Predictive Maintenance of Pumps at ‘Den Magiske Fabrikken’, Using Machine Learning Techniques

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Abstract

In this work, we investigate machine learning methods to predict the failures of progressive cavity pumps (PCP). The PCPs are located in a biogas plant, Den Magiske Fabrikken, in Norway, which is transforming food waste and animal manure to biogas and biofertilizer. Available measurements were pump on-signal, speed, current, torque and control signal, inlet flow, inlet pressure and outlet pressure, and several vibrations derived signals.

Five categories were defined to categorize the operation of the pumps as: *stopped*, *normal running*, *7 days from failure*, *1 day from failure* and *1 hour from failure*. The objective was to train a Machine Learning model to predict these categories. The data was pre-processed to clean gross outliers and scale the signals using different techniques.

This paper presents results from the same Long Short-Term Memory (LSTM) model using two different approaches for scaling the data. The results are evaluated using confusion matrices where one scaling method clearly improves the results when testing on new data points.

Keywords: Machine Learning, Predictive Maintenance, Long-Short Term Memory, Progressive Cavity Pump

1 Introduction

This project investigates and evaluates progressive cavity pump failures used in a waste processing plant by applying machine learning (ML) methodology. In the industry, maintenance costs account for significant losses in profit for companies. Predictive maintenance methods and their tools have changed the way in how to approach problems through advanced control analysis.

Lindum operates a waste management company that produces biogas and biofertilizer as a result of processing animal manure and food waste. During the processing phase, the highly corrosive and acidic liquid flows through the pipes and causes severe effects on the pumps. To prevent any production losses and increase the pump lifetime, pumps are maintained periodically. Obviously, excessive manual supervision of the pumps may result in increased labor force demand and increase the spare part costs. However, increased periodic surveillance do not prevent unexpected failures completely. Consequently, the objective of this project is to develop methods for preventing pump failures by analyzing pump parameters with ML algorithms and proposing a model to detect faults.

1.1 Progressive Cavity Pumps and Predictive Maintenance

Positive displacement pumps can handle solids, high viscosity and low flow rates. Besides, progressive cavity pumps are one type of positive displacement pump. Centrifugal pumps, on the other hand, are suitable for low viscosity and high flow rates. The pump efficiency will decrease at both higher and lower pressures for centrifugal pumps, whereas the pump efficiency will increase with increasing pressure in positive displacement pumps.

In this project, the analyzed pump type is ‘Nemo’ brand progressive cavity pumps produced by Netzsch Pumpen & Systeme GmbH. These types of pumps provide a large capacity and pressure range. During the operation of the process in the factory, the pumps suffer from changing viscosity and corrosive materials in each batch. Figure 1 illustrates the progressive cavity pump that is used in the process. The pump has the following components: rotor (1), stator (2a, 2b), drive chain (3), shaft sealing (4), suction and discharge housing (5). Typical problems in progressive cavity pumps are elastomer expansion, rotor, and stator material corrosion which are caused by high temperature or fluid type (Lea et al., 2003).

There are some points to avoid pump failure specifically in progressive cavity pumps. These are:

- Choosing the right elastomer type by taking into account temperature and fluid physical properties
- Avoiding dry running conditions

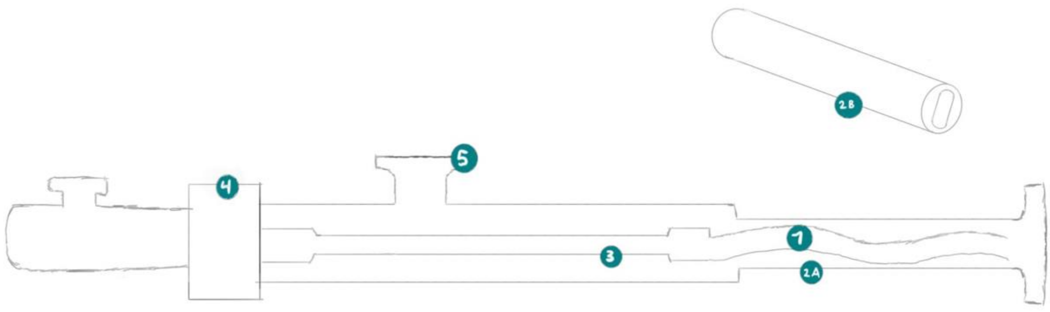

Figure 1. Illustration of the progressive cavity pump that is used in the process.

- Selecting suitable rotor material to stay away from abrasive wear on the rotor

Predictive maintenance aims to transform advanced analytical and process data into valued outcomes. Hence, equipment failure or breakdown can be prevented just before it occurs. Additionally, predictive maintenance may take advantage of ML algorithms to build a systematic approach. Besides, predictive maintenance minimizes the cost of maintenance and improves the equipment lifetime without causing unpredicted production losses. Thus, the process will run as long as possible without interruption.

1.2 Machine Learning Methods

Various type of data is gathered from the process equipment. ML algorithms are able to unveil unseen or hidden patterns and relationships within a data set. With the progressively increase of computational power, and development of new ML algorithms, there is an increasing trend in publications in the literature related to data analysis through ML algorithms (Carvalho et al., 2019). One method is the LSTM algorithm, which is considered especially successful in time series applications, where long-term dependencies in the data needs to be detected (Géron, 2019, pp.511-523). Simply, the function stores a value and determines how long it should be stored. This makes long short - term memory one of the most common models when working with time-dependent data (Rivas et al.,2019). Wisyaldin (2020) compared Autoregressive Moving Average (ARMA), Recurrent Neural Network (RNN), and LSTM models for analyzing vibration signals to predict the health condition of bearings of a water circulation pump and LSTM produced better accuracy. Even though LSTM is used to calculate remaining useful time and anomaly detection in various processes, there are few studies for progressive cavity pump failure analysis with LSTM found in the literature.

2 System Description

2.1 Features

The system under scrutiny in this paper consists of a progressive cavity pump with measurements control signal [%], current [A], torque [%] and speed [%] from a frequency converter. In addition, inlet pressure [Bar], outlet pressure [Bar] and inlet flow [m^3/h] is measured. These will be used as the features for the machine learning model. The sampling rate for all the measurements is 30 seconds. Although the selected pump is part of a system of pumps and may be impacted by other pumps earlier in the process, this potential impact has been ignored in this work. The system cyclically pumps fluid for 45-60 minutes, it will always start the cycle again after 60 minutes whether it has just ended or ended 15minutes ago.

The analyzed feature data spans 17 months, with some missing data. During this period, the pump considered has been replaced 14 times due to pump failures.

2.2 Predictions

The goal is to predict one of the five operational categories: pump is (0) *stopped*, (1) *running normally*, (2) *less than one week from failure*, (3) *less than one day from failure* or (4) *less than one hour from failure*. Where running normally is assumed to be anything which is not covered by the other categories.

These categories have been assumed useful as there was little information concerning the breakdown of the pumps, only sparse information about when they had been replaced was available.

3 Methods and Methodology

3.1 Long Short-Term Memory Configuration

The LSTM model architecture was set up as a two layered LSTM block with a dense output layer as seen in Figure 2. The first layer has 7 feature inputs with a sequence length of 120 and 32 output neurons. The layer has the parameter return_sequence set as true (Chollet, LSTM layer, 2015) which means a sequence will be returned, compared to only return the last estimate of the sequence, which is the case when set to false. The sequence length of 120 samples correspond to one hour which is the cycle time for the pump sequence. The pump sequence is determined by the process operation. The 32 neurons from the first layer serves as inputs to the second layer. However, it outputs only 16 neurons as the return sequence is set to false. Both the LSTM layers are using standard configurations for all other parameters. Lastly, a dense layer using the softmax activation function with the 16 neurons from the previous layer as inputs and outputting a probability for each of the categories. The output with the highest probability is assumed to be correct for a given sequence thus giving a positive for one of the five categories. The loss function, categorical crossentropy (Chollet, 2015), is minimized using the Adam optimizer (Kingma, 2017).

