CHAPTER 3

Data-driven maintenance of military systems

Potential and challenges

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Abstract

The success of military missions is largely dependent on the reliability and availability of the systems that are used. In modern warfare, data is considered as an important weapon, both in offence and defence. However, collection and analysis of the proper data can also play a crucial role in reducing the number of system failures, and thus increase the system availability and military performance considerably. In this chapter, the concept of data-driven maintenance will be introduced. First, the various maturity levels, ranging from detection of failures and automated diagnostics to advanced condition monitoring and predictive maintenance are introduced. Then, the different types of data and associated decisions are discussed. And finally, six practical cases from the Dutch MoD will be used to demonstrate the benefits of this concept and discuss the challenges that are encountered in applying this in military practice.

Keywords: Data collection, Diagnosis, Prognosis, Data analytics, Condition monitoring

3.1. Introduction

Military systems like naval ships, aircraft, helicopters and armed vehicles are operated all around the world in harsh environments. Their quality is essential for the success of a military mission, and failure of the systems may have severe consequences. Therefore, maintenance is important to military organisations, and it has also attracted much research attention in the past decades. In recent years, the collection and storage of all kinds of data has become common practice. For the military domain, this yields many possibilities to use the data for offensive and defensive purposes. But data also offers a lot of opportunities to improve the maintenance and logistic processes, which ultimately leads to more reliable and better available military systems.

In this work, case studies from the Dutch Ministry of Defence (MoD) will be used to illustrate the potential of data-driven maintenance, but also to discuss the challenges encountered on implementing a data-driven maintenance policy. In section 3.2, the basic concepts of data-driven maintenance are introduced, while section 3.3 describes the different data types and types of applications. Section 3.4 to 3.6 then discuss a number of case studies that demonstrate the potential and challenges. Section 3.4 covers manually collected data, section 3.5 concerns autonomously collected control system data and section 3.6 discusses autonomously collected condition monitoring data. Finally, some conclusions are forwarded in section 3.7.

3.2. Concepts in data-driven maintenance

This section will first introduce the basic motivation for data-driven maintenance and will then discuss the different maturity or ambition levels.

3.2.1. Primer on data-driven maintenance

Society heavily relies on the quality of technology. A retained quality cannot be taken for granted, it typically requires deliberate effort that originates from decisions. This effort is known as maintenance. Maintenance can be defined as:

> *The combination of all technical and administrative actions, including supervision actions, to retain or to restore an item's quality.*

This definition paraphrases the CEN 2001[1] and IEC 1990[2] definitions of maintenance by introducing the term *quality*, which is defined as:

> *The degree to which a set of inherent characteristics of an object fulfils requirements (ISO norm[3]).*

In this definition, *inherent* means existing in and not assigned to an item or system. Therefore, inherent characteristics are measurable by sensors as the decision maker's mind state is not involved. However, a decision maker's mind state determines the *requirements* that express the needs or expectations for the system (performance). Requirements are not immediately observable which impedes data driven maintenance. So, quality is not immediately observable, but it excellently represents a decision maker's observable concern.

Decisions involving quality are typically group decisions. Such a group exists because its members have chosen to collaborate, which requires decision makers to agree on (*i*) their goals and on (*ii*) their actions. Decision makers can only align with the organisation's goals and with the organisation's decision rules once these goals and rules are made explicit. A notion of "quality" may convey the group's common sense. This common sense is essential to make quality observable. So, data driven maintenance relies on common sense about quality. Once quality has been defined properly for a specific system, data-driven maintenance can assist in retaining or restoring that system's quality efficiently and effectively. The various ways to do this, i.e. the different maturity levels of data-driven maintenance, will be discussed next.

3.2.2. Maturity levels of data-driven maintenance

Data can support (predictive) maintenance decision making in many different ways. To structure these various approaches, different maturity levels can be identified. In the world of industrial digitalisation (Industry 4.0), the concept of prescriptive or autonomous maintenance is considered as the ultimate maturity in data driven maintenance. In that case, the system automatically takes a diagnosis, predicts the remaining useful life of a specific component, and fully prescribes what maintenance task needs to be executed at what moment in time. And in case of autonomous maintenance, this task is also executed without human interaction. This situation can be visualised by a control system as in Figure 3.1. The system's operation is fully described by some control loop, where the control model (C) adequately responds to any disturbance faced by the process (P).

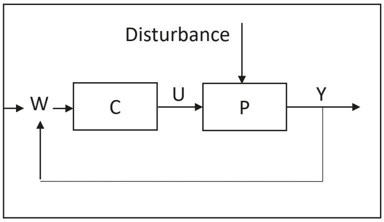

Fig. 3.1. Example of an autonomous control loop.

In practice, the control model (*C*) can only handle the a-priori known disturbances, implying that the control model (*C*) occasionally fails to provide the inputs (*U*) that steer the outputs (*Y*) towards the required value. In that case, a *fault* has occurred, which is defined as:

> *an anomaly that leads to a quality non-conformity.*

Faults can therefore be considered as symptoms of impending quality nonconformities. Such a symptom may be represented by some usage, load or health characteristic, which in some cases can also be observed or even measured. Figure 3.2, that originates from classical Fault Detection and Diagnostics (FDD) theory[4], shows that controlling these faults includes five steps: detection, isolation, identification, prediction and recovery. Conventional FDD includes:

- Fault detection: the determination of faults, present in a system and the time of detection;
- Fault isolation: the determination of the kind, location, and time of detection of a fault;
- Fault identification: the determination of the size and the time variant behaviour of a fault;
- Recovery: the actions, following from the identification, that restores the system quality;

