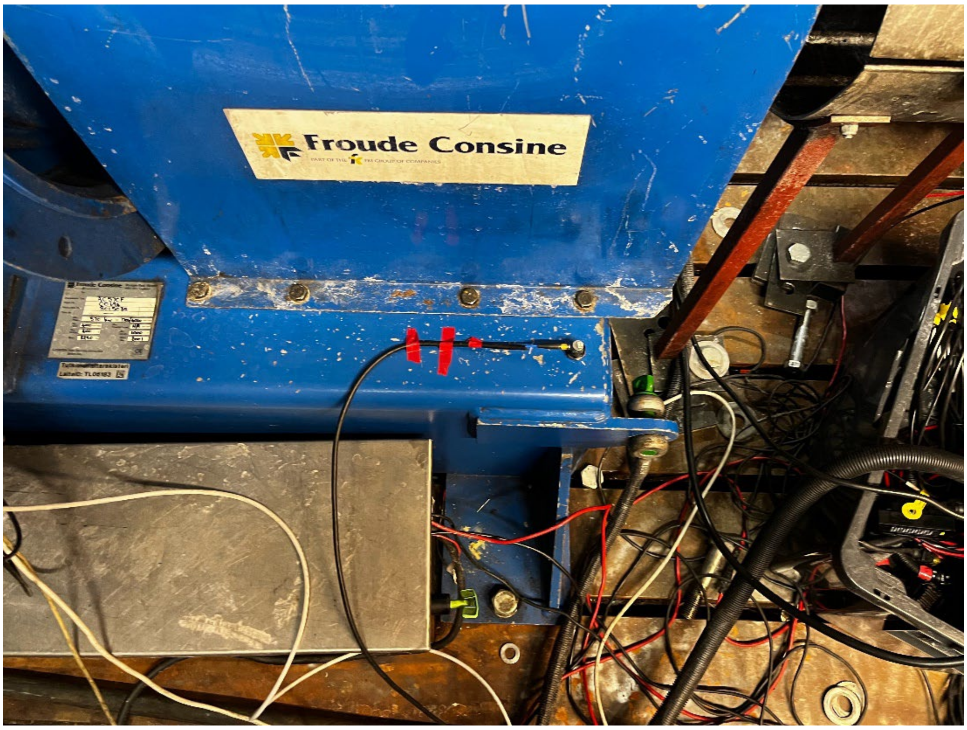
RESEARCH REPORT VTT-R-00272-24



Operational State Estimation of Compression Ignition Engines

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beyond the obvious

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Operational State Estimation of Compression Ignition Engines	
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Summary

The NL ROSE project aims to reach the next level (NL) of real-time operational state estimation (ROSE) of rotating machines by extending the state estimation capabilities from constant speed to variable-speed operation. Real-time operational state estimation is a fundamental building block of mechanical digital twins (DTs) which in turn are seen to create additional value to the machinery industry. Feature extraction and machine learning (ML) methods based on measured acceleration vibration data were previously developed and studied for the purpose of the operational state estimation of a Wärtsilä generating set operating at constant speed as part of the project called DigiBuzz funded by Business Finland. During the DigiBuzz project it was shown that the demand to produce large amounts of high-quality data for the purposes of ROSE model development is high. Thus, creating the ability of efficient in-house data production is key for this project as well as future work to accelerate the development process of DTs and reach our goals faster.

The demonstration targets of this project were two variable-speed internal combustion engines (ICEs) manufactured by ACGO Power. The vibration acceleration measurements of the two ICEs were carried out during emission tests performed at VTT engine laboratory. The applicability of the previously developed feature extraction and ML methods as well as other two openly available feature extraction methods for time series, namely MiniRocket and TSFEL, was validated using the measured data. As was expected based on previous work, the accuracies of all models were relatively high in general. However, the measurement point location proved to have a significant effect on the model accuracy. The models based on the vibration accelerations measured at the engine block drive-end side (MP4) were the most accurate at large.

The models based on the previously developed feature extraction method performed similarly as the models in the previous studies. In fact, the models of this study were somewhat more accurate. Especially the models based on the accelerations measured at MP4, for which the lowest accuracy was 96.699 % and the rest were over 99.9 % accurate.

The two openly available feature extraction methods performed extremely well at the task. The models based on the features extracted with either of the two methods were in most cases 100 % accurate, and 99.74 % accurate in the worst case. Feature selection showed that the number of features can be reduced radically without significant effect on the accuracy. 100 % or close to 100 % accuracy can be achieved in most cases by using only the best 25 of 9996 MiniRocket features or the best ten of the over 800 TSFEL features.

The data measured in this study are not enough to cover the whole range of operation of the studied engines. However, the results show that the ROSE of variable-speed ICEs could be possible if data were available sufficiently. Thus, further development of the studied subject requires measurements covering the operational range of ICEs more comprehensively.

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Contents

1. Introduction

Real-time state estimation has previously been applied for simplified cases at VTT e.g., for internal combustion engines (ICEs) operating at constant speed. Anyhow, common operation environment for almost any industrial application is diverse and complex. Therefore, the real-time state estimation methods and procedures need to be developed separately considering products and their use cases and operational conditions individually. Building such methods and processes demands large amounts of high-quality data which VTT has previously not produced. Thus, creating the ability of efficient in-house data production is key for this project as well as future work.

The development of the ML methods for operational state estimation of rotating machines was initiated in the project called DigiBuzz funded by Business Finland. As part of the DigiBuzz project, feature extraction and ML methods were developed and studied for the purpose of the operational state estimation of a Wärtsilä generating set [1] and [2]. The models developed were based on measured acceleration data. The work continued in a customer project called Artie with Wärtsilä in which the developed methods were tested on simulated data [3]. The development of the simulation methods to produce applicable acceleration data, that is data with variance, was a necessary and significant part of the Artie project [3].

Through this project we will extend VTT's knowledge in the field of operational state estimation of rotating machines especially to the variable-speed environment. Real-time operational state estimation is a fundamental building block of component and system level mechanical digital twins (DTs) which in turn is the excellence target of the BA5511 team (BA4303 team from beginning of 2024) and are seen to create additional value to the machinery industry.

On the other hand, past customer projects have made it evident that VTT has not been able to produce the data needed for the purposes of developing and testing operational state estimation methods, especially considering ICEs. In this project we will develop our capability of in-house data production and thus accelerate the development process of DTs and reach our goals faster.

2. Goal

The objective of this study is to develop (near) real-time state estimation methods and procedures in variable-speed operation environment based on measured vibration acceleration responses. The demonstration targets are variable-speed ICEs available at the VTT engine laboratory. During this project the excellence and knowledge about the process of automatic online fault recognition of rotating machines is developed further and in-house data production is launched. Thus, the developed excellence can be exploited in a wide range of industrial applications.

VTT engine laboratory performs emission testing of high-speed ICEs. The aim of this study is to perform the vibration acceleration measurements with permission from the customer on the applicable ICEs tested at the VTT engine laboratory during the year 2023. The applicability of the previously developed feature extraction and ML methods presented in [1] for the operational state estimation of variable speed ICEs is validated using the measured data. Other feature extraction methods and libraries namely MiniRocket [4] and time series feature extraction library (TSFEL) [5] are tested as well, and the ML models based on the different extracted features are compared.

3. Description

Two applicable ICEs for the purposes of this study were tested at the VTT engine laboratory during the year 2023. Both were compression ignited four-stroke engines manufactured by AGCO Power. The first, an inline-three engine, was tested between March and April. The second, an inline-six engine, was tested during June.

The VTT engine laboratory testing facilities are mostly used for emission and fuel tests of ICEs. An engine dynamometer (Froude Consine, UK Model: Froude AC 570 F) is used for torque and rotational speed measurements and the engine load control. In structural terms the engine test bench at the laboratory comprises of the dynamometer and four supports (two on both sides of the engine) for the engine under test mounted on a base plate. The base plate is vibrationally isolated from its surroundings by air suspension. The engine under test is connected to the dynamometer with a flexible clutch and rubber isolation is used between the engine and the supports. A schematic structural drawing of the test bench is presented in Figure 1.

