Predicting Critical Failures Using Physics of Failures: Opportunities and Challenges

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ABSTRACT

In this paper, a generic approach for applying physics of failure methods for component life prediction is described, which has been applied to several cases in the military domain in recent years. Three of these cases are discussed in more detail to demonstrate the potential and limitations: a CV90 vehicle sprocket wheel, a printed circuit board from a naval radar system and a shock absorber in a NH-90 helicopter. After that, the challenges encountered during development, testing and application of these models are discussed, and potential solutions and directions for research are indicated. The first challenge is the selection of the (critical) parts. The second challenge is the validation of the developed models, which suffers from the lack of well-documented failure data. The third challenge addressed is the link with data analytics. In recent years a lot of additional sensors have appeared in many weapon systems. However, interpretation of datasets and data analyses without proper knowledge on the system and its failure behaviour appeared to be rather difficult. Suggestions for combining artificial intelligence methods with physics of failure will be given, heading for the development of hybrid prediction methods.

1.0 INTRODUCTION

Applying an efficient and effective preventive maintenance policy to military systems is very important. As most of the subsystems and components are critical, i.e. their failure has considerable consequences, the adopted maintenance policy has to be effective to ensure that failures are prevented. At the same time, the policy must be efficient, which means that premature replacement of components must be prevented. The solution would be a just-in-time, or on-condition, maintenance policy, where components are replaced or repaired just before the end of their service life. And specifically for a military context, this approach has the additional benefit that it allows for opportunistic work paced by operational needs: knowing the remaining life time of systems, a proper cost trade-off of a removal earlier than just before a failure can be made.

Applying such a just-in-time policy requires that information on the actual condition of the component or the expected remaining life time is available. Two options exist to achieve this: (*i*) monitoring the condition of the system, or (*ii*) calculating / predicting the degradation and associated life time. For the first option, the condition is measured, either continuously or periodically, and maintenance is performed when a predefined threshold is exceeded. An example of such an approach is vibration monitoring of rotating equipment. Although maintenance can be executed just-in-time, the drawback of this option is the rather reactive character: when the condition monitoring system indicates that the threshold is exceeded, more or less immediate action is required, depending on the P-F interval (i.e. the time between the detection of an upcoming failure, P, and the actual occurrence of that failure, F) of the used technique.

The second option, focusing on calculating or predicting the degradation and life time, allows a more pro-active approach: as the expected failure is known in advance, maintenance tasks can be properly planned, including provisions for required spare parts, facilities and personnel. The first option can be considered as a diagnostic approach, whereas this second option is the domain of prognostics. However, a reliable prediction of the remaining useful life (RUL) requires a proper model, for which again several options exist: (*i*) fully data-driven methods, (*ii*) models based on the physics of failure, and (*iii*) combinations of these, i.e. hybrid approaches. The data-driven approaches are based on large (failure) datasets and analytics techniques like machine learning, whereas the model-based approaches start from physical models describing failure mechanisms like fatigue, wear or corrosion.

The fast advance in artificial intelligence methods, in combination with the wide availability of all types of sensors and associated data, has led to many data-driven methods in diagnostics and prognostics. But these approaches have one common disadvantage: they heavily rely on examples of failures in the datasets, which are used to train the methods. But, as maintenance is intended to prevent failures, especially for critical systems the number of failures is per definition limited. This limits the application of fully data-driven methods, and calls for including physics of failure into the prognostic methods, as these rely less heavily on failure data.

This paper will therefore focus on the use of physics of failure in the prediction of critical failures. Both fully model-based methods and hybrid approaches will be discussed, and the opportunities and challenges of these methods will be discussed. The paper is organized as follows: in the next section the basic approach of physical model based prognostics is introduced. Section 3 then presents a number of case studies, demonstrating how the approach has been applied to some real military systems in previous work. The most important contribution of this paper is in section 4, where the main challenges are discussed, and suggestions are provided to tackle these. Finally, section 5 forwards the conclusions.

2.0 PHYSICAL MODEL BASED PROGNOSTICS

The basic idea of physical model based prognostics is that detailed knowledge of the failure process is used to predict the time to failure. The physical principles underlying mechanisms like fatigue, corrosion and wear are captured by a numerical model, which typically quantifies the relation between the applied load to a system, and the resulting time to failure (Tinga, 2013b). As a large part of the relation is based on physical principles, data is only required to find the proper values of the model (or material) parameters. This is opposite to the data-driven and artificial intelligence methods, which start without any knowledge on the underlying physics, and thus also have to derive the type and structure of the relation from the data. This typically requires more data, and a sufficient number of failure examples.

Application of physics of failure models in life time prediction is visualized in Figure 1 (Tinga, 2010). For any system (or in military: platform) a relation exists between how the system is operated (*usage*) and the associated time to failure (*remaining life*). However, for most operators of systems, this relation is unknown, which means that it is hard to assess what the expected RUL is for a certain operational usage profile. In that case understanding the physics of failure can be useful, as it depends on the specific failure mechanism how (changes in) the usage profile affect the RUL of the critical components. For example, for a component failing due to fatigue, the number of stress cycles is relevant (e.g. the number of start / stops of a gas turbine), but for a corrosion-related failure, the calendar time is expected to be much more relevant. Figure 1 shows that selecting a suitable failure model allows to translate the component loads to a life time prediction, which provides input to the prognostics of the complete system.

In addition to the models, also monitoring of the system is required, as either the usage, loads or condition of the component under consideration must be measured. Condition monitoring directly assesses the degradation of the component, which allows to decide on required maintenance activities. This does not require any physical model, but it also yields a rather reactive maintenance policy, as was discussed in section 1. If the condition cannot be directly monitored, it must be calculated using a failure model. This requires quantifying the loads by either direct measurements (load monitoring, e.g. applying a strain gauge or thermocouple to the component) or by calculating them from the measured usage of the system. An example of the latter is the calculation of centrifugal forces in a rotating part from the (monitored) rotational speed variation.

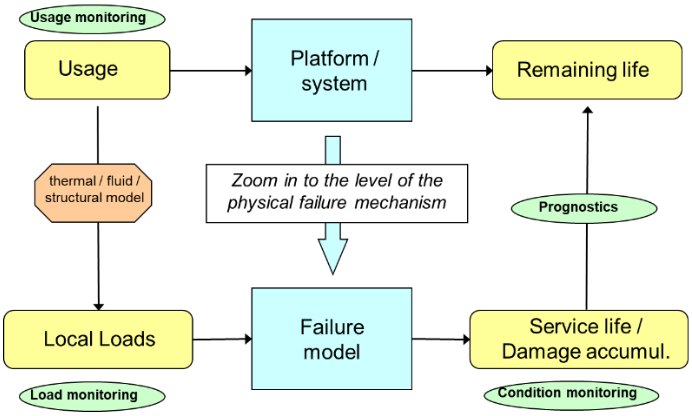

Figure 1: Relation between system usage, loads and life time, using models for physical failure mechanisms (Tinga, 2010).

The approach shown in Figure 1 is generic, as the platform / system can be any system (e.g. helicopter, diesel engine, bridge), and also the failure mechanism could be any mechanism (fatigue, wear, corrosion). So this approach can be applied in any situation where (*i*) the remaining life of a system or component must be determined, (*ii*) the failure mechanism is known and a failure model is available and (*iii*) either the usage, loads or condition are monitored. In the next section, three cases are presented in which this approach is applied to some military system.

3.0 CASE STUDIES

The approach introduced in the previous section has been applied to a range of case studies within the Dutch Ministry of Defence in the last couple of years. Most of them have been published before, but this section will briefly summarize three specific cases to demonstrate the approach and potential.

3.1 CV90 track wear

The first case presented here is on the CV90 infantry vehicle as shown in Figure 2. The aim is to predict the wear of the depicted sprocket wheel, which drives the track of the vehicle. This wheel must be replaced when it has worn too much. To minimize the vehicle downtime due to such a replacement, the wear and associated

Figure 2: CV90 infantry vehicle, operating in a sandy environment and the sprocket wheel (right).

RUL must be predicted for a specific operational usage profile (Tinga et al., 2014) (Tinga et al., 2021). An assessment of the most critical failure modes, both in terms of cost drivers and performance killers, identified the track and sprocket wheel to be top priority failures. The failure mechanism of the sprocket wheel is wear due to the abrasive action of sand particles sliding along the wheel during operation in sandy conditions. For this situation, a physical model was developed (Woldman et al., 2015) that describes the effect of different sand particle properties (size, shape) on the wear rate.

3.1.1 Model description

The physical model used here is the Archard law, that describes the wear volume as a function of normal force (F_n), sliding distance (s) and specific wear rate (k)

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

The specific wear rate [mm^3/Nm] is a proportionality factor including the effects of all other factors, e.g. hardness, amount of lubrication, surface roughness, etc. The generic process in Figure 1 indicates that the local loads that are used as input for the failure model must now be associated to the usage of the system.

The normal force that is exerted by the track on the sprocket wheel in the contact area is related to the power setting of the engine. By using the gear box transmission ratios, the number of sprocket wheels and number of teeth on each sprocket wheel, the magnitude of the force for every power setting can be calculated. The sliding distance is in this case the distance the track moves relative to the sprocket wheel, which is a constant distance per revolution. The sliding distance can thus be related to the driving distance of the vehicle.

The final parameter in the wear law is the specific wear rate k. This parameter is related to the material properties of the sliding components, but also depends on whether or not sand is present in the contact, and on the properties of the sand. An extensive research project was executed to quantify the effect of different sand particle properties on the wear rate (Woldman et al., 2012; Woldman et al., 2013). Some examples of different sand types investigated are shown in Figure 3, indicating a large difference in particle size and shape.

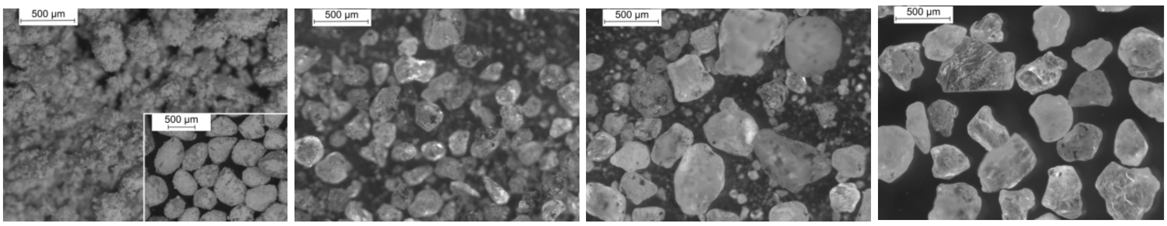

Figure 3: Different sand varieties from Afghanistan, Gambia, the Netherlands and silver sand.

The effect of sand particle properties on the specific wear rate has been quantified and can be expressed by the following relation

$$\frac{k}{k_{ref}} = \left(\frac{\Omega_i}{\Omega_{ref}}\right)^3 \cdot \left(\frac{n_i}{n_{ref}}\right)^{1.5} \cdot \left(\frac{\kappa_i}{\kappa_{ref}}\right)^{2.5} \tag{2}$$

where Ω is the particle size, n the particle feed rate (i.e. the number of particles in the contact area) and κ the particle sharpness (Woldman et al., 2012). The reference values are the silver sand properties. The size and sharpness values have been determined for a range of sand types, whereas the feed rate is associated to the way the vehicle is operated. When it is driving on a paved road, the feed rate in the sprocket – track contact will be low, whereas it will be high when driving in terrain.

3.1.2 Application and results

The model is applied by defining a usage profile for the vehicle. This means that the fraction of travelled distance in three different terrain types (Asphalt, Unpaved, Heavy soil / loose sand) and different levels of terrain unevenness (Light, Medium, Heavy) has been specified, based on interviews with operators. This yields a 3x3 matrix of travelled distance in each of the nine combinations, e.g. 12% on unpaved road at medium unevenness. The amount of particles that is expected to be present in the contact (i.e. the feed rate n) is related to the surface type, while the required power (governing the normal force F_n) is related to both surface type and unevenness.

For this usage profile, the expected number of kilometres to failure has been calculated for six different sand types. Failure is in this case defined as reaching a critical amount of volume loss on the sprocket wheel, which is derived from the allowable dimensional change as prescribed by the manufacturer. The results are shown in Figure 4 (standard scenario). Also a more severe usage profile, increasing the fraction of kilometres driven in heavy soil and loose sand, has been constructed, for which the resulting life time is also shown in Figure 4 (modified scenario).

These results clearly show that the sand type present in the operational area has a large effect on the expected sprocket wheel service life. The reference situation (silver sand) is rather modest, but between the different real sand types the sprocket wheel life shows a factor 2 – 3 variation. This is very useful information when decisions have to be made on how many spare parts must be shipped for a specific deployment. It is difficult to directly compare the predicted values with real observations to determine the accuracy of this model. A considerable number of assumptions has been made during the model set-up. These uncertainties prohibit the accurate prediction of a service life in an absolute sense. This issue will be discussed in more detail in section 4. However, the model in its present form is still valuable, as it can be used to perform comparative studies.

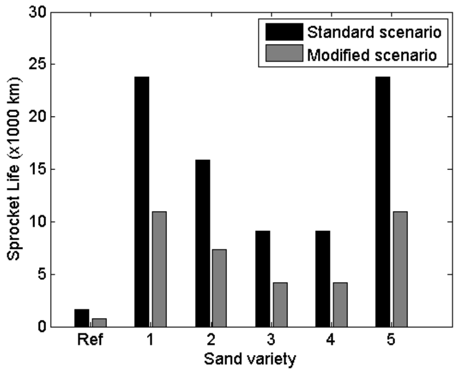

Figure 4: Effect of sand properties on sprocket wheel life time for two different usage profiles.

Finally, the present model required quite an extensive research effort to determine the wear performance of various sand varieties. Such an effort in model development, or a similar effort in setting up a monitoring system, is not always feasible. Therefore, recently a more pragmatic approach is presented, which is called the Functional Usage Profile based Maintenance (FUBM) policy (Tinga et al., 2021). It is suggested to only define a limited number of functional usage profiles (as the 3 x 3 profiles used for this case), and replace detailed physical models by direct relations between usage profiles and system lifetime (e.g. based on expert opinion). For sure this yields less accurate methods, but often at a hugely reduced cost.

3.2 Electronics failure in naval radar

The second use case discusses the failure prediction for electronic parts in a naval radar system (Politis, 2015), (Tinga et al., 2017). The common belief is that electronics fail in a purely random manner, and failure prediction is not feasible. However, also in electronic parts the laws of physics are valid. This means that developing suitable models and monitoring the proper quantities makes RUL prediction for electronics feasible (Vichare & Pecht, 2006; Vichare et al., 2007). The phased array radar system on a navy ship considered here contains a large number of so-called column assemblies (CA), which in their turn contain a number of printed circuit boards (PCB), see Figure 5. As the PCBs of the CA appear to fail regularly and unexpectedly, a prognostic method for these components could increase the radar availability and assist in improving the logistic process of these parts. Note that this radar has a ‘graceful degradation’ process, which implies that a single element failure does not directly lead to a non-performing radar: the performance gradually decreases upon failure of consecutive elements, and only drops below a critical limit when around 5% of the elements have failed. Still, as failure of at least several elements is expected during a longer mission, prediction of these failures yields clear benefits for the logistic process.

3.2.1 Model description

The first step in model development was to determine the actual failure mechanisms responsible for the functional failure of the PCB. These appeared to be *thermal fatigue*, driven by changes in operating temperature of the PCBs and *mechanical fatigue* due to vibrations. For both mechanisms, models are available in literature.

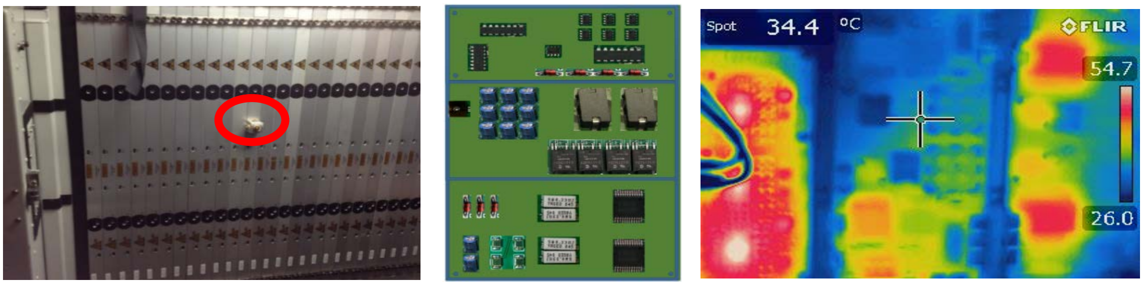

Figure 5: a) Stacking of PCBs in radar with installed vibration sensor (red circle); b) Typical layout of printed circuit board; c) Thermal camera image of temperature distribution.

The thermal fatigue is modelled with the Manson-Coffin relation, adapted for crack growth in solder materials (NIST/SEMATECH, 2012). The number of (temperature) cycles to failure N is a function of the magnitude of the temperature cycle (ΔT), the maximum temperature (T_{max}) and the cycling frequency (f):

$$N = Af^{-a}\Delta T^{-b}G(T_{max}) \tag{3}$$

The constants A, a and b are model parameters. The mechanical fatigue due to vibrations is modelled according to (Steinberg, 2000):

$$N_0 = N_c \left(\frac{Z_{3\sigma limit}}{Z_0} \right)^{6.4} \tag{4}$$

The number of cycles to failure N_0 at a certain vibration induced peak amplitude displacement Z_0 is a certain fraction of a reference number of cycles N_c at a critical displacement amplitude $Z_{3\sigma limit}$. The latter value can be determined from the dimensions of the PCB and the type and position of the component considered. The actual displacement is obtained from the natural frequency of the board and the power spectral density (PSD) of the vibration encountered by the PCB.

3.2.2 Application and results

The next step in the process is then to quantify the loads on the PCB, and relate these to the usage profiles of the radar system. As the PCB is in the radar during operation of the ship, the variations in both temperature cycles and vibration levels have to be determined. The thermal loads have been quantified by simulating the operational cycles in a testing machine, where a thermal camera measures the temperature cycles (see Figure 5c). As the number of operating cycles is limited, the input parameters for the model (ΔT, T_{max}, f) can now directly be linked to the on/off switching of the radar and the specific operational mode. To determine the mechanical loads, an accelerometer has been placed inside the radar (see Figure 5a), and vibration measurements have been performed for a range of operating conditions (ten Zeldam, 2016): various sea states, with diesel engine or gas turbine propulsion.

As the switching history and vibration levels are not continuously monitored, a limited number of operating profiles are defined. For each profile, using expert opinion, the switching frequency and vibration level variation (based on the different measured operational conditions) are specified. It is then possible to compare different scenarios, each containing a certain sequence of operating profiles with specified duration. The damage accumulation can be calculated with the models in equations (3) and (4), and the remaining useful life of the PCBs can be estimated. The results for four different operating profiles are given in Table 1, comparing diesel and gas turbine propulsion, as well as various speeds and weather conditions. It is clear that gas turbine propulsion is less damaging for the radar PCBs, as the vibration levels in the ship are lower in that case.

Table 1: Calculated PCB damage (per time unit).

Scenario	Damage
A (Die / medium speed / medium weather)	1.41
B (Die / medium speed / bad weather)	5.55
C (GT / medium speed / medium weather)	0.70
D (GT / high speed / medium weather)	2.10

Die = diesel, GT = gas turbine propulsion

Although the numbers in Table 1 can now be used to compare different scenario's, the accuracy of these numbers (in absolute sense) is hard to determine (see also section 4.2). To fully validate the predictions, the history of an individual PCB is required. However, the configuration management is too limited to fully trace on which specific radar system a PCB has been used, and what the usage profile of that radar (i.e. ship) has been in a specific period of time. However, until this kind of information is available, the model can still be used in a comparative manner.

3.3 NH-90 helicopter landing gear

The final use case is on the NH-90 helicopter, for which the RUL of the landing gear shock absorber is predicted (Heerink et al., 2012; Tinga, 2013a). Although the majority of aircraft maintenance is based on flight hours, the rather advanced Health and Usage Monitoring System (HUMS) in this helicopter allowed to study the potential of prognostic approaches. After studying the occurring failure modes of the NH-90 helicopter, as obtained from the computerized maintenance management system (CMMS), it was concluded that one of the persistent failure modes is oil leakage in the landing gear shock absorbers, see Figure 6.

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. This is plotted in Figure 7a, 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 the most relevant failure parameter in this case. A physical model-based prognostic method is expected to perform better.

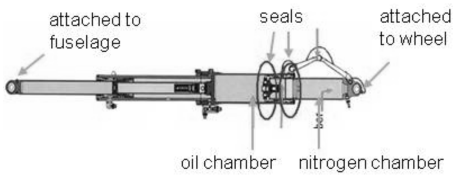

Figure 6: NH-90 helicopter and a schematic representation of the landing gear shock absorber.

3.3.1 Model description

A root cause analysis was performed to determine the failure mechanism and governing loads. Wearing of the rubber seal was found to be the cause of the leakage. If the seal gets damaged, oil from the internal oil chamber leaks to the environment. A detailed analysis of this wear process reveals that the governing loads in this case are (as in the first use case) 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 again expressed by the Archard law for wear processes, see Eq. (1) in 3.1.1.

3.3.2 Application and results

These loads must be related to the usage of the helicopter. The normal load F_n on the seal is a constant value, which can be estimated from the relative contraction of the seal and it's elastic properties. The sliding distance (s) 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. The specific wear rate in this case is determined by the material properties and the lubrication conditions, which are both considered to be constant here.

The on-board health and usage monitoring system (HUMS) registers both the number of landings in each period and the helicopter weight during each landing. Using that information, the amount of wear at the moment of failure of the seal for each specific helicopter can be approximated with the physical model. This is done for each helicopter where a failure was detected, as is shown in Figure 7b.

Comparing the plots in Figure 7a and b clearly shows 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. The observed variation in the results is now much lower. Except for the first two cases, the points appear in two distinct groups: one 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 by the OEM as a response to the quickly failing seals. This new seal was used in the absorbers that failed at 50 mm^3 of wear: it clearly has a better wear resistance than the original seal, since the oil leakage occurs at a later stage.

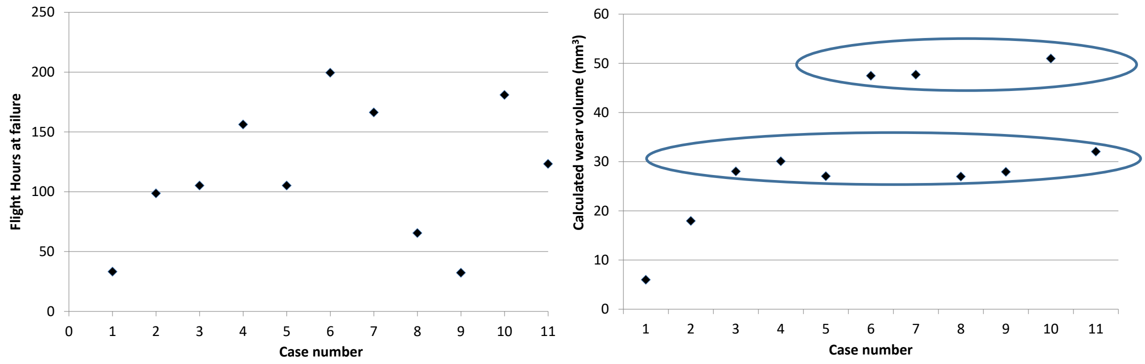

Figure 7: a) Number of flight hours for 11 events; b) predicted amount of wear for same events.

4.0 CHALLENGES AND OPPORTUNITIES

The case studies in the previous section have demonstrated that the approach presented in section 2 can be applied to a range of military systems. They also show that prognostic methods based on the physics of failure have quite some potential, as they don't need a large amount of failure data, and at the same time allow for a prediction which can be quite far ahead (provided that the future usage profile is known or can be estimated). Still, there are some challenges for these type of methods, which need additional attention before the physic-based prognostics can be widely applied in (military) practice. These challenges are (*i*) the gap between system and component level, and the associated selection of critical parts; (*ii*) the validation of prognostic methods; and (*iii*) the development of hybrid methods, where physics and data-driven methods are combined. This section will discuss these three challenges and provide suggestions for tackling these.

4.1 Component vs. system level and critical part selection

Military systems are typically complex systems consisting of many different (sub)systems and components. From a (military) operational perspective, the main question is whether the complete system can fulfil its mission, i.e. whether the system is available and deployable when needed. A suitable predictive maintenance policy thus needs to be capable of predicting upcoming failures on the system level. However, most prediction models are not on the system level, but on the component level. And this is especially the case for the physics-of-failure methods, as it is infeasible to model all physical processes for a complete system. Some data-driven approaches might be capable of predicting (part of) the system-level failures, but it would then require a huge training data set to learn these models all potential failure modes.

Therefore, the challenge here is to achieve an acceptable estimate of system failure probability within an acceptable amount of computational and model development effort. Developing physics-of-failure models for all component for sure is not feasible, so a well-motivated selection of important / critical components must be made. And indeed, especially for mechanical components, there is large range in criticality amongst the components in a system: some are responsible for many system failures, e.g. because they have no back-ups (redundancy), have short failure times (inherent reliability, MTBF), or are largely affected by specific operating conditions. On the other hand, many other components hardly ever fail, and therefore any effort spent on life prediction methods would be a waste.

The solution to this challenge could be twofold. The main direction is to do a well-motivated selection of the critical parts, and focus model development and prognostics on these parts, thus covering the majority of the system-level failures. A procedure to select the critical parts has been proposed recently (Tiddens et al., 2018). The first step in this procedure is filtering the different failures using methods like the 4-quadrant method originally proposed by (Lee et al., 2014), and modified in (Tinga et al., 2017). As shown in Figure 8, this method clusters the failures based on two aspects: failure frequency and failure consequence (in this case downtime, but can also be costs). The failing parts in quadrant 1 (A1 in Figure 8), 2 and 3 can best be covered by other policies (i.e. modification, more spare parts, regular maintenance), but the parts in the 4th quadrant are the ones that are suitable for a predictive maintenance policy: these failures do not occur frequently, but when they occur, the consequence is considerable. After this first filtering of critical parts, the set can be further refined by the criteria explained in (Tiddens et al., 2018), i.e. identifying showstoppers and executing detailed feasibility studies.

A second direction for solving the system vs. component level challenge is to find ways for speeding up the prognostic model development: if component-level prognostic models can be easily derived, the large number of models needed is not a big problem anymore. Also deriving prognostic methods on the subsystem / assembly level could help, although this is still challenging for purely physics-based methods. However, combining physical models with data-driven approaches may enable this, as will be discussed in subsection 4.3 on hybrid methods. Another option is to use models for standard equipment types (e.g. pump, bearing, shaft, e-motor) from reliability handbooks. These models are relatively simple, and not very accurate, but can be used to cover a large amount of components in a complex system with minimal effort, see e.g. (Alves da Silveira et al., 2021).

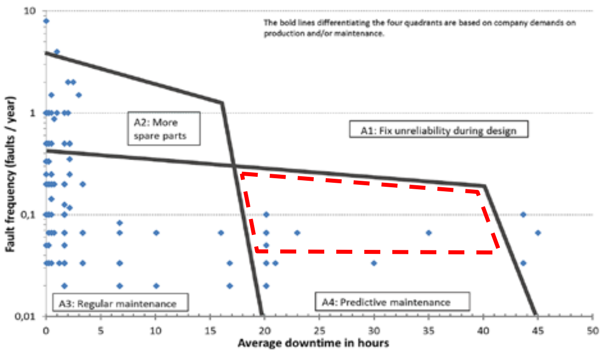

Figure 8: Clustering of a set of failures. The dashed region indicates the failures that are suitable for predictive maintenance.

For the CV90 and NH-90 cases, such a part selection procedure has been applied to obtain the components (i.e. the sprocket wheel and landing gear shock absorber) for which a model would have to be developed. For the electronics case, this selection (PCB) was based on the availability of a model in literature.

4.2 Validation of prognostic methods

The second challenge encountered in applying physics of failure for critical parts is the validation of the models. Although the models are based on first principles, and therefore do not heavily rely on data, they can only be applied with confidence when it can be proven that the predicted time to failure is close to the actually observed value. The precise value that the model predicts typically depends on the model (material) parameters that have been derived for the case under consideration. These are either based on field data, or are obtained from handbooks.

The challenges in this validation process are (*i*) that at least a number of actual failures must be available to compare with the model predictions, and (*ii*) for these failures, the complete usage or load history must be known. The latter is important, because the physical models require a load sequence as input. Only using the specific history of an observed failure allows to make a comparison with the model prediction, but such a detailed history is often not available. This will be discussed using the previously described cases.

For the CV90 sprocket wheel, the load history must be derived from the usage profile, i.e. a registration of km's driven at different terrain types and unevenness. Although it is known what the fleet wide average is, this info is not available for an individual vehicle. Moreover, registration of replaced sprocket wheels is not complete, and the amount of wear on a rejected wheel is also not registered. This lack of detail in the registrations makes it impossible to calculate the amount of wear for an individual vehicle, and compare this with the amount observed in practice. Recently, the on-board monitoring of several usage parameters with sensors has started, which gives potential for more detailed information in the (near) future. For the electronics case the situation is quite similar. To fully validate the model, the history of an individual PCB is required. However, the configuration management is too limited to fully trace on which specific radar system a PCB has been used, and what the usage profile of that radar (i.e. ship) has been in a specific period of time. The only case that could be fully validated is the helicopter case. For the shock absorber life prediction, the number of landings and weight of the helicopter is required. The installed HUMS system precisely registers these parameters for each individual helicopter, which allows to simulate that history in the model, and compare the model prediction and actually observed time to failure. The solution for the load history challenge is thus to utilize more advanced monitoring systems to collect (and store) detailed information on load histories for individual systems.

The remaining challenge for the lack of actual failures originates from the fundamental point that preventive maintenance is intended to prevent failures, i.e. components are replaced (far) before they fail, and the real lifetime is never revealed. Therefore, the amount of failures is limited *by definition*. One way to tackle this is applying the *front runner* concept, which is presently being explored. The idea is to select from a fleet of systems (or components) a limited number of systems, and stop maintaining these. The system(s) that are the front runners in terms of operating hours are selected, as these are expected to fail the soonest. Off-course, this can only be done with systems for which a failure does not have catastrophic consequences. Once the front runner fails, the actual time to failure is known, and can directly be used to extend the intervals of the remaining systems in the fleet (which are lagging behind, so are not yet prone to failure). Additionally, extensive monitoring of the selected systems is arranged, which means that data patterns that belong to (almost) failing systems can be gathered. The latter is very useful for training AI algorithms, and allows to predict these type of failures in the future. So sacrificing a small number of systems yields insight and data to potentially save hugely on the rest of the fleet.

4.3 Hybrid approaches

The final challenge to be discussed is the development of hybrid approaches that combine physics of failure with data-driven methods. Both approaches have their own pros and cons: physical models typically focus on component level, and are time-consuming to develop, they require a certain amount of domain knowledge, but don't need large amounts of data, and can also predict failures that have not been observed yet in practice; data-driven methods can be developed more quickly, and don't require domain knowledge, but depend on the availability of high quality data, and only predict failures that are included in the training data. Combining these two types of methods is expected to provide better performing methods, as the strengths of both are combined. The challenge is how to achieve that.

The first approach is a *parallel approach*, where both a physics-of-failure and a data-driven method are simultaneously used to calculate a time to failure of remaining useful life, and the results of the two methods are combined (in a weighted manner). This approach is typically followed when the performance (i.e. the predictive capability) of the two types of models is more or less similar, but using only one of them yields an unacceptably low prediction accuracy.

The second approach is called *physics-to-data*, where a first principles model is used to simulate data that is subsequently used as input for a data-driven prognostic method. In this approach, the physical model can solve (part of) the data shortage that a data-driven method could suffer from. This approach is typically suitable in situations where an accurate physical degradation or failure model is lacking, but high-fidelity process simulation models are available to generate relevant data for a range of operating conditions. Some well-known examples in this category use gas turbine simulation programs to generate data for GT prognostics.

The third and final approach is *data-to-physics*, where physics of failure models, or their parameters, are updated with data obtained from measurements on a real system. This allows to periodically tune the model in such a way that it tracks the degradation process accurately. An example of this approach, is an Unscented Kalman Filter being used to update a crack propagation model (Keizers et al., 2021). This approach can be followed when a rather accurate physical degradation model is available, but considerable uncertainty is present with regard to the model parameters and / or operating conditions. This uncertainty can then be reduced by updating the model with measurement data.

5.0 CONCLUSION

This paper has introduced a framework for the prediction of failures in critical components, using the physics of failure. Three distinct cases that have been studied in the past years using this framework have been discussed, showing the potential of these type of methods in prognostics. After these case descriptions, three important challenges in this field have been discussed, i.e. the selection of critical parts, the validation of prognostic models and the development of hybrid methods. Solutions and directions for further research have been given, allowing to further extend the potential of the physics of failure based prognostic methods for military systems in the near future.

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