

Article

Analysis of Changes in the Characteristics of the Multifractal Spectrum During Diagnosing the Technical Condition of Rolling Bearings

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Abstract

This paper presents a study conducted with a view to analysing the sensitivity of measures determined based on the characteristics of the multifractal spectrum when detecting damage in rolling bearings. The research was conducted using vibration signals of a real rotating machine shaft supported by bearings, each of which was in a different technical condition. The effects of damage-induced changes in vibration signals on the calculated waveforms of multifractal spectra and the measures determined from them were analysed. In addition, qualitative and quantitative analyses of the effect of additional signal interference on changes in the characteristics of the spectra were carried out. The study shows that the application of vibration signal processing using a multifractal spectrum enables fast and unambiguous demonstration of changes occurring in the signals that can be linked to damage of bearings. Irrespective of the type of bearing damage symptoms present in the vibration signals—whether high-energy quasi-correlated impulse or medium and low-energy stochastic—an increase in measures determined from the multifractal spectrum was identified. The study shows that, regardless of the level of vibration signal interference, the calculated quantitative measures of the spectra were indicative of damage to rolling bearings.

Keywords: multifractal spectrum; rolling bearings; signal measures; signal processing

1. Introduction

Measurements and analyses of the vibration and noise of components of machinery, equipment and means of transport during normal operation make it possible to obtain a great deal of relevant information about their temporary technical condition. The changes recorded in the signals are a valuable source of information, necessary above all for making decisions about their continued operation or shutdown and repair. Various methods of signal recording are used in testing on real objects [1–3], which, in the simplest way, can be divided into contact and non-contact tests. In solutions where access to the measurement locations is convenient, contact vibration measurement methods are used, which take advantage of, e.g., piezoelectric transducers [4–8]. At sites with limited access, non-contact methods of vibration measurement using, for example, laser vibrometers [9] or acoustic signal monitoring [10–12] can be used. Advanced vibroacoustic signal processing methods enable early detection of wear or damage, even from heavily noised signals [13–16]. Much of the diagnostically relevant information contained in the signals is difficult to detect, as the amplitude-phase changes that result from changes occurring in the equipment generate



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symptoms that are difficult to identify. Another group of research methods related to detecting the technical condition of bearings involves the development of new signal processing methods that can be useful for damage type classification. In these cases, the signal processing methods developed are also useful for the automation of measurement and decision-making processes.

1.1. Research into Rolling Bearings

Rolling bearings play an important role in ensuring the reliable operation of machinery and equipment. A significant amount of research is being carried out into the possibility of detecting their technical condition. An analysis of the effect of the lubricant applied to a rolling bearing on the variation in the recorded vibration signals is provided in ref. [13]. Single Ensemble Empirical Mode Decomposition was used in ref. [16] to diagnose heavily noised signals. Ref. [17] presents tests of bearings aimed at developing calibration diagrams useful for assessing the condition of rolling element bearings. Research into the possibility of assessing rolling bearing damage based on changes in the characteristics related to their frequency of occurrence is presented in [18]. A complex de-noising algorithm was developed for the detection of faults in highly distorted vibration signals, as reported in [19]. The authors of ref. [20] proposed the use of multiband demodulation to monitor rolling element bearings. The automation of processes which allow for the detection of rolling bearing damage has also been implemented using artificial neural networks [19–21]. An example of a study in which a multi-scale convolutional neural network incorporating multiple attention mechanisms for bearing fault diagnosis is presented in ref. [21]. As part of the study discussed in ref. [22], the developed signal processing method was tested using neural networks for diagnosing rolling-element bearings of wind turbines. Research into the detection of pulsed signals related to bearing fault from heavily noised signals is presented in refs. [23–25], where spectral kurtosis was used, among other things, to process time-varying signals. The authors of the study presented in [26] proposed the use of a method based on the square of amplitude gain model for diagnosing rolling element bearing faults, while in ref. [27], the recursion analysis was used to diagnose bearing faults.

1.2. Research Using Fractals

Fractal methods are widely used in research related to the evaluation of changes in condition and damage detection. In paper [28], fractal methods were applied to diagnose rotating machines using vibroacoustic signals. A modified multifractal detrended fluctuation analysis was used to study damage to rolling bearings in paper [29], and in paper [30], fractal analyses were used and the scaling exponent was calculated. Paper [31] investigated the properties of fractal geometry of wavelet decomposition in the analysis of dynamic phenomena. Fractal methods have also been used in the study of internal combustion engines. The study presented in ref. [32] used, inter alia, the morphological fractal dimension to investigate diesel engine condition monitoring, and ref. [33] utilised digital image processing and fractal theory to extract fractal features of bispectral images, which can provide a basis for detecting faults in the timing gear. The authors of ref. [34] used multifractal analyses to assess tool wear during the milling process. In paper [35], the authors applied the above-mentioned analysis to investigate rapidly changing degradation phenomena in composite materials. Multifractal analysis has also been used, for example, in studies related to monitoring the conditions of structures, as reported in [36].

The research problems presented indicate that the development of measurement and signal processing methods makes it possible to extend the scope of the research conducted to include new objects and their components. The methods being developed provide new

insights into well-known research problems and now also make it possible to tackle issues that are difficult to analyse.

