MŰEGYETEM 1782
BUDAPEST UNIVERSITY OF TECHNOLOGY AND ECONOMICS
FACULTY OF MECHANICAL ENGINEERING
DEPARTMENT OF MECHATRONICS, OPTICS AND MECHANICAL ENGINEERING INFORMATICS

BOOKLET OF PHD THESIS

VIBRATION DIAGNOSTICS BASED REAL-TIME OPERATING STATE DETERMINATION OF ROTARY MACHINES

GÁBOR GÁRDONYI

Supervisors:
DR. KRISZTIÁN SAMU
Budapest University of Technology and Economics, Budapest, Hungary
Department of Mechatronics, Optics and Mechanical Engineering Informatics

DR. ÁKOS BERECZKY
Budapest University of Technology and Economics, Budapest, Hungary
Department of Energy Engineering

Budapest, 2019

Introduction

In the last century, it has been a critically important task to define accurate, measurement based methods for indicating internal processes of technical equipments or estimating the operational state of machines. In our rapidly developing world the evolution of control technology, the efficiency and performance growth of drive systems, the possibility of predicting failures all justify research and development of alternative measurement techniques for accurate state observation. The expanding toolbox of electronics and sensor technology offers almost unlimited possibilities to determine physical quantities. The collected information – with the help of digital techniques – can be used and stored for later analysis. Measured values can be processed even in real-time to make the decision and the intervention as early as possibe.

The aim of this dissertation is to describe such novel diagnostic procedures that are able to accurately determine – one of the most important operating parameters of rotating or alternating devices – the operational speed by using only the information originating from the measured vibration of the test equipment. The question of how one could measure the key parameters of an operating machine – particularly the rotating speed – may arise if the engineers did not perform these measurements in the early stages of design. Mounting sensors into a device is usually not an easy task, especially if doing so requires the modification of a rotating component. The difficulty is mainly caused by the compactness of modern devices. These parts are usually not directly accessible to users and there tends to be insufficient free space near the drive. In these instances vibration diagnostics that uses additional acceleration sensor and spectral analysis methods can be the best alternative solution.

Vibration signal analysis is nowadays the most commonly used method for troubleshooting and for operating state determination of rotary machines [1]. After a vibration acceleration sensor has been fixed on the housing of the analysed machine, by applying spectral evaluation and statistical analysis of the sampled signal, the rotational speed or the characteristic periodicity can be easily determined.

Objective and outline

In the last few decades, spectrum [2]–[5] and cepstrum [2], [6], [7] based methods used for rotational speed and malfunction analysis have attracted much attention from research teams. However, there are very few publications available that discuss and compare the reliability of these two calculation methods [2], [6], [7]. In the case of data acquisition systems, most of the settings are usually constant during a single measurement process. The two most relevant parameters are the sampling frequency and the buffer size of the data acquisition. Buffering measurement data causes the result of real-time processing to be delayed. However, it is not a significant disadvantage in the case of spectral calculations. For spectral analysis, also in non-real-time applications, a complete dataset is usually needed, which can be evaluated at once. In the case of buffered data streams, it is advisable to determine the buffer size at least as large as the input array size of spectrum calculation. Traditional spectral analysis is concerned with the study of how the power of a signal is distributed in the frequency domain. After decomposing original data series into sinusoidal components, it is relatively easy to detect power content that corresponds to the rotational frequency [1]. x coordinate of this peak represents the main operational frequency.

Cepstrum was originally defined as the power spectrum of the power spectrum's logarithm. Later, a newer definition was coined; cepstrum being the inverse transform of the power spectrum's logarithm [6], [7]. Cepstrum calculation of a signal only results in an evaluable output if its spectrum contains harmonic families as it searches for periodic changes in the spectrum. This method converts the signal into so-called quefrency components. Similarly to autocorrelation cepstrum output reveals nothing about absolute frequency only about the spacing of spectral peaks. The variable of cepstrum data series possesses the dimensions of time, but is mostly referred to as quefrency. Height of a certain quefrency peak indicates the total relative power of corresponding harmonic families in the frequency domain.

