Sprayer Issue Detection in Alfa Laval's PureSOx using Data-Driven Approaches

Alfa Laval's scrubber removes SOx from the exhaust gas of large vessels using water sprayers. To optimize scrubber performance, Alfa Laval aims to apply predictive maintenance on the sprayers, which requires models that can detect the early stages of sprayer issues. It is uncertain whether the current data is adequate to show the sprayer issues. Two experiments were performed to explore the visibility of the sprayer issues and how the data quality influences this. The results show that, for some vessels, worn-out sprayers can be identified, however, most of the results were inconclusive. The data quality should be improved to make accurate predictive maintenance models in the future.

1 Introduction

This internship was performed within the Automation Development team at Alfa Laval Nijmegen, where solutions for the marine industries are designed. Alfa Laval's PureSOx is a scrubber system that removes sulphur oxides (SOx) from a vessel's exhaust gas by scrubbing it with water. SOx needs to be removed to adhere to SOx emission regulations. The scrubbing of the exhaust gas with water happens in the jet and absorber sections, see Figure 1. The flow of water through the sprayer layers is controlled per layer using a valve per layer.

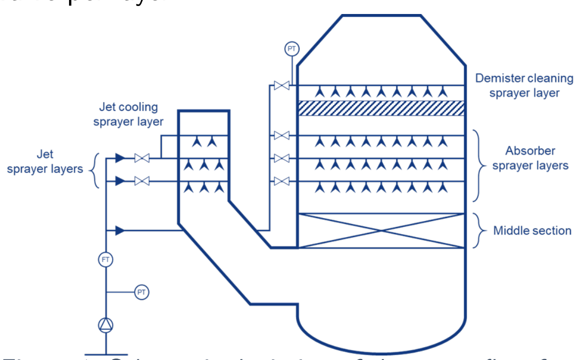

Figure 1: Schematic depiction of the water flow from pumps to sprayers in a typical scrubber.

Alfa Laval wants to use collected scrubber process data in predictive maintenance models to monitor the condition of the sprayers and identify sprayer issues like clogging and wear and tear. Predictive maintenance is the ability to use data-driven analytics to optimize the overall operation of a system [1]. Clogging is linked to a lower water flow rate than expected and worn-out sprayers are linked to a higher water flow rate than expected. Therefore, we can compare the water flow measured on the vessel and an expected water flow resulting from a model to get information about sprayer issues. However, it is uncertain whether the current data is adequate to show the sprayer issues because there is a lack of scrubber process data and information about the sprayer conditions. This leads to two research questions:

1. How does the quality of the scrubber process data influence the identification of the blockage or worn-out sprayers?
2. Is the scrubber process data adequate for detecting sprayer issues?

2 Methods and Approach

Two experiments were performed to answer the research questions. Experiment 1 focuses on the influence of data quality on the identification of the sprayer issues by varying the pre-processing steps and data set size. Experiment 2 investigates the consistency between the water flow and the sprayer condition for multiple vessels.

2.1 Data and Data Challenges

Scrubber process data of four vessels from three customers was used. The number of vessels was limited to four because of data availability. At least one validation event and four months of data are available for the vessels. A validation event refers to a report that is made after an internal inspection and contains information about clogging or corrosion of the sprayers and recommendations about whether sprayers need to be replaced.

There are several challenges related to the data that cause difficulties when making a predictive maintenance model for sprayer issues. For example, vessels are sometimes offline for several months due to connection issues. Additionally, there are only one or two internal inspections per year, therefore, there is no information about the sprayer conditions most of the time. Moreover, it is possible that the crew replaces sprayers during their maintenance procedures, but we do not have access to this information.

2.2 Models

We would like to compare the measured water flow with an expected water flow that follows from a model. The input features for the models can be put into the following categories: running status of the scrubber, open/closed status of the sprayer valves, theoretical water flow, engine load, pressure transmitters, pump currents and gas temperatures.

Four models are used in the experiments. The first three all predict the water flow based on the input features. They differ in how the input features are combined. The Multiple Linear Regression model (MLR) combines the input features linearly while the Feedforward Neural Networks (FNN, FNN$_{tiny}$) can make non-linear combinations. The FNN is four times larger than the FNN$_{tiny}$. For the evaluation of the results, we look at the difference between the measured and the predicted water flow, this is called the water flow deviation. The fourth model, the autoencoder (AE), tries to reconstruct its input features to learn the standard ratio between the input features. A high reconstruction loss is returned for data periods with sprayer issues. For evaluation, we look at the height of the reconstruction loss. Because worn-out sprayers are a more prominent issue than clogging, we focus on the identification of worn-out sprayers. A high deviation or a high loss indicates that the sprayers are worn out.

3 Experiments and Results

In both experiments, we inspect the visibility of the sprayer issues using the following hypotheses:
1. The deviation/loss increases between maintenance events due to wear and tear, because over time, the sprayer performance should degrade.
2. After a maintenance event, the deviation/loss is lower than before the maintenance event. The sprayer performance should increase after cleaning and/or replacement.

3.1 Experiment 1

Experiment 1 explores how the visibility of the sprayer performance changes based on train data set size and pre-processing algorithm. To perform a comprehensive comparison, data of only one vessel, referred to as vessel 1, is used for experiment 1. This vessel is chosen because approximately one fifth of the sprayers were replaced and that should be visible in the water flow.

For pre-processing the data, three different algorithms were used, with each algorithm removing more abnormal-looking data points or periods than the previous one. We expect that the algorithm that removes the most abnormal-looking data points and periods performs the best, as outliers can often hurt the performance of machine learning algorithms.

