Slovak University of Technology in Bratislava
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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
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Training workplace:	Institute of Computer Engineering and Applied Informatics
Thesis supervisor:	Ing. Marcel Baláž, PhD.
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SLOVENSKÁ TECHNICKÁ UNIVERZITA V BRATISLAVE
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Návrh zadania diplomovej práce

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Študent:

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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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A Resume

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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

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-mo` `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

[52]

- 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

Difference between fault (degrating performace of the machine - higher friction and power consumption) and failure (machine is unusable). [2] (picture)

- 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.
- Predictive - model of expected lifetime, warns about unexpected faults before they become too serious and before affecting the machine.

Wear process curve [2] 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

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. [24]

- 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

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 [2]. 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 [3].

- 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[40]

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) [53] [59]

- 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

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 [58] - 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 - [52]- 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.

Signal denoising and filtering

Blind source separation, PCA, ICA vibration analysis tools:

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

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 + Harmonic Product Spectrum + 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. [59] - 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

`https://scikit-learn.org/stable/modules/outlier_detection.html#outlier-detection`

2.3.1 Novelty detection

Fault or no fault - anomaly detection solutions - unsupervised [16]. mean shift clustering algorithm

- Robust Covariance (Mahalanobis distance)
- One-class SVM with non-linear kernel (RBF) - classifying new data as similar or different to the training set
- Local outlier factor - local density deviation of a given data point with respect to its neighbours
- Isolation forest

Types of faults - clustering

- BIRCH
- DBSCAN - density based params: 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).
- OPTICS - better DBSCAN - clusters in data of varying density

2.3.2 Label propagation in semi-supervised learning

Transductive Support vector machine(TSVM), Label Propagation Algorithm(LPA)

2.4 IoT in Industry 4.0

Wireless protocols limitation: IEEE 802.11, IEEE 802.15.4e, OpenThread Power consumption Devices and sensors

The Fig. 1 shows a generalist architecture supported in the context of Industry 4.0, fault detection systems in electrical machines based on vibration analysis The Operational Technology (OT) and Information Technology (IT) parts were aligned to design an Industrial Control System (ICS) in the laboratory, for acquiring, controlling and monitoring the operating status of rotating machines, producing reports, automatic alerts and recommending actions to take as a prescriptive maintenance system. [16]

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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. Meeting schedule is established.
2nd week	Outline of key sections of the analysis part of the thesis.
3rd week	Match supporting literature with analysis sections. Further invesigation on the feature engineering in condition monitoring.
4th week	TBD (Descibe machinery physics and maintanance strategies.)

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: