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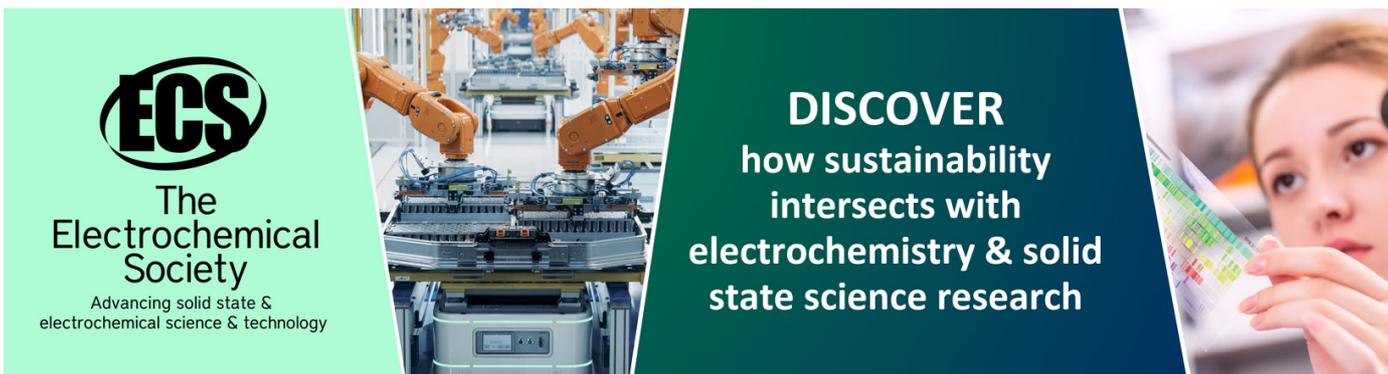
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Rolling element bearings fault classification based on feature extraction from acceleration data and artificial neural networks

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Abstract. This paper presents the development of an artificial neural network (ANN) model for rolling element bearings fault classification that uses features extracted from acceleration data collected during run-to-failure experiments. The presented approach initially employs a wavelet decomposition method for signal denoising and subsequently relies on a Fourier transform to analyse the acceleration signal in the frequency domain. Several features that correspond to the entire signal range as well as to specific frequency bands are then extracted and used as inputs in the ANN model, which is trained to identify three different operational states, namely, no fault, inner race fault and outer race fault. The developed ANN model is validated using experimental data from the publicly available dataset provided by the Center of Intelligent Maintenance Systems (IMS) of the University of Cincinnati. The results show that the trained ANN model has a classification accuracy of 90.2% in the training data and 100% in the test data.

1. Introduction

Predictive or condition-based maintenance (CBM) refers to a maintenance strategy where the relevant equipment is monitored during operation so as to identify patterns that are representative of evolving fault and failure mechanisms. Appropriate measures and actions can then be scheduled and performed only when they are necessary, resulting in significant cost savings and minimized equipment downtime compared to the, more common, preventive maintenance strategy [1]. Any effective implementation of CBM therefore requires a three step approach: i) design and deployment of an appropriate sensor and data collection system, ii) development of the required fault prediction and/or component reliability models based on the collected data and iii) design and deployment of an efficient decision making policy that dictates the most appropriate actions to be performed depending on the previous prediction models.

Modern manufacturing mainly uses equipment with rotating parts and components and among them, machine tools play a critical role in the global economy [2]. Focusing on cutting processes, one of the most important subsystems of a CNC machine tool is the main spindle assembly as it is responsible for providing the required power over a specific speed range while ensuring the desired precision [3]. The final performance characteristics of the spindle assembly depend on the individual performance of its components, especially the motor, shaft and bearings. For the latter, their role is to support and accurately locate the shaft, while reducing friction despite the static and dynamic loads and thermal conditions that they are subjected. While there are many types of bearings that are used in spindle



assemblies, the most common type is rolling element bearings due to their low cost and ease of lubrication.

Bringing the concepts of CBM and machine tool spindles together, there have been studies that have identified spindle failures as one of the key sources of machine tool downtime [4] and similarly, bearing problems as one of the key sources of spindle failures [5]. The recommended approach for CBM implementation in these cases is to monitor mechanical vibrations. Initially, a baseline level that corresponds to normal operation is established, which is compared to any other subsequent measurement. As the vibration levels increase, the larger the deviation from this baseline becomes, which indicates a larger probability for failure to occur. There is an abundance of published work that studies the various vibration characteristics to evaluate the actual condition of bearings. Regardless of the specific approach that is adopted, a common initial step is followed, dealing with feature extraction from the collected experimental data. Typically extracted features include RMS, kurtosis, skewness and crest factor in the time domain and power peak, spectral area and kurtogram in the frequency domain [6-8]. In recent years, there is a trend of using data-driven, i.e. machine learning methods to fuse such features so as to develop the relevant predictive models [9-12]. The main advantages of these methods is that the developed models can be easily integrated in on-line monitoring and control schemes, they possess an inherent robustness when dealing with noisy data and can offer increasingly higher prediction accuracy as more data are collected over time [13].

This paper focuses on developing an artificial neural network (ANN) model that is able to classify the operational state of a rolling element bearing in one of three possible classes, namely without fault, with inner race fault or with outer race fault. To achieve this goal, the ANN model uses as inputs features that have been extracted from acceleration data collected during run-to-failure experiments. Section 2 presents the proposed approach, which involves signal denoising based on wavelet decomposition, frequency domain analysis through a Fourier transform, feature extraction and finally ANN model development. Section 3 presents the model validation procedure using a publicly available dataset and the obtained results and finally, Section 4 summarizes the obtained conclusions and offers suggestions for future work.

2. The proposed approach

The proposed approach can be implemented according to the flowchart shown in Figure 1.

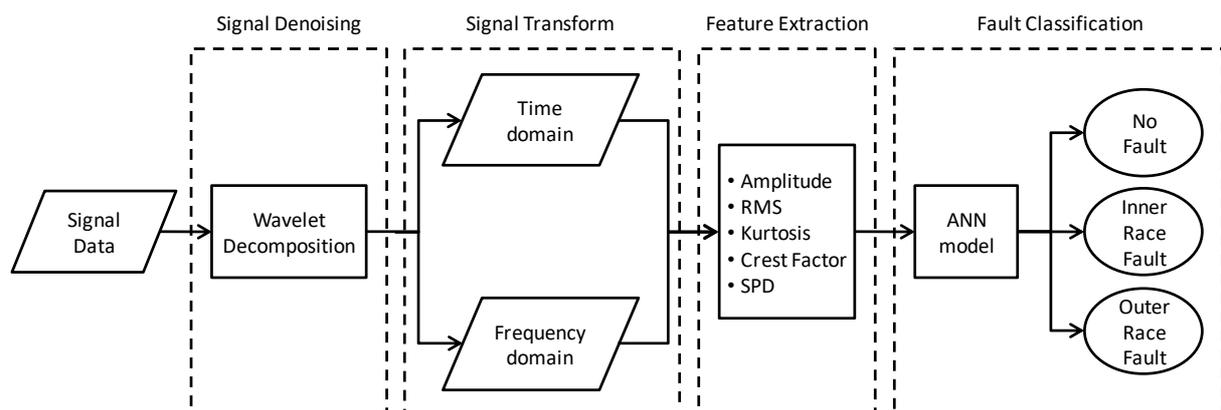


Figure 1. Flowchart of the proposed approach.

The approach is independent of the way that the necessary mechanical vibration signal is collected. Instead, it assumes that the relevant data are already available and focuses on how to process them so as to successfully develop the fault classification model. As can be seen, there are four main stages involving signal denoising, signal transform, feature extraction and fault classification respectively.

2.1. Signal denoising

In the majority of applications, vibration data are collected through appropriate sensors, e.g. accelerometers, that are installed on, or as close as possible to, the bearing housing. Any such experimental setup will also include additional mechanical components and parts that effectively act as significant noise sources therefore corrupting the measurements that characterize the bearing operational state. In the general case, the noisy signal can be represented by equation (1):

$$x(n) = s(n) + \sigma w(n) \tag{1}$$

where $x(n)$ is the noisy signal, $s(n)$ is the desired signal, $w(n)$ can be considered as Gaussian white noise and σ is a constant number indicating noise level. Therefore, the objective of the denoising process is to suppress $w(n)$ and recover $s(n)$.