There are two options for the train data set size, the train data set ends approximately 15 or 30 days before the maintenance event. Because the models should learn the optimal scrubber behavior, the training data should only include data where the scrubber was in 'optimal' condition. Data closer to the maintenance event is less likely to represent 'optimal' behavior. Therefore, we expect that the sprayer issues are better visible if the train data ends 30 days before maintenance.

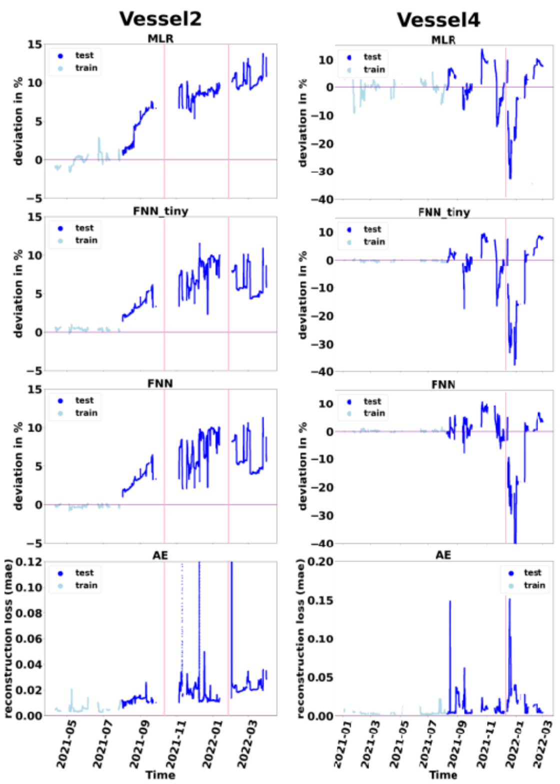

Figure 2: The results for vessel 2 and 4. The deviation/loss for the four models are displayed vertically. The pink lines indicate the maintenance events. Each data point is the average deviation/loss of one day.

Vessel	Deviation/loss increases between maintenance events	Deviation/Loss decrease directly after maintenance event
Vessel 1	Deviation/Loss became more negative, shows a worse performance but not in the way we expected.	Deviation/Loss became closer to 0, but became less negative instead of less positive.
Vessel 2	Clear increase in deviation/loss over time.	No clear drop after maintenance events, can be due to small percentage of sprayers that are replaced.
Vessel 3	Deviation/Loss fluctuates a lot, no steady increase visible.	No clear drop after maintenance events, can be due to small percentage of sprayers that are replaced.
Vessel 4	Deviation/Loss fluctuates a lot, no steady increase visible.	Deviation/Loss is closer to 0 after maintenance but water flow looks abnormal so the hypothesis cannot be confirmed.

Table 1: Result summary of experiment 2. Green: the result is consistent with the hypothesis. Orange: the result is somewhat consistent with the hypothesis. Red: the result is inconsistent with the hypothesis.

3.1.1 Results

The sprayer issues are better visible when the train data set ends at least 30 days before the maintenance event, which confirms our hypothesis. Contrary to our hypothesis, the sprayer issues were best visible with the pre-processing algorithm that removes abnormal-looking data points but no abnormal-looking data periods. We expect that the most extensive outlier removal algorithm performs worse because too many informative data points are removed.

3.2 Experiment 2

Experiment 2 explores whether changes in the sprayer performance can be noticed after maintenance and whether there is a steady deterioration of the sprayers. The visibility hypotheses that apply to this experiment are described at the start of Section 3.

3.2.1 Results

The results for all vessels are summarized in Table 1. We briefly explain the results for vessel 2 and 4 here.

For vessel 2, between maintenance events, the deviation or loss increases, see Figure 2. This confirms that the sprayers deteriorate over time. However, we cannot confirm that the deviation or loss is closer to zero after maintenance events. There are some small decreases in deviation after the second maintenance event, but they cannot be linked to the sprayer replacement because the replacement date is unknown. It is possible that there are no significant drops in deviation because only a few sprayers were replaced.

For vessel 4, the deviation is not consistently above or below zero, see Figure 2. Therefore, we cannot say that the deviation or loss between maintenance events increases. Moreover, after the maintenance event, the deviation is lower than before the maintenance event for approximately two months. After two months, the deviation has reached values similar to before the maintenance and, therefore, a similar sprayer condition. This result is strange because it indicates that all sprayers are worn-out again after two months, while sprayers typically last a few years. Upon further investigation, the water flow values after maintenance look abnormal. These values can be caused by wrong sensor readings or other malfunctioning parts in the scrubber. In the end, we cannot conclude whether the deviation or loss after maintenance decreases with certainty.

4 Conclusion

The goal of this project was to explore whether predictive maintenance for the sprayers is feasible. Two experiments were performed, experiment 1 investigated the influence of the data quality on the identification of the sprayer issues and experiment 2 explored the visibility of the sprayer issues for different vessels. Experiment 1 showed that train data should end at least one month before the maintenance event. Moreover, the optimal pre-processing procedure removes abnormal data points but not whole data periods. Experiment 2 showed that, for some vessels, the sprayer performance gets worse over time. However, data limitations lead to many inconclusive results. These data limitation include: not having adequate training data and a general lack of information. The overall conclusion is that the sprayer performance cannot be inferred from the current data. Therefore, the data quality needs to be improved before predictive maintenance can successfully be applied.

5 References

[1] R Keith Mobley. *An introduction to predictive maintenance*. Elsevier, 2002.

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