PREDICTIVE MAINTENANCE & MACHINE LEARNING

PREDICTIVE MAINTENANCE BY MAKING USE OF MACHINE LEARNING AND CURRENTLY AVAILABLE INSTRUMENTATION

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14-10-2020

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PROCESS & PLATFORMS

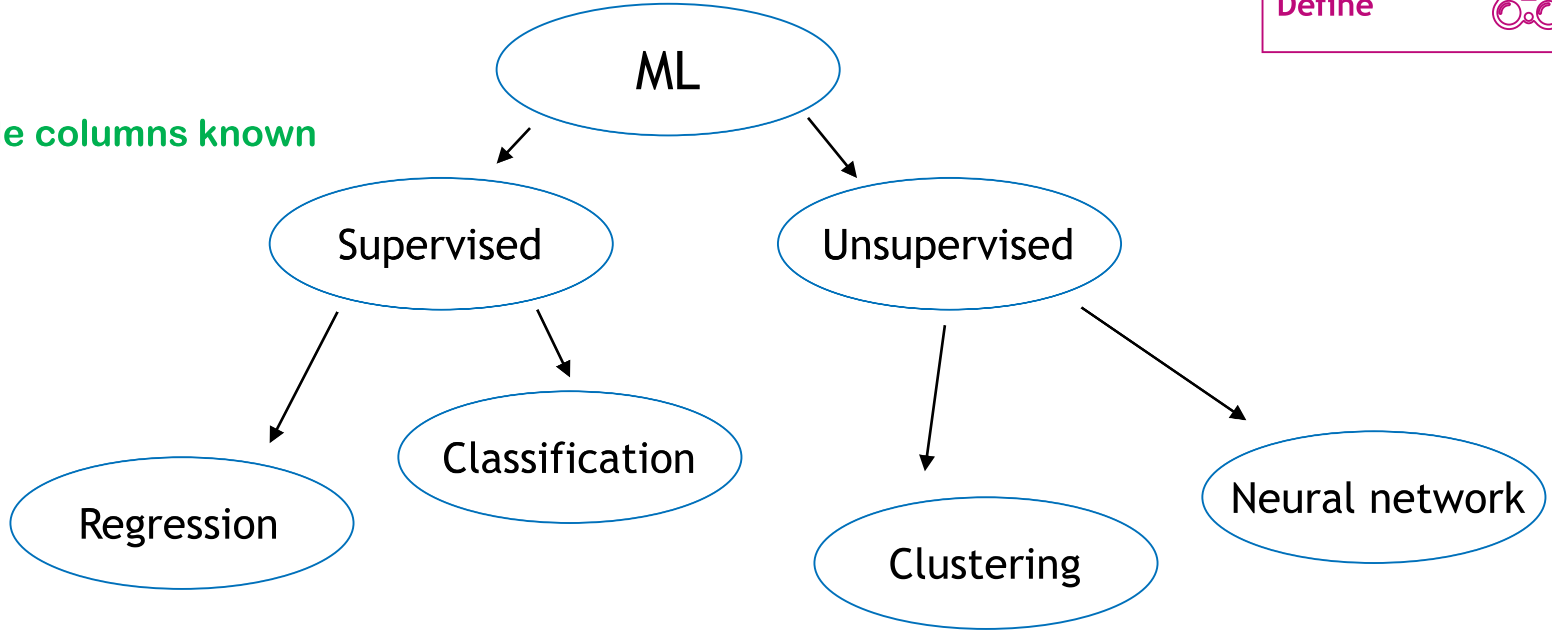
Platforms related to DAP:

- Historical data from AspenTech
- Data warehousing on Amazon Redshift
- Machine Learning in Alteryx
- Dashboards via Tableau
    - Alarms and trends for Production & Maintenance

CRISP-DM – Standard Process for Data Mining

Define

Table columns known



Most suitable for time-series

- Multivariate Linear Regression
- Cox Regression (survival analysis)

MULTIVARIATE LINEAR REGRESSION
-- YEAST CENTRIFUGES --

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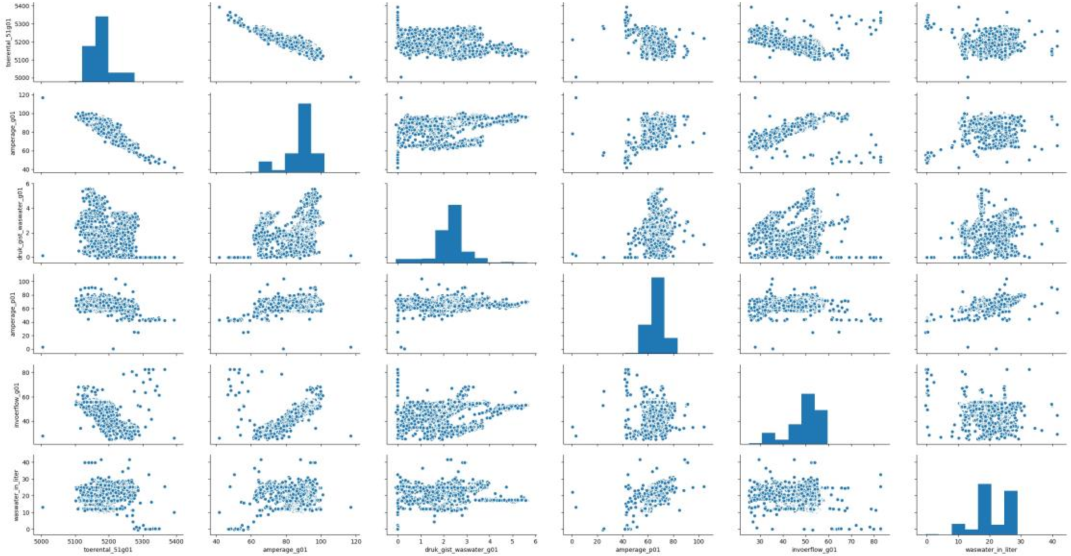

Engineer

Model

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots$$

Y = Current G01

X_1 = Revolutions
X_2 = Current P01
X_3 = Flow feed G01
X_4 = Flow water
X_5 = Pressure water

Notifications from SAP PM

08.06.2020 08:54:31 CET Maureen Bosch - CKC (CKC)
Yeastcentrifuge G01 has high amperage

10.06.2020 07:21:44 CET Benjamin Soest van (SOESTB)
Centrifuge opened and found worn out sealcups

