Using ship sensor data to achieve smart maintenance?

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Synopsis

In the present paper, the potential of using ship sensor data for achieving smart maintenance of naval ships is discussed. In modern ships, a lot of installations and equipment contain sensors that monitor and register the operation of these systems. This work will exemplify the value of the (long term) collection and analysis of sensor data. This will mainly focus on assessing the present performance or condition of systems and the detection of faults or failures, but also on the longer term ambition of predicting upcoming failures. The theoretical benefits of sensor data are checked against a real case study of a naval ship sea cooling water system. Different scenarios with increasing amounts of sensors are compared, and the importance of domain and system knowledge is discussed.

Keywords: sensor data, data analytics, diagnostics, prognostics, reliability

1. Introduction

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. 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. This can only be improved when maintenance is applied more smartly.

Smart maintenance is defined here as using a prediction of either the degradation (rate) or the failure of the system to optimally plan the preventive maintenance tasks. This is also called Predictive Maintenance. Several approaches for predicting failures have already been proposed in the last decade. Fully data-driven approaches based on data analytics have been developed to detect and predict failures, see e.g. (Fink, et al., 2020) for a review on deep learning applications in prognostics. Alternatively, physical models for failure mechanisms like fatigue, wear (Woldman, Tinga, van der Heide, & Masen, 2015) or corrosion can be used to predict failures. These models require input of measured loads (Tinga, 2010) or registered usage profiles (Tinga, Wubben, Tiddens, Wortmann, & Gaalman, 2020).

However, (Tiddens, Braaksma, & Tinga, 2015) showed that application of these (theoretical) approaches in industrial practice is rather limited. The main reason is that the amount and quality of data required for these predictive maintenance methods is not readily available in many organizations. The high ambition of many organizations to accurately predict the failures of individual systems in their fleet therefore does not match with the low amount and quality of their data. The latter is often caused by low sampling frequencies and the predominantly manual registrations of failures and operating regimes.

Recognizing this (often present) mismatch is the first step in developing an organization towards smart maintenance. It often triggers organizations to improve their data collection and storage processes. At the same time, modern systems are increasingly equipped with sensors, that rather accurately and automatically collect large amounts of data. Although many of the sensors are not intended for diagnosing a system or even predicting its failures, but for controlling the system (e.g. SCADA systems, PLC's), in some cases they still can be used for smart maintenance purposes. Moreover, where data has traditionally been stored on-board for only days or weeks, thus enabling ad-hoc fault finding, nowadays the value of long term (on-shore) storage is recognized, as it enables reconstructing long usage histories of specific systems or even complete ships.

This paper will present such a case in a maritime application. It will be investigated how the different sensors installed on an installation on-board a ship could be utilized for smart maintenance decision making. In the next section, the theoretical benefits of (time series of) sensor recordings will be discussed. Section 3 then presents a real case study of the sea water cooling pumps in a naval vessel, showing in four different scenarios what kind of

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data is collected and how it can be utilized. Then, in section 4, the results of the case study are discussed and related to the theoretical benefits from section 2. Finally, the conclusions are drawn, and recommendations are provided.

2. Expected benefits of sensor recordings in supporting maintenance decision making

This section will exemplify the expected benefits of sensor recordings in supporting maintenance decision making (Rijsdijk, 2020), (Rijsdijk & Tinga, 2018). As an example, Figure 1 shows the trajectory of the pressure difference over a heat exchanger that predominantly suffers from fouling. When the pressure difference surpasses some predefined limit, the fouling is thought to be excessive and an alarm signal should trigger some cleaning action. In a traditional setting, the operator has only sight on (a short history before) the current sensor recordings and alarms to enhance his situational awareness. Only an extensive history of the executed maintenance tasks is available (typically as work order logs). This paper aims to show that access to an extended history of the sensor recordings enables better decision making. From a theoretical point of view, the recording of (in this case) the pressure difference may be valuable for several reasons.

Firstly, the sensor recordings in Figure 1 enable a better validation of a decision rule, as compared to the situation where only the alarms are available. The sensor recordings straightforwardly show whether an alarm has been ignored or whether cleaning took place prematurely. The alarm demonstrably grounds on some “objectively” observable pressure difference, which provides a fundament for a group of operators / decision makers to agree on whether cleaning is needed or not. If only work order recordings were available, a cleaning action could not be related to an alarming pressure difference afterwards.

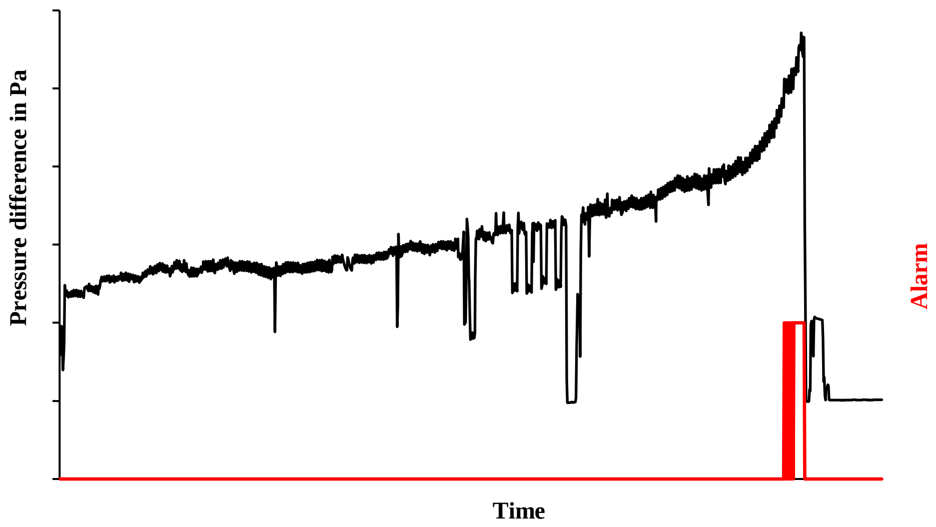

Figure 1: sensor recordings (black) and alarms (red) collected during a single uptime period.

Secondly, the sensor recordings in Figure 1 enable a better prediction of an alarm. It is not bold to assume that time by itself does not cause an alarm. Eventually, an alarm just associates with time. Here, the alarm depends on the pressure difference by definition. Therefore, the evolution of the pressure difference in time is a better predictor for an alarm than just time. Better predictions allow a decision maker to anticipate more adequately. If only work order recordings were available, Figure 1 would only show a single cleaning action which only allows for a point estimate of the time to cleaning.

Thirdly, the sensor recordings in Figure 1 enable the decision maker to learn about the system behavior. The evolution of the pressure difference shows some drift changes and spikes that enable a decision maker to seek (qualitative) explanations. If only work orders were available, potentially interesting information about the system behavior would have remained unknown.

Finally, the sensor recordings in Figure 1 potentially show an immediate response to a specific decision by changes in the evolution of the pressure difference. For example, the observed pressure difference after the cleaning action may indicate the “repair quality”: a pressure difference similar to the value observed for a newly installed system would indicate a high-quality cleaning. If only work order recordings were available, many cleaning intervals might have been needed to identify the effect of a different cleaning method.

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In conclusion, the expected benefits of sensor recordings in maintenance decision making are (*i*) an improved ability to validate decision rules, (*ii*) an improved ability to predict alarms (*iii*) an improved ability to learn about the system behavior and (*iv*) an improved sight on the response to a decision.

3. Case study

This section will identify whether the expected benefits of sensor recordings in maintenance decision making apply to a realistic case study. Firstly, the choice of this case study will be motivated and then a scenario with and without sensor data will be detailed.

This case study is about the sea water cooling pumps that have been installed on several vessels of the Royal Netherlands Navy. The sea water cooling pumps are expected to operate under relatively stable conditions, as the speed of these pumps is not controlled by a frequency converter and sea water cooling pumps are expected to operate as soon as a vessel is sailing. As the operating conditions remain constant, they can be excluded as a cause for potentially observed variations in the sensor recordings.

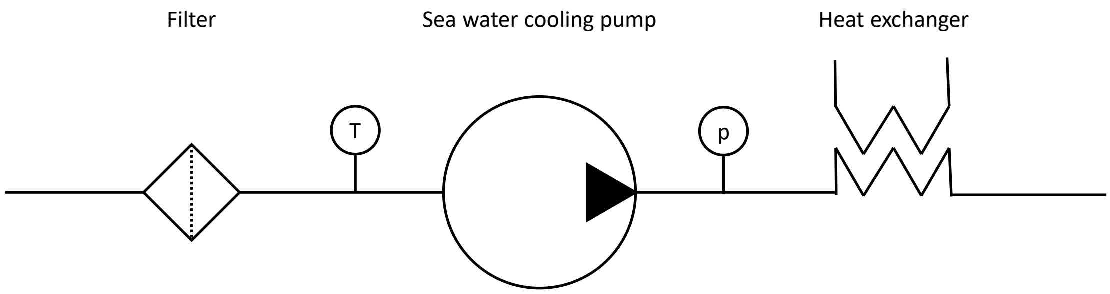

Figure 2: Simplified layout of the sea water cooling system, including sensors measuring the pressure (p) and temperature (T).