This paper undertakes research related to the application of a multifractal spectrum, and measures calculated from the characteristics of the spectrum thus calculated, to rolling bearing damage detection. The research and analysis undertaken represent a further stage in the development of research in this area and extend the knowledge hitherto presented in previous papers [37–39].

Furthermore, the following issues are addressed in this paper: in Section 2, selected issues concerning the theoretical basis of calculations enabling the determination of the multifractal spectrum and the measures adopted that can be determined from it; in Section 3, the method of acquiring real vibration and noise signals; in Section 4, the calculation of spectra and measures, together with an analysis and discussion of the results; and finally, in Section 5, the conclusions resulting from the research.

2. Signal Processing Method

Ongoing diagnostic tests of various components and assemblies of machinery and means of transport indicate that the recorded signals contain components with different energy and various natures of information content. Therefore, in addition to the standard quantitative and qualitative measures that are used to evaluate signals, advanced signal processing methods are applied. Such an approach, through the use of complex signal processing, allows us to detect signal components with linear and non-linear characteristics, including those that are rapidly changing, thereby providing important information about changes in technical condition. In this paper, the use of a multifractal spectrum is proposed for the analysis of high-energy quasi-correlated and medium- and low-energy stochastic impulsive signals that are symptoms of bearing damage and signal noise.

2.1. Multifractal Spectrum—Basic Dependencies

In studies using a multifractal spectrum, we use discrete wavelet analysis calculations and the derivation of fractal leaders, $w(i, s)$.

$$w(i, s) = \sup_{s' < s} \left| \frac{1}{N_s} \int_{-\infty}^{\infty} f(t) \Psi\left(\frac{u - i'}{s'}\right) dt \right| \quad (1)$$

where

$f(t)$ indicates a time series, and

$$\Psi_{s', i'}(t) = \Psi\left(\frac{u - i'}{s'}\right) \quad (2)$$

indicates a stretched and displaced waveform.

The wavelet leader calculations enable the scaling function to be determined by the relationship

$$S_w(q, s) = \left\{ \frac{1}{N_w} \sum_{i=1}^{N_w} \{w(i, s)\}^q \right\}^{\frac{1}{q}} \quad (3)$$

Based on the determined Hölder exponents h , the local regularity is determined, and based on the size of the set of Hölder exponents, the personality spectrum $F(h)$ is determined.

$$h = \frac{d\tau(q)}{dq} \quad (4)$$

$$F(h) = \inf_q (qh - \tau(q)) \quad (5)$$

where

q is the order of certain moments and $\tau(q)$ is the mass-exponent function.

A characteristic feature of the determined multifractal spectrum is the ability to assess how the signal changes over time. A typical signal with monofractal characteristics, with regular changes over time, has a narrow multifractal spectrum and a linear plot of scaling exponents. For a signal with multifractal characteristics—showing changes in regularity over time—the multifractal spectrum is broad, and a non-linear plot of scaling exponents occurs.

Calculations of the personality spectrum of vibration signals allow for the characteristics of this spectrum to be determined, which can be used in condition assessment-related research. The analysis of the personality spectrum distribution was used, *inter alia*, by the authors of the following publications in their research: [35–43].

2.2. Quantitative Measures

On the basis of the determined multifractal spectra and scaling components, a qualitative assessment of changes occurring in the signals can be performed, as well as a quantitative assessment of these changes based on the developed characteristics of the distributions. In this paper, six measures are proposed to describe changes in the character of signals after processing using multifractal spectra:

$$cp \quad (6)$$

is the value of the Holder index h for which the value of the personality spectrum $F(h) = 1$,

$$\text{Sum } h(1-5) \quad (7)$$

is the sum of the values of the Holder coefficient h , which is expressed by the range $h \in \langle h_1, h_5 \rangle$,

$$\text{Sum } h(7-11) \quad (8)$$

is the sum of the last five values of the Holder coefficient h , which is expressed by the range $h \in \langle h_{max-5}, h_{max} \rangle$,

$$\Delta h \quad (9)$$

is the difference between the Holder indices h_{max} and h_{min} , which characterises the width of the spectrum,

$$\Delta F \quad (10)$$

is the difference between $F(h_{max})$ and $F(h_{min})$: the value of the personality spectrum, and

$$\Delta \tau \quad (11)$$

is the difference between $\tau(q_{max})$ and $|\tau(q_{min})|$.

The proposed measures enable the determination of the sensitivity of the fractal spectrum to changes occurring in signals recorded during measurements of bearings in various technical conditions, including those additionally disturbed by noise. The calculated measures make it possible to assess the mono- and multifractality of signals recorded during tests of rolling bearings and to draw conclusions regarding their diagnostic usefulness in the testing of transport vehicle components.

Figure 1 shows an example of a multifractal spectrum and a graph of scaling indicators, with the measures adopted for the study highlighted.

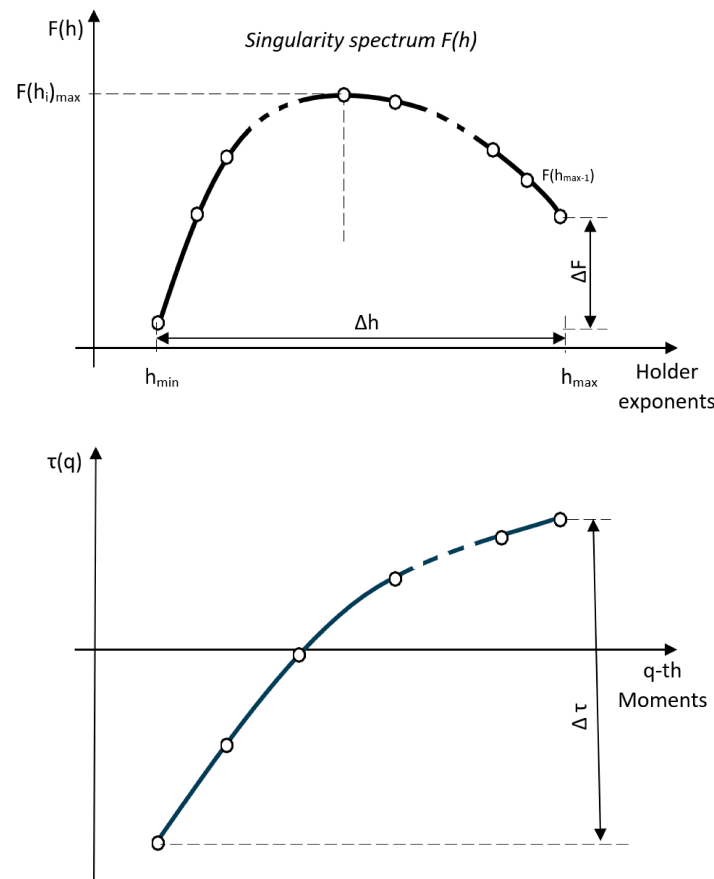


Figure 1. Baseline characteristics determined in the calculations and the graphical basis for the measures determined.

3. Method of Acquiring Signals for Analyses

Vibration signals recorded on the laboratory bench, as well as additionally noisy signals, were used to test the signal processing method proposed in Section 2 and the characteristics and measures determined from it.

In bench tests, transverse vibration velocity signals of the gear shaft were recorded using an Ometron laser vibrometer from Image Automation Ltd. [44]; the signals are extensively discussed in ref. [14]. The signals were recorded at a frequency of 25.6 kHz using a DSPT SigLab signal analyser from DSP Technology Inc., and Matlab-Simulink R2024a software was used to process the signals. The tests were carried out at a constant rotational speed of the test rig and under a constant load, with time-domain waveforms of the transverse vibration velocity of gearbox shafts, lasting several seconds, being recorded each time. Such an approach made it possible to obtain long-term time signals that contained multiple repetitions of the cycle of interactions between the test rig and the bearings operating within it. For the shaft on which tests of bearings (in a different technical condition) were performed, the rotational frequency was $f = 30$ Hz.

This method of recording signals made it possible to measure shaft vibrations in the immediate vicinity of the location of bearings in various technical conditions, and to acquire signals with unambiguous damage symptoms for further analysis. Bearings in good condition and with significant local damage to the outer and inner raceways, made for the purpose of laboratory experiments, were used in the study; additionally, a bearing was used with significant damage to all mating elements as a consequence of its long-term operation. The local damage to the bearing raceways, prepared artificially, simulated fractures of the raceway. The defects in the bearing had the form of a single transverse groove (made using

a milling method) across the entire width of the bearing raceway, causing damage to the outer and inner raceways, accordingly, with a depth of <1 mm, as described in detail in ref. [14]. The extent of the damage to the bearings corresponded to the damage that may occur in components of means of transport, as described in detail, inter alia, in [45]. The measurement method performed using a laser vibrometer enabled measuring the vibration that contained significant energy pulses generated when the bearing ball came into contact with the damaged site on the raceway. Detection of these faults by contact methods, i.e., using a piezoelectric transducer, did not give such unambiguous results.

In further studies, simulation tests were conducted to assess the sensitivity of the measures developed to determine the possibility of detecting rolling bearing damage based on the characteristics of the multifractal spectrum. In these tests, the recorded signals of the shaft vibration velocity, denoted by $x(t)$, were disturbed by noise, denoted by $y(t)$, with random characteristics. As a result of this process, a non-stationary signal $x(t) + y(t)$ was obtained, which is the sum of signals with the characteristics of the vibration signal components of a real device and an artificial signal with strong interfering noise. Introducing a disturbance into the actual shaft vibration signal resulted in a several-step reduction in the amplitude ratio of the actual shaft vibration velocity signal for bearings with different technical states relative to the disturbance. Thus, the introduction of signal interference has an influence on the change in the signal-to-noise ratio, which will alter the characteristics of the multifractal spectrum and the calculated measures.

The study adopted the following dependence for determining the signal-to-noise ratio:

$$SNR = 20 \log_{10} \frac{(\int_1^t (x(t) + y(t))^2)^{1/2}}{(\int_1^t (y(t))^2)^{1/2}} \quad (12)$$

where

$x(t)$ —the recorded signal at the test bench;

$y(t)$ —noise.

4. Results and Discussion

The first objective of the research was to assess the influence of changes occurring in the recorded vibration signals of the gear shaft, supported by bearings in different technical states, on the multifractal spectra.

Figure 2a–d present the time waveforms of the recorded gear shaft signals, where local increases in the amplitude of the recorded signal can be observed due to local damage to the raceway and damage caused by the long-term service of the bearing.

In these cases, damage to the outer and inner raceways of the bearings causes significant local energy changes in the recorded signals. It can be observed that when the bearing ball comes into contact with a defect in the raceway, there is a significant increase in the amplitude of the gearbox shaft's vibration velocity. In the case of damage to the outer raceway, due to the specific nature of the damage location, regular increases in amplitude are observed in the vibration signal each time the ball comes into contact with the damaged area. In the case of in-service damage to the bearing, these changes are also significant but are difficult to correlate with a specific type of damage. The changes in vibration amplitude that occurred clearly caused the characteristics of the recorded signals to become more random.

In further research, in order to calculate multifractal spectra, the recorded vibration signals were processed using a developed method based on dependencies (1)–(4). Figure 3a–c show the calculated spectra of the signals recorded when the shaft was oper-

ated with bearings representing different technical conditions, with reference to a bearing in good condition.

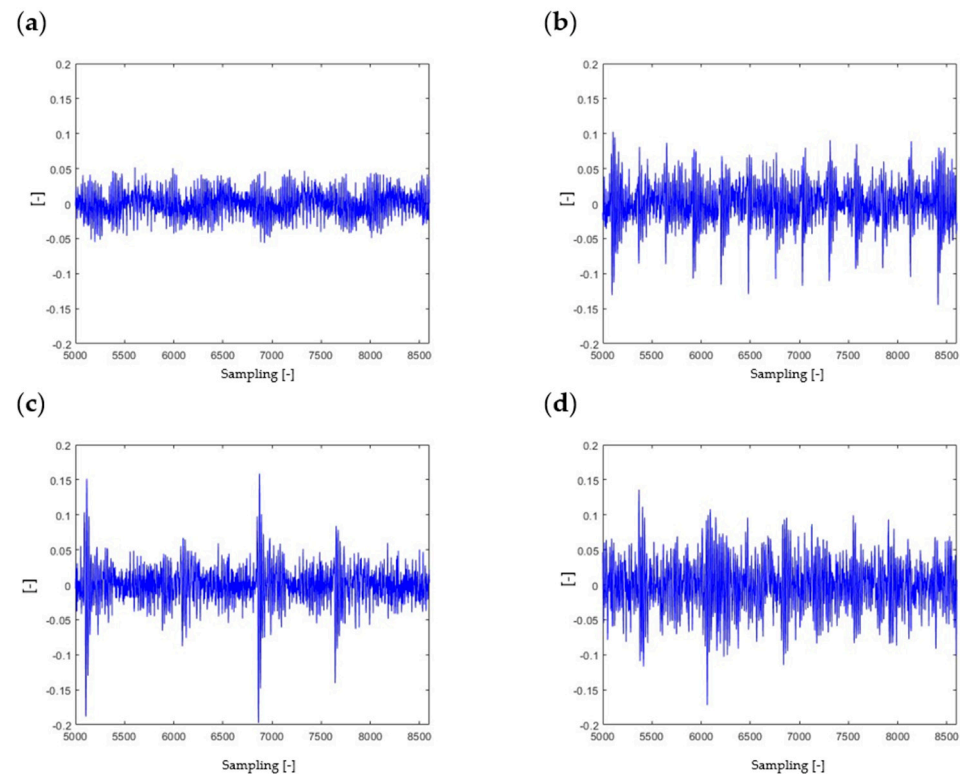


Figure 2. Real vibration signals of the gear: (a) bearing in good condition, (b) bearing with a damaged outer race, (c) bearing with a damaged inner race, and (d) bearing with in-service damage.

The energy changes recorded for the signal of a gear shaft supported by bearings with different kinds of damage (Figure 3) strongly influenced the change in the characteristics of the multifractal spectrum. The determined spectrum characteristics testify to the change in the nature of the signal, which in the case of a bearing in a good condition has quasi monofractal characteristics, while in the case of vibration signals of damaged bearings, the signals have typically multifractal characteristics. Calculations performed for the vibration signal of a shaft supported by bearings in good condition indicate a distribution of Holter exponents h in the range of 0.05–0.26, with the personality spectrum $F(h)$ varying between 0.7 and 1. For a damaged bearing, the values of Holter h indicators increase and are in the range of 0.05–0.55, and the personality spectrum takes on $F(h)$ values above 0.3. The shape of the multifractal spectrum varies markedly depending on the technical condition of the bearing.

Faults of rolling bearings are often heavily masked by changes in the amplitude of vibration signals generated by other sources, including difficult-to-correlate, narrow- or broadband noise. In further analyses, a comparison was made between the sensitivity of the multifractal spectrum used for signal processing to the qualitative and quantitative change in vibration signals of a shaft supported by bearings in different technical states. The study analysed the actual vibration signals of the gear shaft disturbed by random noise. Adding noise to the recorded vibration signals resulted in qualitative and quantitative changes to the signals, affecting their diagnostic interpretation towards fault detection. The disturbed signal-to-noise ratio (SNR) was approx. 14 dB, 10 dB, 7dB and 5 dB, respectively, which reduced the ratio in the signals and the possibilities of interpreting the damage present in the bearing. Examples of signals with a distortion of approximately 7 dB are presented in Figure 4.

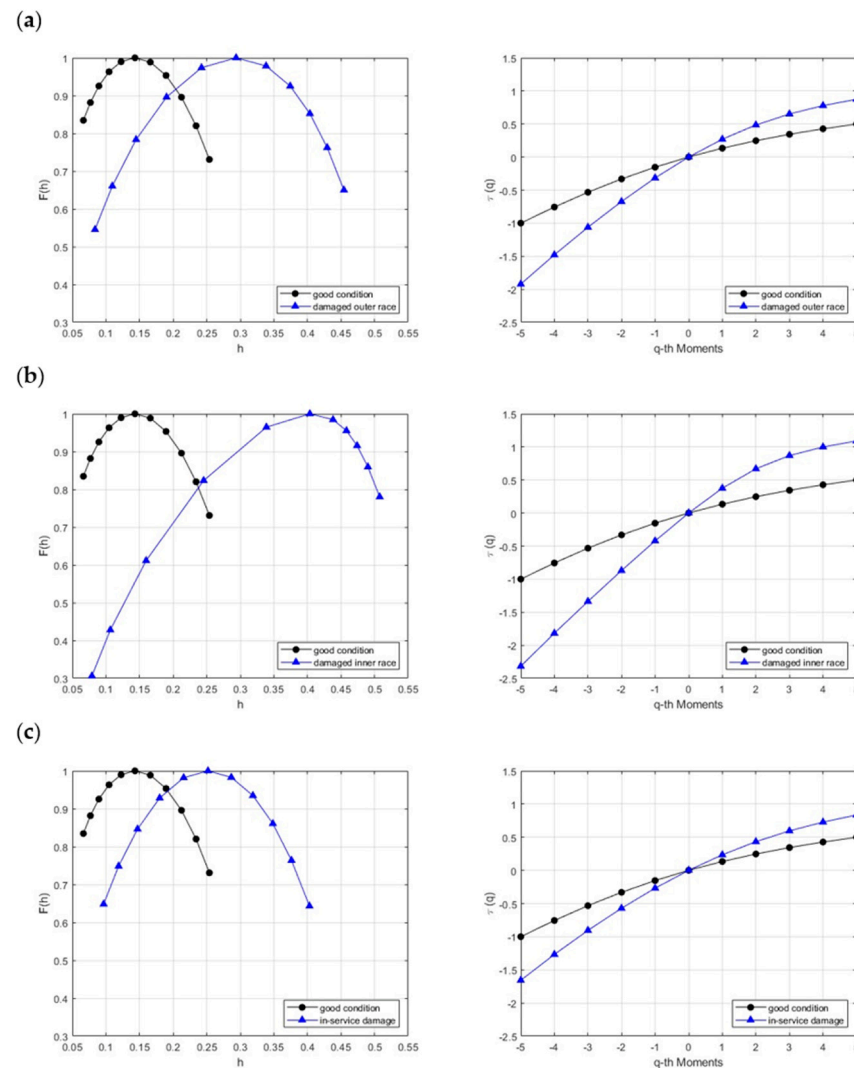


Figure 3. Determined multifractal spectra (bearings with different conditions in relation to a bearing in good condition): (a) bearing with a damaged outer race, (b) bearing with a damaged inner race, and (c) bearing with in-service damage.

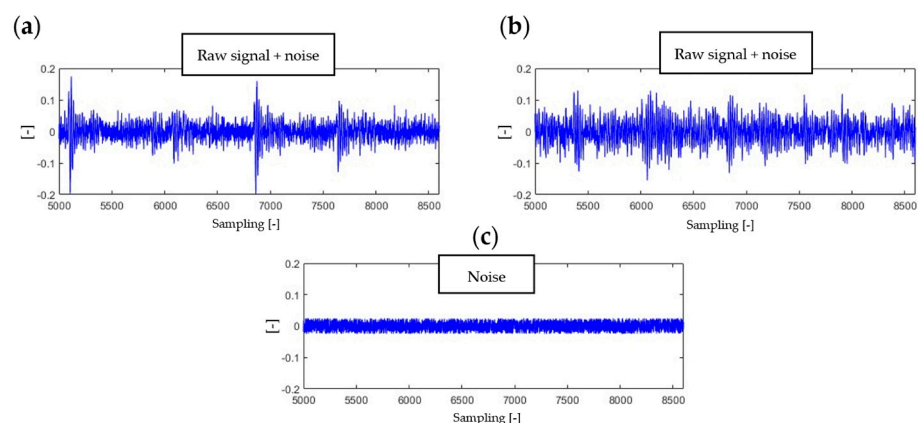


Figure 4. Examples of vibration signals disturbed by noise, SNR = 7 dB: (a) bearing with a damaged inner race, (b) bearing with in-service damage, (c) noise.

In further studies, vibration signals recorded on the test bench and disturbed by random noise were processed using multifractal analysis (1)–(3). The results of these tests are shown in Figure 5.

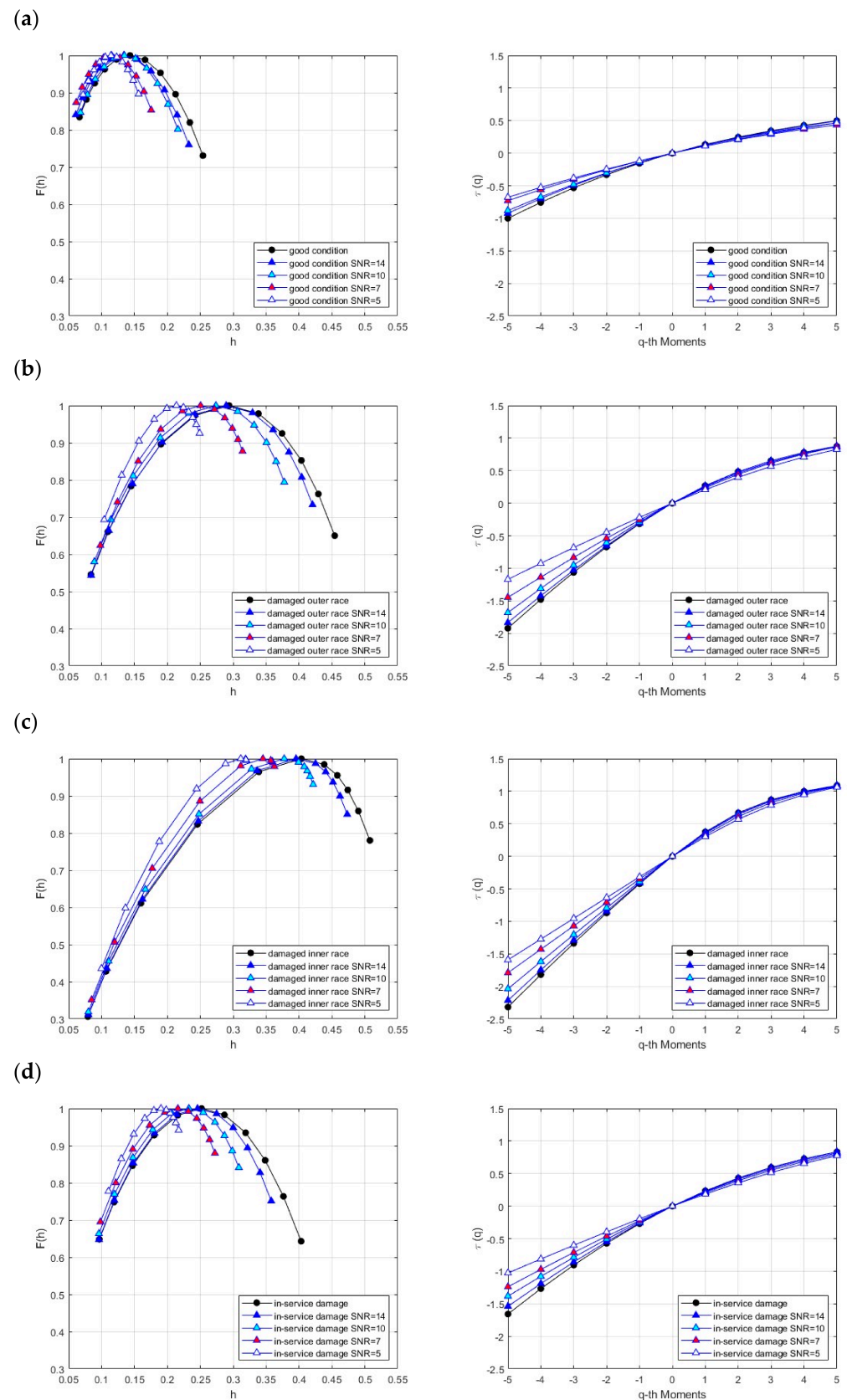


Figure 5. Determined multifractal spectra for signals with different disturbances: (a) bearing in good condition, (b) bearing with a damaged outer race, (c) bearing with a damaged inner race, and (d) bearing with in-service damage.

By analysing the results obtained, it can be concluded that an increase in the interference of the recorded signals with random noise alters the multifractal characteristics. The spectral characteristics narrow as the level of disturbance increases, indicating a decrease in the significance of the multifractal characteristics of the disturbed signals. Similar changes are observed in the scaling exponent plots, where a reduction in the level of non-linearity is observed as the level of disturbance increases. An increase in the level of signal interference results in a decrease in the width of the distribution of the Holter h -indices, regardless of the bearing condition. A particularly significant change occurs in the range of maximum values of the calculated Holter index, where the values decrease with increasing signal noise to those recorded for a bearing in good condition. The values of the calculated personality spectrum increase with increasing noise values. It can be seen from this research that the shape of the multifractal spectrum in the range of small interference values does not change for individual faults in the bearing. This indicates a low sensitivity of the change in the shape of the calculated multifractal spectrum caused by the disturbance, regardless of the bearing condition.

In order to assess the effect of additional noise on the shape of the multifractal spectrum characteristics, its basic quantitative measures were calculated (6)–(11). All of the previously analysed signals of undamaged bearings and those in various conditions, including those additionally disturbed by noise, were used in the tests. The results of these studies are presented in Tables 1 and 2 and in Figure 6.

Table 1. Values of the measures determined from multifractal spectra—a bearing in good condition and a bearing with a damaged outer raceway.

SNR (dB)	Undamaged					Outer Damage				
	Raw signal	14.26	10.16	7.18	5.2112	Raw signal	14.25	10.24	7.13	5.1037
cp	0.143	0.133	0.129	0.115	0.1144	0.293	0.289	0.273	0.251	0.2137
Sum _h (1–5)	0.460	0.428	0.431	0.407	0.4432	0.770	0.776	0.773	0.789	0.7707
Sum _h (7–11)	1.05	0.972	0.887	0.760	0.6986	2.000	1.899	1.732	1.466	1.1881
hmin	0.066	0.060	0.062	0.061	0.0719	0.083	0.084	0.088	0.093	0.104
hmax	0.254	0.232	0.207	0.175	0.1562	0.454	0.420	0.377	0.309	0.2491
Δh	0.187	0.171	0.145	0.113	0.0844	0.370	0.336	0.288	0.215	0.1451
F (hmin)	0.834	0.840	0.848	0.873	0.8949	0.545	0.543	0.579	0.598	0.6932
F (hmax)	0.730	0.760	0.808	0.853	0.8966	0.650	0.733	0.794	0.891	0.9257
ΔF	−0.103	−0.080	−0.040	−0.020	0.0017	0.104	0.189	0.214	0.293	0.2324
τ (qmin)	−1.000	−0.923	−0.848	−0.730	−0.6777	−1.921	−1.836	−1.682	−1.438	−1.171
τ (qmax)	0.497	0.463	0.464	0.433	0.4644	0.873	0.877	0.864	0.868	0.8267
$\Delta \tau$	−0.503	−0.459	−0.383	−0.296	−0.2133	−1.048	−0.959	−0.817	−0.570	−0.3443

The calculations indicate that all measures analysed showed a significant increase in value due to bearing damage, compared with a bearing in good technical condition. The increase in the measures ranges from approximately 30% to more than 250%, depending on the bearing damage. It can be seen that the highest increase in the measures occurred in the case of local damage to the bearing race, which showed local impulse changes in the amplitude of the signals. In the case of in-service bearing damage, where damage resulted

in stochastic changes of medium and low energy in the signal, a smaller effect of damage on the dynamics of the change in the considered measures of the multifractal spectrum can be observed.

Table 2. Values of the measures determined from multifractal spectra—a bearing with a damaged inner race and a bearing with in-service damage.

SNR (dB)	Inner Damage					In-Service Damage				
	Raw signal	14.38	10.27	7.19	5.1616	Raw signal	14.26	10.06	7.21	5.1898
cp	0.403	0.395	0.377	0.347	0.3114	0.251	0.245	0.232	0.215	0.1902
Sum h (1–5)	0.93	0.933	0.932	0.942	0.9564	0.758	0.758	0.747	0.736	0.7345
Sum h (7–11)	2.368	2.252	2.057	1.827	1.5955	1.733	1.595	1.420	1.267	1.0409
hmin	0.079	0.080	0.079	0.085	0.0998	0.096	0.096	0.095	0.098	0.1105
hmax	0.507	0.473	0.421	0.368	0.3194	0.403	0.357	0.308	0.272	0.2172
Δh	0.428	0.393	0.341	0.283	0.2196	0.306	0.261	0.212	0.174	0.1067
F (hmin)	0.305	0.311	0.318	0.356	0.4354	0.648	0.647	0.663	0.695	0.7774
F (hmax)	0.780	0.850	0.930	0.973	0.9955	0.643	0.751	0.840	0.879	0.942
ΔF	0.474	0.539	0.611	0.617	0.5602	−0.005	0.103	0.177	0.184	0.1646
τ (qmin)	−2.318	−2.216	−2.038	−1.818	−1.5925	−1.658	−1.540	−1.383	−1.240	−1.0278
τ (qmax)	1.089	1.089	1.080	1.073	1.0635	0.834	0.832	0.815	0.795	0.7751
$\Delta \tau$	−1.228	−1.127	−0.957	−0.745	−0.529	−0.823	−0.707	−0.567	−0.444	−0.2527

Analysing the results of research on the effect of a random disturbance on the changes in the measures of the multifractal spectrum, it can be seen that four of the measures considered, i.e., $Sum\ h(7-11)$, Δh , ΔF and $\Delta \tau$, are sensitive to changes caused by the simulated external disturbance, while two others show little change in cp and $Sum\ h(1-5)$. It can therefore be concluded that, when diagnosing the technical condition of a bearing on the basis of recorded low-noise vibration signals, it is worth analysing the changes in all considered measures of the multifractal spectrum. In the case of a signal changing qualitatively over time, i.e., when its noise level increases, or it has strong characteristics of the recorded signal with random components, changes in the amplitude of the cp and $Sum\ h(1-5)$ measures can play a major role in determining the condition of bearings in a rotating machine.

The research results presented here expand the scope of diagnostic testing aimed at detecting damage to rolling bearings. The use of signal processing based on the multifractal spectrum and the use of measures derived from the multifractal spectrum points to further possibilities for diagnosing the condition of rolling bearings. The method developed may offer an alternative to the previously known signal processing methods, which utilise time-domain and time-frequency processing of vibroacoustic signals, as described in the literature.

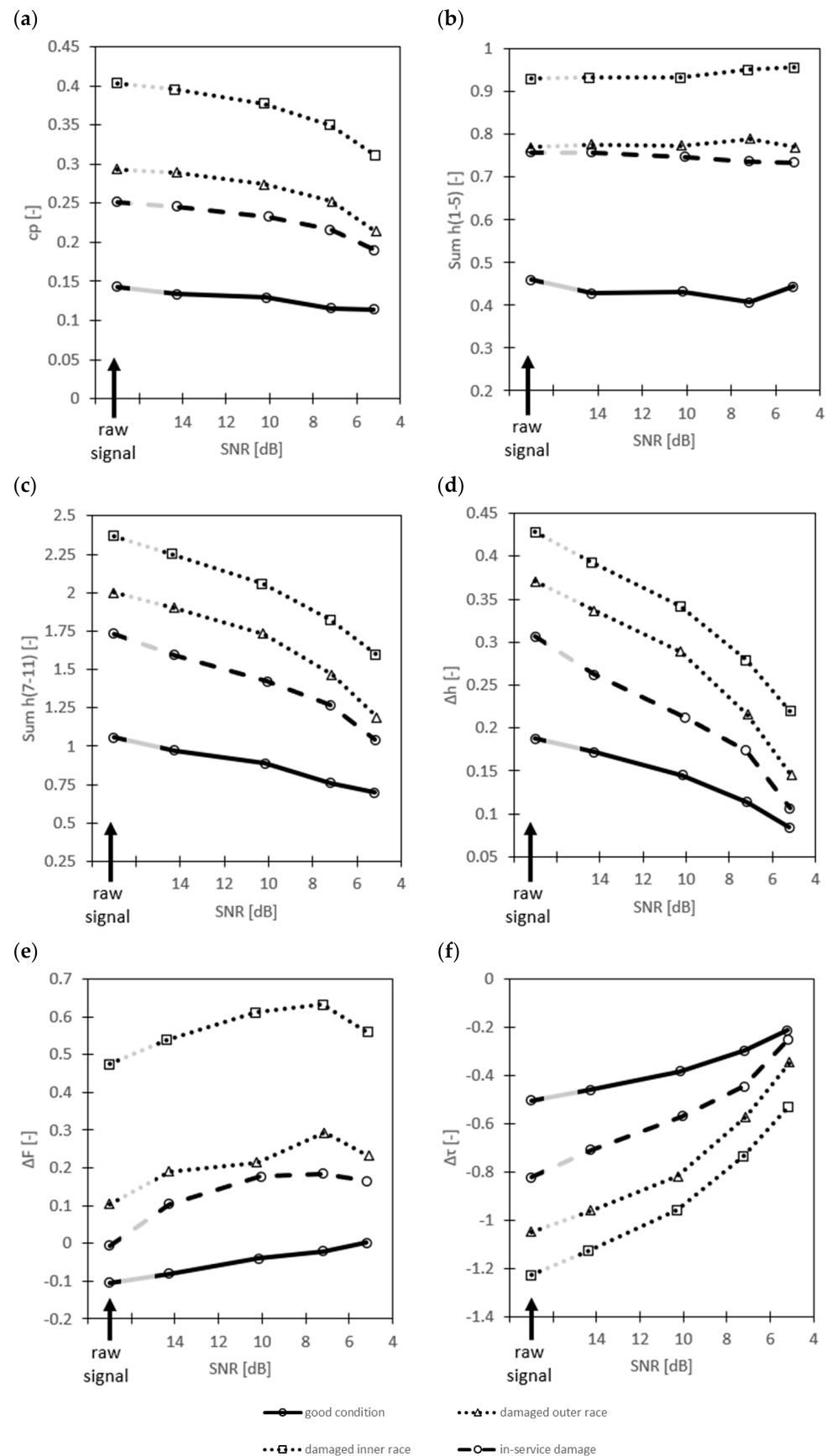


Figure 6. Changes in the values of measures determined from multifractal spectra as a function of the technical condition of the bearing and signal interference: (a) cp , (b) $Sum h(1-5)$, (c) $Sum h(7-11)$, (d) Δh , (e) ΔF , and (f) $\Delta \tau$.

5. Conclusions

Vibroacoustic tests of rotating machinery allow for early detection of symptoms of wear or damage to its components. The development of new methods for processing recorded signals makes it possible to expand diagnostic capabilities, reduce the risk of incorrect decisions and avoid unforeseen failures.

The application of multifractal spectrum calculations and measures that characterise the spectrum for the processing of vibration signals in diagnostic tests extends the existing state of knowledge in this area. The research has confirmed the sensitivity of the multifractal analysis to changes occurring in vibration signals, which are symptoms of bearing damage. The tests showed that local changes in signal amplitude caused by damage to the outer and inner race of the bearing strongly influence the change in spectrum characteristics. In the case of in-service bearing damage, changes in the signal amplitude also induce changes in the characteristics of the multifractal spectrum; however, the dynamics of such changes are smaller in this case.

The measures of the multifractal spectrum determined in the study showed significant sensitivity to bearing damage, regardless of the quality of the recorded and simulated signals. The study has revealed that two of the six measures considered do not show any significant changes in their values due to disturbances that may occur in addition to the recorded signals. This information is very important from the point of view of measuring vibroacoustic signals under different environmental conditions, as well as when the load on the rotating machine changes.

The tests performed as part of the study indicate significant changes in the characteristics of the multifractal spectrum resulting from qualitative and quantitative changes in the vibroacoustic signals. The impact of disturbances, which is highly significant during the decision-making process involved in assessing technical condition, must be taken into account by analysing a range of measures, as demonstrated in the study.

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Data Availability Statement: The data presented in this study are available upon request from the corresponding author.

Conflicts of Interest: The author declare no conflicts of interest.

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