Slovak University of Technology in Bratislava
Faculty of Informatics and Information Technologies

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Bc. Miroslav Hájek

Machinery vibrodiagnostics with the industrial internet of things

Master's Thesis

Thesis Supervisor: Ing. Marcel Baláž, PhD.

May 2023

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Study programme:	Intelligent Software Systems
Study field:	Informatics
Training workplace:	Institute of Computer Engineering and Applied Informatics
Thesis supervisor:	Ing. Marcel Baláž, PhD.
Departmental advisor:	Ing. Jakub Findura
Consultant:	Ing. Lukáš Doubravský

May 2023

SLOVENSKÁ TECHNICKÁ UNIVERZITA V BRATISLAVE
FAKULTA INFORMATIKY A INFORMAČNÝCH TECHNOLÓGIÍ

Návrh zadania diplomovej práce

Finálna verzia do diplomovej práce [1]

Študent:

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Študijný program:	Inteligentné softvérové systémy
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Výskumník:

Meno, priezvisko, tituly:	Marcel Baláž, Ing. PhD.

Projekt:

Názov:	Vibrodiagnostika strojov s priemyselným internetom vecí
Názov v angličtine:	Machinery vibrodiagnostics with the industrial internet of things
Miesto vypracovania:	Ústav počítačového inžinierstva a aplikovanej informatiky, FIIT STU, Bratislava
Oblasť problematiky:	Internet vecí, Spracovanie signálov, Feature engineering

Text návrhu zadania[2]

Monitorovanie prevádzkového stavu rotačných strojov za účelom včasného odhalenia poškodení je dôležité pre plynulý priebeh priemyselných procesov bez náhleho zlyhania kľúčového technického vybavenia. Nadmerné vibrácie alebo graduálna či náhla zmena ich charakteru sú spoľahlivými indikátormi opotrebenia dielcov. V mnohých prípadoch bývajú zavedené iba pravidelné pôchodzkové merania s následným vyhodnotením časových a frekvenčných priebehov kvalifikovaným personálom. Kontinuálna diagnostika a prediktívna údržba rozširujúca sa so zariadeniami IIoT spôsobuje enormný nárast objemu zaznamenaných dát. Sledovanie výchyliek operátorom a manuálna identifikácia súčiastok vyžadujúcich údržbu v celom závode sa tak stáva prakticky nerealizovateľná.

Preskúmajte spôsoby zisťovania bežných poškodení strojov z vibračných signálov a analyzujte algoritmy na redukciu množstva posielaných dát zo senzorov vzhľadom na osobitosti aplikačnej domény. Navrhnite reprezentáciu údajov na základe typických čŕt signálu, ktorá zníži výpočtové nároky na zvyšok komunikačného reťazca. Zvolený spôsob predspracovania má zároveň umožniť diagnostiku poškodení zvoleného stroja. Implementuje vaše riešenie s ohľadom na možné nasadenie na prostriedkami limitovanú senzorovú jednotku. Následne posúďte efektívnosť, porovnajte dosiahnuté presnosti diagnostiky a verifikujte voči zaužívaným postupom.

[1] Vytlačiť obojstranne na jeden list papiera

[2] 150-200 slov (1200-1700 znakov), ktoré opisujú výskumný problém v kontexte súčasného stavu vrátane motivácie a smerov riešenia

Literatúra[3]

- NANDI, Asoke Kumar; AHMED, Hosameldin. Condition monitoring with vibration signals: compressive sampling and learning algorithms for rotating machines. Hoboken, NJ, USA: Wiley-IEEE Press, 2019. ISBN 978-1-119-54462-3.
- YU, Gang. A Concentrated Time–Frequency Analysis Tool for Bearing Fault Diagnosis. IEEE Transactions on Instrumentation and Measurement. 2020, vol. 69, no. 2, pp. 371–381. ISSN 1557-9662. DOI: 10.1109/TIM.2019.2901514. Conference Name: IEEE Transactions on Instrumentation and Measurement.

Vyššie je uvedený návrh diplomového projektu, ktorý vypracoval(a) Bc. Miroslav Hájek, konzultoval(a) a osvojil(a) si ho Ing. Marcel Baláž, PhD. a súhlasí, že bude takýto projekt viesť v prípade, že bude pridelený tomuto študentovi.

V Bratislave dňa 22.2.2023

Podpis študenta   Podpis výskumníka

Vyjadrenie garanta predmetov Diplomový projekt I, II, III

Návrh zadania schválený: áno / nie[4]

Dňa: ....

Podpis garanta predmetov

[3] 2 vedecké zdroje, každý v samostatnej rubrike a s údajmi zodpovedajúcimi bibliografickým odkazom podľa normy STN ISO 690, ktoré sa viažu k téme zadania a preukazujú výskumnú povahu problému a jeho aktuálnosť (uveďte všetky potrebné údaje na identifikáciu zdroja, pričom uprednostnite vedecké príspevky v časopisoch a medzinárodných konferenciách)

[4] Nehodiace sa prečiarknite

Declation of Honour

I hereby declare on my honour that I wrote this thesis independently under supervision of Dr. Marcel Baláž, after consultations and with use of cited literature.

Bratislava, May 2023 ....

Bc. Miroslav Hájek

Acknowledgement

Annotation

Slovak University of Technology in Bratislava

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Anotácia

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Fakulta informatiky a informačných technológií

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Vedúci diplomovej práce:	Ing. Marcel Baláž, PhD.

Máj 2022

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1 Introduction

Manufacturing is experiencing a shift in the traditional practices of asset operational status evaluation and utilization. The rise of Industry 4.0 means greater automation and robotization of the production halls to achieve optimal usage of available resources. The secondary aspect in the enterprises' endeavor, however not less important, is to keep track of the equipment wear and tear. The corrective action be it repair or replacement should be taken on time in response to the key indicators.

The goal is to preserve required safety and production efficiency when extending the useful life of machine moving parts. In the factories and logistics where this sort of equipment is vital, there is a rising interest in the ability to monitor in real-time the health of the machines and to proactively diagnose the fault to repair it without adding unnecessary costs.

Vibrations are the most nonintrusive way with which such faults can be sensed. The experts use it to distinguish faulty states and to identify the malfunction's root cause. In critical circumstances such as in the case of the large turbines in the power plants, the precautions leading to regular machinery check-ups are already in place. To reach wider acceptance and spread, the monitoring solution has to be sufficiently independent, reliable, and as self-sufficient as the model design allows it to be.

The main issue to consider in large-scale machinery monitoring using vibrations are lots of uninformative streams of samples not directly useful for the production line operator. The dashboard must aggregate these flows into trend variables with severity levels categorized based on industrial standards. The majority of signals are viewed once at the maximum therefore to store or even transmit them from the edge device in its entirety would be wasteful. The complex overview of the mechanical equipment status is attainable only when agent devices and sensors are cheap enough with a long lifespan on battery power and preferably remain physically small to reduce the additional clutter.

Attempted machine and deep learning approaches have the crucial impediment that the construction of every single machine is unique to some extent because of tolerances and variable load. The model must be trained specifically for the target environment to achieve the ideal performance. In addition, the failures are relatively rare events occurring usually in the span of multiple months. In these circumstances, it is hard to obtain a large enough sample of fault events quickly. Novelty detection is a technique that can be applied in this case.

The thesis is organized in the following manner. In the first chapter of analysis in section 1 we explore the mechanical maintenance approaches and industry standards on common fault identification. Then section 2 is all about measuring vibrations and transforming them into features meaningful in automatic fault pattern recognition. In section 3 we delve into modes of diagnosis based on reduced relevant indicators. Section 4 deals with evaluation datasets used to determine computational requirements on IIoT infrastructure. Chapter 2 defines data format and proposes processing steps to diagnose the imminent failure and different fault types. The approach taken is evaluated and validated in Chapter 6.

2 Problem analysis

In the problem analysis chapter we expore the feature extraction methods and machine learning algorithms for the fault diagnostics. The basis we build upon is the domain knowledge of the mechanical engineers in vibration signal measurement and its evaluation.

2.1 Condition monitoring

All rotating machinery eventually fails because of the long-term strain on the individual parts or incorrect workmanship, installation, or operational procedures. In the end, these factors cause the equipment not to fulfill its intended functionality. Many instrumentation methods are practiced to reveal evolving faults: vibration and acoustic noise monitoring, electric supply line measurements, thermography, oil and particle analysis, ultrasonic testing, etc. Vibration signals are the preferred tool for rotating machinery monitoring [1].

The defect needs to be either repaired or replaced, preferably without significant production downtime, further damage to the other attached elements, or any endangerment of the responsible personnel. The maintenance strategies are chosen according to the machine's importance as a result of its failure effect evaluation on the system. The guide to set appropriate maintenance procedures is outlined by the IEC 60706-2 standard and involves reliability-centered maintenance analysis [2].

2.1.1 Maintenance strategies

There are three different approaches to maintenance across the industry: reactive, preventive, and predictive [3]. In general, the more sophisticated methods are beneficial in a high-stakes environment. The unexpected machine shutdown can have a negative economic impact on the enterprise, resulting in decreased product quality and demands spare parts be ready in the supply inventory at all times. However, in certain situations suffice to utilize a simpler maintenance program, but predictive maintenance gains interest in the Industry 4.0 to optimize assets' usage [4].

Reactive maintenance allows machinery to run to complete failure. This is the most inappropriate way to maintain the production line, but it is straightforward. It requires a large stock of replacement parts on-site and breakage inflicts a 'crisis management mode' upon the plant [3]. On-demand repairs are justified if short downtime is an acceptable, full, and quick replacement of a broken machine with a backup is possible or there is no threat of failure to the surrounding environment [5].

Preventive maintenance is performed before any issue is detected. Maintenance occurs at regular intervals derived from a predetermined period in the calendar or expected machine running time (e.g. MTTF - Mean Time To Failure). The schedule is crucial but can result in components being replaced in good condition when further utilization is possible or too late after the machine breaks. In this case, conservative planning is usually the norm to keep the machine always in a perfect state and therefore more frequent intervention. [1].

Predictive maintenance known as condition-based maintenance (CbM), improves the predictability of reactive maintenance and eliminates the waste in overall resource utilization of cautious prevention. The machine downtime is scheduled after the detection of unhealthy trends in fault monitoring with sensors and troublesome components are identified.

A measurable decrease in effectivity allows us to order necessary parts in advance and organize repairs of several machines at a convenient time. The misdetection leads to increased costs compared to previous methods and raises the expectation that faults are distinguishable among themselves [6].

The P-F curve is a widespread representation of equipment degradation over time based on historical records (Fig. 2.1). Corrective action should be taken between the event of potential failure (P), when the fault detection is activated, and functional

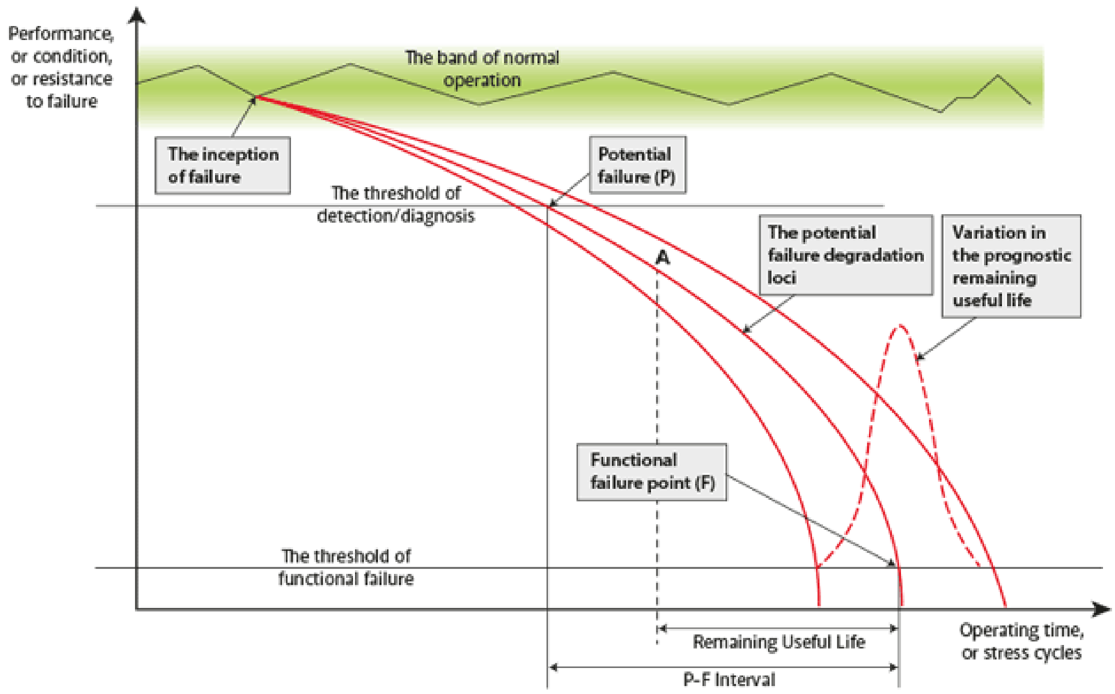

Figure 2.1: P-F curve represents the evolution of the asset's health [7]

failure point (F) in the P-F interval [8]. These division points are not exactly set but have statistical distribution to them.

The Remaining Useful Life (RUL) of the specific running machine in the given instance can be merely estimated analytically, with the survival probabilities of the individual components, and based on the model of the 'run-to-failure' histories and usage parameters [9]. Predictive condition monitoring aims to extend the machine lifespan to the maximum by predicting expected RUL.

