Degradation Modelling of Centrifugal Pumps as Input to Predictive Maintenance

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The current development in sensor technology combined with improvements in systems for collecting, storing and analyzing large amounts of data, often associated with the term Industry 4.0, offers the opportunity to identify a larger proportion of faults before they turn into failures. A more proactive maintenance strategy has the potential to reduce maintenance costs by allowing maintenance organizations to focus resources on the right equipment at the right time, and to improve safety and availability by reducing the level of unplanned corrective maintenance. This paper explores the possibilities for predictive maintenance on a set of centrifugal pumps used at an offshore oil platform. As a basis for the analysis, sensor data and maintenance records for 15 centrifugal pumps collected over a period of four years is used. The data is split into a training and a test dataset. Causal tree diagnostic modelling is used to establish the link between failure mode and symptoms for one selected fault, impeller damage. Remaining useful life predictions (RUL) for impeller damage is developed based on a stochastic approach. The paper ends with a discussion of how the insights from the analysis can be used to improve maintenance performance.

Keywords: Degradation modelling, oil and gas industry, prognostics, Industry 4.0, predictive maintenance, causal tree diagnostic modelling, RUL, centrifugal pumps.

1. Introduction

In this paper the possibilities for predictive maintenance based on data from online monitoring is explored on a set of fixed speed centrifugal pumps installed on an offshore oil platform. The oil platform in question has an extensive system for online monitoring and is because of this considered as a good candidate for trying to apply predictive maintenance in practice.

In the next section of this paper theory related to Industry 4.0 and predictive maintenance is presented. In section three the example used in this paper is presented, followed by the result in section four. The paper ends with a discussion and conclusion in section five and six.

2. Industry 4.0 and Predictive Maintenance

2.1 *Industry 4.0*

The recent development in sensor technology and systems for collecting, storing and analyzing large amounts of data has the potential to bring big changes across business functions and industry sectors (Porter and Heppelmann 2015). When it comes to maintenance in the era of Industry 4.0, it is often predictive maintenance (PdM) that is highlighted as an application that can have a big impact (STAUFEN.AG 2019).

The falling cost of online monitoring has made it possible to monitor not only a handful of carefully selected critical equipment, but to monitor parameters throughout the whole process (Schuh et al. 2017, 16). In the offshore oil and gas industry this is an important technology in order to make remote-operated, unmanned production facilities possible. This can bring considerable savings in operating cost, but also in capital cost because platforms without living quarters can be made simpler and lighter, compared to manned installation (Offshore-technology 2019).

The disadvantage with unmanned platforms is that it will take longer time and cost more to mobilize for active maintenance. This calls for predictive maintenance in order to keep the number of visits to the platform at a minimum while at the same time obtaining acceptable availability.

2.2 *Predictive maintenance (PdM)*

PdM is in CEN 13306:2017 defined as "condition-based maintenance carried out following a forecast derived from repeated analysis or known characteristics and evaluation

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of the significant parameters of the degradation of the item" (CEN 2017).

Prognostics is a corresponding term that is used in the ISO standards, and is defined as "analysis of the symptoms of faults to predict future condition and residual life within design parameters" (ISO 2012b).

According to ISO 13381-1:2015 "The goal of prognostics is to provide the user with the capability to predict remaining useful life (RUL) with a satisfactory level of confidence" (ISO 2015,4). RUL is in the same standard defined as "remaining time before system health falls below a defined failure threshold".

The terms fault and failure will in this paper be used in line with ISO 13372:2012. Fault is in this standard defined as the "condition of a machine that occurs when one of its components or assemblies degrades or exhibits abnormal behavior, which may lead to the failure of the machine". While failure is defined as "termination of the ability of an item to perform a required function" (ISO 2012b). However, in practice often machines are shut down at a more conservative level than the level where failure is expected to occur, in order to avoid the hazards often associated with failures. This level will then be the defined failure threshold (ISO 2015, 7).

