UNIVERSITATEA „POLITEHNICA” din BUCUREŞTI

ŞCOALA DOCTORALĂ DE INGINERIE MECANICĂ ŞI MECATRONICĂ

Nr. Decizie .... din

TEZĂ DE DOCTORAT

Monitorizare și mentenanță inteligentă a unui sistem mecatronic

Intelligent monitoring and maintenance of a mechatronic system

REZUMAT

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BUCUREŞTI

2022

CHAPTER 1
INTRODUCTION. THESIS OBJECTIVES

This chapter offers an introduction to fault diagnosis and emphasizes its importance by shortly describing a mechatronic system, of the faults that can affect its behavior and of the economical effects that the faults bring. The chapter describes the thesis and research objects as well as the thesis' structure.

Fault diagnosis gets more important in today's industry and by using state of the art artificial intelligence, more and more researchers search for new methods to keep a system working and to avoid downtime. This can lead to a more efficient and uninterrupted production. Lately, there have been a lot of articles written in this area, especially in the field of predictive maintenance and its advantages in a system's diagnosis.

1.1 Faults of components and subsystems in mechatronics and robotics

1.1.1. Components of a mechatronic system

A mechatronic system usually has other subsystems, each responsible of the behavior of a certain part of the main system. These subsystems can be split up into 6 categories:

1. Mechanical subsystems
2. Actuating subsystems
3. Electric and electronic subsystems
4. Data acquisition subsystems and sensors
5. Control subsystems
6. Graphical user interface (GUI) and human-machine interaction (HMI) subsystems

1.1.2. Usual faults of components and subsystems

1.1.2.1 Actuating systems faults:

a) Electrical faults:

- Power fluctuations
- Voltage drops
- Phase oscillations
- Phase losses
- Current variations
- Short circuits

b) Mechanical faults

- Stuck rotor

- Overloads
- Coil overheat
- Coil circuit interrupt

1.1.2.2 Electrical and electronic systems faults:

a) Isolation faults
b) Contact faults
c) Printed circuit board faults
d) Switch faults
e) Semiconductor faults

1.1.2.3 Mechanical systems faults:

a) Wear, failure or slip of transmission belts can cause the interruption of motion or change of the transmission ration
b) Gear teeth wear or failure
c) Wear of bearings and drives can cause looseness and precision loss
d) Elastic elements and shaft failures
e) Loss of airtightness for fluid-working devices

1.2 Functional and economic effects of faults

In his PhD thesis, Michael Patrick Brennan [1] analyses the economic and technological impact that faults can have in a production environment. The costs can be classified as follows:

1. Proactive costs for preventing faults or reducing their occurrences
2. Reactive costs for locating existing faults, repairs, and maintenance

In domain literature there is a rule called “rule of 10” which shows that ***for every economic unit spent on prevention, 10 economic units are saved for fixing internal faults and 100 units are saved for fixing external faults.*** There is an important number of research papers on this subject and that propose new methods for estimating the time between two fault occurrences, and by doing this being able to develop a reliability model. ***That’s why developing a robust fault diagnosis system is of utmost interest for industry units, all of them using electromechanical systems.***

1.3 Thesis objectives

I. Literature research to find state-of-the-art methods for fault diagnosis algorithms to improve them or propose new methods of assessing a system’s state based on vibration data.

II. Identifying possible faults in mechatronic systems and ways to diagnose them using vibrations.
III. Extraction of main features from vibration data of the system's mobile components, sampled by acquisition of the acceleration signals from the monitored components and analyzing them using machine learning algorithms
IV. Development and implementation of a robust fault diagnosis algorithm for different fault frequencies that can be used on multiple components
V. Development and implementation of a monitoring and predictive maintenance algorithm for a mechatronic system formed by an actuating subsystem, transmission subsystem and the actuated subsystem (effector).

CHAPTER 2
CLASSIFYING FAULTS AND THEIR VIBRATORY FEATURES

This chapter describes the usual mechanical faults that can occur in mechatronic systems that have a translation or rotation motion. Also, vibration features of these faults are presented.

2.1 Faults that can occur in mechanical subsystems motion

2.1.1 Unbalance

The result of an eccentricity that appear when the center of mass of a cylindric piece (shaft) is not aligned with its rotation axis, creating an unbalance that can produce transversal vibrations.

2.1.2 Shaft misalignment

This fault appears usually when two shafts are not correctly aligned by their revolution axis or when the shaft's axis have major angular deviations from the bearings or gearboxes axes.

2.1.3 Mechanical looseness

This can occur due to improper mounting, excessive wear, or component failure.

2.2 Component faults

2.2.1 Bent shaft

This fault has the same frequency features as misalignment, phase analysis being needed to differentiate between these 2 faults. If this is not possible, these two faults can be considered part of the same fault class since both need shaft verification.

2.2.2 Bearing faults

Most of the time, bearing faults are consequences of overloading, bad lubrication, high working temperature, corrosion, or raceway contamination with external impurities. In [2] faults that appear mostly in rolling bearings are presented, but without causes or functional consequences:

- **a.** Faults caused by excessive wear
- **b.** Faults caused by abrasive wear
- **c.** Faults caused by adhesion wear
- **d.** Faults caused by impacts
- **e.** Faults caused by corrosion
- **f.** Faults caused by improper mounting

The above classification is a systematization based on physical or chemical phenomenon by combining the resources available in [2] and „Bearing fault analysis" of Timken [3]. Most of the faults are due to improper lubrication or improper mounting. Although the faults, themselves, do not have features, the bearing components have intrinsic frequencies that can help identify the faulty component.

Intrinsic fault frequencies for each component can be computed using bearing geometry variables; if a fault occurs in a certain component, in the frequency domain, an amplitude peak will be visible at the component's intrinsic frequency.

It's important to note that the signal energy analysis is of great interest for mechanical faults. This is because an impact produced by the fault can be hidden in the frequency domain by the components that stand between the place where the impact is made and the place where the vibrations are monitored (sensors). Therefore, the increased amplitude can be modulated in higher frequencies, phased by damping components. The frequency spectrum would contain amplitude peaks distanced on the frequency scale by a value equal to the fault frequency. Energy-wise, the impact will generate a frequency response that increases the amplitude at the natural frequency and so, by analyzing the energy spectrum, the frequency of this amplitude can be determined [4]. Another approach specific to vibration signal analysis in bearings and gearboxes is to determine the signal's envelope and then look at the envelope spectrum.

2.2.3 Belt-transmission faults

Belt transmissions have multiple advantages like transmitting into the system a smooth and soundless rotation motion. This can be sustained through force for the adhesion-based belts or through form. Other advantages of this type of transmission are the low vibrations and low production and maintenance costs. Also, the force is not transferred to the system in case of a short-term overload, phenomenon that could otherwise lead to faults in the other components. Belt transmissions are not very sensitive at improper mounting or setup and can distribute the power from the rotating shaft to multiple other shafts.

As presented in [5] and [6], the faults that can appear in this type of transmissions are:

a. Failure

b. Wear

2.2.4 Gearbox faults

Gearboxes represent a mean of transmitting and transforming the rotational motion, transferring the power from one shaft to another with a very good efficiency ratio. This kind of transmission has a high durability and a transmission ratio which is theoretically constant. The disadvantages of this type of transmission is that the manufacturing process has to be very precise and that during functioning it gives out a high level of vibrations and sound [7].

The main gearbox faults that can occur besides the mounting ones are those related to the gears' teeth:

a. Teeth failure
b. Teeth side wear
c. Teeth side wear due to slips

2.2.5 Electrical faults in actuating subsystems

Electromechanical components offer vibration features in case of some electric faults as well. These can be easily monitored, using two times the supply current's frequency, given that one every rotation there are two magnetic pulls to the closest magnetic pole, which makes the electrical signal to oscillate between 0 and two times the supply current frequency.

It can be concluded that there is a large set of usual faults that can appear in mechatronic systems and their components. Given that these faults have specific vibration features, a low-cost method for monitoring can be implemented using vibration analysis and intelligent algorithms for diagnosis.

CHAPTER 3
METHODS, MEANS AND RESEARCH ABOUT MONITORING, PREDICTION AND DIAGNOSIS OF FAULTS IN MECHATRONIC SYSTEMS

3.1 Reliability and maintenance

The term of reliability appeared because of the importance the industry equipments security received lately. The term represents the characteristic of an equipment to run without failure. Mathematically, it is possible to establish the behavior of a system in certain working conditions.

Reliability can be:

- Qualitative
- Quantitative

Failure is the fundamental phenomenon that occurs when a devices ceases to execute its designed function. Failures can be:

- Minor
- Major
- Critical

All the technical and logistic actions that are taken in order to restore a system to be working again is called maintenance.

Maintenance costs have a high weight in running costs of industrial system, varying between 15 and 60. Optimal and performant running of industrial systems is related to fault prevention for defects that can occur due to wrong maneuvers, operator negligence or random overloads. That's why monitoring and diagnosis techniques have a positive impact on reliability and maintenance.

Four types of maintenance can be mentioned:

Reactive maintenance

Corrective maintenance

Preventive maintenance

Predictive maintenance – this type of maintenance means that there is a periodical or specific monitoring of the mechanical, electrical state of the system or other functional parameters to increase the time between repair actions and to avoid downtime.

Predictive maintenance improves the entire industrial system. This type of maintenance uses vibration monitoring, thermography, tribology, etc. to be able to monitor the functional parameters of the monitored system. Using this type of maintenance, downtimes can be avoided, and small faults can be diagnosed before becoming major issues. Most of the faults effects can be minimized by early diagnosis.

3.2 Methods and means to detect and diagnose faults in literature

In this section there are presented many methods from literature used for monitoring and diagnosing faults in mechatronic systems or in their components. A differentiation is made between different methods of diagnosis: model-based methods and data-based methods as shown in figure 3.1.

The model-based faults offer detailed fault diagnosis, the dynamic behavior of the system being mathematically modelled. This way, the signals can be sampled from any component and so-called residual signal can be computed based on a reference given by the analytical model and the results of the measurements made on the real system. These residuals can give information about the monitored system state. However, the modern system models are getting more and more complex and have a lot of non-linearities that can add errors during the numerical computation, the obtained results not representing the real system. That's why, because of the growth of computational power, more and more algorithms appeared that can create dynamical models based on data. The intrinsic non-linearities are part of the data-based model and so this model can be used successfully on complex systems

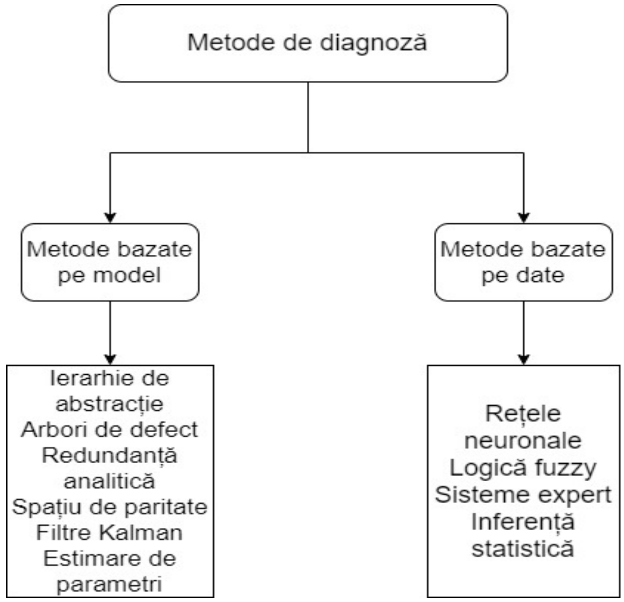


Figura 3.1: Methods and algorithms for diagnosis [8]

To get a fault's feature, the monitored system needs be defined by some signals that offer information on the dynamics and the state of the system.

Vibration analysis is the cheapest and non-invasive diagnosis method. In [9] it is shown the difference between detection and analysis, emphasizing that only detecting a fault or it's effect is not helpful because the root cause needs to be fixed. Vibrations are the dynamic system's components response to internal or external forces. Each mechanical or electrical issue generates a unique response so that through vibrations feature analysis the faults can be diagnosed. The main components that can be analyzed through vibrations are:

- **Frequency –** represents the number of occurrences of an event in a certain time span
- **Amplitude –** represents the "size" of the vibration's oscillation. Usually, it shows the existence of a fault and it corelates with the fault's severity.

Faults can be diagnosed through the before mentioned characteristics and using mathematical methods and models built around these characteristics.

CHAPTER 4
SENSORS, VIRTUAL INSTRUMENTATION, DATA ACQUISITION AND SIGNAL PROCESSING

This chapter presents monitoring ways of an electromechanical system (vibration analysis, thermography) and describes different types of sensors, especially accelerometers and how they work. Also, details are given about the needed virtual instrumentation for data acquisition and signal processing methods for extracting meaningful features.

4.1 Vibration analysis

It is one of the most used methods of fault diagnosis in electromechanical systems. Through this method, the system's vibration parameters are determined, usually with an accelerometer, and then the amplitudes at certain frequencies are analyzed (figure 4.1) to identify the peaks given that the system has certain intrinsic frequencies while running. The change of amplitude in certain harmonics can indicate the presence of a fault.

Through vibrations, there can be diagnosed faults like unbalances, bearing faults, structural resonance, rotor faults. The data sampling is fast and non-invasive, the monitored system's work regime not being affected.

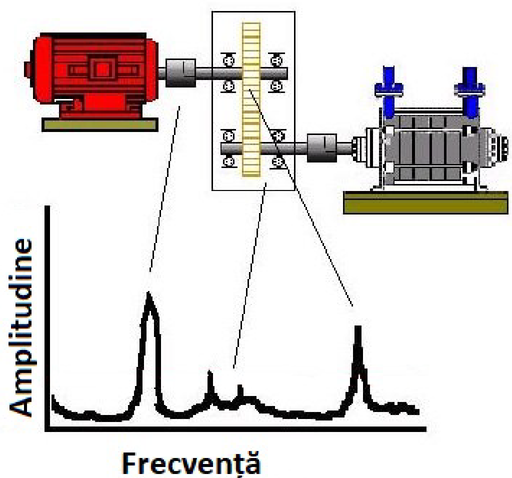


Figure 4.1: Vibration analysis [10]

For each electromechanical system, before going into production stage, a reference level for vibrations needs to be set so that any deviation from this level could indicate a fault. There is a standard that sets the levels of vibrations for different devices at different running speeds. These can be used as reference level when comparing data sampled during production.