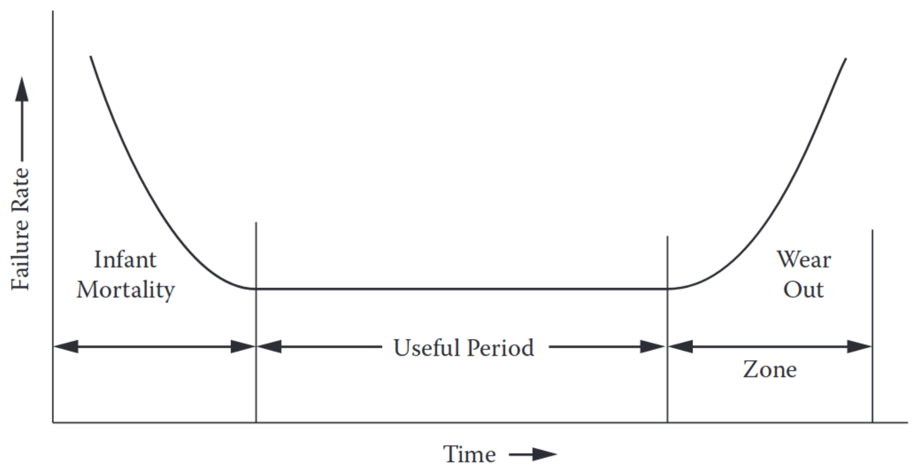

Figure 2.2: Bath tub curve [1]

A high failure rate is present not only at the worn-out stage when the parts are fatigued or corroded but also in the early stages soon after assembly. Causes can be found in manufacturing or material defects, inadequate installation, or improper start-up procedures. During the stable middle phase, malfunction can occur after the machine's excessive overload. The time plot to failure rate is known as the bath tub curve (Fig. 2.2).

2.1.2 Vibration fault types

Mechanical problems during machinery operation bring about vibrations in the vast majority of cases. Therefore vibroacoustic diagnostics is considered one of the most important methods in early component fault identification [5].

The cause of vibration comes out of the changing force in its magnitude or direction. The most emerging defects can be encompassed by explaining the deficiencies of the mechanical structure broadly categorized as **unbalance, misalignment, looseness, excentricity, deformation, crack and influence of the external force** (e.g. friction) [6]. It is important to stress that our concern are not the underlying deficiencies in mechanical parts, but the correct fault classification based on the signal waveform.

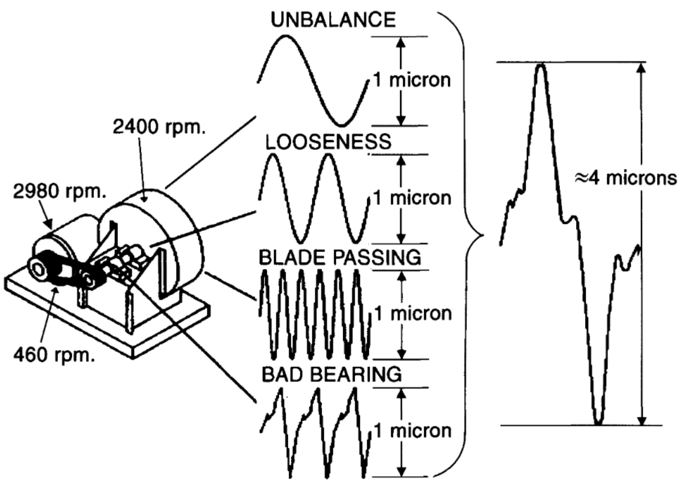

Figure 2.3: Complex machinery vibrations [6]

Rotating machine disorders do exhibit frequency signatures at various ranges in the frequency spectrum with supplementary symptoms carried in phase. Most of the occurring faults can be tied to the main rotational speed of the component under investigation (Fig. 2.3) [6]. Imbalance, misalignment, and looseness normally appear at frequencies up to 300 Hz. These low-frequency faults are associated with the movement of the shaft and primarily coincide with revolution speed and its harmonics. Bearing and gearbox defects in the late stages of development, show up in the range between 300 Hz to 1 kHz. Higher frequencies measured traditionally to a limit of 10 kHz help notice the deficiencies in bearings even sooner [10].

One of the methods vibration experts utilize in the identification of the damaged part from the frequency spectrum is **order analysis**. In essence, it is about noticing the excessive peaks at harmonic frequencies that are integer multiples of fundamental frequency (1x RPM) (Tab. 2.1):

Frequency content		**Common case**	**Other causes**
Synchronous	1 x RPM	Imbalance	Eccentric journals Bent shaft / Misalignment (high axial vibration) Bad belt (if RPM of belt)
	2 x RPM	Looseness	Misalignment (high axial vibration) Cracked rotor Bad belt (if RPM of belt)
	3 x RPM	Misalignment	and axial looseness
	Many x RPM	Bad gears Severe looseness	Gear teeth x RPM Fan blade count x RPM
Subsynchrous	<1 x RPM	Oil whirl	Bad drive belt Background Resonance
Non-synchronous	-	Electrical problems (x 50 Hz) Reciprocating forces Aerodynamic forces Bad antifriction bearings	Rubbing

