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

FIIT-xxxx-xxxxxx

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

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SLOVENSKÁ TECHNICKÁ
UNIVERZITA V BRATISLAVE
FAKULTA INFORMATIKY
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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

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Annotation

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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

Contents

List of Figures

1 Introduction

Following is very coarse draft! Manufacturing is experiencing a shift in the traditional asset operational status evaluation and utilization. The goal is to promote safety and production efficiency when the useful life of machine moving parts is extended. In the factories and logistics where this sort of equipment is vital, there is a trend to be able to monitor the health of the machinery parts and above that to diagnose the fault in time to repair it without additional costs. Vibrations are the most nonintrusive way where such faults can be sensed and appear distinctly for an analyst to identify the root cause of the malfunction.

In critical circumstances, such measurements are already in place in some form, but in order to reach wider acceptance, and not remain just a quirk/trend system has to be sufficiently independent, reliable, and as self-sufficient as the model design allows it to be.

The thesis is structured in a following manner. In Chapter 1 we explore the theoretical (analytical) model view, mechanical maintenance approaches, and industry standards where common fault identification is described. Chapter 2 is all about taking vibration measurements (procuring) and transforming them into features meaningful in automatic fault pattern recognition. The methods for ranking are reviewed to obtain the most important and correlated features with machine health status. We delve into modes of diagnosis based on reduced relevant indicators in chapter 3. Chapter 4 takes a look into IoT communication infrastructure limiting the data throughput and devices that can be deployed (accommodate) in the factory environment. Chapter 5 defines measurement vectors and proposes processing steps to diagnose the reoccurring failure, RUL (remaining useful life), and fault types. The approach taken is evaluated and deployed in Chapter 6.

2 Problem analysis

2.1 Condition monitoring

[**thomson_theory_1993**] - All bodies possessing mass and elasticity are capable of vibration. Thus, most engineering machines and structures experience vibration to some degree, and their design generally requires consideration of their oscillatory behavior. - s.58 - rotor unbalance - Chapter 12 (Classical methods) - The exact analysis for the vibration of systems of many degrees of freedom is generally difficult and its associated calculations are laborious. Many DOF - the results beyond the first few normal modes are often unreliable and meaningless. For this purpose, Rayleigh's method (fundamental frequency of multi-DOF systems) and Dunkerley's equation are of great value and importance. In many vibrational systems, we can consider the mass to be lumped. A shaft transmitting torque with several pulleys along its length is an example. Holzer devised a simple procedure for the calculation of the natural frequencies of such a system. Holzer's method was extended to beam vibration by Myklestad and both methods have been matricized into a transfer matrix procedure by Pestel.

[1] p.36 - Regular measurement of mechanical oscilatory motion we can find out beginning of the fault (or future failure) and monitor its progress. Method of trend tracking - extrapolation. p.40 - normal level, level indicating significant change, level coresponding to fix p.50 - the total magnitude of the oscillation can be compared with reference values set by norms or defined for each type of the machine. p.54 - oscillation measurement allows us to quantify dynamic load capacity of mechanical systems a its analysis. p.100 - principles of oscillation measurement - choice of sensor type, exclusion of errors caused by resonance, placement and direction of the sensor, mounting of acceleration sensor, the influence of the environment p.110 -

types of signals - periodic, quasiperiodic, nonstationary p.114 - transmission of the oscillation signal through the environment - through discontinuity and construction p.139 - signal averaging - linear, exponencial, peak based p.148 - kurtosis - high kurtosis means more extreme values - peaks p. 153 - Vibroacustic diagnosis is one of the most important methods of early identification of component faults p.165 - severity levels for vibrartion amplitudes (same as in ISO standard). p.178 - reference mask p.185 - overview of root causes of machine faults - imbalance, misalignment, resonance, excentricity, loosnessnes, p.243 - displacement, speed, acceleration p.253 - Quanitative evaluation criteria - band A, B, C, D p.256 - warning, alarm p.261 - characteristics of typical faults

[2] p.36 - Condition monitoring is much more than a maintenance scheduling tool. Condition monitoring is thus a management technique that uses the regular evaluation of the actual operating condition of plant equipment, production systems and plant management functions, to optimize total plant operation. The output of a condition monitoring programme is data. Until action is taken to resolve the deviations or problems revealed by the programme, plant performance cannot be improved p.40 - This data is compared to either a baseline reading taken from a new machine or to vibration severity charts to determine the relative condition of the machine. Normally an unfiltered broadband measurement that provides the total vibration energy between 10 and 10000 Hertz (Hz) is used p.38 - Condition monitoring utilizing vibration signature analysis for example is predicated on two basic facts: - 'All common failure modes have distinct vibration frequency components that can be isolated and identified.' - 'The amplitude of each distinct vibration component will remain constant unless there is a change in the operating dynamics of the machine train.' p. 269 - Whenever vibration occurs, there are actually four forces involved that determine the characteristics of the vibration. These forces are: 1. the exciting force, such as unbalance or misalignment; 2. the mass of the vibrating system; 3. the stiffness of the vibrating system; 4. the damping characteristics of the vibrating system. p. 294 - Even machines in the best of condition will have some vibration and noise associated with their operation due to minor defects. It is therefore important to remember that: 1. every machine will have a level of vibration and noise which is regarded as inherent normal; 2. when machinery noise

