Application of vibro-acoustic methods in failure diagnostics

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Abstract. The present study is concerned with the presentation of diagnostic strategies and methods based on vibro-acoustic signals that are able to check the operation of mechanical structures (e.g. internal combustion engines) or to detect faults on test bench during operation. The main goal of this study is to summarize and review the state-of-the-art monitoring procedures and diagnostic methods based on vibrational and acoustical signals by the help of literature sources. A further goal is to familiarize the reader with the theoretical background of these procedures and concepts adjusted to the topic. The paper seeks to illustrate the application of each methods through practical examples, so it may be useful for those who wish to understand what kind of fault can be detected by using vibro-acoustic diagnostic systems. Last, but not least, the arose difficulties and limitations associated with use of this methods are mentioned. This paper is focusing principally on some of signal-based methods in time- and frequency domain, such as Fast Fourier Transformation, Short Time Fourier Transformation, orbit portraits, symmetrized dot pattern method and time synchronous average.

1. Introduction

The modelling of vibro-acoustic physical system is far from being trivial, in case of complex structures it can be a very complicated challenge. The behaviour of the elements of a mechanical structure can be observed through physical parameters, such as temperature, pressure, rotating speed and vibro-acoustic characteristics. The vibration signal is sensitive to all faults, while torque, pressure or other measurements are able to detect only some specific faults. Due to the malfunctions and wearing of machine elements during operation the emitted noise and vibration values change compared to the intended operating conditions. Tracking of these parameters in diagnostic way help the professionals to mitigate the maintenance costs, preserve the planned lifetime and plan the maintenance activities reliably. Therefore, the noise and vibration analysis technically can be an efficient tool for faulty condition detection. Dr. Jálics [1] collected the vibro-acoustical symptoms of defected motor, powertrain, brake system and bodywork in case of four-cycle engine with plain shaft bearings. Chapter 3 will pan out about his work. In order to advance product development a „predictive” tool or a „predictive” procedure is required by the design engineers aswell to help them find solutions without increasing costs and wasting time in the early stage of development process. Damages of structural components were initially observed by visual inspection and over time a variety of procedures have been propagated to assesses structural damages. Industrial vibro-acoustic procedures went through a significant advancement in the last decades thanks to the more powerful computers and advanced numerical processes and methods (e.g. artificial intelligence). Technical progress allowed to determine the sound transmission in a structure and the associated radiation characteristics. Currently the applied methods in the industry are based on Statistical Energy Analysis (SEA) [2] and Finite Element Method (FEM) [3], but combinations of these with Boundary Element Method (BEM) [4] [5] are take place also. These combined procedures are called hybrid procedures in the literature. The advantage of this so-
called hybrid methods is that they expand the applicability of each method and the content of the provided information [6]. In contrast to element-based techniques wave-based methods have been made to exceed the frequency limits of the noticed techniques above. In addition, methods based on vibration and acoustic signals are also suited for detecting the location of failures.

2. The role of the diagnostic in maintenance system

Maintenance includes all technical and organizational activities that enable the required reliability and economical operation of machinery and vehicles. The maintenance and repair work avoid the unexpected failures, as a result decrease downtime. Within this, the task of maintenance is to delay the process of physical wear and to preserve reliable operation condition. During the maintenance and repair of the machines, several systems developed:

- standard (obligatory) maintenance system,
- simple maintenance system (fault correction),
- periodic (cyclical) maintenance system,
- condition-dependent maintenance system.

In the case of standard maintenance system regulations prescribe the test dates of the components based on the lifetime of parts, which takes into account the expected risk. In the course of simple maintenance (error correction), the necessary repair is performed after the failure has occurred. It is advisable to use when the equipment is not complex and the fault is simple, can be solved in a short time. The periodic (cyclical) maintenance system, as a methodical preventive maintenance, is a renovation carried out at specified intervals based on a statistical evaluation of waste-rate. The machines and equipment are inspected and repaired according to plan at specified moments. The maintenance actions will be executed independently of the condition of machinery. It is important to emphasize that the equipment is operational at the start of the maintenance procedure. When using a condition-dependent maintenance system, the machine or equipment is periodically or continuously inspected with devices. The obtained information is used for repair work. The expected date of maintenance work is determined based on the systematic monitoring of condition of the machines and equipment. During condition-dependent maintenance, tests can be performed periodically, at specified times, or continuously using built-in sensors. The using of condition-dependent maintenance is justified for high-value, complex machines, where downtime due to unexpected failures results in high losses. In addition, there are more modern maintenance systems, such as Total Productive Maintenance (TPM), Reliability-Centred Maintenance (RCM) and Computerized Maintenance Management System (CMMS). These are mainly maintenance systems for expensive, complex systems (power plants, production systems, naval equipment, flight equipment). Therefore, the purpose of the diagnostic is to check the operation conditions or to detect the malfunctions inside the machines. Basically, the diagnostic procedures can be categorized based on the: purpose of diagnostic (operational or fault); result of diagnostic (complex or partial); evaluate of results (subjective or objective); method of application (off-line or on-line); range of the diagnostic (full or partial) [7].

