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Detection of Structural Damage of Technical Objects with the Use of Multidimensional Analysis

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Abstract The paper presents a damage identification method of technical objects with the use of multidimensional analyses. The studied objects were rolling bearings tested on a laboratory test stand as well as vehicle wheel rims. The rims were examined by an Automated Tester. A group of variables describing the condition of the bearings included basic parameters of acceleration signal such as: RMS, peak value, functions describing the envelope of vibration spectrum and additionally the experimental coefficient of friction for the oscillatory motion. Diagnostic measurements data can be input into the proposed mathematical models and compared with a database of cases of the object technical states. Results of the multidimensional analysis of diagnostic parameters are presented in the form of diagrams (cluster trees). On this basis, the technical condition of the tested object can be easily interpreted. The proposed models supported the classification of wheel rims into groups characterized by similar frequencies and amplitude based on shock tests.

Keywords: multidimensional analysis, vibration, wheel rim, resonant frequency

1. Introduction

1.1. Rationale for the study

Accurate evaluations of the structural condition of technical objects require analyses of numerous diagnostic signals. Analysis of vibration signals often involve estimates of physical dimensions and dimensionless quantities, frequency analyses, analyses of the envelope spectra of vibration signals, and signal parameters. The relevant diagnostic methods are multidimensional analyses [1-6] which are carried out to identify sets of structural defects and damage. Datasets composed of a single element are easiest to analyse. In analyses that produce several solutions, the applied method should support the identification of the most probable defect. Degrees of certainty, probability, improbability or other measures of similarity or distance are used to facilitate an accurate diagnosis.
The following types of tools and solutions are used in multidimensional analyses [7, 8]:
– decision tables (matrices of diagnostic data),
– expert systems that are based on complex inference rules and calculate the degrees of certainty,
– neuronal models developed based on sets of numeric or fuzzy values,
– genetic algorithms,
– fuzzy logic,
– mathematical analyses for identifying the measures of similarity or distance.

Multidimensional analyses (cluster analysis and discriminant analysis) that can be applied to complex datasets (numerical, qualitative, fuzzy data) and facilitate accurate diagnoses of structural defects were used in this study. Multidimensional analyses have been long used to model engineering problems, including:
– to select diagnostic parameters and identify external factors that affect the wear rate of rolling bearings in rotors [9-12];
– to identify the structural wear of working elements in machines that are operated in soil [13, 14];
– to evaluate the abrasive wear of different structural materials [13];

– to evaluate fatigue wear [13].

In this study, multidimensional analyses were used to:

– appraise the technical condition of rolling bearings (based on the results of spectral analyses and the values of the coefficient of friction for oscillatory motion);
– determine the impact of numerous forced vibrations and their direction on the technical condition of vehicle wheel rims on the basis of the natural frequency analysis.

1.2. Discriminant analysis

Discriminant analyses can be performed to identify variables which discriminate between two or more naturally occurring groups of diagnostic symptoms that are characteristic of a given type of defect. The aim of the analysis is to identify rules that assign multidimensional object to one of many populations with known parameters, while minimizing classification errors [15].

In the simplest terms, discriminant analyses involve the following operations and procedures [6]:

– Procedures that describe and interpret differences between groups. These procedures can be used to answer the following questions during the interpretation of diagnostic data:
– Can the analyzed groups be effectively discriminated based on a set of several variables?
– How effectively are the analyzed groups discriminated based on the selected variables?
– Which variables discriminate the analyzed groups most effectively?
– Classification procedures, i.e. procedures for classifying new cases based on the observed or experimental data.

Canonical discriminant functions that discriminate between groups are determined in the first step of a multidimensional analysis. These functions can have any form, but linear functions are most widely used in practice. Therefore, canonical discriminant functions have the following form:

$$D_{kj} = \beta_0 + \beta_1 x_{1kj} + \ldots + \beta_p x_{pkj}\ , \tag{1}$$

where: p – number of discriminant variables, , D_{kj} – value of the canonical discriminant function for the k^{th} case in j^{th} group, k=l, ...,n (n – number of samples in the group) and j=l,..., g (g – number of groups), x_{ikj} – value of the i^{th} discriminant variable for the kth case in j^{th} group, i=1,...,p, β_i – coefficient of the canonical discriminant function determined based on the function's attributes.