and vibration increase or become excessive, some mechanical defect or operating problem is usually the reason; 3. each mechanical defect generates vibration and noise in its own unique way. p. 300 -machinery vibration signatures taken in the horizontal, vertical and axial directions at each bearing point on the machine; imbalance will show up predominantly in the horizontal or vertical directions, whereas misalignment will reveal relatively high amplitudes in the axial direction. p. 301 - When selecting the measurement parameter for analysis, there are two factors to consider. First, why is the reading being taken? Secondly, what is the frequency of the vibration? - For general machinery analysis, use velocity whenever possible. Amplitude readings in velocity are directly comparable to severity without the need to cross refer amplitude with frequency. Where vibration frequencies are very low (approximately below 600 CPM p. 308 - The crest factor, defined as the ratio of the peak to RMS levels, has been proposed as a trending parameter as it includes both parameters (Braun, 1980). However, investigations by the author have shown that this parameter usually increases marginally with incipient failure, and subsequently decreases due to the gradually increasing RMS value typical of progressive failure. Quite often, the trend recorded by this parameter has been found to be similar to another time domain parameter, the Kurtosis factor p.312 Kurtosis - sensitive to failure in rolling element bearings (Dyer and Stewart, 1978). However, an independent evaluation of this technique (Mathew and Alfredson, 1984) has shown that high Kurtosis values would only be obtained if the original time waveform was of an impulsive nature p.326 - evaluate changes occurring in the signature spectrum is to form a spectral mask. This is derived from the baseline signature, plus an allowable tolerance limit (Randall, 1981a)

What are predicted variables - result of diagnoses

- - Presence of the Fault
- Type of fault present (different characteristics - e.g. frequency content)
- Remaining Useful Life (time until failure) - machines of the same type and different degradation curves

Remainig useful life models (RUL) - is the expected life or usage time remaining before the machine requires repair or replacement. `https://www.`

`mathworks.com/help/predmaint/ug/rul-estimation-using-rul-estimator-models.html`

- Similarity - run to failure history of similiar machines in database
- Degradation - known failure threshold (warning, alert threshold)
- Survival - life-span of components and correlated variables

[3]

- Indirect Measurement: indirect and approximate measurement over the vibration phenomenon of the target equipment.
- Noisy and Unaligned Observations: well aligned / may contain huge amount of noise.
- Variance on Initial Status: initial status of the target equipment different from each other.
- Diversity on Lifetime model: the usage and lifetime model - number of unknown and external factors.

2.1.1 Maintenance strategies

[4] Difference between fault (degrating performace of the machine - higher friction and power consumption) and failure (machine is unusable). (picture) reaction-based, time-based, or condition-based maintenance

- Reactive - run equipment until failure occurs - low stakes operation. Failure can have negative economic impact or can damage adjacent parts
- Preventive - predetermined schedule when assets are diagnosed and repairs are made. Crutial to set appropiate maintanance interval. Good parts are replaced before they are completely worn out, preventing critical failure, but creating unneccesary waste. Sometimes faults are not detected soon enough. industrial average life statistics, such as Mean Time To Failure (MTTF),
- Predictive - model of expected lifetime, warns about unexpected faults before they become too serious and before affecting the machine.

- During operation, machines give out information or signals in the form of noise, vibration, temperature, lubricating oil condition, quality and quantity of the motor current drawn, and the like - Once the faults have been detected and diagnosed, the next question is how long the machine will last in the present condition or what is the remaining useful life (RUL) of the machine under observation.

Wear process curve [4] Bath tub curve (page 10)

- Initial - large roughness
- Normal - contact area fomred
- Severe - high friction

Rotordynamics (chapter 4) (p. 29) - p.97 - Fault types, p.127 - faults in electric motors

Campbell diagram, Bode plot, forced spring-mass-damper system

In order to understand, and correctly diagnose the vibratory characteristics of rotating machinery, it is essential for the machinery diagnostician to understand the physics of dynamic motion. This includes the influence of stiffness and damping on the frequency of an oscillating mass — as well as the interrelationship between frequency, displacement, velocity, and acceleration of a body in motion. p.395 - Common malfunction F = ma, torque,

$$F_centrifugal = m * r(deviation) * RPM^2$$

,

$$v = v_0 + \int a$$

The synchronous, or running speed, or fundamental, or 1X motion of a rotating element is an inherent characteristic of every machine. It should be recognized that all machines function with some level of residual unbalance. The radial forces from an eccentric element will vary with the speed squared as described by expression

- SYNCHRONOUS RESPONSE (p.395) - physically impossible to produce a perfectly straight and concentric rotor.vibration response is inversely proportional to the restraint or stiffness when the applied force is held constant

- MASS UNBALANCE (p.398) - Mass unbalance represents the most common type of synchronous excitation on rotating machinery. Every rotor consists of a shaft plus a series of integral disks. high dimensional tolerances, a residual unbalance is present in each element. Centrifugal force

- BENT OR BOWED SHAFT (p.400) - Bent rotors and shaft bows represent another major class of synchronous 1X motion. It was previously mentioned that all machine parts contain some finite amount of residual unbalance. In a similar manner, all assembled horizontal rotors (and some vertical rotors), will exhibit varying degrees of rotor bows.

- ECCENTRICITY (p.406) - Large machine elements or high rotational speeds are the most susceptible to high forces due to an eccentric element. many motor problems only appear under load.

- SHAFT PRELOADS (p.410) - The presence of various types of unidirectional forces acting upon the rotating mechanical system is a normal and expected characteristic of machinery. Just as residual unbalance, rotor bows, and component eccentricity are inherent with the assembly of rotating elements, the presence of shaft preloads are an unavoidable part of assembled mechanical equipment. Gravitational preloads

- RESONANT RESPONSE (p.416) - Machines and structures all contain natural frequencies that are essentially a function of stiffness and mass. f = sqrt(k/m) lowest order resonant frequency. For more complex mechanical systems an entire family of resonant responses must be addressed. The range of natural frequencies may vary from 60 CPM (1 Hz) for the foundation and support systems, to 1,800,000 CPM (30,000 Hz) for turbine blade The actual number of system natural frequencies may vary from 20 to 50 or more. Campbell diagram - natural frequencies (or eigenfrequencies)