3. Techniques and methods based on vibration and acoustic signals

Malfunctions of mechanical structures are often accompanied by abnormal vibrations, so electrical signals came from mechanical vibrations can indicate the failure of the operation (figure 1). The vibration signals of most relatively simple machine elements such as gears or roller bearings – in contrast to complex mechanical structures (internal combustion engine, gearbox, etc.) – can be analysed easily, because their dynamic behaviour is well-known [8] [9]. It does not mean that no attempts have been made to apply techniques based on vibration signals in complex structures. In 2002 Mazda Motor Corporation placed an order for a large 220 channel PULSE system for modal analysis applications to optimise noise and vibration parameters in vehicle powertrains. A lot of accelerometers were located around the gearbox and engine assembly so as to investigate the vibration characteristics of the
powertrain. The development times have been significantly shortened by applying test data at the design stage. Besides this, microphones were placed in front of passenger seat to measure cabin noise [10].

3.1 Theoretical background

Generally, two different diagnostic and monitoring strategies are distinguishable in order to detect faults in machines. To carry out the first strategy a model of the entire mechanical system - prepared with using of Finite Element Method (FEM) or lumped-parameter techniques - is required. On this model potential faults can be simulated. The result of the vibro-acoustic simulation of the system is comparable with the real system. For diagnostic purpose the examination of both healthy and faulty conditions is necessary. The diagnosis will be performed by using a decisional algorithm. The second monitoring and diagnostic strategy provides a graphical representation of vibro-acoustic signals measured on real components experimentally. By using decisional algorithm this features then can be processed to perform diagnosis and register the presence of the faults. Regarding to the first strategy Kimmich and his fellows [11] examined a model of intake and injection systems as a part of a diesel engine. The data were obtained from the on-board ECU (engine control unit) system and compared with the model. The diagnostic procedure was carried out by using fuzzy logic. As regards the second strategy FAG 1204 rolling bearings were studied in an experimental setup by Rubini and Meneghetti [9]. Consider figure 1 to get an insight into the details of their results. In this study they investigated the vibration behaviour of bearing under faulty conditions, namely defects with different dimensions on outer and inner races and on the rolling elements. The vibration acceleration was measured directly on the bearing case. In the context of strategies procedures can be divided into two groups: parametric and non-parametric procedures. When signal analysis techniques can detect signals experimentally on a real element, then they are known as non-parametric methods. On the other hand, the parametric methods are using a created experimental model. This model produces a similar signal to the observed signal. Parametric signal analysis techniques create the models in different ways (e.g. Auto-Regressive Moving Average ARMA). The time or frequency characteristics of a random signal only depend on the parameters of the model and mostly used when significant data reduction should be achieved. The following considerations have to take accounts, when using signal – based techniques: operating conditions (stationary or non – stationary); signal characteristic (periodic or random, deterministic or stochastic, simple or complex; constant or variable etc.); machine type (rotating, reciprocating, simple or complex etc.); signal domain, which provides the most information considering the decision/evaluation algorithm.
(angular, time, frequency, time – frequency, cepstral, cyclical etc.). Below figure 2 represents the fundamental principle of the damage detection systems.

Figure 2. Main components of structural damage detection systems.

S. Delvecchio et. al [12] reviewed the existing vibro-acoustic monitoring procedures and the related decisional algorithms used for internal combustion engines.

3.2 Signal analysis in time domain
Time-domain analysis is based on the time waveform itself. The type of the signal (stationary or non-stationary) and the existence of periodicities can be identified with a visual inspection. Traditional methods calculate specific features, such as peak, mean, peak to peak interval, crest factor, standard deviation, high-order statistics: root mean square, kurtosis, skewness, etc. The time signals can be fitted with simple metrics to get useful information. By using analysis of probability such metrics can be obtained. Dispersion and uniformity parameters (shape of signal) and energy parameters (energy of signal) are necessary to perform such analysis. For such an energy parameter the RMS (Root Mean Square) value is an example, which determines the energy of the signal. Another implementable metric is the Temporal Kurtosis (TK). It able to identifies transients and spontaneous events within vibration signals.

$$TK = \frac{1}{N} \sum_{i=1}^{N} \frac{(s(i) - \bar{s})^4}{\sigma^4}$$

where \(s(t)\) is the instantaneous amplitude of the signal, \(\bar{s}\) is the mean value, \(\sigma\) is the standard deviation and \(N\) is the number of samples. The TK value is constant and not depends on the signal amplitude or frequency.