Test & Implement

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SURVIVAL ANALYSIS WITH PROPORTIONAL HAZARDS
-- YEAST CENTRIFUGES --

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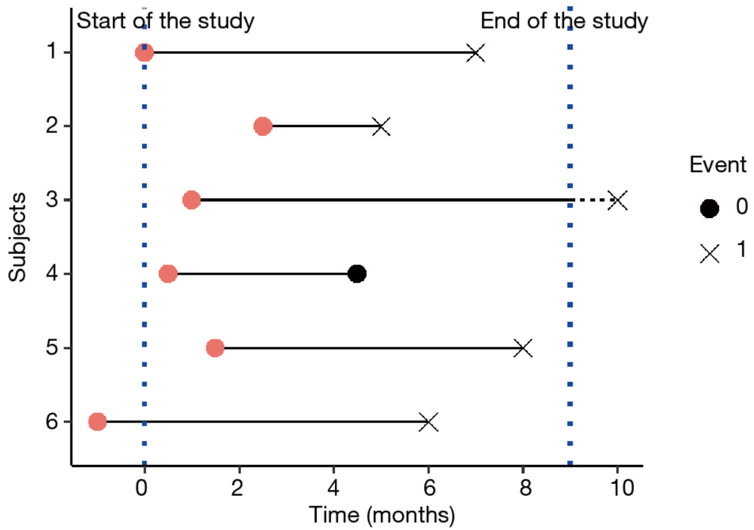
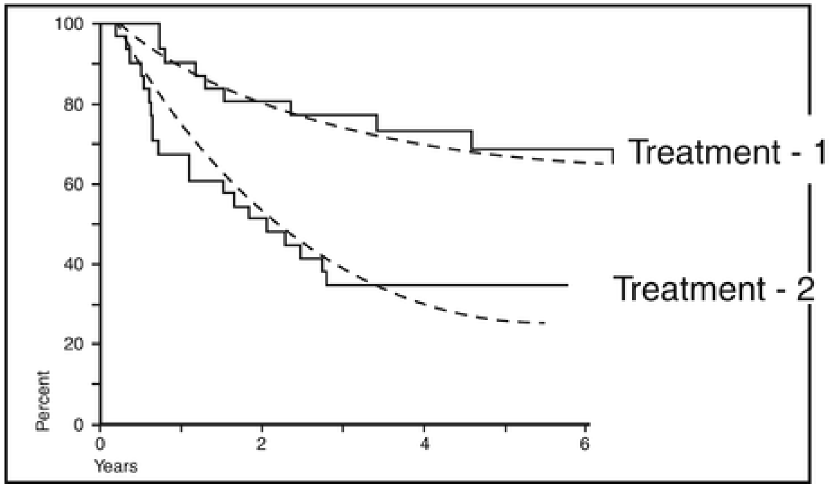
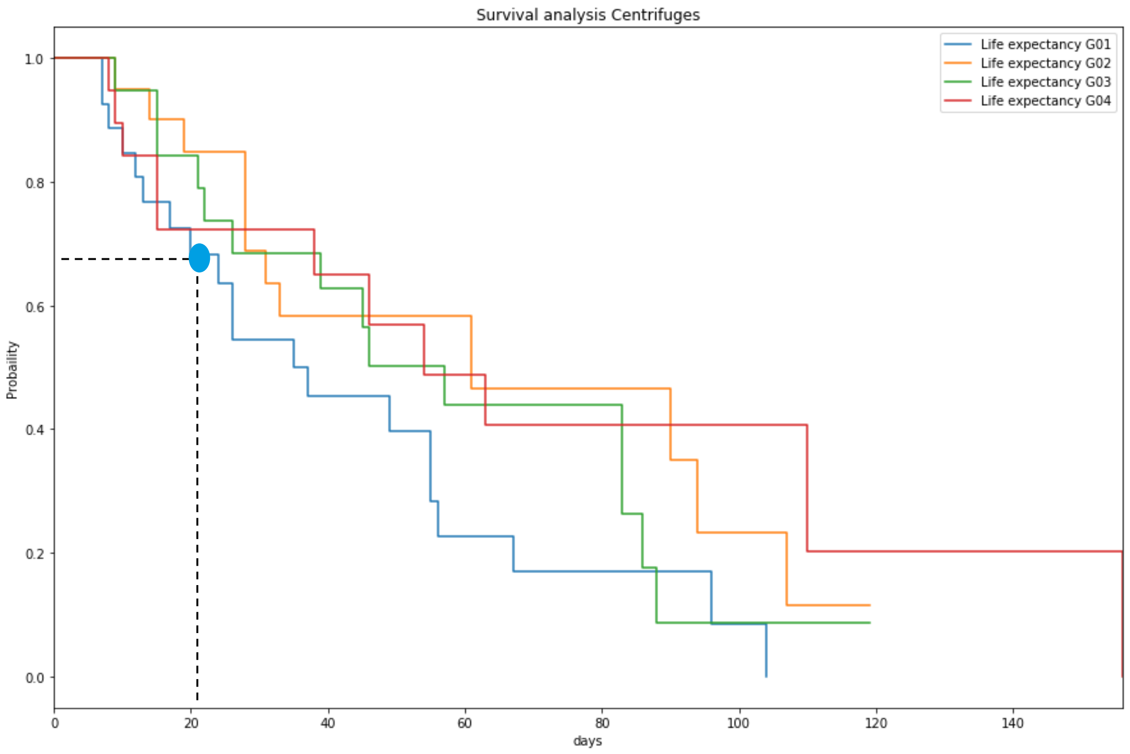
SURVIVAL ANALYSIS USED FOR MEDICINE





SURVIVAL ANALYSIS FOR CENTRIFUGES



Survival analysis for Yeast Centrifuges:

- 162 failure of all centrifuges

Example:

- G01 has a 67% probability of 3 weeks running without failure.