Table 2.1: Expert observed likely vibration causes (based on [6, 5, 11])

Because of inherent tolerances in machine manufacturing and assembly, the rotational frequency always manifests itself, even in baseline signature [6, 11]. In the most likely scenario, some faults appear as compared to rotational frequency solely in**synchronous, subsynchronous, or non-synchronous components**. The defects can occur also in a predictable combination of the ones mentioned. Other common patterns experts look for are modulation sidebands typical for bearings and gears extractable with cepstrum analysis [5]. Therefore procedure relying on elimination narrows down unrelated causes effectively.

2.1.3 Technical standards

Vibration-based condition monitoring practices adopted in the factory's predictive maintenance management must comply with normative guidelines formalized in ISO international standards. The standards are concerned with each step in the process that originates with transducer placements and data acquisition. They prescribe conventions for setting fault severity levels and provide empirically observed vibration characteristics of common defects. Two relevant standards for IoT diagnostics systems are *ISO 20816* (updated from ISO 10816) and *ISO 13373*.

ISO 20816-1:2016 establishes the approach to vibration measurement and evaluation on non-rotating housing of machinery parts [12]. The measurement units are agreed upon for kinematic quantities of vibrations. Acceleration is to be measured in meters per second squared (m/s^2), velocity in millimeters per second (mm/s), and displacement in micrometers (μm). It is customary to evaluate broad-band vibration velocity in terms of root mean square value (RMS), as it has a relation to its signal energy. No simple direct relationship is expressible among these quantities, except in stationary signals.

The vibration severity is the maximum magnitude value measured in two radial directions (horizontal, and vertical) or supplemented with a third direction along the shaft in the axial axis. Multiple measurement locations, i.e. on several bearings or couplings, should be assessed independently.

Criteria introduced to judge vibration severity are its absolute vibration magnitude, change in the magnitude vector, and rate of change. In terms of maximal magnitudes the machines of varied sizes are split into four severity zones defined in the chart (Tab. 2.2). The table values serve as guidelines towards realistic requirements between machine manufacturers and customers.

Zone A is reserved for newly commissioned machines. *Zone B* signifies suitability for long-term operation. In *zone C* is the machine deemed in unsatisfactory condition and corrective action should be taken soon. Finally, in zone D vibrations

<table>
<tr><th>Vibration velocity
RMS [mm/s]</th><th>Class I
Small machines</th><th>Class II
Medium machines</th><th>Class III
Large machines
Rigid supports</th><th>Class IV
Large machines
Flexible support</th></tr>
<tr><td>0.28</td><td rowspan="3">Good (A)</td><td rowspan="4">Good (A)</td><td rowspan="5">Good (A)</td><td rowspan="6">Good (A)</td></tr>
<tr><td>0.45</td></tr>
<tr><td>0.71</td></tr>
<tr><td>1.12</td><td rowspan="2">Satisfactory (B)</td></tr>
<tr><td>1.8</td><td rowspan="2">Satisfactory (B)</td></tr>
<tr><td>2.8</td><td rowspan="2">Unsatisfactory (C)</td><td rowspan="2">Satisfactory (B)</td></tr>
<tr><td>4.5</td><td rowspan="2">Unsatisfactory (C)</td><td rowspan="2">Satisfactory (B)</td></tr>
<tr><td>7.1</td><td rowspan="5">Unacceptable (D)</td><td rowspan="2">Unsatisfactory (C)</td></tr>
<tr><td>11.2</td><td rowspan="4">Unacceptable (D)</td><td rowspan="2">Unsatisfactory (C)</td></tr>
<tr><td>18</td><td rowspan="3">Unacceptable (D)</td></tr>
<tr><td>28</td><td rowspan="2">Unacceptable (D)</td></tr>
<tr><td>45</td></tr>
</table>

Table 2.2: ISO 20816 vibration severity chart with typical magnitudes [12]

can cause damage to the machine. The span of acceptable values differs on machine class from I through to IV with an output power of 15 kW (class I), 75 kW (class II), 10 MW (class III), or greater.

The operational limits in the form of *alarms* and *trips* are usually established on the zone boundaries or close to them. Alarms are placed between zones B and C and provide a warning about reaching the threshold significant for noticeable change. Trips in between zones C and D urge immediate action or machine shut down. Both limits should not exceed 1.25 times the upper boundary or lower zones and initially are set based on previous experience with the machine [11].