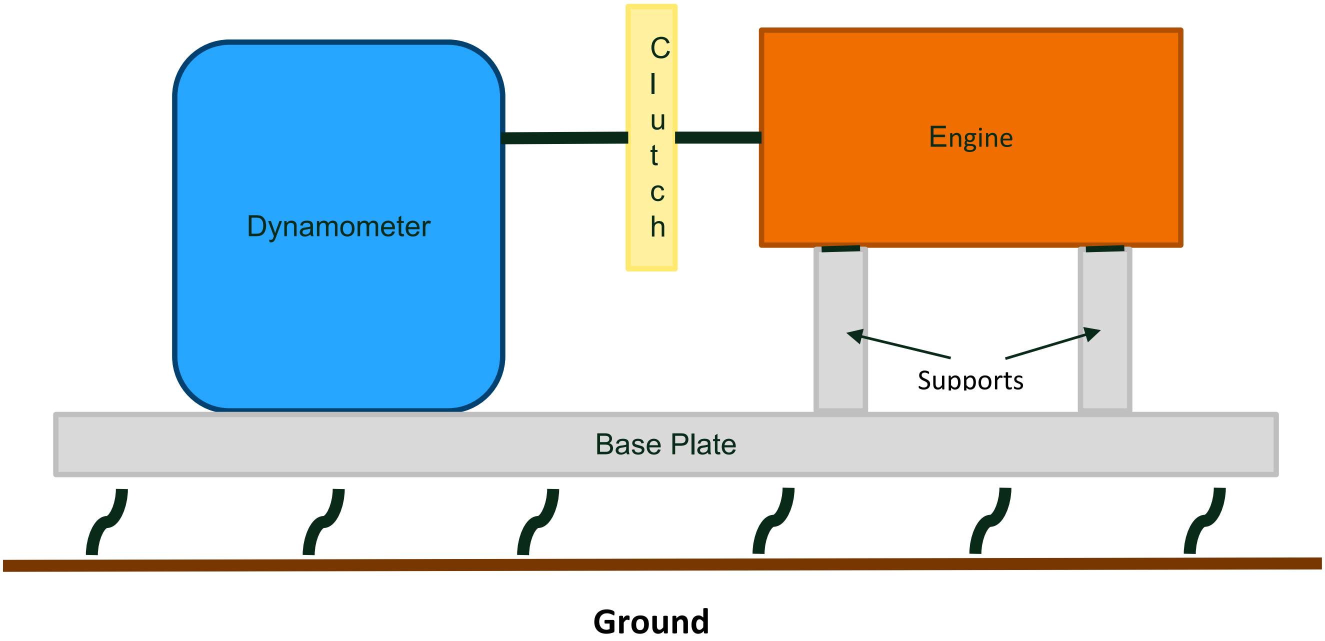

Figure 1. Schematic structural drawing of the VTT engine laboratory test bench.

4. Limitations

The operational states of the engines, i.e., operation at constant torque and rotational speed, during the vibration acceleration measurements were defined by the exhaust emission test cycle requirements.

Determining the most suitable vibration acceleration measurement points by simulation was not possible, due to the absence of structural simulation models of the engines and the test bench. No structural changes were made to the engines nor the test bench to facilitate the vibration acceleration measurements.

5. Methods

Classification models based on measured vibration acceleration data for operational state estimation of variable-speed ICEs were built in this study. In this study a state of normal operation of an ICE denotes constant power output, or constant torque, at a constant rotational speed. The vibration accelerations were measured during exhaust emission tests performed at VTT engine laboratory. Three different feature extraction methods were used, and classification models based on the features extracted using the different methods were compared.

5.1 Exhaust emission test schedule

The exhaust emission tests for both engines were performed as indicated in ISO 8178 C1 schedule. The ISO 8178 C1 schedule has 8 modes as follows:

I. Modes 1 – 4: 100 %, 75 %, 50 %, and 10 % torque at rated speed.
II. Modes 5 – 7: 100 %, 75 %, and 50 % torque at intermediate speed.
III. Mode 8: 0 % torque at idle

A short introduction to the ISO 8178 standard is given e.g., in [6].

5.2 Vibration acceleration measurement arrangements

5.2.1 Measurement system

Measurement system consisted of National Instruments (NI) USB CompactDAQ DAQ-9178 chassis (Figure 2), five NI-9234 acceleration modules (Figure 3), Monarch Remote Optical Laser Sensors (ROLS) tachometer (Figure 4) and a measurement computer with LabView runtime to run created measurement software on it.

The NI USB CompactDAQ DAQ-9178 chassis can hold in total eight measurement modules and form a connection to a measurement computer with a USB3 port. In the current measurements five of the eight slots were equipped with NI-9234 vibration acceleration modules. Each vibration acceleration module has four channels that can measure simultaneously at up to 51.2 kHz/channel with 24-bit resolution. In the current measurements, an acquisition rate of 5.12 kHz/channel was used which is adequate for the studied engines with rotation speeds below 3000 rpm i.e., 50 Hz. Anti-aliasing filtering was carried out by NI-9234. The engine rotation speed was measured using the Monarch ROLS tachometer attached to a magnetic holder next to the motor and reflective tape was attached to the wedge groove of the flywheels. The tachometer can measure up to 250000 rpm. Each time the reflective tape passes the laser, a pulse is detected, and a 5V step is recorded with the measurement system.

The created measurement software calculated in real-time the selected features as:

- Peak amplitude of the windowed FFT from selected frequency band(s)
- Vibration acceleration RMS (1 sec moving window)

and store them to hard drive for final analysis calculation and development.

Figure 2. NI CompactDAQ cDAQ-9178 8 slot chassis (ni.com).

Figure 3. NI-9246 IEPE acceleration module (ni.com).

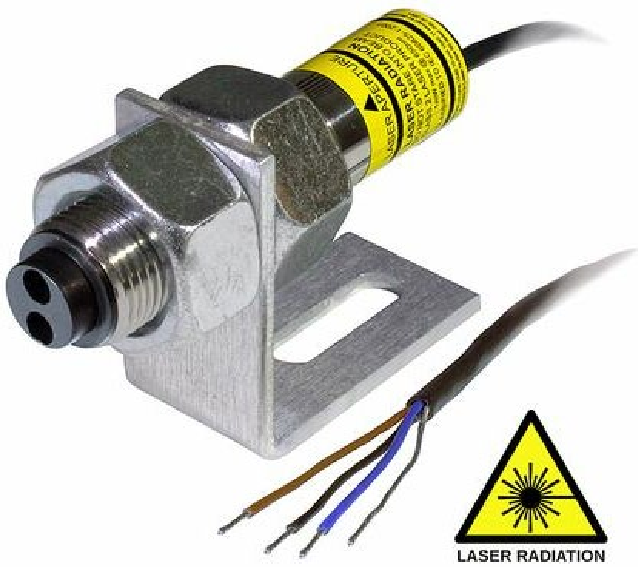

Figure 4. Monarch Remote Optical Laser Sensors (monarchinstrumentation.com).

5.2.2 Coordinate system and sensor locations

The measurement coordinate system (right-handed) is defined as follows:

I. X-axis located on the engine crankshaft centreline with positive direction from the dynamometer towards the engine.
II. Z-axis with positive direction perpendicular to gravity.
III. Location for origin on X-axis is not defined.

Vibration accelerations were measured at six locations, of which three were on the engine, two on the engine supports and one on the dynamometer. Descriptions of measurement point (MP) locations are given in Table 1 and the MP locations are indicated in Figure 5.

Table 1. Descriptions of measurement point locations.

MP	Component	Location	Global Y-coordinate
1	Dynamometer	Base, drive end side	Negative
2	Engine support, non-drive end side	Bottom flange	Negative
3	Engine support, drive end side	Bottom flange	Negative
4	Engine	Block, drive end	Negative
5	Engine	Drive end, above shaft	Zero
6	Engine	Block, non-drive end	Negative

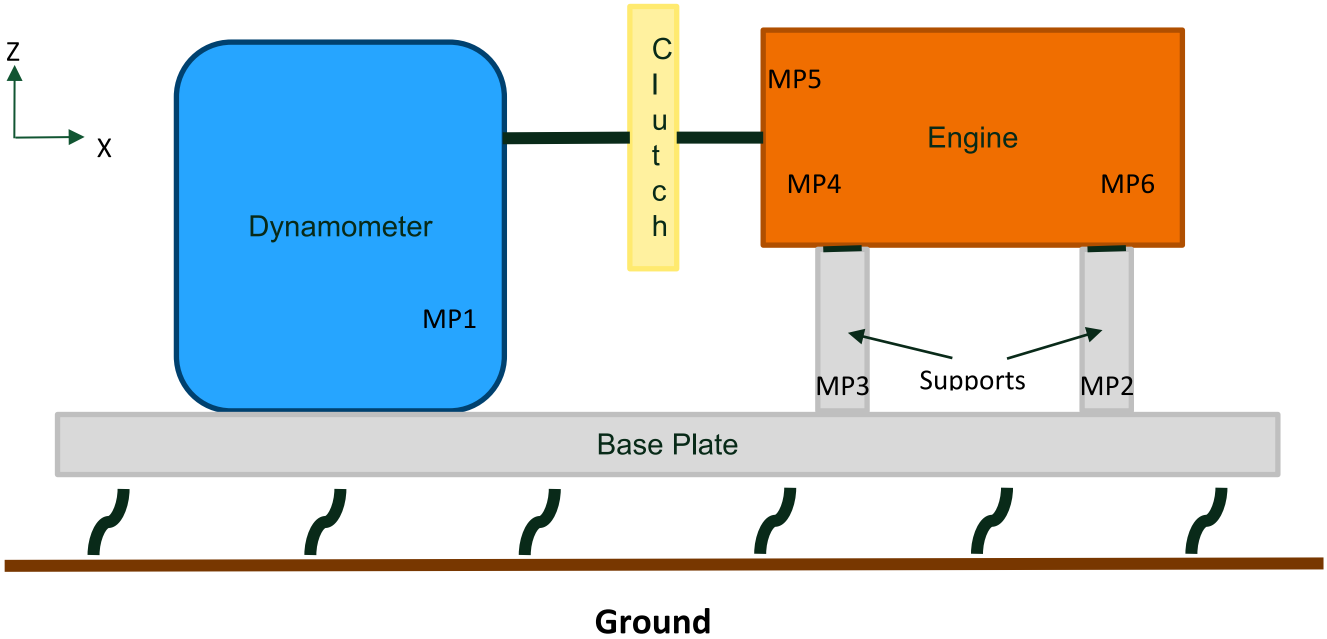

Figure 5. MP locations in the schematic structural drawing of the VTT engine laboratory test bench.

The local coordinates directions corresponding to the global coordinate directions for the MPs are presented in Table 2.

Table 2. Global coordinate directions in MP local coordinate directions.

MP	Global X	Global Y	Global Z
1	+X	+Y	+Z
2	-Z	-Y	-X
3	-Z	-Y	-X
4	+Z	-Y	+X
5	-Z	+X	-Y
6	+Z	-Y	+X

5.3 Feature extraction methods and classification

Three different methods for feature extraction from the measured vibration acceleration data were used. The first being the previously developed feature extraction method presented in [1]. The two other methods, namely MiniRocket and TSFEL, are openly available methods for feature extraction from time series data.

5.3.1 Previously developed feature extraction method

The previously developed classification models are based on a combination of six features: the signal powers and the amplitudes of the third harmonic of the engine cycle of the vibration acceleration signals of a triaxial sensor. The models can be used for accurate classification of normal operational states of a spark-ignited generating set. The accuracy of the classification depends on the length of the signal segment from which the features are extracted. The signal segment lengths used in the previous study were multiples from one to seven of the length of an engine cycle. High classification accuracy (98.7 %) was achieved by using features extracted from two engine cycle long segments. The classification accuracy was significantly lower (95.1 %) using features extracted from one engine cycle long segments. The highest accuracy (99.7 %) was achieved using segment length of six cycles. The afore mentioned accuracies were achieved using logistic regression algorithm for classification. However, the accuracy of the model is not the only criteria for its evaluation since classification based on shorter segments gives predictions closer to real-time. [1]

In this study the features were extracted from the measured vibration acceleration data with the previously developed method using signal segment lengths of one and two engine cycles. The frequency components of the signal are computed using the fast Fourier transform (FFT). The previously developed feature extraction process uses the sliding window technique for which the window size is the segment length. The feature extraction using the previously developed method was done using MATLAB 2023a Software. As the sliding window technique is parallelizable, the usage of GPU computing, which is easily available in MATLAB, significantly reduces the computational time of the feature extraction process compared to CPU computing.

5.3.2 MiniRocket features

The MiniRocket algorithm is based on calculating convolutions of the time series with a predetermined set of kernels. The algorithm extracts in total 9996 feature values which are the portions of positive values of the different convolutions. The time series given as input to the algorithm can be either one- or multidimensional. Regardless of the high number of features the extraction process is fast. [4]

In this study the values of the 9996 MiniRocket features were extracted from three-dimensional vibration acceleration signals i.e., the combination of all three signals of a triaxial sensor, instead of extracting the 9996 feature values from each of the three signals individually. Signal segment length of one engine cycle was used only. The implementation of the MiniRocket algorithm in an open-source Python library called sktime presented in [7] and [8] was used in this study. Parallel processing (CPU) is enabled in the used implementation.

5.3.3 TSFEL features

TSFEL is a Python library for extracting statistical as well as time and frequency domain features from a time series. The parallelization of the feature extraction in TSFEL is disabled in Windows. An overview the TSFEL features is presented in [9]. The TSFEL feature labelled FFT mean coefficient_3 is equal to the second feature extraction function of the previously developed method (amplitude of the signal at the third frequency component).

In this study the TSFEL features were extracted from each of the three signals individually. Signal segment length of one engine cycle was used only.

5.3.4 Effect of engine rotation speed on engine cycle and signal segment length

The duration of an engine cycle depends on the rotational speed of the engine. Considering four-stroke engines, such as the engines of this study and in [1], an engine cycle equals two rotations of crankshaft. Thus, the amount of data samples in an engine-cycle-length-based signal segment depends on the rotational speed of the engine if the sampling frequency is constant. The variation of rotation speed i.e., rotation frequency, must be considered especially when extracting frequency domain features by adjusting the length of the signal segment length accordingly. This in turn makes the feature extraction and hence, the classification processes of variable-speed engines very complex as they must be individually defined for the different rotation speeds.

The previously developed feature extraction method and the TSFEL features include frequency domain features. However, the MiniRocket features are not frequency domain features as such. Therefore, the MiniRocket algorithm as well using only statistical, or time domain features of the other two methods enable single feature extraction and classification processes for the whole rotation speed range. The signal segment length used must be fixed based on the lowest rotation speed which is when the engine cycle lasts the longest. The actual signal segmentation can still be made based on the actual rotation speed if the segments are afterwards padded with zeros to the fixed length. That was done in this study considering only the MiniRocket feature extraction process.

5.3.5 Classification and model evaluations

Logistic regression algorithm was proven to be applicable for the operational state estimation in terms of accuracy and computational efficiency in [1] and [2]. Therefore, all classifier models of this study were built using the logistic regression algorithm, to be exact its implementation in a machine learning Python library called scikit-learn [10]. The effect of the size of the training set on classification accuracy was studied in [1]. As expected, larger training set leads to more accurate classifiers, but the differences are small. For example, the classification accuracy increased from 98.61 % to 98.65 % when the training set size was increasedfrom 5000 to 50000 samples per class using signal segment length of two engine cycles. The training set sizes used in this study were made depending on the number of features extracted with each method and not exceeding the amount of 50000 samples per class. The allocation of the feature values to training and test sets was random.

The classifier models were built separately for each of the measured rotation speeds of the engine at which the accelerations were measured at more than one engine torque value. The different classes are thus the different levels of torque at the specific rotation speed.

The classifier models were built separately for each feature extraction method to enable the comparison between the methods. As the number of extracted features varies significantly between the methods, the effect of reducing the number of features on the classification accuracy was studied as well. The number of MiniRocket and TSFEL features were reduced gradually to one. The reduction of features, or feature selection, was done using a dedicated algorithm implemented in the skicit-learn Python library called SelectFromModel. It can be used to choose the most important features for classification based on the importance assigned to the features by the classifier [10].

6. Results

6.1 Measured accelerations

The vibration accelerations of the two engines at the six MPs were measured during the exhaust emission tests at the following combinations of rotation speeds and torques (operational states):

- Inline-three engine, March:
  - 2100 rpm: 246.0 Nm, 172.1 Nm, 115.2 Nm, and 23.3 Nm
  - 2131 rpm: 230.5 Nm, 171.9 Nm, 115.0 Nm, and 23.3 Nm
  - 1573 rpm: 334.1 Nm, 253.9 Nm, and 169.9 Nm
  - 808 rpm: 2.3 Nm
- Inline-three engine, April:
  - 2131 rpm: 230.2 Nm, 171.9 Nm, 115.1 Nm, and 23.2 Nm
  - 1573 rpm: 336.0 Nm, 253.9 Nm, and 170.1 Nm
  - 809 rpm: 6.8 Nm
- Inline-six engine, June:
  - 1950 rpm: 1460.1 Nm, 1096.0 Nm, 731.1 Nm, and 146.1 Nm
  - 1463 rpm: 1762.3 Nm, 1327.0 Nm, and 885.0 Nm
  - 750 rpm: 8.2 Nm

The measurements at each rotation speed were continuous and the different operational states were run in ten-minute intervals.

6.2 Feature extraction

The features were extracted from the measured accelerations using three different methods: the previously developed, MiniRocket, and TSFEL. One-minute-long segment was cut from the start and end of each of the ten-minute intervals of the measured acceleration signals before feature extraction. This was done to avoid the mixing of different operational states with each other, and that steady operation has been established after switching from one operational state to another. Different amounts of features were extracted depending on the computational efficiency of each method. The number of extracted features at different rotation speeds per a ten-minute interval for each feature extraction method is presented in Table 3.

Table 3. Number of extracted features per a ten-minute interval with each feature extraction method.

Feature extraction method	Number of features				
	2100 rpm	2133 rpm	1573 rpm	1950 rpm	1463 rpm
Previously developed	2457307	2457312	2457209	2457285	2457180
MiniRocket	84735	87762	63006	79268	59932
TSFEL	8416	8533	6301	7801	5865

The number of features extracted using the TSFEL algorithm from a single segment of signal depends on the segment length. The longer the signal the larger the number of features extracted. The number of features extracted from single segments of triaxial accelerometric signals at the studied rotation speeds is presented in Table 4.

Table 4. Number of extracted features at the studied rotating speeds using TSFEL.

Number of features				
2100 rpm	2133 rpm	1573 rpm	1950 rpm	1463 rpm
843	837	990	876	1032

6.3 Classification

The number of extracted features using the previously developed method and the MiniRocket algorithm were sufficient for using training set sizes of 50000 samples per class and the number of features extracted using TSFEL was sufficient for using training set size of 5000 samples per class. The accuracies for the different classifier models are presented in Table 5 – Table 9.

Table 5. Accuracies for classifier models of inline-three engine at 2100 rpm.

MP	Previously developed		MiniRocket	TSFEL
	One cycle	Two cycles		
1	91.716 %	97.687 %	99.957 %	100.000 %
2	99.340 %	99.864 %	99.999 %	100.000 %
3	92.821 %	97.961 %	99.998 %	100.000 %
4	99.996 %	99.997 %	100.000 %	100.000 %
5	99.894 %	99.995 %	99.999 %	100.000 %
6	98.767 %	99.832 %	99.996 %	100.000 %

Table 6. Accuracies for classifier models of inline-three engine at 2133 rpm.

MP	Previously developed		MiniRocket	TSFEL
	One cycle	Two cycles		
1	94.598 %	98.045 %	99.903 %	100.000 %
2	93.060 %	96.027 %	99.998 %	100.000 %
3	98.584 %	99.330 %	99.999 %	100.000 %
4	99.905 %	99.989 %	99.999 %	100.000 %
5	99.794 %	99.995 %	99.999 %	100.000 %
6	92.381 %	95.783 %	99.991 %	100.000 %

Table 7. Accuracies for classifier models of inline-three engine at 1573 rpm.

MP	Previously developed		MiniRocket	TSFEL
	One cycle	Two cycles		
1	87.510 %	94.754 %	99.961 %	100.000 %
2	90.882 %	95.125 %	99.998 %	100.000 %
3	86.233 %	91.854 %	100.000 %	100.000 %
4	100.000 %	100.000 %	100.000 %	100.000 %
5	98.787 %	99.924 %	100.000 %	100.000 %
6	99.900 %	99.990 %	100.000 %	100.000 %

Table 8. Accuracies for classifier models of inline-six engine at 1950 rpm.

MP	Previously developed		MiniRocket	TSFEL
	One cycle	Two cycles		
1	97.172 %	99.284 %	99.974 %	99.991 %
2	90.136 %	95.167 %	100.000 %	99.991 %
3	91.289 %	95.920 %	99.998 %	99.991 %
4	96.699 %	99.511 %	100.000 %	99.991 %
5	82.173 %	89.885 %	99.999 %	99.991 %
6	88.574 %	95.716 %	99.997 %	99.991 %

Table 9. Accuracies for classifier models of inline-six engine at 1463 rpm.

MP	Previously developed		MiniRocket	TSFEL
	One cycle	Two cycles		
1	99.475 %	99.896 %	100.000 %	100.000 %
2	99.689 %	99.970 %	100.000 %	100.000 %
3	92.976 %	95.788 %	100.000 %	100.000 %
4	99.964 %	99.997 %	100.000 %	100.000 %
5	91.410 %	98.570 %	100.000 %	100.000 %
6	92.475 %	97.657 %	100.000 %	100.000 %

The above results show that the most accurate classifier models are achieved using the accelerations measured at MP4. Thus, the feature selection is performed on the MiniRocket and TSFEL features extracted from accelerations measured at MP4. The results of the feature selection i.e., classification accuracies of models trained with different numbers of features, are presented for MiniRocket features in Table 10 and Table 11 and for TSFEL features in Table 12 and Table 13.

Table 10. Feature selection results (accuracy [%]) for MiniRocket features, inline-three engine.

rpm	Number of features									
	9996	1000	100	50	25	10	6	5	3	2	1
2100	100.00	100.00	99.97	99.90	99.71	96.74	95.57	91.02	78.38	69.11	59.86
2133	100.00	99.99	99.94	99.77	98.79	94.39	89.62	87.60	70.10	58.80	47.00
1573	100.00	100.00	99.98	99.75	98.03	91.27	78.16	74.50	71.43	62.04	55.36

Table 11. Feature selection results (accuracy [%]) for MiniRocket features, inline-six engine.

rpm	Number of features										
	9996	1000	100	50	25	10	6	5	3	2	1
1950	100.00	100.00	99.93	99.75	99.22	97.16	90.53	91.86	89.41	71.44	68.12
1463	100.00	100.00	100.00	100.00	100.00	99.97	99.91	99.88	72.80	63.02	59.92

Table 12. Feature selection results (accuracy [%]) for TSFEL features, inline-three engine.

rpm	Number of features										
	All	< 500	100	50	25	10	6	5	3	2	1
2100	100.00	100.00	100.00	100.00	100.00	99.99	98.49	88.92	72.08	71.14	57.58
2133	100.00	100.00	100.00	100.00	100.00	99.80	98.40	97.20	93.90	69.79	50.53
1573	100.00	99.99	99.99	100.00	100.00	99.93	99.00	99.64	93.24	90.78	86.99

Table 13. Feature selection results (accuracy [%]) for TSFEL features, inline-six engine.

rpm	Number of features										
	All	< 500	100	50	25	10	6	5	3	2	1
1950	99.99	99.98	99.97	99.97	99.96	99.86	99.73	99.16	98.96	96.17	93.81
1463	100.00	100.00	100.00	100.00	100.00	99.96	97.15	99.92	95.53	98.15	73.41

The best ten TSFEL features for each classifier model are presented in Table 14. The letters X, Y and Z in Table 14 indicate the direction of the signal from which the feature has been extracted in the global coordinate system.

Table 14. The best ten TSFEL features for each classifier model.

Feature	2100 rpm	2133 rpm	1573 rpm	1950 rpm	1463 rpm
1	Z FFT mean coefficient_135	Z FFT mean coefficient_6	Z FFT mean coefficient_1	Z FFT mean coefficient_6	Z FFT mean coefficient_186
2	Z FFT mean coefficient_33	Y FFT mean coefficient_135	Z FFT mean coefficient_18	Y FFT mean coefficient_6	Y FFT mean coefficient_13
3	Y FFT mean coefficient_3	Y FFT mean coefficient_33	Z FFT mean coefficient_31	X FFT mean coefficient_24	Y FFT mean coefficient_77
4	Y FFT mean coefficient_44	Y FFT mean coefficient_9	Y FFT mean coefficient_12	X FFT mean coefficient_8	X FFT mean coefficient_11
5	X FFT mean coefficient_14	X FFT mean coefficient_12	X FFT mean coefficient_12	X Spectral slope	X FFT mean coefficient_12
6	Z FFT mean coefficient_3	Z MFCC_7	Z FFT mean coefficient_11	Z Spectral skewness	Z FFT mean coefficient_9
7	Y FFT mean coefficient_11	Y FFT mean coefficient_3	Z FFT mean coefficient_25	X FFT mean coefficient_17	Y FFT mean coefficient_3
8	Y FFT mean coefficient_33	Y FFT mean coefficient_8	Z FFT mean coefficient_32	X FFT mean coefficient_6	Y MFCC_7
9	Y FFT mean coefficient_8	Y Fundamental frequency	X FFT mean coefficient_11	X Spectral skewness	X FFT mean coefficient_111
10	X FFT mean coefficient_29	X FFT mean coefficient_48	X FFT mean coefficient_24	X Wavelet variance_8	X FFT mean coefficient_50

7. Conclusions

The vibration accelerations of two compression ignited four-stroke variable-speed engines at different operational states were measured during the project. Operational state estimation models were built based on the measured accelerations. As was expected based on previous work the accuracies of all models were relatively high in general, however the measurement point location has a significant effect on the accuracy. The models based on the vibration accelerations measured at MP4, which was located on the engine block drive-end side, were the most accurate in general. The models of the previous studies are not based on accelerations measured at the engine but at the surrounding structures, that is the base frame and generator frame of the generating set [1] and [2].

The models based on the previously developed feature extraction method performed similarly as the models in the previous studies. In fact, the models of this study were somewhat more accurate which might be due to the more stable operation of compression ignited engines (this study) compared to spark ignited engines (previous study). The models based on the features extracted from the two-engine-cycle-long segments were as or more accurate than the models based on the features extracted from the one-engine-cycle-long segments. However, unlike in the previous study, very accurate models based on features extracted from one-engine-cycle-long segments using the previously developed feature extraction method were built in this study. Especially the models based on the accelerations measured at MP4, for which the lowest accuracy was 96.699 % and the rest were over 99.9 % accurate.

The two openly available feature extraction methods, MiniRocket and TSFEL, tested in this study performed extremely well at the task. The models based on the features extracted with either of the two methods are in most cases 100 % accurate and 99.74 % accurate in the worst case. An excessive number of features is extracted by both methods by default. Feature selection showed that the number of features can be reduced radically without any effect on the accuracy. 100 % or close to 100 % accuracy can be achieved in most cases by using 25 MiniRocket features or ten TSFEL features.

Comparison of the models based on the previously developed feature extraction method, which includes six features, with the models based on the best six TSFEL features shows that generally the latter are almost as accurate as the first mentioned. The models based on the best six MiniRocket features are mostly significantly less accurate. The best TSFEL features are all frequency domain features. The amplitude of the signal at the third frequency component, which is the other feature of previously developed feature extraction method, is among the best ten features of three out of five TSFEL features based models.

The features extracted using the previously developed and TSFEL methods are physics-based, whereas the features extracted using the MiniRocket algorithm are not, at least not evidently. The fact that more accurate models can be achieved using the same number of physics-based features than non-physics-based features advocates the use and further study of explainable artificial intelligence (XAI). However, the MiniRocket algorithm has an advantage over the other two feature extraction methods as a single operational state estimation model based on MiniRocket features could cover the whole rotating speed range of the engine, at least in theory. Whereas the features extracted using the other two methods are strongly dependent on the rotaion speed, or frequency, which leads to the need of building individual models for different rotation speeds.

The operational states measured in this study are not nearly enough to cover the whole range of operation of the engines. However, the results show that the real-time operational state estimation could be possible using the studied methods if sufficient data was available. Therefore, acceleration measurements of an ICE covering the operational range more comprehensively than the standard emission test schedules are needed for further development of the studied subject.

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