  Rotodynamics

$$\mathbf{M}\frac{\partial^2\mathbf{q}(t)}{\partial t^2} + (\mathbf{C}+\mathbf{G})\frac{\partial\mathbf{q}(t)}{\partial t} + (\mathbf{K}+\mathbf{N})\mathbf{q}(t) = \mathbf{f}(t)$$

  M is the symmetric Mass matrix C is the symmetric damping matrix G is the skew-symmetric gyroscopic matrix K is the symmetric bearing or seal stiffness matrix N is the gyroscopic matrix of deflection for inclusion of e.g., centrifugal elements. in which q is the generalized coordinates of the rotor in inertial coordinates and f is a forcing function, usually including the unbalance. axially symmetric rotor rotating at a constant spin speed Ω. The gyroscopic matrix G is proportional to spin speed Ω. The general solution to the above equation involves complex eigenvectors which are spin speed dependent.

- ROTOR RUBS (p.440) - The physical contact between rotating elements and stationary machine parts can generate a variety of rub conditions In the frequency domain, the intermittent rub looks like a loose bearing housing with integer fractions of rotative speed (e.g., X/2, X/3, or X/ 4) plus a string of fractional frequencies (e.g. 3X/2, 5X/2, 7X/2, etc.)
- CRACKED SHAFT -Machines that are subjected to frequent startups and shutdowns appear to be more susceptible to shaft cracks due to the increased number of cycles through the rotor resonance(s), plus the process heating and cooling. Cracks may originate at high stress points such as the square corners

p.704 - maintenance activities may be categorized as either reaction-based, time-based, or condition-based maintenance

Machinery Diagnostic Methodology (s.747)

- Diagnostic objectives - solving the problem
- Mechanical inspection - hands on examination of the machinery
- DATA ACQUISITION AND PROCESSING - requires the assembly of the proper transducers and test instrumentation. ata acquired is really a function of the specific machine, the associated problem, and the individual test plan
- Data interpretation - summary and correlation of all pertinent data acquired during the project. This includes the mechanical configuration, process and maintenance history, field testing data, plus any supportive calculations or analytical models

The 30,000 horsepower gas turbine behaves quite differently from a similarly rated steam turbine. Hence, the data must be interpreted in accordance with the physical characteristics of the particular machine type and the operating environment. One approach is to view the data in terms of normal behavior for a particular machine type, and then look for the abnormalities in response characteristics.

[5]

- Forced Vibration Mechanism
  - Mass Unbalance
  - Misalignment
  - Shaft Bow
  - Gyroscopic
  - Gear Contact
  - Rotor Rubs
  - Electrical Excitations
  - External Excitations
- Free Vibration Mechanism
  - Oil Whirl
  - Oil or Steam Whip
  - Internal Friction
  - Rotor Resonance
  - Structural Resonances
  - Acoustic Resonances
  - Aerodynamic Excitations
  - Hydrodynamic Excitations

[6] - The analysis of the behavior of such signals reveals that the most of the changes that occur are either changes in the mean level, or changes in spectral characteristics. In this framework, the problem of segmentation between “homogenous” part of the signals (or detection of changes in signals) arises more or less explicitly

- the key for their common success resides in the proper design of the statistical criteria according to which separation is forced - It can be noted a moving of the spectra to the low frequency area, with increased values of the PSD, after the fault produced

2.1.2 Vibration fault types

There are a few methods of machinery fault identification in vibrational signals based on domain expertise. Data points can be viewed in the time domain and frequency domain. Either as individual stationary profiles obtained during the short duration in the time of measurement, or multiple spaced-out observations with the intent to highlight the long-term trend, e.g. shown in a waterfall plot [1]. The descriptor variable can be any meaningful statistical quantity, e.g. peak-to-peak, RMS, crest factor, kurtosis, which can be applied to recorded samples or frequency bands.

Mechanical faults manifest themselves in the vibration signal at various frequencies. In the low-frequency range (up to 1 kHz) shaft's unbalance, misalignment, bend, crack, and mechanical looseness is present. High frequencies (up to 16 kHz or more) contain bearings faults and gear faults.

Under fault-free circumstances, shaft speed appears as the strongest frequency component. In case of shaft and gear imbalance or damage, synchronous multiples of shaft frequency (harmonics) are amplified. When rub, bad drive belts and chains, or looseness is occurring in the machine then sub-synchronous harmonics or even non-synchronous frequencies appear [4]. Therefore it is useful to rescale the horizontal axis to RPM or orders of rotational speed. Complementary methods of fault symptom identification are phase and orbital analysis [7].

- Bearing faults - vibration on each rotation of rolling elements, CFC (characteric fault frequencies with impulse
- Rotor bar faults - current will not flow - forces diffrent on both sides of rotor
- Eccentricity Faults - uneven air gap between stator rotor
- Misalignment - parralel / angular
- Cavitation - pumps

- Gearbox fault -broken teeth

measuring vibration with current, thermal, flux is improvement, +acoustic elminited (detect similiar faults) vibration is better alone, then other methods alone (80 vs. <60[8]

2.1.3 Technical standards

The maintenance procedure usually involves data acquisition cards inside handheld devices with accelerometer sensor probes then mounted firmly to the machine frame by either screwing in, magnets or wax [1]. The probe placement in axial and perpendicular radial directions is standardized in ISO 20816. The severity of vibrations is mostly assessed in units of velocity (mm/s), but acceleration (m/s^2) and displacement (μm) are also used. Based on the observed vibration intensity and one of the four classes of machines (I, II, III, IV) by output power and size, zones (A, B, C, D) for accepted levels are proposed. It is customary to establish operational limits in the form of alarms and trips [**iso_20816**].