Wavelet decomposition has been successfully applied for denoising vibration signals as shown in [14]. The method involves three steps:

- Signal decomposition that is accomplished by initially choosing a wavelet and level N and subsequently computing the wavelet decomposition of the $x(n)$ signal at level N
- Thresholding of detail coefficients, during which a threshold is selected for each level from 1 to N and is applied to the detail coefficients and
- Signal reconstruction that is accomplished by using the original approximation coefficients of level N and the modified detail coefficients of levels 1 to N.

The main advantage of this method is optimal noise reduction with simultaneous preservation of the signal. Moreover, it can also be implemented with computational efficiency in either software and/or hardware form as shown in [15] and for these reasons, it was adopted in this work.

2.2. Signal transform

The sensors that collect the vibration data essentially provide a series of amplitude measurements as a function of time. The analysis of such vibration data in the time domain is limited to only a few statistical parameters that mostly quantify the strength of the vibration profile such as amplitude, RMS, kurtosis and crest factor to name the most common (see Table 1).

Table 1. Time domain statistical parameters.

Parameter	Usage	Definition
RMS	Value increases gradually as fault develops	$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2}$
Kurtosis	Ideally, for rolling element bearings without faults it should be equal to 3	$Ku = \frac{1}{N} \sum_{i=1}^N \left(\frac{x_i - \bar{x}}{\sigma} \right)^4$
Crest factor	Appropriate for impulsive signals	$CF = \frac{\max(x_i)}{\sqrt{(1/N) \sum_{i=1}^N x_i^2}}$

However, it is also important to determine the frequency characteristics of the vibration and therefore the analysis also takes place in the frequency domain after a Fourier transform has been performed. In this way, the causes of the vibration can be identified by observing peaks at specific frequencies. In the case of rolling element bearings, this is highly desirable for two reasons. Firstly, because the evolution of faults in the bearing will generate characteristic failing frequencies that can be typically found in low ranges and which can be easily verified by observing the spectrum. Such examples are the ball pass

frequency outer (BPFO), ball pass frequency inner (BPFI) and ball spin frequency (BSF). Secondly, because through further evaluation of the obtained spectrum, specific frequency bands (close to the failing frequencies or to their harmonics) can be selected for feature extraction based on the assumption that these frequencies will contain the most useful information for fault detection.

To further enhance this assumption, the kurtogram method was also used to detect the presence of nonstationary transient faults and accurately indicate their location in the frequency bands [16].

2.3. Feature extraction

The main task of the third stage is to extract the appropriate features from both the time and frequency domains in an attempt to gather as much information as possible about the current vibration state of the rolling element bearing. Especially for the frequency domain and as previously described, some of these features will be extracted from the entire frequency range, while there will also be features specific to certain frequency bands that are identified through manual inspection of the spectrum and kurtogram.

For each of the identified frequency bands the features of Table 1 will be extracted, supplemented by the Power Spectral Density (PSD) value. The reason to include PSD in the approach is that in this way random vibrations can also be accounted for. This is possible since PSD is computed by multiplying each frequency bin in an FFT by its complex conjugate, which results in the real only spectrum of amplitude, and then normalizing this amplitude to the frequency bin width.

Therefore, the final set of features that will be extracted will depend on the number of identified frequency bands and in general will have the following composition (Figure 2).

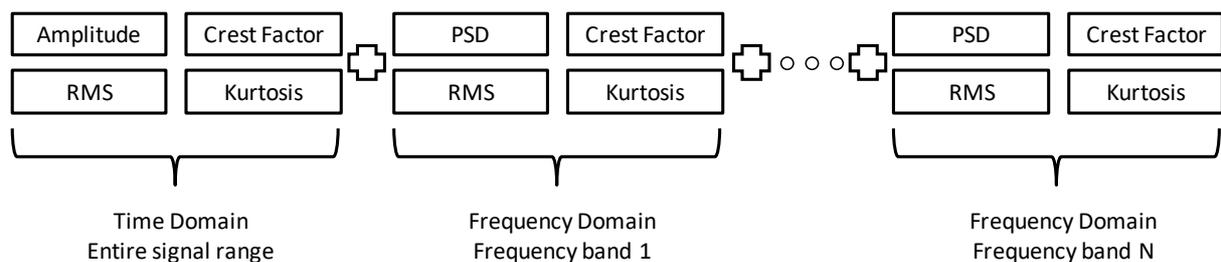


Figure 2. Set of extracted features.

2.4. Fault classification

The final stage of the proposed approach deals with using the extracted features to develop a fault classification model. As previously mentioned, machine learning methods have exhibited very good results in successfully developing accurate and consistent predictive models, see Section 1. In the proposed approach, a feedforward ANN is used to treat the fault prediction as a classification problem. The aim is to be able to classify the operational state of the rolling element bearing in one of three distinct classes, namely without fault or with an inner race fault or with an outer race fault. Therefore, the architecture of the ANN model comprises as many input neurons as the number of extracted features and three output neurons, effectively adopting the "1-of-C" coding scheme for its output in order to perform the actual classification task.

It has to be noted that determining the optimal number of hidden layers and hidden neurons is a case dependent problem. In the simplest implementation, a repetitive trial-and-error procedure can be followed, while more systematic approaches can be used as well.

The choice of a feedforward ANN model, combined with the choices made in the previous stages of the approach, ultimately aims at developing a rolling element bearing fault classification system with low computational requirements that can be deployed as a near real-time health monitoring system with low additional effort and cost. Once the ANN model has been trained, it can be straightforwardly deployed through an FPGA for an on-the-edge application.

3. Experimental validation and results

3.1. Validation

In order to validate the proposed approach a publically available dataset was used provided by the Center for Intelligent Maintenance Systems (IMS) of the University of Cincinnati with support from Rexnord Corp. [17]. The dataset comprises data collected from a specially designed test rig as shown in Figure 3. The test rig used an AC motor and belt to drive a shaft that was supported by four double row bearings. A constant radial load was applied by means of a spring mechanism and a constant rotational speed of 2000 RPM was selected. A set of accelerometers and thermocouples at each bearing was used to sample data at 20 kHz and the test rig was left to run until a failure in any of the bearings occurred. This experiment was ran three times; in the first run, the third bearing developed an inner race fault and the fourth bearing developed a rolling element fault, in the second run, the first bearing developed an outer race fault while in the third run, the third bearing developed an outer race fault.

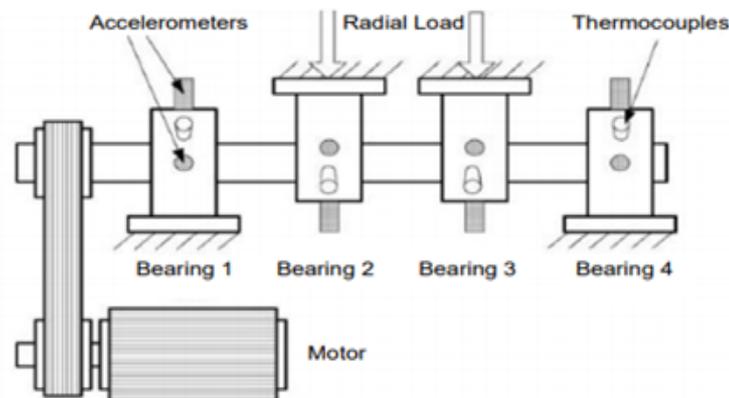


Figure 3. Test rig for IMS bearing dataset [14].

In this paper, data corresponding to the first and second runs were used so that a total of three operational states could be evaluated, namely a bearing with no fault, a bearing with inner race fault and a bearing with outer race fault. Furthermore, as the original data spanned a very large time interval of several days until the faults occurred, a uniform sampling procedure was employed. Thus, a total of 102 samples were selected, with 52 samples originating from the first experimental run and 50 samples originating from the second experimental run. Additionally, the 52 samples from the first experimental run were further divided so that 30 samples represent the no fault operational state and 22 samples represent the inner race fault operational state. Similarly, the 50 samples from the second experimental run were further divided so that 30 samples represent the no fault operational state and 20 samples represent the outer race fault operational state.

3.2. Results

As per the proposed approach, the raw time domain data were denoised using the described wavelet decomposition method. For the specific application, a level of $N=5$ was selected for the signal decomposition step along with Stein's unbiased risk estimate (SURE) thresholding selection rule for the wavelet coefficients. Figures 4 and 5 present the raw and denoised signals respectively.