One of the earliest applications of cepstrum theory can be found in the study of signals containing echoes [8] and in the study of speech analysis [9]. The discussed applications was aimed at detecting harmonic structures of measured sound as well as exploring transmission characteristics. So-called harmonic families can be detected by gearbox analysis [6] or alternatively by any kind of analysis of rotary machines [10]. The method proved to be very effective in practice. Nowadays, cepstrum based algorithms are widely used for malfunction detection and state observation of rotary machines.

Purpose of the development of the spectrum and cepstrum based hybrid speed determination method, which has been presented in the thesis, was to create an accurate method that is capable of calculating the rotational speed of rotary machines more accurately than any of the aforementioned methods when used alone. The aim of the hybrid spectral process is to use as few sensors as possible, meanwhile getting more accurate state estimation. The hybrid method uses fusion of background algorithms. Signal processing is carried out on sampled data series, meaning that we have only get known values at discrete moments. We deduce usually therefrom to the continuous physical phenomena. When using digital signal processing methods spectrum as well as cepstrum resulted data remain discrete. Spectral speed determination is based on the fact that usually a dominant frequency peak appears in the vibration spectrum that shows a frequency value, which is proportional to the machine speed. However, the frequency indicated by the maximum value of the spectral peak actually does not represent the true value of speed because of the discrete resolution. The same can be stated about the discrete cepstrum and the detectable quefrency peaks. The thesis explains how to calculate the applicable ranges, as well as the main decision levels of the novel hybrid methodology.

Since the 18th century there has been a growing interest in statistical hypothesis testing. In the literature, several theories have been already proposed to extend the applicability of the mathematical background or to optimize calculation. However, new methodologies and applications of statistical hypothesis tests are published every year. The results of Neyman and Pearson [11] had inspired Abraham Wald in the mid-1940s to reformulate it as a sequential analysis problem [12]. A great summary about the evolution of sequential hypotheses tests and the early stages of the development can be found in Walds paper [12] in Chapter B. In later publications Wald has introduced further generalised theories and calculation methods about sequential decision functions [13], optimum character estimation of SPRT [14]. When using hypothesis tests, it is often not just the purpose of classifying already available data series. In some cases, changes in statistical distribution must be detected immediately on continuously incoming measurement data. The latter occurs usually in machine diagnostics, in particular by predicting failures of observed machines. Graphical representation of these tests is possible by drawing a CUSUM curve based on sequentially calculated LLR values. Most of CUSUM procedures used in practice evaluate fixed-size data blocks at once. In the case of real-time applications sliding windowing techniques could provide corresponding output value for each input data. The key of the LLR-based CUSUM algorithm is the negative pre-change mean of the LLR and the positive post-change mean. If the analysed signal contains a changed subsection with a given length, the local result of the CUSUM could be the highest at the end of the changed subsection if the cumulative calculation has been started just before the first change [15]. This is the basic idea that lay the foundation for the later detailed SSPR process.

Until the dissertation has been written, the adaptation of SPRT method proved successful in many application areas. For example, by identification of place and material of knocking objects in flow induced vibration [16], real-time acoustic emission event detection during thermodynamic fatigue tests of reactor materials [15], [17], [18], vibration based quality control of electric drives [19], [20] or vibration based state determination of internal combustion engines [21]. The used SPRT algorithm has proven to be a robust and effective sequential evaluation method in all these applications.

In order to calculate the length of the event, we need to define the starting and final dates of the event as accurately as possible. The difference of these two timestamps results in an estimated event length. The novel way of processing has been named as Scaled SPRT or SSPRT and it also provides new display modes. The motivation for defining the new methodology was that determining length of detected events has been proved to be a regular issue. Accurate localisation of statistical changes remain always a hard mission, especially in noisy environment. The new method gives direct information about the most likely event length based on the partial results of classic SPRT evaluation. The three-dimensional surface produced by the new method can be displayed and can help in studying internal structure of detected events.