3.2.1 Time Synchronous Average (TSA)
A popular time-domain analysis method is time synchronous average (TSA). It is a widely used signal processing technique, which can be used to highlight periodic signals and to eliminate or at least reduce disturbing noise from external sources, in order to strengthen the signal sections of interest. The TSA is given by the following equation:
\[ \bar{s}(t) = \frac{1}{N} \sum_{n=0}^{N-1} s(t + nT), \quad 0 \leq t \leq T, \tag{2} \]

where \( s(t) \) denotes the signal, \( T \) is the averaging period and \( N \) is the number of samples for averaging. TSA is a basic algorithmic tool for diagnose the condition of rotating machines for purposes of vibration analysis. During the procedure the vibration data will be resampled synchronously with a shaft and it is the basis of numerous shaft and gear diagnostic algorithms. Hence for gearbox analysis the TSA is feasible. Inside the gearbox one gear - considered as a noise source - can be separated from other noise sources, in other words from the other gears that are not synchronized with the analysed gear. In addition, the method allows us to covert rough signals in time-domain into angular domain, it is called angular resampling. With using of TSA the deterministic part of a vibro-acoustic signal can be also remove. In [13] performance characteristics of TSA algorithms were studied and a Matlab code for Time Synchronous Averaging based on resampling the time domain data was given. They found that both time and frequency domain TSA have similar performance, but the frequency domain TSA techniques are more sensitive to failures. The experimental results show that the statistical distribution of the amplitude of a shaft order is Rayleigh, if no eccentricity is present, otherwise it is Rician, if eccentricity is present e.g. due to an imbalance. In fact, TSA is ergodic. McFadden’s work [8] demonstrate the application of TSA. He analysed the main rotor gearbox of a helicopter. At the root of one of the teeth of the input spiral bevel pinion gear a fatigue crack in early stage was occurred. In figure 3 the time domain average of the cracked gear is illustrated.

**Figure 3.** Gear vibration caused by early fatigue crack: (a) original signal; (b) residual signal.

Obviously this early fatigue crack changes the vibration behaviour of the mechanical system, but the position of the change can not be found in the time domain compared to healthy condition. The figure b) illustrates the outcome of time synchronous averaging. On the middle of the time axis a bit higher acceleration peak is clear, caused by the fatigue crack. The residual signal separate the cracked gear from the other noise sources and enable the crack to be detected.

### 3.2.2 Non-linear diagnostic methods

The more advanced time-domain analysis methods apply time series model to waveform data. Based on this time series approach a waveform data to a parametric time series model is fitted and according to the parametric model features it will be extracted. The autoregressive moving average (ARMA) model and the autoregressive (AR) model are the most popular models in the literature [14]. A number of other time-domain techniques are existing to analyse waveform data. Wang et al. [15] reported about three non-linear diagnostic method: correlation dimension, pseudo-phase portrait and singular spectrum analysis correlated to signal time series analysis theory. Generally, the rotating machines consist complicated non-linear vibration – systems. For efficient failure inspection it is reasonable to develop non-linear diagnostic methods, such as orbit portrait, time-frequency analysis, FFT spectra, cepstra etc.
The description of linear dynamics method is based on mathematical models. This mathematical model makes contact between the parameters and dynamic behaviour of a mechanical system.

### 3.2.2.1 Pseudo phase portrait

Basically, in an ordinary phase portrait the velocity and dislocation are usually recorded with their ordinates. Conversely, in the engineering practice it is difficult to measure all these changing parameters of the system. The first thing in the investigating of a dynamical system is state – space reconstruction. Takens [16] has drawn a method announced as „method of delay’s”. The method of delays is saying that it is not necessary to define the derivatives which possesses the orbits; only the lagged variable is enough to create the state space. Without mathematical explanation: The pseudo-phase space or embedding space is created from the raw time series. The dimension of embedding space is the embedding dimension. Practically the pseudo-phase portrait is the obtained orbit itself in the pseudo-phase space. In it’s actual form there are many disadvantages of application of the method of delay’s. It is convenient to pay attention to the selection of two relevant parameters, lag $\tau$ and embedding dimension $m$. These parameters must be correctly chosen in order to ensure that the state space reconstruction is correct. In case of correct state space reconstruction the reconstructed system and it’s original system are qualitatively equivalent. There are numerous different techniques to select the lag time, for example: wavering product, mutual information, high-order correlation, fill factor, etc. In the near past it has been advised that the embedding window length $\tau_w$ should be selected instead of selecting the $m$ and $\tau$ separately. The embedding window length $\tau_w$ is depends on lag $\tau$ and embedding dimension $m$ [17].

Takens conception suppose that unlimited amount of noiseless data is available and gives no restrictions on the choosing of lag $\tau$. However, in daily diagnostic practice the data length come from the vibration signals are limited and most frequently contaminated by noise.

The pseudo – phase method has simple computer demand and receptive to specific failure types. In figure 4 one can see the pseudo-phase portraits which contains the shaft orbits of a rotating machine with points from the time series. Instead of a regular ellipse diffused curves and angular shapes are revealed when fault happens in the machine.

![Figure 4](image-url)

**Figure 4.** Pseudo-phase portraits of a large rotating machine with a rotor- to- stator rub failure: (a) slight rub failure (rotor-to-stator) and (b) serious rub failure (rotor-to-stator).
3.2.2.2 Singular spectrum analysis

The singular spectrum is a method to investigate the non-linear dynamical response of a system. First Broomhead and King [18] proposed the application of the singular spectrum for non-linear problems. The theoretical background of the procedure is same as Taken’s theorem. In singular spectrum approach the normalised singular values are depend on the window length $\tau_w$ and not separately on the embedding dimension $m$ or the lag time $\tau$. Broomhead and King explored how the embedding window length affects the singular spectra. They demonstrated that the singular spectrum not so depend on embedding dimension and lag time separately as window length. Therefore, the difficulty of diagnostic signals can be influenced by singular spectrum. One of the most important property of such a spectrum is that it can be defined without exact knowledge of dynamic system. By the way, with the help of singular spectrum the signal part and the noise contaminated part are isolable from each other in the time series.

