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The application of wavelet analysis and neural networks in the diagnosis of rolling bearing faults in induction motors

***Abstract**. The paper describes a monitoring method of damage detection in induction motor rolling bearings. The method is based on wavelet transform analysis of vibration. The possibility of the application of neural networks to detect bearing faults was presented. The quality of bearing faults detection and identification methods was tested experimentally. The experiments have been conducted on induction motors with bearing faults. The correctness of the proposed methods has been confirmed by satisfactory tests results.*

***Streszczenie.** W pracy przedstawiono metodę monitorowania stanu łożysk tocznych silników indukcyjnych opartą na analizie falkowej. Omówiono dyskretną transformatę falkową oraz jej uogólnienie w postaci pełnego przekształcenia falkowego. Przedstawiono możliwość zastosowanie sieci neuronowych do wykrywania uszkodzeń łożysk tocznych. Eksperymentalnie sprawdzono możliwość wykrywania oraz identyfikowania uszkodzeń poszczególnych elementów konstrukcyjnych łożysk. Przedstawiono przykładowe wyniki badań laboratoryjnych. Dokonano oceny skuteczności wykrywania uszkodzeń łożysk tocznych w silnikach indukcyjnych przy wykorzystaniu analizy falkowej przyspieszenia drgań oraz sieci neuronowych. (**Zastosowanie analizy falkowej i sieci neuronowych do diagnostyki łożysk tocznych silników indukcyjnych**)*

Keywords: condition monitoring of rolling bearings, induction motors, wavelet analysis, neural networks.
Słowa kluczowe: monitorowanie stanu łożysk tocznych, silniki indukcyjne, analiza falkowa, sieci neuronowe.

Introduction

The non-stationary character of the available diagnostic signals results in the fact that in recent years wavelet analysis has been used more and more frequently used to detect fault symptoms in induction motors. The approach assumes that the diagnostic signal in the time domain can be decomposed to components of various time windows and various frequency bands, and the information obtained in this way can be presented in a time-scale domain. On account of the character of the frequency response, the approach is effective for both long, low frequency signals and short, high frequency signals. The wavelet approach has advantage over the traditional Fourier transform in the case of the analysis of incoherent and short-impulse signals (non-stationary processes). The Fourier transform brings the change of signal representation from the time domain to the frequency domain, which results in a loss of time information and in consequence interpretation difficulties. The wavelet transform is free from this disadvantage as the signal it represents is shifted and rescaled in relation to the so called wavelet matrix. This allows for signal frequency information analysis during its development in time. The ability to represent the signal simultaneously in the time and frequency domains is a very important advantage of wavelet transform [1], [2].

It turns out that non-stationary signals with sharp changes may be easier recognized when an irregular wavelet is used than in decomposition to regular sinusoids [3]. This is why the choice of appropriate type of wavelet is so important when the wavelet analysis is used. Currently the most commonly used wavelet in the diagnostics of induction motors is the Daubechies wavelet [4], [5], [6].

The article presents the results of the application of the wavelet analysis of vibration acceleration in detection of rolling bearing faults in mains-electricity powered induction motors. Wavelet analysis algorithms, available in the LabVIEW programming environment, were used in the research. In addition the article presents the possibility of using neural networks, based on the information obtained from the wavelet analysis in rolling bearings fault detection.

Wavelet analysis – basic information

Continuous Wavelet Transform (CWT) is defined by the following equation [1]:

$$CWT\ x(a,b)=\int_{-\infty}^{\infty} x(t)\cdot\psi^{*}_{a,b}(t)dt \tag{1}$$

where: a – scale coefficient, b – displacement coefficient, * – complex function conjugate, and

$$\psi_{a,b}(t)=\frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right) \tag{2}$$

where: $a,b \in$ R i $a \neq 0$.

In the case of continuous wavelet transform, it is assumed that the scale coefficient a and the displacement coefficient b are continuous functions. When the transform parameters are discreet functions, transformation (1) describes the so called Discrete Wavelet Transform (DWT). Since it is assumed that the scale coefficient a and the displacement coefficient b change at multiplicity 2, displacement (1) takes the following form [2]:

$$DWT\ x_{jk}=\sum_{n=0}^{N-1} x(n)\psi^{*}_{jk}(n) \tag{3}$$

where:

$$\psi_{jk}(n)=2^{-j/2}\psi\left(2^{-j}n-k\right) \tag{4}$$

It is assumed that: $n \cdot T$ – signal duration time $x(t)$, T – signal sampling time $x(t)$, N – number of samples defined by wavelet occurrence limits $\psi_{jk}(n)$.