4.2 Sensors

In [11], Stephen Hanly presents different vibration measurement sensors and indicates how the vibration analysis can be done properly. Hence, the vibration sensors can be classified as follows:

- Accelerometers.
- Velocity sensors
- Microphones or acoustic pressure sensors
- Laser displacement sensors
- Capacitive displacement sensors

Accelerometers can be also split up as follows:

- Capacitive accelerometers – the smallest and cheapest accelerometers that are used usually in mobile phones. The data quality is low, especially at high frequencies and they are not appropriate for industrial use; the production technology is based on MEMS (micro electromechanical systems)
- Piezoelectric accelerometers – these are the most popular and used sensors for industrial applications, their lead zirconate titanate (PZT) sensing element producing electric charge or output under acceleration. The downside is that the coupling is made through AC current, and they can't measure gravitational acceleration.
- Piezoresistive accelerometers – these sensors are commonly used for impulse/impact measurements; the seismic mass deforms the elastic element on which piezoresistive elements are mounted, therefore they need amplification and temperature compensation; they are coupled through DC current

4.3 Data acquisition, virtual instrumentation

An instrument is a device that sample data from the environment or from a system, processes the data and shows the result to the user. Oscilloscopes, multimeters, spectrum analyzers, etc. are examples of physical instruments. Virtual instruments are another class of instruments which is formed by software and modular hardware that gives the user the possibility to adapt the sampling system to his needs [12].

A defining trait of a virtual instrument is that it can change its main function through software, being flexible and reliable in many applications. That's why the software component is the most important part of a virtual instrument [13].

A virtual instrument is made up of multiple modules (figure 4.2):

- Sensor module
- Sensor interface
- Computing module
- Graphical interface

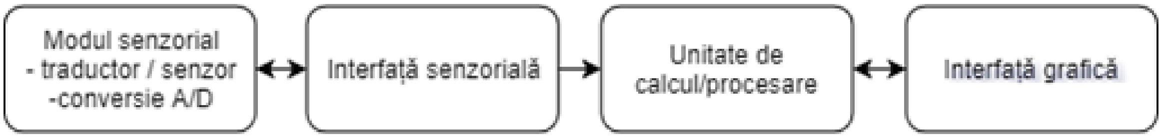


Figure 4.2: Virtual instrument architecture

The used virtual instruments for data sampling will be described further. These instruments have the purpose of sampling data, process it and extract meaningful features for fault diagnosis in a mechatronic system using vibration analysis. The monitoring system will use a reference level that describes the system before the production stage, when it is considered that it's running without faults.

The monitored mechatronic system is represented by an actuating system (motor), transmission system (cinematic chain) and a system that is actuated and must execute a certain motion (effector). The vibration measurement is made with 2 sensors, one being mounted on the motor and one on the effector (figure 4.3). Hence, the sensor module will be formed by::

- Vibration sensors
- Data acquisition board

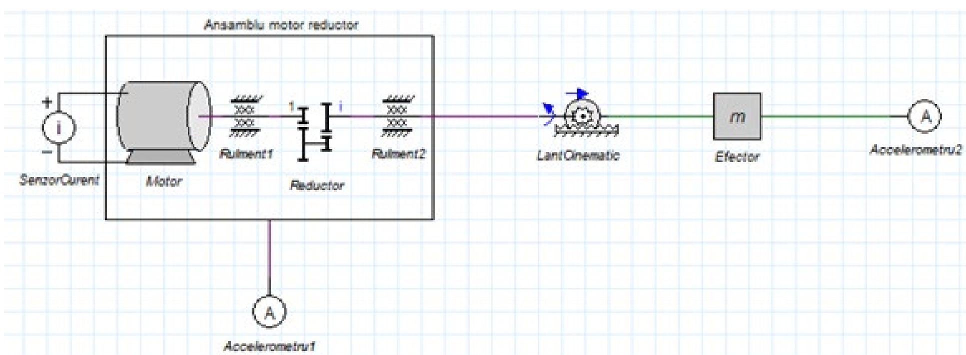


Figure 4.3: Monitored single-axis mechatronic system

The sensor interface will be a wired one to allow real-time data sampling when the system is running. Another way of sampling data is by using a microcontroller instead of a dedicated data acquisition board which can then send the data through a wireless interface. Therefore, the sensor interface is composed of:

- Data acquisition board / microcontroller
- Computer cu wireless network card / serial port

The computing unit is a computer which has a wireless network card or a serial port to communicate with the sensor interface.

The graphic interface is made up of a software program that can show the processed features of a signal and can notify the user if a fault is diagnosed/present in the system.

4.4 Signal processing

Signal processing is an important step in a diagnosis module because by using it, important information can be extracted that is relevant to the monitored system's state. The signal processing domain in a huge one therefore only some theoretical concepts will be presented that will be later applied in different experiments and fault diagnosis methods.

4.4.1 Signal processing methods

A signal can be processed in the time domain, frequency domain or time-frequency domain. For each domain, there are different methods for extracting useful signal features. Some concepts will be briefly presented further.

4.4.1.1 Signal processing in the time domain

The data sampled in time by a sensor gives out a signal in the time domain from which statistical information can be extracted. Besides the signal's form and its statistical features, another two measures are of interest, specifically the signal's energy and the signal's power. These two can offer important information on how strong a signal is in a given interval. For transient signals, the energy is important in a time frame as the power is useful for stationary processes.

4.4.1.2 Signal processing in frequency domain

For signal processing the frequency domain, the Fourier transform is used. This allows the time domain signal to be converted in the frequency domain through the decomposition of the initial signal into sine-like components of different periods and by finding the amplitudes of these components. This representation in the frequency domain is also known as the frequency spectrum of the signal, term used further for the graph formed by the signal's amplitudes at different frequencies.

The Fourier Transform

The Fourieri transform extracts the processed signal's correlations with sinusoidal signals the have different frequencies. Hence, if a signal *x(t)* needs to be represented in the frequency domains, the following equation can be used:

$$X(f) = \int_{-\infty}^{\infty} x(t) e^{-j2\pi f t} dt \tag{4.1}$$

where *f* is the frequency of sinusoidal component and *X(f)* its amplitude.

Obviously, the equation (4.1) is useful for analogical signals. Usually, a signal is sampled with a certain sample rate, and it needs digital processing, hence the discrete Fourier transform is used (DFT):

$$X(k) = \frac{1}{N}\sum_{i=0}^{N-1} x(i)e^{-\frac{j2\pi ki}{N}} \tag{4.2}$$

where N is the number of points of the signal after applying the DFT. This transform can be efficiently computed by using the Fast Fourieri Transform (FFT), however FFT requires that N is a power of 2 [14].

As per Parseval's theorem and the law of energy conservation [15]:

$$\sum_{n=0}^{N-1}|x_n|^2 = \sum_{k=0}^{N-1}|X_k|^2 \tag{4.3}$$

where x_n is the initial signal, N is the number of points amd X_k is obtained using (4.2). Equation (4.3) expresses the fact that the signal's energy in time domain is equal to the signal's energy in frequency domain.

Generalized Goertzel algorithm

Another method of signal processing in frequency domain is by obtaining the DFT coefficients of the signal at specific frequencies by using the Goertzel algorithm. This algorithm is very useful if only a certain number of frequencies need monitoring, as presented [16]. This method requires only N multiplications and $2N$ adding operations. It more efficient than the DFT if the number of computed frequencies K is less than $4N/7$ [17]. Another advantage of this algorithm is that N doesn't have to be a power of 2 to be computational efficient.

4.4.1.3 Signal processing in time-frequency domain

The two types of signal processing presented above lose information that could be useful in fault diagnosis. Also, the Fourier transform is not useful for processing transient signals, which usually appear in real system faults. That's why there are more methods to process a signal in both domains (out of which only 3 will be detailed, these being used for fault diagnosis algorithms available in the thesis):

- <u>Short time Fourier transform (STFT)</u> – in this method, the signal is basically split up in multiple frames using a window of a certain duration; on each frame the Fourier transform is applied.
- <u>Wigner-Ville distribution</u> – this method gives out the probability distribution of the signal at a certain frequency and at a specific moment in time.

- Wavelet Transform – it is a method that decomposes the signal using a Wavelet mother function, which must satisfy certain criteria, and which can be dilated and translated, offering resolution in both time and frequency domains.
- **Hilbert-Huang Transform** – this method combines the Hilbert transform and the empirical mode decomposition. It is a method specifically created for the analysis of non-linear and non-stationary signals [18]. The intrinsic mode functions extracted are dependent on the signal itself, meaning that this is an adaptive algorithm which offers a very good resolution in time and frequency. It was presented by Huang et al. in [19].
- **Wavelet Packets Transform** – a method which is built on top of the discrete Wavelet transform but which substitutes the Wavelet mother function with two filters (Wavelet function and scaling function) with which the initial signal can be decomposed in an iterative way.
- **Mel frequency cepstral coefficients** – a method which his very useful in extracting features from a signal for speech recognition. It is built on top of the STFT and the discrete cosine transform.

CHAPTER 5
FAULT DETECTION AND ISOLATION USING ARTIFICAL INTELLIGENCE

This chapter is an overview of the artificial intelligence domain and gives some insight into some theoretical notions of different machine learning algorithms used for fault diagnosis.

5.1 Artificial intelligence

Artificial intelligence is a subcategory of computer science that deals with the intelligence of the machines, which gives the adjective of "artificial". Usually, the main goal of artificial intelligence is to maximize the probability of success in a certain operation. For instance, if playing chess, an artificial intelligence algorithm will compute the probabilities of winning of every possible move and will make the move with the highest change of success

5.1.1 Artificial intelligence algorithms

Artificial intelligence has solved many complex problems in the field of computer science using different methods and algorithms. The main methods that are used in artificial intelligence can be split into the following classes [20]:

- Search and optimization methods
- Logical methods
- Probability methods
- Classification and statistical inference methods

- Neural networks

5.1.2 Machine learning

Machine learning is a subdomain of artificial intelligence that is composed of techniques through which a system can automatically learn. After the learning stage, the system will build a model which will be used for approximating future results for the problem it was trained, no matter what the input is.

The models can be classified in:

- Neural networks
- Decision graphs
- Support vector machines (SVM)
- Bayesiene networks
- Genetic algorithms

5.2 Artificial intelligence algorithms for fault diagnosis

In [21], Chang et. al. presents different ways through which a machine can be monitored using artificial intelligence. It can be observed that neural networks are more and more used in this type of industry. Neural networks can be classified as:

- Recurrent neural networks – a type of neural networks that creates a directed graph between its nodes (neural units) for a timespan
- Deep neural networks – it's a type of neural networks used in deep learning; these networks have multiple hidden layers and can make better estimations with fewer neural units than classical neural networks. However, these networks tend to create an overfitted model.
- Convolutional neural networks – a type of deep neural networks, they are usually regularized to avoid overfitting.

5.2.1 Anomaly detection

Usually, a neural network model is used in supervised learning algorithms. For example, for classifying more types of faults, in the training set there must be data for each type of fault.

If only the detection of a fault is needed, unsupervised learning can be used. Different models can be implemented starting from the data sampled from the system that runs without faults.

5.2.1.1 Anomaly detection algorithm using normal distributions

This algorithm is built using the probability density of the distribution of each dimension of the analyzed feature vector x. It is important to note that the data used for training has to be processed so that the probability distribution function is a bell-shaped graph (Gaussian distribution).

5.2.1.2 Isolation Forest

This algorithm was introduced in 2008 by Liu and Ting through [22], being a new method to detect anomalies through a new approach: isolation. The algorithm is built around the idea that the anomalies are rare and very different than the reference data and hence, they are more susceptible to isolation.

An isolation forest has the following advantages:

- It is formed of isolations trees. Their advantage is that they create partial models which deal with small data sets. A small set decreases the chance of a false positive or false negative.
- It doesn't use distance or density measurements to find anomalies, hence eliminating a major cost in the computational needs
- It has a linear time complexity and a small space complexity
- It deals very well with big data sets with a high number of features

In a tree built from random data, the partitioning of each point is done recursively until all the points are isolated. Because anomalies are very different, the partitioning will be very short and the path from the root to the leaf will be very short. Hence, when an isolation forest produces short paths for certain data points, those points are considered anomalies.

5.2.1.3 Kolomogorov-Smirnov statistical test

Another method to detect a potential fault is through the comparison of two statistical distributions built from the dynamic features extracted from a system. The first distribution (the reference one) is built by the features of the system running without fault while the second distribution is built from the data sampled from the system during production stage.

The Kolmogorov-Smirnov test (K-S test) is a statistical test to decide whether a data point or set is part of a given distribution. This is achieved by comparing the one-dimensional probability distributions. It is a non-parametric test which can compare a dataset with a theoretical distribution, or it can compare two datasets. It can also be used as a goodness of fit test. This method is using null hypothesis testing using a statistic called *D-stat*. Also, K-S test gives a value p that, if it is smaller than 0.05, rejects the null hypothesis.

5.2.2 Unsupervised classification algorithms

5.2.2.1 K Nearest Neighbours - kNN

This algorithm allows a system to classify new data by assigning it to a set learned on previous measurements; the classification process is made based on the Euclidean distance or other type of measure that can be applied to multidimensional data, like the Minkowski measure: [18]:

$$\|x' - x_n\|_p = \left(\sum_{i=1}^{M} |(x_i)' - (x_i)_n|^p\right)^{\frac{1}{p}} \tag{5.1}$$

where x' is a new data sample, x_n is a previous data sample and is part of $\mathbb{R}^M$.

The algorithm's training stage is basically when a new data sample is classified, making this method very robust and easy to use.

In [18], the author uses weighted-kNN successfully for fault diagnosis in gears by setting different weights to the distances to different fault classes.

This algorithm represents an easy way to integrate in a monitoring system faults that are not known before the production stage and that may appear while the system is running. The faults can be classified by the operators upon their detection so that later the same category of faults will be successfully classified.

CHAPTER 6
SOFTWARE FAULT DIAGNOSIS THROUGH SIGNAL PROCESSING

In this chapter there are described proprietary algorithms for vibration features extraction, algorithms that are needed in fault diagnosis and a complex software application is presented that can process signals and diagnose faults.

6.1 Fault diagnosis algorithm for a complex mechatronics system

One of the thesis' objectives is to design and implement a robust fault diagnosis system for faults that may appear in a mechatronics system. To design such a system, first the structure of the observed system must be settled upon and asses its complexity.

In this thesis, the monitoring algorithm is used for a one-axis cartesian system that is composed of an actuating subsystem, bearings, gearbox, transmission subsystem and effector subsystem. This system is presented in figure 4.3.

Starting from this monitored system, an intelligent diagnosis algorithm was designed which is presented in figure 6.1. In the figure, the steps and the modules of the diagnosis processes can be seen.