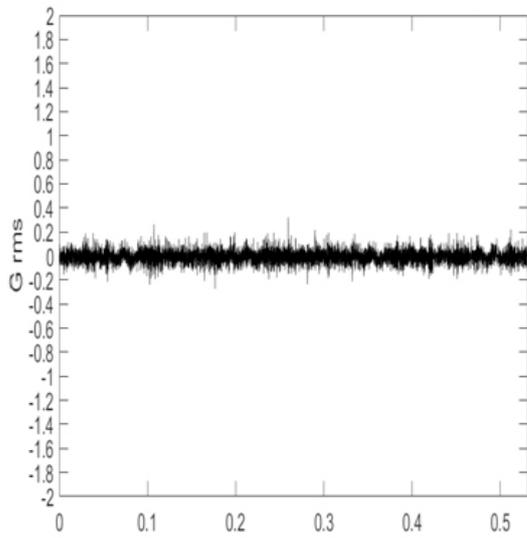


Figure 4. Raw acceleration signal in the time domain.

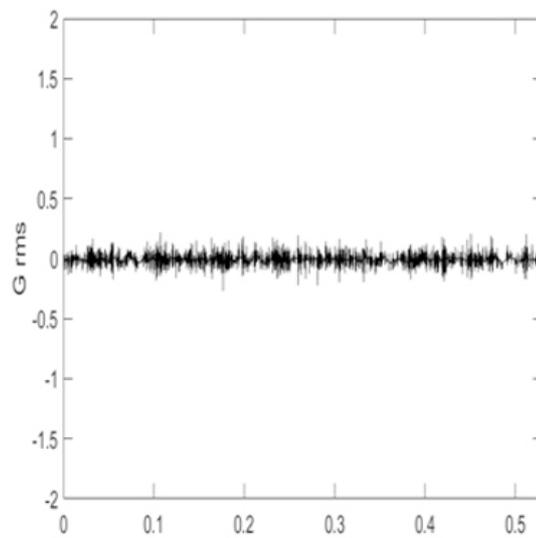


Figure 5. Denoised signal after wavelet decomposition.

Following with the signal transform stage, FFT was performed to obtain the signal in the frequency domain. Figure 6 shows the spectrum corresponding to a sample of the first experimental run for which the inner race fault has already occurred, resulting in the presence of characteristic failing frequencies and harmonics.

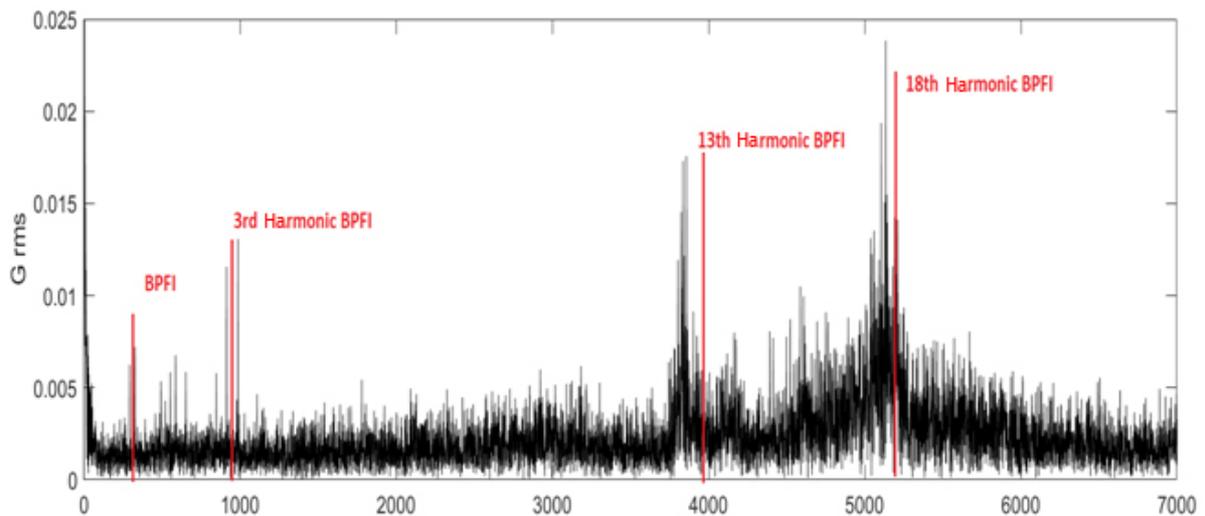


Figure 6. Frequency spectrum of acceleration signal corresponding to inner race fault.

