ÓBUDAI EGYETEM
ÓBUDA UNIVERSITY

BOOKLET OF PHD THESIS

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Hybrid Evaluation Method for Rotating Machine Transient Vibration Analysis Using Signal and Image Processing Methods

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List of Acronyms

BCG	Brightness-Contrast-Gamma. 17
DTM	Differential Tracking Method. 10, 11
DUT	Device Under Test. 5
FD	Frequency Domain. 6
ICE	Internal-Combustion Engine. 4
MAPTM	Moving-Average-Predictive Tracking Method. 11, 12, 14
OBD	On-Board Diagnostics. 4
SNR	Signal-noise Rato. 16, 17
STFT	Short-Time Fourier Transform. 5–7, 10, 11, 13, 16, 17
TF	Time-Freuqency. 5, 13
TFD	Time-Freuquency Domain. 6

1 Introduction

The main purpose of this research is to analyse and measure transient vibration signals in non-laboratory environment acquired by industrial vibration sensor mounted on rotating machines. This could be emphasized by the combination of multiple disciplines, in order to extract information from vibration measurements in non-laboratory environment in case of transient signals acquired by an industrial vibration sensor mounted on rotating machines. The extracted information can be used to support more detailed vibration post- or real-time diagnostics of rotating machines during transient states by providing the basic, pre-processed time-frequency information.

The transient analysis is an important criterion as rotating machines are primarily used during variable operational states, therefore the reaction of the elements of the construction under variable circumstances needs to be observed. The industry is moving towards to the direction of alternative drives so besides Internal-Combustion Engine (ICE), hybrid and pure electric drives begin to receive much more focus. For this reason, electric motors needed to be kept in mind while conducting the research. A standard industrial vibration sensor is always mounted on the rotating machine during the manufacturing process and its signal can be used for measurements in non-laboratory environment. On the other hand, cost effective application of this sensor enables to obtain operational conditions about the construction. However, high frequency ranges could not be analysed properly due to the bandwidth (30 Hz - 25 kHz) of this type of sensor. There is a possibility of end-of-line transient testing of the mechanical construction itself after manufacturing or using onboard diagnostics after signal evaluation and preparation obtaining the signal via e.g. On-Board Diagnostics (OBD) protocol. Therefore, information could be collected about the stationary and transient behaviours of the rotating machine during manufacturing tests or daily usage and it could be utilised for predictive maintenance or malfunction detection.

In summary, a method needed to be developed with the capability to analyse in low and mid-frequency ranges the stationary and transient vibration measurements derived from rotating machines using an industrial vibration sensor. This research was inspired based on a previous study cited in reference [1] about the combination of multiple disciplines such as signal and image processing with the aim of the research was scheduled to extend the signal processing part and define a slightly more efficient and scalable method to support the input of rotating machine diagnostics.

2 State-of-the-art

Vibration measurement is influential enabling faster and more accurate production error and malfunction detection. Various research articles represent basic vibration-based case studies on theoretical basis [2–4]. These studies apply the basics of vibration analysis are frequently used in engineering practices in expert systems. Some parts of these systems were tailored for condition monitoring and fault diagnosis of rotating machines. Reference [5] represents a complex solution considering the analysis of multiple rotating elements in one construction using basic spectrum analysis or amplitude distribution. The expert systems in [6–8] can be used mainly for condition monitoring and malfunction detection. In case of condition monitoring tasks, the Device Under Test (DUT) operates with non-stationary speed (Rotation Per Minute (RPM)), therefore in order to analyse rotating machines in this transient state, the elementary Time-Freuqency (TF) domain methods [9, 10] are not appropriate. A higher-level method such as Wavelet-transformation could be a suitable method to obtain the actual information about operational conditions [11, 12]. Furthermore, details about a review containing the utilization of wavelets for fault diagnosis can be found in [13]. Besides Wavelet-transformation the Short-Time Fourier Transform (STFT) based methods are often applied [14–17] as well but not only to exclusively vibration diagnostics and condition monitoring. Nowadays, neural networks are gaining more space in expert system applications tailored for analysing rotating machines among different conditions [18,19]. Additionally, Industry 4.0 solutions are gaining more and more weight, therefore at larger manufacturers (e.g. SKF or Schaeffler) the integration of vibration diagnostics solutions is a priority research and development topic. References [20–22] represent such kind of realized applications, research directions and results.

In case of the spectrogram it could be an approach to use image evaluation and processing methods. Reference [23] uses STFT for image to sound conversion. Zhang et al. [24] operates with the STFT to analyse diffractions. In the condition monitoring of ICEs obviously the spectral components on the STFT spectrogram need to be tracked or extracted. Markov models [25] and image processing [26] were also research guidelines in order to perform this action. Czarnecki et al. [27] represents new guidelines in spectrogram image processing, which can be the basis of this and further research works. Besides these, references [28] describes new research methods in condition monitoring based on spectrograms and image processing presented before. In addition to these, [29–33] describe research initiatives and reviews for condition monitoring based on time-frequency domain, spectrograms and image processing with the extension of tracking methods.

3 Thesis outline

The thesis starts with an overview of the current state of science in the indicated topic followed by a more detailed introduction of Frequency Domain (FD) signal analysis methods. After that the general overview of the Time-Freuquency Domain (TFD) methods will come to the fore from which one will be highlighted - the STFT method which method is the basis of this thesis used for vibration signal analysis. Therefore, a detailed mathematical background of the STFT will take place and demonstrated on simulated signals.

Afterwards the image preparation and evaluation methods will be demonstrated and then further will be used to extract the vibration signal's frequency component information of a rotating machine from a spectrogram image.

After that those steps and solutions will be presented which prepares the main step of the evaluation method to be presented in the dissertation. Image processing methods generate additional auxiliary content and information on the spectrogram images which embeds the possibility of further evaluation. The main target is to obtain the vibration frequency component information from the spectrogram image itself which can be achieved by using so-called component tracking methods. These methods will be introduced during the sections with their calculation background supplemented by its advantages and disadvantages illustrated on the example simulated signals. The final part of this chapter will give an overview about how the obtained information can be transferred back to frequency-time domain from image-domain in order to support rotary machine diagnostics and condition monitoring tasks.

In the validation and verification part the simulated signal and real rotating machine measurement evaluation results will be captured in order to test and validate the created method. The purpose of this evaluation is to check the operation of the method and discover the boundaries. Besides the interpretation of the simulated signal generation, the complete description of the measurement test rig and used devices will be presented.

The final parts of the thesis will give an outlook about how this research result can be used in other disciplines and how the complete method can be improved in the future.

Thesis 1

Generally, not only stationary signals have to be analysed in frequency domain. The main problem in the case of transient signals is that the Fourier Transform (FT) can not represent the signal's time-variant behaviour. The STFT is a function based on Discrete Fourier Transform (DFT) that determines the sinusoidal frequency and phase components of specific sections of a time-dependent continuous signal. In practice, in the production of STFT, a longer time signal is split into several smaller segments of equal length, on which the discrete Fourier transform is performed one by one. The result gives the frequency spectrum of each section. The essence and significant advantage of the STFT method lies in the fact that it can analyse the time and frequency dependence of a signal at the same time. The equation that mathematically describes the method is shown below as

$$\mathrm{STFT}(t,\omega) = \int \mathrm{x}(\tau)\gamma^*_{t,\omega}(\tau)\mathrm{d}\tau = \int \mathrm{x}(\tau)\gamma^*(\tau - t)e^{-j\omega\tau}\mathrm{d}\tau, \tag{1}$$

where $\gamma^*(\tau)$, called window function, usually has a short duration compared to the input signal $\mathrm{x}(t)$. For this reason, the calculation STFT is also called a windowed Fourier transform. An approach to the calculation process of the formula is shown in Fig. 1.

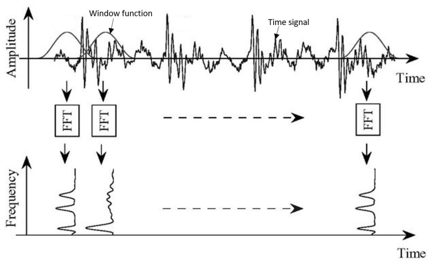

Figure 1: Illustration of the Short-Time Fourier Transform (STFT) [34]

To get the most informative results from the signal, besides the high sampling frequency of the time signal, it is also necessary to optimize STFT time and frequency resolution. As several rotating elements can be found in a construction, it was decided to achieve high frequency resolution in a time segment for spectrogram creation with the application of an overlapping windowing technique. During the analysis it was assumed that the time segments are narrow enough to be considered as quasi-stationary segments. The calculations of the spectrogram in the first analyses were considered time-consuming. The basis memory management was improved, which means dedicated memory segments were allocated to perform the Fast Fourier Transform (FFT). Thanks to this, several FFT calculation can be performed parallel and using the proper indexing, the reconstruction of the STFT can be achieved. This can be performed because theoretically, the windowing is not else than cutting a section from the original time signal and performing the analysis on this time signal. When the complete signal is transformed, the results will be collected from the assigned memory addresses to display the spectrogram image for post-processing purposes. An example of a simulated time signal and its generated spectrogram can be seen in Fig. 3.

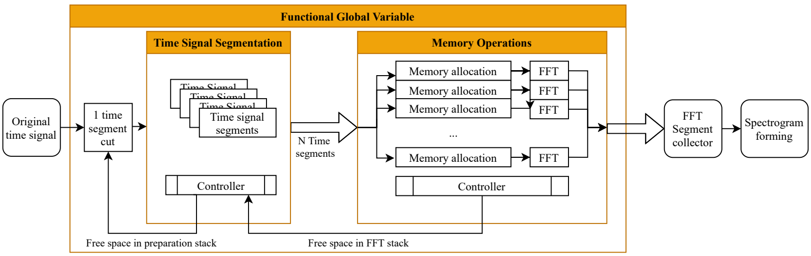

Figure 2: The block diagram of the improved STFT algorithm

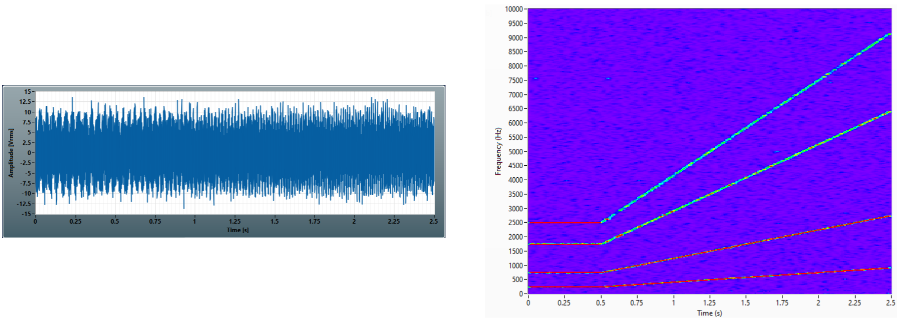

Figure 3: An example simulated signal (left) and the resulted STFT spectrogram(right)

Algorithm enhancement for Short-Time Fourier Transform

The applied window function facilitates the enhancement of the Short-Time Fourier Transform process of a rotating machine vibration signal by parallelization of the calculation. The parallelization requires the definition of a batch of time segments for Fast Fourier Transform, dedicating a single processor core and allocating dedicated memory areas to parallelly process the defined time segment.

Related publications: [MG1]

Thesis 2

The novel, multi-discipline evaluation method for evaluating vibration based STFT spectrograms was derived into three main phases which is visualised with a flowchart in Fig. 4. The first part is a sequence of general vibration signal preparation and evaluation methods followec by the process where the evaluation of the spectrogram image derived from the pre-processed signals takes place. The final phase is a transformation back into the TF domain to describe the operational state and create a basis for further diagnostics of the rotating machine.

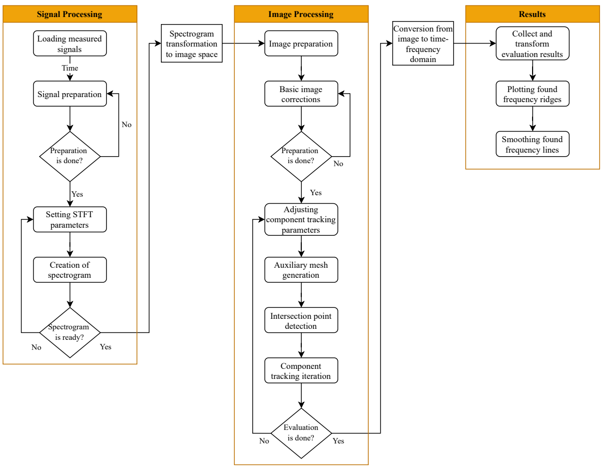

Figure 4: The flowchart of the novel, multi-discipline evaluation method

Method steps for information extraction from a greyscale vibration spectrogram image

Frequency components of the power spectra spectrogram resulted from the commonly used Short-Time Fourier Transformation method used in rotating machine diagnostics can be detected using image processing methods. Both stationary and transient components in a vibration signal can be detected by converting the spectrogram into a greyscale image, performing the following sequence of steps.

1. Short-Time Fourier Transformation execution with the enhanced algorithm with a time resolution, not less than the estimated time period and a frequency resolution as high as possible.

2. Conversion of the resulted spectrogram into a greyscale image.

3. Elimination of noisy and information-irrelevant areas with image manipulation methods.

4. Generation of an auxiliary raster grid on the greyscale image.

5. Edge detection - obtaining the intersection points of possible frequency ridges and the vertical auxiliary grid lines.

6. Linking the found intersection points with the differential (extreme value-based) or moving-average prediction (gradient-based) component tracking algorithm.

7. Conversion of the found frequency ridges found in the greyscale image to the time-frequency plane.

8. Smoothing the converted results for further evaluations using averaging or point-by-point windowed filtering.

Related publications: [MG1, MG2, MG3, MG4]

Thesis Group 3.

The main objective of the research was to find out how to extract information from spectrograms more efficiently and reliably without losing any kind of information. As the spectrogram was able to be corresponded to a map where the third dimension is represented with colours or colour-densities, it was possible to correlate it to a Moiré-image. In this aspect the black "Moiré" lines represent the exact frequency component trends as well as the basis of the next steps of the research. In the beginning an auxiliary mesh generation and edge detection are necessary to find those points that can be the part of a frequency component on the image. In the first step of the detection, the algorithm creates several, parallel, vertical auxiliary grid lines in the image, based on an adjustable line-density setting in pixels where the mesh lines intersect the frequency lines (black lines) therefore rising and falling edges are detectable on the image. Then this an intersection point can be inserted and this representing one point of a frequency component. An example for the greyscale export and mesh generation can be seen in Fig. 5.

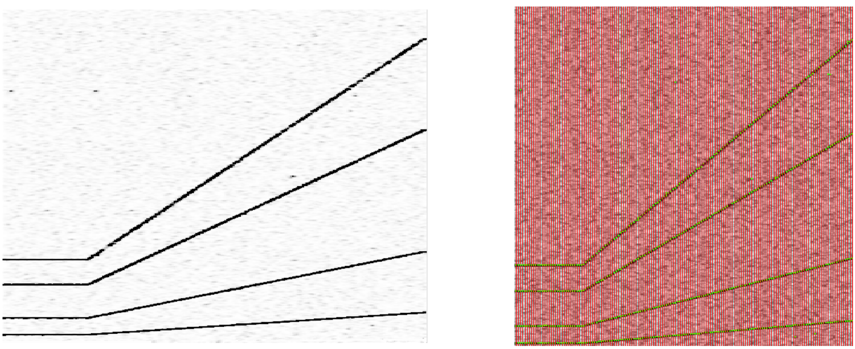

Figure 5: An example greyscale spectrogram (left) with mesh generation and edge detection (right)

Thesis 3.1

Auxiliary raster grid creation and edge detection on spectrogram

In order to track frequency ridges, the same image preparation method can be used as for evaluating medical diagnostic Moiré images. The tracking of frequency components is feasible by averaging the results of rising and falling edge detection on a created auxiliary raster grid on a greyscale STFT power spectra spectrogram derived from vibration signals of rotating machines.

Related publications: [MG1, MG2, MG3, MG4, MG5, MG6, MG7]

Thesis 3.2

As mentioned before, the black lines indicate a frequency component on the image. To receive the most reliable result, the method monitors coherent rising and falling edges and calculates their average vertical pixel coordinate of these. Thus, the middle of the thicker black line needs to be considered due to dominance of the frequency component. These intersection points are capable to closely represent one frequency component visually only but in order to capture a result suitable for processing, so-called component tracking algorithms needed to be implemented to link the those coherent points to each other during a horizontal sweep through the auxiliary grid lines which belong to one frequency component. In order to connect the detected intersection points so-called tracking algorithms were developed. An example for the component tracking results can be seen in Fig. 6.

Frequency component tracking on the image

The Differential and the Moving-Average-Predictive Tracking Methods - which have the same initial and end conditions but their core are mathematically different - can track frequency ridges on a greyscale STFT power spectra spectrogram derived from vibration signals of rotating machines.

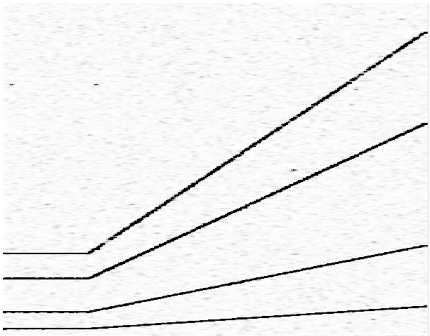

Figure 6: Image after the execution of the Moving-Average-Predictive Tracking Method (MAPTM) method on an example greyscale spectrogram (red - vertical mesh lines, black - frequency components, green points - found edges, blue - result of the component tracking)

Differential Tracking Method

The basics of the differential algorithm, which can track frequency ridges on a greyscale STFT power spectra spectrogram derived from vibration signals of rotating machines, are described by the following equations. The algorithm calculates the absolute vertical distance between the starting point and the detected points on the following line of the auxiliary grid as

$$\mathbf{d}_n = y_{i+1,n} - y_{i,j}, \tag{2}$$

where $\mathbf{d}$ is the vector of the calculated vertical differences, $y_{i+1,n}$ is the y coordinate of an intersection point on the $i+1$ vertical grid line and n is a running index which iterates over the elements of j. From the calculated differences the algorithm chooses the minimum absolute value and performs further examination on the detected $P_{i+1,j}$ point (in Eq. 3).

$$P_{i+1,j}(x_{i+1,j}; y_{i+1,j}), \tag{3}$$

where

$$x_{i+1} = x_i + \Delta_{mesh}, \tag{4}$$

$$y_{i+1,j} = y_{i,j} + \min|\mathbf{d}| \quad \text{if} \quad \min|\mathbf{d}| \leq \varepsilon \tag{5}$$

or

$$y_{i+1,j} = y_{i,j} \quad \text{if} \quad \min|\mathbf{d}| > \varepsilon, \tag{6}$$

where $P_{i+1,j}$ is the closest point based on differences; Δ_{mesh} is the difference between two vertical mesh lines; $\min|\mathbf{d}|$ is the minimum absolute value in the $\mathbf{d}$ vector and ε is the tolerance in pixels. If all of the differences in the collected vector are outside of the ε range the algorithm jumps to the next i vertical line. As the result of the tracking algorithm the found frequency components are collected into an $\mathbf{f}_k$ vector.

Related publications: [MG1, MG3, MG4]

Moving-Average-Predictive Tracking Method

The Moving-Average-Predictive Tracking Method estimates vertically where the next point of the actual frequency component has to be located on the following grid line and takes it as the initial point of the logic.

$$\tilde{P}_i(\tilde{x}_i; \tilde{y}_i), \tag{7}$$

where

$$\tilde{x}_i = x_{i,j}, \tag{8}$$

$$\tilde{y}_i = y_{i,j} + \tilde{\delta} \tag{9}$$

where $\tilde{\delta}$ is a predictor value, calculated by

$$\tilde{\delta} = \frac{\sum_{n=0}^{i} \mathbf{D}_n}{\dim(\mathbf{D})}, \tag{10}$$

where

$$\mathbf{D}_i = \min|\mathbf{d}|, \tag{11}$$

$$\tilde{\mathbf{d}}_n = y_{i+1,n} - \tilde{y}_i, \tag{12}$$

where $\mathbf{D}$is the collected minimum absolute difference values along with the points of a found, complete frequency component.

Then the algorithm performs further examination on the detected $P_{i+1,j}$ point (in Eq. 13).

$$P_{i+1,j}(x_{i+1,j}; y_{i+1,j}), \tag{13}$$

where

$$x_{i+1} = x_i + \Delta_{mesh}, \tag{14}$$

$$y_{i+1,j} = \tilde{y}_i + \min|\tilde{\mathbf{d}}| \quad \text{if} \quad \min|\tilde{\mathbf{d}}| \leq \varepsilon \tag{15}$$

or

$$y_{i+1,j} = y_{i,j} \quad \text{if} \quad \min|\tilde{\mathbf{d}}| > \varepsilon, \tag{16}$$

where $P_{i+1,j}$ is the closest point based on differences between the predicted point and the found points; $\min|\tilde{\mathbf{d}}|$ is the minimum absolute value in the $\mathbf{d}$ vector and ε is the tolerance in pixels. If all of the differences in the collected vector are outside of the ε range the algorithm jumps to the next i vertical line.

Related publications: [MG1, MG3, MG4]

Thesis 3.3

After several component ridges were found by the algorithm on the image, the next step is to convert the results back into TF domain. The bases of this transformation are the parameters exported in-parallel with the grey-scale spectrogram export in the end of the vibration signal processing. Based on those resolution parameters the detected lines can be transferred back into exact frequency components. The detected lines on the images need to be post processed because of the frequency resolution problem of the spectrogram and to provide a more processable form for other rotating machine diagnostic methods. It should be pointed out that during this step the algorithm eliminates the false frequency line detections which means, lines without specific ending - do not meet the end of line criterion mentioned in the previous section - will be removed. It occurs when the tracked line brakes somewhere along the image or merges into another tracked line. An example for the back transformation results can be seen in Fig. 7.

Image to TF transformation

The frequency ridges, found after the execution of the component tracking algorithms on a greyscale STFT power spectra spectrogram derived from vibration signals of rotating machines, can be transferred back from the image to the time-frequency domain using the following parameters of the spectrogram image creation:

(a) Image resolution in pixels

(b) Frequency resolution in pixels

(c) Resolution in pixels

Related publications: [MG1, MG3, MG4]

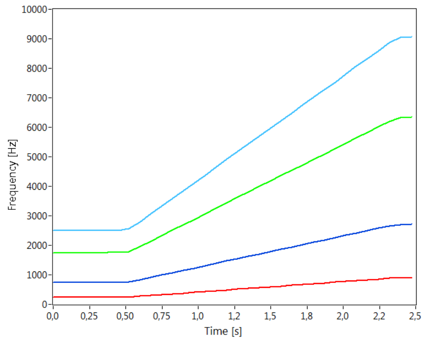

Figure 7: Obtained frequency components from an example spectrogram image after back-transformation (colours represent the found components)

Thesis Group 4.

In order to complete the validation of the method several anaylsis of simulation signals were performed. The results show that the method works appropriately when the rotating frequency changes rapidly. In terms of further results, it can be stated that the system can track and determine the transient frequency components, without increasing the time of calculation, in signals with various Signal-noise Rato (SNR) if SNR is higher than -23 dB. If SNR is lower, the components on the image will be so blurred that the evaluation will not be reliable. This threshold was determined by automatically distorting the greyscale spectrogram images of available, recorded signals on multiple rotating machines until the system could clearly distinguish the falling and rising edges.

Thesis 4.1

Frequency component tracking

Rotating machine transient frequency components can be detected independently of their gradient by evaluating a greyscale STFT spectrogram image using image processing and tracking methods in case of vibration signals with SNR value higher than -23 dB.

Related publications: [MG1]

The created analysing method was demonstrated on ICE measurements. During these measurements, physical quantities such as vibration, speed of rotation are recorded with the mentioned standard industrial knock sensor. During the test of the method on a real application, a 3.0L V6 diesel engine was mounted on a dynamometer. This engine type is a commonly used construction in passenger cars on the market. The measurement system represented in Fig. 8 contains the dynamometer, dynamometer control and fuel consumption measurement. The fuel consumption measurement system itself controlled fuel temperature. In parallel, the intake air has been temperature-controlled as well in order to be able to repeat the same mass related air to fuel in-cylinder parameters.

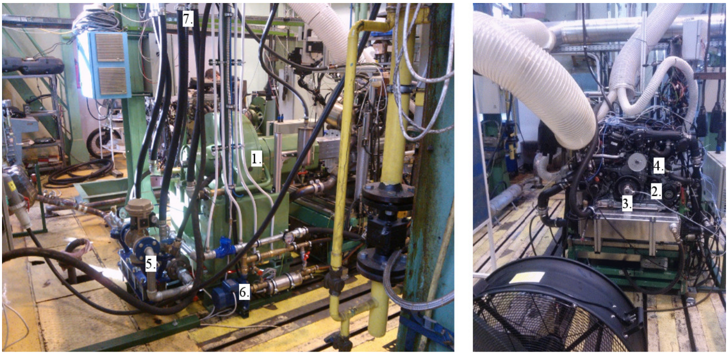

Figure 8: The test rig used for validation (1 - Dynamometer, 2 - 3.0 V6 Diesel engine, 3 - Mounted encoder, 4 - Mounting position of the knock sensor, 5 - KW system, 6 - Intercooler coolant heat exchanger, 7 - Cooling circuit connection)

Vibration measurement was carried out with a piezoelectric knock sensor (Siemens 07K-905-377-C, with 1-20 kHz measurement range and 35 ± 8 mV/g @ 5 kHz accuracy) attached to its designated location on construction. It is advantageous to use this sensor as it was mounted on the rotating machine during the manufacturing process, and the construction does not need to be disrupted. In a particular case, the outcome of this test can state that the analysis without mounting any additional vibration sensor on the construction can be performed. In order to acquire the speed of rotation information, an incremental optical encoder (Kübler 8.5802.2173.1024, with 0-12000 RPM range and 1024/RPM resolution) was attached to the crankshaft. For data acquisition, via analogue and counter input, an NI USB-6361 was used. The analogue channel had a 16-bit resolution with a maximum 2 MS/s sampling frequency on a maximum ± 10 V range.

In addition, the counter channel has a 32-bit resolution with a maximum 100 MHz internal base clock. The measurement and complete analysis were performed with the above mentioned self-developed software package.

Thesis 4.2

Dedicated frequency component determination

Selected rotating machine frequency component can be detected indirectly using image processing methods by evaluating the power spectra spectrogram as a greyscale image, resulting from the STFT method used in vibration diagnostics.

Related publications: [MG1, MG3, MG4]

Thesis 4.3

Parameter optimization possibilities for different types of rotary machines

The complete process, which is capable of tracking frequency components using image processing methods by evaluating the power spectra spectrogram as a greyscale image, can be optimised for different types of rotating machines. This optimization can be performed using a custom-developed software package with the fine-tuning of the parameters of the method steps which are

(a) sampling frequency,

(b) time resolution of the Short-Time Fourier Transform,

(c) frequency resolution of the Short-Time Fourier Transform,

(d) Fourier Transform window width and overlapping,

(e) image resolution,

(f) Brightness-Contrast-Gamma correction values,

(g) auxiliary raster grid resolution,

(h) edge detection pixel threshold,

(i) tracking algorithm type,

(j) tracking algorithm tolerance.

Related publications: [MG1, MG2, MG8, MG9, MG10]

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