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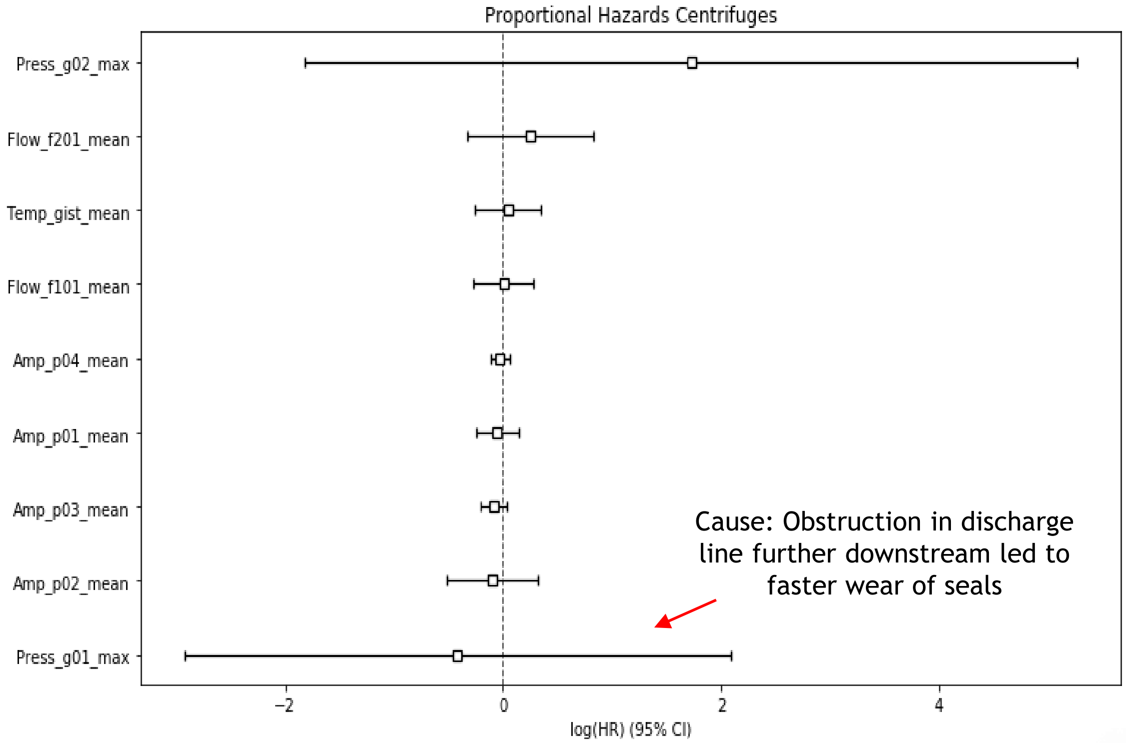
SURVIVAL ANALYSIS WITH HAZARDS

Positive influence on lifetime
(with spread)

Little influence on lifetime
(with spread)

Negative influence on lifetime
(with spread)



Cause: Obstruction in discharge line further downstream led to faster wear of seals

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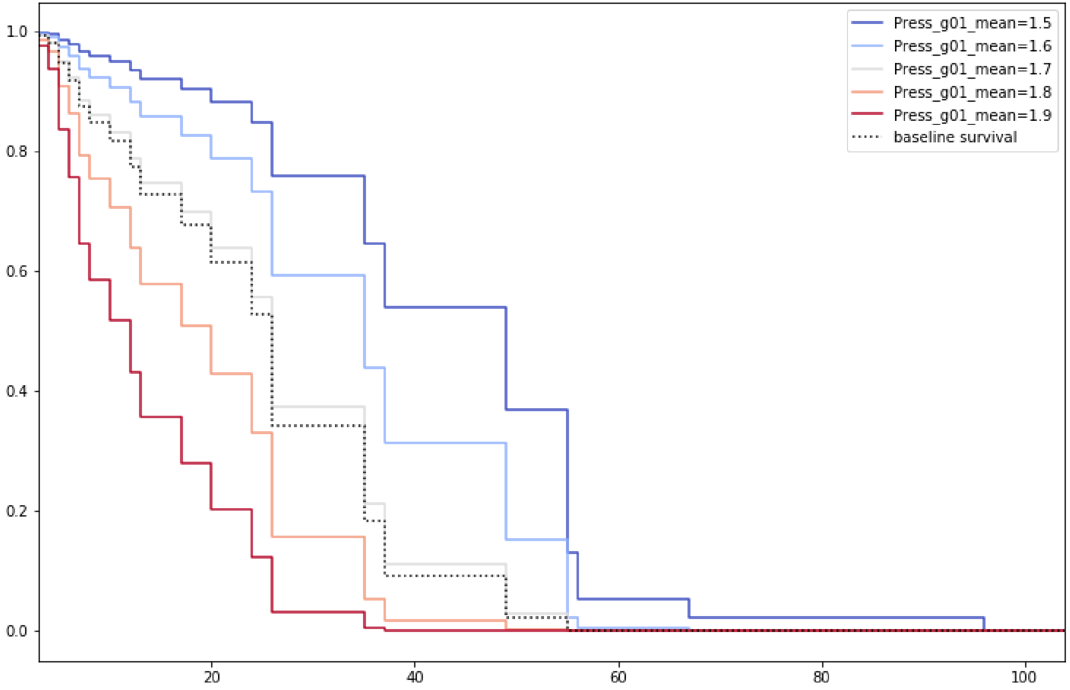
SURVIVAL ANALYSIS PREDICTED LIFETIME