As also discussed in section 2.2, kurtograms were calculated to assist in identifying desirable frequency bands for feature extraction. Figure 7 shows the kurtogram for the same sample as the one in Figure 6. As supported by both Figures 6 and 7, the frequency band between 4 and 6 kHz that contains the 13th and 18th harmonics of BPF1 are good candidates for feature extraction.

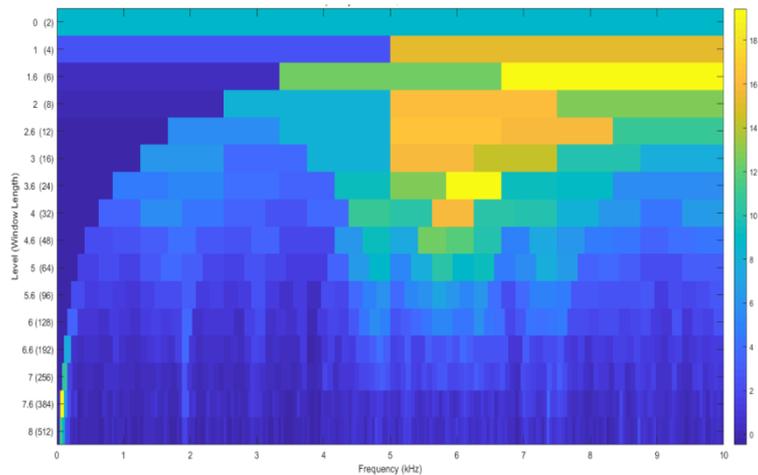


Figure 7. Kurtogram corresponding to inner race fault.

Furthermore, another two frequency bands between 100 to 500 Hz and between 500 Hz to 1 kHz were also selected resulting in a total of 20 extracted features to be used as inputs for the feedforward ANN model.

To develop and train the ANN model a repetitive trial-and-error procedure was selected using confusion matrices to evaluate the performance of each model. As is typical, the total 102 samples were divided to form three subsets, one used for training (approx. 80% or 82 samples), one used for early stopping of the training procedure (approx. 10% or 10 samples) and one to be used as unknown data (approx. 10% or 10 samples) so as to test the ANN's generalization ability. The ANN with the best performance had 2 hidden layers with 20 hidden neurons each for a 20x20x20x3 final architecture. The confusion matrices of the training and test subsets are shown in Figures 8 and 9 respectively. Class 1 represents the no fault state, class 2 the inner race fault and class 3 the outer race fault. It can be clearly seen that the ANN model has very high accuracy both in training (90.2%) and testing subsets (100%) and is therefore suitable for rolling element bearing fault classification.

Training Confusion Matrix

	1	2	3		
Output Class	1	46 56.1%	2 2.4%	5 6.1%	86.8% 13.2%
	2	0 0.0%	17 20.7%	0 0.0%	100% 0.0%
	3	1 1.2%	0 0.0%	11 13.4%	91.7% 8.3%
		97.9% 2.1%	89.5% 10.5%	68.8% 31.3%	90.2% 9.8%
	Target Class				

Figure 8. Training confusion matrix.

Test Confusion Matrix

	1	2	3		
Output Class	1	6 60.0%	0 0.0%	0 0.0%	100% 0.0%
	2	0 0.0%	2 20.0%	0 0.0%	100% 0.0%
	3	0 0.0%	0 0.0%	2 20.0%	100% 0.0%
		100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%
	Target Class				

Figure 9. Testing confusion matrix.

4. Conclusions and future work

This paper presented the development of a rolling element bearing fault classification approach based on an ANN model. The ANN model uses as inputs features that are extracted from the time and frequency domains and correspond to the entire signal range as well as to specific frequency bands. In summary, the following conclusions can be drawn:

- The presented approach is generic and can be applied to any rolling element bearing fault classification problem.
- The extracted features represent the entire time domain as well as specific frequency bands that are manually identified by observing FFT obtained spectrums and kurtograms.
- The final ANN model is able to classify with very high accuracy (90.2% in training data and 100% in testing data) the different fault types of rolling element bearings.

In terms of future work, the two main directions that will be explored concern the investigation of dimensionality reduction techniques to decrease the number of ANN inputs without loss of classification performance and the automated kurtogram evaluation to systematically identify critical frequency bands.

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