Standard ISO 13373 categorizes three types of vibration monitoring systems: permanent, semi-permanent, and mobile. More importantly, a structured diagnostic approach is developed here complete with recommendations for formalizing diagnostic techniques [**iso_13373**]. The next step is the signal analysis with the use of proper units and transformations is the subject of the ISO 18431 [**iso_18431**].

ISO-10816 Vibration Severity Chart Typical faults produce unusual low-frequency vibrations (10 to 1000 Hz). Imbalances, misalignments and looseness are recorded at frequencies up to 300 Hz.

Sensor placement

2.2 Feature engineering

2.2.1 Feature extraction

Statistical features in Time-domain (and correlation to blade wear) [9] [10]

- Root mean square (0.98)

- Mean (0.17)
- Amplitude (0.81)
- Kurtosis (0.042)
- Peak to peak (0.463)
- Signal strength (0.119)
- Standard deviation (0.908)
- Peak value (0.488)
- Shape factor (0.007)
- Skewness (0.118)
- Avearge signal level (0.46)
- Crest factor (0.056, spikeness of the signal - rms/amplitude)

Selection according to high correlation (graph: sawn-trough section vs feature) Features in time domain with high correlaction: RMS, Standard deviation, Amplitude

Transform -> SVD vs. FFT vs. EMD Statistical features in Frequency domain (PSD analysis) r >= 0.8 db3 analysis

- Root mean square (0.402)
- Mean (0.497)
- Peak frequency (0.670)
- Kurtosis (0.852)
- Peak to peak (0.076)
- Standard deviation (0.799)
- Peak value (0.787)
- Shape factor (0.851)
- Skewness (0.819)

- Frequency centroid (0.775)

skewness (PSD_S), kurtosis (PSD_k), and shape factor (PSD_Sf), centroid frequency (FFT_fc), wavelet packet energy entropy (WPD_EP) = 0.85 - The WPD energy E8, E10, and E12 - Energy ratios P8 and P13 of frequency bands 8 and 13

Spectral features [11] - 1. Spectral shape description

- Coherence function - correlation between two signals PSD
- Spectral centroid - barycenter of the spectrum (weighted mean of the frequencies present in the signal, with their magnitudes as the weights)
- Spectral spread
- Spectral skewness
- Spectral kurtosis
- Spectral slope - comupted with linear regression - amount of decresing of the spectral amplitude
- Spectral roll-off - 95% of the signal energy is contained below this frequency
- 2. Temporal variation of spectrum - spectral flux - correlation of normalized cross-correlation between two succesive amplitude spectra

Harmonic features

- Fundamental frequency - Maximu likelihood algorithm
- Noisiness - ratio - energy of noise to the total energy
- Inharmonicity - energy weighted difference of the spectral components from the multiple of fundamental frequency
- Harmonic Spectral Deviation - deviation of amplite harmonics peaks from global spectral envelope

Harmonic peak feature - [3]- group of pairs of significant peaks' value and frequency in PSD. Harmonic peak distance Dij

- Standardization - Min-max scaler, Standard scaler (clustering - feature have different scales)
- Transformation - Log transformation, Box-Cox

major drawbacks of PSD

- PSD is a highdimensional feature (i.e., 1024 dimensions in our case) that often generates singular matrix = regression algorithms.
- PSD feature is unreliable due to a large random fluctuation in their amplitudes over frequency due to measurement noise inherent in MEMS sensor.

[12] measure the **spectral flatness** of the ratio between the observations (the peaks) with respect to the model (the spectral envelope):

Signal denoising and filtering

PCA on features to find most separation - Singular Value Decomposition (QR algorithm) - eigenvalue algorithm , ICA - FastICA to separate sources vibration analysis tools:

- ICA (independent component analysis),
- TFA (time-frequency analysis),
- ED (energy distribution) and

Time-frequency features

The PSD is the overall expectation of the AE signal. It needs to be calculated by estimation methods. The estimation of the power spectrum is realized by Welch method (cite) Time Synchronous Averaging of Real FFT vs. FastCWT - Synchrosqueezing

Harmonics identification

Cepstrum (for gearboxes) Peak identification

2.2.2 Feature selection

Feature importance ranking of Numeric features - Filtering

- High correlation with predictor - band saw blade width of flank face — to signal statistics
- Low correlation (Decorrelation) among predictors themselves - if they are correlated they produce same response
- ANOVA with F-Test - Variance of the feature - high variance - is high response
- Linearly dependent features are a waste of space and computation power because the information could have been encoded in much fewer features. [10] - solve by PCA

Vibration levels are dependent on the type of work (load) of the machine (cite)

- **Sawing process database**: it contains basic information such as sawing machine tools model, band saw blade model, sawing parameters, and the material and size of the workpiece to match the relevant online monitoring model.
- **Online monitoring model database**: it stores online monitoring models of band saw blade wear based on different sawing processes.

2.3 Diagnostics techniques

Inbalanced data, Feature space Scale - Normalize and log transform multi class classification - dynamic

2.3.1 Novelty detection

Fault or no fault - anomaly detection solutions - unsupervised [13]. mean shift clustering algorithm **Types of faults - clustering** - Multimodal non-Gaussian multivariate probability distribution

- **DenStream** - (based on DBSCAN) density based params: - continous regions of high density minPts (the minimum number of data points that need to be clustered together for an area to be considered high-density) eps (the distance used to determine if a data point is in the same area as other data points). - compare to MAD. OPTICS for not same density.

- **IForestASD - Isolation Forest Algorithm for Stream Data method** - isolation teqnique (map feature space to anomaly score) - how many uniform splits does it take before point is isolated (alone in group)

- **Label propagation algorithm** - Temporal Label Propagation - Graph-Based Methods in semi-supervised learning (p.9)

[14] p.5

- Semi-supervised smoothness assumption: If two points x1,x2 in a high-density region are close, then so should be the corresponding outputs y1,y2.