Coefficients β_i are determined by solving the following matrix equation:

$$(\mathbf{M}\text{-}\lambda\mathbf{W})\boldsymbol{\beta} = 0, \tag{2}$$

where: **W** – intragroup matrix of squares and mixed products, **M** - intergroup matrix of squares and mixed products, $\boldsymbol{\beta}$ - vector of the coefficients of canonical discriminant functions, $\boldsymbol{\lambda}$ - matrix value.

In successive steps of the analysis, the resulting models are evaluated and interpreted. A broad range of computational and visualization techniques can be used for this purpose [16], but only two methods (listed below) were applied in this study due to space constraints.

– Distribution of canonical values for selected pairs of canonical functions. This diagram is highly useful for determining each function's discriminant power.
– A priori probability, i.e. the probability that a given case will be classified in a given group without any previous knowledge about the values of the modeled variables. For example, the fact that a given failure occurs frequently can be deduced a priori. If the probability of other failures (defects) is known, the existing knowledge can be used to determine whether the probability of the same defect is higher or lower than the probability of other failures.

The development of discriminant functions should be preceded by an analysis of discriminant variables and the following assumptions:

– multivariate normal distribution,
– homogeneity of variance/covariance,
– absence of correlations between average variables within groups and between groups,
– variance/covariance matrices are homogenous within groups.

The procedures for verifying the above assumptions were not described in the article, but the verification process was carried out in each analyzed case.

1.3. Cluster analysis

In cluster analysis, objects are divided into "similar" groups that are not "similar" to the objects in the remaining groups. The grouping process can expand our understanding of the structure of the factors that contribute to various types of damage, in particular [17, 18]:

– by determining the presence of any regularities in the obtained clusters, such as a relationship between symptoms and the technical condition that facilitate an accurate diagnosis,
– by reducing a large dataset to the average values of individual groups,
– by using the resulting groups in successive multidimensional analyses.

Technical objects can have highly complex structure. Therefore, in diagnoses that involve a very large number of variables (symptoms), all variables should be taken into account in the identification of a defect or failure. As a result, the selection of variables is dictated by two mutually opposing criteria (described below).

– A comprehensive diagnosis should be based on a full set of interrelations and the highest possible number of variables (symptoms) to identify a defect or failure in the most reliable manner.
– A highly reliable diagnosis is costly and time-consuming. Therefore, the applicable models should be simplified. In diagnostic processes involving a very large number of variables, statistical procedures (including analyses performed with software tools) are highly complex or even impossible to perform. Large data sets are also very difficult to interpret. Not all variables are significant or strongly correlated with other variables. Symptoms that play a critical role in diagnosis can also be lost.

Cluster analysis involves several object classification algorithms [19]. In this study, the agglomeration method was used to produce hierarchical clusters. The clusters and the distance between the grouped objects can be displayed in dendrograms. The distance between new clusters was determined by the complete linkage method, where the distance between clusters is equal to the longest distance between any two objects belonging to different clusters. The Euclidean distance was applied as the measure of distance between clusters.

2. Description of objects and experiment conditions

2.1. Bearing analysis

The aim of the analysis was to determine whether a set of symptoms characteristic of various types of damage in 6305 ZVL bearings can be identified based on measurements of vibration and the measured values of RMS, peak vibration, envelope spectra of vibrations in a given frequency range, and the values of the coefficient of friction for oscillating movement (Table 1). The identified symptoms were classified by cluster analysis.

Tab. 1. Specification of 6305 ZVL bearings.

Weight [kg]	0.23
Inner diameter *d* [mm]	25
Outer diameter *D* [mm]	62
Width [mm]	17
Clearance	C3
Number of rows	Single row
Manufacturer	ZVL

Five bearings which had been used in agricultural machines and were characterized by different degree of wear were selected for the experiment (Table 2). These bearings were evaluated in a preliminary analysis to determine whether the selected set of symptoms supports the identification of the most common types of wear. Two bearings with symptoms of combined wear were also selected to determine whether these bearings would be correctly assigned to similar groups in the model built with the use of cluster analysis.

