Predictive Maintenance

Phd candidate: Ewa Laskowska
(09.2018-09.2021)
Supervisor: Professor Jørn Vatn
Agenda:

• Case of study
• Data
• Existing model
• System diagnosis (qualitative)
• Data analysis
• Possible health indicators
• Prognostics: ideas
• Anomaly detection: idea
Emergency Shutdown Valve (ESV) – SISs final element

A Safety Instrumented System (SIS) is used for providing protection against failures of safety critical systems which is associated with potential harm of people, economy and/or environment (Rausand, 2014).

Final elements may be regarded as the most vital subsystems as they (upon events like process upsets) interact directly with the process, but due to the force and motion to be exerted when action is asked, these devices are rather vulnerable to creeping degradation processes (Wu et al. 2018)
The data regarding system condition monitoring:

1) Reports from maintenance
2) Activation times of valves
3) Torque registered during valves activations
Condition Monitoring Data:

- Maintenance reports
- Activation times
- Torque

Existing model: Data analyzed: To be analyzed
Condition Monitoring Data:

- Maintenance reports
- Activation times
- Torque

What to look for?

Existing model

In analysis

To be analyzed
Activation times:

- The activations are random, they don’t have a constant frequency
- Number of “operations” in each activations are also random and differ from case to case
Analysis of Activation times of ESVs

“In terms of the final elements of an ESD, they can suffer several failure mechanisms (...) For example, closing time on demand is an indicator of the performance of a shutdown valve.” (Zhang, Zhang et al. 2020)

Contributors to Closure time:

1) Time between activations
2) Number of actions within each “activation series”
3) Average closure time within each “activation”
Analysis of Activation times of ESVs

Assumed correlation (some of them):

1) Closure time vs Time between activations
2) Number of “operations” within each “activation series” vs time
3) Average closure time within each “activation” vs time
Analysis of torque

“The risk of spring fatigue depends on other factors too, such as the designed stress in the spring, **alongside the amplitude of the pulsation** and the material’s maximum tensile strength.”
Analysis of torque

Health Indicators:

1) Breakaway force >> valve stuck in the position >> require more testing
2) Pattern in valve movement >> more friction leading to faster fatigue >> less tests
Challenges related to the data

- Lack of failure data for the analysis
- Unknown threshold of degradation: fatigue or others
- There can be some hidden behaviors making analysis difficult
## System knowledge & Data analysis: HI & contributors

<table>
<thead>
<tr>
<th>DOP</th>
<th>Health Indicator</th>
<th>Contributors/explanatory variables</th>
</tr>
</thead>
</table>
| Sticky actuator       | Time to close valve                   | • Time between activations ?  
• Time to LO  
• Gradient on LO  
• Differences in actuator pressure and torque  
• Time since last action                                                                 |
| Valve stuck in the position |                                       | • Time between activations  
• Time between activations  
• Torque integral to LO                                                                 |
| Friction on valve stem |                                       | • Time from LO to RC  
• Average amplitude in torque  
• Maximal amplitude  
• Total time spent in travel                                                                 |
## System knowledge & Data analysis: HI & contributors

<table>
<thead>
<tr>
<th>Friction on valve stem</th>
<th>Torque integral</th>
<th>Contributing factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>FTC</td>
<td>Health Indicator</td>
<td>Time from LO to RC</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Average amplitude in torque</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Maximal amplitude</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Total time spent in travel</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Total time spent in travel (cumsum of closure times from previous operations)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Total torque integral (cumsum from previous operations)</td>
</tr>
</tbody>
</table>

- Aging: Fatigue, creeping
PHD Multiphase Markov model for degradation, testing and maintenance of ESVs

Model extension: Condition based inspection policy

![Diagram showing states: Long, Medium, Short, Failure.]

Graph showing probability of failure on demand (PFD) over time (in hours) for different intervals of condition-based testing routines.
**System prognostics : Phasetype Markov model**

![Diagram of Markov model]

<table>
<thead>
<tr>
<th>Competing risk Markov model</th>
<th>Existing phase-type Markov model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Consider two competing failure modes DOP and FTC</td>
<td>1. The structure already exist</td>
</tr>
<tr>
<td>2. Based on the historic data (OREDA) and expert judgment set up “theoretical” distribution of each failure mode</td>
<td>2. The condition described by 5 states would a HI and closure time or torque integral could be used as covariates</td>
</tr>
<tr>
<td>3. Find the phase-type structure for each failure mode</td>
<td>3. Data doesn’t match (dates and number of maintenance inspections vs ESV activations</td>
</tr>
<tr>
<td>4. Set up health indicators and covariates (from previous slide)</td>
<td></td>
</tr>
<tr>
<td>5. Estimate coefficients for variables</td>
<td></td>
</tr>
</tbody>
</table>
System prognostics: Phasetype Markov model

\[ \lambda = e^{\beta_0 + \beta_1 z_1 + \beta_2 z_2} \ldots \]

Since they modeled the expected value of \( T \), they suggested to multiply the intensity matrix by a factor \( \exp\{-\beta'x\} \).

(Bo Lindquist, Phase-Type Distributions for Competing Risks)

A least square approach to estimate \( \beta = [\beta_0, \beta_1, \beta_2, \ldots] \) is now given by minimizing Equation (12):

\[ Q(\beta) = \sum_{j=1}^{J} \left( s_{j,2} - E(Y_j(t_2)|Y_j(t_1) = s_{j,1}) \right)^2 \]  \hspace{1cm} (12)

(Jørn Vatn, Maintenance Optimization Course compedium)
Anomaly detection: Machine Learning

Particularity of my data:

- Activations of ESVs are data are times series on its own – just due to having measurements at different points of time
- Each activation of ESV is a time-dependent variable with some pattern.
- The activations frequency is not constant – it’s random variable which by itself could be an indication of some problems
- Because of the above point the data are not cyclic data and the times between activations can differ a lot
- Time needed to perform an activation of valve is way smaller than intervals between activations what makes a presentation of the data on the timeline unreadable
Anomaly detection: Machine Learning

<table>
<thead>
<tr>
<th>PCA: correlation in the data</th>
<th>Time series Analysis: search for trend</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlations</td>
<td>Trend</td>
</tr>
<tr>
<td>1. Is PCA feasible on the «my» data</td>
<td>1. How the data should be formatted/presented</td>
</tr>
<tr>
<td>2. How to set up covariates?</td>
<td>2. Do exist suitable methods to analyze the data I have?</td>
</tr>
<tr>
<td></td>
<td>3. What are popular time series models?</td>
</tr>
</tbody>
</table>

To investigate: Cazes et al. [8] and Lauro and Palumbo [21] have introduced principal component analysis methods that are suitable for interval-valued data.

Current idea: Interval-valued time series

Interval-valued time series are interval-valued data collected in a chronological sequence. Interval-valued data arise quite naturally in many situations in which such data represent uncertainty (for instance, confidence intervals), variability (minimum and maximum of daily temperature), etc.
Anomaly detection: Machine Learning

Models proposed for interval-valued time series:
- autoregressive (AR) model
- autoregressive integrated moving average (ARIMA) model
- ANN
- on a hybrid methodology that combines both ARIMA and ANN models

Time series where the time axis is actually “time in use”
Thank you
## System diagnosis - motivation

<table>
<thead>
<tr>
<th>Motivation</th>
<th>Application</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Investigation of dependencies between failure modes to improve testing optimization</td>
<td>• Recognize <strong>leading failure mechanisms</strong> for optimization of inspection strategy under assumption of testing negative impact</td>
</tr>
<tr>
<td>• System knowledge as the input for torque data analysis</td>
<td>• Setting up <strong>health indicators</strong> based on the understanding of the system degradation</td>
</tr>
</tbody>
</table>

“... having a good understanding on the stress mechanisms related to the tests becomes paramount in deciding on the test interval duration in the equipartitioned case” (Hafver, Oliveira et al. 2019)
Safety critical failure modes and degradation mechanisms:

- **ESV failure**
  - DOP: Focus on the valve
    - Sticky actuator
    - Valve stuck in the position
  - FTC: Focus on actuator spring
    - Friction on valve stem
    - Aging: Fatigue, creeping

- Aging:
  - Fatigue, creeping
Safety critical failure modes and degradation mechanisms:

- **ESV failure**
  - **DOP** Focus on the valve
    - **Sticky actuator**
    - **Valve stuck in the position**
      - **Friction on valve stem**
        - **Aging:** Fatigue, creeping
          - Test less
          - Test more
  - **FTC** Focus on actuator spring
    - Test less