- Cluster assumption: If points are in the same cluster, they are likely to be of the same class.

- The cluster assumption can be formulated in an equivalent way: Low density separation: The decision boundary should lie in a low-density region.

- Manifold assumption: The (high-dimensional) data lie (roughly) on a low-dimensional manifold.

- Consider as an example supervised learning, where predictions of labels y corresponding to some objects x are desired. Generative models estimate the density of x as an intermediate step, while discriminative methods directly estimate the labels.

Classification can be treated as a special case of estimating the joint density P (x,y), but this is wasteful since x will always be given at prediction time, so there is no need to estimate the input distribution. The terminology "unsupervised learning" is a bit unfortunate: the term density 1. We restrict ourselves to classification scenarios in this chapter estimation should probably be preferred. Traditionally, many techniques for density estimation propose a latent (unobserved) class variable y and estimate P (x) as mixture distribution

The semi-supervised learning problem belongs to the supervised category, since the goal is to minimize the classification error, and an estimate of P(x) is not sought after

2.4 IoT in Industry 4.0

Devices and sensors + Wireless protocols limitation: IEEE 802.15.4e, OpenThread RAMI 4.0 [13]

`https://riverml.xyz/0.15.0/`

Literature

1. ŽIARAN, Stanislav. *Technická diagnostika*. 1. vyd. Bratislava: Vydavateľstvo STU, 2013. ISBN 978-80-227-4051-7.
2. DAVIES, A. Techniques for Vibration Monitoring. In: *Handbook of Condition Monitoring: Techniques and Methodology*. Dordrecht: Springer Netherlands, 2012, pp. 267–374. ISBN 978-94-011-4924-2. OCLC: 958541223.
3. JUNG, Deokwoo; ZHANG, Zhenjie; WINSLETT, Marianne. Vibration Analysis for IoT Enabled Predictive Maintenance. In: *2017 IEEE 33rd International Conference on Data Engineering (ICDE)*. 2017, pp. 1271–1282. Available from DOI: `10.1109/ICDE.2017.170`. ISSN: 2375-026X.
4. MOHANTY, Amiya Ranjan. *Machinery Condition Monitoring: Principles and Practices*. 2015.
5. EISENMANN, Robert C. *Machinery Malfunction Diagnosis and Correction*. 1997. ISBN 0-13-240946-1.
6. POPESCU, Theodor D. Blind separation of vibration signals and source change detection – Application to machine monitoring. *Applied Mathematical Modelling* [online]. 2010, vol. 34, no. 11, pp. 3408–3421 [visited on 2023-02-11]. ISSN 0307-904X. Available from DOI: `10.1016/j.apm.2010.02.030`.
7. SCHEFFER, C.; GIRDHAR, P. *Practical Machinery Vibration Analysis and Predictive Maintenance*. IDC Technologies, Elsevier, 2004. ISBN 0-7506-6275-1.
8. GOEL, Anuj Kumar; SINGH, Gurmeet; NAIKAN, Vallayil Narayana Achutha. A Methodology for Selection of Condition Monitoring Techniques for Rotating Machinery. *International Journal of Prognostics and Health Management* [online]. 2022, vol. 13, no. 2 [visited on 2022-11-12]. ISSN 2153-2648. Available from DOI: `10.36001/ijphm.2022.v13i2.3205`. Number: 2.

9. ZHUO, Rongjin; DENG, Zhaohui; CHEN, Bing; LIU, Tao; GE, Jimin; LIU, Guoyue; BI, Shenghao. Research on online intelligent monitoring system of band saw blade wear status based on multi-feature fusion of acoustic emission signals. *The International Journal of Advanced Manufacturing Technology* [online]. 2022, vol. 121, no. 7, pp. 4533–4548 [visited on 2023-02-11]. ISSN 1433-3015. Available from DOI: 10.1007/s00170-022-09515-3.
10. ZHENG, Alice; CASARI, Amanda. *Feature Engineering for Machine Learning*. O'Reilly Media, 2018. ISBN 978-1-4919-5324-2.
11. PEETERS, Geoffroy. A large set of audio features for sound description. 2004.
12. LAGRANGE, Mathieu; BADEAU, Roland; RICHARD, Gael. Robust similarity metrics between audio signals based on asymmetrical spectral envelope matching. In: *2010 IEEE International Conference on Acoustics, Speech and Signal Processing* [online]. Dallas, TX: IEEE, 2010, pp. 405–408 [visited on 2023-02-12]. ISBN 978-1-4244-4295-9. Available from DOI: 10.1109/ICASSP.2010.5495783.
13. TORRES, Pedro; RAMALHO, Armando; CORREIA, Luis. Automatic Anomaly Detection in Vibration Analysis Based on Machine Learning Algorithms. In: MACHADO, José; SOARES, Filomena; TROJANOWSKA, Justyna; YILDIRIM, Sahin; VOJTĚŠEK, Jiří; REA, Pierluigi; GRAMESCU, Bogdan; HRYBIUK, Olena O. (eds.). *Innovations in Mechatronics Engineering II*. Cham: Springer International Publishing, 2022, pp. 13–23. Lecture Notes in Mechanical Engineering. ISBN 978-3-031-09385-2. Available from DOI: 10.1007/978-3-031-09385-2_2.
14. CHAPELLE, Olivier; SCHÖLKOPF, Bernhard; ZIEN, Alexander (eds.). *Semi-supervised learning*. Cambridge, Mass: MIT Press, 2006. Adaptive computation and machine learning. ISBN 978-0-262-03358-9. OCLC: ocm64898359.
15. TIWARI, Prashant; UPADHYAY, S. H. Novel self-adaptive vibration signal analysis: Concealed component decomposition and its application in bearing fault diagnosis. *Journal of Sound and Vibration* [online]. 2021, vol. 502, p. 116079 [visited on 2022-08-27]. ISSN 0022-460X. Available from DOI: 10.1016/j.jsv.2021.116079.