![Figure 5](image)

**Figure 5.** Signals ensued from analysis results of aerodynamic excitation failure in a large rotating machine (b) pseudo-phase portrait of raw vibration signal; (c) pseudo-phase portrait based on singular spectrum analysis.

Figure 5 illustrates the analysis results of signals in a large rotating machine with an aerodynamic excitation fault. Since with the application of pseudo-phase portrait based on singular-spectrum the noise is reduced, hence the obtained spectrum is more regular in contrast with the pseudo-phase portrait which is reconverted directly from rough vibration signals.

3.2.2.3 Correlation dimension

The correlation dimension determines an evaluation of the number of degrees of freedom that a non-linear dynamic system occupy. On the strength of correlation dimension J. D. Jiang and J. Chen [19] used non-linear time series analysis conception for condition monitoring of a gearbox. The influence of the sample size and noise level and computational effort of correlation dimension are discussed in this paper. The correlation integral $C_m(r)$ will be determined in the m-dimensional space when the state space is reconstructed. The calculation accuracy significantly influenced by proper factors such as noise level, data length, embedding dimension and lag.
Figure 6. Analysis of correlation dimension in a large rotating machine in different operating conditions when an aerodynamic excitation fault (a, b) and (c, d) oil whirl fault occurred.

Figure 6 demonstrate the analysis results of correlation dimension in a large rotating machine with an aerodynamic excitation and oil whirl fault. The state-space dimension of the aerodynamic excitation failure is around 4. This value is higher than the of oil whirl fault possess. It follows the presented result on Figure 6 shows that the aerodynamic excitation is more critical than the oil whirl fault from correct operation point of view.

As a summarizing of this this brief review, we can say that this three non – linear method mentioned as pseudo-phase portrait, correlation dimension and singular spectrum analysis can provide some information about dynamical system and make sure the possibility of classification of certain faults logically.

3.2.3 Symmetrized dot pattern

Acoustic emission of vibration and acoustical signals can be described as the superposition of sinusoidal signal (Fourier theorem). The history of the acoustic/vibration signal can be visualized as symmetrized dot graphs (figure 7). Visual dot pattern method provides an easy-to-understand figure that is a visual expressing of the sound problem. The main object is to transform a discrete signal to a polar coordinate graph. The method displays the signal waveforms as patterns of dots – which characterise the measured acoustic/vibration signal – in order to identify the amplitude and frequency fluctuation of sound and vibration signals. The computational requirements of this method due to it’s mathematical background are low. The experimental study [20] is presenting the validity of symmetrized dot pattern method in fault diagnostic. This work is focusing on an internal combustion engine with special regard to the cooling fan and drive axle shaft of vehicle. The principle of visualized dot pattern method is to generate dot patterns that belong to the normal conditions and then to compare the graphics obtained from faulty conditions. Figure 8 shows the result of the visualized dot pattern of a cooling fan obtained from acoustic signals in different operation conditions.
Wu and Chuang [20] invented a matching system for the purpose of fault diagnosis in mechanical system based on symmetric dot pattern method. The function of this matching system is the comparison of image templates resulted from normal and faulty conditions. For this end they created a data base consists of acoustical and vibrational signal patterns of different failures. The input signal pattern of fault is compared with the template pattern obtained from the data base. The best match of the comparison identifies the type of failure and provide the output signal of failure pattern.

S. Delvecchio et.al [21] proposed a procedure to identify malfunctions in diesel engines by symmetrized dot pattern method. The basic idea is based on the comparison of the ratio of the white dots with healthy and faulty engine condition. First of all, the limit of similarity should be determined. The limit of similarity means the percentage ratio of common white pixels in proportion to the total number of white pixels from responded signal of the set of healthy engines. The pattern, which belongs to the normal condition (normal pattern) is obtained from the engine that possesses the minimum limit of similarity (correlation threshold). Then the normal pattern will be set against the images come from the faulty condition and verified if it is lower than the correlation threshold so to distinguish the faulty condition from the healthy one.
3.3 Signal analysis in frequency domain
In the first place, the Fourier transformation and other time domain techniques are the bases of stationary signal analysis. The frequency means the repetition of a periodic phenomenon – shall we say vibration – in other words frequency describes that how many times an event is repeated per units of time.

