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Predictive Maintenance of Military Systems Based on Physical Failure Models

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Preventive maintenance is required to keep critical systems available at reasonable costs. Instead of applying the traditional experience-based approach of statistical analysis of failure data, the present paper proposes to adopt a predictive maintenance policy that relies on detailed knowledge of the physical failure mechanisms. A structured scheme for this approach is presented. Then three case studies from the military, a helicopter, a naval gas turbine and a military vehicle, are used to demonstrate the benefits of this approach.

1. Introduction

Military systems are often operated in extreme and highly variable conditions. The resulting large variations in required maintenance are however hardly recognized, since traditionally these systems are subject to a static maintenance concept with fixed intervals. Moreover, these intervals are often very conservative due to the critical nature of the systems, which yields a quite inefficient maintenance process (Tinga, 2010). Also, the traditional approach in determining maintenance intervals is experience based and relies on statistical or stochastic analysis of failures (Singpurwalla, 1995; van Noortwijk, 2009; Zio, 2012). The operational efficiency of the assets can be improved significantly when the maintenance is performed in a more dynamic manner, i.e. by taking the variations in usage and operating environment into account.

This predictive maintenance approach is only possible when firstly the relation between the degradation rate and the operational conditions can be quantified, and secondly the variations in these conditions are monitored. The first requirement can be met by adopting physical failure models that quantitatively describe the damage rates as a function of the system usage. For most common failure mechanisms, like e.g. fatigue, wear and corrosion, failure models are available now (Tinga, 2013b). The key to applying these models in a predictive maintenance concept is the monitoring of the suitable usage parameter and its translation into the appropriate internal load.

In the present paper, this concept will be described in general terms and will then be demonstrated on three different case studies: a helicopter, a navy frigate and a military vehicle. For all three cases the critical failure mechanisms will be identified and the associated failure models will be defined. Moreover, for the helicopter and frigate the specific usage parameters for the critical subsystems will be selected and the prognostic capability of the method will be demonstrated. For the military vehicle, the usage of the system will be defined in more general usage profiles. Also for this less detailed approach, it will be demonstrated that predictive maintenance provides clear benefits as compared to the traditional static approach.

2. Methodology

As was mentioned in the introduction, a predictive maintenance strategy, that takes into account variations in usage, requires (*i*) a quantitative relation between the degradation rate and the operational conditions, and (*ii*) monitoring of the variations in these conditions. Although an estimate of the average degradation rate can be obtained from a (large) collection of failure data, the precise relation with operational conditions is hard to obtain. Therefore, understanding the physical failure mechanisms is essential, as is illustrated in Figure 1. This figure shows that the quantitative relation between usage of a system and its remaining life can only be assessed when the underlying physical failure mechanisms and associated loads are considered.

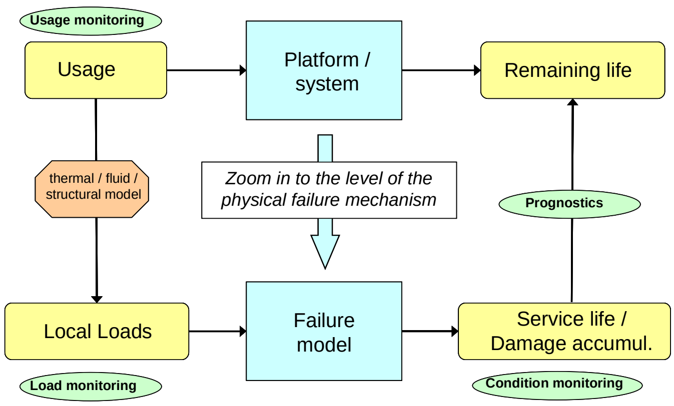
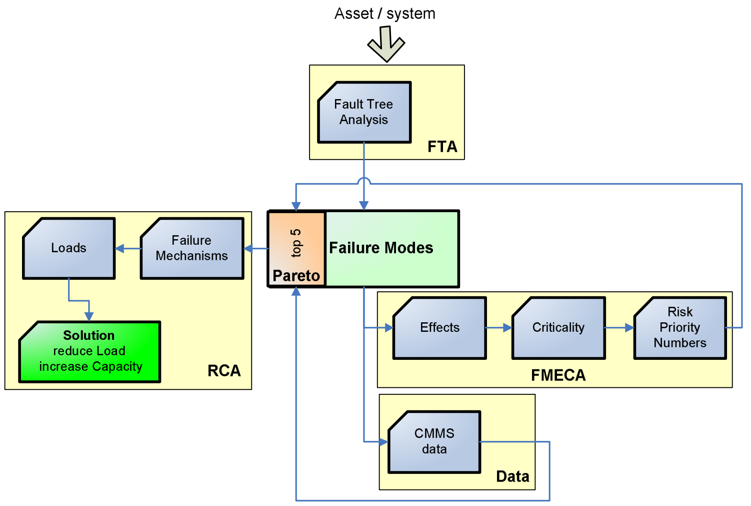


Figure 1: Relation between usage, loads and service life consumption of a system or component.

The second requirement for a predictive maintenance approach is the monitoring of usage or loads. The challenge in that case is to find the parameter that is most relevant for the failure mechanism considered. For example, if a fatigue failure is considered, not the number of operating hours, but the number of start-stops of a (rotating) system (which determines the number of load cycles) governs the service life consumption. Again, only knowledge on the physical mechanisms enables to select the appropriate parameter to monitor.
However, application of the presented approach to all components and failure mechanisms is not feasible. Therefore, a suitable method to select the critical components is required. A structured approach for this selection process was recently developed (Tinga, 2013a), as is shown in Figure 2.



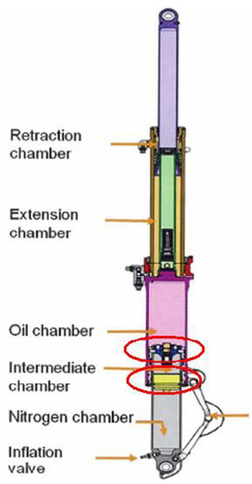


Figure 2: Mechanism based Failure Analysis: selection of the most critical components and the associated failure mechanism and loads.

Figure 3: Helicopter landing gear shock absorber.

In this approach, an overview of all possible failure modes of a (sub)system is created using a fault tree analysis (FTA). Then a selection procedure is applied to obtain the 5 most critical failure modes. Note that the criticality can be due to either cost issues or performance issues. If failure data is available in a maintenance management system (CMMS), then analysing this data provides the top 5 failure modes. If this data is not available, a failure mode, effects and criticality analysis (FMECA) can be executed. The risk priority numbers (RPN) obtained from such an analysis then enable to define the top 5 failure modes.

The final step in the procedure is to asses for each (critical) failure mode the failure mechanism and the governing load, which together constitute the root cause of the failure. If the load-carrying capacity (Tinga, 2013b) of the system appears to be insufficient, a redesign or modification of the system should be considered. If the failure appears to be caused by a load that has been too large, the usage of the system must be changed to reduce the loads. However, in many cases this is not feasible due to operational constraints. Then predicting the moment of failure using physical models and adopting a preventive maintenance policy is the only way to prevent failures from occurring. In the next section, three examples will demonstrate how this predictive maintenance policy can be developed and applied.

3. Applications

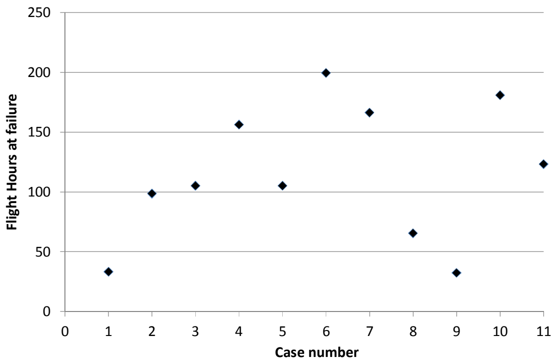
3.1 NH-90 helicopter

Analysing the list of failure modes of the NH-90 helicopter, as obtained from the CMMS, revealed that one of the persistent failure modes is oil leakage in the landing gear shock absorbers, see Figure 3. In a certain period, 11 oil leakage failures occurred within the fleet. The number of accumulated flight hours of the helicopters at the moment of these failures could be obtained (Heerink et al., 2012). This is plotted in Figure 4a, showing that there is a large variation in time to failure: the numbers of flight hours at failure range from 33 to 220 hours. The lack of correlation shows that the number of flight hours is not a relevant failure parameter.

A root cause analysis was then performed and wearing of the rubber seal was identified to cause the leakage of oil from the internal oil chamber to the environment. A detailed analysis of this wear process reveals that the governing loads in this case are the normal load (F_n) applied to the seal and the distance (*s*) travelled by the seal relative to the counter surface. The resulting wear volume (*V*) is expressed by the Archard law for wear processes

$$V = kF_n s \tag{1}$$

where *k* is the specific wear rate. Finally, these loads must be associated to the usage of the system. The normal load on the seal is related to the amount of compression. This is a constant value, which can be estimated from the relative contraction of the seal and it's elastic properties. The travelled distance is directly related to the movement of the cylinder. At each landing, the cylinder will be compressed to absorb the shock. The total weight of the helicopter determines the stroke of the cylinder. Since both the number of landings in each period and the helicopter weight during each landing can be obtained from the on-board health and usage monitoring system (HUMS), the amount of wear of the seal for each specific helicopter can be approximated. This is done for each helicopter where a failure was detected, as is shown in Figure 4b.