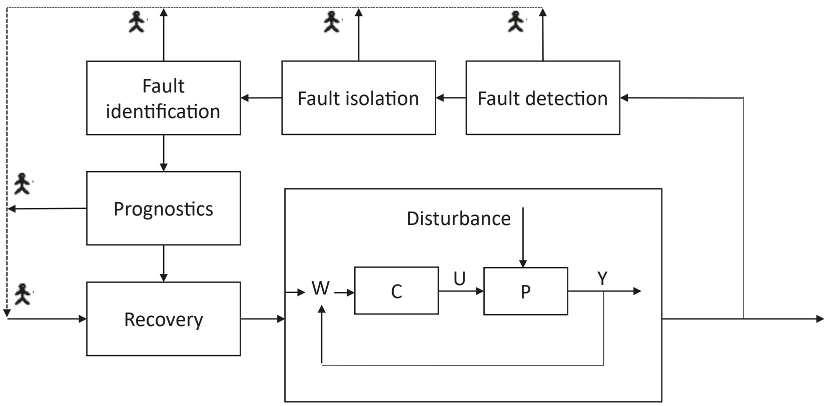

Fig. 3.2. Example of an autonomous control loop extended with fault control.

In the context of predictive maintenance, a new step can be inserted before the recovery step, i.e. *Prediction*. In this step a prediction of the time to failure is made, which not only allows for assessing the present health state of the system, but also the future states. The latter allows a more accurate decision on the recovery actions.

The resulting first four steps of this modified FDD process then coincide with the maturity levels typically considered in predictive maintenance[5]:

- Detection: is something wrong?;
- Diagnosis: what is wrong?;
- Health assessment: to what extent is it wrong?;
- Prognostics: how long does it take before it gets really wrong, i.e. fails?

Note further that rudimentary fault control is entirely human driven, which means that each of these steps requires a human analysis and decision to be taken (as represented by the human symbols in Figure 3.2).

Now, data-driven maintenance intends to reduce the human involvement in fault control by untangling the implicit human expertise and implementing this in algorithms. Data driven maintenance will thus make fault control more consistent and autonomous. Ultimately, all the steps in the fault control process may become fully autonomous, which yields the ambitioned prescriptive (autonomous) maintenance. Note that in modern (and critical) systems, reconfigurations, switch-overs and emergency precautions are already increasingly triggered autonomously.

Figure 3.3 shows a model of the steps an organisation that intends to mature in data driven maintenance needs to follow. This also shows that the minimal requirement is to ensure access to the data that allows for autonomous fault *detection* (being the lowest maturity step). As the locations of the data collection and the Fault Detection and Diagnostics (FDD) process may differ, data transport becomes essential. The Dutch MoD experienced that transporting data from the installed control systems of some weapon systems to an analysis environment is not trivial at all, as it triggered quite some issues related to data security and data ownership.

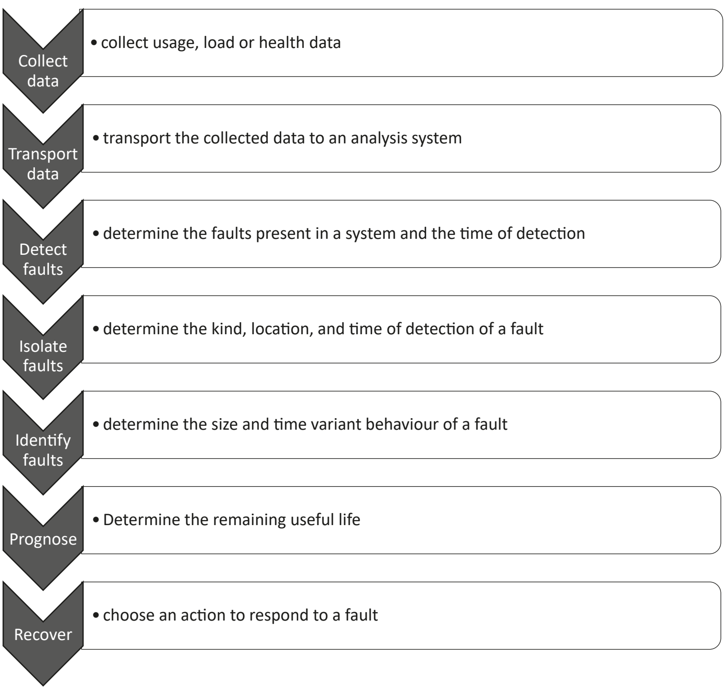

Fig. 3.3. Model to mature in data driven maintenance.

Maturity in data-driven maintenance heavily depends on the degree to which the first four tasks are performed autonomously. Figure 3.3 suggests that maturity growth in data-driven maintenance follows the flow of the fault control loop in Figure 3.2. So, maturity growth in data-driven maintenance should start with autonomous fault detection. Only if this level is accomplished, can the next step in maturity be made. This is confirmed by the framework proposed by Tiddens et al.[6,7], indicating that maintenance ambition level and type and amount of data should match to enable a successful increase in maintenance maturity level.

3.2.3. Data-driven maintenance model selection

As maintenance involves decisions that can only influence the yet-to-be-observed-future, a model is required that can go beyond a sample of historic data. The selection of such a model can be supported by several processes[8,9,10]. Figure 3.4 classifies the various model types. Knowledge-based models rely on knowledge of the physics that prescribes the variables, the parameters, and the structure of the model. Knowledge-based models are superior in making claims about unprecedented circumstances. A history-based model is a resort when knowledge of the model properties is lacking. It just employs data to estimate unknown model properties or to weigh some arbitrary set of candidate models. Because history-based models rely on data from the past, claims about unprecedented circumstances are risky. Figure 3.4 shows that history-based model selection may take place from labelled data or from unlabelled data. Here, the label indicates the item's quality (e.g. failed or healthy). Labelled data allows for supervised machine learning whereas unlabelled data only allows for unsupervised machine learning. Finally, advanced cases of data driven maintenance typically comprise a hybrid model selection as both historical data and expert knowledge are imperfect, but they may be complementary (see section 3.6.4).

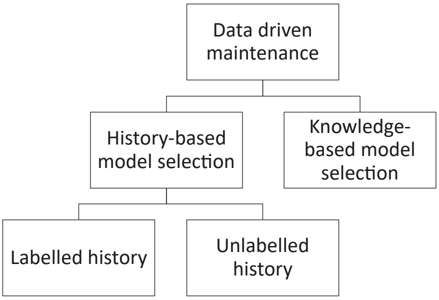

Fig. 3.4. Classification of data driven maintenance.

3.3. Data types and maintenance decisions

During the life cycle of a military system, comprising the design and build, the operational phase and the phase-out of the system, many decisions have to be taken. These decisions range from short term to long term, and from individual systems to complete fleets. Also, the range of data types that can be used to support these decisions is very wide and can originate from many different sources. Therefore, this section will first provide an overview of the various data types and sources, and then the various ways to apply data-driven decisions in the life cycle management (LCM) process will be discussed.

3.3.1. Different types of data

The previous subsections described the various maturity levels in data-driven maintenance. These all require at least some data, but large differences in the specific requirements to data exist. The various types of data and associated sources are clustered in the following three categories:

A. Manually collected system data
Data that is collected from registrations or inspections performed by persons. The data is typically entered into a computer system or database manually. This concerns the following subcategories:

– *A1. Maintenance data:* information on the executed (or planned) maintenance tasks (repair, replacement, lubrication), typically obtained from enterprise resource planning (ERP) or computerised maintenance management systems (CMMS);
– *A2. Inspection data:* obtained during periodic inspections, using sensors or measurement devices that are not installed in the system. This provides insight into the health of the system at the moment of inspection. This can be binary data (system up or down), as well as continuous data (e.g. remaining profile depth in tyres);
– *A3. Operational (or usage) data*: information on how the system has been used (machine settings, type of product, rates, …)
– *A4. Configuration data*: provides information on the specific configuration of a system, like type, version, etc.;

B. Autonomously collected system data

Data that is collected by the system itself, and also directly stored into a computer system or database, without any human intervention or action. This concerns the following subcategories:

– *B1. Control system (sensor) data*: obtained from sensors installed in the system, providing values for e.g. temperature, pressure, vibration level, flow, rpm, etc. This type of data is obtained from sensors present in the system for control purposes, e.g. in a supervisory control and data acquisition (SCADA) system. Also, event data is part of this category, providing registrations of events that occurred, like commands or notifications (of faults or quality nonconformities);
– *B2. Condition monitoring (sensor) data:* obtained from sensors installed in the system, with the specific purpose of monitoring the condition of the system. Examples are vibration sensors, oil quality sensors, corrosion sensors, etc.;

C. Background data

This data provides insight into the context / surrounding / environment that the system is operated in, like:

– *C1. Environmental data*: information on the environmental conditions in which the system is operated, like temperature, humidity, wind, climate. Can be obtained from (on-board) sensors, or from (weather) databases.
– *C2. Location information*: provides insight into the (geographical) location of the system, e.g. specified by a GPS position or the type of surface;

For the development of data-driven maintenance, the autonomously collected (sensor) data (*B*) is the most important, as sensors typically provide data with a high sampling frequency, and are less affected by human errors. The latter largely reduces the quality of the manually registered category *A* data. It is observed that in recent years the volume of category *B* data collected within the MoD has grown significantly, e.g. through Flight Data Recorders in helicopters and data recorders in vehicles and on ships. This enables reaching the 1st maturity level (autonomous data collection) in Figure 3.3.

3.3.2. Application of data-driven maintenance in the LCM process

As was mentioned earlier, many different decisions have to be taken during the life cycle of a military system. Data can be used to support these decisions, but this can be applied in various ways. The control loop and associated decisions in Figure 3.2 are related to a single system: these will be referred to as maintenance decisions. But the collected data and derived insights can also be used to optimise long-term and fleet-wide maintenance programs, and the associated service supply network (spare parts, capacity planning). The latter type of decisions will be referred to as LCM decisions. Therefore, the following applications of data-driven maintenance can be distinguished:

I. Situational awareness & health assessment: for a military system it is very important that its present state and capabilities are known to the operator. Based on that information, the commander or operator can decide what type of missions or actions can (still) be performed. This type of decision is typically short term (what is the state *now*) and on the level of an individual system. Data can assist in doing such an assessment using the FDD process (Figure 3.2). This process can be fully manual but can also be made more autonomous using artificial intelligence to increase the efficiency and ensure a quicker response.

II. Short term maintenance planning: to prevent system downtime, maintenance must be performed, preferably before a failure occurs. To properly plan these types of maintenance tasks, the operator needs to know how long the system can be used before it fails, but also how the operation can be adapted to ensure a certain period of failure-free operation. Also, these types of decisions are rather short term (~ weeks) and are on the level of the individual system. The main difference with the previous decision type is the addition of a prediction (of the remaining useful life) to the health assessment. In this case, data can assist in prognostics (Figure 3.2 and sections 3.4.2 and 3.6.3).