Results and theses

Basically two novel diagnostic methods with very different backgrounds have been introduced and presented separately. The first described method relies on analysing spectral content of measured vibration acceleration. Well known and widely used digital signal processing algorithms – spectrum and cepstrum – give the core of the new hybrid way of evaluation.

The second method is sensitive to statistical changes of the measured signal and can be described as an enhanced evaluation method of the classic sequential probability ratio test. The core method is well suited for event detection. In addition, using the enhanced method, endpoint and length of events can be determined directly. The structure of output data provides new display possibilities for analysing internal structure of events.

Although both new signal processing methods have been developed during vibration diagnostic research of rotary machines – first and foremost of internal combustion engines – the general mathematical background allows the analysis of arbitrary originated discrete data series. Based on the performed measurements it can be stated, in addition to internal combustion engines, the new methods are able to give accurate estimation for many electric drive systems' rotational speed as well. Speed determination could be performed based on any other measurable physical quantity which fluctuates with the characteristic speed together such as coil current, pressure, force or torque. However, this dissertation rely only on acceleration measurement. Most of the measurements have been carried out with a preamplified triaxial piezosensor fixed with screw, neodymium magnet or special beeswax on the machine housing. If the experimental setup allowed, the measurement assembly also contained high-precision digital encoder that has provided reference measurement for the tests.

Each point of the discrete spectrum is located even spaced along the frequency axis, where df is the distance between neighbouring data points expressed in Hz. Depending on sensor location, orientation and on the operational state of the examined device, spectrum could show $f_{\omega_{SpectMain}} = f_{\omega_1} \cdot p/r$ as directly detectable frequency component, which is proportional to the wanted f_{ω_1} rotational frequency. Parameters p (number of Poles) and r (number of shaft revolutions made during one full operating period) must be selected according to the machine structure and the applied measurement assembly. The introduced parameters can be used to define relative error level of speed estimation as the function of actual speed: $E_{Spect}(f_{\omega_1}) = r \cdot F_S/(f_{\omega_1} \cdot p \cdot N_t)$, where F_S shows sampling frequency of the source signal and N_t is the number of time-domain data samples used for spectral calculation. In the case of discrete cepstrum, its points are also equidistantly located along the quefrency axis. The space between two points can be expressed in s and marked as dq. Directly detectable quefrency components show usually period values $T_{\omega_{CepsMain}} = r/f_{\omega_1}$ that correspond to frequencies which are proportional to f_{ω_1} wanted frequency. In this case, possible relative error level of speed estimation can be calculated with the following equation: $E_{Ceps}(f_{\omega_1}) = f_{\omega_1}/(r \cdot F_S)$.

Thesis 1

When using discrete spectra and cepstra for speed determination of rotary machines, by locating the dominant peak in the resulted data series that corresponds to a given rotational frequency, the possible relative speed estimation error resulting from the finite resolution of the representations depends on the source signals sampling frequency, on the used windows sample size and on the relationship of the wanted rotational frequency and the frequency value that corresponds to the location of the easiest detectable component of each representation. Relative error curves of the core methods intersect each other where the rotational frequency equals to

$$f_{chang} = r \cdot F_S/\left(p \cdot \sqrt{N_t}\right)$$

where f_{chang} is the frequency at the intersection, F_S is the sampling frequency, N_t is the number of samples, p and r are the parameters which describe the rate of the searched and the detectable vibration components.

Related publications: [P1], [P3]-[P4], [P8]-[P11]

Thesis 2

Considering practical limitations caused by the finite resolution of discrete spectra and cepstra, spectrum based speed estimation method could only be used in the range between $f_{Spect\,min}$ and $f_{Spect\,max}$, cepstrum based estimation can provide reliable result in the range between $f_{Ceps\,min}$ and $f_{Ceps\,max}$, which can be defined as

- $f_{Spect\,min} = r \cdot F_S/(p \cdot N_t)$,
- $f_{Spect\,max} = r \cdot F_S \cdot (N_t - 2)/(2 \cdot p \cdot N_t)$,
- $f_{Ceps\,min} = 2 \cdot r \cdot F_S/N_t$,
- $f_{Ceps\,max} = r \cdot F_S$,

where $f_{Spect\,min}$, $f_{Spect\,max}$ and $f_{Ceps\,min}$, $f_{Ceps\,max}$ are the lower and upper applicability limits of the spectrum and cepstrum based methods, F_S is the sampling frequency, N_t is the number of samples, p and r are the parameters which describe the rate of the searched and the detectable vibration components.

Related publications: [P1], [P3]-[P4], [P8]-[P11]

Thesis 3

The spectrum and cepstrum based combined speed determination method provides the instantaneous speed of a rotating or alternating test equipment based on vibration signals and results always with the possibly lowest relative estimation error level.

Related publications: [P1], [P3]-[P4], [P8]-[P11]

The SSPRT (Scaled Sequential Probability Ratio Test) makes decision based on the result of many parallel cumulative sum calculations instead of one sequentially calculated z_i value. The caluculation produces a series of $S_{j,i}$ values for each input data. Output values can be displayed as three-dimensional surface, where local maximum points show most likely end-time and best estimation for the length of detected statistical change. It is also a great tool for analysing internal structure of detected events through visual display possibilities. SSPRT also has various scaling options. The advantage of linear scaling appears when relatively narrow range of event length is taken into account. In the case of linear scaling simple calculations provide an easily evaluable output also by visual inspection. In some diagnostic applications it could give better overview if the output data has logarithmic scaling. In this case, rapid changes appear more detailed in the output, while slow transients do not have unreasonably high resolution. When using logarithmic scale it becomes possible to analyse much wider range of relevant event length. In the case of the introduced variable windowed scaling, the shortest applied window is square shaped, the second is a double length triangle, the followings are more and more wide and similar to the Gaussian window. Despite its well optimized background calculations, it provides an easily evaluable output. Disadvantage of the latter scaling is that minor changes (details of event structure) within the detected events are not sharp due to the smoothing effect of the applied Gaussian windows. It is important to note that this scaling type, compared to the linear and logarithmic types, provides slightly delayed final decision.

Thesis 4

Based on sequentially calculated logarithmic likelihood ratio values, implementation of the linear, logarithmic and variable windowed scaling of the scaled sequential probability ratio test can be defined by the following recursive formulas:

- **linear scaling by**

$$z_i \rightarrow \begin{cases} S_{-1,i} = z_i \ , \\ S_{j,i} = S_{j-1,i} + z_{i-jd-} \quad + z_{i-jd-} \quad , \end{cases}$$

where z_i is the logarithmic likelihood ratio calculated for the i^{th} input data, $S_{j,i}$ corresponds to z_i and can be found in the j^{th} row of the SSPRT output, d is the increment between adjacent window sizes and $z_i = 0$ for all $i < 0$ cases,

- **logarithmic scaling by**

$$z_i \rightarrow \begin{cases} S_{-1,i} = z_i \ , \\ \\ S_{j,i} = S_{j-1,i} + \displaystyle\sum_{k=i-g^{j+1}+1}^{k=i-g^{j}} z_k \ , \end{cases}$$

where g is the ratio of the lengths of two neighbouring windows,

- **varying windowed scaling by**

$$z_i \to \begin{cases} S_{0,i} = w_0 z_i \,, \\ S_{j,i} = S_{j,i-1} + w_j\left(S_{j-1,i} - S_{j-1,i-\Xi}\right), \\ w_0 = 1 \,, \\ w_j = \dfrac{j\Xi + 1}{(j-1)\Xi^2 + j\Xi + 1}, \end{cases}$$

where $\Xi + 1$ is the odd number of samples of the square shaped window used to produce the first row, w_j is an additional parameter destined for declining average compensation of base windows, w_j can be calculated in advance for each raw.

Related publications: [P1]-[P3], [P5]-[P8]

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