of bearing life. For this case, the focus will be on cracking in the outer race, resulting in dynamic behaviour of the bearing related to the response to an impulse excitation. Figure 2 shows the vibration signal for the pristine bearing. The red line in the figures is a sinusoidal signal with the rotor speed frequency and an amplitude approximately equal to the maximum of the pristine bearing vibration.

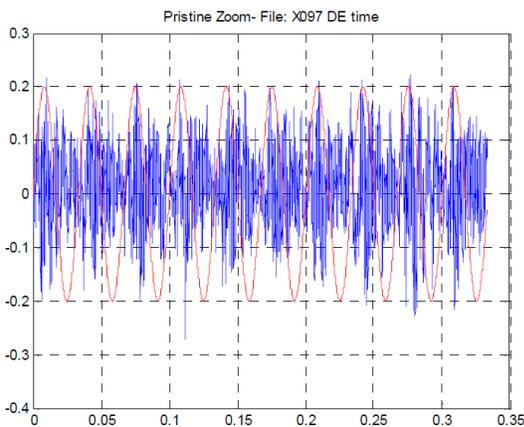


Figure 2. Vibration signal for pristine bearing.

The signal for the damaged bearing is shown in Figure 3. The first way to identify a failure is to compare the signal of the (damaged) bearing to the baseline signal (red line). Figure 3 clearly shows that the amplitude bandwidth has increased considerably, indicating that a failure is present. However, the challenge is then to characterize or localize the fault. A first step in this analysis is to transform the signal to the frequency domain, and zoom in to the region with the highest energy content by applying a filter. For this bearing, the range of interest appeared to be in the 2500 - 4000 Hz region. Valuable information about the source of the damage can be extracted by looking at the vibration signal, the rate at which the events occur and the possible variation of the amplitude (modulation).

The modulations can be analyzed further by extracting the envelope of the vibration signal, and identifying the main modulating frequency f_m , i.e. the frequency of the variation in signal amplitude. This is shown in Figure 4, where a clear frequency peak around 150 Hz occurs, which represents f_m .

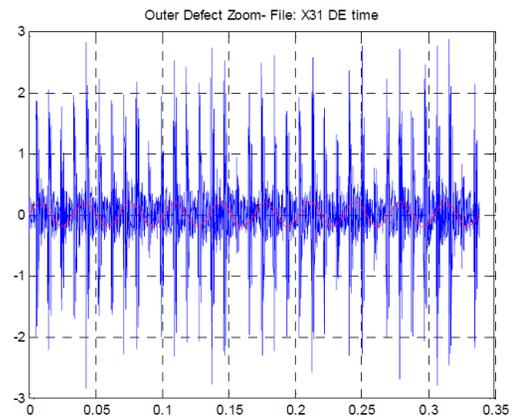


Figure 3. Vibration signal for damaged bearing.

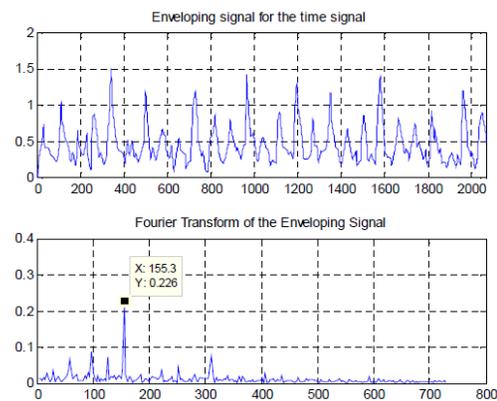


Figure 4. Enveloping of the time signal with its corresponding frequency spectrum.

Finally, once the frequency range of interest and the main modulating frequency are known, the analysis will be based on shorter time periods related to the main modulating frequency. Here the instantaneous carrier frequencies are determined from the time signal segments that have been extracted according to the main modulation observed in the signal. Both the instantaneous frequencies and amplitude are extracted, as well as their ratio, as is shown in Figure 5. The variation of these quantities can be used as indicator of developing damage on the bearings.

In summary, this case study showed how a typical condition monitoring technique as vibration monitoring can be used to detect and assess bearing damage. The methods presented here are only a small subset of the large variety of analysis methods available, but a special focus has been put here on computational inexpensive methods that enable application in a wireless sensor network.

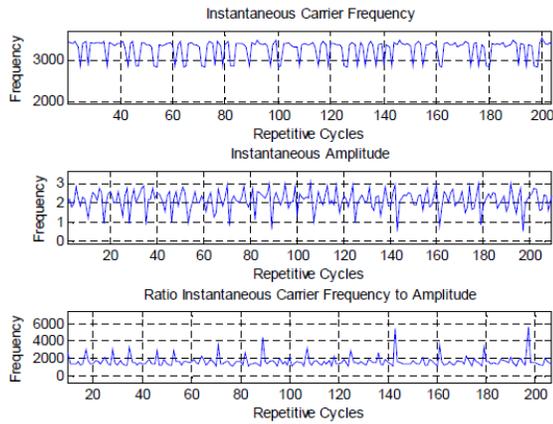


Figure 5. Instantaneous frequency and amplitude of the signal.

3.2. SHM - damage assessment in composite structure

Our SHM case study concerns the assessment of damage in a skin stiffener composite structure (Loendersloot, Ooijevaar, Warnet, Boer, & Akkerman, 2011; Ooijevaar, Loendersloot, Warnet, Boer, & Akkerman, 2010; Ooijevaar, Warnet, Loendersloot, Akkerman, & Boer, 2012), shown in Figure 6. Structural vibration techniques are adopted here to detect and locate (and possibly quantify) a delamination in the composite structure. The structure is actuated by a shaker, while the response is measured by piezo electric diaphragms. The damage sensitive parameter extracted from the structure is the mode shape curvature, while the Modal Strain Energy – Damage Identifier (MSE-DI) algorithm (Stubbs & Farrar, 1995) is selected as the damage classifier. The damage feature is selected based on the expected damage (a delamination between the skin and the stiffener, as shown in Figure 7) and the expected change in dynamic response: the local stiffness reduction induced by the damage results in a local change of the mode shapes, and more specifically of the mode shape curvatures.

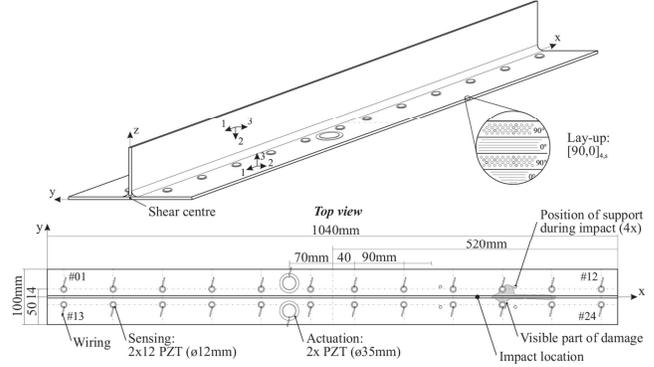


Figure 6. The composite skin-stiffener structure, equipped with piezo electric diaphragms. The damaged area is indicated in the bottom figure.

This change is an indication of the presence and the location of damage and even serves as an estimation of the severity of the damage, provided a (physical) relation can be established between the size of the delamination and the criticality of the damage.

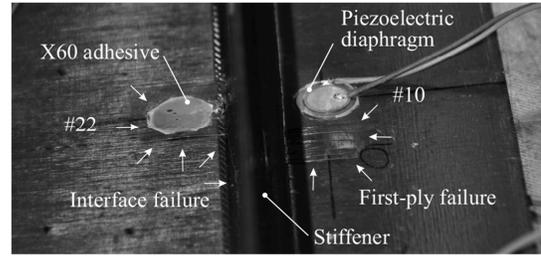


Figure 7. First-ply delamination failure caused by the impact to which the structure was subjected.

The MSE-DI algorithm is based on the comparison between the curvatures of the mode shapes of the pristine and damaged structure. Given the relative bending energy $\hat{U}_{B,i}^{(n)}$ of the i^{th} beam segment, of the n^{th} mode, is defined as:

$$\hat{U}_{B,i}^{(n)} = \frac{U_{B,i}^{(n)}}{EI_i} = \frac{1}{2} \int_{x_{i-1}}^{x_i} \left(\frac{\varepsilon_x^{(n)}(x)}{z} \right)^2 dx \quad (1)$$

Where $\varepsilon_x^{(n)}$ represents the axial strain amplitude for the n^{th} participating mode shape. Note that the strain is directly measured by the piezo diaphragms. The total modal strain energy is approximated by the sum of Eq. (1) over a subset of mode shapes N_{freq} . The damage index value is based on a number of mode shape curvatures, since the location and the size of the damage determine the effect the damage has on the mode shape curvatures.

The damage index β for the i^{th} segment of the structure is defined as the summed fractional stiffnesses:

$$\beta_i = \sum_{n=1}^{N_{freq}} \left(\frac{\int_{x_{i-1}}^{x_i} \tilde{w}^{(n)} dx / \int_0^l \tilde{w}^{(n)} dx}{\int_{x_{i-1}}^{x_i} w^{(n)} dx / \int_0^l w^{(n)} dx} \right) \quad (2)$$

Where $w^{(n)}(x)$ represents the integrand of Eq. (1) and the tilde refers to the damaged case. The normalized damage index Z_i , a statistical measure to identify outliers, is defined as:

$$Z_i = \frac{\beta_i - \mu}{\sigma} \quad (3)$$

Where μ is the mean value and σ the standard deviation of the damage index over all elements. The normalized damage index Z is shown in Figure 8. The value of the damage index around $x = 0.8$ m is close to -4 , implying a significant (4σ) deviation of the fractional stiffness compared to the intact situation. This is a clear indication of the presence of the damage. The actual damage location corresponds to the location indicated by the MSE-DI algorithm.

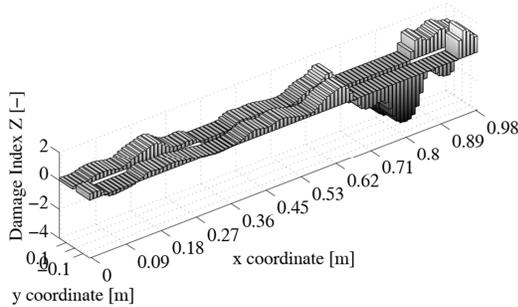


Figure 8. The normalized damage Z for the entire composite structure. The location of the damage corresponds with the deviating values around $x = 0.8$ m.

3.3. PHM – predicting helicopter shock absorber failure

The prognostics and health management approach is demonstrated by a case study on a helicopter landing gear. The landing gear contains a shock absorber (see Figure 9), that after some period starts to leak oil, caused by a damaged seal. The shock absorber inspection and maintenance schedule is based on flight hours (as is the case for most aircraft components).

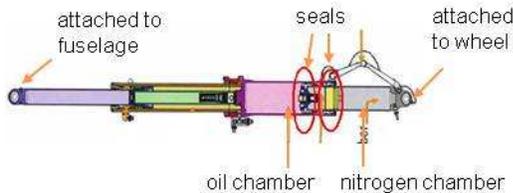


Figure 9. Landing gear shock absorber.

However, for a landing gear, the number of flight hours is not the most appropriate usage parameter for predicting the

failures. This is shown in Figure 10, where the number of flight hours at failure are plotted for 11 shock absorber seal failures: there is no correlation between the failures and number of flight hours, and it is difficult to predict when a seal failure will occur. However, this helicopter contains a Health and Usage Monitoring System (HUMS), which collects a large number of parameters on the usage (flight hours, altitude) and health (vibration data) of the helicopter. This data can be used to develop a prognostic method for the seal failure (Tinga, 2013). The physical mechanism causing the seal failure is sliding wear, which is governed by the normal force F_n applied to the seal, the sliding distance s and the specific wear rate k . Archard's law can then be used to calculate the amount of wear in terms of lost volume V :

$$V = kF_n s \quad (4)$$

The values of F_n and k can be obtained from the geometry and material properties of the seal. The sliding distance is governed by the usage of the landing gear, i.e. the number of landings and the weight of the helicopter during the landing. These latter two parameters are available from the HUMS, so for every seal failure the usage history is known and the amount of wear can be calculated, as is shown in Figure 11.

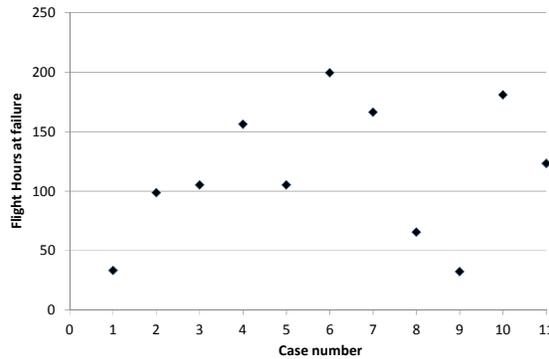


Figure 10. Number of flight hours for 11 failure events.

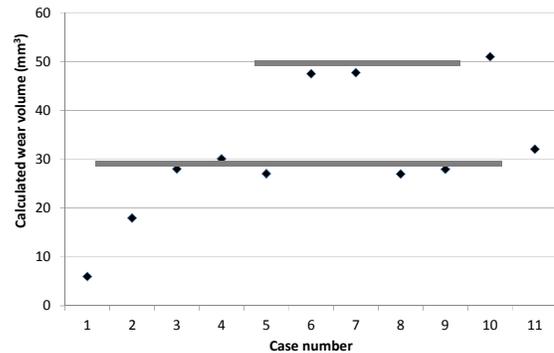


Figure 11. Calculated amount of wear for 11 failure events.

These results clearly show that the calculated amount of wear, based on the number of landings and landing weight, has much more predictive power than the number of flight hours, since the variation in these values is much lower. Except for the first two cases, the failures either occurred around 30 mm³ of lost volume, or around 50 mm³. The observed difference between the two groups can be explained by the fact that another type of seal was introduced in the absorbers that failed at 50 mm³ of wear. This new seal clearly has a better wear resistance than the original seal, since the oil leakage occurs at a later stage. It can thus be concluded that selection of the appropriate usage parameter, in this case the number of landings and landing weight, and using a suitable physical failure model enables to set-up a prognostic model.

It is now rather straightforward to assess at any moment the remaining useful life (RUL) of the shock absorber in terms of number of landings. The amount of wear can be calculated from the monitored landing information (HUMS) and the amount of landings before seal leakage is expected can be calculated, thus providing a much better RUL assessment than with flight hours.

3.4. Summarizing the cases

The case studies in this section have illustrated many of the aspects mentioned in section 2. The CBM illustration case is mainly data-driven, only a limited amount of system and failure behaviour knowledge is used. Also, the source of the vibration (and its anomalies) is the rotation of the bearing itself. The SHM illustration case is also mainly data-driven, although in this case the dynamic behaviour of the system (i.e. mode shapes) is known as well as the effect the damage (delamination) has on the dynamic response. This information is used to select the damage feature and classifier. Finally, the PHM illustration case clearly has a physical model based approach, where the selection of monitoring data and its processing is motivated by the known physical behaviour of the shock absorber seal.

4. RELEVANCE OF UNDERSTANDING FAILURE BEHAVIOUR

In the case studies in the previous section it can be observed that knowledge on the failure behaviour of the systems is used to some extent in all three cases. This is one of the major differences between the approaches that was already stated in section 2. However, it is the authors' conviction that understanding the failure behaviour and underlying physical mechanisms has the potential to increase the performance of the CBM and SHM disciplines. The motivation for that is in the relation between the usage of a system and the resulting system degradation (or remaining life consumption), as is shown schematically in Figure 12 (Tinga, 2010). The upper three blocks in the figure represent this relation and ideally the dependency of the remaining useful life on the actual usage of the system is explicitly

known. However, while the usage of a system is normally known by the operator, its effect on the remaining life consumption is typically unknown. The author believe that zooming in to the level of the physical failure mechanism (e.g. fatigue, wear) enables to quantify this relation, provided that either the usage (operating hours, rotational speed) or loads (strain gauge, thermocouple) are monitored.

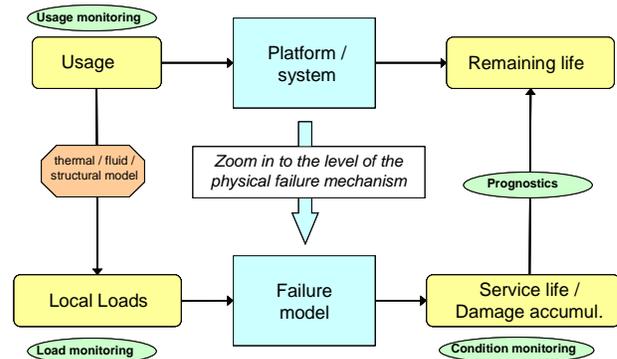


Figure 12. Relation between system usage and remaining life consumption is governed by failure mechanism.

The figure also shows that condition monitoring is a third option for monitoring, and since information about the system condition is obtained directly, no detailed understanding of the failure mechanism is required. This is exactly the reason that in CM and SHM many data-driven approaches have been successfully developed. Just monitoring the condition (or some associated damage feature) enables to detect the exceedance of a predefined threshold, and then to trigger some maintenance activity. However, this approach (neglecting the actual physical failure behaviour) has three important drawbacks:

- Selection of quantities to measure, sensor locations and data processing algorithms is mostly based on a trial-and-error process;
- The interpretation of the measured data and relating it to the damage or degradation is in many cases rather difficult; In general, it is only possible if a considerable set of failure data is available, which might be difficult to achieve for critical systems and systems that re operated in a variable way;
- The method is only diagnostic, extension to a prognostic method is often difficult.

These drawbacks can be addressed if the physical failure behaviour is understood. The selection of the appropriate monitored quantities and their locations can largely benefit from the knowledge on failure behaviour. The common approach in both CBM and SHM is to apply considerable numbers of sensors and start collecting large amounts of data. Only after a certain period of data collection, the analysis and interpretation of the data is considered. It is then often discovered that non-relevant parameters have been monitored and that other essential quantities are

missing. A much better approach is to start with identifying the system's most critical failure mechanisms and their governing loads. These results can then be used to select suitable sensors and locations. For example, if a (rotating) system or component fails due to fatigue, the governing load is a cyclic stress. It is then not useful to monitor the number of operating hours or temperature, but much more useful to monitor the number of starts of the system and the rotational speeds, since that determines the number of stress cycles and their magnitude. Only a limited number of papers advocating this physics-based approach for CM system development is available, see e.g. (Banks, Reichard, Hines, & Brought, 2008).

The next challenge after collecting the appropriate data is the interpretation of the data and retrieving information on the degradation of the system. If the knowledge on the system and its failure behaviour is limited, the only way to obtain that information is the experience-based approach: after collecting a sufficiently large amount of data, patterns or relations may be found in the data. This is the typical approach in data mining processes, but also approaches based on artificial neural networks and fuzzy logic follow this route. The drawbacks are that, firstly, relations can only be found when the data set is sufficiently large. For some (critical) systems the number of failures can be very limited, which significantly reduces the potential of the approach. Secondly, the failure identification is only reliable for conditions that have occurred at least once (and are present in the historic data). For systems that are operated in largely variable conditions (e.g. military, off-shore), this aspect yields a big limitation to the approach. However, when the system behaviour and associated physics of failure is well understood, the data sets no longer consist of anonymous numbers, but contain relevant information. Retrieving that information is generally much more straightforward, and requires much less data and experience, than in the purely data driven approaches.

Finally, the ultimate challenge is to extend the methods to the prognostics. As was mentioned before, the traditional diagnostic methods in CBM and SHM sometimes use trending methods to do some prognostics. However, if the operational conditions of the system vary considerably, a trend based on historical data is not very representative for the present or future behaviour. It therefore has a limited prognostic capability. But, if physical models are used to quantify the failure behaviour, the expected degradation rates can be calculated (also when the conditions change) and reliable prognostic methods can be added to the diagnostic capabilities of CBM and SHM methods.

5. ALIGNING CBM, SHM AND PHM

Now the three disciplines have been described (section 2), have been compared and demonstrated with cases (section 3), and the relevance of understanding the physical failure

mechanisms has been discussed, it will be possible to align them. The proposed integral approach is shown in Figure 13. As was mentioned before, the differences between CM and SHM are not large, and their aim is actually very similar. Except for SHM level 5 (prognostics), they also act at the same level of maturity / complexity (see Figure 1). This means that both methods could be used to monitor the (initiation or progression) of damage in a part or system. The specific application (e.g. rotating or static) will then determine whether a SHM or CBM technique is most suitable. On the next higher level, both monitoring strategies can then be connected to the CBM policy, which is used to govern the maintenance decisions (mainly when to replace a part). Instead of the CBM policy, also a usage based maintenance (UBM) or a load based maintenance (LBM) policy (Tinga, 2010) can be adopted. In that case also another monitoring strategy will have to be selected.

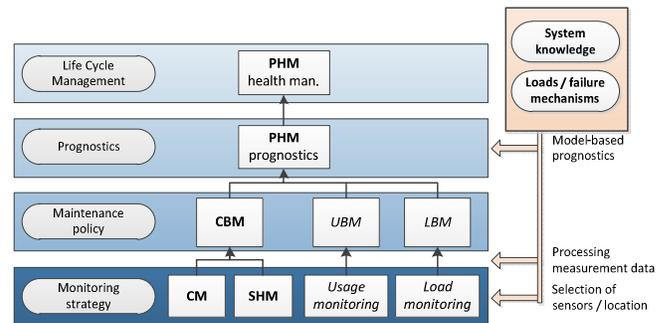


Figure 13. Relation between system usage and remaining life consumption is governed by failure mechanism.

Then, regardless of the adopted maintenance policy, a prognostic approach will have to be selected to assess the RUL at any moment, and there the PHM methods can play an important role. Finally, to guide all the maintenance related decisions (replace, repair, inspect, etc.) during the whole life cycle of the system, a suitable life cycle management approach must be arranged. Also for that purpose, several approaches developed in the PHM field are very suitable. This means that in the approach proposed in Figure 13, all three disciplines can be combined, where each of them has its own role and scope and the strengths of the individual disciplines are combined.

One important additional aspect of the proposed approach is the inclusion of knowledge on the physical system and failure behaviour. As is indicated in Figure 13, and was also discussed in section 4, this fundamental knowledge improves the approach at three essential stages: (i) in the selection of the quantities to be monitored and their locations; (ii) in the processing of the measurement data to retrieve the required information on the system degradation;

(iii) in the prognostics, where a physical model-based approach improves the performance.

In summary, instead of considering CBM, SHM and PHM as separate disciplines, the present work has shown how the three fields, their objectives and approaches can be aligned to achieve an integrated strategy to improve the life cycle management of any (complex) system.

6. CONCLUSION

In this paper the three disciplines of condition based maintenance (CBM), structural health monitoring (SHM) and prognostics and health management (PHM) have been described, compared and demonstrated using illustrating case studies. Several commonalities between the disciplines appeared, but also differences in scope and objectives could be identified. This insight enabled us to align the three disciplines and propose an integrated approach, in which the understanding of the physical system failure behavior appears to be an essential aspect. The proposed integral approach starts from defining an appropriate monitoring strategy (CM and SHM), applying the appropriate maintenance policy (CBM), performing prognostics (PHM) and eventually supporting the decision making that leads to an optimal maintenance process throughout the life cycle of the asset.

ACKNOWLEDGEMENTS

The work and input provided by Ted Ooijevaar, Andrea Sanchez Ramirez and Nick Heerink is gratefully acknowledged.

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BIOGRAPHIES

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