Moreover, the sea water cooling system directly transfers its temperature and pressure recordings to the data logger of the platform management system (Figure 2). So, the measurements are not transformed by some controller before they are logged. Further, to apply data driven methods, it is necessary to have a sufficiently large installed base. In this case, the installed base at the Royal Netherlands Navy consists of twelve of these sea water cooling pumps. Finally, the sea water cooling pumps are known to suffer from cavitation. By directing this case study to cavitation, one may expect to actually observe cavitation damage propagation in the (sensor) data.

In conclusion, the sea water cooling system has been selected because (*i*) the operating conditions are not expected to cause drifts in the sensor recordings, (*ii*) the sensor recordings are not transformed by some local control unit, (*iii*) the installed base enables a comparison of several pump configurations and (*iv*) a dominant failure mechanism is present. So, the idea is to start with a simple case based on CMMS data, and then compare this to three cases in which sensor data is utilized: 1. focusing on cavitation detection, 2. focusing on reliability prediction and 3. identifying the benefits of additional sensors.

3.1. Scenario CMMS

This subsection will present the scenario that does not involve sensor recordings, but in which recordings from the computerized maintenance management system (CMMS) are available. The CMMS records notifications (i.e. failures) and maintenance actions. Let's depart from a plot of the four notifications, each involving three impellers from the installed base of the twelve sea water cooling pumps (Figure 3). So, each of these pumps had an impeller replacement or refurbishment within three to five years. One may presume that these notifications arrived randomly in time, implying that the data in Figure 3 have been produced by a homogenous Poisson process. A homogenous Poisson process implies that the number of arrivals k_i at a discrete time interval *i* is a trial from a Poisson distribution. So, the likelihood of a history of *t* of these discrete time intervals *i* is given by:

$$Pr\left(\bigcap_{i=1}^{t} K_i = k_i \,|HPP(\lambda)\right) = \prod_{i=1}^{t} \frac{\lambda^{k_i}}{k_i} e^{-\lambda} \tag{1}$$

Then, the maximum likelihood estimation of the Poisson parameter λ (i.e. the failure rate) is for this specific case given by:

$$\frac{\sum_{i=1}^{t} k_i}{t} = \frac{12}{1517} = 0{,}0079\ days^{-1} \tag{3}$$

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The 90% acceptance region in Figure 3 shows the 5% upper bound and the 5% lower bound of the number of arrivals of impeller notifications, given the homogenous Poisson process. Figure 3 shows that one of the observed arrivals is located outside the 90% acceptance region. This implies that the homogenous Poisson process is (just) refuted by the observed arrivals of impeller notifications, which requires an explanation. As time is merely an associated variable rather than the cause of damage, this explanation is not in Figure 3. In this discussion, we delimit to the expert knowledge that has been recorded in the CMMS.

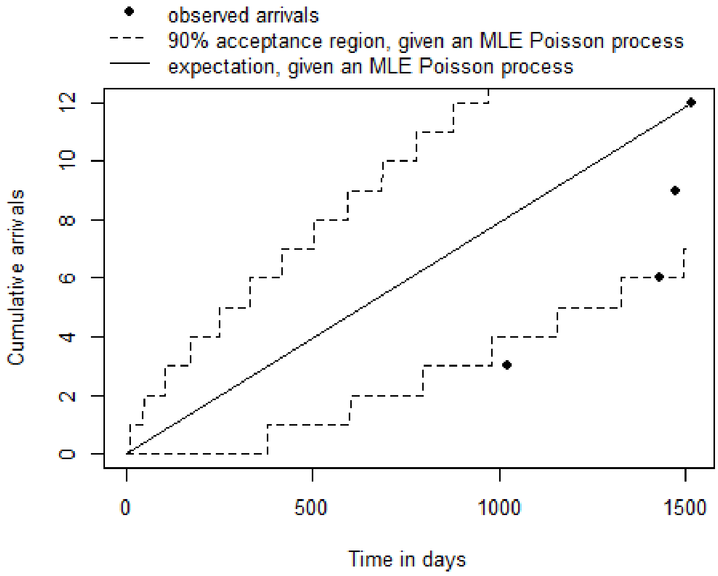

Figure 3: Arrivals of impeller failures in time (solid points) and expected failures (line + confidence bounds) when assuming a homogeneous Poisson process.

Table 1 shows an anonymized extract from the CMMS to illustrate some issues. It firstly reveals that none of the notifications has been entered as a real failure implying outage of the sea water cooling system, but all are (preventive) refurbishments. And secondly, each vessel had the impellers on all its three pump locations replaced at the same time. In fact, the arrivals of these notifications have been driven by a schedule and not by a homogenous Poisson process. The scatter in time just originates from staggering and the opportunity to do the jobs. The homogenous Poisson process in Figure 3 should therefore not be used to predict impeller failures due to cavitation.

Table 1 Anonymized extract from the CMMS

Notification type	**Description**	**Location**	**Bill of materials**
Refurbishment	Refurbish valves	Vessel A	3 impellers+…
Refurbishment	Replace impellers	Vessel B sea water cooling	3 impellers+…
Refurbishment	Replace pumps	Vessel C	3 impellers+…
Refurbishment	Refurbish pumps	Vessel D	3 impellers+…

Another issue is that the job descriptions in Table 1 are not evidently referring to impeller replacements or refurbishments. It is just due to the bill of materials that they have been identified as such. Generally, CMMS recordings are prone to human factors and they are hard to connect to an observable reality afterwards. Therefore, it is not clear to what extent the events in Figure 3 refer to an impeller reliability problem.

Finally, the description of the location in Table 1 just refers to a vessel rather than to a specific pump location on that vessel. Differences in impeller cavitation damage at the various pump locations have not been recorded. Evidently, this will severely delimit the possibility to associate observed impeller cavitation damage with sensor recordings from a specific pump location.

In conclusion, the scenario CMMS failed to even detect the magnitude of the cavitation damage problem, let alone that it could be predicted. The scenario CMMS provided human entered recordings of notifications that were not self-evident. A prediction from a distribution of the arrivals appeared to be problematic because (*i*) the notifications were in fact scheduled and (*ii*) the notifications failed to provide any insight into the impeller

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cavitation damage at a specific pump location. So, the scenario CMMS only gave account of some replacements and refurbishments at a vessel and *not* of the health of the impellers involved.

3.2. Scenario sensor data

This subsection will present the scenario that involves sensor data originating from the platform management system of the vessel. Note that the sensors have not been installed with the objective of health monitoring. The sea water cooling system (Figure 2) only has a temperature sensor for the inflowing sea water and a pressure measurement at the discharge flange. In this case, focusing on cavitation, the temperature of the inflowing sea water will not be involved as it will not rise beyond the permissible 32ºC.

Let's depart from the typical evolution of the static pressure at the discharge flange for one year (Figure 4). The static pressure at the discharge flange evolves non-stationarily and it heavily oscillates after day 278. The latter has been explained by a vessel mooring. As the main engines are off then, less cooling capacity is needed, and the sea water cooling pumps automatically start "on demand".

Evidently, the static pressure at the suction flange would have been a more adequate cavitation indicator, as a low suction pressure is the main cause of cavitation. However, since this quantity is not measured, *the range* of the static pressure at the discharge flange will be used as a suboptimal 'cavitation indicator' in this case.

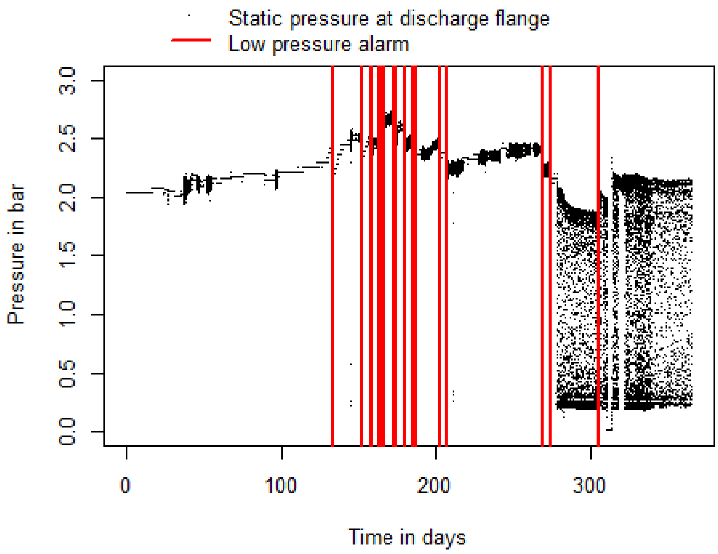

Figure 4: Evolution of the static pressure at the discharge flange.

The static pressure at the discharge flange in Figure 4 ranges from 2,0 bar to 2,7 bar when the vessel is sailing (day 1 – 278), whereas the static pressure at the inlet of the sea water can safely assumed to be rather constant. Although, the pump head (h) during operation is unknown, its *range* (Δh) may be estimated from the variation in the discharge pressure (Δp, in Pa), the sea water density (ρ, in kg/m^3) and the gravitational constant g (m/s^2) by (Karassik, Messina, Cooper, & Heald, 2001):

$$\Delta h = \frac{\Delta p}{\rho \times g} = \frac{70000}{1025 \times 9{,}81} = 6{,}96m \tag{5}$$

Plotting this range of 6,96m on the pump characteristic in Figure 5, either ±3,5 m around the Best Efficiency Point – BEP, or up to 7 m above or below the BEP, reveals that this sea water cooling pump might well have drifted quite far away from its Best Efficiency Point (BEP). Possibly, this explains the cavitation.

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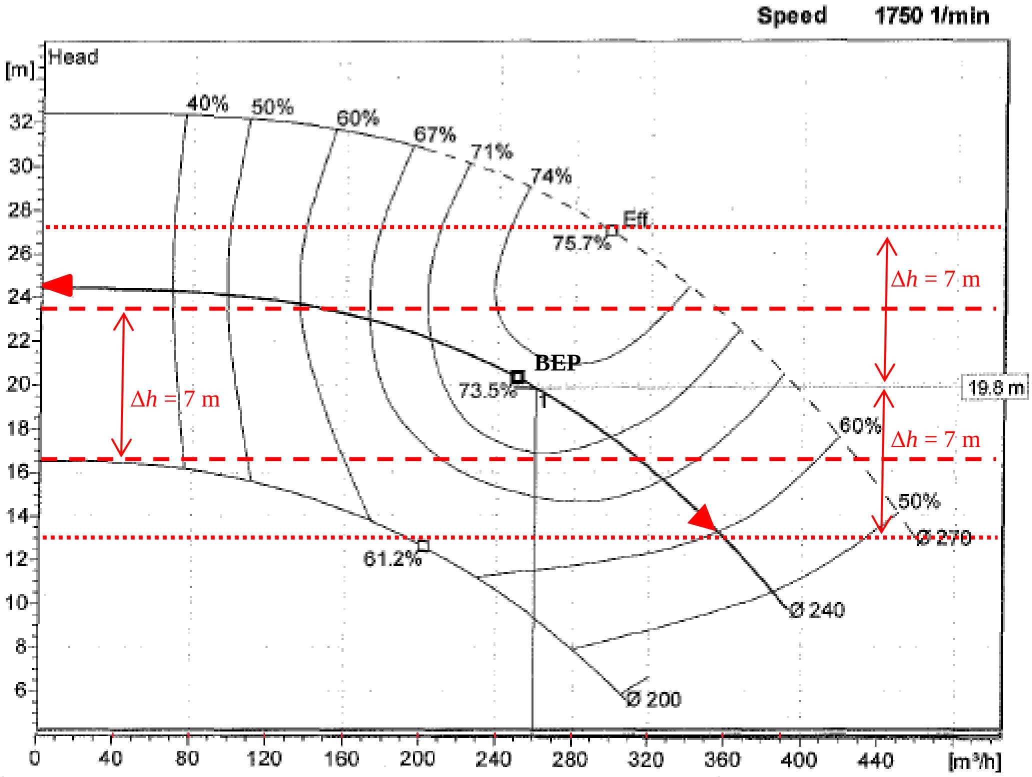

Figure 5: Characteristic of the sea water cooling pump, showing the potential deviations from the BEP.

Figure 4 also shows a low-pressure alarm that has consistently been triggered when the static pressure at the discharge flange dropped below 1,5 bar. This alarm is inactive during the mooring regime. More importantly, the static pressure at the discharge flange is discontinuous after each alarm in Figure 4. The suspicion here is that these alarms are triggered by crew actions like filter or heat exchanger cleanings. Unfortunately, these actions have not been recorded in the CMMS to verify this suspicion.

To summarize, the scenario “sensor data” also failed to directly detect the cavitation at the sea water cooling pumps. A suboptimal ‘cavitation indicator’ revealed some non-stationarities that might, but not necessarily do, relate to the cavitation. Although this suboptimal cavitation indicator is available at each pump location, the actual severity of the cavitation is unavailable. Therefore, it remains impossible to associate these quantities in a predictive model. Each jump in the suboptimal cavitation indicator is suspected to coincide with a crew action, but the CMMS does not provide any records to confirm this suspicion. In conclusion, the scenario “sensor data” shows potential for each of the four benefits suggested in section 2, i.e. (*i*) an improved ability to validate decision rules, (*ii*) an improved ability to predict alarms (*iii*) an improved ability to learn about the system behavior (*iv*) an improved sight on the response to a decision. However, the limited number of sensors (only discharge pressure, no suction pressure or flow) and the lack of registration of cavitation events and maintenance activities does not allow to prove or demonstrate this with the present data. However, the analysis has revealed which information / data should be collected to harvest the potential benefits.

3.3. Scenario reliability estimation

In the previous two sections, the aim was to directly detect or predict the occurrence of a cavitation failure, both with CMMS data (3.1) and sensor data (3.2). Yet another approach would be to use methods from handbooks to estimate the pump reliability or probability of cavitation-related failures. For a centrifugal pump, the failure rate can be expressed as a combination of the failure rates of the different components in the pump (NSWC, 2011):

$$\lambda_p = \lambda_{se} + \lambda_{sh} + \lambda_{be} + \lambda_{ca} + \lambda_{fd} \tag{6}$$

where the individual failure rates relate to the seals (*se*), shaft (*sh*), bearing (*be*), casing (*ca*) and fluid driver (*fd*). As cavitation is mainly affecting the impeller (i.e. fluid driver), this component will be focused on in this paper. The impeller failure rate has a basic value ($\lambda_{fd,b}$), which is affected by several operational factors, like % flow (*pf*),

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operating speed (*ps*), contaminants (*c*) and service factor (*sf*). This is represented by the following multiplication factors:

$$\lambda_{fd} = \lambda_{fd,b} C_{pf} C_{ps} C_c C_{sf} \tag{7}$$

Finally, the different multiplication factors can be related to the operational conditions of the pump. For cavitation, the percentage flow factor is the most relevant, so that factor will be examined here:

$$\begin{aligned}
&0.1 \le Q/Q_r \le 1.0: && C_{PF} = 9.94 - 0.90\left(\frac{Q}{Q_r}\right) - 10\left(\frac{Q}{Q_r}\right)^2 + 1.77\left(\frac{Q}{Q_r}\right)^3 \\
&1.0 \le Q/Q_r \le 1.1: && C_{PF} = 1 \\
&1.1 \le Q/Q_r \le 1.7: && C_{PF} = -30.6 + 36\left(\frac{Q}{Q_r}\right) - 4.5\left(\frac{Q}{Q_r}\right)^2 - 2.2\left(\frac{Q}{Q_r}\right)^3
\end{aligned} \tag{8}$$

where Q is the actual operating flow and Q_r the maximum pump specified (i.e. BEP) flow. This shows that a flow that is deviating considerably from Q_r yields a high failure rate multiplication factor.

To quantify these numbers, the actual flow in the pump (Q) is required. In the considered case of the sea water cooling pump, this quantity is not measured directly. The flow could also be derived using the pump characteristic (Fig. 5), as it is directly related to the total head of the pump. However, in this case only the discharge head (i.e. discharge pressure) is measured, while the total head in Fig. 5 is the *difference* between suction and discharge head (or pressure). Without a measured suction pressure, this total head, and the associated flow, can thus not be accurately determined. For some pump configurations, it could be assumed that the suction head is constant over time and the discharge head is not affected by variations in upstream resistances. In that case the (measured) discharge head directly reflects the variations in the flow. But again, that does not hold in this cooling water pump case: the suction pressure is affected by the filter in the inlet section of the system, while the discharge pressure is affected by the resistance of the heat exchanger connected to the outlet of the pump.

To conclude, the situation in which only the discharge pressure is measured does not allow to determine, or even estimate, the flow, and thus also makes the reliability or failure rate calculation infeasible. This can only be solved by adding at least one measurement / sensor to the system, as will be discussed in the final scenario.

3.4. Future scenario with additional sensors

The final scenario that is considered is based on the planned installation of additional sensors in the ship. For the sea cooling water system, this implies that both a flow sensor and a pressure sensor at the suction flange of the pump will be installed, as well as two temperature sensors (suction and discharge side). Especially the flow and pressure sensors will be useful additions, as the pump flow and suction pressure appeared to be essential missing parameters in the previous subsections.

To demonstrate the benefits of these additional sensors, some calculations have already been done with the present data. With the measured suction pressure, a much more reliable cavitation indicator would be available. As the suction pressure directly affects the occurrence of cavitation, setting an alarm at a critical lower threshold of this pressure will be easy to implement. The value of this threshold can be the *net positive suction head* (NPSH) that is provided by the pump manufacturer as the minimal required suction head to prevent cavitation, see Figure 6.

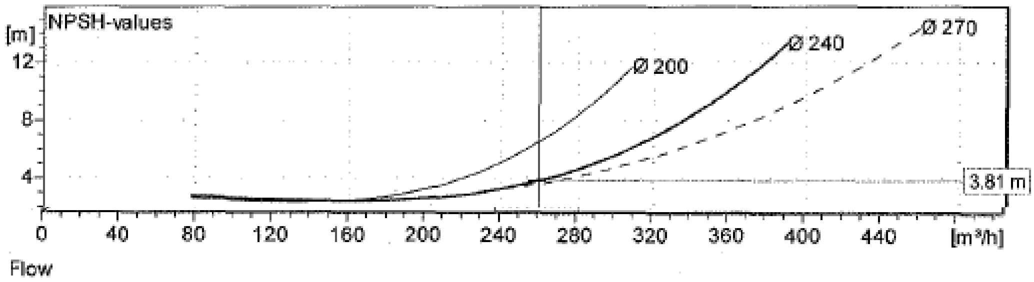

Figure 6: Net positive suction head at different flow values.

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This alarm can even be incorporated as a function of the (measured) flow, by using the curve in Figure 6. Further, the measured suction pressure can also be used to calculate the total head of the pump at any moment, and with the measured flow, the pump characteristic (Figure 5) can be verified.

Another benefit is that the measured magnitude of the flow can be used in equation (8) to calculate the percentage flow factor C_{pf} to estimate the effect of changes in the pump operating conditions on the failure rate. To illustrate this, it is assumed for the present sea cooling water pump that the suction head is constant and equal to zero (this would in reality lead to cavitation, but is now a convenient assumption to demonstrate the process). In that case the total head equals the discharge head, which means that the flow at each moment in time can be derived from the measured discharge pressure using the pump characteristic (Figure 5). The pressure history from Figure 4 then yields the distribution of pump operating points shown in Figure 7. The best efficiency point (BEP) at 260 m^3/h nicely coincides with the high density region of the distribution.

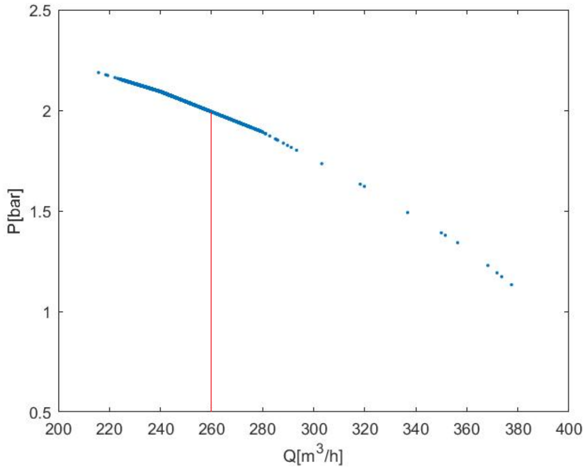

Figure 7: Observed variation of the measured discharge pressure and the pump flow (estimated from pressure).

The next step in the procedure is then to use these flow values in equation (8) to calculate the percentage flow multiplication factor for each moment in time. The results are shown in Figure 8, revealing that the measured variation in discharge pressure yields a considerable variation in the multiplication factor. This implies that the failure rate will deviate from (i.e. will be higher than) the basic failure rate, but the exact variation of the pressure will determine the precise value. Note that the absolute values in this case are not representative, as not the actual flow, but the estimated flow (Figure 7) with a unrealistic assumption is used. However, the plots do demonstrate that in the planned situation with additional sensors, the percentage flow multiplication factor can easily be quantified.

To conclude, the addition of two additional sensors to the system, i.e. a flow and pressure sensor at the suction side, will largely increase the possibilities to detect cavitation events in the pump, as well as predicting cavitation related failures. Also, the other expected benefits of using sensor data, i.e. validating decision rules, understanding system behavior and checking the response to a decision are expected to become available.

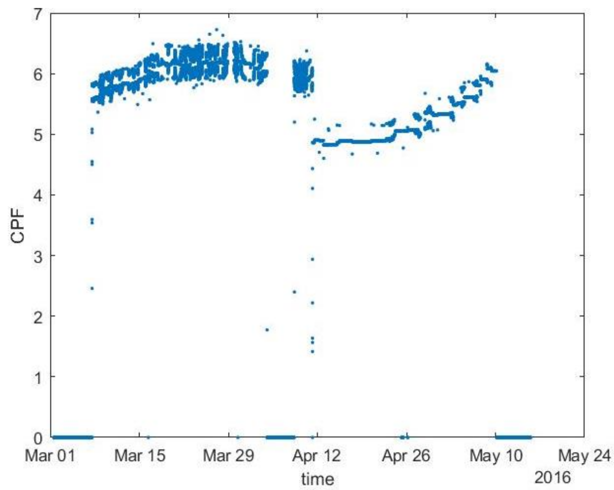

Figure 8: Variation of the percentage flow multiplication factor (CPF) over time.

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4. Discussion

This section will evaluate to what extent the expected advantages of sensor recordings from section 2 applied to the case study from section 3. Section 2 mentioned that sensor recordings improve:

- The ability to validate *decision rules*,
- The ability to *predict* alarms,
- The ability to learn about the *system behavior*,
- Sight on the *response* to a decision.

The case study lacked a *decision rule* to prevent or to recover cavitation. The decision to replace or to refurbish all impellers in this case study cannot be underpinned by a surpassing of some threshold value. The sensor recordings in this case study neither provided this threshold value as they could not indicate cavitation damage. However, the planned additional sensors, particularly the suction pressure sensor, will enable to set such an alarm based on the NPSH.

The case study failed to *predict* cavitation. The application of the homogenous Poisson process in Figure 3 appeared to be problematic as the arrivals were scheduled and the magnitude of the cavitation has not been documented in each case. The sensor recordings in this case also could not represent cavitation, let alone predict it. As mentioned before, future recordings of the static pressure at the suction flange will enable cavitation detection, but predicting cavitation might still be difficult due to the sudden occurrence of cavitation-prone operating conditions. However, prediction of cavitation-related impeller failures might be feasible with the additional sensors, as the handbook models enable to quantify the effects of changing operational conditions, especially the flow.

The sensor recordings in the case study provided a more refined view on the *system behavior*. The CMMS scenario only gave account of the fact that the impellers of the sea water cooling system had been subject to action. The sensor recordings at least gave some sight on the load history at each individual pump location and it showed a variety of discontinuities that require an explanation. Addition of more sensors to the system will allow even more detailed insights in the system behavior, as important parameters like total head and flow are fully known then.

The sensor recordings in the case study did not show a *faster response* to any decision to prevent or to recover cavitation, simply because the case study lacked an indicator for cavitation. Future additional sensors will enable the detection of cavitation, and therefore will also allow a faster response to such a situation.

In conclusion, the case study in its present form did not yet yield the expected benefits from sensor recordings, mainly because it lacked an indicator for the cavitation damage. As soon as the static pressure at the suction flange becomes available in the future, a *decision rule* to prevent cavitation straightforwardly follows from comparing the available net positive suction head (NPSH) with the required NPSH and the *response* to these precautions will also be straightforwardly visible. To validate the *decision rule* and to *predict* the cavitation damage, it is essential to keep directly track on the cavitation damage propagation or, indirectly, on the accumulated time in a cavitation-prone operating condition, preferably corrected for the various operating conditions (i.e. with influence factors).

The CMMS recordings are important to provide sight on the actions. This case revealed some data quality issues that hamper the inference and validation of predictive models. Experiments with on-site recordings via a handheld application appeared to be an important contributor to an improved data quality in other cases.

The current sensors have only been installed to control the sea water cooling system and not to monitor its health. As was mentioned in the future scenario (3.4), additional sensors for health monitoring will be introduced soon, in close collaboration with the original equipment manufacturer. The choice of these sensors has in this case been based on operating experience and the predominant failure mechanisms (NSWC, 2011). This case is just another example where the organization's ambition regarding smart maintenance is constrained by the amount and the quality of the data (Tiddens, Braaksma, & Tinga, 2015).

The insights gained on this specific case study could be generalized to other and maybe more complex cases. The common feeling that more data always leads to better decisions appears to be false: only *relevant* and *high quality* data potentially improves the decision making. This means that in most cases domain and system knowledge is strictly necessary to select the proper parameters and sensors. Moreover, as in more complex systems not all individual components can be monitored and analyzed, again thorough domain knowledge and operating experience must be utilized to select those critical components that dominate the system service life.

5. Conclusion

This paper has discussed the use of time series of ship sensor data for the purpose of smart maintenance. From a theoretical point of view, four potential benefits for maintenance decision making are identified:

- improved ability to validate decision rules,

- improved ability to predict alarms,
- improved ability to learn about the system behavior,
- improved sight on the response to a decision.

A realistic case study on a naval ship sea cooling water system has been used to identify whether these potential benefits can be obtained in practice. After studying four scenarios with increasing amounts of sensor data, the main conclusions are:

- registrations in the computerized maintenance management system (CMMS) are typically insufficient to detect or predict failures or to validate maintenance decisions;
- the number and type of sensors typically installed in maritime systems (for control and safety purposes) does not directly allow detection or prediction of failures or validation of maintenance decisions. However, the time series do reveal special situations or conditions, which after further investigation could lead to improved insights in system behavior or response to maintenance decisions;
- based on domain knowledge, regarding both system and failure behavior, the selection of some relevant additional sensors is rather easy. A small number of these additional sensors will typically allow detection or even prediction of failures and will enable validation of decision rules and speed-up responses;

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