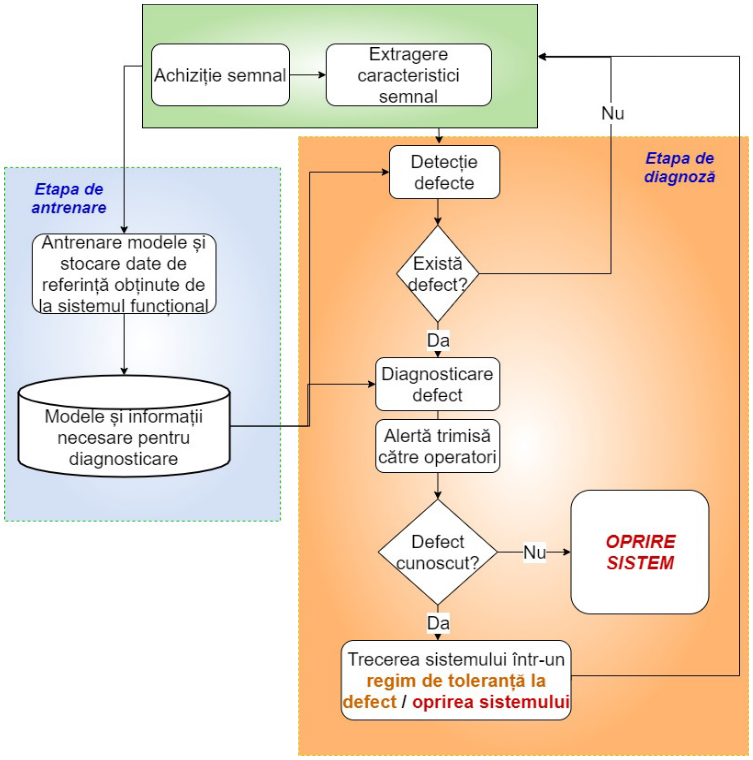


Figure 6.1: Steps and modules of the designed fault diagnosis algorithm

6.1.1 Signal acquisition

The first step of the algorithm consists of getting the vibration characteristic signals from the monitored system. For this step, choosing the right accelerometers and the right sensorial interface is important. For the sensorial module, piezoelectrical accelerometers can be used such as Brüel & Kjær, which can measure acceleration oscillations of very high frequencies.

For the acquisition of the data from the sensors, a professional data acquisition board can be used from National Instruments, which can be easily used and configured using LabView.

For a real-time system, it is important to implement a continuous data stream to the signal processing module, which is easily done in python, a programming language that has a many optimized libraries for this purpose.

6.1.2 Signal feature extraction

The sampled data from the system needs to be processed in order to extract the information needed by the diagnosis modules. The designed fault diagnosis system uses vibration analysis for identifying faults, so the methods described in chapter 4 are useful for feature extraction. To obtain features that can characterize different mechanical and electrical faults, certain frequencies must be computed for which the amplitude increases if the correspondent fault is present, as described in chapter 2.

In chapter 4 a comparison between the 3 methods of signal processing in frequency-time domain is made: the Wavelet packets transform (WPT), Hilbert-Huang transform (HHT) and the extraction of mel-frequency cepstral coefficients (MFCC). Moreover, in chapter 7, the three methods are tested on data sampled from bearing. Out of these three methods, in the software solution WPT and HHT have been implemented, the two offering a very good time-frequency resolution.

6.1.2.1 Feature extraction using the Goertzel algorithm

Many faults can be identified in the frequency domain, by monitoring the amplitude of certain frequencies, that can be computed based on system parameters. The amplitude of the sine components with different frequencies is important in detecting fault signals, hence a fast algorithm is needed for monitoring a system while running.

The feature extraction algorithm based on the Goertzel algorithm has the following steps:

- The rotation speed of the actuating system or of the shaft is stored. As described in chapter 2, all the fault frequencies are depending on the rotation speed. Certain components (like bearings) need other parameters for computing the needed frequencies
- Identify the needed parameters for computing the fault frequencies
- Compute the fault frequencies which need to be monitored
- Apply the Goertzel algorithm to get the Discrete Fourier Transform coefficients for the above-mentioned frequencies and compute the spectral amplitude for each frequency.

In figure 6.2 the above algorithm is presented. The data acquisition from an accelerometer can be done through any method, if the sampling frequency is high enough to cover all the computed frequencies.

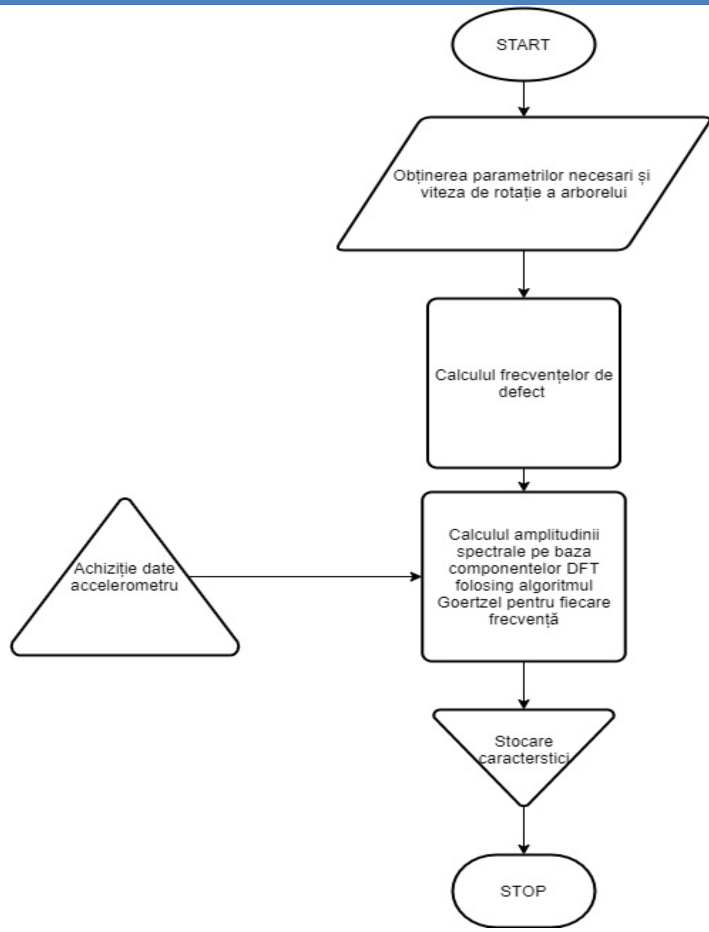


Figure 6.2: Feature extraction algorithm using the Goertzel algorithm

Pentru calculul amplitudinii spectrale pe baza componentelor DFT se folosesc ecuațiile (4.32) și (4.33).

Minor faults cannot be diagnosed in the signal's frequency spectrum because they can be masked by the amplitudes of the rotation frequencies. The impulses caused by a fault should increase the signal's energy in the frequency interval correspondent to the period of impact appearance due to the fault. So, as per Parseval's theorem from equation (4.3), the frequency bandwidth with the highest energy can be found and analyzed for diagnosing the fault.

6.1.2.2 Complex algorithms for extracting and processing the vibration features needed for fault diagnosis

For extracting relevant features through the algorithm presented above, the sampled signal needs to be processed to get relevant information for the physical phenomenon that appears due to the fault of a component. As it was mentioned above, for such a processing, there were chosen two methods: WPT and HHT.

Through these two methods different frequency bandwidths can be observed, that are relevant to the appearance of an impact in the vibratory behavior of the observed system and even more, statistical data can be extracted from signals sampled from a component that has an unknown fault. This data can be later used for classifying similar faults.

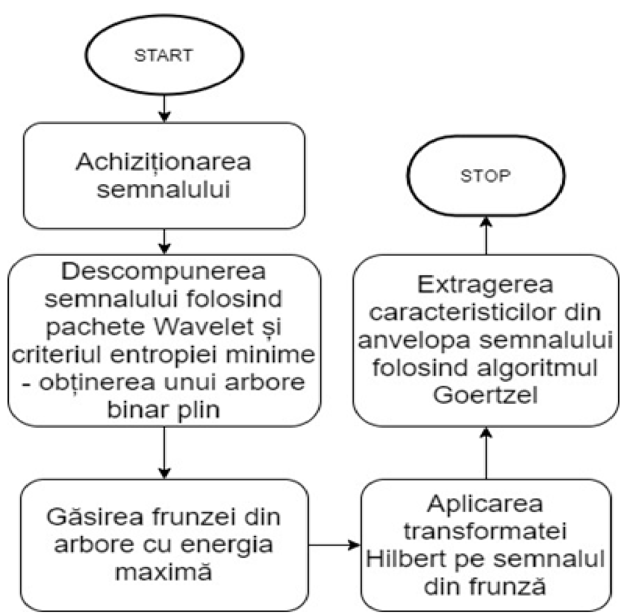
Further on, there will be presented a way to use the Wavelet packets transform or the Hilbert-Huang Transform will be presented, and additionally ***a new criterion to stop the empirical mode decomposition, which can be used to also diagnose faults.***

Using the Wavelet packets

This method allows analyzing the signals in different frequency bandwidths and hence it represents a good algorithm for extracting features based on the computed fault frequencies. By applying the WPT, a perfect binary tree will be computed. However, some packets will not offer additional information, the decomposition being redundant. For avoiding this situation, a signal entropy-based decomposition can be used for computing a full binary tree, where every node has either 0 or 2 children. In other words, a basis is searched for the signal.

After computing a basis for the signal (an optimal tree), the signal energies of the tree's leaves can be analyzed. The algorithm will search for the node in the tree with the maximum energy. Once this node is located, the fault can be identified by extracting the features from the node's signal.

The algorithm can be described by the following figure:



Figur3 6.3: Algorithm for feature extraction using the WPT

For fault diagnosis used in bearings and gearboxes, the signal's envelope is of great interest, and the envelope's frequency spectrum. The signal's envelope is computed by using the

Hilbert Transform on the signal and by computing the amplitude of the formed vectors from the transformed signal (which will be complex). The envelope is used as a signal out of which characteristic features can be extracted for the fault frequencies. Hence, instead of the signal's frequency spectrum, the features can be directly extracted from the envelope's frequency spectrum by using the Goertzel algorithm.

This algorithm is implemented in section ***WPTHandler.py*** from ***Anexa A***, where the PyWavelets [6] library is used.

Using the Hilbert-Huang Transform

This algorithm is especially used for extracting intrinsic functions for the analyzed signal a use them for computing the Hilbert spectrum. The Hilbert spectrum is built using the instantaneous energy which can be looked at by using the instantaneous frequency.

Another approach is by using a similar method as used with the WPT where, once the intrinsic functions are computed, the envelope of each function can be calculated and out of the envelope, features can be extracted by using the Goertzel algorithm. Since the decomposition stops only when a maximum number of functions is computed (a maximum number chosen beforehand) or when the residual signal is a constant or monotonic function, ***a criterion of early stopping for the empirical mode decomposition by identifying the fault itself.*** In this way, a swift decision can be taken if a fault is diagnosed, especially in the case of a mechatronics system where time is of the essence.

The HHT implementation is done in section ***HHTHandler.py*** of ***Anexa A***, where the PyEMD [7] library is used for the empirical mode decomposition (EMF).

A stopping condition to empirical mode decomposition based on the Goertzel algorithm for detecting frequency-based faults

A criterion that accelerates the EMF for diagnosing certain faults is represented by learning certain features that can show the existence of a fault in the extracted intrinsic mode function (IMF). These features can be represented by statistical information computed for the distributions formed by the DFT coefficients computed by using the Goertzel algorithm in each IMF. ***When a new set of data is considered to be an outlier to the reference levels of the features, a fault can be considered diagnosed and the EMF can stop.***

Un criteriu care accelerează descompunerea empirică în moduri proprii de oscilație, pentru diagnosticarea anumitor defecte este reprezentat de învățarea anumitor caracteristici care indică prezența unui defect în cadrul unei funcții proprii extrase. Aceste caracteristici pot fi reprezentate de informații statistice calculate pentru distribuțiile compuse din coeficienții DFT extrași prin algoritmul Goertzel din fiecare funcție proprie. ***În momentul în care un nou set de date ar fi considerat în afara valorilor admise pentru caracteristici, se poate considera că funcția proprie conține un defect și descompunerea poate lua sfârșit.***

To have a comparison dataset, the proposed algorithm will have two main stages:

1. The training stage – done on data extracted for the system with no faults
2. The diagnosis stage – the algorithm will run continuously and compare the extracted features for new data with the stored features extracted during the training stage

The extracted statistical information will be represented by the mean, variance, and range for each of the distribution.

These 3 features are enough to characterize a distribution for the purpose of checking how a new sample affects the recorded distribution for each of the monitored frequencies.

The algorithm can be split into the following steps:

1. Create a list of monitored frequencies
2. Start the EMD algorithm on a training signal for a functional system
3. Once all the IMFs have been computed, let A be a matrix with m by n (m is the number of monitored frequencies and n is the number of IMFs) filled with the absolute values of the DFT coefficients extracted using the generalized Goertzel algorithm for the fault frequencies for each IMF signal
4. Each row in A represents a dataset for which the measures presented in equations (8), (9), (10) must be extracted and stored; besides these features, also the A matrix is stored
5. During the diagnosis stage, once every IMF is extracted, the DFT coefficients are computed for the monitored frequencies and their absolute values are added as a new column to the A matrix, forming a new B matrix
6. The statistical features are extracted from the B matrix and compared to the ones stored at point 4. If each of the feature values have changed with more than an a priori chosen coefficient, the fault has been detected and the IMF decomposition can stop

The coefficient can be chosen through an automatic process during training. This coefficient represents the maximum offset allowed for any of the characteristics. The method of finding the coefficient is made up of two steps:

- On the training data, the characteristics would be extracted using steps 1-4
- Starting with a coefficient of 0.1, this was increased with a step of 0.1 until the algorithm would not detect a fault anymore for the validation data set (which is part of the functional data). This way, the coefficient can be chosen based on the functional data only, specific to each monitored system.

This algorithm is implemented in ***CustomHHT.py*** of ***Anexa A.***

Computing the fault frequencies

Based on the data shown in chapter 2, a high number of faults can be identified through vibration analysis by monitoring the amplitudes at certain frequencies. This way, the frequencies become features that must be monitored in a vibration-based diagnosis model. Given that faults in bearings and gearboxes are detected more easily through analyzing the signal given by the original signal's envelope. Hence, both the original signal's frequency spectrum and the envelope's frequency spectrum are recorded for reference.

Computing the fault frequencies is implemented in section ***DiagnosisHandler.py*** in ***Anexa A.*** These are computed based on the construction data of the mechatronics system and its components. Choosing the method for signal processing is made by the engineer that installs the monitoring system. The method is chosen based on the data sampled from the system, WPT being faster than HHT, but the WPT Wavelet function needs to be known beforehand, while the HHT is an adaptive method.

6.1.3 Fault detection module

For detection and diagnosis, the software application will load the saved models to have reference levels and pre-trained models for diagnosing known faults.

For fault detection, the features extracted through WPT are used. The reason for which WPT was chosen as processing method was the speed and the fact the Daubechies Wavelet function have similar vibration features to the ones computed through HHT, features that can be successfully used for the diagnosis of the monitored mechatronics system. These features are evaluated by an isolation forest (algorithm presented in 5.2.1.2), obtaining a correspondence between the leaves of the decomposition tree (signal coming from the actuating system and the effector system). ***Given more data samples and given the possibility of false negative results, there will be a statistical mean used for the isolation forest results. Hence, if the mean is positive, there is no fault and if it is negative, a fault is detected.***

The method is applied on the matrices A and B, composed of the packets computed for the sampled signals by the two accelerometers. A and B have the shape n x m, where n is the number of samples in the signal of a packet on the last level of the decomposition tree from WPT and m is the number of packets ($m=2^l$ where l is the last level of the tree).