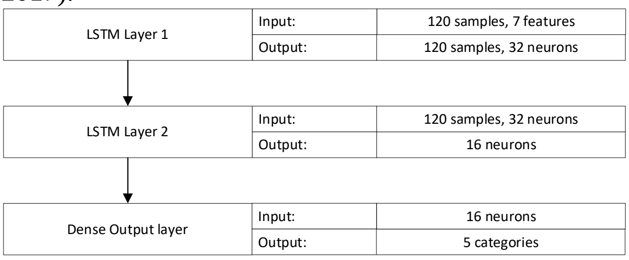

Figure 2. LSTM model architecture

3.2 Scaling

Standardization is used to scale the data, using Eq. (1) where z is the scaled sample, x is the sample that should be scaled, μ is the mean and σ is the standard deviation.

$$z = \frac{x - \mu}{\sigma} \tag{1}$$

The standardization is used in two ways, one where the data from all the pumps are scaled using the same scaler for the merged dataset, from hereon named Merged Dataset Scaling (MDS). The other approach is to collect data during one hour of operation for each pump and use this data to calculate individual means and standard deviations to scale the new data. This second method is called Separate Dataset Scaling (SDS). Both approaches are shown in Figure 3.

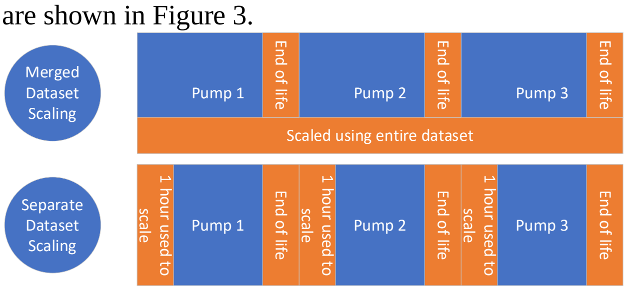

Figure 3. Two methods to scale training data.

The reasoning behind this approach can be seen by inspecting parts of the data shown in Figure 4. There are several normal distribution-like structures in the current when including data from all the pumps in the same histogram. This may indicate that the level of current (and other variables) may vary between the pumps that have been replaced, and thus the level near the end of the lifetime may vary. This gives the ML method ambiguous signals as to what is considered a degraded pump.

Figure 5 shows one single pump scaled with the first hour of its own data. The distribution now seems closer to a single normal distribution, yet, it still has two distinct tops. Investigating other plots reveals that many look like Figure 5 and some are a lot closer to a narrow normal distribution.

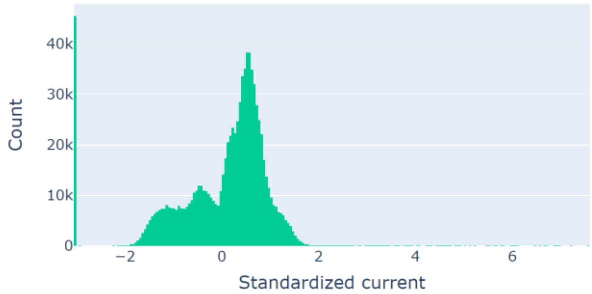

Figure 4. Histogram including all pump failures with previous original scaling method for current.

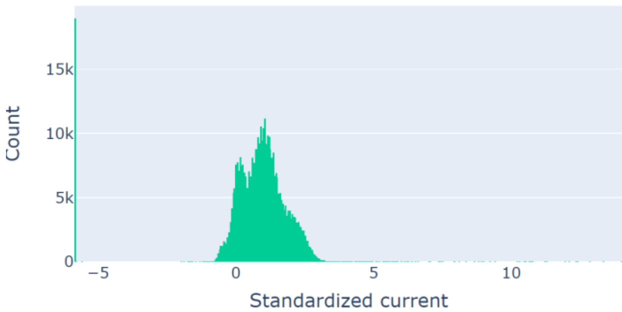

Figure 5. Histogram for one pump failure for the feature current, scaled.

It thus appears that there are individual characteristics of the pumps, and hence they have various distributions. This may confuse the LSTM-model as there will be many levels of data points where the pump is ok for one pump, but not for another.

Continuing this approach and using data from only the first hour of the pump's active lifetime yields a distribution as seen in Figure 6. This distribution looks more coherent, yet there are more outliers and a higher span.

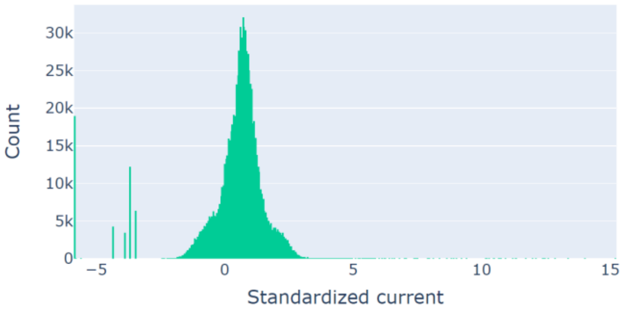

Figure 6. Histogram including all failures with scaling Method 2.

3.3 One hot encoding

The outputs are one hot encoded from integer encoded, meaning that the labels have been converted to numbers as seen in Table 1. These in turn has been transformed into a one hot encoded format, where each row indicates an example where only one label is true, and others are false. As per definition of one hot encoding (Géron, 2017).

Table 1. Integer encoded labels

Label	Description
0	Stopped
1	Normal running
2	Less than one week before failure
3	Less than 24 hours before failure
4	Less than 1 hour before failure

4 Results and Discussion

4.1 Scaling pump data using Merged Dataset Scaling

Before the data is used for training, the features are standardized. All the 14 failures are scaled using one scaler and the data is split into sequences. The outputs are one hot encoded. After this, the data is split into training, validating and testing datasets with 60% used for training, 20% for validation and 20% used for testing. The validation data is used during training to check if the model is improving or not, while the test set from this distribution is used in Figure 7.

Using the MDS method, the results on the confusion matrix based on the training set can be seen in Figure 7 and appears very good. Figure 8 however shows the results in a more realistic manner where the data tested on was not involved in training the model. The model was trained on data from March 2020 to September 2021 and was then tested on data from September 2021 to October 2021. The confusion matrix for the test data shows that all the three categories where it was less than one week before failure of the pump, was considered “normal operation”, or in some rare cases “stopped”. Some of the reason for this might be related to an extensive number of “normal operation” in the data, compared to the other. That will affect the model. Comparing Figure 7 and Figure 8, there is a clear indication of a generalization problem with the model. As already mentioned, the MDS method has its shortcomings, which is improved in the SDS method.

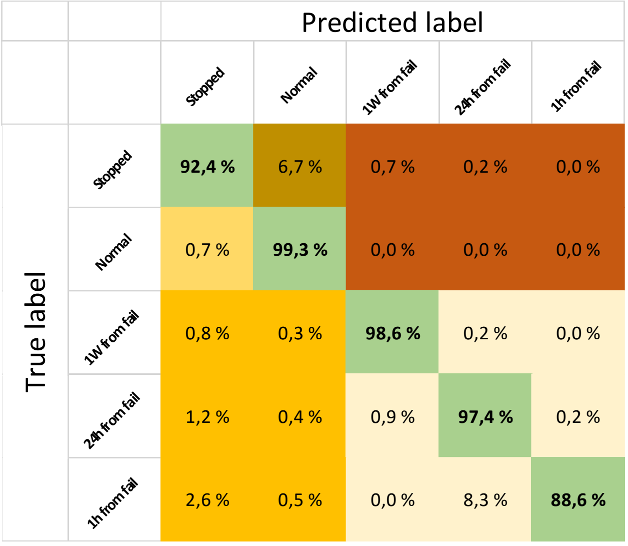

Figure 7. Confusion matrix based on training data

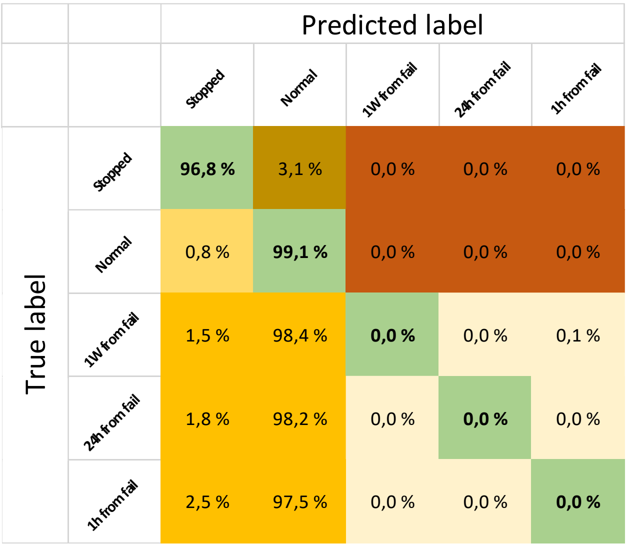

Figure 8. Confusion matrix based on test data

4.2 Scaling pump data using Separate Dataset Scaling

Using the SDS method for scaling the data has reduced the overall accuracy of the model based on the training data, as seen in Figure 9. It can however be noted that most false positives in the failure categories for the most part end up in another failure category.

The test set shows that the model is greatly improved by using the SDS method in Figure 10. The total accuracy becomes 78.5% where the total accuracy is defined by how many samples are correct for each label divided by number of samples tested on.

True label \ Predicted label	Stopped	Normal	1W from fail	24h from fail	1h from fail
Stopped	**93,6 %**	5,4 %	0,8 %	0,2 %	0,0 %
Normal	1,0 %	**98,9 %**	0,0 %	0,0 %	0,0 %
1W from fail	0,7 %	0,0 %	**98,8 %**	0,5 %	0,0 %
24h from fail	0,9 %	0,0 %	8,4 %	**90,6 %**	0,2 %
1h from fail	0,5 %	0,0 %	14,7 %	37,8 %	**47,0 %**

Figure 9. Confusion matrix on test data with SUS method from training data

True label \ Predicted label	Stopped	Normal	1W from fail	24h from fail	1h from fail
Stopped	**97,1 %**	1,2 %	0,6 %	1,2 %	0,0 %
Normal	0,8 %	**99,2 %**	0,0 %	0,0 %	0,0 %
1W from fail	1,3 %	0,0 %	**55,2 %**	43,5 %	0,0 %
24h from fail	1,1 %	0,0 %	45,0 %	**53,9 %**	0,0 %
1h from fail	0,9 %	0,0 %	50,5 %	48,6 %	**0,0 %**

Figure 10. Confusion matrix on test data completely separate from training data using the SUS method

The expectation to be able to predict one hour before failure may have been high, however, the other failure categories appear to be reasonable, at least a combination of them. Assuming all failure modes are merged to one, the total accuracy of the model becomes 98.9%. One week from fail: 98.7%, One day from fail: 98.9%, and one hour from fail: 99.1% when adding together each row.

However, the model does never predict a normal operation as an upcoming failure for the given test set. The results indicate that there is a small risk of having a false alarm, and performing pump replacements without any good reason, with this approach. Simultaneously, there is a good chance of being able to detect an approaching error within a pump in advance. On the other side, it is a risk for not being able to detect precisely when the pump failures will occur.

The model was only tested on one pump failure, while trained on many. As such there may be a lucky draw that the model was able to predict as well as it did. It has already been seen that the data varies from pump to pump, and it may be that other pump failures are not that well picked up.

In the process of LSTM modelling, noise was not removed from the input data and only raw data was fed into the model. One might argue that noise filtering can increase accuracy. However, it was concluded that noise in data still can hold valuable information, and disregarding noise in data might reduce the model performance.

5 Conclusions and Further Work

This paper has aimed at evaluating and predicting of progressive cavity pump failures in the waste processing plant, maintained by Lindum AS. After gathering information from field instruments, measurement data classified 5 different pump working time cycles such as stopped or normal condition, 1h, 24h, and 1 week from failure. Analyzed data covered 17 months of operation that consist of 14 replacements, and with 30s sampling rate. The time series data was handled well by the LSTM algorithm and produced reasonable results. However, it became evident that scaling for the entire dataset led to information loss on pump failures, that is using the MDS method. Instead, improved results were obtained by scaling pump data with one hour of operational data for each pump replacement, the SDS method. Thus, each pump data was captured on the scaled dataset, separately. The total accuracy of the model with the proposed scaling method becomes 78.5%.

Further work is being done on trying to generalize the model such as to fit onto similar pumps in the process. This requires some features to be removed and use data from many more pumps (Holm, 2022).

As the stopped label is already known, it is not really needed to predict and will be removed in further studies. The one hour from failure label is never predicted outside the training data and is thus removed from further studies.

More work should be done on setting correct parameters of the LSTM structure.

The initial project (Holm et al., 2021) also explored other ML techniques such as Support Vector Machine, Naïve Bayes and Principal Component Analysis. These were not tested with the new scaling method and may be worthwhile to investigate further.

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