16. NUNES, Leonardo; ESQUEF, Paulo Antonio; BISCAINHO, Luiz. Evaluation of Threshold-Based Algorithms for Detection of Spectral Peaks in Audio. In: 2007.

17. ARTS, Lukas P. A.; BROEK, Egon L. van den. The fast continuous wavelet transformation (fCWT) for real-time, high-quality, noise-resistant time–frequency analysis. *Nature Computational Science* [online]. 2022, vol. 2, no. 1, pp. 47–58 [visited on 2022-08-27]. ISSN 2662-8457. Available from DOI: `10.1038/s43588-021-00183-z`. Number: 1 Publisher: Nature Publishing Group.

18. GERBER, Timothée; MARTIN, Nadine; MAILHES, Corinne. Identification of harmonics and sidebands in a finite set of spectral components. 2013, vol. 1.

19. VANCE, John M.; MURPHY, Brian; ZEIDAN, Fouad. *Machinery vibration and rotordynamics*. Hoboken, N.J: Wiley, 2010. ISBN 978-0-471-46213-2.

20. ADIKARAM, K.K. Lasantha Britto; HUSSEIN, Mohamed; EFFENBERGER, Mathias; BECKER, T. Non-Parametric Local Maxima and Minima Finder with Filtering Techniques for Bioprocess. *Journal of Signal and Information Processing*. 2016, vol. 07, pp. 192–213. Available from DOI: `10.4236/jsip.2016.74018`.

21. HERRERA, Roberto; BAAN, Mirko; HAN, Jiajun. Applications of the synchrosqueezing transform in seismic time-frequency analysis. *Geophysics*. 2014, vol. 79, pp. V55–V64. Available from DOI: `10.1190/geo2013-0204.1`.

22. BRUNTON, Steven L.; KUTZ, Jose Nathan. *Data-driven science and engineering: machine learning, dynamical systems, and control*. Cambridge, United Kingdom, New York, NY: Cambridge University Press, 2022. ISBN 978-1-00-908951-7.

23. MEIGNEN, Sylvain; OBERLIN, Thomas; PHAM, Duong-Hung. Synchrosqueezing transforms: From low- to high-frequency modulations and perspectives. *Comptes Rendus Physique* [online]. 2019, vol. 20, no. 5, pp. 449–460 [visited on 2022-08-28]. ISSN 1631-0705. Available from DOI: `10.1016/j.crhy.2019.07.001`.

24. LUO, Bo; WANG, Haoting; LIU, Hongqi; LI, Bin; PENG, Fangyu. Early Fault Detection of Machine Tools Based on Deep Learning and Dynamic Identification. *IEEE Transactions on Industrial Electronics*. 2019, vol. 66, no. 1, pp. 509–518. ISSN 1557-9948. Available from DOI: 10.1109/TIE.2018.2807414. Conference Name: IEEE Transactions on Industrial Electronics.

25. 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.

26. WANG, Yung-Hung; YEH, Chien-Hung; YOUNG, Hsu-Wen Vincent; HU, Kun; LO, Men-Tzung. On the computational complexity of the empirical mode decomposition algorithm. *Physica A: Statistical Mechanics and its Applications* [online]. 2014, vol. 400, pp. 159–167 [visited on 2022-09-01]. ISSN 0378-4371. Available from DOI: 10.1016/j.physa.2014.01.020.

27. YANG, Yang; CAO, Qiang; JIANG, Hong. EdgeDB: An Efficient Time-Series Database for Edge Computing. *IEEE Access*. 2019, vol. 7, pp. 142295–142307. ISSN 2169-3536. Available from DOI: 10.1109/ACCESS.2019.2943876. Conference Name: IEEE Access.

28. HU, Fei; HAO, Qi. *Intelligent Sensor Networks: The Integration of Sensor Networks, Signal Processing and Machine Learning* [online]. 1st ed. Boca Raton: CRC Press, 2012 [visited on 2022-09-23]. ISBN 978-0-429-06696-2. Available from DOI: 10.1201/b14300.

29. VOLANTE, Daniel C. *Condition Monitoring for Rotational Machinery*. 2011. Diplomová. McMaster University.

30. JACK D., Peters. *Frequency Limitations Resulting from Mounted Resonance of an Accelerometer*. Connection Technology Center, Inc., [n.d.].

31. FIALA, Jakub. Literární rešerše souboru technických norem z oblasti vibrace, rázy a měření vibrací a rázů. 2019, p. 52.

32. 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. Available from DOI: 10.1109/

TIM.2019.2901514. Conference Name: IEEE Transactions on Instrumentation and Measurement.

33. CALDERO, Pau; ZOEKE, Dominik. Multi-Channel Real-Time Condition Monitoring System Based on Wideband Vibration Analysis of Motor Shafts Using SAW RFID Tags Coupled with Sensors. *Sensors*. 2019, vol. 19, p. 5398. Available from DOI: 10.3390/s19245398.

34. SHENG, Hao; CHEN, Zhongsheng; XIA, Yemei; HE, Jing. Review of Artificial Intelligence-based Bearing Vibration Monitoring. In: *2020 11th International Conference on Prognostics and System Health Management (PHM-2020 Jinan)*. 2020, pp. 58–67. Available from DOI: 10.1109/PHM-Jinan48558.2020.00018. ISSN: 2166-5656.

35. VILAKAZI, Christina Busisiwe. *Machine Condition Monitoring Using Artificial Intelligence: The Incremental Learning and Multi-agent System Approach*. Johannesburg, 2006. Dizertačná.

36. GOUMAS, Stefanos; ZERVAKIS, Michalis; STAVRAKAKIS, G. Classification of washing machines vibration signals using discrete wavelet analysis for feature extraction. *Instrumentation and Measurement, IEEE Transactions on*. 2002, vol. 51, pp. 497–508. Available from DOI: 10.1109/TIM.2002.1017721.

37. MOHAMMADI, Hamed. *Early Detection of Imbalance in Load and Machine In Front Load Washing Machines by Monitoring Drum Movement*. 2020. Diplomová.

38. CAKIR, Mustafa; GUVENC, Mehmet Ali; MISTIKOGLU, Selcuk. The experimental application of popular machine learning algorithms on predictive maintenance and the design of IIoT based condition monitoring system. *Computers & Industrial Engineering* [online]. 2021, vol. 151, p. 106948 [visited on 2022-10-13]. ISSN 0360-8352. Available from DOI: 10.1016/j.cie.2020.106948.

39. OULMANE, A; LAKIS, A.; MUREITHI, Njuki. Automatic fault diagnosis of rotating machinery using fourier descriptors and a fuzzy logic. *Mechanical system and signal processing 2015*. 2015.

40. WANG, Gang; NIXON, Mark; BOUDREAUX, Mike. Toward Cloud-Assisted Industrial IoT Platform for Large-Scale Continuous Condition Monitoring. *Proceedings of the IEEE*. 2019, vol. 107, no. 6, pp. 1193–1205. ISSN 1558-2256. Available from DOI: 10.1109/JPROC.2019.2914021. Conference Name: Proceedings of the IEEE.

41. TIMUSK, Markus; LIPSETT, Mike; MECHEFSKE, Chris K. Fault detection using transient machine signals. *Mechanical Systems and Signal Processing* [online]. 2008, vol. 22, no. 7, pp. 1724–1749 [visited on 2022-11-12]. ISSN 0888-3270. Available from DOI: 10.1016/j.ymssp.2008.01.013.

42. BECHHOEFER, Eric; KINGSLEY, Michael. A Review of Time Synchronous Average Algorithms. 2009.

43. *ISO 20816-1:2016* [online]. International Organization for Standardization, 2016 [visited on 2022-11-14]. Available from: https://www.iso.org/cms/render/live/en/sites/isoorg/contents/data/standard/06/31/63180.html.

44. LI, Zheng; MING, Anbo; ZHANG, Wei; LIU, Tao; CHU, Fulei; LI, Yin. Fault Feature Extraction and Enhancement of Rolling Element Bearings Based on Maximum Correlated Kurtosis Deconvolution and Improved Empirical Wavelet Transform. *Applied Sciences*. 2019, vol. 9, p. 1876. Available from DOI: 10.3390/app9091876.

45. YONGGANG, xu; LI, Shuang; TIAN, Weikang; YU, Jun; ZHANG, Kun. Time and frequency domain scanning fault diagnosis method based on spectral negentropy and its application. *The International Journal of Advanced Manufacturing Technology*. 2020, vol. 108. Available from DOI: 10.1007/s00170-020-05302-0.

46. XU, Yonggang; ZHANG, Kun; MA, Chaoyong; SHENG, Zhipeng; SHEN, Hongchen. An Adaptive Spectrum Segmentation Method to Optimize Empirical Wavelet Transform for Rolling Bearings Fault Diagnosis. *IEEE Access*. 2019, vol. 7, pp. 30437–30456. ISSN 2169-3536. Available from DOI: 10.1109/ACCESS.2019.2902645. Conference Name: IEEE Access.

47. HATEM, G. M.; SADAH, J. W. Abdul; SAEED, T. R. Comparative Study of Various CFAR Algorithms for Non-Homogenous Environments. *IOP Conference Series: Materials Science and Engineering* [online]. 2018, vol. 433, no. 1, p. 012080 [visited on 2022-12-09]. ISSN 1757-899X. Available from DOI: 10.1088/1757-899X/433/1/012080. Publisher: IOP Publishing.

48. RABINER, Lawrence R.; SCHAFER, Ronald W. *Introduction to digital speech processing*. Boston, Mass: Now, 2007. Foundations and trends in signal processing, no. v. 1, Issue 1-2, 2007. ISBN 978-1-60198-070-0. OCLC: ocn221455696.

49. ZHAO, Yikai; ZHONG, Zheng; LI, Yuanpeng; ZHOU, Yi; ZHU, Yifan; CHEN, Li; WANG, Yi; YANG, Tong. Cluster-Reduce: Compressing Sketches for Distributed Data Streams. In: *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining* [online]. Virtual Event Singapore: ACM, 2021, pp. 2316–2326 [visited on 2023-02-11]. ISBN 978-1-4503-8332-5. Available from DOI: 10.1145/3447548.3467217.

50. VASS, Jiří; RANDALL, Robert B.; KARA, Sami; KAEBERNICK, Hartmut. Vibration-based Approach to Lifetime Prediction of Washing Machines. *15th CIRP International Conference on Life Cycle Engineering*. 2008.

51. Blind Source Separation. In: *Biomedical Signal and Image Processing*. 2008.

52. JOHNSON, Max Kuhn {and} Kjell. *Feature Engineering and Selection: A Practical Approach for Predictive Models* [online]. 2019. [visited on 2023-02-26]. Available from: http://www.feat.engineering/.

53. *Three Ways to Estimate Remaining Useful Life for Predictive Maintenance* [online]. [visited on 2023-02-26]. Available from: https://www.mathworks.com/company/newsletters/articles/three-ways-to-estimate-remaining-useful-life-for-predictive-maintenance.html.

54. AGGARWAL, Charu C.; REDDY, Chandan K.. *Data Clustering: Algorithms and Applications*. CRC Press/Taylor & Francis, 2014. ISBN 978-1-4665-5821-2.