For the first detection filter there are two models that are used created using two isolation forests. This way, any anomaly in the vibration behavior of the motor or the effector can be easily detected. For the existence of a fault in the transmission system between the motor and the effector the following algorithm can be used.

6.1.3.1 Modelling of the cinematic chain through a regression neural network

To use a machine learning algorithm, the sampled data must be processed for obtaining information with intrinsic information to the system and which characterize the signal mathematically. This property needs to be useful for a cost function which is minimized by the machine learning algorithm. To extract the important spectral features a processing algorithm that can compute the features in a vectorial way needs to be used.

The computed features are used to model the cinematic transmission system of the monitored mechatronics system.

Description of the problem and solution

The approached problem is to estimate the vibration behavior of the effector system based on the features from the actuating system. To solve this non-linear problem a data-based model is needed, model which is represented by the weights of the trained regression neural network. Let *A* be a space with its based formed by the vectors of the extracted features sampled from the motor signal and *B* the space that has the feature vectors computed using the features from the effector; if *T* is a system then:

$$\tilde{Y}(t) = X(t)T \tag{6.2}$$

where $\tilde{Y}(t)$ is the estimation of system *T* at time *t* if the input is *X(t)*. Finding a system *T* that can estimate correctly $\tilde{Y}(t)$ allows the monitoring of the transmission system and identification of some unknown issues which may occur due to the different involved factors. By using a model-based model, any cinematic system used for transmission can be modelled this way (without changing the algorithm or its implementation).

The above-mentioned algorithm was tested using different signal processing methods, like mel-frequency cepstral coefficients (MFCC) or WPT. The results of the test done through MFCC were presented in "***International Conference of MECHATRONICS & CYBER-MIXMECHATRONICS***" (2020). The article [4] was published in the journal "***International Journal of Mechatronics and Applied Mechanics***" indexed ***SCOPUS***. In this thesis the algorithm is implemented in ***NeuralNetManager.py*** from ***Anexa A.***

Extracting features and using them for fault

Let a new sample x_{ij} be for every accelerometer, each being processed through WPT and computing the optimal decomposition tree based on entropy (as presented in 6.1.2):

$$X_{prelucrat_j} = Extragere_{WPT}(x_{ij}) \tag{6.3}$$

$X_{prelucratj}$ can be *A* or *B* based on index *j*:

$$\begin{array}{c} A, if\ j = 1 \\ B, if\ = 2 \end{array} \tag{6.4}$$

Next, *A* and *B* are tested:

$$\begin{aligned} scor_{izolare_{motor}} &= Test_{model_{motor}}(A) \\ scor_{izolare_{manipulator}} &= Test_{model_{manipulator}}(B) \end{aligned} \tag{6.5}$$

If the motor score is -1, then a motor fault has been detected. If the score obtained from the effector signal is -1, then there's a fault either in the transmission system or in the effector system itself.

To detect where the defect comes from, the T transformation system will be used to compute the following equations:

$$B^{'} = AT$$

$$B_{eroare} = B - B' \tag{6.6}$$

To compute the matrices A and B, a window of known duration is used to split the signal into short signals which represent training samples for the neural network model and for the isolation forest models. For the signal in each window, the WPT is applied. To store the packets, a tridimensional vector is used: the first dimension of the vector is the number of samples, the second is the number of the tree's leaves and the third dimension is the number of points in a packet signal.

The detection algorithm is implemented in ***DiagnosisHandler.py*** from ***Anexa A,*** function ***startDiagnosis.*** It is important to note that the detection and diagnosis modules are implemented in the same section but in different functions.

6.1.4 The diagnosis module

After the localization of the defects (either in the motor signal or in the effector signal), the WPT is applied and then the node with the maximum energy from the decomposition tree is found. The tree was already built in the detection step, so there is no complexity penalty in finding this node.

If a fault is found at a frequency common to multiple faults, the faults could be identified based on the amplitude value.

For the diagnosis of the motor, sample groups of known sizes are created (the higher the size, the higher the statistical accuracy). For each group, a distribution given by each frequency feature is computed, the frequencies being computed for the frequency spectrum and the envelope frequency spectrum. The signal is extracted from the node with the highest energy. After the distributions of the freshly sampled data are computed, they are compared with reference distributions loaded from the trained model.

Basically, the diagnosis is done using binary vectors (that contain only 1 or 0), built upon the features extracted from the functional system during training. Such a vector has the size equal to the number of monitored frequencies and the value of each element is 0, if the distribution of the newly sampled data amplitudes is not different than the reference distribution, either 1 if there is a difference between the two. Two compare the two distributions, the following algorithm can be used:

6.1.4.1 Fault diagnosis algorithm using the Kolmogorov-Smirnov test

In [1] an algorithm for bearing fault detection and diagnosis is presented using the method presented in 5.2.1.3. The algorithm was presented at the conference "***THE 9th INTERNATIONAL CONFERENCE ON ADVANCED CONCEPTS IN MECHANICAL ENGINEERING"*** and it was published in "***IOP Conference Series: Materials Science and Engineering***", a journal indexed ***ISI Web of Science*** and ***Scopus***. Briefly, the algorithm is using the following steps:

1. Store the features into a matrix for each of the possible faults. A matrix will have the dimensions *m* by *n* where *m* is the number of samples and *n* the number of frequencies
2. Record new data for the same time as for the training
3. For each possible fault, apply the K-S test where the data is represented by each column in the matrix, comparing the D-stat with the critical D-stat
4. The probability that a fault is detected on the corresponding part for that sample is given by:
$$P_{eșantion} = \frac{\#ipoteze\ nule\ respinse}{\#frecvențe} \tag{6.7}$$
5. Given *n* samples, one could even apply conditional probability by using the law of total probability, which states that if several disjoint measurable events take place, then an event A of the same probability space would have the probability of:
$$P(A) = \sum_{i}^{n} P(A|B_i)P(B_i) \tag{6.8}$$
6. Considering A as being the event where the bearing has a fault in that specific component and B_i the event of the bearing having a fault present in the recorded data of the sample, the probability that A has happened given B_i is equal to the probability of B_i over the entire sample space:
$$P(A|B_i) = \frac{P(B_i)}{n} \tag{6.9}$$

The algorithm was implemented in section ***DiagnosisHandler.py*** from ***Anexa A,*** function ***doKSTest***. The function uses the implemented of Kolmogorov-Smirnov test from the library scipy [2], computes the critical D-stat (step 3) and returns value 1 if the two distributions are not the same and value 0 if they are part of the same distribution class. The function is further used in the function ***diagnoseMotor***, which implements steps 4, 5 and 6 to compute a fault probability and diagnose the fault (if it exists) in the system.

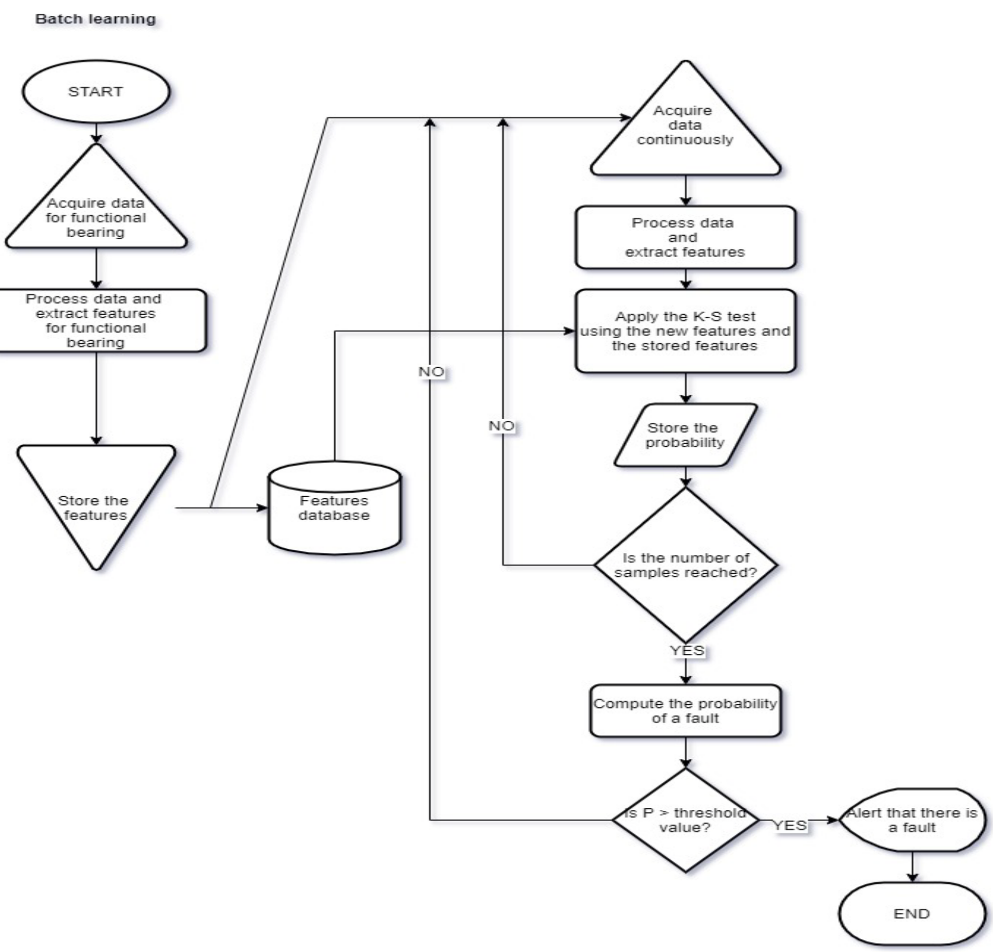


Figure 6.4: Flowchart of the algorithm using extracted features with Goertzel algorithm and applying the K-S test on them.

For the feature extraction any algorithm can be used, like the one presented by the author at the conference "***International Conference of MECHATRONICS & CYBER-MIXMECHATRONICS***" (2019) and it was published in "***International Journal of Mechatronics and Applied Mechanics***" with the index ***SCOPUS***. In thesis, a modified version of this algorithm is implemented in ***Utilities.py*** from ***Anexa A,*** function ***getGoertzelCoeffs.***

The implementation of the fault diagnosis in done in section ***DiagnosisHandler.py*** from ***Anexa A*** function ***diagnoseMotor. If the fault cannot be classified***, time-domain features are extracted from the signal, for every leaf in the decomposition tree (implemented in ***DiagnosisHandler.py*** from ***Anexa A*** function ***getSignalFeaturesFromWptData)*** and next fault with similar features are searched by using an unsupervised classification algorithm, kNN (k Nearest Neighbours) using the scikit [8] library.

If the fault classification fails, the system is stopped automatically, and the operators are alerted that there is an unknown fault. At this moment, all the features are stored. After the fault is repaired, the operators are asked to label the fault for a future classification.

The stored feature vectors will be used in the kNN system. When a new fault that can't be classified by the first part of the algorithm, the kNN algorithm will try to classify it into one of the already existing classes. If this is not possible, a new class will be made based on the extracted vibration features.

6.1.5 Operators alerting module

The operators in the factory or other interested parts of the system's condition need to be alerted if a fault has occurred. That's why an alerting module is needed that can be display error messages on the system's dedicated screens, which can send electronic messages or send different sound or visual signals. This will happen whether the fault is known or not. After the fault was identified, this module will show the type of the defect that was diagnosed. This module is part of the section ***DiagnosisHandler.py*** from ***Anexa A*** being used in the function ***addToDiagnosticText.***

6.1.6 Model training and data storing module

Although the training of the models takes place before the diagnosis process, the first step depends on the diagnosis algorithms and that's why these were first presented, to offer a better understanding of the training process and of the data used and saved to have a valid reference.

This module trains the data-based models, computes the fault frequencies, and stores the amplitudes for these frequencies, to create a reference used later in the diagnosis step. The models built are used by the isolation forests, the neural network, and the diagnosis algorithms.

The diagnosis vectors, with the fault frequencies computed as mentioned in 6.1.2.2 will represent the reference for diagnosing new sampled data.

Feature extraction and model training

As it was presented in chapter 4, to identify certain patterns in signal, these have to be processed. After the processing, relevant features can be extracted that can offer important information about the system's condition.

For the fault detection, as presented in 6.1.3.1, matrices A and B need to be defined. Two training signals are built based on the data sampled from the motor and effector.

These matrices are then used for training the neural network and the isolation forest models. After the training, the models are save into user-named files.

The same Wavelet packets tree is used form using the fault frequency model. On every node signal, the Hilbert Transform is applied, and the envelope is extracted. From this signal and the original signal, the amplitudes at the fault frequencies are extracted using the Goertzel algorithm. The results are stored into two tridimensional vectors, one for the envelope spectrum and one for the original signal's spectrum. The dimensions of the vectors are p x 2^l -1 x k_i, where *p* is the number of samples, *l* is the maximum level of the tree and k_i is the number of fault frequencies for the envelope (*i*=1) and for the original signal (*i*=2). These vectors are saved into user-named files.

The implementation of this module is available in section ***DiagnosisHandler.py*** from ***Anexa A*** function ***startTrainingAllModels.***

6.2 Software application description and objectives

The software application has two main objectives:

1. Signal processing through different methods and visualizing of the results, allowing the user to change different the parameters so that different vibration features can be observed
2. ***Online fault diagnosis of a mechatronics system with the automatic alerting of the operators in case a fault is detected and the automatic stopping of the monitored system***

The first objective is meant for the users with the purpose of allowing them to see different features of a signal. The processing methods are WPT and HHT. Based on these, a user can observe what is the best processing algorithm for a sampled signal from a functional system. Based on this decision, the user can use the chosen method for training a diagnosis model that represents the system in normal working conditions.

The second objective allows the user to get diagnosis models in an offline environment (the data was sampled in the past – the training and analysis is done on a personal computer), so that these can be later used in an online environment where the data is sampled in real time. In this case, the diagnosis algorithm can run on a microcontroller as well (but this scenario must be carefully assessed because signal processing can be an exhaustive operation). When the monitoring system detects a fault, the observed system automatically stopped or driven into a fault tolerance working scenario. Either way, the operators are alerted about the existence of a fault in the system.

CHAPTER 7
RESULTS REGARDING FAULT DIAGNOSIS IN COMPONENTS AND MECHATRONIC SYSTEMS

7.1 Experiment on a test stand used for assessing the dynamic behavior of shafts

7.1.1. Test stand description

The test stand is used for measuring dynamic behavior of a shaft in vertical and horizontal directions. The measurement is done for various rotation speeds, from zero to above critical rotation speed. The critical rotation speed is surpassed to assess the dynamic behavior of the system in the presence of transversal vibrations.