PdM can offer value compared with a more traditional CBM approach where one wait for measured condition to reach a defined level before active maintenance is executed. This is because PdM with RUL-predictions allow for longer mobilization times for spares and maintenance. This can bring considerable savings in remote locations like offshore oil platforms. Another advantage is that it can allow for grouping of maintenance jobs in a way that improve both availability and maintenance cost.

But for predictive maintenance to be possible one need a good overview of the relevant failure modes and one must have the capability to observe the progression of these failure modes. In addition, the rate of degradation or the PF-interval must have a level of consistency so that predictions can be made with a reasonable level of accuracy (ISO 2015).

Failure mode is here understood as the "observable manifestation of a system fault" (ISO 2012b) and PF-interval is the time from a fault is observable to failure occur (Rausand and Høyland 2004, 395).

2.3 *Failure modelling*

In order to make a RUL-prediction a model of the degradation until failure has to be made. According to ISO 13381-1:2015, failure modeling can be grouped into five different approaches: physics-based; statistical (or stochastic); heuristic (or knowledge based); data-driven; or hybrid modeling, which is a combination of the approaches above (ISO 2015,19).

In this paper a stochastic approach will be used to estimate the RUL.

3. Example from an Offshore Oil Platform

All the data in this section is collected from an offshore oil platform located on the Norwegian Continental Shelf (NCS).

The oil platform is continuously manned with internal maintenance personnel that are responsible for the daily maintenance, while contracted personnel and specialist are used for overhauls and modifications. A technical support organization located onshore supports the offshore organization with maintenance planning and advise.

There is a total of 22 fixed speed centrifugal pumps installed at the platform. Seven of the pumps have however seen very little use (less than one month) and have been excluded from further study.

For the 15 remaining pumps, sensor data from the four first years of production has been collected together with the maintenance records.

For the sensor data only one data point has been collected for each day (at 00:00:00). This has been considered as a high enough sampling rate for this application.

The data has been split into two datasets where the first three years has been labeled as the training dataset. This dataset has then been explored for possible faults where predictive maintenance can be used. The remaining one year of data has been labeled the test dataset. This dataset has been saved for validation of possible findings from the training dataset.

14 of the pumps are set up with two pumps in parallel, but only one pump running at the time. The remaining 15th pump has no redundancy. All pumps have sensors that measure pressure before and after the pump in addition to flow. Some of the pumps are fitted with additional sensors like temperature sensors. In total data from 123 sensors that monitor different aspects related to

the operation condition and performance of the 15 pumps has been collected.

To assist in the monitoring of the health of the pumps an asset monitoring software is used to present the sensor readings to the maintenance personnel. In addition, several health indicators are calculated as well. Among these are: Net Positive Suction Head deviation (NPSHd), pump efficiency and head deviation.

A set of symptoms of faults are defined for the pumps and warning, and alarm limits are set for all these symptoms.

3.1 *Maintenance records*

The maintenance records for the 15 pumps contains 248 corrective maintenance (CM) and preventive maintenance (PM) workorders in the time period of the training dataset. 21 of these workorders are corrective maintenance according to CEN 13306:2017 definition ("maintenance carried out after fault recognition and intended to restore an item into a state in which it can perform a required function") (CEN 2017). Workorders not related to active maintenance on physical parts (like software changes) has been excluded.

Grouped by the fault that caused the workorder to be initiated the list look like this:

- Damaged seals (10)
- Bearing damage (3)
- Oil leakage (3)
- Impeller damage (2)
- External shock (2)
- Sealing medium leakage (1)

Some of the faults in this list are clearly not possible to predict given the available data. One example is faults caused by external shock, where one of the workorders for instance was caused by someone stepping on a delicate part of the pump. Another is the category "bearing damage" given that vibration monitoring, or data from other sensors directed at bearings not have been collected.

The faults labelled oil leakage and sealing medium leakage has all been discovered by visual inspection before the faults have shown up in the sensor data. Visual inspection has also been used to discover nine of the ten instances of damaged seals. One of the instances of damaged seals was however discovered by online condition monitoring, but the time from observable fault to failure was only three days. For faults with this short PF-interval, predictive maintenance offers little practical advantage over CBM.

This leaves only the faults related to impeller damage as a good candidate for predictive maintenance in this dataset.

3.2 *Impeller damage*

The remainder of this section will focus on impeller damage.

To get a better understanding of this fault a causal three diagnostic model has been made. See figure 1 below.

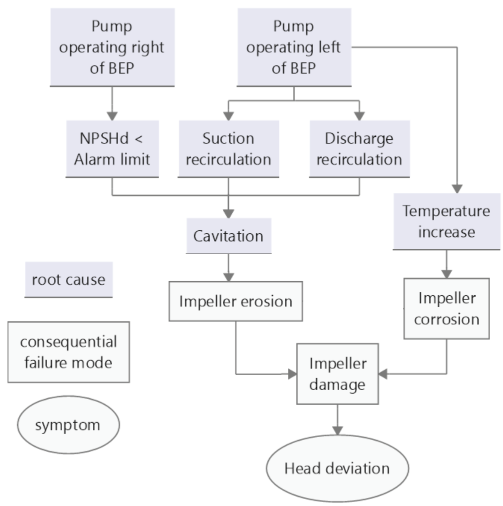

Fig. 1. Causal three diagnostic model based on (ISO 2012a). The causal links from root cause to symptom are based on Karassik and McGuire (1998). BEP = Best Efficiency Point. NPSHd = Net Positive Suction Head deviation.

From figure 1 one can see that head deviation is a symptom that one can expect as a result of the selected fault. Head deviation is here defined as:

$$Head_{dev} = \frac{100 * (Head_e - Head_a)}{Head_e} \qquad (1)$$

The expected value of the head ($Head_e$) is based on the head-flow curve provided by the pump manufacturer. The value of the actual head ($Head_a$) is calculated based on the measured pressure before and after the pump. This is then converted into head based on the specific gravity of the pumping medium and adjusted based on coefficients for the system friction. These coefficients have been provided by the operator of the oil platform.

Both the two instances of impeller damage listed above are from two pumps that are installed in parallel and perform the same function. These pumps will be called the A and B pump. In addition, there is a third workorder (at the B pump), that was initiated because of an oil leakage, where a new impeller has been installed in the training data time period. Figure 2 a and b below shows the trend of the head deviation.

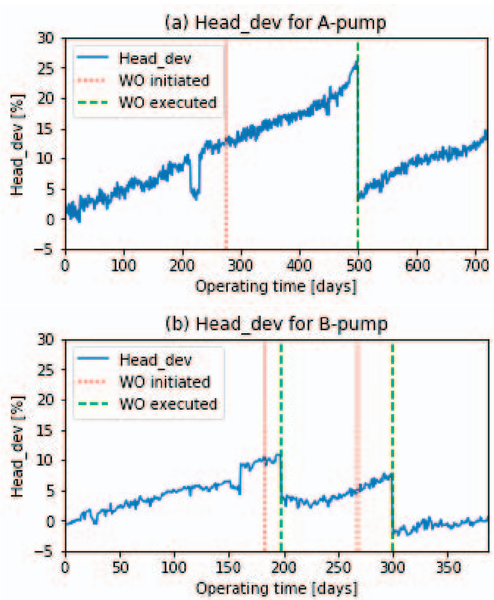

Fig. 2 a and b. The two figures above show how the degradation develop over time for the two pumps.

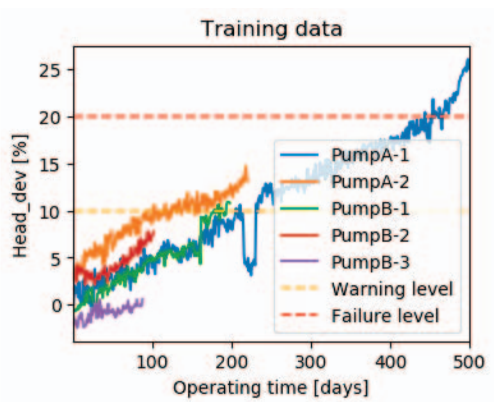

Fig. 3. The separate degradation paths in the training data split into separate lines. The dashed lines indicate the warning level of degradation and the defined failure threshold set by the operator of the oil platform.

In figure 3 one can see that the head deviation starts at different levels for the different degradation paths. This is most likely because not all the parts that has been subject to wear, like for instance impeller casing, has been replaced in the repairs.

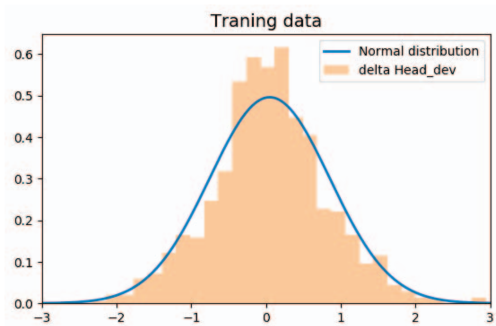

Fig 4. The change in head deviation from one sample to the next compared to the normal distribution.

The histogram in figure 4 show the change in head deviation from one sample to the next ($\Delta head_{dev}$). The mean is 0.049 and standard deviation is 0.804. The histogram appears similar to the normal distribution. However, based on D'Agostino's K-squared test the null hypothesis that the sample comes from a normal distribution is rejected with p-value $3*10^{-38}$.

Below in figure 5 is a plot of the test data. We will only use the degradation path that goes past the warning level in our testing.

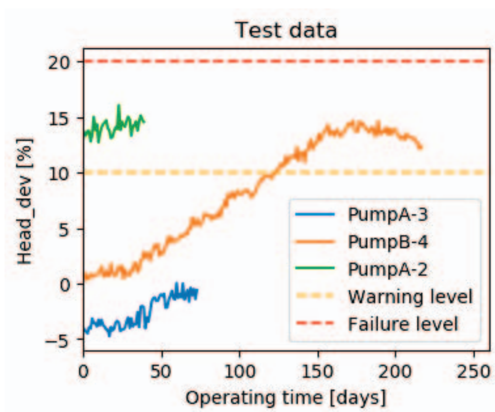

Fig. 5. The test data.

4. Prognosis for Impeller Damage

Based on the trend in head deviation and the fact that the pumps are running at flow of only 20 to

30 % of BEP the diagnostic model in figure 1 indicate that the pumps are subject to cavitation.

Closer inspection of one of the impellers removed from the pumps show damage to the outside of the impeller vanes and on the inside of the impeller inlet. Something that reinforces the assumption that the root cause of the impeller erosion is discharge and suction recirculation (Karassik and McGuire 1998,567).

After the diagnosis the next step in prognostics is to make a RUL-prediction.

4.1 *Predicting remaining useful life (RUL)*

In this section a stochastic approach based on the Inverse Gaussian distribution (IG) is used to predict RUL.

IG is a probability distribution that can be used to model the first passage time of a Wiener process. For a process to be a Wiener process each increment has to be independent and the difference between each consecutive step has to be normally distributed (Chhikara and Folks 1989, 23).

As shown in the previous section the requirement of normal distribution is not fulfilled in this example. But according to Chhikara and Folks: "[a]lthoug it is appealing to base the use of the IG distribution upon an underlying Wiener process, it is not at all critical". They make a comparison with the normal distribution which has become "acceptable to use (…) to describe all sorts of data" and that "[t]he situation with the IG distribution seems to be similar" (Chhikara and Folks 1989, 159-160).

We then formulate the degradation process as a Wiener process in line with Zhang et al. (2018):

$$X(t) = x_0 + vt + \sigma B(t) \quad (2)$$

Where x_0 is the level of degradation at $t = 0$, v is the drift parameter and σ is the diffusion coefficient. Further on x_t is the level of degradation at time t and T is the first passage time of the failure threshold (L).

Because we have no degradation path in the test dataset that goes all the way to the failure threshold (20%), we will instead use the 10% warning level as our L when predicting the RUL in this paper.

Next we assume that T can be modelled by the Inverse Gaussian (IG) distribution with mean μ and shape λ (Rausand and Høyland 2004,p 50):

$$T \sim IG(\mu_t, \lambda_t) \quad (3)$$

Where $\mu_t = (L - x_t)/v$ and $\lambda_t = (L - x_t)^2/\sigma^2$.

In order to validate how well the IG distribution fits our data we have done a Monte Carlo (MC) simulation with 10^4 runs. The MC has been done by drawing random samples of Δx_t from the training dataset and counting the number of draws until $\sum \Delta x_t \geq L$.

In figure 6 a and b below the Probability Density Function (PDF) and Cumulative Density Function (CDF) of the IG distribution is compared with histograms based on the MC simulation. The MC simulation seems to fit reasonably well with the IG distribution. Something that reinforces the assumption that the IG distribution can be used in this case.

However, one weakness of using the MC simulation for validation in this case is that both the MC simulation and the IG distribution have the assumption that the degradation is happening in independent steps.

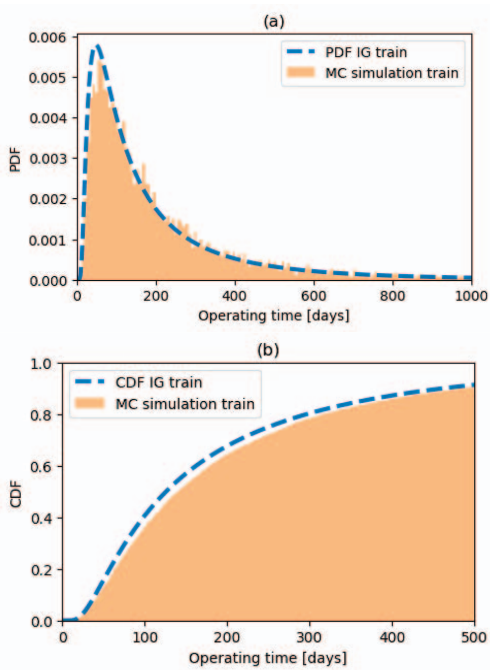

Fig. 6 a and b. Comparison of the PDF of the IG distribution (dashed line) and the MC simulation (histogram). Both are based on the training dataset.

The average RUL in the training data, and expected value based on the IG (E[T]) is 206 days. But based on the CDF of our IG-model, at this time the pump will already have failed in 69 % of the cases.

Because the cost associated with doing maintenance to late is often much higher than the other way around a more conservative measurement for the RUL prediction will normally be sensible to use.

This can be optimized if one knows the expected cost of PM and CM. But because we don't have access to this data, we have chosen the 10th percentile when estimating RUL. We then get RUL(IG,10) = 40 days at $x_0 = 0$.

The corresponding RUL based on the MC is RUL(MC,10) = 44 days, a 10% deviation against the IG.

4.2 *RUL prediction based on training data*

In the first approach for predicting RUL (RULtrain) we assume that v and σ are constant, and the parameters for Wiener process will be based on the training data ($v_{train} = \overline{\Delta x_{train}}$ and $\sigma_{train} = s_{\Delta x(train)}$).

Next we calculate the parameters for the IG: $\mu_t = (L - x_t)/v_{train}$ and $\lambda_t = (L - x_t)^2/\sigma^2_{train}$.

In figure 7 it is visualized how RULtrain at the median and 10th percentile perform against the actual RUL (RULa) as the degradation approaches L. RULa for the one degradation path that reaches 10% deviation in the test dataset is 121 days with $x_0 = 0{,}33$.

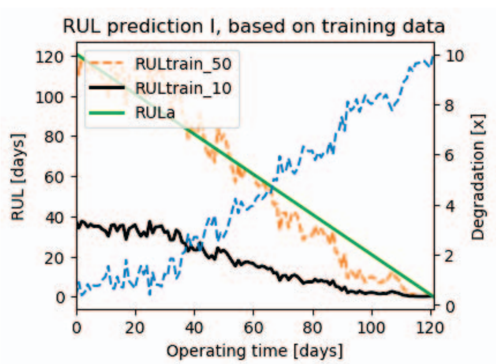

Fig. 7. Predicted RUL at the 10th percentile and median (RULtrain_10 and RULtrain_50) compared to the actual RUL (RULa), as RULa goes to 0 in the test degradation path. The degradation path is shown on the right y-axis.

As one can see from the plot in figure 7 the median RUL prediction (RULtrain_50) is within +/- 20 days of RULa throughout the degradation path. The RUL prediction at the 10th percentile is however much lower than RULa. This gives that if one chooses this as the measure for when to mobilize for active maintenance, the decision to mobilize will be made much earlier than is needed in the specific example in figure 7.

4.3 *RUL prediction with Bayesian inference*

In this section we open for the possibility that v and σ can change with new degradation paths. One rationale for this can be that for every repair, small differences in how the pumps are reassembled together with the state of parts that have not been repaired can affect the subsequent performance and degradation of the pumps.

If this assumption is true, we can never know the actual v and σ when predicting RUL for a future degradation path. One way to meet this challenge is to use Bayesian inference to update our prediction as data from the current degradation path becomes available.

In this paper we will perform the analysis first assuming that drift is unknown and that the diffusion coefficient is fixed, and then the other way around. Both these assumptions are admittingly not very realistic, but they simplify the problem of finding the posterior for the unknown parameters and make it possible find analytical solutions.

4.3.1 Assuming v unknown and σ fixed

In this approach we will use $v_0 = \sum v_i/N$ as our prior estimate for the drift, with precision $\tau_0^2 = 1\,/\,s^2_{v(i)}$. Where v_i is the drift for the i-th degradation path and N is the number of degradation paths in the training dataset.

We will use the degradation path in our test dataset to update our posterior distribution as the data becomes available. The estimate of the drift parameter based on the test data at time t will then be: $\overline{\Delta x_t}$ with precision $\tau_t^2 = 1\,/\,s^2_{\Delta x,t}$.

Based on Cowles (2013, 87) the posterior distribution for the drift at time t (v_t^*) can be found with the following expression:

$$v_t^*|\boldsymbol{x} \sim N\left(\frac{t\tau_t^2\overline{\Delta x_t} + \tau_0^2 v_0}{t\tau_t^2 + \tau_0^2}, \frac{1}{t\tau_t^2 + \tau_0^2}\right) \quad (4)$$

Based on Eq. (4) we can find the expected value and 95% credible interval for the posterior of the drift. We then update the mean for our IG distribution: $\mu_{B,t} = (L - y_t)/v_t^*$. We keep the same shape parameter as in the previous approach: $\lambda_t = (L - y_t)^2/\sigma_{train}^2$.

As we can see from the graphs in figure 8 the RUL prediction at the 10th percentile is almost the same whether v is based on the training data or the posterior from Eq. (4).

The reason for this is that the variance in the different trends of the degradation paths in the training dataset is so much smaller than the variance of Δx in the test degradation path.

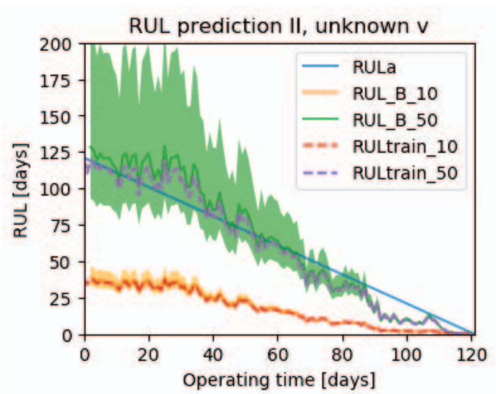

Fig. 8. The solid lines are the actual RUL (RULa) and RUL prediction based on Bayesian inference (RUL_B_10 and RUL_B_50) with shaded regions for the 95% credible interval for v. The dashed lines are the RUL predictions based on the training data.

4.3.2 Assuming v fixed and σ unknown

In this approach we assume that the trend in the Wiener process is constant and the diffusion coefficient is changing. Based on Cowles (2013, 98) the posterior distribution for the precision of a normal distribution (τ^2) can be expressed as:

$$\tau^2|\boldsymbol{x} \sim Gamma(\alpha + \frac{t}{2}, \beta + \frac{ts_{\Delta x,t}^2}{2}) \qquad (5)$$

We estimate the α and β parameters for the gamma distribution for τ^2 based on the following formulas:

$$\gamma = \ln\left(\frac{1}{N}\sum_{i=1}^{N}\tau_i\right) - \frac{1}{N}\sum_{i=1}^{N}\ln(\tau_i) \qquad (6)$$

$$\alpha \approx \frac{3-\gamma+\sqrt{(\gamma-3)^2+24\gamma}}{12\gamma} \qquad (7)$$

$$\beta = \frac{\alpha N}{\sum_{i=1}^{N} x_i} \qquad (8)$$

Where τ_i^2 in Eq. (6) is the precision of the i-th degradation path, and N is the number of degradation paths in the training dataset. Based on Eq. (6 – 8) we get $\alpha = 8.3$ and $\beta = 3.7$. Based on this we can estimate expected value and 95% credible interval for $\sigma^2 = 1/\tau^2$. We then use this to update the shape parameter for the IG distribution $\lambda_{B,t} = (L - y_t)^2/(\sigma^2)$, while the mean is kept the same: $\mu_t = (L - x_t)/v_{train}$.

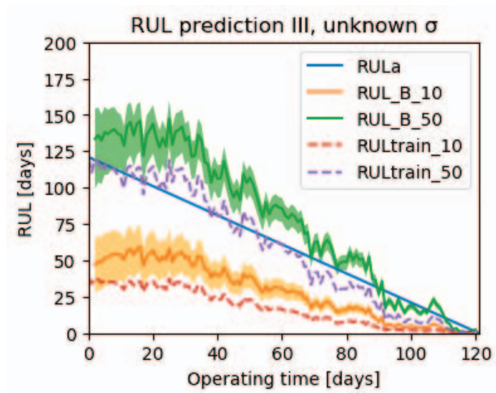

Fig. 9. RUL prediction based on Bayesian inference with 95% credible interval for σ (solid lines with shaded region). The dashed lines are RUL the predictions based on training data.

Of cause a more realistic assumption would be to assume both v and σ as unknown at the same time. This is something that can be pursued in future work either by numerical integration or by using the Markov chain Monte Carlo method (Cowles 2013).

But the calculations in the two previous sub-section demonstrate that the uncertainties in v and σ have a considerable impact on the RUL-prediction.

5. Discussion

As presented in the introduction and section two, there are high expectations to the possibilities of PdM in relation to the fourth industrial revolution. However as seen in this paper there are several challenges related to successful employment of PdM.

One challenge met in this paper was that few of the faults of the pumps in question was observable with the available sensor data.

One possible solution to this challenge is to install more sensors. In order to find out what sensors to install and data to collect a method called Failure Mode and Symptoms Analysis (FMSA) can be used. This method offers a systematic approach to ensure that the installed sensors can monitor the relevant failure modes (ISO 2012a).

Another challenge met in this paper was that because of the limited time period and number of equipment in the dataset the number of identified faults was few. This contributes to the large uncertainty in the predicted RUL.

One possible approach to face this challenge is to get a bigger dataset in order to get better predictions. This could be in partnership with the equipment manufacturers or other operators of similar equipment.

The challenges related to successful implementation of predictive maintenance has also been recognized in a survey of 323 German companies in 2019. According to the consulting firm Staufen: "companies have extensive experience with wear and tear on their machines as well as suitable on-site maintenance intervals, making the added value of predictive maintenance lower than is often asserted." (STAUFEN.AG 2019).

6. Conclusion

Given the complexity of implementing predictive maintenance the added value of this in traditional plants like the oil platform in this paper is probably limited.

However, in other settings where cost and/or mobilization time for active maintenance are considerable larger the kind of RUL prediction done in this paper can be an important contribution.

As pointed out in section two unmanned offshore platforms can offer considerable savings in terms of investment and operating cost, and unmanned solutions can be a necessity in order to make some marginal offshore oilfield in remote locations profitable.

But in order to secure the profitability of such a solution predictive maintenance with accurate RUL-predictions will be crucial in order to achieve acceptable availability and maintenance cost.

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