ISO 13373-1:2002 delves into further nuances of vibration monitoring and expands on procedures outlined in the vocabulary of ISO 20186. According to the standard, the data collection operates in continuous or periodic observation modes which follow an event or intervals. Both designs can be permanently mounted, but in continuous, collection 'multiplexing rate is sufficiently rapid so there is no significant data or trends lost' [11]. When channels are scanned successively with gaps between data points the system is known as 'scanning'.

The condition monitoring programme is run according to a flowchart adapted from one designed in the standard specifically to best benefit the plant. Those steps can be summarized as follows [11]:

1. Review machinery history and establish failure modes.
2. When vibration monitoring is not applicable check for other condition moni-

toring techniques or resort to preventive maintenance.

3. Select monitoring points and take preliminary vibration measurements
4. Select vibration monitoring techniques: broadband, frequency analysis, or special techniques, and set parameters of measurement units.
5. Take baseline measurements.
6. Change levels that would warrant investigation.
7. Carry out routine condition monitoring.
8. If an alarm was exceeded, notify appropriate personnel to review data and trends, perform diagnostic evaluation, and repair as necessary. In case a new baseline is needed continue in the step of taking baseline measurements.
9. Shut down the machine when the trip level is exceeded. Then proceed the same as after the alarm trigger.

Measurement of vibrations should be accompanied by a description of the machine and its operating conditions. The machine description includes the machine identifier and its type, power source, rated rotation speed and power, configuration (shaft or belt driven), and machine support. Measurement parameters such as timestamp, transducer type, sensor location and orientation in MIMOSA code, measurement units and units qualifier (p-p, RMS), and other processing options (filters, number of averages, etc.) are to be recorded alongside the measurement value itself [11].

The transducer of choice for condition monitoring is the accelerometer which can provide the acceleration value of the body and velocity after signal integration. However, standard cautions against double integrating for displacement. The recommended frequency range for an accelerometer is 0.1 Hz to 30 kHz. The choice of transducer mount significantly lowers its resonance frequency which is least influenced by stud mount and stiff cement mount. The resonance is reduced to around 8 kHz with the use of soft epoxy or permanent magnet.

Broadband measurement requires 'frequency ranges of 0.2 times the lowest rotational frequency to the highest frequency of interest' [11], not exceeding 10 kHz, with

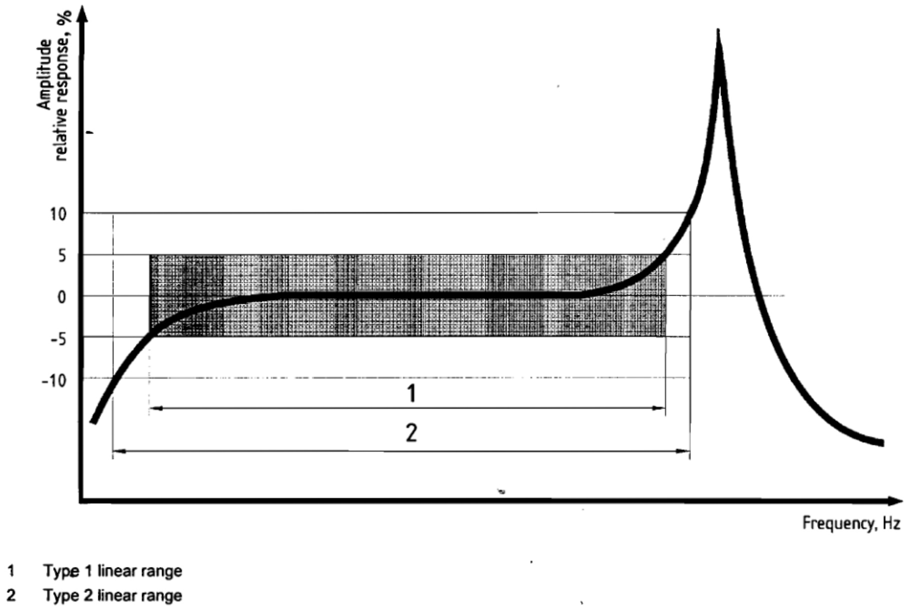

Figure 2.4: The transducer linear response and resonance in tolerance intervals [11]

RMS velocity 0.1 - 100 mm/s. Bearings and gears diagnosis may push the upper-frequency limit even higher. The tolerances of amplitude and frequency calibrations fall into two types with allowable tolerances of ±5% or ±10% (Fig. 2.4).

Equipment's 'health' can be mischaracterized when there are significant differences in the machine's normal operating conditions. Baseline measurements in all acceptable conditions are to be acquired to reduce the error in vibration evaluation. According to bath tub curve (Fig. 2.2) reference signatures should be obtained after the initial part wear-in period. The reference spectral mask of the baseline condition is designed if maximal acceptance amplitudes are different for each significant frequency band [5].