III. Long-term maintenance planning & scheduling: the operator of a system has to plan the short-term maintenance tasks (see previous decision), but for a fleet of systems it might not be optimal to plan this on an individual basis, as this may lead to peaks in the maintenance workload. Therefore, long term planning and scheduling for the complete fleet is more efficient. This is therefore an LCM decision rather than a maintenance decision. However, the way the individual systems are used (severe missions or easy training program) determines their maintenance demand, which should be incorporated into the maintenance optimisation. In this case, data can assist in:
- Specifying the usage profiles of the systems (see section 3.5.1 and 3.5.2)
- Predictions of failures based on these profiles (see section 3.4.1)
- Optimising the maintenance intervals (planning and scheduling) to achieve the highest fleet-wide availability (see section 3.4.2)

IV. Optimising supply chain processes: once the maintenance process is properly optimised, the associated demand for work force, facilities and spare parts is also known. This means that these LCM processes can also be optimised. Data can in this case assist in:

– Calculating the optimal inventory levels for spare parts
– Determining the best moments for purchasing parts
– Planning and scheduling of facilities and work force (see section 3.4.2)

In the Autonomic Logistics Information System[11] (ALIS) of the F-35 fighter aircraft several of these functionalities have already been implemented. This means that many logistic activities are (automatically) triggered by degradation and upcoming failures in the operational aircraft.

In the remainder of this work, a number of cases from the Dutch MoD[12] will be discussed in terms of potential and challenges. These cases (see Table 3.1) will be organised along the types of data introduced in 3.3.1: in section 3.4 the challenges of human entered data (*A*) will be discussed. Section 3.5 then addresses the potential and challenges of autonomously registered control data (*B1*), while section 3.6 focuses on condition monitoring sensor data (*B2*). Moreover, for each of the cases it will be specified which maturity level (1 – 4) is covered (detection, isolation, identification, prediction), and what type of maintenance decision (I – IV) is supported.

Table 3.1. Overview of case studies and associated data types, maturity levels and decision types (ST = short term, LT = long term)

Case study (section)	**Data type**	**Maturity level**	**Decision**
Vehicle inspections (4.1)	A	0 – No FDD	I – Situational awareness
Ship corrosion optimisation (4.2)	A	4 – Prediction	III / IV – LT Optimis./ planning
Vehicle speed registration (5.1)	B1	0 – Usage monitoring	II / III – ST + LT optimisation
Vessel water temp. registr. (5.2)	B1	2 – Fault isolation	I / II – Sit. awaren. + ST optimisation
Corrosion monitoring (6.1/6.2)	B2	3 – Fault identification	I / II / III ST + LT optimisation
Corrosion prediction (6.3)	B2	4 – Prediction	III – LT optimisation

3.4. Decisions based on manually collected system data

Traditionally, most of the registrations of either executed maintenance or the results of (visual) inspections within the MoD are entered manually in a Computerised Maintenance Management System (CMMS). Although some basic analyses can be done on this type of data, the two cases in this section will demonstrate that this data has some clear drawbacks.

3.4.1. Vehicle inspections using a hand-held device

The conventionally collected notifications of vehicle maintenance actions in a CMMS proved to be prone to human errors and they only incidentally entailed a narrative about the nonconformity in quality, let alone about underlying faults. The use of hand-held electronic devices appeared to be prosperous to increase the level of detail and to include the time stamp of visual inspections[13]. A pilot project with a hand-held application at the MoD illustrated that the arrival rate of quality nonconformities resulting from visual inspections significantly depended on the inspector and on the operating regime.

To illustrate this, in Figure 3.5 the number of detected quality nonconformities registered with the hand-held device is plotted versus the usage intensity (kilometres divided by time). This reveals that the relations between quality nonconformities and the usage intensity are very different for the two operating scenarios considered. This indicates a clear dependence of system degradation on usage intensity, which could be further explored and used for long term maintenance optimisation (LCM decision type III). Without the handheld application, the number of quality nonconformities was hard to retrieve efficiently, so this analysis would not be possible.

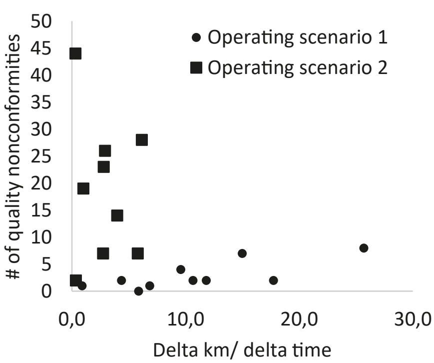

Fig. 3.5. Scatter plot of quality nonconformities versus usage intensity given two operating regimes.

It should be realised that this handheld application predominantly collected quality nonconformities that already occurred. Quantitative data that enables FDD, let alone predicts a specific quality nonconformity (*prognosis*), is not provided by the CMMS and neither by this hand-held application. To conclude, CMMS data alone appeared to be insufficient to mature in data-driven maintenance, while the structured data collection enabled by the hand-held device allowed a one step increase in maturity.

3.4.2. Naval ship corrosion maintenance optimisation

Navy ships require maintenance on the corrosion protection coating systems on a regular basis. If repairs or replacement of the coatings are performed too late, the underlying steel structures of the ship hull may be degrading. On the other hand, if maintenance is performed too early, unnecessary costs are made, and the often-required docking of the ship might lead to a long period of non-availability. To optimise the maintenance decisions regarding navy ship coatings, a previously proposed model[14] for infrastructure maintenance was adapted to the vessel case[15].

Firstly, the coating degradation is modelled with a non-stationary gamma process. The parameters of this process have been derived from information provided by maintenance experts (data type A1 and A2). As the state of the coating is only assessed periodically (i.e. once a year) and visually (i.e. the % of the hull area that has a degraded coating), the resulting gamma process still contains quite some uncertainty. The left-hand plot in Figure 3.6 shows the obtained degradation over time, which depends on the maintenance option that is applied. A *full replacement* of the coating (with the ship docked) restores the condition to the as new situation. The options *repainting* and *spot-repair* only provide a slight improvement of the condition, and also yield a higher degradation rate after the maintenance action (due to the imperfect treatment). The magnitude of these effects is also derived from expert interviews.

Once the degradation behaviour of the coating is properly captured by the gamma process, the second step is to optimise the maintenance decisions over time. Given a threshold for the amount of degradation allowed and the costs associated with each of the maintenance options, the model returns the sequence of maintenance activities that minimises the total expected life cycle costs. The results for a specific case are shown in Figure 3.6 (right), indicating at each age of the vessel what the best maintenance option is (if maintenance must be executed at that moment in time). One of the boundary conditions is that the ship will be docked every five years, which makes full replacement the best option at those moments. At all other moments in time, the high costs of (additional) docking and full replacement do not outweigh the resulting lower degradation rate, and either repainting or spot repair are the best options.

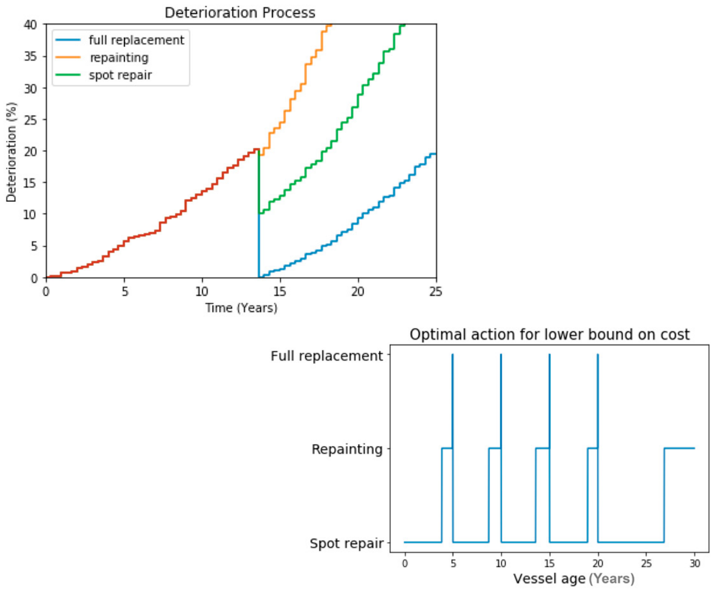

Fig. 3.6. Deterioration behaviour of the coating for various repair options (left) and optimal actions proposed by the model (right).

This case study shows that even low quality, human entered data can be used for long-term maintenance optimisation (LCF decision type III and IV). However, the low frequency of inspections (once a year) and visual assessment make the data very crude, which introduces a large amount of uncertainty in the degradation curves, and thus also in the decisions advised by the model. One of the recommendations of this project is therefore to increase the frequency and amount of detail of these hull coating inspections. This can, for example, be achieved by using drones that on a weekly basis scan the vessel hull surface and apply image processing techniques to automatically calculate the fraction of the coating surfaces that has degraded.

3.5. Decisions based on autonomously collected control system data

A control system steers a (weapon) system to the desired state and intervenes when potential unsafe situations occur (e.g. over-speeding or over-heating). By collecting the data that flows through a control system, many details about the usage and the loads during operations may be retrieved. As usage causes a load that may deteriorate the system health, yielding a nonconformity in quality, fault signatures may be based on control data. Therefore, data-driven maintenance becomes more prosperous when control data is available in addition to CMMS data. As the generation of control data is often "designed in" in many military systems, it provides an accessible entry to mature in data-driven maintenance. Field experiments with control data enable the Dutch MoD to learn about data-driven maintenance practices that include (*i*) the original equipment manufacturer involvement, (*ii*) data governance and (*iii*) the selection of prosperous case studies.

Still, it should be realised that the control systems of weapon systems intend to support *operations* rather than *maintenance*. Dedicated health monitoring systems may provide better fault signatures of impending nonconformities in quality, as will be discussed in section 3.6. The present section introduces two realistic case studies at the Dutch MoD on the use of just control data. The first case study[16] exemplifies the reconstruction of usage and load characteristics of a vehicle corresponding with the "collect data" step in the maturity model (Figure 3.3). The second case study[17] illustrates the "fault isolation" step in the maturity model using a knowledge-based model selection (Figure 3.4).

3.5.1. Military vehicle speed registration

The control system of a military vehicle records the velocity of the vehicle which allows a reconstruction of the variation in the vehicle speed (Figure 3.7). From this signal and knowledge of the mass of the vehicle, the acceleration forces and the deceleration forces can be calculated.

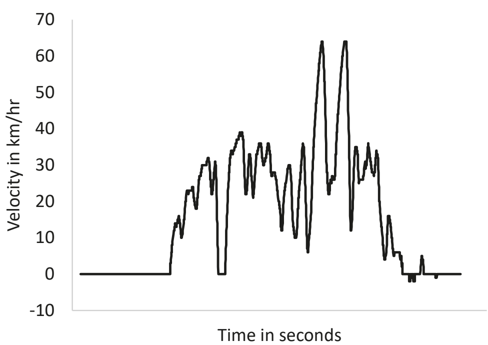

Fig. 3.7. Variation of the speed of a vehicle as registered by the control system.