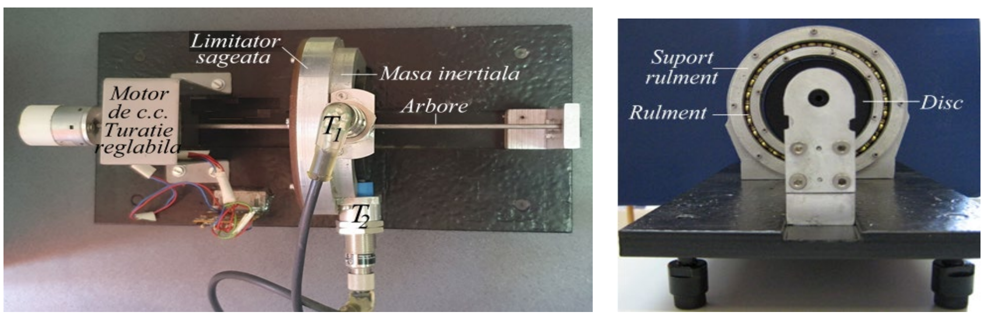


Figure 7.1: Test stand

The amplitudes and the transversal vibration frequencies of the shaft and the disk (inertial mass) from figure 7.1 are measured in real time by the inductive transducers T_1 and T_2-(Wenglor, IW045CM65MG31). The signals are sampled using an acquisition board NI-6221 from National Instruments. The shaft rotation speed is tunable between 0 and 1500 rotations/min and it is measured by using an incremental transducer attached to the motor. To limit the displacement of the inertial mass, a support is used that has a bearing 61816, with rotating inner ring.

7.1.2. Data acquisition

The software to sample data is developed using the programming environment LabView from National Instruments. Using it, the data was sampled and saved in .tdms files. The experiment has provided data about different rotation speeds, during nominal conditions and when the speed was above the critical value. Also, data was sampled when there was an exterior perturbance of the system by slowing down the shaft’s speed.

7.1.3. The experiment execution

The objectives of the experiment were to verify the efficiency of the developed algorithms and software applications, to emphasize the perturbance of the system that can be treated as an accidental collision and the exceeding of the critical rotation speed. For this purpose, data was sampled during normal running conditions, as well as during the two faulty conditions presented before, by using the setup in figure 7.2.

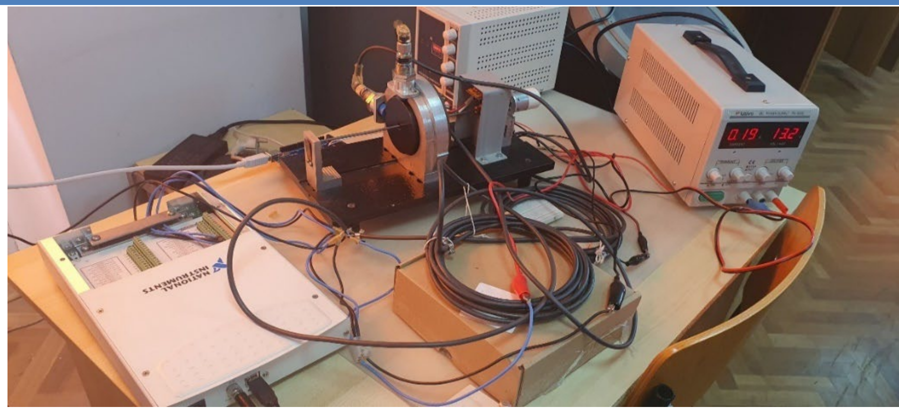


Figure 7.2: Setup for experiment execution

The motor was supplied from a continuous current source, through a potentiometer that could adjust the rotation speed. A second electrical source was needed to supply a voltage of 20V to the transducers T_1 and T_2. Going into the critical rotation speed domain, a load dynamic behavior of the shaft was observed, this being acquired by the transducers. Data was recorded also when the shaft's rotation speed was slowed down using an external brake, at an interval of 4 seconds.

7.1.4. Data processing

After the experiment was executed and the data was recorded, the latter was pre-processed by median elimination (4.5.4.1). The processed data was loaded in the application described in chapter 6.2. By applying the Wavelet Packet Transform and the Hilbert-Huang Transform, the braking is observed and can be identified through the isolation forest algorithm (presented in chapter 5). This algorithm is being used in the diagnosis system described in chapter 6.1 for early fault detection. In figure 7.3 and 7.4 the signals are presented processed through WPT for the normal running conditions and for the perturbation introduced through braking.

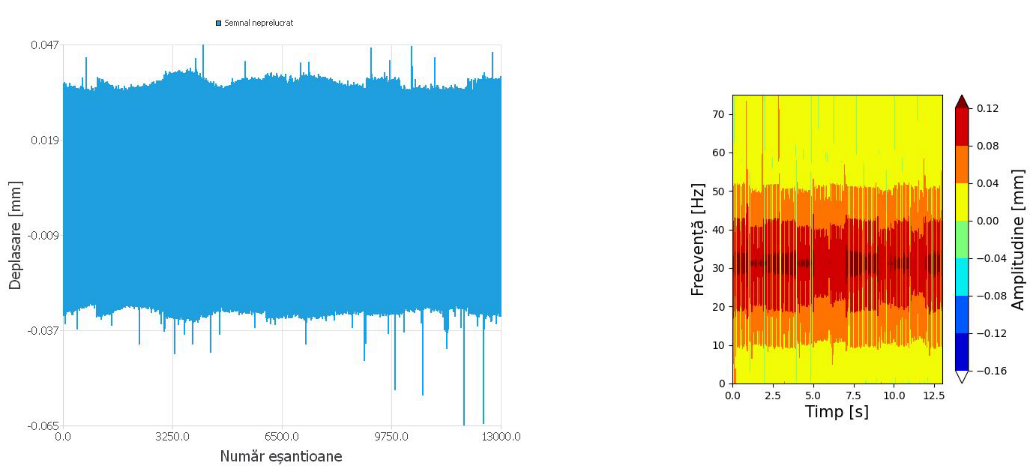


Figure 7.3: Signal sampled during nominal running (left) and the WPT scalogram (right)

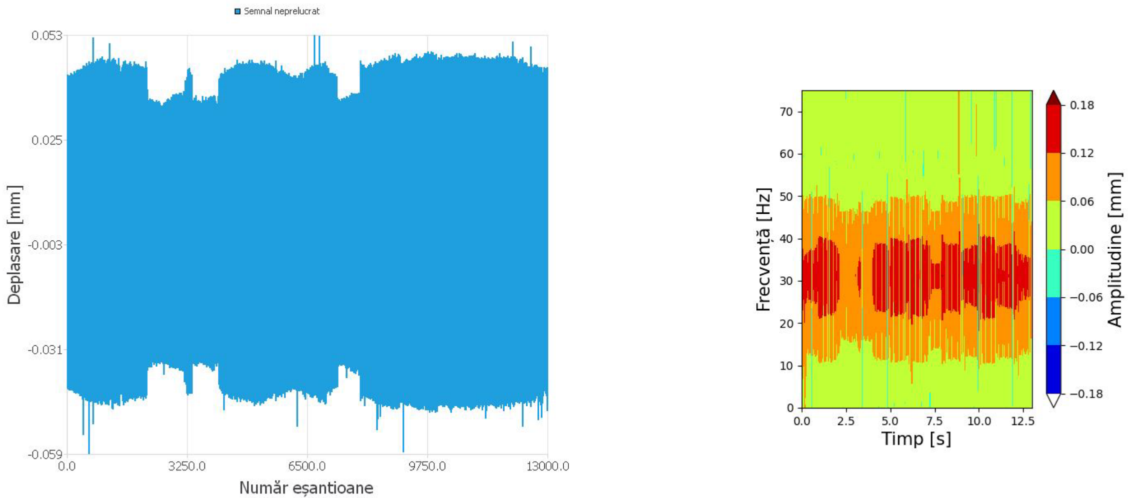


Figure 7.4: Signal sampled during braking (left) and the WPT scalogram (right)

From figure 7.4 energy decreasing can be observed when the braking of the shaft is executed (seconds 2.5 and 7.5). Data was recorded for when the rotation speed of the shaft goes over the critical value and the amplitude of the shaft's displacement increases (figure 7.5).

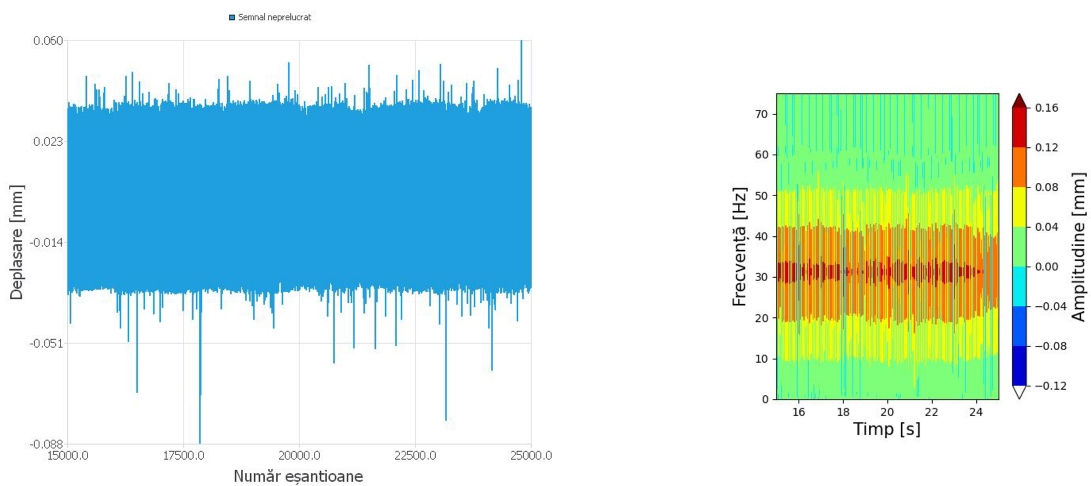


Figure 7.5: Sampled signal when the rotation speed goes outside the nominal running interval (left) and it's WPT scalogram

Evaluating the data presented graphically in figure 7.4 and 7.5, split up in samples by using a 500 ms window, the isolation forest identified a defect in the signal with the added braking with a probability of 65% and in the signal where the rotation speed goes beyond the critical value with a probability of 95%. In these situations, the algorithm sends a command to the microcontroller attached to the system for stopping it, avoiding further degradation. The results show that the diagnosis system is robust, and the probabilities show that even in the perturbance scenario, only a part of the samples can be considered as faults, those samples that are affected by the brake; as for the critical value of the rotation speed, almost all the samples are considered faults, reflecting the dynamics of the physical system.

7.2 Results obtained on data sampled from bearings

7.2.1 Differences between signal processing methods

In chapter 4 three signal processing methods were presented for the signals sampled by accelerometers. These methods are relevant for extracting useful features for an intelligent and vibration-based fault diagnosis system. Using these methods, features were extracted from a signal sampled by accelerometers from a bearing with the purpose of observing which method is more robust and can offer relevant information for complex mechatronic systems.

For testing the 3 methods, data sampled from bearings was used. The data comes from the University “Case Western Reserve”. The data is available at [29]. The tests were made using the application described in chapter 6.2 and the code developed by the author in python programming language is available in ***Anexa D***. Part of the functions reuse the code of the application in ***Anexa A***.

In the analyzed files there is data for functional bearings and for bearing with different faulty components. The faults are made through electromechanical discharge, and they are basically small dents on the surface of the component. The diameters of the punctures are between 0.178 mm and 1.1016 mm. The data was sampled with a sampling frequency of 12 kHz. The bearings type is 6205-2RS JEM SKF and the rotation speed is 1797 rpm. In Table 7.1 the bearing geometrical characteristics are displayed and in table 2 the fault frequencies are computed.

Tabelul 7.1: Bearing data

Interior diameter	25 mm
Exterior diameter	52 mm
Width	15 mm
Ball diameter	7.94 mm
Pitch diameter	39.04 mm

Tabelul 7.2 Fault frequencies for the observed bearings

Ford	107.36 Hz
Fird	162.18 Hz
Fbd	141.16 Hz
Fc	11.92 Hz

By applying the method of extracting MFCC (mel-frequency cepstrum coefficients), the cepstograms displayed in figures 7.6, 7.7, 7.8 were obtained. O cepstogramă este similară cu o scalogramă, însă axa ordonată conține numărul coeficienților cepstrali, fiecare coeficient corespunzând unui interval de frecvențe.

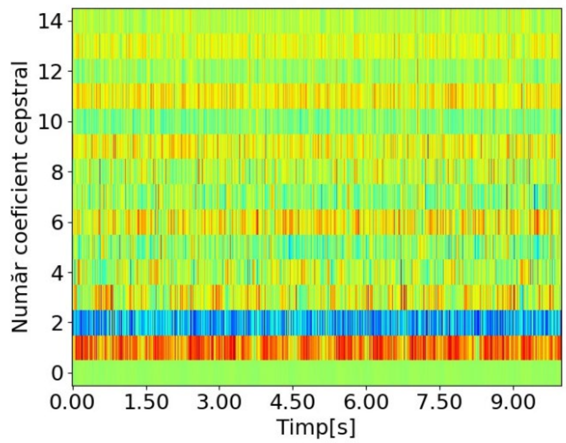


Figure 7.6: MFCC for a functional bearing

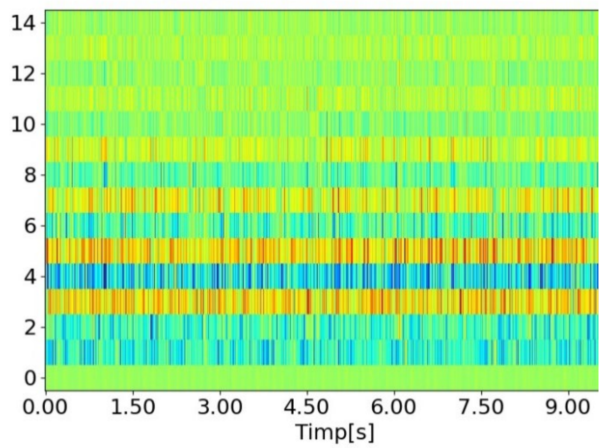


Figure 7.7: MFCC for a bearing with a fault on the inner ring

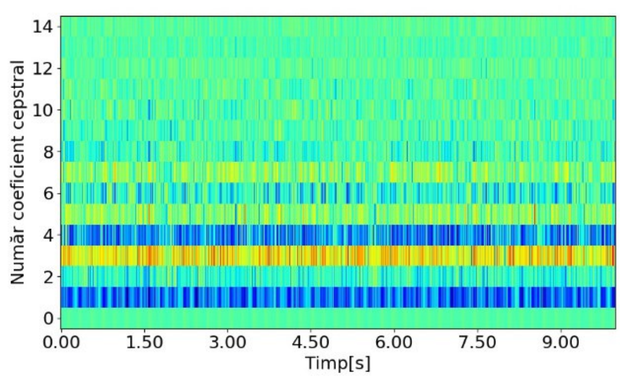


Figure 7.8: MFCC for a bearing with a fault on the outer ring

From figures 7.6, 7.7 and 7.8 there are differences between the cepstograms. A machine learning algorithm can easily classify the 3 states if there was data available for faults for each monitored component. This is not feasible though for a complex system, the fault diagnosis system having to store the knowledge gained in the industry about the vibration behavior of the components when a fault is present. This would allow classifying known faults based on vibration features. Another disadvantage of this method is that low frequency resolution.

A second method to process the signal is through decomposing it is using Wavelet packets. For the signal analysis, the application presented in 6.2 was used.