The vibration baseline is defined by broad-band magnitudes and phases of motion vectors, waveforms in time and frequency domain, the rotational speed of the machine as well as its frequency response to different speeds during start-up and coast-down captured in the Bode plot and waterfall plot. Changes during the machine operation are then depicted in value trends. Trends can be shown of overall amplitudes or limited to frequency bands.

2.2 Feature engineering

Large domain knowledge with compared to other areas of machine learning (mechanics - physics)

2.2.1 Preprocessing

- Detrending - DC removal filter
- Time synchronous averaging

2.2.2 Feature extraction

[13] [14] [15] [16] [17] [18] [19] [20] [21] [22]
[23]

Statistical measures

- Standard Deviation
- Max. amplitude
- RMS amplitude
- Skewness
- Kurtosis
  —
- Spectral centroid
- RMS frequency
- Root variance frequency
- Spectral kurtosis / Fast kurtogram
- Harmonics (peaks) [24] [25] [26] [27] [28] [29]
- Spectral Envelope

- Harmonic spectral deviation

  —

- Energy
- Spectral negentropy [30]
- TKEO - Teager-Kaiser energy operator [31]

Signal decompositions - sparse approximations Matching pursuit algorithm optimalization problem [32]

- FFT - Short Time Fourier Transform with Hamming window and Welch averaging [**oulmane_automatic_2015**]
- CWT-SST - Synchrosqueezing Wavelet Transform (vs. Transient-extracting transform) [33] [34] [35]
- WPD - Wavelet Packet Decomposition - to approximation and detail coef. (Fejer-Korovkin wavelet) [36] [37]
- EWT - Empirical Wavelet Transform - (Meyer wavelet) [38] [39] [32] [40] [41] [42] [43] [44]

2.2.3 Feature transformation

- Principal Component Analysis (PCA)
- Log transformation (Box-Cox Transform) to normal distribution
- Normalization (min-max, standardize)

2.2.4 Feature selection

Filter method - SelectKBest in evaluation phase

- Variance Threshold
- Pearson correlation

- ANOVA F-value
- Mutal information
- Fisher score
- Spectral feature selection algorithm (SPEC)

2.3 Diagnostics techniques

Idenification of faulty states in data streams in semi-supervised learning

[45]

2.3.1 Novelty detection

[46]

- Local Outlier Factor, Local Correlation Integral (Anomaly score) [47] [48]
- DenStream (Density based clustering - DBSCAN) [49] [50] [**aggarwal_data_2014**] [51] [52]
- Half-space Trees (Isolation forest) [53] [46]

2.3.2 Classification

- kNN + Metric Tree (M-Tree for neighbourhood queries) + Euclidian Mahalanobis distance / RBF similarity

  [54] [55] [56]

[57] [58] [59] [60]
[61]

2.4 Evaluation Datasets

(Pictures of machines)

MAFAULDA SpectraQuest's Machinery Fault Simulator (MFS) Alignment-Balance-Vibration (ABVT) 50 kHz, 5 sec. recordings, Imbalance, Horizontal/Vertical misalignment, Bearings (Overhang / Underhang) - Inner, Outer, Cage

[62]