55. EGAJI, Oche A; EKWEVUGBE, Tobore; GRIFFITHS, Mark. A Data Mining based Approach for Electric Motor Anomaly Detection Applied on Vibration Data. In: *2020 Fourth World Conference on Smart Trends in Systems, Security*

and Sustainability (WorldS4). 2020, pp. 330–334. Available from DOI: 10.1109/WorldS450073.2020.9210318.

56. LIU, Fei Tony; TING, Kai Ming; ZHOU, Zhi-Hua. Isolation Forest. In: *2008 Eighth IEEE International Conference on Data Mining*. 2008, pp. 413–422. Available from DOI: 10.1109/ICDM.2008.17. ISSN: 2374-8486.

57. BEN-HUR, Asa; HORN, David; SIEGELMANN, Hava T; VAPNIK, Vladimir. Support Vector Clustering. 2001.

58. JANSSENS, Jeroen; POSTMA, Eric. One-class classification with LOF and LOCI: An empirical comparison. 2007.

59. TOGBE, Maurras Ulbricht; BARRY, Mariam; BOLY, Aliou; CHABCHOUB, Yousra; CHIKY, Raja; MONTIEL, Jacob; TRAN, Vinh-Thuy. Anomaly Detection for Data Streams Based on Isolation Forest Using Scikit-Multiflow. In: GERVASI, Osvaldo; MURGANTE, Beniamino; MISRA, Sanjay; GARAU, Chiara; BLEČIĆ, Ivan; TANIAR, David; APDUHAN, Bernady O.; ROCHA, Ana Maria A. C.; TARANTINO, Eufemia; TORRE, Carmelo Maria; KARACA, Yeliz (eds.). *Computational Science and Its Applications – ICCSA 2020* [online]. Cham: Springer International Publishing, 2020, vol. 12252, pp. 15–30 [visited on 2023-03-24]. ISBN 978-3-030-58810-6 978-3-030-58811-3. Available from DOI: 10.1007/978-3-030-58811-3_2. Series Title: Lecture Notes in Computer Science.

60. MA, Haoran; GHOJOGH, Benyamin; SAMAD, Maria N.; ZHENG, Dongyu; CROWLEY, Mark. Isolation Mondrian Forest for Batch and Online Anomaly Detection. In: *2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC)* [online]. 2020, pp. 3051–3058 [visited on 2023-03-24]. Available from DOI: 10.1109/SMC42975.2020.9283073.

61. MONTIEL, Jacob; NGO, Hoang-Anh; LE-NGUYEN, Minh-Huong; BIFET, Albert. Online Clustering: Algorithms, Evaluation, Metrics, Applications and Benchmarking. In: *Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining* [online]. New York, NY, USA: Association for Computing Machinery, 2022, pp. 4808–4809 [visited on 2023-03-24]. KDD '22. ISBN 978-1-4503-9385-0. Available from DOI: 10.1145/3534678.3542600.

62. WAGNER, Tal; GUHA, Sudipto; KASIVISWANATHAN, Shiva Prasad; MISHRA, Nina. Semi-Supervised Learning on Data Streams via Temporal Label Propagation. In: *Proceedings of the 35th International Conference on Machine Learning*. 2018.

63. YU, Kangqing; SHI, Wei; SANTORO, Nicola. Designing a Streaming Algorithm for Outlier Detection in Data Mining—An Incrementa Approach. *Sensors* [online]. 2020, vol. 20, no. 5, p. 1261 [visited on 2023-03-24]. ISSN 1424-8220. Available from DOI: 10.3390/s20051261. Number: 5 Publisher: Multidisciplinary Digital Publishing Institute.

64. GHESMOUNE, Mohammed; LEBBAH, Mustapha; AZZAG, Hanene. State-of-the-art on clustering data streams. *Big Data Analytics* [online]. 2016, vol. 1, no. 1, p. 13 [visited on 2023-03-24]. ISSN 2058-6345. Available from DOI: 10.1186/s41044-016-0011-3.

65. CAO, Feng; ESTERT, Martin; QIAN, Weining; ZHOU, Aoying. Density-Based Clustering over an Evolving Data Stream with Noise. In: *Proceedings of the 2006 SIAM International Conference on Data Mining* [online]. Society for Industrial and Applied Mathematics, 2006, pp. 328–339 [visited on 2023-03-24]. ISBN 978-0-89871-611-5 978-1-61197-276-4. Available from DOI: 10.1137/1.9781611972764.29.

66. SHUKLA, M.; KOSTA, Y. P.; JAYSWAL, M. A Modified Approach of OPTICS Algorithm for Data Streams. *Engineering, Technology & Applied Science Research* [online]. 2017, vol. 7, no. 2, pp. 1478–1481 [visited on 2023-03-24]. ISSN 1792-8036. Available from DOI: 10.48084/etasr.963.

67. XIE, Jierui; CHEN, Mingming; SZYMANSKI, Boleslaw K. *LabelRankT: Incremental Community Detection in Dynamic Networks via Label Propagation* [online]. arXiv, 2013 [visited on 2023-03-24]. No. arXiv:1305.2006. Available from DOI: 10.48550/arXiv.1305.2006.

Appendix A: Resume

Appendix B: Plan of work

B.1 Winter semester

Period	Work
1^{st} week	Consultation with the supervisor on directions of the future work based on literature review during previous semester.
2^{nd} week	Outline the key sections of the analysis part in the thesis.
3^{rd} week	Match supporting literature with analysis sections. Further invesigation on the feature engineering methodology in condition monitoring.
4^{th} week	Summarize notes from condition monitoring articles and video-recordings of tutorials and conferences.
5^{th} week	Research transformation of vibration signal to feature space using time-frequency, harmonic and energy statistical metrics. Progress report meeting with the supervisor.
6^{th} 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.
7^{th} week	TBD (Narrow down wide variety applicable methods for signal decomposition)
8^{th} 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: