Innovative predictive maintenance concepts to improve life cycle management

T Tinga, PDEng, PhD
Netherlands Defence Academy, The Netherlands

SYNOPSIS
For naval systems with typically long service lives, high sustainment costs and strict availability requirements, an effective and efficient life cycle management process is very important. In this paper four approaches are discussed to improve that process: physics of failure based predictive maintenance, advanced data analysis, condition based maintenance and maintenance optimization. For all these approaches, understanding of the failure behaviour and quantifying the effects of variations in usage of the system appear to be the key factor for improvements.

INTRODUCTION
Many of the naval systems in service today have operational service lives of 20 to 30 years. This means that the costs of sustaining the systems during these long periods are considerable and can easily exceed the initial investment costs. It is therefore attractive to develop improved sustainment concepts, that by reducing the costs by only a few percent already yield a significant cost benefit. Another important aspect for the naval systems is the availability during the service life. Also for that purpose, innovative sustainment concepts can aid in keeping the required availability levels, also in the final phases of a system’s service life. All activities to optimize the availability of the system while minimising the costs are contained in the life cycle management (LCM) of the system.

An important aspect of naval system life cycle management is the planning and execution of timely maintenance. Performing maintenance too early implies that parts are replaced (far) before they reach the end of their service life, and unnecessary costs are made. At the same time, extending maintenance intervals increases the risk of failures, which threatens the availability of the systems. The challenge is therefore to perform just-in-time maintenance and achieve the required availability at minimal costs. The current practice for naval systems, however, is the application of maintenance intervals that are fixed in time or operating hours. But at the same time, the operational conditions in which the ships and systems are deployed vary largely in time. As the effect of the real usage of the system is not incorporated, most of the intervals are very conservative in order to achieve the required availability for all different usage patterns.

In the present paper a number of innovative predictive maintenance concepts are presented that enable a more dynamic maintenance planning. In that way, much of the conservatism can be removed, making the maintenance more efficient. At the same time, for systems that are used in a more severe manner, intervals can be reduced to retain the required availability and thus increase the effectiveness of the maintenance process.

The concepts treated in the next sections are: (i) the physics of failure based predictive maintenance approach; (ii) the advanced analysis of usage and failure data; (iii) condition based maintenance and (iv) maintenance optimization on the ship level. For each of those concepts, practical cases will be used to demonstrate the benefits.

PHYSICS OF FAILURE BASED PREDICTIVE MAINTENANCE
The first concept discussed here is the development of predictive maintenance methods based on the physics of failure. By understanding and modelling the component failure mechanisms that lead to a system failure, the

Author’s biography
Prof. dr. ir. Tiedo Tinga is presently chairing the Dynamics based Maintenance group at the University of Twente and is also associate professor Maintenance Technology at the Netherlands Defence Academy. He is leading research programs at both institutes on predictive maintenance, reliability engineering and maintenance optimization. Prior to joining the universities, he has been working as a senior scientist at the National Aerospace Laboratory NLR.
time to failure for a given usage profile can be calculated accurately. That information is then utilized to assess the optimal maintenance interval. The approach (1) followed here is shown schematically in Fig 1.

![Schematic overview of approach to predict service life based on physics of failure](image)

The relation between the usage of the system and the evolution of the remaining useful life is often unknown, especially for an operator. By zooming in to the level of the physical failure mechanism (i.e. fatigue, wear, creep or corrosion) for the critical components, this relation can be quantified. This requires the identification of the local loads (e.g. stress, temperature) and the development of a failure model. Monitoring of the usage or loads then enables to calculate the damage accumulation, which provides insight in the service life consumption. Alternatively, direct monitoring of the system or component condition is also possible, as will be discussed later. The methodology shown here has already been presented before at INEC, where it was applied to a naval gas turbine (2, 3). It will now be demonstrated for another case, i.e. the main bearing of a large radar system.

**Radar main bearing**

The main bearing is one of the critical parts of a large rotating radar system. On the one hand it is essential for the functioning of the radar, which means that seizure of the bearing immediately leads to non-availability of the radar. On the other hand, upon failure it cannot easily be replaced on-board, resulting in a long radar down-time and considerable costs. For these two reasons, the bearing is generally preventively replaced after a fixed number of years or a certain number of operating hours. This means that upon replacement, possibly a (considerable) amount of remaining life is still present. Therefore, since the large bearing is also a very expensive part, a possible extension of the service life would yield a large cost benefit. For such a critical and expensive system a just-in-time maintenance policy would be very attractive.

Based on the failure mechanism based approach introduced before, this system has been analysed (4). The service life of a bearing can be expressed in terms of the $L_{10}$ service life, representing the lower 10% bound of the fatigue service life of a population of bearings. This $L_{10}$ service life is a function of the applied bearing load $P$ and the bearing capacity or load rating $C$

$$L_{10} = \left( \frac{a \cdot C}{P} \right)^p$$

(1)

where $p$ is the load life exponent. In addition to this load dominated expression, also a penalty factor $a$ is introduced that incorporates the effects of misalignment, contamination (dust or water) and improper lubrication. The load on the bearing is caused by the specific usage of the radar system, where the radar weight, wind loads, ship vibrations and shock loads together determine the magnitude, direction and dynamics of the loads. During the design of the radar, a certain usage profile is assumed, where the mentioned loads are quantified in terms of magnitude and occurrence. This yields the design life of the radar bearing, which is also used to determine the fixed replacement interval.

In practice, the real usage profile will in almost any case be different from this assumed profile. Therefore, using equation (1), the actual loads on the system can be related to the service life of the bearing. By monitoring the operational loads, e.g. by applying strain gauges to the radar, the service life consumption can accurately be monitored, and replacement of the bearing can be postponed until it is really necessary.

In a similar way the effects of the penalty factors are incorporated in the model. The amount of misalignment can be assessed at each periodic inspection of the system, while a model is available to quantify the effect of
misalignment on the bearing life. Also the amount and quality of lubrication can be determined (by monitoring the lubricant pump and periodic testing of the lubricant, respectively), which also enables to quantify the effect of lubrication on bearing service life.

Since the required detailed measurement data is not available yet, this concept has been tested on a fictitious case. A certain usage profile is assumed for an operational period of 15 years. The radar is maintained every five years, and traditionally it is replaced after 10 years. This is because the actual state of the radar at that moment is unknown, and the probability that it will fail before the next maintenance opportunity at 15 years cannot be assessed. Using the proposed concept, however, monitoring the actual loads and the availability of the numerical model enable to monitor the actual amount of remaining life (in terms of operating hours). This is illustrated in Fig 2, where for the first 5 years of operation the reduction in remaining useful life is represented by the solid (red) line.

![Fig 2](image)

Fig 2 Prediction of bearing service life using load monitoring and predictive maintenance approach

At that moment, it is known that still 38,000 hours of useful life remain, and a prediction of the evolution of this quantity can be made. Using the proposed model, several scenarios can be analysed. Firstly, the usage profile assumed during the design can be applied. As this profile is generally quite conservative (i.e. severe), the resulting decrease of remaining service life is represented by the lower (blue) dashed line in Fig 2. Alternatively, it is possible to extrapolate the average usage from the first five years, which yields the upper dashed line. This line clearly shows a less severe usage, resulting in a larger amount of remaining life after 10 and 15 years. However, in both scenarios the bearing is expected to reach the next maintenance opportunity (after 10 years) without failure, so replacement of the bearing is not required.

Now the system can be operated for another five years, while simultaneously monitoring the actual usage and loads. And then after 10 years the analysis becomes very interesting: normally the bearing is replaced, but if the actual usage has been considerably less severe than assumed, the actual condition in combination with the prediction for the next five years (following different scenarios) will show whether 15 years of operation is possible without failure.

In summary, by identifying the failure mechanism (fatigue), setting up a failure model (equation (1)) and monitoring the usage (loads, alignment and lubrication), the evolution of the remaining service life could be quantified.

**ADVANCED DATA ANALYSIS**

The second approach for innovative sustainment is based on the advanced analysis of data. In many organizations, but especially in military organizations, a lot of data on all kinds of systems is collected and stored. The registration of failures is rather common, as it is generally connected to issuing the work orders to resolve the failures. The same holds for logistic data related to the ordering of spare parts. But also data on the usage of the systems, i.e. in terms of operating hours, power settings, is in many cases available, although this data is generally stored in separate information systems. And with the increasing use of condition monitoring (CM) and health and usage monitoring systems (HUMS) also data on the condition of systems is collected. But despite the huge amount of data available, utilization of this data to obtain information for maintenance optimization is rather limited. In this section it will be demonstrated that understanding the origin of the
considered data and knowledge on the system or component failure behaviour enables to select the appropriate data sets and parameters, and to utilize that data to improve maintenance performance.

**Landing gear shock absorber**

The NH-90 naval helicopter is equipped with a HUMS system that collects a lot of data on the operation of the helicopter (e.g. flight duration, altitude, number of landings) and on the condition of the system (mainly vibration sensors). However, despite this advanced information system, most of the maintenance activities are still based on number of flight hours, which is the traditional approach in aircraft maintenance. But for some subsystems the number of flight hours does not seem to be the most appropriate parameter to base the maintenance on. One of the recurring failures in the NH-90 fleet appeared to be leakage of one of the seals in the landing gear shock absorbers (see Fig 3). This failure leads to oil leakage and requires an overhaul of the shock absorber by the OEM, which is associated with large costs and non-availability of the helicopter.