For each activation of the brakes, the dispersed energy and the peak power can be estimated from the measured speed variations (Figure 3.8). The cumulative brake energy and the number of "high" peak power cycles may be better predictors of brake failures than the historic arrival rate of brake replacement notifications in the CMMS. These features may generally be helpful to distinguish rough and gentle operating regimes experienced by a specific vehicle and may be used to predict failure rates from that (LCM decision type III).

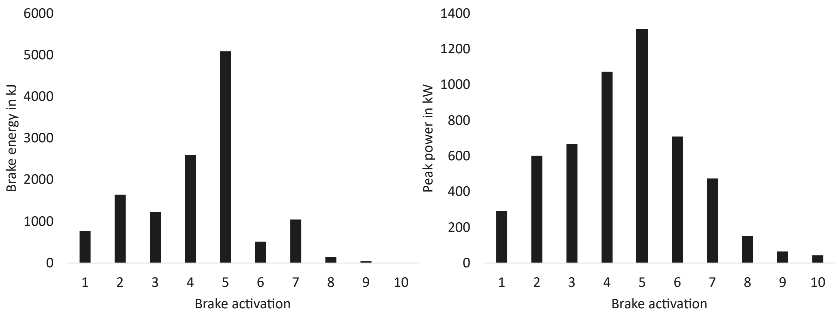

Fig. 3.8. Estimated energy and peak power at consecutive brake activations.

3.5.2. Naval vessel temperature sensor

Four installations on a naval vessel each independently measure the sea water temperature. Each of these temperature measurements has been logged by the vessel's control system, and Figure 3.9 shows the difference in measured temperature of three of the sensors (T2-T4) relative to the first sensor (T1).

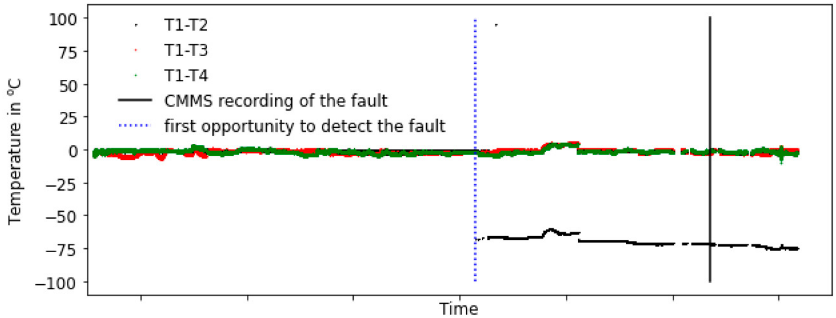

Fig. 3.9. Evolution of four independent measurements of the sea water temperature surrounding a vessel.

Figure 3.9 shows that one of the three sensors shows an offset of 75°C after some time. An expert's model that assumes equality of the four temperature measurements may then autonomously identify a faulty sensor. Figure 3.9 also shows a considerable time lag between the recording of the nonconformity in quality in the CMMS (as indicated by the solid black line) and the first opportunity to detect the fault (the dashed blue line). So, autonomous fault identification might have reduced the downtime of this sensor considerably (maintenance decision type I / II).

3.6. Decisions based on autonomously collected condition monitoring data

As an example of the use of sensors specifically aimed at condition monitoring for a complex failure mechanism, this section will address the use of corrosion monitoring for improving maintenance decisions, and the challenges this poses for their integration in data-driven maintenance.

3.6.1. Corrosion management

Military systems operate under a vast diversity of conditions. These induce a multitude of failure mechanisms, including different types of corrosion, often localised. Corrosion is estimated to cost society over 3% of the world's GDP[18], while for military systems, the consequences of corrosion account for over 20% of the total US DoD maintenance expenditures[19]. This shows that corrosion has serious cost and availability impact on military systems but can also seriously impact their safety.

Corrosion management of military assets is getting more and more demanding due to increasing design complexity. Two important materials-related developments in the industry are causing this. Firstly, the emergence of additive manufacturing processes, which significantly increase the freedom of design by allowing a high geometric complexity. And secondly, the growing use of exotic materials to meet increasingly stringent weight and strength requirements. Examples are combinations of different advanced polymer- and metal-matrix composites, often with lightweight metal alloys, also in complex geometries. These two developments cause the aforementioned increasing design complexity, making it increasingly difficult to predict its corrosion behaviour. Traditional lab-based experiments that expose simple combinations of materials to wet/dry cycles with varying temperature, salinity or pH may prove insufficient to predict specific local corrosion phenomena at micro-environments that arise throughout such geometries.

The understanding and in situ quantitative assessment of a systems response to a variety of combinations of environmental conditions and usage profiles is vital for both short term maintenance decisions (LCM decision type II) and long-term maintenance optimisation (type III). This demands for sophisticated condition monitoring techniques and prognostics, as well as verification and refinement via lab and field-based testing. Prognostic models that translate the condition, or damage accumulation, into a repeatedly updated remaining lifetime should be fed by autonomous in situ monitoring of the systems actual corrosion response to its environment, as will be discussed in section 3.6.3. This can be combined with other relevant failure parameters such as fatigue or contamination. Such an integral, real-time system status is vital for substantiated operational planning and prioritising of maintenance activities, with insight in the availability and safety consequences of e.g. mission extension (decision type I).

3.6.2. Corrosion monitoring challenges

Corrosion sensors can be based on a variety of different techniques, enabling either only fault detection or in addition fault isolation and identification. These techniques all share the same overall aim: to indicate a system's condition. However, each technique has its own disadvantages and flaws.