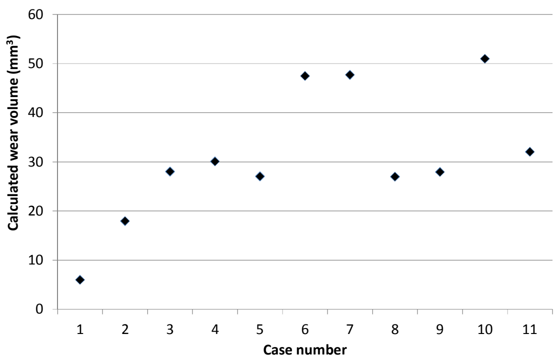


Figure 4a: Number of flight hours for 11 failure events. *Figure 4b: Predicted amount of wear.*

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 points are roughly divided into a group around 30 mm^3 and another group (of three points) around 50 mm^3. 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 mm^3 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 the number of landings, in combination with the landing weight, is a relevant failure parameter that can be applied in a predictive maintenance policy.

3.2 Naval gas turbine

Gas turbines in navy frigates are used as booster engines, which means that they are only used when high speed sailing is necessary. This means that the gas turbines are used for only relatively short periods of time, but at different power settings. In this case study, physical models for the damage accumulation in several gas turbine components are used to compare the damage rates at different power settings (Smeding, 2012).

From a FMECA analysis, the high pressure turbine blades, combuster cans and the turbine disk appeared to be the critical components in this gas turbine. The failure mechanism for these components are creep and fatigue, thermal fatigue and fatigue, respectively. For each of these mechanisms, the governing loads have been identified and the relation with the gas turbine usage has been determined. For the turbine blade, the stress and blade temperature are the governing loads for the creep and fatigue mechanisms. The stress can be estimated from the (monitored) rotational speed (ω), the blade mass (m), distance to the engine centre line (r) and the blade cross sectional area (A):

$$\sigma = \frac{m\omega^2 r}{A} \tag{2}$$

and the thermal strain caused by the temperature difference between the cooled inside (T_{in}) and heated outside (T_{out}) of the blade:

$$\varepsilon_{th} = \frac{\alpha\left(T_{out} - T_{in}\right)}{1 + \frac{A_1 E_1}{A_2 E_2}} \tag{3}$$

where α is the coefficient of thermal expansion and A and E are the blade area and elastic modulus. Using similar expressions for the other components, the fatigue and creep damage rates at different power settings (associated to certain levels of rotational speed and temperature) can be assessed, as is shown in Table 1.

Table 1: Relative damage per operating hour for the three critical components

Power setting	Total Damage Turbine Blade	Fatigue damage Turbine Disk	Fatigue Damage Combustor Can	Dominant Damage Critical Component
1	0.2	0.50	0.01	Turbine Disk
2	0.4	0.70	0.03	Turbine Disk
3	0.6	0.82	0.11	Turbine Disk
4 (normalized)	1.0	1.00	1.00	Turbine Disk
5	17.8	1.25	5.25	Combustor Can
6	1120.2	1.50	23.83	Turbine Blade

As can be noticed, the damage numbers strongly depend on the power setting. The relation between creep and power setting is logarithmic, explaining the large number of total blade damage in the highest load zone. Fatigue damage shows an exponential relation with power setting. The results clearly show that operating in load zone 5 instead of 6, would already result in a much larger turbine blade life time and probably a much larger gas turbine life time as well.

Application of these results in a predictive maintenance policy requires insight in the assumptions the OEM did to determine the maintenance intervals. These prescribed intervals are defined in terms of operating hours, but the results in Table 1 clearly show that one hour operating at power setting 4 is not equivalent to an hour at power setting 2. Since the assumed distribution over the power settings adopted by the OEM is known, the variation across a fleet of frigates can be studied and compared to the OEM assumption. This is shown in Table 2, where the calculated damage in two consecutive years, based on the actual number of hours in each power setting, is compared for four individual frigates. The final row of the table indicates the ratio of the actual damage and the OEM assumed amount of damage.

For the fleet average usage profile, as well as for frigates 2 and 3, the maintenance intervals in terms of operating hours appear to be too long, so failures are expected. On the other hand, for frigate 1 and 4 the intervals are too conservative and maintenance is expected to be performed before it is actually necessary. This analysis clearly shows that a failure mechanism based predictive maintenance approach makes it possible to tailor the maintenance activities to the specific usage profile of each individual system or asset.

Table 2: Variation in damage rates (1/year) over fleet and compared to OEM assumptions of usage profile

	Frigate 1		Frigate 2		Frigate 3	Frigate 4	Fleet avg
Year	2009	2010	2009	2010	2010	2009	-
Turb. blade	$2.9{\cdot}10^{-3}$	$2.6{\cdot}10^{-3}$	$1.78{\cdot}10^{-1}$	$2.5{\cdot}10^{-1}$	$1.3{\cdot}10^{-1}$	$7.6{\cdot}10^{-2}$	$1.1{\cdot}10^{-1}$
Turb. disk	$8.7{\cdot}10^{-3}$	$3.9{\cdot}10^{-3}$	$1.1{\cdot}10^{-2}$	$9.3{\cdot}10^{-3}$	$5.5{\cdot}10^{-3}$	$4.4{\cdot}10^{-3}$	$7.1{\cdot}10^{-3}$
Combustor	$6.0{\cdot}10^{-4}$	$5.2{\cdot}10^{-3}$	$2.9{\cdot}10^{-2}$	$4.3{\cdot}10^{-2}$	$2.0{\cdot}10^{-2}$	$1.5{\cdot}10^{-2}$	$2.0{\cdot}10^{-2}$
Factor OEM	0.1	0.1	2.1	2.9	1.6	0.9	1.2

3.3 Military vehicle

For this third case study a combat vehicle is analysed, see Figure 5. In this case no detailed physical models are applied to predict the maintenance intervals, but a more high level relation between usage profiles and degradation rates is used (Tiddens, 2011). The advantage of this approach is that less knowledge on the details of failure mechanisms is required and less time has to be spent on developing models. The consequence, however, is that the accuracy of the method is lower than for the previous two case studies, where detailed physical models have been used.

Figure 5: Military combat vehicle

From the CMMS data, the critical failure modes have been identified, either being a cost driver or a performance killer. Failure of the track pads appears to be one of the critical failure modes and excessive wear was identified to be the failure mechanism causing this failure. The governing loads for a wear mechanism are the normal load, specific wear rate and travelled distance (see eq. 1). This means for the track pads, that the terrain type is an important factor for the service life. Instead of defining a physical model and monitoring the loads, the usage of this vehicle is defined in terms of a limited number of usage profiles. With a focus on the terrain types, the relative severity for track pad wear is obtained by interviewing several experts. The results are shown in Table 3.

Table 3: Relative severity of different terrain types for track pad wear

Surface type		Roughness of terrain	
Paved road	2.00	Flat	1.00
Unpaved road	1.00	Hilly	1.25
Light terrain	1.00	Mountainous	1.50
Medium terrain	1.25		
Heavy terrain	1.50		

Then the usage of the vehicle is defined by specifying the distribution of the operating hours over the different terrain types, see Table 4. Now a usage of 800 kilometres in a certain period of time is analysed. By applying the fractions in Table 4 and multiplying by the severity factors from Table 3, the effective driving distance in each combination of surface type and roughness can be obtained, see Table 5. Summation of all nine contributions in Table 5 yields a total effective distance of 1432 km. This number implies that a nominal distance of 800 km at this usage profile causes damage to the track pads which is equivalent to driving 1432 km at unpaved roads and light terrain roughness (which is the reference situation with relative severity equal to 1.0). The average usage severity of this usage profile is therefore 1432 / 800 = 1.79.

Table 4: Distribution of driving distance over surface type and terrain roughness

Roughness	Surface type		
	Paved	Unpaved	Heavy terrain
Light terrain	2 %	4 %	14 %
Medium terrain	5 %	10 %	35 %
Heavy terrain	4.5 %	15 %	10.5 %

Table 5: Effective driving distance (km) for different combinations of surface types and roughness (800 km)

Roughness	Surface type			
	Paved	Unpaved	Heavy terrain	
Light terrain	32	32	168	232
Medium terrain	100	100	525	725
Heavy terrain	106	180	189	475
Total	238 km	312 km	882 km	1432 km

It also means that for a vehicle operated with this usage profile, the maintenance intervals should be a factor 1.79 shorter than the intervals for vehicles only driving at unpaved roads and light terrain roughness. To conclude, this case study demonstrates that the effect of variations in usage of the system can be incorporated in the maintenance interval determination, without the development of complex physical models and detailed monitoring of loads or usage. By estimating the quantitative effect of different usage profiles on the system degradation, just specifying the functional usage (mission + context) enables the application of a much more dynamic maintenance policy.

4. Conclusion

In this paper a structured approach to set-up predictive maintenance policies is presented, where knowledge on the physical failure mechanisms and their governing loads is explicitly utilized. In three case studies the approach is demonstrated on real systems. In two case studies, the predictive method is based on physical models, while in the third case study a more functional approach is followed. In the latter case the functional usage of the system is defined by a limited number of usage profiles, which are then related to the degradation rates based on experience of experts. All three cases showed that understanding the failure process enables the application of much more dynamic maintenance strategies, which increase the maintenance process efficiency and effectiveness.

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