Feature engineering –based machine learning models for operational state recognition of rotating machines

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Abstract

Data-based models for operational state recognition and detection of abnormal operation of a gas engine generating set (genset) in near real-time were provided. One model can classify the current power output level very accurately, and the other can detect abnormal operation (novelties), e.g., in fault situations, at a specific load level. Thus, a fast and accurate two-step state recognition model can be built.

Introduction

- Models for operational state recognition and detection of abnormal operation of a gas engine genset in near real-time based on measured or simulated vibration data
- Data source: Wärtsilä 20V31SG genset
  - Rated power: 11 MW
  - Operates at constant speed 750 rpm, 4-stroke cycle
- Power output and operation only virtually constant: notable fluctuations in combustion between engine cycles lead to i.a., constantly varying cylinder pressure profile, rotation speed and vibration response

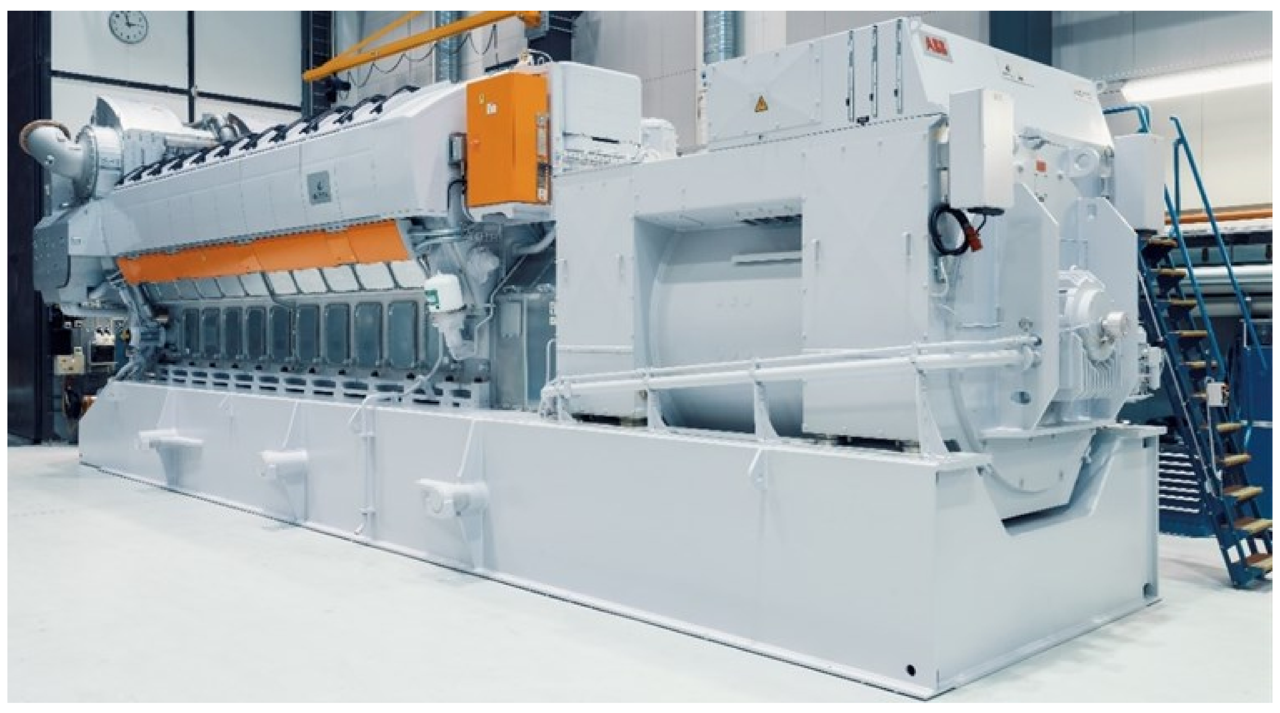

Fig 1. Wärtsilä 20V31SG genset (Image courtesy of Wärtsilä). ©2021 Wärtsilä Corporation

Features

- Newton: F = ma
  - The higher the power output the higher the vibrations
  - F = inertia forces + gas forces
    - Analytical solution for inertia forces (or torque):
      - $M = \frac{1}{2} m_{rec} \omega^2 r^2 \left(\frac{r}{2l} \sin \omega t + \sin 2\omega t + \frac{3r}{2l} \sin 3\omega t \right)$
      - Acceleration at order 1.5 depends only on gas forces → Sensitive to changes in power output
- Two feature extraction functions, f_1 and f_2, were used
  - f_1 = Signal power $P = \frac{1}{N} \sum_{n=1}^{n=N} |x(n)|^2$
  - f_2 = Acceleration amplitude at order 1.5 using FFT
  - Feature values extracted from short signal segments corresponding to the lengths of multiples of engine cycle

Methods

- First models were based on measured vibration data at different load levels with extracted features f_1 and f_2
- Popular classifier and novelty detection algorithms were tested, and their accuracy and speed were compared
- Features and models using simulated (FEM) vibration data of normal operation at different load levels were produced and compared with their measured data equivalents

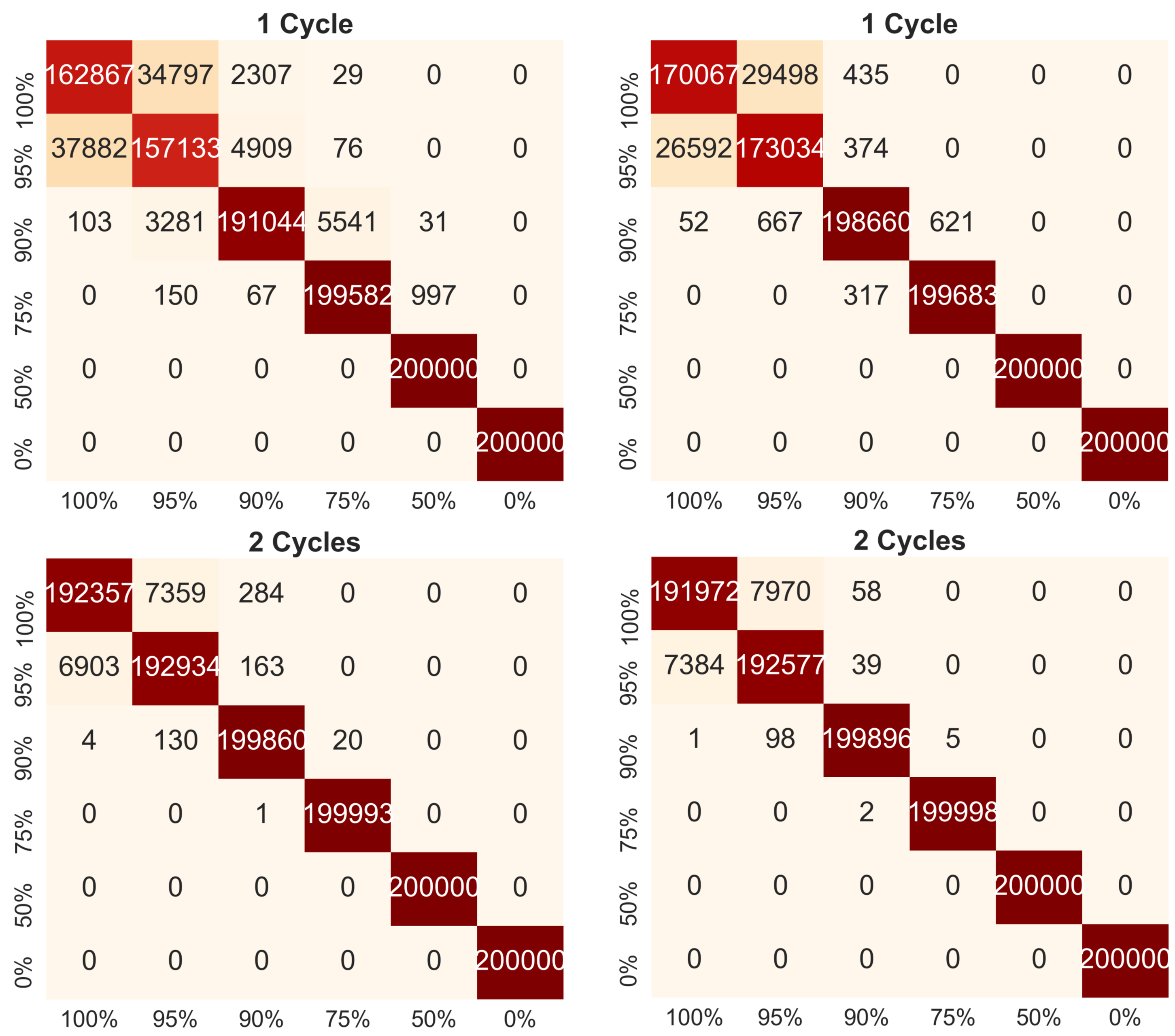

Fig 2. Confusion matrices for the machine learning models trained on features obtained from one or two cycles long signal segments. Left: the Extreme Learning Machine, right: the Logistic Regression.

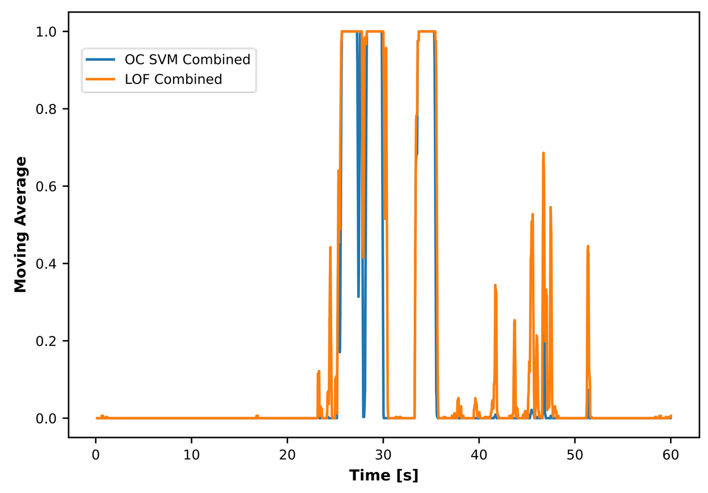

Fig 3. Abnormal operation detected by models trained with two different algorithms

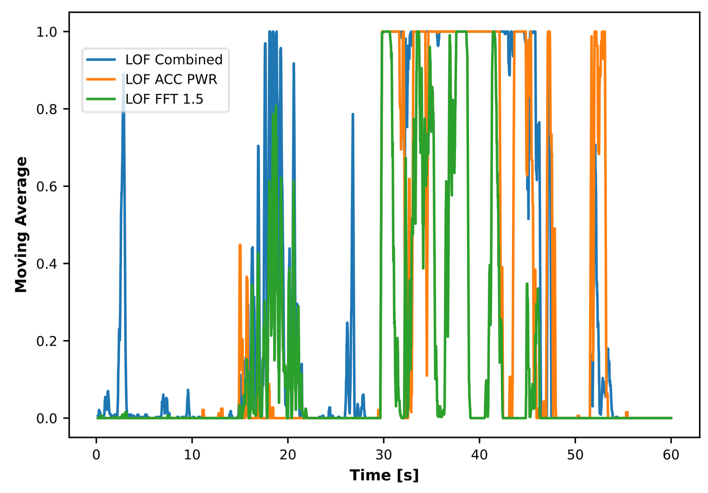

Fig 4. Abnormal operation detected by models trained using the features combined and separately

Table 1. Accuracies (%) of the LR classifiers using both features for the measured (M) and the simulated (S) cases in four different locations (P1 - P4) and obtained from one or two cycles long signal segments.

Signal length (cycle)	Measurement point							
	P1		P2		P3		P4	
	M	S	M	S	M	S	M	S
1	95.1	99.2	92.2	100	95.1	81.6	87.8	100
2	98.7	99.9	96.7	100	97.7	92.9	97.4	100

Conclusions

- **Accurate and fast operational state recognition is possible using a single triaxial accelerometer and computationally light feature extraction and ML methods**
- **Logistic Regression and Extreme Learning Machine for classification and Local Outlier Factor for abnormal operation detection were found efficient**
- **Accurate classification requires all 6 feature values extracted from at least 2 cycles long signal segments**
- **Sufficient measured data to build an operational state recognition model for detecting and recognizing abnormal operation is rarely available**
- **Compared to measured vibration the simulated has less variation and notably different frequency content**
- **Simulation models and methods need further development to be ready to fill the lack of measured data**

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