The discrete wavelet transform allows to divide the input signal $x(t)$ into two components, whose frequency bands occupy half of the band signal $x(t)$. The components are obtained by signal filtration with a low-pass filter and a high-pass filter respectively as well as a signal re-sampling operation, selecting only even samples, i.e. downsampling. The output signal on the low-pass filter is an approximant, and the output signal on the high-pass filter is a detail – it contains the details which complement the approximant. The approximants are the elements of signal $x(t)$ – high scale and low frequency, while the details are the elements of low scale and high frequency. The decomposition process can be repeated to decompose the subsequent signal approximants into an approximant and a detail. Then the process is called a multilevel decomposition. The generalisation of this multi-level decomposition is a complete signal decomposition in which in the subsequent steps not only the subsequent signal approximants are filtered but also its details.

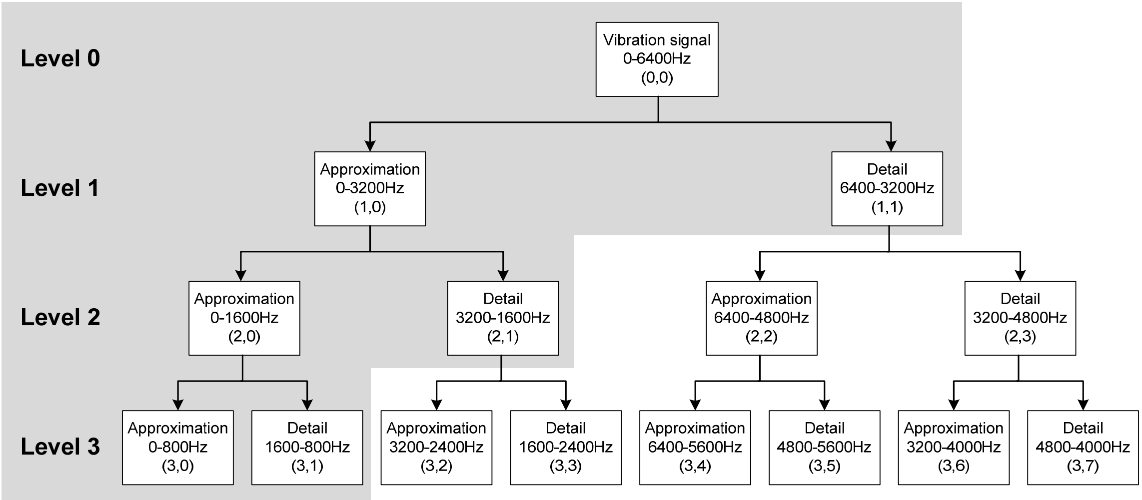

Fig. 1. An example of the complete third level wavelet decomposition of vibration signal. Dark background – example of an incomplete wavelet decomposition tree