Predict lifetime with different scenarios.

Example: use for adjusting process settings to keep running until next turn around

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NEXT STEPS FOR DSM FOOD SPECIALTIES

Implemented regression models:

- Yeast centrifuges (4)
- Steam boilers (4)
- Heat-exchangers in boilers (12)
- Steam pressure control-valves (12)

Future opportunities:

- Air compressors (5)
- Decanters (2)
- Yeast reactors (6)

Survival analysis / Cox regression:

- Survival analysis as part of RCA / FMECA / HAZOP
- Cox regression for predicting maintenance with scenarios

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CONDITION BASED MAINTENANCE – MODEL CENTRIFUGES

Slide Platforms and CRISP-DM

One year ago we started with Machine Learning for Condition Monitoring as part of the ‘Delft Integral Continuous Improvement’ in search for the ‘Golden Batch’. Platforms were therefor already up and running. These platforms are AspenTech for process measurements, Amazon Redshift to extract, transfer and load them (ETL). Alteryx reads data from the server, calculates new values and writes them to the same server. Tableau is a business intelligence tool to read and display the data from the server. It also has the possibility to send alerts by mail to it’s users which is great for the purpose of predictive maintenance. No need to look at the trends all day. Just an alert when equipment starts to show certain behavior.

A general approach for data analysis is the Cross Industry Standard Process for Data Mining. I will take you through the steps that we’ve taken at DSM to come models for predictive maintenance.

Slide Machine Learning methods

- Maybe this is a re-run of other presentations today but I would like to give you some short insight in the methods in Machine Learning. First of all there are two big difference in the big-data and Machine Learning. It can be supervised where the data has known columns as you have with data coming from Aspen. Then there is unsupervised learning, for example clustering of internet users with the same behavior. It is unknown what this behavior precisely is. Just that user appear to look alike.

- For the supervised learning you could use classification where you for example predict a risk category (high/medium/low) or you could use a regression analysis where you predict a value, for example a temperature (in case of weather prediction) or a valve opening in case of the industry. For time series, the regression analysis is most suitable. I will show you our examples two types of regression, Multivariate Linear Regression and Survival analysis (or Cox Regression).

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CONDITION BASED MAINTENANCE – MODEL CENTRIFUGES

- Together with our other Reliability Engineer, Gaitrie Kalloe, we started with our bad actor, the four Yeast Centrifuges. Bad actors, however with not so many comparable failures. As a result, training a classification algorithms (e.g. high/medium/low risk) based on the failures was hardly possible.

- Instead of looking how close you are to failure, it is easier to see how far you are from 'normal' operating conditions. A regression algorithm is an easy was to achieve this. The yeast centrifuges are equipped with measurements of the current and vibrations which are a perfect indicator for failure modes like imbalance, internal leakage and contamination.

Slide Correlations

- Modelling in Python gives you the possibility to find correlations between multiple and unexpected measurements (or features) which could predict an estimator. You could do this in two ways. Start with a logical features to predict your estimator and start expanding the model by adding features which improve your model (modelling takes time but it saves time for data loading). The other option is to start with many features which are in some way related to the estimator and drop the features which are not adding any accuracy of the model (so called 'pruning'). The modelling is easier but the Data Preparation might be more work and slow as you need to prepare and load all the features.

CONDITION BASED MAINTENANCE – MODEL CENTRIFUGES

- When the model is trained and tested on a period the system was functioning well it can be scheduled to calculate the result of the new day/hour/minute. Then it will give a real-time comparison between the estimated values and the actual values. This gives you the possibility to see deviation right at the point they start to happen.

Slide Tableau

- Depending on the time to failure of the failure mode the right person needs to be notified. In the example of the centrifuge the internal leak start and the centrifuge would fail on over-current in less then a week. In this case we needed to inform the operator to write a maintenance request when a deviation would occur. It would save us several days to plan the work while the centrifuge was still running. With four centrifuges this gave less interruptions of the work schedule of the maintenance department.

- For longer times to failure the Maintenance Engineer and/or the Process Engineer should be informed. For example when a heat exchanger gets contaminated, the plug of a control valve starts to wear or the efficiency of a steam-boiler starts to decrease. In that case the cleaning or replacement can be planned.

- Now when Maintenance is planned and executed the model needs to be retrained again for the new situation. This is a challenge. Replacement of a part is pretty clear, but how about a major overhaul or a small overhaul? This is something we need to figure out. Does the Maintenance Engineer need a reset button somewhere on the dashboard? Or can we automate this by using SAP work orders? As we don’t have many models yet we can still do this manually, but when we scale up this needs attention.

- This was one example of the regression model we have set up. Now I’d like to give an example of a survival analysis we have done.

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CONDITION BASED MAINTENANCE – MODEL CENTRIFUGES

Slide Survival analysis used for Medicine

- As the theory behind most algorithms are over more then a 100 years old, there are several fields of expertise where they've been used in for many years. We can benefit a great deal from these fields if we see the parallels to maintenance. An example is the survival analysis. This analysis is used in medical research to estimate life expectancy for people.

- For example, we would like to know the average life expectancy of a man in the Netherlands. A survival analysis can be used for that just by looking at their age at the time of death. However we could also differentiate by estimating the life expectancy of a smoker and a non-smoker. Smoking is called a proportional hazard. To do this we use the Survival Analysis with Proportional Hazards, also the Cox Regression. Now we can see the adjusted life expectancy for different scenario's. For example also different treatments of a patient.

Slide Survival analysis for Centrifuges

- Using the same theory for the life expectancy of centrifuges gives this figure. It gives the expectancies for 4 centrifuges based on all their failures leading to downtime no matter what the failure mode was (similar to the average age of a man in the Netherlands).

- Now we look for proportional hazards for the centrifuge which could have influenced the life time.

Slide Survival analysis with Hazards

- This plot shows the average life expectancy (dotted line) and the influence of the process conditions on the number of failures with the confidence interval. It shows that a higher discharge pressure of G01 has a negative influence on the expected lifetime. And a higher discharge pressure of the G02 has a positive effect. In the end the discharge line of the G01 was blocked giving a higher pressure. Not known at that time was that this pressure apparently has an effect of the seals in the centrifuge causing internal leaks to appear quicker.

CONDITION BASED MAINTENANCE – MODEL CENTRIFUGES

Slide Survival analysis predicted lifetime

- The Cox Regression can now predict the life expectancy for different scenarios for the proportional hazard. These outcomes can be useful to show the effect of higher demand of equipment. Also it enables you to give a base for decreasing your maintenance interval when the proportional hazards are reduced.

Slide Next steps for DFS

- Up to now we have implemented the linear regression models for the centrifuges, steam boilers, heat exchangers and steam control valves. We have studied our bad actors further to see where we see opportunities for models. It is based on the detectability of the main failure modes and the number of useful measurements near the equipment.

- The survival analysis is mainly going to be used for Root Cause Analysis and to estimate the probability of failure as input for risk analysis like FMECA and HAZOP. I believe this is the a big opportunity for process safety studies for aging assets where no accurate failure data is available.

- Thank for your attention.