- Ultrasonic, (fibre-)optics, magnetism, Eddy current and corrosion coupons are all indirect techniques that only detect the corrosion damage, e.g. a wall thickness reduction or the formation of corrosion product. This may well be too late, because detection only occurs if the damage accumulation exceeds a detection threshold. Moreover, most of these techniques are not integrated in the system, and therefore require human effort in the collection (data type *A2*);
- Corrosion coupons, although widely used in the industry, are especially indirect in the sense that the coupons are assumed to be representative for the system under study, which is difficult to acknowledge in practice. Lab-based tests serve as a basis to correlate the condition of the coupon with that of the actual system. Features such as welds, crevices, alloy composition, microstructure, manufacturing process parameters and coating details can differ between the coupon and the system under investigation. These effects impede proper fault detection from corrosion coupons and reduce their validity.
- Environmental sensors are an interesting option, since this technique does not require the position of the sensor at or near the corrosion process. Instead, the detection is based on monitoring the corrosivity of the environment, in section 3.3.1 referred to as background data (type *C1*). Obviously, environmental sensors demand a high level of knowledge of the system's corrosion response to a variety of different types of operational conditions. This monitoring technique is therefore quite common in aerospace. Nevertheless, this knowledge about the system's corrosive properties results from substantial investments in research for each specific type and combination of materials.
- Since corrosion is in essence an electrochemical process, it makes sense to use electrochemistry for monitoring. Techniques such as electrochemical impedance

spectroscopy (EIS) or electrochemical noise (EN) monitor the process itself, i.e. before any significant damage has occurred[20,21,22,23]. This is an important asset, because a robust lifetime prediction model relies not only on the quality of the input, but also on timely input from corrosion sensors. EN and EIS can enable valuable fault isolation and identification as well, which is quite uncommon for a corrosion monitoring technique. Moreover, data can be collected during periodic inspections (type *A2*), but these sensors can also be integrated permanently in the system, which yields autonomously generated data of type *B2*.

Besides type-specific disadvantages, there is also a number of common issues of current corrosion monitoring techniques that require attention:

- Most importantly, all previously mentioned techniques only operate at pre-selected locations. This significantly complicates the detection of the most dangerous, localised forms of corrosion, which are also the most difficult to predict. The most promising ways of monitoring are those that potentially detect localised corrosion over larger surface areas. Unfortunately, the common monitoring techniques applied in industry, e.g. acoustic emission, have their limitation (e.g. effect of noisy environments) and have only been shown to be effective in specific use cases.
- The presence of the sensor can alter, inhibit or accelerate the corrosion process by inducing differences in the local conditions, e.g. in electrolyte composition, with respect to the area around the sensor. Taking into account these differences in a lifetime prediction model is very difficult, as this is not a constant factor, nor is its time-dependence predictable in itself.
- The detection threshold is an important parameter: considering that most non-electrochemical techniques only detect corrosion damage, their ability to serve as an early-warning technique largely depends on the damage accumulation that is required for their detection. This damage can e.g. involve the build-up of the corrosion product (e.g. in the case of fibre-optics) or the propagation of a crack (e.g. in the case of ultrasonic technique).
- The inspection interval should also be selected properly. Corrosion is a relatively slow process that may not require status updates in the millisecond range; however, the use of military systems under extreme conditions can initiate localised corrosion, which subsequently propagates within a timespan of several weeks to months. This initiation can be detected by electrochemical (EIS or EN) techniques and requires the right moment and location of monitoring. In its early stages, the corrosion process can still be mitigated in the presence of a corrosion inhibitor like Cr-VI or a suitable alternative. Once in the propagation phase, the damage accumulation becomes easier to detect but will increasingly compromise system safety.

- It is very difficult or even impossible to monitor locations inside enclosed environments or complex geometries. The often used alternative is to ascertain 'lifetime' corrosion protection, e.g. by the use of coatings with active inhibition components, of which the toxic Cr(VI) is the most widely applied.
- It is likely that the root cause of a corrosion problem is not corrosion-related. The functional degradation of an organic coating is a good example of this: mechanical, thermal or UV radiation loading of the coating can cause a loss of its corrosion protective properties. In this case, the resulting corrosion damage is merely a consequence of coating degradation. This indicates the significance of a proper root cause analysis (RCA) and of a good understanding of the prevalent failure mechanism(s). One may question whether corrosion monitoring would deliver the preferred data input for prognostic models in these cases, or whether monitoring the coating condition would provide more reliable data. Electrochemistry, such as EIS or EN, can monitor both the coating condition as well as the resulting corrosion activity.

3.6.3. Corrosion prediction

As was discussed before, the prediction of corrosion degradation is rather difficult due to the complexity of the physical processes involved. On the other hand, monitoring of corrosion only indicates the present condition, which makes it hard to plan future maintenance activities. However, if these two approaches are combined, a much stronger (hybrid) approach is obtained. Such an approach for a corrosion problem has recently been proposed[24]. A simple physical model has been used in a particle filter approach, which uses regular measurements of the actual condition to tune and adapt the model continuously.

In this work, the corrosion mass loss has been modelled using a multi-factor combination model. This type of corrosion model predicts mass loss using accelerating factors for environmental parameters. In the present model, only the ambient temperature has been included, using the Arrhenius equation. The model then allows for calculating the mass loss for a certain temperature, provided that the values of the four model parameters are known for the material and situation considered. In practice those values are often not known precisely, but the particle filter used here can utilise the periodic measurements to tune the model parameters to the actual situation.