![Fig 3](image)

**Fig 3** Illustration of landing gear shock absorber (left) and number of FH to failure for 11 failures (right)

In a certain period of time 11 failures were identified (5), for which the number of flight hours to failure are shown in Fig 3. It is clear that there is little correlation between flight hours and landing gear failure, as could be expected. This makes prediction of failures, and thus the timely preventive replacement of the absorbers, very difficult. To improve the predictions, a root cause analysis has been performed and the mechanism responsible for this failure appeared to be the sliding wear of the seal. The governing loads for this failure mechanism are the normal load ($F_n$) and the sliding distance ($s$). If these loads are known, the Archard law can be applied to calculate the amount of volume loss ($V$):

$$V = kF_n s$$

where $k$ is the specific wear parameter that depends on the material used. The sliding distance of the seal is determined by the way the helicopter is operated, and is governed by the number of landings and the weight of the helicopter during take-off and landing. These two quantities appear to be available in the HUMS system, which enables to construct a new indicator based on combining the two data fields. The result, a prediction for the amount of wear in the seal, is shown in Fig 4.

The plot shows that, except for the first two failures, all points are on one of two lines representing a certain amount of wear. The three points on the higher line appeared to be associated to a redesigned seal with better wear properties. The results show that understanding of the underlying failure mechanisms and the intelligent selection and combination of available data provides a much better predictability of these failures. The associated benefit is that preventive maintenance can be planned much more accurately, yielding both a reduction of costs and down time.
CONDITION BASED MAINTENANCE

The previous two concepts discussed are based on collecting data on either usage or failures, and applying that data to calculate or predict the expected time to failure. As explained, this can only be achieved when the failure mechanisms are known and can be quantified by numerical models. Another approach that has been applied frequently in the last decades is based on monitoring the condition of the system or component by suitable sensors. Since direct information on the condition is obtained, no detailed knowledge of the failure behaviour is required. As soon as the monitored parameters, e.g. a vibration level or the viscosity of a lubricant, exceed a predefined threshold value, maintenance activities should be employed.

However, in its traditional form, condition monitoring (CM) and the associated condition based maintenance (CBM) has a number of drawbacks. Firstly, waiting till the threshold level is exceeded only provides a diagnostic capability. This means that immediate action is required, but no early warning or prediction is obtained from the system. Moreover, many condition monitoring systems are introduced by providing a (large) number of sensors and a data collection and storage capability, but lack the required analysis methods to translate the raw measurement data into useful information that would enable condition based maintenance. Also, in many cases the type of sensor and its location appear to be suboptimal (or completely wrong) after some period of monitoring.

Therefore, also for condition monitoring the knowledge of the system failure behaviour is beneficial, as it assists in developing and operating the monitoring systems properly and in adding a prognostic capability to the systems. This means that effort should be put in developing design guide lines for CM systems, but especially in developing methods to analyse the obtained measurement data. A nice example is the recent development of analysis procedures for electro-chemical noise measurements, that can be used for corrosion monitoring (6).

MAINTENANCE OPTIMIZATION

Finally, where the first three concepts mainly focus on the component level, the final concept shows how the link to the system level maintenance optimization can be made. Finding the optimal maintenance policy for one of the components in a specific subsystem is not yet the solution for optimizing the maintenance of the complete ship. Therefore, a model of a frigate, containing four different subsystems with different usage patterns and failure behaviour, is developed, as is shown in Fig 5 and Fig 6.

The model (7) is used to demonstrate how the deployment of the frigate affects the optimal maintenance intervals. This means that the following challenges are faced:

1. The optimal maintenance interval for a sub system depends on the way it is operated, as was discussed in the first section of this paper. So to find the optimal maintenance interval for all individual subsystems on board, the usage of each of them must be monitored, and quantitative models must be available to link the usage to their degradation rates.
Once the optimal intervals are determined for each subsystem individually, the optimal policy for the complete ship must be derived from those locally optimal policies. If all subsystems would be maintained at their optimal intervals, the maintenance activities would be scattered in time. A balance must therefore be found between minimizing the number of maintenance periods, the system downtime and the total maintenance costs.