3.3.1 Fast Fourier Transformation
The principle of frequency-domain analysis is the transformation of signals exist in time domain into frequency domain. With the using of frequency-domain analysis the identification and isolation of certain frequency components of interest is possible, this is the benefit of frequency-domain analysis over time-domain analysis. The most common and popular method for analysing engineering structures is to record a spectrum. The Fast Fourier Transformation (FFT) is a technique which able to create the spectrum. The Fourier transformation is a mathematical progress, which essence is to convert a time dependent signal into frequency dependent one. The Fourier theorem states that any time domain waveform can be described as a weighted sum of sine and cosine functions. The Fourier transform gives us another way to represent a waveform, since everything in the world can be described via waveform, e.g. function of time. The Fourier series open the door to analyse especially periodical signals. The measurements on low frequencies are periodical by nature. Torque, crankshaft speed and pressure are typical precedents of periodical signals in internal combustion engines. A small countable number of Fourier coefficients give an opportunity to describe periodical (discrete) signals perfectly. The practical application of the analysis mainly results from the fact that every single phenomenon has its own proper frequency. Thus, the observation of certain phenomenon within the machines through the frequency components enable to engineers to identify mechanical failures or operational deviations. It is often more practical to use orders instead of frequency, because the frequency of some phenomena can change with speed, while orders remain the same. The figure 1 shows a frequency versus amplitude spectrum. In the case of continuous random signal, the calculation of Power Spectral Density (PSD) is necessary. The PSD gives the distribution of the power of the signal with frequency and it is obtained from the autocorrelation function with using Fourier transformation. For estimating the PSD an averaging operation is needed (i.e. Welch periodogram). By reason of averaging operation, the PSD does not provide proper results when the machine speeds changes, so it is not adequate for diagnostic purposes. In this case smearing of frequencies and frequency spacing variations (speed-dependent) appears in the result, caused by the averaging operation. With the exception of Fourier Transformation, the estimation of Power Spectral Density could be also accomplished by using parametric methods (e.g. Auto-Regressive Moving Average, ARMA). For condition monitoring purposes the parametric methods are not exactly well-suited, more for identification goals. Lyon [22] report about a quality control technique on the production line in a sewing machine company. The main idea is to measure the noise of the sewing machines in a small semi anechoic chamber in the end of the production line by an operator. If the quality control supervisor read more than 72 dB during this sewing operation, then the machine was to be rejected. This action was necessary to prevent waste production and redundance cost. In [23] an industrial forward - curved blades centrifugal fan was tested in order to investigate it’s own performance and noise characteristics. In course of the testing the geometries of the volute tongue and the hub-volute clearance were modified. The goal of the work was to reduce the noise of the fan and avoid the dropping performance in the whole flow range. Figure 9 illustrates the effect of hub-volute clearance modification. The A-weighted Sound Pressure Level (SPL) of broadband noise of four centrifugal fans was measured by microphones. According to the experimental results the sound pressure level of four centrifugal fans is nearly the same at high volume flow rate, but at low volume flow rate the noise is higher than that of the original fan because of the increase of the overall noise level of all three modifications.
In my thesis I investigated the main noise sources of a jigsaw in order to reduce the emitted noise by the machine. For the purpose of noise source identification both the FFT and STFT analysis was used (see the next 3.3.2 section for more details regarding to STFT analysis). According to the measured Fourier spectra (figure 10) I found that the mechanical unit – consists of crank gear – produce most of the noise. Thanks to the plastic parts (POM) which were used in the engine that make an end of metal contact 2 dB sound pressure level reduction was achieved compared to the original machine. Furthermore, regarding to the tooth direction the spur cylindrical gears was modified into helical gears for that increase the value of the contact ratio. This modification provided us 0.5 dB less noise, than the serial machine.

**Figure 9.** A-weighted sound pressure level spectrum of the original and three modified fans at volume flow rate $Q = 32m^3/min$

![Figure 9](image)

**Figure 10.** A-weighted sound power level spectrum of the original machine measured by three microphones in order to identify critical noise components

![Figure 10](image)
Jálics tried to prove the theory that the malfunctions are detectable through noise and vibration analysis. The noise and vibration behaviour of a motor vehicle shown in figure 11 was studied. The comparative measurements were made between two different dates (29 June 2012 – 12 November 2012). In this interval the privately owned car run approximately 15 km. The goal was to check the vibration and acoustic behaviour of the car after usage, so as to determine the possibly occurring early defects and evaluate the lifetime mileage. Figure 12 shows one of the measurement results.

For the sake of simplicity and quick setup the measurements were made at engine speed 780 rpm and 2100 rpm when the vehicle’s position was stationary. The idle speed was selected for it’s easy adjustment. The other speed was selected as a medium speed according to a typical daily practice. The duration of the measurements was 15 sec in each case. Prior to measurements the microphone and acceleration sensor were calibrated and the environmental properties (air pressure, air temperature, relative humidity) were recorded as well.

Figure 11. The test arrangement; vehicle: Skoda Superb 2.0 TDI; NTI 2210 microphone and B&K 4382 acceleration sensor

Figure 12. The change of sound pressure level near of the engine at speed 2100 rpm in the form of a narrowband FFT diagram

Based on the performed measurements, it can be said that with the available options and with the recorded measurement data within the obtained frequency range on a given vehicle and mileage was not possible to determine a characteristic sign of a failure. For further investigations would be convenient to take into the account the following considerations:
• Extension of the frequency range to ultrasound range: many failures (e.g. tribological problems of plain bearings) only in ultrasound frequency range provide an evaluable faulty signal.
• The examination of margin of error of the method: it is highly probable that the accuracy of the actual mileage determined by acoustic methods will not be less than 10,000-20,000 km. Therefore, the difference in mileage of about 15,000 km used in the above measurements is still within the margin of error, so it is not detectable.
• Determination of the necessary number of measurements: it is convenient to preform large number of measurements on vehicles with different mileage and condition in order to track the behaviour of noise characteristics influenced by the operation circumstances.
• The modification of the operational conditions: it may be appropriate to select one or more more reproducible operating conditions for detailed and systematic analysis.

3.3.2 Short Time Fourier Transformation
Typical signals (e.g. in an internal combustion engine) are continuous non-stationary signals. The above-mentioned kinds of techniques, which based on the assumption of stationarity, are not always effective to examine signals formed by non-stationary dynamic phenomena, so they are usually dealt with using time-frequency techniques. The time-frequency techniques allow analysis of the time history in such a way as that individually the time and frequency analysis do not. In general, these methods work on a way that convert one-dimensional time signals into a three-dimensional plane. In this way the determining frequencies of signals can be revealed in function of time. Therefore, these methods are more effective tools for the analysis of non-stationary signals that can’t be analyse by Fast Fourier Transformation. A uniform resolution in both the time and frequency domains can be achieved by the use of the classic Short Time Fourier Transform (STFT). Other time-frequency analysis methods for instance Discrete Wavelet Transform (DWT), Continuous Wavelet Transform (CWT) and Wigner-Ville Distribution (WVD) are applied for diagnostic purposes.

The Fourier transformation does not reveal how the frequency range of a signal varies over time. The Short-time Fourier Transformation (STFT) consists of sequences of Fourier-transformed windowed signal. During the process the longer time signal is split into shorter parts with equal length. After the splitting the Fourier spectrum is calculated on each shorter part separately to clarify how frequency components of a signal changes over time. The plotted changing spectra as a function of time known as spectogram or waterfall plot. Moreover, different approaches to the concept of time-frequency spectra are existing. Roughly they can be classified as linear representations (evolutionary spectra, Gabor forms, time scale forms of the wavelet transform) and quadratic representations (centred on the Wigner-Ville distribution and the associated Cohen class of distributions). In the case of linear representing the main idea of signal representation is that add up a sequence of another (simpler) components, which raise the original signal. In this approach the Fourier series is the simplest form of a linear representation relating to periodic signals. For concept of non-stationarity the modification of Fourier form is needed on a way that retain the concept of frequency. Time-frequency methods are approached from „energetic” perspective through the quadratic representations. These quadratic representations similarly to STFT and wavelet transform display the energy of the signal on spectogram or scalogram. The roots of Wigner-Ville distribution or simply the Wigner time-frequency distribution goes back close to 1932. However, the importance of Wigner-Ville distribution was not admitted in signal analysis until much later [24]. Now it plays a central role in time-frequency analysis. In the work of Hammond and White [25] the fundamentals of time-frequency distributions were reviewed briefly and a summarizing of the interrelations between time-frequency distributions were made. Furthermore, the results of applying distinct analysis methods on time histories was reported.

Paper [21] deal with vibration measurements of diesel engines for quality control at the end of assembly line through the cold test technology. In this work the STFT is calculated in order to have a time-frequency method easy to be implemented for the application of the pass/fail procedure.
Figure 13 shows the STFT spectogram of a diesel engine obtained from a normal and faulty condition (piston inverted). Using STFT the resonances between mechanical components are easy to recognize.

Since the STFT uses the same window length for the analysis of the whole signal, therefore it provides constant resolution for all frequency range. To overcome this problem wavelet transform is applied for multi-scale analysis: at low frequencies, high frequency resolution and low time resolution, till at high frequencies high time resolution but a low frequency resolution can be obtained. The STFT is only provide a feasible outcome when the patterns have approximately the same size, so as to ensure the considerably high resolution of expressed signal. The permanent resolution reveals only one of all possible sizes. For example, a spectogram obtained from Gabor representation in order to the detection of gear tooth damage. The proposed value of the window width for the detection can be chosen in the conscious of the meshing period of one tooth. This recommended width satisfies the need of detection of certain scale of local damage on a tooth but does not well-suited for other faults. To overcome this limitation a changing width function is used in the recently developed wavelet transform so a series of resolutions can be visualized in time display. During the Fourier transformation process the signal is decomposed on to a sinusoid function basis, while a more common function is used by the wavelet transform as the basis. This produces more comprehensive transform results. However, the application of the wavelet transformation faces major difficulty, namely the selection of a wavelet basis [26].

In short, due to signal segmentation spectogram has some disadvantage, namely the limitation in time–frequency resolution and it can only be applied to non–stationary slowly-changing signals. To overcome this limitation wavelet transform uses a changing width function. In addition, bilinear transforms such as Wigner–Ville distribution are not use signal segmentation, so it does not suffer from the time–frequency resolution problem. In Jang Yin et. al.’s study [27] internal combustion engine vibration signals were studied by popular time-frequency analysis techniques, i.e., STFT, analytic wavelet transform (AWT) and S transform (ST). Without aiming to give an exhaustive list the conclusions of the paper: 1. the vibration signals of an internal combustion engine appear at low frequencies, while the intermittent part appears at high frequencies. Both parts can not be clearly separated with a unique window width. 2. The spectrograms of three time - frequency transforms are closely connected with the window width (for STFT) or the quality factor (for ST or AWT). 3. In case of cylinder head vibration; STFT spectrograms can localize better the frequency components of interest of a signal with an appropriate window width without significantly sacrificing time resolution than either ST or AWT. In many applications STFT is very useful including vibro-acoustic source identification, fault diagnosis and transfer path analysis.
It is practical to consider the FFT spectrum as a function of speed. Then the coincidence between some resonances and harmonics is easily noticeable. The figure 14 shows an STFT measurement result associated with the jigsaw which was mentioned before.

![Figure 14. Waterfall plot of a power tool](image1.png)

The spectrogram is a little bit smeared, because the running up of the speed was not perfectly continuous from 0 rpm to 3000 rpm. Apart from this trouble the result was still assessable and gave the same conclusion as the FFT analysis: the noise problem significantly occurred because of the mechanical units. The waterfall plot of an earth-moving machine prepared by Jálics is an additional example of a waterfall plot illustrated in figure 15.

![Figure 15. The sound pressure spectrum of an earth-moving machine powered by a 6-cylinder diesel engine; measured at the driver's ear between 900 rpm and 1800 rpm at part load](image2.png)

The frequency is displayed on one horizontal axis, the time (or speed in the case of automotive engines) on the other axis, and the acoustic characteristic on the vertical axis. This can be done either with an actual amplitude value (Campbell-diagram) or by replacing the actual amplitude values with a colour scale (waterfall plot).
Figure 16. The Campbell-diagram of an earth-moving machine powered by a 6-cylinder diesel engine; measured at the driver's ear between 900 rpm and 1800 rpm at part load.

An example of Campbell-diagram is shown in figure 16 where the same phenomenon is represented as in the figure 15. The use of the Campbell-diagram for vibration and noise measurement in automotive engines has generally become widespread. It clearly shows the characteristic frequencies varying with increasing speed as well as the resonances forming the vertical line and sound level rise.

3.3.3 Cepstrum
The cepstrum can be defined as the power spectrum of a logarithmic power spectrum. A lot of similar terms can be found in the literature e.g., cepstrum from spectrum, quefrency from frequency or rahmonic from harmonic. By comparison, the autocorrelation function is the inverse Fourier transform of the power spectrum without logarithmic conversion.

Figure 17. (A) Cepstrum analysis result of a faulty bearing; power spectrum on linear and logarithmic scale.

Figure 17 (A) illustrates the analysis of a vibration signal of a false bearing. In figure 17 (A) the same spectrum is plotted on linear and logarithmic amplitude axes. On the figure the effect of linear versus logarithmic amplitude scale in power spectrum is shown. In figure 18 the autocorrelation (B) and cepstrum (C) are illustrated. Regarding to figure 18 (C), the application of the logarithmic power
spectrum discovers the presence of a family of harmonics which are hidden in the linear visualization. The family of harmonics can’t be detected in the autocorrelation function, while in the cepstrum (denoted ➀, ➁, etc.) they presence are clearly made evident. The quefrequency axis of the cepstrum is a time axis, most closely related to the X axis of the autocorrelation function.

The power cepstrum suitable for detect a periodic structure in the spectrum, for example, families of spaced harmonics and/or sidebands. Family of harmonics can’t be detected in the autocorrelation function, while in the cepstrum (denoted ➀, ➁, etc.) they presence are clearly made evident. The quefrequency axis of the cepstrum is a time axis, most closely related to the X axis of the autocorrelation function. The power cepstrum suitable for detect a periodic structure in the spectrum, for example, families of spaced harmonics and/or sidebands.

![Figure 18](image)

**Figure 18.** The harmonics of a defected bearing; the autocorrelation function obtained from linear representation (B) and cepstrum obtained from logarithmic representation (C).

The cepstrum has to contains a reasonable amount of corresponding harmonic or sideband family to obtain distinct peaks. In the spectrum these consistently spaced components must be adequately arranged. As a guide, the original spectrum should contain at least eight lines to detect the spacing components. The complex cepstrum is defined as the inverse Fourier transform of the complex logarithm of the complex spectrum. Complex cepstrum uses phase and logarithmic amplitude information at each frequency in the spectrum; this is the difference between complex cepstrum and power spectrum. Thus, it is reconversable to a time function. In practice the source and transmission path effects act on measured vibration signals. In the autocorrelation function and in the spectra they both are mixed in the signals, but in the cepstra they are separated into distinct spots, which allows a detection of source and transmission path effects in an externally measured signal [28].

Several methods are now reachable to separate deterministic and random signals included TSA and cepstrum (CEP): linear prediction, self-adaptive noise cancellation (SANC) and discrete/ random separation (DRS). Randall [29] compared these different separation methods with each other and presented the advantages and disadvantages of each methods through practical examples. He found that the cepstrum analysis gives a chance to extract some periodic groups of harmonics, while the others remain the same. The method is not sensitive to smearing effects of peaks since it is based on periodicity of the spectrum. By fixed bandwidth of other comb filters (such as TSA and DRS) the slightly smearing of spectral peaks may not be eliminated.

The use of cepstrum analysis is beneficial for detecting periodicities in the power spectrum since it provides the distribution of the frequency components.
Figure 19. demonstrates the measurement result of an auxiliary gearbox driving on a gas-turbine-driven oil pump. The spectrum and the corresponding cepstrum analysis can be shown before and after the development. The motivation factor of development was a fault on one of the bearings.

![Spectra (A)](image1)

![Cepstrum (B)](image2)

**Figure 19.** Analyses of vibration of an auxiliary gearbox; spectrum analysis (A); the corresponding cepstrum analysis (outer raceway defect) (B).

Further, in the cepstrum the global “power” content of a whole family of harmonics or sidebands can be represented by one component irrespective of phasing between amplitude and phase modulation, machine-load condition and selection of measurement location. Cepstrum analysis make it possible to determine the frequencies precisely, thus it is useful for detection faults of industrial machines as a condition-related parameter. The post-processing techniques gives the opportunity of the manipulation of cepstrum, for example: taking out selected parts of the cepstrum and then transforming the cepstrum back to the frequency and/or time domain.

Further examples for separation of source and transmission path and applications to diagnostics of variable speed machines may be find in Randall’s other study [30].

**Conclusions & key learnings**

This section would like to highlight the best method from failure diagnostic point of view based on a scoring system, see the table 1. below.

![Table 1](image3)

**Table 1.** Evaluation table of the studied methods
During the determine of the criteria we kept in mind the applicability of each methods in failure diagnostics. The importance of different criteria was taken account with the weight factor (S). According to this scoring system one can say that the STFT and cepstrum methods are the most suitable for fault detection, while the methods got lower score may not identify the malfunctions so clearly. The application feasibility of STFT method is wide, such as the non-linear methods, because they are applicable for various non-linear and variable problems. The results of FFT, STFT and cepstrum methods are more usable than TSA, non-linear methods or symmetrized dot pattern method. The lower scored techniques do not provide sufficient information about the vibration problem from diagnostic perspective. They only tell us that something is wrong, but do not tell us where the problem is. TSA method is hard to evaluate since its domain is in the time. Following the changing phenomena within the machine in the function of time is rather difficult than in frequency domain. That is why methods in time domain got lower points during the scoring process in the “evaluation” column than frequency domain analysis. Symmetrized dot pattern method is an exception to this statement. It is in frequency domain and its result is very similar to the non-linear method’s result. They both can determine the malfunctions and estimate the severity of the failure, but still do not provide information about the location of failure. TSA is more likely a preprocessing tool than a proper diagnostic tool. With the help of TSA the localization of failures could be easier in diagnostic process. Over against time domain techniques FFT, STFT and cepstrum give the frequency distribution of a sound property. The principle is the same as in time domain techniques: compare the results under healthy and faulty conditions; but the mentioned techniques just now give the opportunity of the observation of the frequency components as well. It means that a calculation is enough to detect the busted machine elements within the machine. In this case the magnitude of the failure is localized and quantified compared to TSA, non-linear methods and symmetrized dot patterns, where the decision (failed or healthy) made only by a visual inspection of the results. The difficulty of preparation progress is the same for each method: almost the same equipment and devices are needed for sound or vibration measurements. There is needed much pre-knowledge to perform non-linear methods due to its mathematical background. This statement is right also, when we are talking about the spectral analysis, because the knowledge of the analysed machine is indispensable to diagnose the machine in proper way. Finally, the conclusion is that the FFT, STFT and cepstrum analysis are the most efficient methods for failure diagnostics from among the studied six methods. In the next step some of these methods will be examined with the help of simplified experimental methods. Based on this examination the statement of the above illustrated table will be validated and actual benefits of each method will be detailed. As practical benefit, after this work we will be able to select an appropriate method for subsequent test to determine the location of the fault in a vehicle.

Summary
Currently, number of techniques are available for engineers to predict malfunctions and specify the reason of failures. Our question sounded at the beginning of this study like this: “What kind of vibro-acoustic methods are existing to identify malfunctions in mechanical structures?” According to this question this paper makes attempt to review the existing methods based on literature sources, which able to detect faults in engineering systems. Certain methods were selected and studied so as to know them in detail, highlight their advantages and disadvantages through an evaluation table. The reader can meet with our own measurement results and observations as well. In this paper an introduction is carried out to show possible applications and limitations of these methods. The study is mainly focusing on signal-based methods rather than the statistical energy analysis, boundary element method and finite element method or combination of these procedures; mentioned in introduction at the beginning of this paper. However, the importance of non-signal-based methods are not negligible, actually it’s application area is sufficiently wide. For this reason and the continuous advancement of vibro-acoustical methods further investigations and more critical reviews are necessary.
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