This is shown in Figure 3.10, where the particle filter has been trained with the corrosion mass loss measurements for a certain period of time, as bounded by the dashed vertical line: 5 months for the left plot, 15 months for the right plot. From that moment in time, the physical model (with the tuned parameters) is used to predict the evolution of the corrosion mass loss (the green line) until the end of the time period (40 months), given a certain (seasonal) variation of the ambient temperature. In these plots the actual mass loss is also shown (the blue line). The left-hand plot shows that after five months the prediction of the mass loss is rather inaccurate, considerably underestimating the time to failure. But the right-hand plot shows that using the measurements up until month 15, the model can be tuned much better to the actual situation, and the resulting prediction of the time to failure is much more accurate.

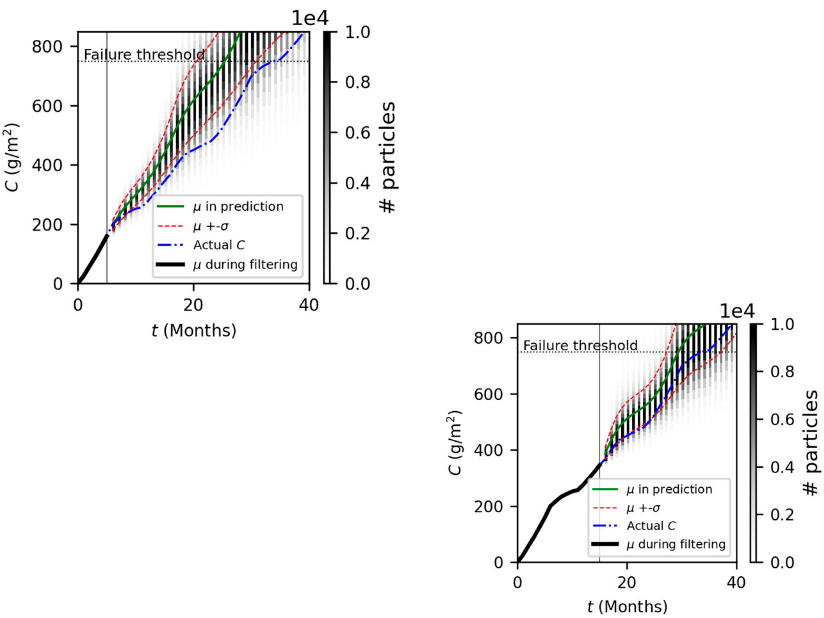

Fig. 3.10. Corrosion mass loss prediction after 5 months (left) and after 15 months (right).

This model shows that prediction of corrosion mass loss purely based on a physical model is rather difficult but strengthening the model with measurements yields a considerably improved prediction. Further, this model only considers the simple situation of mass loss of coupons due to uniform corrosion. Extension to a more realistic situation with localised corrosion on a real structure is still very challenging.

3.6.4. Final remarks on corrosion monitoring

From the discussion and cases in this section it can be concluded that data-driven maintenance for inherently dynamic, difficult to predict and spontaneously occurring processes such as corrosion is not straightforward. Looking at the cost, availability and safety figures, corrosion is an undeniably important problem for the Dutch MoD. However, to improve corrosion management, it is essential to be aware of the limitations of data-driven maintenance. The data required for the detection, identification or even prediction of corrosion is very specific, and cannot be expected to be available from standard control systems. Therefore, the Dutch MoD is currently not able to tackle an important failure mechanism such as (localised) corrosion based on data-driven maintenance. If there is an ambition to do so, investments in dedicated monitoring techniques and data collection must be done.

3.7. Conclusions

This work has discussed the potential of data-driven maintenance, as well as the challenges encountered in developing these approaches. The main conclusions regarding these two aspects are given next.

3.7.1. Potential of data driven maintenance

Data-driven maintenance potentially supports the life cycle process by (*i*) an enhanced situational awareness, (*ii*) short-term maintenance planning, (*iii*) long-term maintenance planning and scheduling and (*vi*) optimised supply chain processes. An enhanced situational awareness appeared the easiest attainable potential for an organisation in the process of maturing in data-driven maintenance, like the Dutch MoD. This finding corresponds with conventions about maturity growth in data driven maintenance that claim that autonomous fault *detection* precedes the more advanced levels of fault *isolation*, fault *identification* and *prognostics*.

3.7.2. Challenges in data-driven maintenance

The case studies predominantly covered the beginning of the maturity growth in data-driven maintenance. The following conclusions can be drawn from these cases:

- The (autonomous) registration of usage (profiles) – *maturity level 0* – does not directly lead to detection or isolation of faults, but does support the understanding of its effect on system degradation;
- The conventional use of human entered (failure) events in a CMMS – *maturity level 1 & 2* – is prone to human factors. To improve the data, (i) collecting the data with a hand-held device and (ii) using autonomously collected data from

a control system were shown to increase the possibilities for data-driven maintenance;
- The quantification of damage – *maturity level 3* – is still challenging, as is shown by the corrosion monitoring case. Although techniques are available, their application in a real operational setting, as well as the analysis and interpretation of the data, is not trivial;
- The two corrosion prediction cases (3.4.2 and 3.6.4) showed that *maturity level 4*, i.e. the prediction of failures, is theoretically already possible, and could even work with 'low level' data. However, validation and demonstration can only be done when this data is actually collected in a structured manner.

Notes

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11 See https://www.lockheedmartin.com/en-us/products/autonomic-logistics-information-system-alis.html
12 More cases are available on the internal network of the MoD (https://doscoportal.mindef.nl/sites/0400/010/).
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