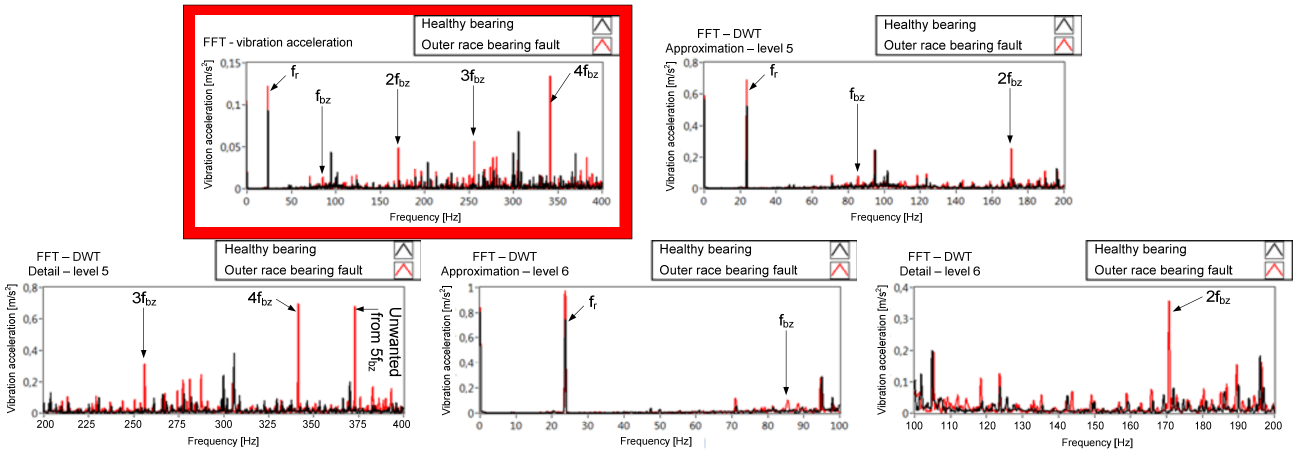

Fig. 2. Sample FFT spectra of vibration acceleration (in the box) and discreet wavelet transform up to the fifth and sixth decomposition level for an undamaged bearing and for a bearing with a damaged outer race

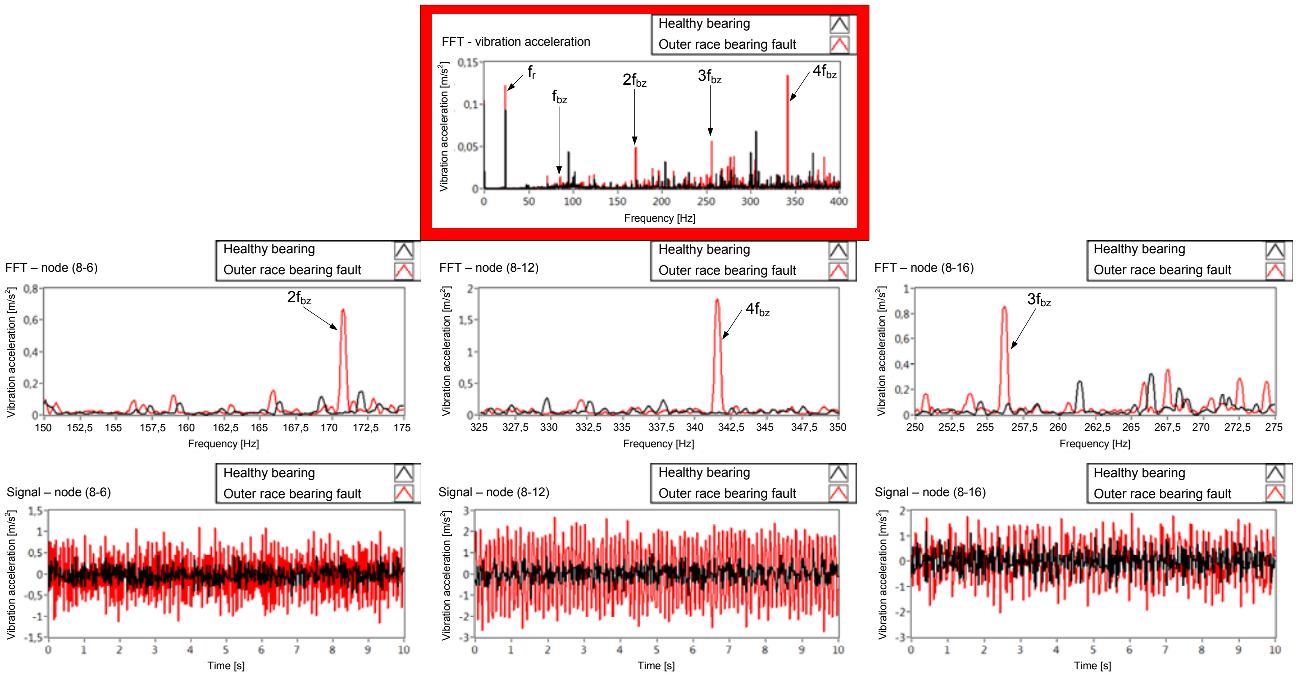

Fig. 3. Sample FFT spectra of vibration acceleration (in the box), discreet wavelet transform and complete discreet wavelet transform as well as timing of the selected knots from the eighth level decomposition for an undamaged bearing and for a bearing with a damaged outer race

Figure 1 presents an example of the complete third level signal decomposition. Dark background was used to mark a sample incomplete wavelet decomposition tree of signal vibration (also third level). The multilevel decomposition process can be continued until a single sample is obtained, and in the case of images – a single pixel. Signal decomposition makes it possible to analyse selected frequency ranges which are responsible for particular decomposition tree knots.

Laboratory research results

The laboratory research was conducted on mains-electricity powered Sh-90L-4 motor, made by INDUKTA, with 6205 2Z type rolling bearings with an artificially modelled ball, inner and outer bearing race defects. The measurements were carried out using an industrial computer NI PXI 8186 equipped with an industrial card NI PXI 4472. Diagnostic signal acquisition measurement data analysis was conducted using a virtual tool developed in the LabView environment. Vibration measurements were conducted using a single axis accelerometer, M622B01 type, made by IMI SENSORS, it was located in the motor bearing cover (axis direction vibration measurements). The signal was measured by 12.8kS/s sampling at fixed time – 10s, which allowed to obtain 0÷6.4kHz band spectrum, 0.1Hz resolution.

Vibration acceleration signal underwent wavelet analysis. The selection of decomposition level depended on the intention to show characteristic bearing defect frequencies. In the case of the discreet wavelet transform, the analysis was performed at the fifth and sixth level of decomposition. The obtained approximant and detail band width at the sixth level decomposition was 100Hz, and at the fifth level it was 200Hz. This made it possible to show defect frequencies in bandwidths not higher than 400Hz. In the case of complete wavelet transformation, the analysis was conducted at the eight decomposition level and 25Hz frequency band was obtained. Such a narrow band facilitates isolating characteristic defect frequencies. Figure 2 presents sample results obtained in discreet wavelet transformation of vibration acceleration of a motor operating under rated load with an outer bearing race fault.

The results summary presents FFT spectra of approximants and details for the fifth and sixth level decomposition. Additionally in the box there is the FFT analysis of motor vibrations in the case of an undamaged and damaged bearing. The arrows show characteristic defect frequencies. The comparison of the wavelet transform spectrum with the accelerated vibration spectrum allows to notice that the characteristic defect frequencies have much larger amplitudes in wavelet transform. Additionally, except for basic components kf_{bz}, one can also notice the undesired frequency of component $5f_{bz}$.

The occurrence of undesired frequencies in the wavelet analysis results from overlapping filter bands [3], [6]. Unfortunately the applied filters were not ideal, in consequence they have certain goodness in the barrier band depending on filter order. Undesired frequencies occur when a very large amplitude frequency occurs near the border of the neighbouring frequency range (of an approximant or a detail).

In the case of a complete wavelet transform, the analysis was carried out at the eighth decomposition level. A detailed analysis of eighth level knot signals allowed to choose the ones which best reflected the effects of the damaged outer bearing race (Fig. 3). Analogically to the discreet wavelet transform in the box, the classical FFT analysis of vibration acceleration is presented with arrows indicating characteristic defect frequencies. Additionally there are signal timings at selected knots. This allowed to show the influence of a bearing defect on vibration acceleration at a given knot. In the case of a complete wavelet transform, the amplitudes of characteristic frequencies are also several times larger than the ones obtained in the classical FFT analysis of vibration acceleration. At selected knots it is possible to find characteristic defect frequencies showing that there is a fault of a bearing construction element.

Neural detectors of rolling bearings

The usefulness of the information obtained from the wavelet analysis of vibration acceleration in the construction of a neural fault detector of rolling bearings has been checked. On the basis of the assessment of the obtained results, it was possible to select the knots which showed symptoms of rolling elements, outer and inner race faults. Figure 4 presents a sample structure of the tested neural detector. The effective value of signal at a given knot was selected as the input data of the neural detector (nonlinearities, which occur at the limits of signal, were removed as they are a disadvantageous consequence of wavelet transform). Additionally, to take into account the load changes, the input vector was expanded by rotational frequency f_r.

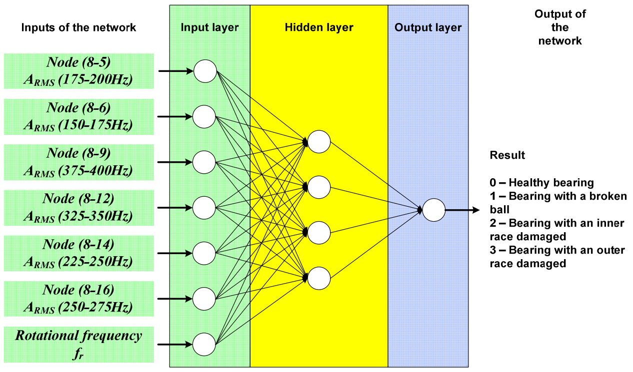

Fig. 4. The structure of a neural detector for rolling bearing construction faults in mains-electricity powered induction motors based on information obtained from wavelet analysis of vibration acceleration