To address the first challenge, a usage profile of the frigate has been defined in terms of mission types and mission phases. 9 different mission types, ranging from anti-piracy to anti-submarine, are identified and each of these mission types contain a certain number of mission phases (e.g. transit, surveillance). Further, it has been identified how severe (fraction of time) each of the modelled subsystems are used in each of the mission phases. This is illustrated in Fig 6. Note that the SMART-L and the gas turbine are considered as single systems, while for the chillers (3 systems) and diesel generators (4 systems) a certain amount of redundancy is present. The definition of a usage profile (fraction of time spent in each mission) for the frigate then enables to calculate the variation in the usage of the individual subsystems. Then the failure behaviour of the subsystems is defined in terms of a representative service life, which is initially assumed to be consumed proportional to the number of operating hours. This means that for a certain usage profile, the expected number of failures in a four year period between two overhauls can be calculated. Finally, two maintenance options are available, corrective or preventive maintenance. For corrective maintenance, the subsystem is only repaired after it has failed. This maximizes the utilization of the service life, but also leads to down time and possibly consequential damage. For preventive maintenance, the subsystem is repaired or replaced after a certain fraction $\beta$ (e.g. 90%) of the service life.
life has been reached. In this policy some remaining life of the subsystem is not used, but the maintenance costs are generally considered to be only a fraction $\alpha$ (e.g. 50%) of the costs of corrective maintenance.

**Frigate level optimization**

To address the second challenge, it is assumed that in between two overhauls 1 up to 9 intermediate maintenance periods are available. The simulation model is now used to calculate the optimal policy (i.e. number of intermediate maintenance periods $n$ that minimizes the total maintenance costs) under the boundary condition that the frigate availability is at least 80%. If too less maintenance is performed (small value of $n$), many subsystems will fail, the subsystem downtime will increase and (for the non-redundant subsystems) the frigate availability will decrease. On the contrary, if too much maintenance is performed (large value of $n$), the total costs will increase.

![Fig 7 Total maintenance costs for various numbers of intervals ($n$) and ratio’s between preventive and corrective maintenance costs ($\alpha$)](image)

The resulting total costs for a given value of the preventive maintenance threshold ($\beta = 0.05$) are shown for various numbers of intervals ($n$) and ratio’s between preventive and corrective costs ($\alpha$) in Fig 7. This figure shows that for lower values of $\alpha$, preventive maintenance is so cost effective that a policy with many short intervals ($n = 9$) is preferable. On the other hand, for high values of $\alpha$, the higher costs of preventive actions make it more attractive to wait until the subsystems fail, which yields a policy with long intervals ($n = 5$) to be the most attractive.

**Effect of specialization**

Finally, the model is used to study the effect of specialization within a fleet. It is assumed that a fictitious fleet of 3 frigates has to perform 300 missions, consisting of a certain mix of the 9 mission types. In the reference situation, the complete set of missions is distributed equally over the three frigates. Now a certain amount of specialization is introduced, which means that all the highly demanding missions in hot regions (e.g. anti-piracy) are performed by one specific ship. Further, all the missions in colder climate nearby the base are performed by another frigate and the third frigate takes account of all remaining missions.

The simulation results are shown in Table I. As was observed in Fig 7, the optimal maintenance policy is either $n = 5$ or $n = 9$. The optimal policy (minimal total maintenance costs) for each of the specialized frigates can be determined, as is indicated by the * in the second column of the table.

From these results, the following observations can be made: (i) the optimal policy is not the same for all specialized ships. For ship 1, the policy is the same as for the reference situation ($n = 5$), but for ship 2 and 3 using $n = 9$ yields the minimal costs; (ii) for the reference situation, where all three ships take an equal share of all mission types, the total maintenance costs are $3 \times 395.8 = 1187.4$. But the total costs for the three specialized ships together appears to be significantly lower, i.e. 884.3. This reduction of 25% in total maintenance costs is due to the fact that the maintenance policies of the three individual ships can be tailored to the specific usage.
To summarize, it was shown that tailoring the maintenance policy to the specific usage of a system may lead to considerable advantages. Again, this is only possible when the quantitative relation between usage profile and (sub)system failure behavior is available through a model.

**CONCLUSION**

The present paper has discussed four different approaches to improve the life cycle management of naval systems: (i) the physics of failure based predictive maintenance approach; (ii) the advanced analysis of usage and failure data; (iii) condition based maintenance and (iv) maintenance optimization on the ship level. These approaches enable a more dynamic maintenance planning, which removes much of the conservatism that is present in more traditional approaches, making the maintenance more efficient. At the same time, for systems that are used in a more severe manner, intervals can be reduced to retain the required availability and thus increase the effectiveness of the maintenance process. In all these approaches, understanding of the failure behaviour and quantifying the effects of variations in usage of the system appear to be the key factor for improvements. For each of the four concepts, practical cases have been used to demonstrate the benefits.

**REFERENCES**