In the below figures, the scaolograms for the 3 analyzed signals are presented:

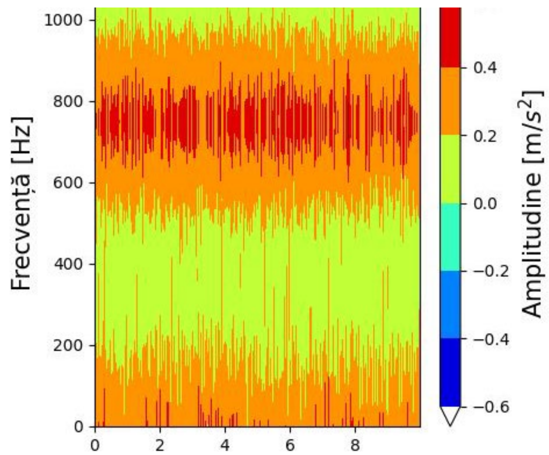


Figure 7.9: Scalogram for the signal sampled by an accelerometer from a functional bearing

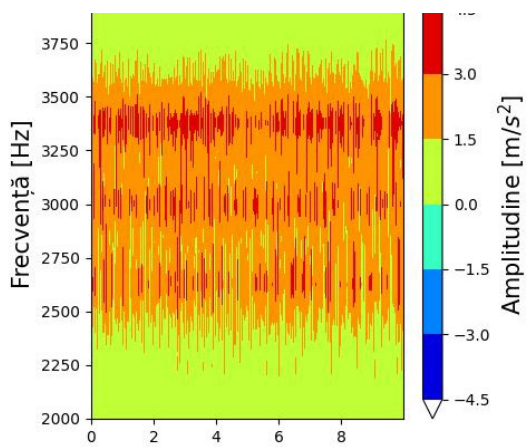


Figure 7.10: Scalogram for the signal sampled by an accelerometer from a bearing with a fault on the outer ring

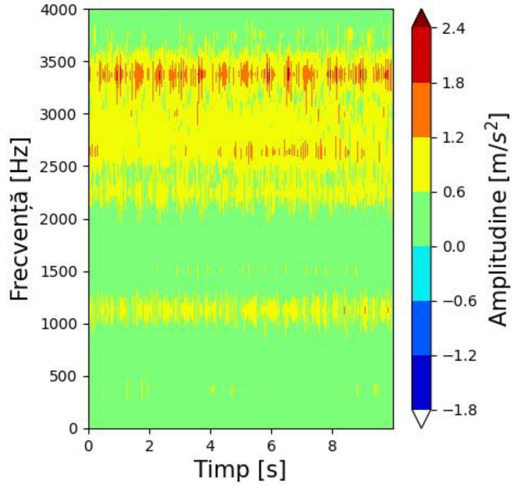


Figure 7.11: Scalogram for the signal sampled by an accelerometer from a bearing with a fault on the inner ring

The differences between the 3 scalograms are clear. Extracting the Wavelet packets binary trees and by analyzing the nodes' energies, the trees are different because the information that is relevant is only present in certain frequency bands, where the impact generated by the fault increases the signal's energy.

Using the algorithm described in 6.1.2 and analyzing the leaf nodes with the maximum energy from the optimal binary trees, the envelope spectrum signals for these nodes are:

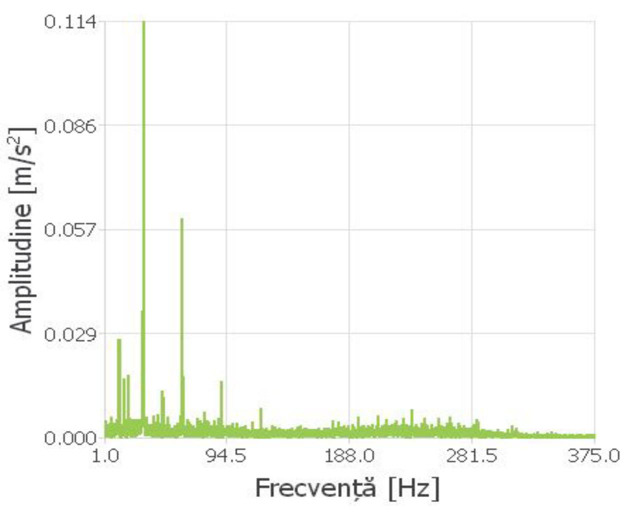


Figure 7.12 Envelope spectrum for the signal of a functional bearing for the 4th node on the 4th level of the decomposition tree (frequency band 750-1125 Hz)

For the functional bearing the dominating frequency is approximately 30 Hz, frequency correspondent to the rotation speed of the shaft of 1797 RPM.

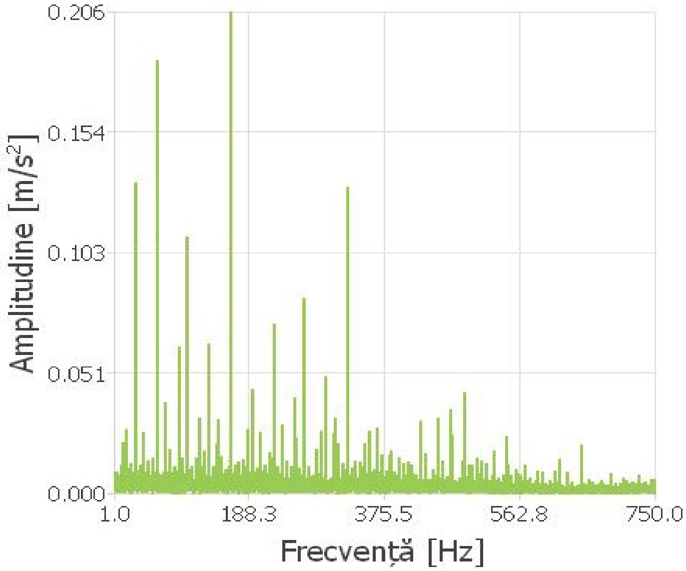


Figure 7.13: Envelope spectrum for the signal of a bearing with fault on the inner ring for the 7th node on the 3rd level of the decomposition tree (frequency band 3000-3750 Hz)

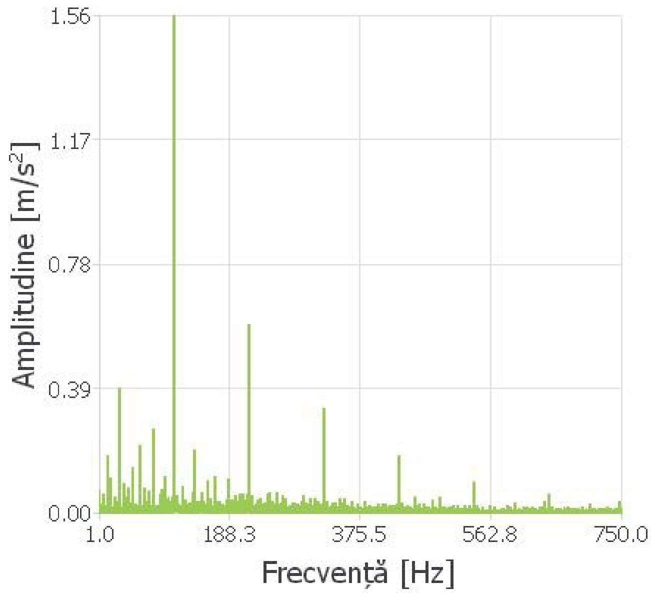


Figure 7.14: Envelope spectrum for the signal of a bearing with fault on the outer ring for the 7th node on the 3rd level of the decomposition tree (frequency band 3000-3750 Hz)

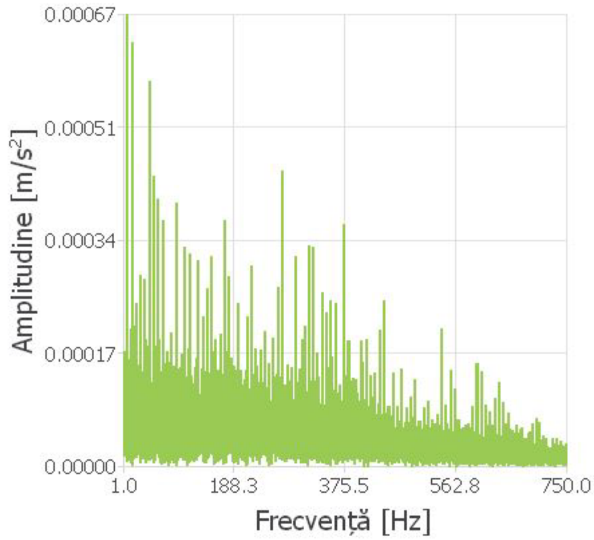


Figure 7.15: Envelope spectrum for the signal of a functional bearing for the 7th node on the 3rd level of the decomposition tree (frequency band 3000-3750 Hz)

In figures 7.13 and 7.14 the frequency peaks are at the fault frequencies (162 Hz and 107 Hz) for the inner and outer ring. In figure 7.15 the envelope spectrum of the node with the same frequency band is displayed as in the 7.13 and 7.14, but this time for a functional bearing. The amplitude values are very small compared to the peaks present for a faulty bearing.

Another important thing to consider is that the vibrations given by the faults are modulated in the same frequency band which is physically obvious given that the shaft's rotation speed is the same.

By applying the Goertzel algorithm presented in 6.1 on the signal extracted from the maximum energy node, the following values were obtained for the DFT coefficients:

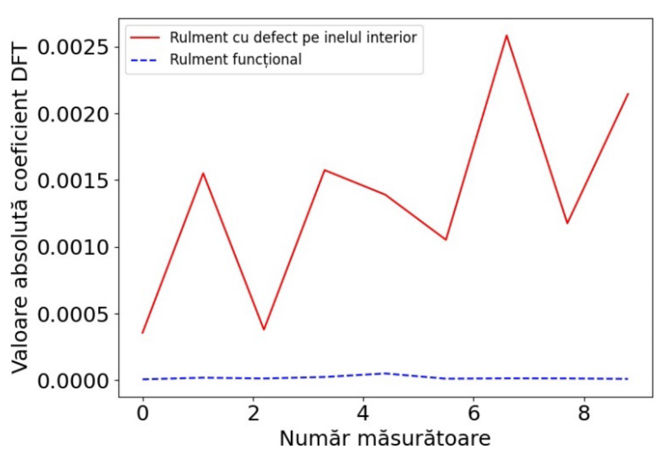


Figure 7.16: Comparison between the absolute values of the DFT coefficients for a functional bearing and a bearing with a fault on the inner ring

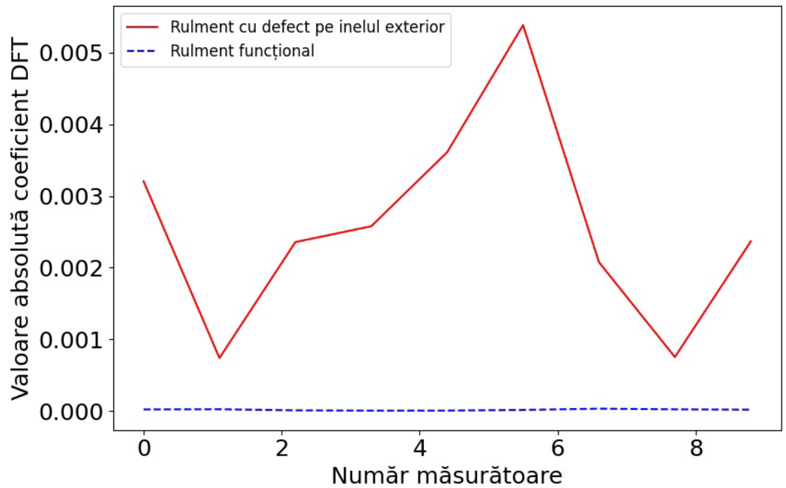


Figure 7.17: Comparison between the absolute values of the DFT coefficients for a functional bearing and a bearing with a fault on the outer ring

In figures 7.16 and 7.17 the differences between the amplitudes extracted using the Goertzel algorithm are clear.

7.2.2 Bearing fault diagnosis using the Kolmogorov-Smirnov statistical test

Using the algorithm described in 6.1.4.1, faults that may appear in bearings can be detected, using features extracted from the sampled vibration signal and using a distribution comparison with the recorded distributions for these features. The features can be extracted through the Goertzel algorithm, the most useful information being the amplitude at a given frequency.

For instance, the distributions from figures 7.16 and 7.17 are obviously different. In the following figures the empirical cumulative distribution functions (ECDF) for this data are presented:

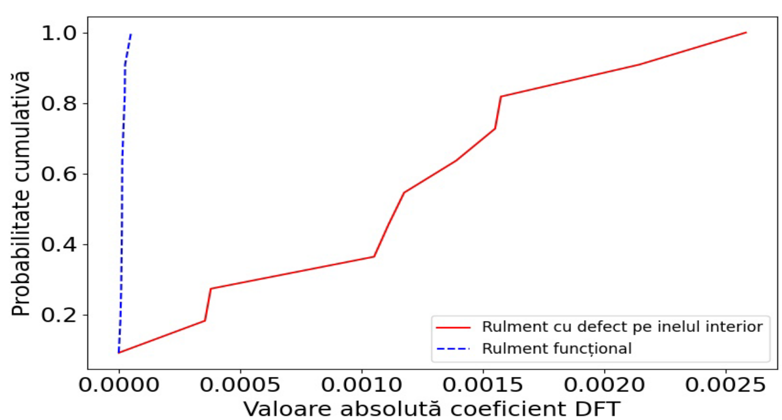


Figure 7.18: Comparison between ECDF of a functional bearing and for a bearing with a fault on the inner ring

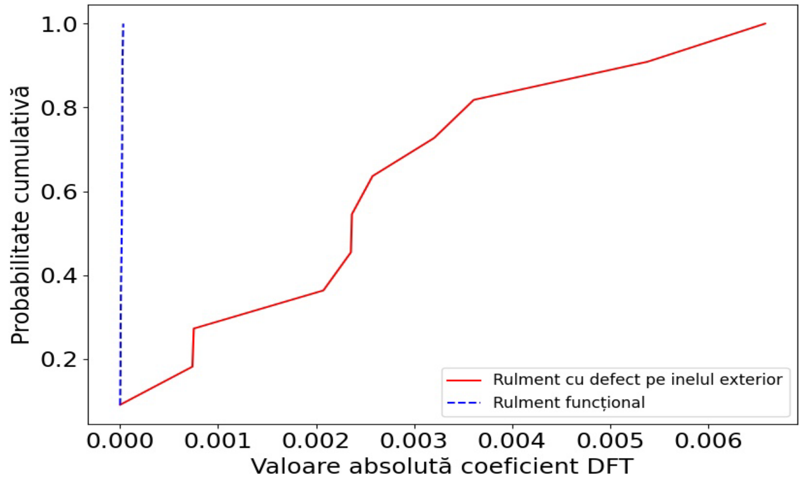


Figure 7.19: Comparison between ECDF of a functional bearing and for a bearing with a fault on the outer ring

If this data is used for applying the KS test (Kolmogorov-Smirnov), the faults are identified with the following probabilities (given 10 samples):

Table 7.3: Fault probabilities for bearings with faults on the inner and outer ring

P_{ext}	P_{int}
100%	100%

where P_{ext} is the fault probability for a fault on the outer ring and P_{int} is the probability for a fault on the inner ring.