The neural detector's task is finding a damaged construction element of a bearing. At network output there is information **0** for an undamaged bearing, **1** for a damaged ball, **2** for a damaged outer race and **3** for a damaged inner race. The output layer consists of only one output neuron. Data from two different measurement series were selected for neural network learning while the third measurement series was tested. Each series consisted of 10 measurements for an undamaged bearing, a bearing with one damaged ball, with damaged outer race (the outer race was cut and there was a two-centimetre long surface damage) and inner race (it was cut and there was a two-centimetre long surface damage). The input vector of neural network learning consisted of 120 elements, and the testing vector of 60 elements. All measurement series were carried out on the same group of bearings. To average the results of the effectiveness of the neural detector of rolling bearings 11 series of learning and testing were carried out.

The effectiveness summary of the tested neural detectors (Table 1) shows that all tested structures are characterised by high average effectiveness at the level of about 98%. Even the lowest effectiveness, obtained for structure 7-3-1 was about 92%.

Table 1. Detection effectiveness of selected rolling bearings construction defects based on information obtained from wavelet analysis of vibration acceleration

Effectiveness of 11 subsequent learning and testing series %	Neural network structure		
	(7-3-1)	(7-4-1)	(7-5-1)
Average	97.6	99.8	98.5
Lowest	91.7	98.3	95.0
Highest	100.0	100.0	100.0

The operation of a neural detector with three neurons at the output layer was tested too. The advantage of this structure over a network with one output neuron, is the possibility of indicating a few faults. In the research the output vectors used in the previous solution were applied. At each of the output neurons there can be information **0** for an undamaged element and **1** for a damaged element. Figure 5 presents such a neural network.

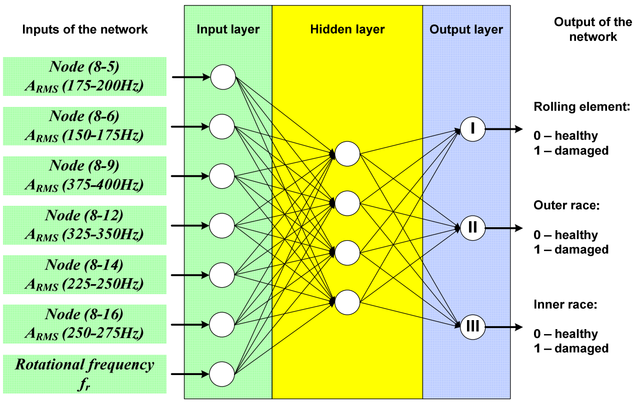

Fig. 5. Structure of a neural detector with three neurons at the output layer based on wavelet analysis information

Table 2. Detection effectiveness of selected rolling bearings construction defects based on information obtained from wavelet analysis of vibration acceleration

Effectiveness of 11 subsequent learning and testing series %	Neural network structure		
	(7-3-3)	(7-4-3)	(7-5-3)
Average	100.0	99.8	99.8
Lowest	100.0	98.3	98.3
Highest	100.0	100.0	100.0

The summary detection effectiveness for selected construction damages of rolling bearings detectors with three neurons at the output layer is presented in table 2. The obtained results show that such a detectors is very efficient in determining the type of damaged construction element of a rolling bearing. Only in very few cases errors occurred.

Summary

In the monitoring processes of rolling bearings effectiveness the significance of methods based on time-frequency transforms is growing. Especially the methods based on wavelet analysis are implemented very intensively. The presented selected research results confirmed high effectiveness of wavelet analysis in the detection and identification of construction faults of rolling bearings. This refers to both partial and complete wavelet packet analysis.

The presented examples show that the information obtained from wavelet analysis can be directly used to monitor characteristic frequencies in approximants and details or indirectly in trained neural networks. It was shown that perceptron neural networks based on information obtained from wavelet analysis of vibration acceleration are highly effective in the detection of rolling bearings construction faults. Moreover, even relatively small neural networks structures ensure high precision in the detection of the type of a bearing fault.

On the basis of the conducted research it can be concluded that the detectors of bearing faults based on artificial neural networks allow on-line monitoring of rolling bearings condition and can be an additional, convenient, diagnostic tool.

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