MULTI-BODY DYNAMIC SIMULATION FOR IDENTIFICATION OF OPERATING SCENARIOS ON A POWERPLANT GENSET USING MACHINE LEARNING

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WÄRTSILÄ

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A BIT OF BACKGROUND INFORMATION ABOUT WÄRTSILÄ

- Global leader in smart technologies and complete lifecycle solutions for the marine and energy markets.
- Focus on sustainable innovation, total efficiency and data analytics to maximize the environmental and economic performance of the vessels and power plants of its customers.
- The company has operations in over 200 locations with 19000 employees in more than 80 countries.
- Wide portfolio of medium-speed engines:
  - Bore sizes 14 – 50 cm
  - Power output 675 kW – 23000 kW
  - Liquid fuel, Gas or Dual fuel, Hybrids
Knock sensors and cylinder pressure sensor have high failure rate. A powerplant V20 engine has 20 knock sensors and 20 pressure sensors that can fail.

This condition jeopardizes the reliability of failure detection systems.

Is it possible to detect abnormal situations only by analyzing the speed of the crankshaft?
APPROACH

• Create and validate a V20 generating set model in GT-SUITE
• Use the model to simulate different operating conditions
• Process the simulated flywheel speed to highlight the main features of the signal
• Two families of machine learning algorithms were tested:
  ➢ Pattern recognition algorithms
    ✓ Three
    ✓ Discriminant
    ✓ SVM
    ✓ kNN
    ✓ Ensembles (boosted and bagged Trees, subspace Discriminant, subspace kNN)
  ➢ Neural network (2-layer feed forward).
MULTI-BODY POWERPLANT GENERATING SET MODEL

Valvetrain

Generator

Cranktrain

Intermedi- ate shafts

Coupling

Intermedi- ate shafts

Vibration damper
MODEL DETAILS

- All shafts are torsion shafts, no bending accounted for
- Simple journals and pins modeled as revolute joints
- Damper and coupling modeled as torsion spring and damper in parallel
- Valvetrain modeled up to the lifter and calculated contact forces applied to it
  - No need for an accurate model of valves
  - Reduced computing load
- Generator model limited to the rotor with imposed speed:
  - In the real installation the generator is connected to a large electric grid, which constrains the rotating speed to the frequency of the grid. For simulations with engines running at constant speed this has been observed to be a valid simplification.
SIMULATION SETUP

• Input:
  • Individual pressure curves measured from test engine (use of permutation to increase the amount of cases)
  • Pressure curves of repetitive misfire, heavy knock and overpressure, simulated in one cylinder at a time per case.

• Output:
  • Speed of the flywheel.

• Engine running at 100% load and 750 RPM constant speed.

• Simulated cases:
  • 100 cases of normal operation
  • 60 cases of heavy knock
  • 60 cases of misfire
  • 60 cases of overpressure (on 3 different levels).

• Each case outputs a dataset corresponding to 50 engine cycles.
CORRELATION WITH MEASURED DATA
DATA ANALYSIS: PROCESSING OF THE SIMULATION RESULTS

Creation of subsets
• Every dataset is divided in sub-sets of 2 cycles each. This to have sets closer to the actual measurement arrangement (avoiding the averaging over a long dataset) and to further increase the amount of samples available.

FFT analysis
• Output the amplitude of the constituent waves of the speed signal (RPM vs Hz)

Peaks isolation
• The peaks of every half-order in the 0-200 Hz range are isolated

Creation of the case matrix
• Every set of peaks is flagged according to the corresponding scenario (normal, knock…) and they are collected in the same matrix.
SIMULATION RESULTS

[Graph showing simulation results with different colors representing normal, heavy knock, misfire, and overpressure scenarios. The x-axis represents orders, the y-axis represents amplitude [RPM], and the z-axis represents cases.]
PATTERN RECOGNITION ALGORITHMS (PRA)

• It is a family of machine learning algorithms that aims to classify the samples by analyzing their geographical location in the domain.

• The scope of these algorithms is to classify data in predefined categories.

• The training of the algorithms is supervised, which means that the algorithm knows a priori to what category the sample belongs to and tries to define the boundaries in the space accordingly.

• The number of dimensions of the space is defined by the amount of column in the input matrix (in this case the number of peaks accounted, 32)
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### PRA: ENSEMBLE (SUBSPACE KNN)

The confusion matrix illustrates the success rate of a trained algorithm to predict the real class of a sample.

<table>
<thead>
<tr>
<th>True class</th>
<th>Normal</th>
<th>Knock</th>
<th>Misfire</th>
<th>Overpres</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>&gt;99%</td>
<td>0%</td>
<td>&lt;1%</td>
<td>&lt;1%</td>
</tr>
<tr>
<td>Knock</td>
<td>1%</td>
<td>95%</td>
<td>4%</td>
<td>0%</td>
</tr>
<tr>
<td>Misfire</td>
<td>1%</td>
<td>4%</td>
<td>95%</td>
<td>0%</td>
</tr>
<tr>
<td>Overpres</td>
<td>4%</td>
<td>&lt;1%</td>
<td>0%</td>
<td>96%</td>
</tr>
</tbody>
</table>

- The ensemble algorithms meld results from many weak learners into one high-quality ensemble model.
- k-Nearest Neighbor (kNN) classifies the samples on the basis of their distance to points (or neighbours) in a training dataset.
- The strong skill of this algorithm is in the detection of normal behaviour (accuracy >99%).

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ARTIFICIAL NEURAL NETWORK

The neural network is a 2-layer feed-forward network with 10 sigmoid hidden neurons and softmax output neurons.

This neural network classifies accurately the anomalies but generates some false detections in the classification of normal samples.

Network structure:
CONCLUSIONS
RESULTS

- The best pattern recognition algorithm (Subspace kNN) showed a high level of accuracy in the classification (97%) and a particularly low rate of false negatives (<1%) when classifying the normal samples.

- The neural network had a lower level of accuracy in the detection of the anomalies (94.3% on average) but it was more capable than the PRA to discern the different anomalies and a bit less accurate in the distinction between them and the normal cases.

- Both the approaches showed already at this stage interesting classification capabilities and room for further refinement, for example, by analysing a wider range in the spectrum or including measurements from additional sensors.
LIMITATIONS OF THE STUDY

- The dataset is limited to a specific engine speed and load. This makes the actual trained algorithms and network unable to evaluate other situations.
- The engine simulations account only one engine model in a specific operating setup and only its main components.

FURTHER IMPROVEMENTS

- Increase the complexity of the simulations:
  - Multiple anomalies
  - More variety in the simulated scenarios
  - More scenarios in the training.
- A sensitivity analysis of the parameters affecting the algorithm performances
- Testing and validation with field data
- Test unsupervised learning approaches.
CONCLUSIONS

• At a glance, monitoring the crankshaft speed seems a promising approach to detect misbehaviour in the engine.

• Simulation results are preliminarily assessed from an acknowledged point of view, showing beforehand identifiable peculiar trends.

• In parallel with the understanding of the phenomena, data-driven approaches are adopted to improve the quality of the anomalies detection (e.g. spectrum peaks isolation).

• The tested machine learning algorithms show that it is possible to recognize different scenarios after a training with a reasonable number of samples.
THANK YOU!

Questions?

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