7.2.3 Results obtained by applying a stop criterion to the empirical mode decomposition

In comparison to the Wavelet Packets decomposition, the signal processing through HHT can consume a lot more resources and time because of the way the intrinsic functions are extracted. The time wasted can be optimally eliminated by using the algorithm presented in chapter 6.1.2.2.

By applying this criterion, the following results were obtained:

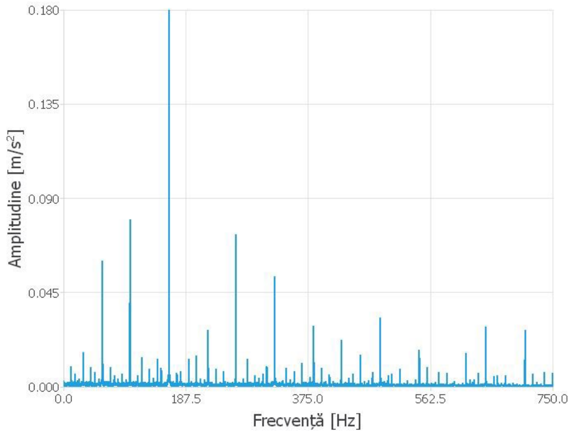


Figure 7.20: Spectrum of the intrinsic function at which the decomposition has stopped for a bearing with a fault on the inner ring

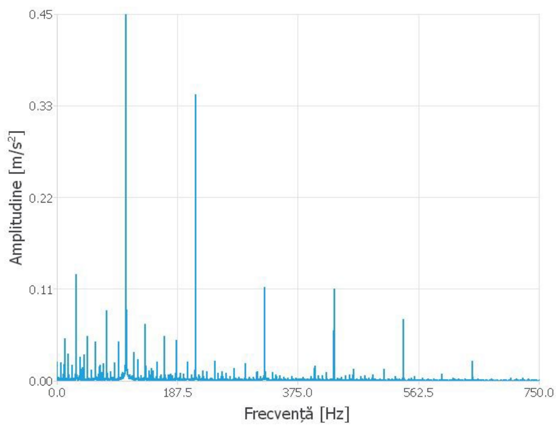


Figure 7.21: Spectrum of the intrinsic function at which the decomposition has stopped for a bearing with a fault on the outer ring

It can be noted from figures 7.20 and 7.21 that the algorithm stops at the correct intrinsic function, detecting the fault corresponding to the monitored frequencies.

As execution times, the following results were obtained:

Table 7.4: EMD execution time for a 10-second signal

Faulty component	EMD execution time without the optimization algorithm [s]	EMD execution time with the optimization algorithm [s]
Inner ring	64.1	5.2
Rolling element	12.9	1.1
Outer ring	81.1	31.6

Table 7.5: EMD execution time for a 1-second signal

Faulty component	EMD execution time without the optimization algorithm [s]	EMD execution time with the optimization algorithm [s]
Inner ring	0.7	0.1
Rolling element	0.2	0.07
Outer ring	2.9	2.7

7.3 Testing the detection algorithm on a mathematical model for the torsional vibrations in a gearbox

Some faults can be detected only through torsional vibrations, but sometimes these signals are very hard to sample from a real system. Having a working mathematical model for this kind of vibrations is useful for testing and implementing a diagnosis system. The described model is the subject of the article [30], published by the author in *Lecture Notes Network Systems, vol.143, 2020*.

7.3.1 Gearbox model

During the research of the PhD thesis, an article was published through which a model for the torsional vibrations given by a gearbox can be built. For implementing the mathematical model in a simulation environment, the software 20-sim was used, the equations being represented through the “Bond Graphs” framework. By using distributed parameters, a gearbox composed of two identical gears can be represented as:

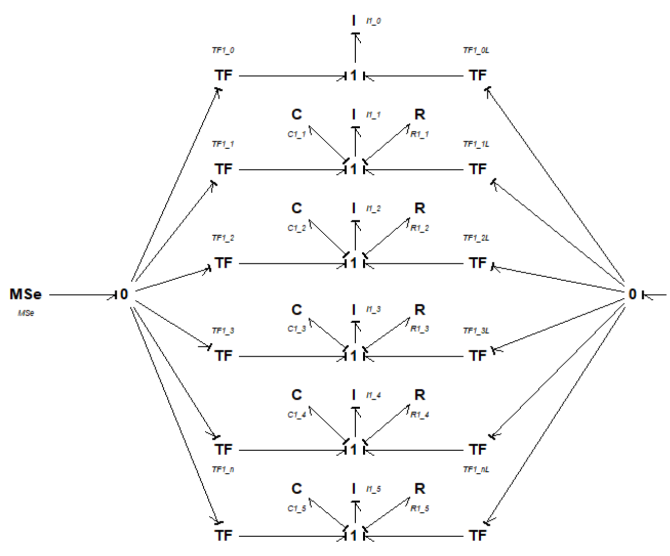


Figure 7.22: Bond Graph for the driving gear of a gearbox

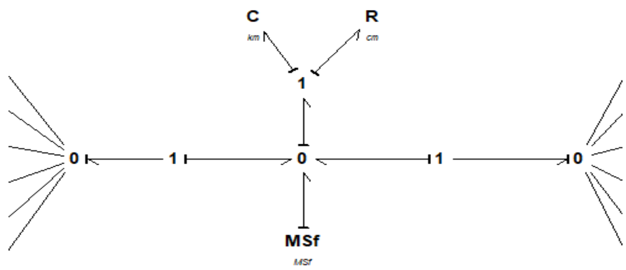


Figure 7.23: Bond Graph for the gears meshing

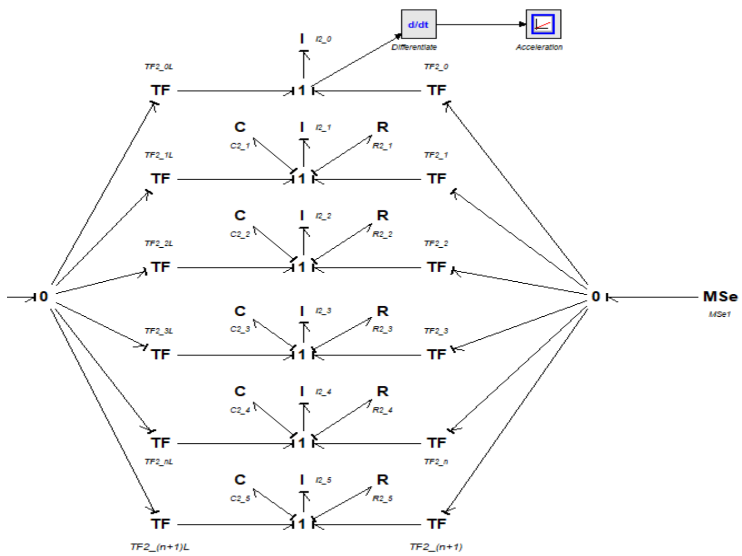


Figure 7.24: Bond Graph for the driven gear

7.3.2. Simulating torsional vibrations

The simulation was made using Bond Graphs and the software 20sim.

In the model from figure 7.22 there is a modulated flux source that allows adding an additional velocity in the model for the simulation of the fault. The velocity should be proportional to the rotation speed of the shaft and with the size of the fault. To test the above model, a gearbox composed of two identical gears is used and identical shafts. After the simulation with and without a fault, the rotational acceleration measured creates the following signals:

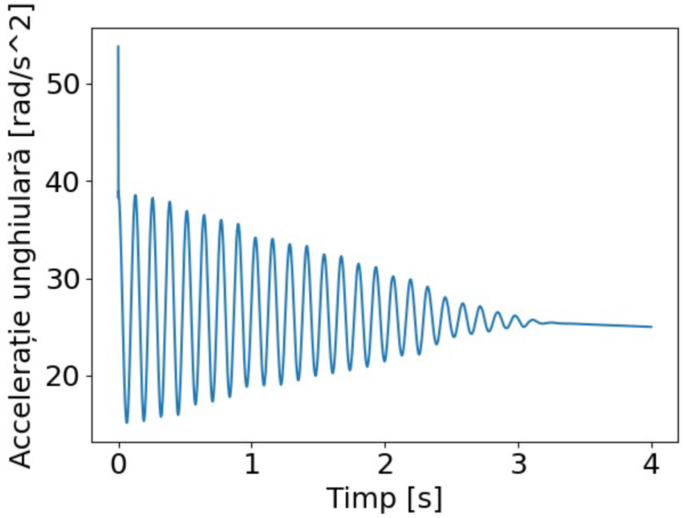


Figure 7.25: Rotation acceleration of the driven shaft for the gearbox without a fault

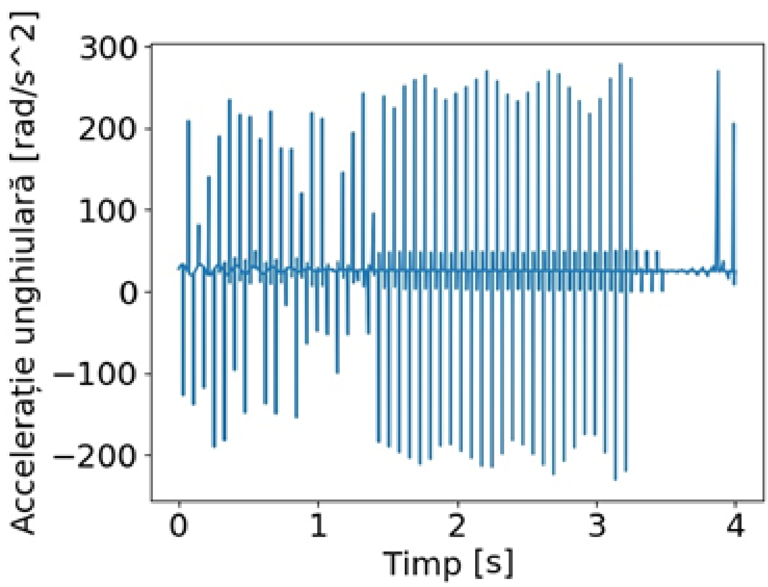


Figure 7.26: Rotation acceleration of the driven shaft for the gearbox with a fault

When impacts are generated every rotation, they have a pulsation of 85 rotations/s or 13.53 Hz, these being clearly visible in the signal's chart, offering the possibility to detect a fault. Hence, in figure 7.27 and 7.28 these signals were decomposed through Wavelet packets and the nodes with maximum energy were analyzed.

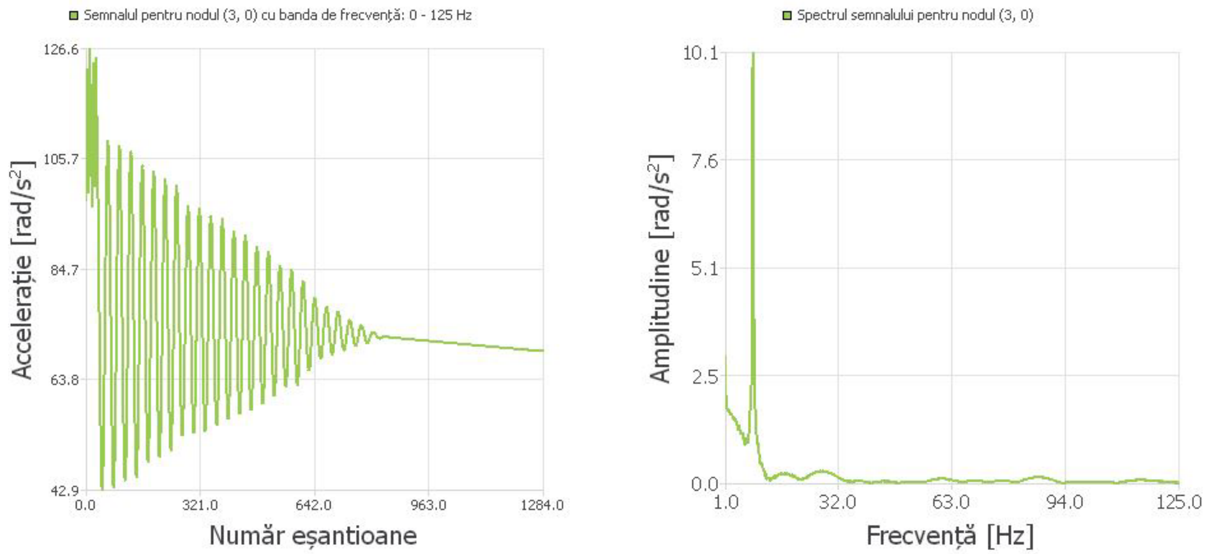


Figure 7.27: Signal from the node with maximum energy computed through WPT for the gearbox without a fault

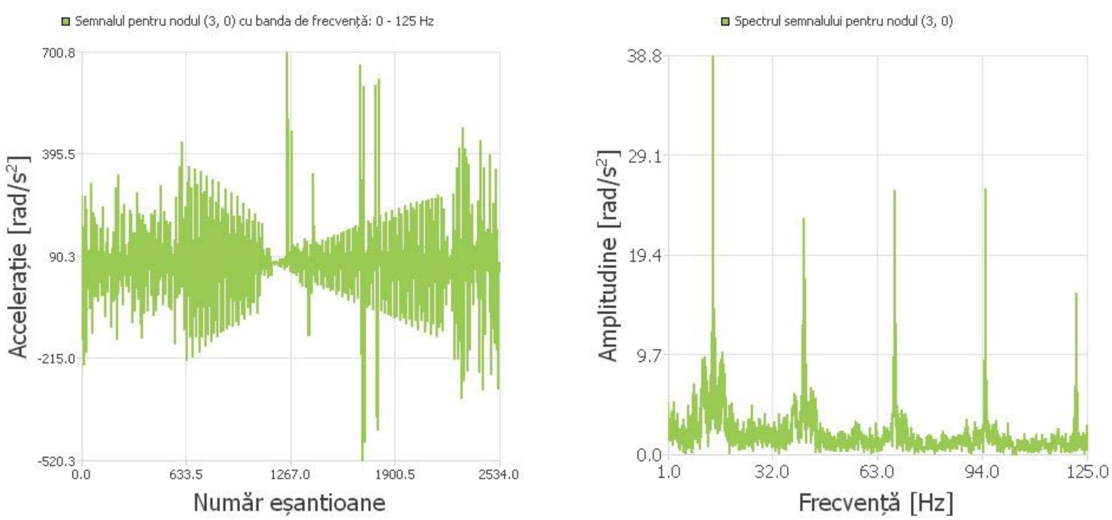


Figure 7.28: Signal from the node with maximum energy computed through WPT for the gearbox with a fault

In figure 7.28 in comparison to the same node from figure 7.27, the frequency with the maximum amplitude that dominates the signal is at 13.5 Hz, being the exact same frequency with which the fault is modulated in the system.