Tab. 2. Description of the condition of the tested bearings

Bearing number	Condition	Acronym
B1	Corroded inner race and rolling elements	KOR
B2	Thermal wear	TER
B3	Minor lubricant contamination	SM
B4	Significant lubricant contamination	BSM
B5	Excessive clearance	LUZ
BX6	Corrosion and thermal wear	Y1
BX7	Lubricant contamination and excessive clearance	Y2

Vibrations were measured on a laboratory test stand simulating simple rotor systems (Fig. 1) that are used in agricultural machines such as grain cleaners.

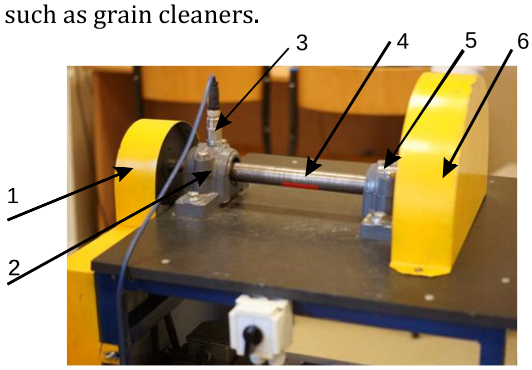

Fig. 1. Test stand for measuring bearing vibration. 1 – belt drive, 2 – tested bearing, 3 – sensor, 4 – shaft, 5 – bearing, 6 – flange under the shield.

The sensor was connected to a KSD multichannel analyzer [20] for recording of vibration acceleration and determining acceleration spectra in the frequency range of 10-4000 Hz.

The coefficient of friction for oscillating movement was determined on a test stand for analyzing the technical condition of rolling bearings as a quasi-dynamic model [18], and it was calculated with the use of equation 3:

$$\mu_{op} = \frac{320 \cdot m_w \cdot l \cdot (1-\cos\varphi)}{\pi \cdot \varphi \cdot (m_w+m_o)\frac{d_z+d_w}{2}}, \tag{3}$$

where:
μ_{op} – experimental coefficient of friction for oscillating movement, l – distance between the pendulum's center of gravity and the pivot point, d_w – inner diameter of the bearing, d_z – outer diameter of the bearing, i – number of pendulum swings, φ – angle of the first pendulum swing (55°), m_w – pendulum mass (0.727 kg), m_o – mass of the element fixing the pendulum to the bearing (0.783 kg).

2.2. Wheel rim testing

The tests were carried out on an Automated Wheel Rim Resonant Frequency Tester (AWRRFT) (Fig. 2) designed for assessing the technical condition of wheel rims based on resonant frequencies and geometric parameters (axial and radial runout). The device can also be used for wheel rim balancing.

The purpose of multidimensional analysis was to evaluate influence of multiple of forced vibrations and selection of points where they took place on identification of characteristic frequency range for tests on the AWRRFT stand.

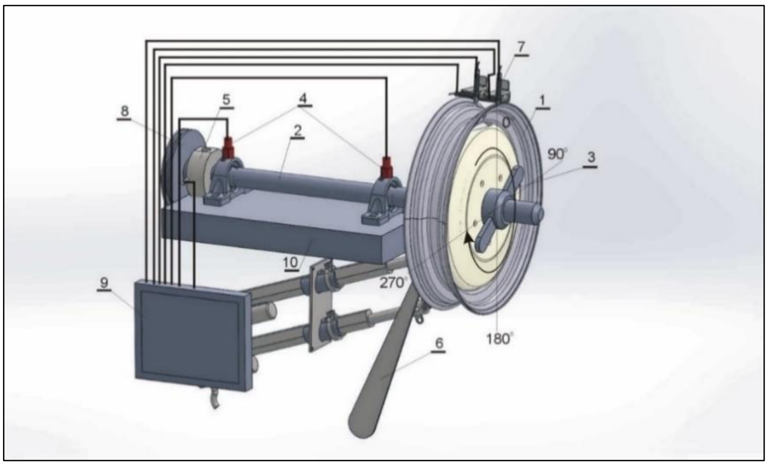

Fig. 2. Structure of the AWRRFT: 1 – wheel rim; 2 – shaft for mounting the wheel rim; 3 – nut for holding the wheel in place, 4 – vibration acceleration sensors, 5 – rotary shaft-angle encoder, 6 – gravitational vibration exciter, 7 – axial and radial head sensor, 8 – power drive for the balancer shaft, 9 – control and diagnostic system, 10 – support frame.

Condition research of the wheel rim were determined with the AWRRFT according to the following procedure:

– assembly of the rim,
– generating shocks for the position of the rim every 90° (Fig. 3),
– recording of time courses of vibration accelerations,
– fast Fourier transform (FFT) of vibration acceleration signals and determination of amplitude spectra in the frequency range of: 135-155 Hz, 710-750 Hz, 210-330 Hz,
– comparison of amplitude spectra with the database of cases,
– measurement of axial and radial runout.

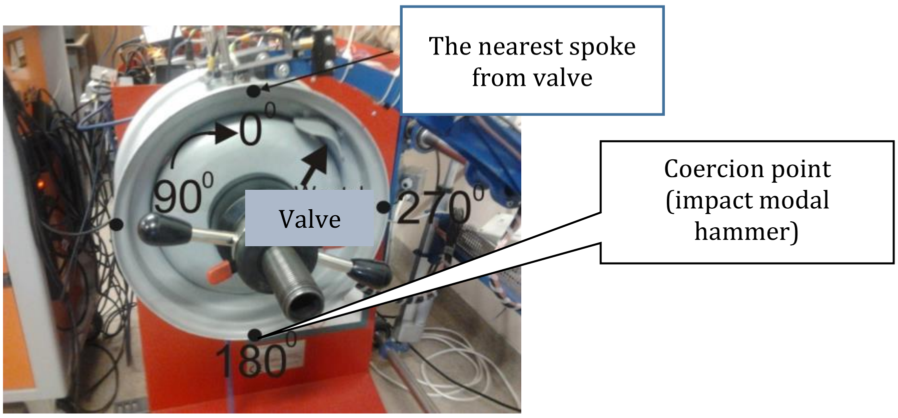

Fig. 3. Diagram of the measurements performed with AWRRFT to identify the characteristic frequencies of wheel rims.

3. Results

3.1. Results of the bearing tests

Determined amplitude spectra of vibration accelerations in the frequency range of 2000-3200 Hz and the functions characterizing the distribution of spectrum distribution (envelope of spectra) are presented in Figures 4. The frequency range was selected based on the results of a preliminary analysis of vibration spectra. The preliminary analysis demonstrated that the distribution of amplitudes within the frequency range of 2000-3000 Hz differs for various types of defects.

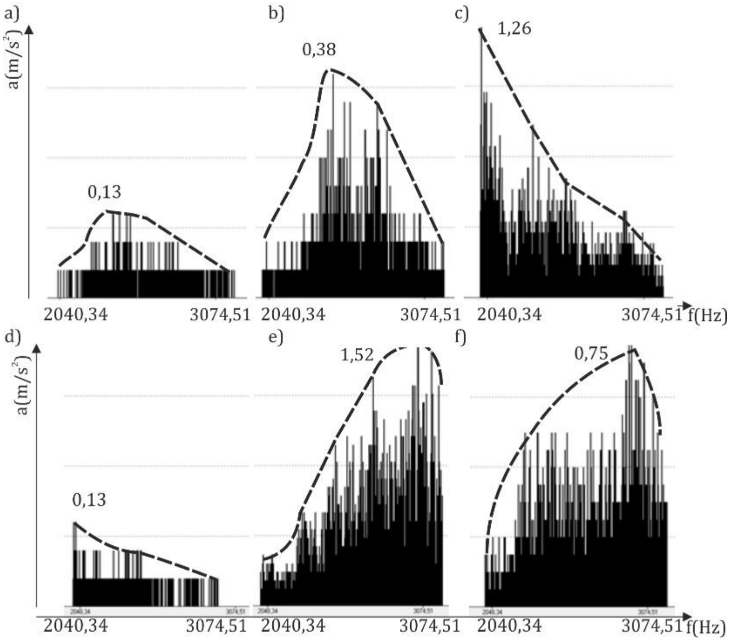

Fig. 4. Vibration acceleration spectra (frequency range 2000-3200 Hz): a) new bearing, b) bearing B1, c) bearing B2, d) bearing B3, e) bearing B4, f) bearing B5.

Selected symptoms of bearing damage which were used in cluster analysis as variables that influence clusters are presented in Table 3.

Tab. 3. Parameters measured for 6305 ZVL bearings.

Bearing number	RMS [m/s²] with 2000-3000 Hz filtering	Peak value [m/s²] with 2000-3000 Hz filtering	Experimental coefficient of friction for oscillating movement μ_{op}	Regression coefficients		
				a	b	c
BN – New bearing	0.11	0.13	0.11	-0.0002	0,28	48.26
B1	0.18	0.38	0.16	-0.0007	0.85	69.85
B2	0.46	1.26	0.28	0.0002	-1.05	1126.10
B3	0.05	0.13	0.13	0.0001	-0.19	85.25
B4	0.62	1.52	0.12	-0.0015	2.50	162.53
B5	0.35	0.75	0.13	-0.0007	1.13	148.89
BX6	0.51	1.32	0.32	0.0008	0.75	860.12
BX7	0.75	1.97	0.17	-0.0007	1.24	168.23

The envelope correlation coefficients were determined in regression analysis. The second-order polynomial regression model was applied in all cases:

$$y = af^2 + bf + c, \tag{4}$$

where: a, b, c – regression coefficients, y – amplitude [m/s^2], f – frequency [Hz].

The empirical envelope function and the envelope function determined from the regression model are presented in Figure 5. The results of the cluster analysis are shown in Figure 6.

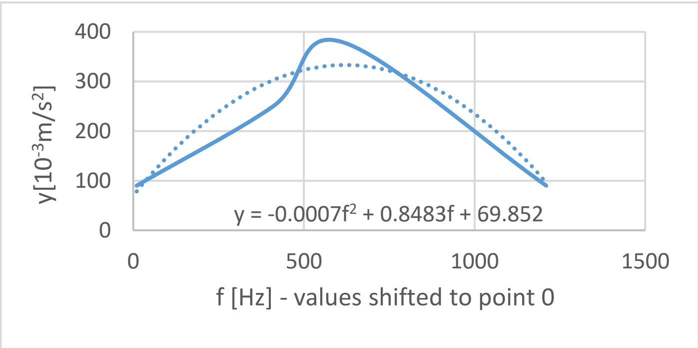

Fig. 5. Goodness-of-fit of the envelope function. Results for bearing B1.

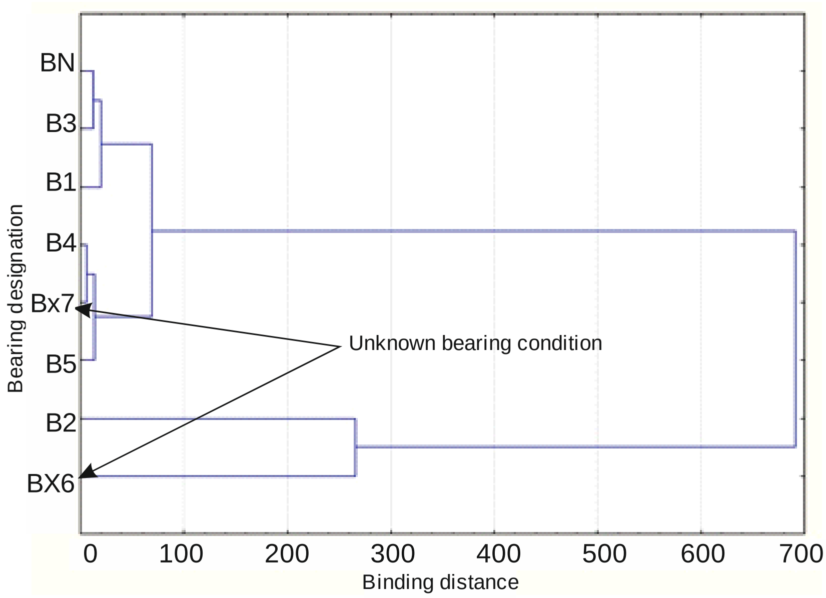

Fig. 6. The results of cluster analysis - grouping of bearing condition.

Cluster analysis allows the unknown condition of bearings (BX6 and BX7) to be assigned to the group most similar in terms of symptoms and these are bearings characterized by heat consumption and significantly contaminated grease. Verification (organoleptic) tests of BX6 and BX7 bearings confirm their belonging to the identified states (types of defects).

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Table 4 and Figure 7 present the results of the discriminant analysis.

Tab. 4. Coefficients for variable canonical functions

Coefficient	Function 1	Function 2
RMS	-2.54	-2.35
P-P	2.23	5.72
μ_{op}	-2.12	-4.97
a	13.03	5.08
b	3.280	1.87
c	-8.390	4.22
Eigenvalues of the function	1823.51	391.15

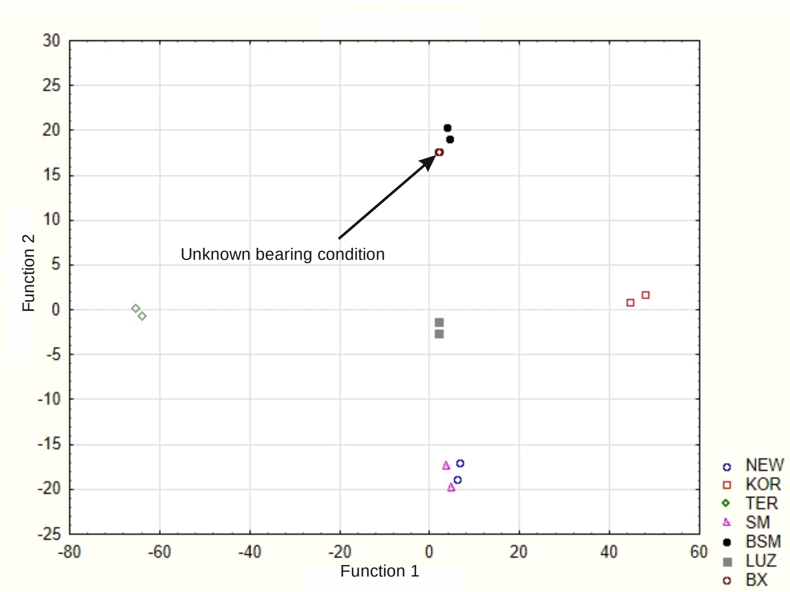

Fig. 7. Value graph of canonical functions.

The determined discriminant functions allow us the separate individual types of failures. although D1 function distinguishes three sets: {TER}. {BSM. LUZ. SM. NEW}. {KOR}. while the D2 function separates the set {BSM. LUZ. SM. NEW}. to: {BSM}. {LUZ}. {SM. NEW}. The examination of the bearing of unknown state of BX classifies it to the BSM group. which was confirmed by the organoleptic tests.

3.2 Results of the wheel rim analysis

The presented research results are related to a case of 12×4.25 in. rims with excessive dimensional errors (Tab. 5). The registered time runs and vibration spectra that were used in cluster analysis are presented in Figure 8.

Tab. 5. Geometric discrepancies of the tested wheel rim

The type of geometric nonconformit	Value
Axial runout of the left side [mm]	1.58
Axial runout of the right side [mm]	2.14
Radial runout of the left side [mm]	2.03
Radial runout of the right side [mm]	0.48

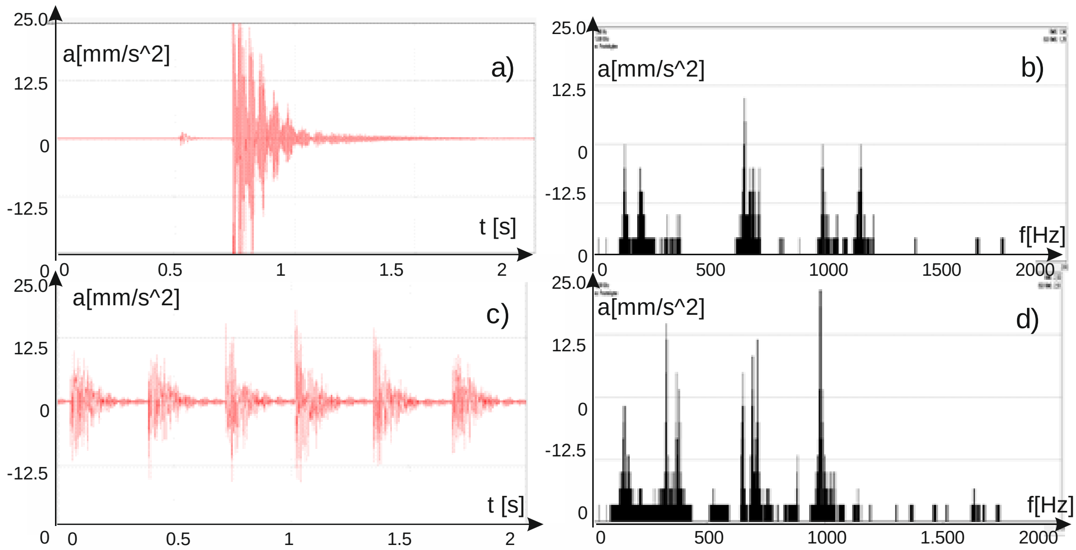

Fig. 8. Exemplary results for a 180° excitation point: a) time run for 1 strike, b) acceleration spectrum for 1 strike, c) time run for multiple strikes, d) acceleration spectrum for multiple strikes.

The data for the above example are presented in Table 6. The characteristic frequencies and the corresponding vibration amplitudes were the variables that influenced the clusters.

Tab. 6. Data for cluster analysis

Variant	f1[Hz]	a1 [m/s²]	f2 [Hz]	f2 [m/s²]	f3 [Hz]	a3 [m/s²]
K0	152	0.34	329	0.24	730	1.48
K90	135	0.19	326	0.24	712	1.02
K180	154	0.29	337	0.24	732	1.37
K270	151	0.24	215	0.15	734	0.48
K0X	152	0.39	333	0.44	729	0.73
K90X	135	0.34	329	0.73	710	0.98
K180X	154	0.34	334	0.59	732	0.53
K270X	151	0.39	209	0.39	734	0.63

The experimental variant with multiple strikes is marked with the symbol X

The results (Fig. 9) are presented in horizontal dendrograms for three characteristic frequency ranges: 135 – 155Hz. 210-330 Hz and 710-750 Hz.

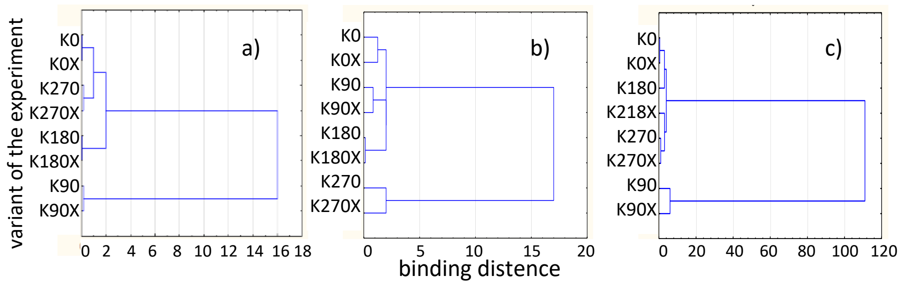

Fig. 9. The results of cluster analysis of 12×4.25in. rims with geometric defects – on basis of components of spectra frequency: a) for 135-155 Hz, b) for 710-750 Hz, c) for 210-330 Hz (The experimental variant with multiple strikes is marked with the symbol X).

Based on the charts presented in the Fig. 9 it can be concluded that for different angles of excitation the results constitute a separate group of concentration. Especially noticeable is the difference for angle of 90°, for range of frequency of 135 – 155 Hz and 210 -330 Hz. The distinguishing group for range of 710 – 750 Hz are the results of forced vibration at 270°. It means that performance of the tests for all 4 points (every 90°) on the AWRRFT stand is crucial. Single or multiple forced vibrations have smaller influence on evaluation of the state of wheel rims (groups of concentrations for those impacts are adjoining) – thus eventually only one forced vibration is applied in the procedure of investigation on the AWRRFT stand.

4. Summary

The presented examples confirm the thesis that the use of multivariate analyses can be an effective and efficient tool in identifying faults based on a set of symptoms (with a more or less diagnostic usefulness).

All cases of bearing condition (initially unknown) were correctly identified through multivariate analyses. It was confirmed by organoleptic tests and measurements of the friction coefficient.

The assessment results for the other cases of damage state of wheel rims (e.g. defective welding joints) which have not been presented in the paper confirm that: there is no crucial influence of number of forced vibration on identification of state, whereas the assessment procedure of 4 points of impact (every 90°).

Based on the previous conclusion on lack of essential influence of number of forced vibrations on identification of the state of the rims it does not follow that the measurement results in the form of vibrations spectra do not differ for single or multiple strikes but those differences finally do not influence a diagnostic decision.

Additional information

The authors declare no competing financial interests.

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