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

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Introduction

Alfa Laval's PureSOx removes SOx from a vessel's exhaust gas by scrubbing it with water.

Figure 1. Large container vessel that uses PureSOx.

Goal: use predictive maintenance to identify sprayer issues like clogging and wear and tear. The water flow measured on the vessel can be compared with the expected water flow resulting from a model to get information about the sprayer issues.

Problem: the current data might not be informative enough to make an accurate water flow model.

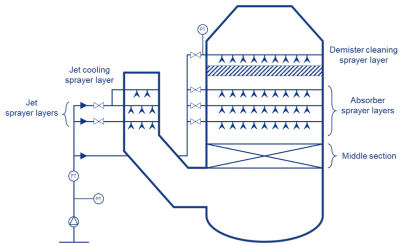

Figure 2. Schematic depiction of the PureSOx system.

Figure 3. The PureSOx system.

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?

Methods & Materials

Data

- Scrubber data of 4 vessels over 3 customers
- At least 4 months of data and 1 validation event

Data challenges

- Connectivity issues
- Lack of validation events
- Crew maintenance

Models

- Multiple Linear Regression (MLR): Statistical approach that describes the water flow with a linear formula.
- Feedforward Neural Network (FNN, FNN_{tiny}): Neural network version of the MLR that uses a non-linear function.
- Autoencoder (AE): Neural network that reconstructs input features.

Overarching Hypotheses

1. The deviation/loss increases between maintenance events due to wear and tear.
2. After a maintenance event, the deviation/loss is lower than before the maintenance event.

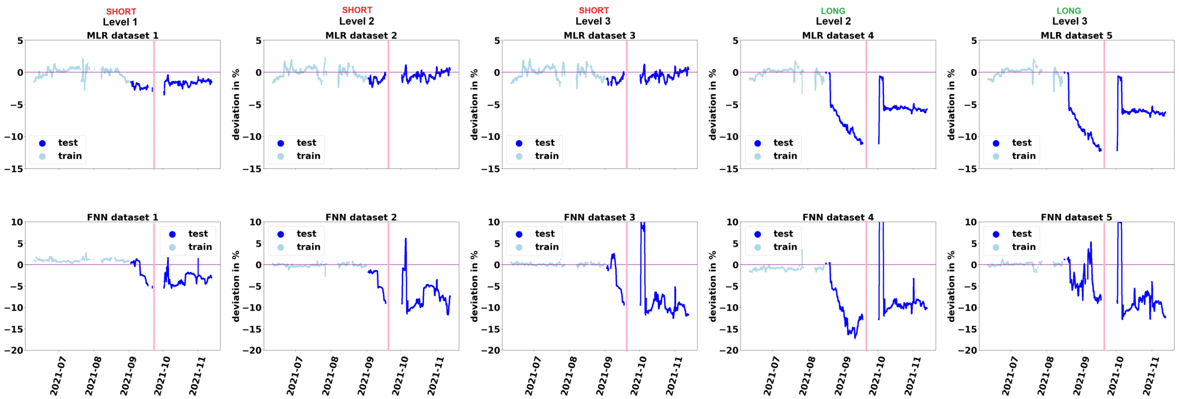

Figure 4. The results of the MLR and FNN in experiment 1.

Experiment 1

Explores how the visibility of the sprayer performance changes based on train data set size and pre-processing algorithm.

Vessel 1: 7 sprayers worn-out on 21/9/2021.

Dataset	Period before maintenance	Pre-processing
1	Short (~15 days)	Scrubber off
2	Short (~15 days)	Basic outliers
3	Short (~15 days)	Abnormal periods
4	Long (~30 days)	Basic outliers
5	Long (~30 days)	Abnormal periods

Table 1. Overview of the datasets used in Experiment 1.

Hypotheses

1. Long period before maintenance event is best
2. Pre-processing with abnormal data period removal is best

Experiment 2

Explores whether the sprayer performance changes after maintenance and whether there is a steady deterioration of the sprayers.

Vessel 2: 1 sprayer worn-out on 10/1/2021. 2 sprayers worn-out on 28/1/2022.

Vessel 4: All sprayers worn-out on 9/12/2021.

Result Summary

Experiment 1

- Long period before maintenance is best
- Pre-processing with basic outliers is best

Experiment 2

1. Increase in deviation/loss over time
   - Clear decrease in vessel 1
   - Clear increase in vessel 2
   - No clear increase or decrease in vessel 3 and 4
2. Deviation/loss after maintenance is closer to 0
   - Deviation is closer to 0 in vessel 1
   - No clear decrease in vessel 2 and 3
   - Inconclusive results in vessel 4

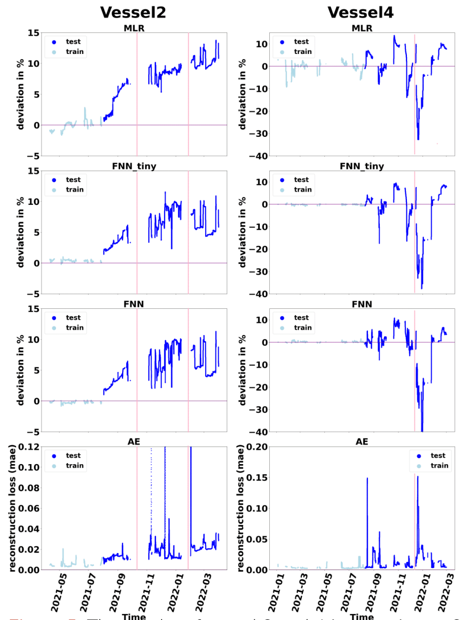

Figure 5. The results of vessel 2 and 4 in experiment 2.

Conclusion

Sprayer performance cannot be reliably inferred from the current data. Data limitations lead to inconclusive results. The data quantity and quality need to be improved before predictive maintenance can successfully be applied.