7.3.3. Diagnosing gearbox faults using the statistical test Kolmogorov-Smirnov

The algorithm presented in 7.2.1 and 7.2.2 was applied on the signals from figures 7.27 and 7.28 and the fault was successfully detected, bringing out the robustness of the algorithm and that it can be used on any fault that has a specific frequency.

The distribution of the absolute values of the DFT coefficients is below:

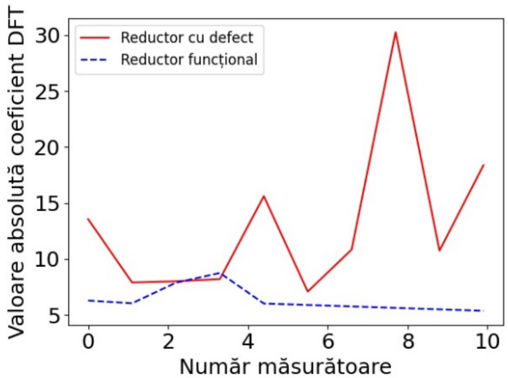


Figure 7.29: Comparison the absolute DFT coefficient values for a functional gearbox and for a faulty gearbox

The fault was identified with a probability of 100%. It needs to be noted that this algorithm must be tested on multiple datasets to have a meaningful statistical accuracy.

7.4 Testing the diagnosis system on a mechatronic translation positioning system

To test the proposed algorithms on a complex system, data was sampled from a mechatronic system. Based on this data, the above-mentioned algorithms were tested, and new intelligent approaches were proposed for diagnosing complex faults.

The accelerometers were mounted on a translation axis of a cartesian system as below:

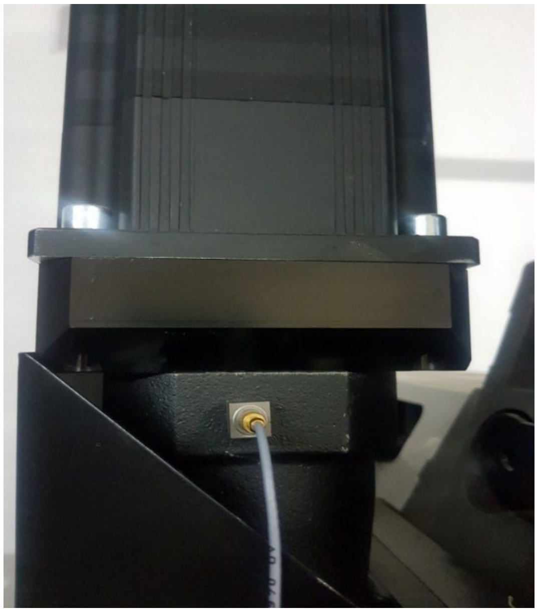


Figure 7.30: Mounting the first accelerometer on the exterior of the motor that puts into motion the monitored translation axis

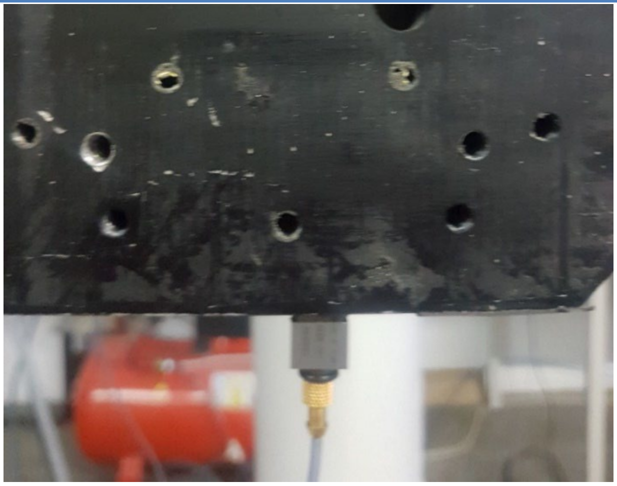


Figure 7.31: Mounting the second accelerometer on the effector in the movement direction of the axis actuated by the motor

As an acquisition board, NI 9234 from National Instruments was used:

Figure 7.32: Acquisition board NI 9234

For vibration sampling the software offered by National Instruments, LabView, was used.

In the next figures, the sampled data is charted during the motion of the monitored axis for a duration of 60 seconds:

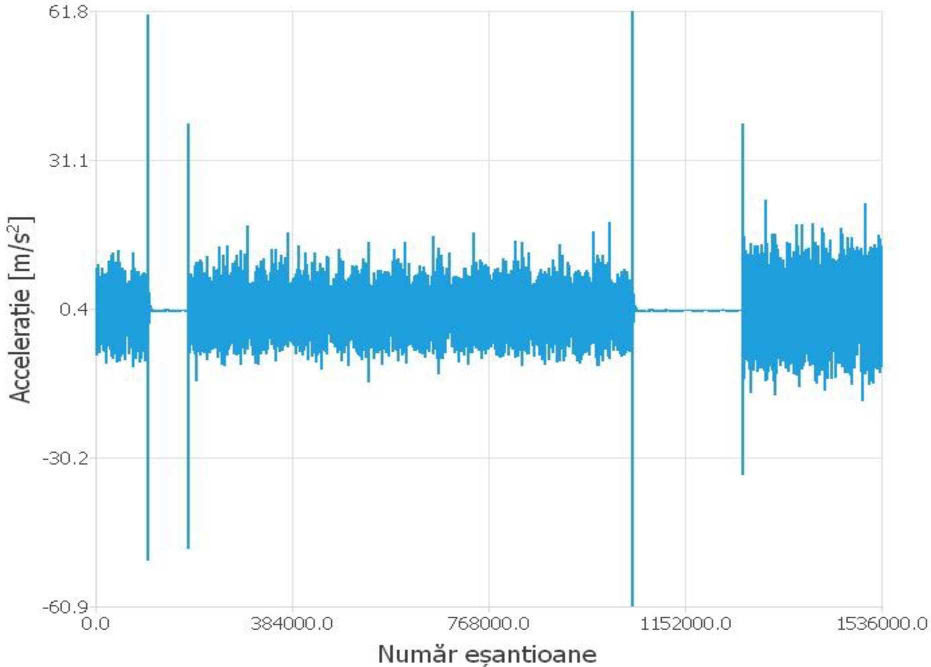


Figure 7.33: Motor signal

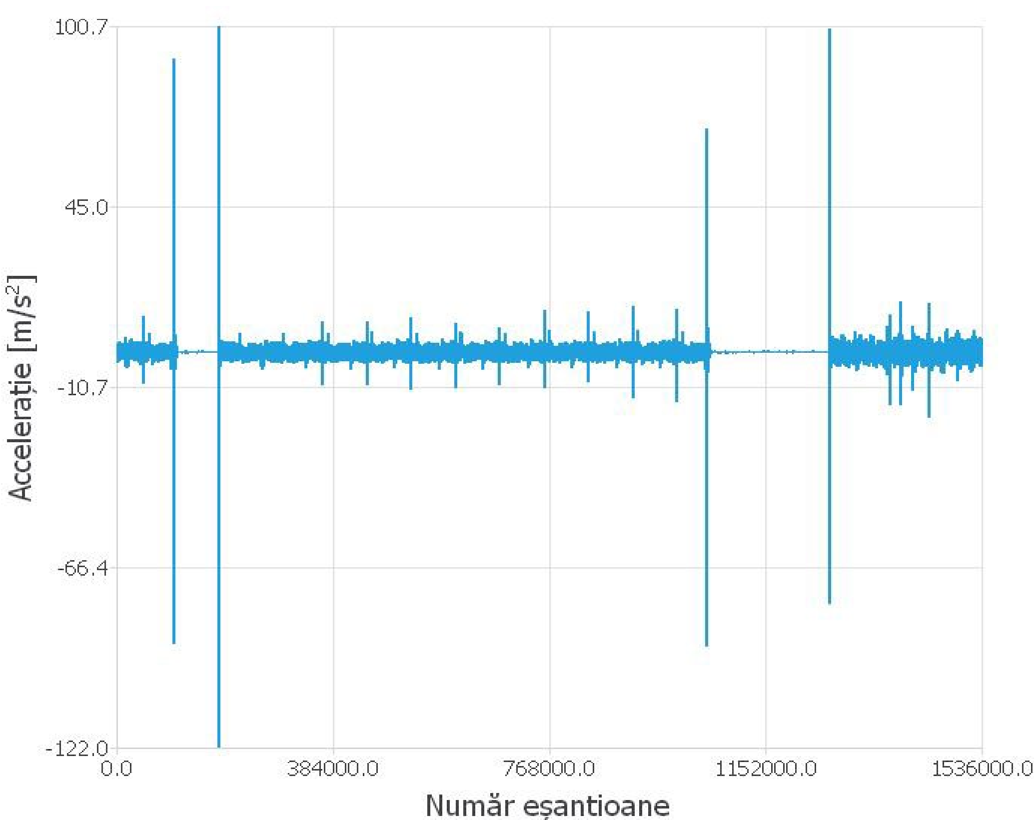


Figure 7.34: Effector signal

From figures 7.33 and 7.34 a correlation exists between the two signals so that the different behavior of the vibrations given by the motor affects the vibration signal sampled from the effector. Between the two signals, a mapping can be done which can represent the cinematic system that binds the actuating system from the driven system, the mapping representing a transformation operator. ***For obtaining the charts the application described in 6.2 was used. It is important to emphasize the importance of the developed software in signal analysis and applying different processing methods to assess the effectiveness on the analyzed signals.***

CHAPTER 8
CONCLUSIONS AND FURTHER WORK

8.1 Thesis objectives fulfillment

The goal of thesis is to develop a robust fault diagnosis system that may occur in a mechatronic system. The monitoring system can assure the adaptation of the machine's working program so that a fault tolerance behavior can be kept. Reiterating over the proposed objectives in the introduction, these have been fulfilled as follows:

I. "*Literature research to find state-of-the-art methods for fault diagnosis algorithms to improve them or propose new methods of assessing a system's state based on vibration data was done*" which demonstrates the enhancement and adapting the existing method for creating a robust fault diagnosis system (chapter 3).

II. "*Possible faults in mechatronic systems and ways to diagnose them using vibrations were identified.",* thing that helped identifying certain diagnosis algorithms that can be used for monitoring multiple components in the mechatronic system (chapter 2).

III. *"Main features from vibration data of the system's mobile components were extracted, sampled by acquisition of the acceleration signals from the monitored components and analyzing them using machine learning algorithms".* The features provide important information about the status of the system and can be easily analyzed by statistical algorithms or machine learning algorithms. Chapter 4 presents the methods of acquiring acceleration signals as well as different algorithms for processing them to obtain information of interest, intrinsic to the system.

IV. *"A robust fault diagnosis algorithm for different fault frequencies that can be used on multiple components was developed and implemented*". Chapter 6 presents different algorithms developed and implemented for the analysis of signals from different components that have known fault frequencies and based on which the system can be monitored. The results of applying these algorithms to different components are presented in Chapter 7.

V. *"A monitoring and predictive maintenance algorithm was developed for a mechatronic system formed by an actuating subsystem, transmission subsystem and the actuated subsystem (effector)"*, monitoring algorithm that combines signal processing techniques with specific artificial intelligence algorithms (Chapter 5) to detect and identify both faults with known and unknown vibratory behavior (by subsequent classification based on information from operators). Chapter 6 presents an application built for both this purpose and the advanced processing of acceleration signals to obtain useful features. The complex mechatronic system is dynamically characterized using only 2 accelerometers attached to the drive subsystem and the effector. Using data-based models and signal correlations, the power transmission system is also monitored, with the data acquisition subsystem being inexpensive and non-intrusive.

8.2. Personal contributions

The research and realization of the thesis lasted 4 years, of which 2 years were during the pandemic, which affected the possibility of extensive testing of the diagnostic system on real systems. However, different resources available in the virtual environment have been used to research and test different algorithms on different mechanical components and where this has not been possible, a mathematical model has been created for obtaining data through simulations.

In a robust diagnostic system that aims to diagnose as many defects in a mechatronic system as possible only through vibration signals, an interdisciplinary team usually works to ensure both mathematical correctness in relation to the acquired signals and the characteristics of known defects. as well as the implementation of the necessary programs for such a diagnostic system.

Thus, during the research and development of the thesis, the following contributions were made by methods, some of which, at the time of publication (to the author's knowledge), had not been addressed.

The main thesis contributions are:

- Using the Goertzel algorithm for extracting the Discrete Fourier Transform coefficients for the fault frequencies computed for bearings and gearboxes – the Goertzel algorithm is more time-efficient than the Fourier Transform when a small number of frequencies must be monitored. Thus, by using this algorithm, features were extracted that model the dynamic behavior of bearings and gearboxes
- Developing an intelligent statistical algorithm by using the Kolmogorov-Smirnov test, for fault detection from the feature distributions extracted for faults that appear in bearings and gearboxes – an intelligent method to "learn" the dynamic behavior of bearings/gearboxes given by the extracted features from the vibration signals

- *Modelling and simulating torsional vibrations in a gearbox by using distributed parameters and Bond graphs* – the torsional vibrations are harder to sample in real systems, but through a dynamic model using distributed parameters and Bond Graphs, the vibration signals were simulated, and the data was used to test fault diagnosis algorithms
- Modelling and training a neural network for characterizing the cinematic chain between the actuator and manipulator, using the features extracted from the data sampled by the accelerometers mounted on the actuator and manipulator – modelling such non-linear system presents a challenge and most analytical representations are far from the real system. Hence, obtaining a dynamic non-linear model based on data is robust, allowing capturing all the phenomena that may appear in the observed system
- Developing an intelligent stop criterion for the empirical model decomposition for fault diagnosis of faults with specific frequency – this signal processing algorithm is very robust; the decomposition being made in intrinsic modes to the signal. However, once a fault is diagnosed, the decomposition process is meaningless
- Developing a robust diagnosis system for a one-axis mechatronic system which allows the diagnosis of known faults and the recording and learning of new faults using supervised and unsupervised machine learning algorithms – the fault diagnosis is important for a system in time and to avoid production stalls. Sometimes, using a fault diagnosis system may be impossible because of the high cost and because this may be invasive. Developing and implementing a non-invasive and smart diagnosis system based on only 2 sensors could represent a big advantage in industry for whoever uses a mechatronic system which has actuators and effectors
- Developing a diagnosis software application which allows visualizing and processing of the sampled signals, as well as training the diagnosis system – a software application for visualizing and processing of signals sampled from one or two accelerometers through Wavelet Transform or Hilbert-Huang Transform and training the algorithm using this data (the application was written and Python by using QtPython for the user interface)
- Comparing different methods of signal processing for vibration signals by extracting relevant features for mechanical fault diagnosis – there are a lot of signal processing methods for diagnosis, but it is useful to use those that give the most relevant data for features that can be used in machine learning algorithms

8.3. Further work

The monitoring system needs to be extensively tested on complex mechatronics devices that have as many faults as possible. The 1-axis algorithm must be expanded to support additional axes and be as robust as possible.

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