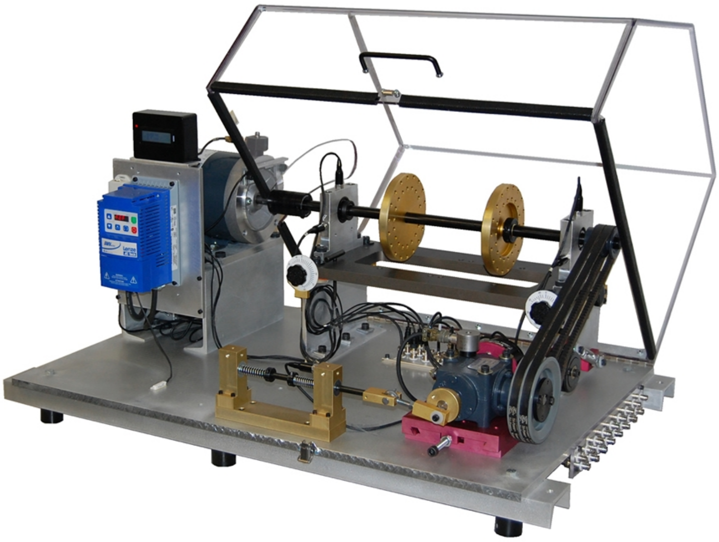

Figure 2.5: SpectraQuest's Machinery Fault Simulator

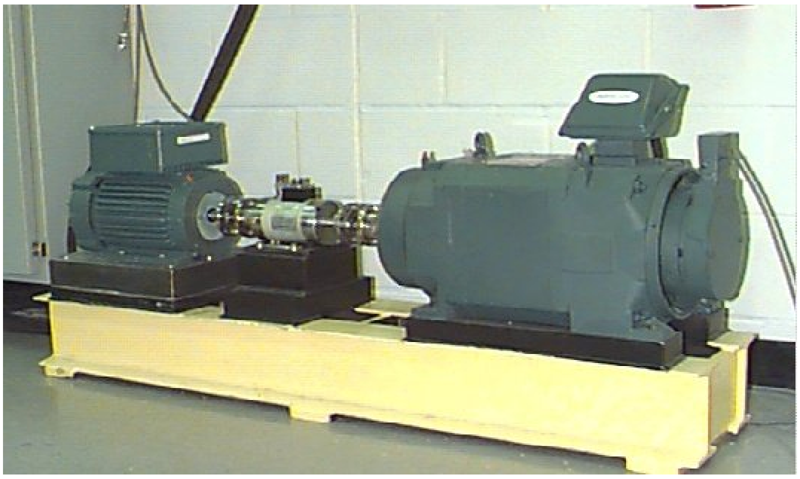

Figure 2.6: CWRU apparatus

CWRU 2 HP (1.492 kW) Reliance Electric motor Bearings - Inner, Outer 12 kHz, 48 kHz fan and drive end bearings Fault diameters of 7 mils, 14 mils, 21 mils, 28 mils, and 40 mils (1 mil=0.001 inches) in diameter were introduced separately at the inner raceway, rolling element (i.e. ball) and outer raceway. Faulted bearings

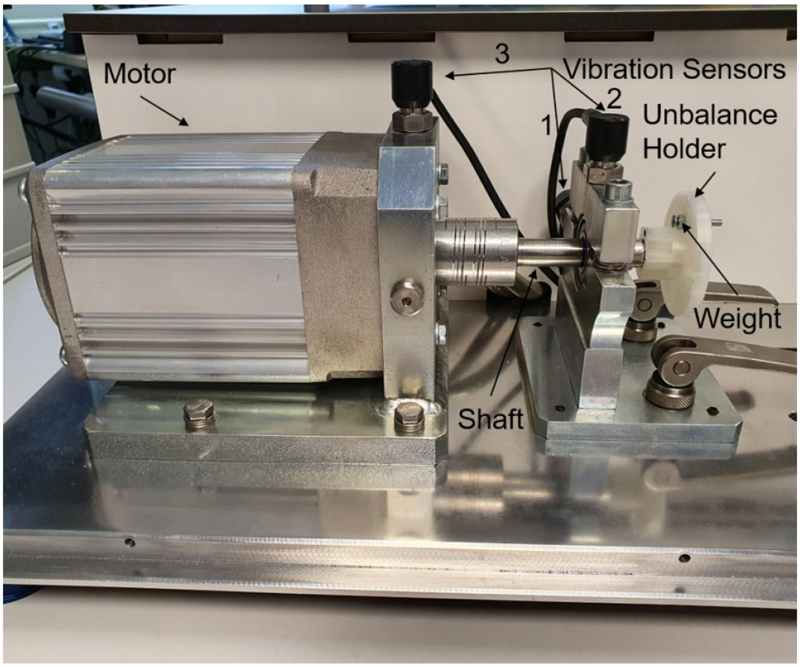

Figure 2.7: Rotating shaft dataset

were reinstalled into the test motor and vibration data was recorded for motor loads of 0 to 3 horsepower (motor speeds of 1797 to 1720 RPM).

[57] [63]

Rotating Shaft Shaft - unbalances of different sizes 4 kHz

2.5 Sensor and microcontroller

[64]

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Appendix A: Resume

Appendix B: Plan of work

B.1 Winter semester

Period	**Work**
1st week	Consultation with the supervisor on directions of the future work based on literature review during previous semester.
2nd week	Outline the key sections of the analysis part in the thesis.
3rd week	Match supporting literature with analysis sections. Further invesigation on the feature engineering methodology in condition monitoring.
4th week	Summarize notes from condition monitoring articles and video-recordings of tutorials and conferences.
5th week	Research transformation of vibration signal to feature space using time-frequency, harmonic and energy statistical metrics. Progress report meeting with the supervisor.
6th week	Find articles and take notes about unsupervised and semi-supervised techniques in streaming data for machinery diagnostics, in order to gather information about suitable features.
7th week	TBD (Narrow down wide variety applicable methods for signal decomposition)
8th week	TBD (Write thesis section on condition monitoring and machinery fault types)

B.2 Summer semester

Appendix C: Digital medium

Evidenčné číslo práce v informačnom systéme: FIIT-xxxx-xxxxxx

Obsah digitálnej časti práce (archív ZIP):

Názov odovzdaného archívu: