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PARAMETRIC EARLY WARNING DIAGNOSTIC METHOD FOR ROTATING MACHINERY DIAGNOSTICS

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Abstract

The aim of the paper is to detect and identify diagnostic symptoms based on parametric modeling with the use of system identification methods in the scope of monitoring techniques intended for rotating machinery under transient operational conditions. The development effort should focus on early warning methods in order to increase detectability and performance of machines operation. The diagnostic symptoms may prove to be a powerful tool for the decision support systems based on easier interpretable parameters of a parametric model. The paper discusses the experimental results obtained with the use of a laboratory test rig as well as data from conducted numerical simulations.

Keywords: rotating machinery, fault detection, early warning, system identification

PARAMETRYCZNA METODA WCZESNEGO OSTRZEGANIA DLA MASZYN WIRNIKOWYCH

Streszczenie

Celem artykułu jest rozpoznanie symptomów diagnostycznych na podstawie modelowania parametrycznego z wykorzystaniem metod identyfikacji systemów w zakresie technik monitorowania przeznaczonych dla maszyn wirnikowych pracujących w przejściowych warunkach operacyjnych. Rozwój metody skupia się na wczesnym ostrzeganiu o pogorszeniu stanu technicznego w celu zwiększenia wykrywalności oraz polepszenia stanu operacyjnego maszyn. Symptomy diagnostyczne mogą okazać się użyteczne dla systemów wspomagania decyzji opartych na łatwo interpretowalnych parametrach modeli parametrycznych. Praca przedstawia wyniki eksperymentalne uzyskane przy pomocy aparatury laboratoryjnej jak również wyniki komputerowych symulacji numerycznych.

Słowa kluczowe: maszyny wirnikowe, detekcja uszkodzeń, wczesne ostrzeganie, identyfikacja systemów

1. INTRODUCTION

The process of monitoring the state of rotating machinery needs the contribution from an early fault and malfunctions detection, in order to succeed in prevention of machine failure. Keeping the machine working point at the conditions that are the most optimal leads to downtime reduction of a machine, which results in economic loss reduction [6]. The diagnostic in industry conditions is difficult regarding many unidentified causes of current technical state. Figure 1 presents the typical complex way of malfunction propagation starting in the preload condition caused by e.g. accumulating contamination on the blades and resulted in many additional malfunctions, finally recognized as rubbing - dominant failure mode.

The discussion of typical machinery malfunctions is presented in [12]. Parametric methods have been frequently used in the past for modal analysis [7-9]. Early attempts to parametric modeling and modal analysis in rotor dynamics are given in [13] including rotor-bearing system identification from operational and experimental data, hydrodynamic bearing identification apart a rotor system using a first principal linearized model with adjustable parameters corresponding to stiffness and damping of the oil film, and advanced studies on hydrodynamic bearings stability.

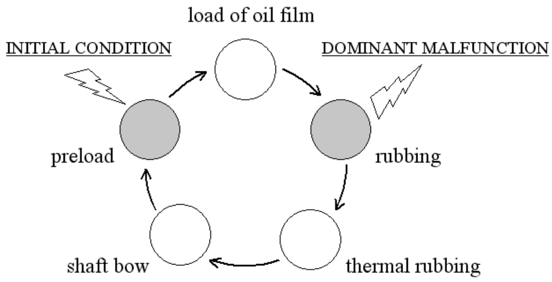

Fig. 1. Exemplary way of malfunction propagation shown schematically [5].

Over the last decades, various diagnosis methods have been developed in order to detect the faults of a rotating machinery. The usage of signal processing techniques, for instance Short Time Fourier Transform (STFT) [1] or Wavelet Transform (WT) [18] enables to deduce the diagnosis information from the vibrational signals. Wavelet transform method can decompose a signal into several time–frequency components. This method been broadly used in the industry to diagnose the rotating machinery, since it has the ability to process the non-stationary and nonlinear signals. Empirical mode decomposition (EMD) method can decompose a signal with use of self-adjusting process and create a series of intrinsic mode functions (IMF) [10]. Moreover, because the IMFs are obtained from the signal itself, EMD method is as well an adaptive signal processing method, which suits very well for the non-stationary and nonlinear signals. Although EMD method has been widely applied to various fields, it has many problems such as boundary effect, mode mixing and over- and undershoot problems [12].

Typical industrial solutions for fault detection of rotating machinery are based on nonparametric methods. In these solutions, amplitude, frequency, and phase contents of vibration signal are used to detect malfunctioning state of operation. The service specialists or experienced maintenance staff are responsible to choose relevant diagnostic symptoms and set appropriate warning/alarm thresholds, e.g. amplitude-phase acceptance regions. However, most of those techniques require an input of expertise and usually presence of an expert engineer whose knowledge is necessary to implement the method and to validate the results. Unfortunately, the expert is usually not available immediately when his presence is needed [17]. Therefore, there is a need for an easier approach, where relatively unskilled operators or maintenance stuff can make a decent decision regarding the health of the machine. When a rotating machinery is subjected to a fault, depending on the type of the fault, several characteristics of the vibration signal will display an obvious change with respect to the reference level. For some cases it is possible to show that those changes can form a specific pattern, called the fault signature of the machine [15]. That pattern could be described and therefore, the problem of rotating machinery early faults detection could be treated as a pattern recognition problem, that would be divided into the following steps: (i) vibration data acquisition, (ii) information extraction, (iii) change pattern recognition, (iv) identification of machines condition.

The paper presents simulation and experimental study investigating the performance of parametric model techniques designed for the purpose of experimental vibration mode analysis of rotating machinery from the viewpoint of input and/or output system analysis. This technique is used in order to describe the dynamic behavior of the rotor supported one sliding bearing and by one hydrodynamic bearing in terms of natural frequencies and damping factors. The method aims to fulfill a need for an easier approach to rotating machinery diagnosis, where the expert engineering knowledge is necessary to set up warning/alarm thresholds at the beginning of machine operation and periodically in order to verify the correctness of the limits and operational condition of machinery. For the rest of the operational time, relatively unskilled operators or maintenance stuff Is supposed to monitor the change in parameters patterns change and make a decision regarding the health of the machine.

3. NUMERICAL ROTOR-BEARING MODEL

In order to provide simulation data, it was necessary to develop a numerical model, for which a MATLAB software was used. The mechanical model of considered system was described using a matrix differential equation:

$$M_{n,n}\ddot{w}+G_{n,n}\dot{w}+D_{n,n}\dot{w}+K_{n,n}w+f\left(\dot{w},w\right)=u \quad (1)$$

where

$$w=\begin{bmatrix} z \\ \varphi \end{bmatrix}, u=\begin{bmatrix} u_z \\ u_\varphi \end{bmatrix}. \quad (2)$$

In the equation (1) $M_{(n,n)}$ represents inertia matrix of translational and rotational vibrations, $G_{(n,n)}$ represents gyroscopic matrix of translational and rotational vibrations, $D_{(n,n)}$ represents damping matrix of translational and rotational vibrations and $K_{(n,n)}$ represents stiffness matrix of translational and rotational vibrations. The global damping matrix has been omitted in the calculations since the damping in the sliding bearing node resulting from the motion of the shaft in the fluid film is considered in this publication. Therefore, equations (1) and (2) yields to the following matrix equation:

$$M_{n,n}\begin{bmatrix} \ddot{z}_n \\ \ddot{\varphi}_n \end{bmatrix}+G_{n,n}\begin{bmatrix} \dot{z}_n \\ \dot{\varphi}_n \end{bmatrix}+K_{n,n-1}\begin{bmatrix} z_{n-1} \\ \varphi_{n-1} \end{bmatrix}+K_{n,n}\begin{bmatrix} z_n \\ \varphi_n \end{bmatrix}+ \\ +K_{n,n+1}\begin{bmatrix} z_{n+1} \\ \varphi_{n+1} \end{bmatrix}+f(z_n,\dot{z}_n,\varphi_n,\dot{\varphi}_n)=\begin{bmatrix} u_z \\ u_\varphi \end{bmatrix} \quad (3)$$

One could expand the complex coordinates from equation (3) with $z_n = x_n + jy_n, \varphi_n = \theta_n + j\phi_n$ obtaining:

$$M_{nxn}\begin{bmatrix}\ddot{x}_n\\ \ddot{y}_n\\ \ddot{\theta}_n\\ \ddot{\phi}_n\end{bmatrix}+G_{nxn}\begin{bmatrix}\dot{x}_n\\ \dot{y}_n\\ \dot{\theta}_n\\ \dot{\phi}_n\end{bmatrix}+K_{n,n-1}\begin{bmatrix}x_{n-1}\\ y_{n-1}\\ \theta_{n-1}\\ \phi_{n-1}\end{bmatrix}+K_{n,n}\begin{bmatrix}x_n\\ y_n\\ \theta_n\\ \phi_n\end{bmatrix}+ \\ +K_{n,n+1}\begin{bmatrix}x_{n+1}\\ y_{n+1}\\ \theta_{n+1}\\ \phi_{n+1}\end{bmatrix}+f(z_n,\dot{z}_n,\varphi_n,\dot{\varphi}_n)=u_n \tag{4}$$

The equation (4) presented above considers the coupled rotor motion in the translational and rotational coordinates as described in the literature [11,14]. The particular matrices from the equation (4) are formulated as follows:

$$M_{n,n}=\begin{bmatrix}m_n & 0 & 0 & 0\\ 0 & m_n & 0 & 0\\ 0 & 0 & I_n & 0\\ 0 & 0 & 0 & I_n\end{bmatrix},$$

$$G_{n,n}=\begin{bmatrix}0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0\\ 0 & 0 & 0 & \Omega I_n\\ 0 & 0 & -\Omega I_n & 0\end{bmatrix},$$

$$K_{n,n-1}=\begin{bmatrix}-2k_{n-1} & 0 & -(kl)_{n-1} & 0\\ 0 & -2k_{n-1} & 0 & -(kl)_{n-1}\\ (kl)_{n-1} & 0 & 1/3(kl^2)_{n-1} & 0\\ 0 & (kl)_{n-1} & 0 & 1/3(kl^2)_{n-1}\end{bmatrix}$$

$$K_{n,n}=\begin{bmatrix}2(k_{n-1}+k_n) & 0 & -(kl)_{n-1}+(kl)_n & 0\\ 0 & 2(k_{n-1}+k_n) & 0 & -(kl)_{n-1}+(kl)_n\\ -(kl)_{n-1}+(kl)_n & 0 & \frac{2}{3}\left[(kl^2)_{n-1}+(kl^2)_n\right] & 0\\ 0 & -(kl)_{n-1}+(kl)_n & 0 & \frac{2}{3}\left[(kl^2)_{n-1}+(kl^2)_n\right]\end{bmatrix} \tag{5}$$

$$K_{n,n+1}=\begin{bmatrix}2k_n & 0 & (kl)_n & 0\\ 0 & -2k_n & 0 & (kl)_n\\ -(kl)_n & 0 & 1/3(kl^2)_n & 0\\ 0 & -(kl)_n & 0 & 1/3(kl^2)_n\end{bmatrix}$$

where rotor stiffness is as follows

$$m_n=m_n^{disk}+(d_{n-1}\rho_{n-1}l_{n-1}+d_n\rho_n l_n)^{shaft}, \\ k_n=\frac{6E_nI_n}{l_n^3} \tag{6}$$

The physical bearing model is based on the Reynold's equation and allows to analyze oil flow in a determined layer, comprising the balance equation for a fluid element and the equations of flow continuity. Reynold's equation provides better insight into the dynamics of a rotor-bearing system specially under transient operation conditions when a nonlinear dynamic analysis need to be carried out. The basic form of Reynold's equation involves the following assumptions:

- lubricating oil is Newtonian fluid,
- constant viscosity and density are specific to lubricating oil (isothermal process),
- laminar flow occurs,
- mass forces of lubricating oil particles are negligible,
- shaft motion has a stable characteristic, and the shaft center is held in its position,
- the shaft and the bearing bushing are not deformed; they ideally smooth/even and shaped in the form of cylinders,
- pressure prevailing in the lubricating oil layer remains unchanged along the layer thickness.

The forces that are generated by the fluid film can be denoted as F_x, F_y and are obtained by solving analytically the Reynold's equation for the short bearing approximation:

$$f(z_n,\dot{z}_n)=\begin{bmatrix}F_x=-\mu\pi RL^3\begin{bmatrix}\dfrac{\Omega y+2\dot{x}}{2(c^2-x^2-y^2)^{3/2}}+\\ +\dfrac{3x(x\dot{x}+y\dot{y})}{2(c^2-x^2-y^2)^{5/2}}\end{bmatrix}\\ F_y=-\mu\pi RL^3\begin{bmatrix}\dfrac{2\dot{y}+\Omega x}{2(c^2-x^2-y^2)^{3/2}}+\\ +\dfrac{3y(x\dot{x}+y\dot{y})}{2(c^2-x^2-y^2)^{5/2}}\end{bmatrix}\end{bmatrix} \tag{7}$$

which can be denoted as:

$$f(z_n,\dot{z}_n)=\begin{bmatrix}F_\beta\cos\theta-F_\alpha\sin\theta\\ F_\beta\sin\theta+F_\alpha\cos\theta\end{bmatrix},\ \begin{matrix}x=c\beta\cos\alpha\\ y=c\beta\sin\alpha\end{matrix} \\ \beta=\frac{\sqrt{x^2+y^2}}{c},\ y=\arctan\left(\frac{y}{x}\right) \tag{8}$$

The presented models have been implemented in Matlab Simulink and parametrized according to the rotor test rig geometry, physical parameters and configuration. Table 1 presents used physical parameters.

Table 1. Rotor properties belonging to models nodes.

		Node 1	Node 2
Imbalance	radius [m]	0.035	0
	mass [g]	0.2	0
	phase [°]	0	0
Disk	mass of disk [kg]	0.8	-
Support	clearance [μm]	-	220
	viscosity [Pa·s]	-	0.002
	length *L* [m]	-	0.03
	diameter *D* [m]	-	0.051
	elevation [m]	-	0

3.1. Rotor-bearing system identification

The considered rotor-bearing model can be represented by time-variant nonlinear adjustable-parameter Ordinary Differential Equations (ODEs) model in the form of set of state-space equations formulated in the continuous-time domain:

$$\begin{aligned} &\frac{d}{dt}x(t) = f(t, x(t), u(t), w(t); \theta) \\ &y(t) = h(t, x(t), u(t), v(t); \theta) \\ &x(0) = x_0 \end{aligned} \tag{9}$$

where vector f(.) is a nonlinear, time-varying function of the state vector x(t) and the excitation vector u(t), while vector h(.) is a nonlinear measurement function; w(t) and v(t) are sequences of independent random variables and θ denotes a vector of unknown parameters. The sum of squared errors is used as an error criterion. The model structure is defined by the function notation as follows:

$$ODE(ny, nu, nx) \tag{10}$$

where *nu* is the number of inputs, *ny* is the number of outputs, and *nx* is the number of the state variables.

The alternative rotor-bearing model representation is time-invariant, linear, discrete-time adjustable-parameter model. The models is represented by discrete-time G(z^{-1},i) and H(z^{-1},i) transfer functions, which represent the input-to-output dynamics and the disturbance-to-output dynamics, respectively. These transfer functions are rational functions of the operator z^{-1} and discrete sample time *i* as follows [2]

$$\begin{aligned} &y(i) = G(z^{-1})u(i) + H(z^{-1})e(i) = \\ &= \frac{B(z^{-1}, i)}{A(z^{-1}, i)}u(i) + \frac{C(z^{-1}, i)}{A(z^{-1}, i)}e(i) \end{aligned} \tag{11}$$

where the polynomials A(z^{-1}), B(z^{-1}), C(z^{-1}) define the structural symbol as follows:

$$ARMAX\,(nA, nB, nC, k) \tag{12}$$

where nA, nB, nC are the polynomial orders and *k* is input-to-output model delay. Nevertheless, this feasibility study applies only AR(nA) model.

The proposed diagnostics approach considers a time-invariant parametric autoregressive model to capture time-invariant dynamics of rotor-bearing system regarding its frequency and damping vibration modes under transient operation. The vibration response of has complex frequency content which in general consist of time-invariant and -variant frequency components. There are three main types of frequency components. The first of these are the 'exogenous modes' corresponding to excitation harmonics (e.g. unbalance), which frequencies depend on a rotational speed. The second and third type of components are the natural frequencies.

4. PROPOSED METHOD

The proposed diagnostic methodology considers a model-based approach in detection of faulty conditions of a rotor system supported on hydrodynamic bearing and sliding bearing under transient operation conditions. The rotor model of considered dynamic system can be expressed as a transfer function 13:

$$H(s, \Omega) = [Ms^2 + D(\Omega)s + K(\Omega)]^{-1} \tag{13}$$

Parameter values of transfer function in the discrete time domain [16] can be estimated with the use of numerous algorithms 13. Structure of such a model consists of polynomials H(z^{-1}) which are rational functions of the operator z^{-1}

$$\mathrm{y(i) = H(z^{-1})\,e(i)} \tag{14}$$

If the input is unknown u(*i*)≡0 then only time series model is determined. The roots of the denominator of G(z^{-1}) transfer function (15) are the poles of a model.

$$z^{nA}\det\{A(z^{-1})\} = 0\,, \tag{15}$$

The orders n of polynomials A(z^{-1}) and are evaluated and properly selected from the measurements. The one of the most commonly applied test intended for determining the model order is the AIC method consisting in the minimization of Likelihood function [6].

The exact procedure used for the purpose of establishment of this diagnostic method can be described as: (i) implementation of a hydrodynamically supported rotor model in Matlab/Simulink environment to validate the method at a conceptual phase, (ii) development of a system identification method with use of Matlab/Simulink tools.

One of the possible post processing methods in case of eigenvalues extraction from a diagnostic model is monitoring of their trends vs. operation time. The core diagnostic algorithm can be formulated as follows: (i) identification of a diagnostic model based on the measurements, (ii) instantaneous extraction of eigenfrequencies and damping decay ratios from identified model parameters, (iii) poles placement monitoring on a complex plain within assumed warning/alarm regions.

Symptoms of abnormal operating conditions are deviations in location of eigenfrequencies on a complex plain. The identified model may have dual representation in the form of a nonparametric model (power spectrum, transient response, Bode diagram, polar diagram) and parametric model (poles/zeros, model parameters). In other words, a parametric model is more general representation of a dynamical system and it can be converted into an arbitrary nonparametric system representation.

A damping ratio and natural frequency are extracted from particular eigenfrequency value to provide direct physical meaning. If a transfer function model is involved, the eigenfrequencies are interpreted as poles and zeros. Figure 2 visualizes the concept with two class of poles corresponding to reference (healthy) and faulty operating conditions (run condition and looseness condition). In reality, the change of class can happen evolutionary (pending malfunction) and is preceded by small deviation in poles locations. A sensitivity of the method depends on the measurement noise affecting model parameter estimation and modeling structure selection (model truncation).

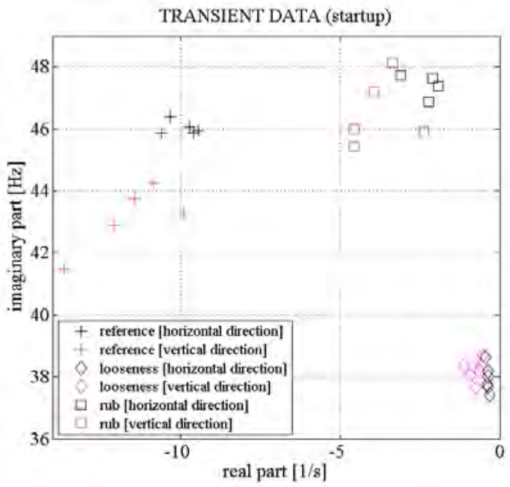

Fig. 2. Average poles placement as the estimate of rotating machinery condition.

A faulty condition is detectable if pole coordinates cross coordinates of 2D region belonging to a given class. A fault isolation is performed if coordinates or membership metrics are known for each of distinguishing classes. Maintenance data and available plant specialist expertise are required to adjust scenarios of poles placement in case of malfunction occurrence and transfer them into diagnostic patterns.

This stage requires subjective judgments since for a non-typical machinery the patterns can be a priori unknown. However, this is also the case if one uses currently available monitoring equipment. The alarm thresholds are adjusted based on the available domain knowledge, gathered measurement data, or simulation results [3]. Nevertheless, creation of scenarios in the proposed method can be supported by self-classification algorithms which preprocess the historical operational data (if available) by partitioning the search space and distributing the patterns in the resulting groups according to the values of their components. Uncertainty of pole location can be quantified using statistical approach based on the standard deviation ellipses obtained for each pole. There two types of uncertainty. The uncertainty of a pole estimation and uncertainty of class representative. The inference (fault isolation) algorithm may use uncertainty estimates to involve confidence intervals assigned to particular classes. The problem of finding which among a set of stored patterns are closest to a given test pattern is of great general interest. There are effective real time applicable methods for coding of the diagnostic scenarios and knowledge [14], e.g. nearest neighbor (NN) searching algorithm, fault or test trees, transition matrices, decision tables, diagnostic graphs, belief networks, real time expert systems.

The fundamental advantages of the parametric model approach consist in a high accuracy of identification of short series of measuring data and possible representation of results in the form of nonparametric models. A parametric model can be converted into arbitrary system representation. High resolution in the frequency domain provides possibility of detection of slight frequency changes according to e.g. rub phenomena. Rub causes local abrupt frequency increase as a result of contact between rotor or blades and non-rotating parts. Parametric model approach allows saving of memory allocation indispensable for recording of a specific history of individual states of the machinery. When the circular buffer has reached the exit status, only a few model parameters are permanently recorded, but not all signals as waveforms. By archiving the model parameters only, there is a possibility of quasi-continuous data recording. In this case system data can be collected at selected intervals (e.g. per 1 minute) at substantial lower usage of data media and computational requirements. Considering the 0.5X component occurring in a spectrum obtained based on relative vibration of journal in a hydrodynamic bearing, it can be clearly pointed out that the nonparametric approach to these problems appears to be not suitable. The frequency of the component is dependent on the type of bearing and the actual state of machinery (e.g. load, bearing clearances, oil

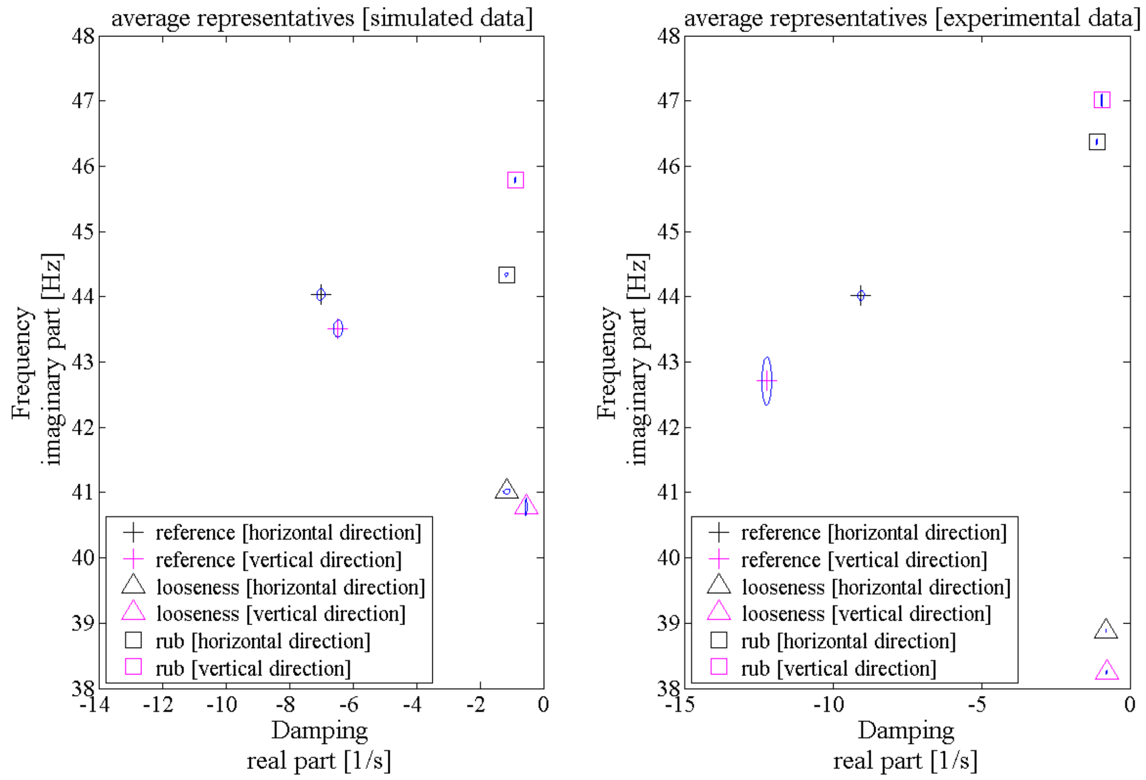

Fig. 3. Poles placement in the case of reference and faulty conditions for the simulated data (left) and experimental data (right) including confidence ellipses.

temperature). The change of 0.5X component according to amplitude and/or phase can indicate a given machinery state. Frequency variation of such a component is high and may change in the range of 40% (0.4X) to 60% (0.6X) of 1X synchronous components. It is difficult to use fixed-parameter filter to select this frequency component. Most of diagnostic systems are not provided with the option for observing this component. Parametric model approach allows identifying the 0.5X component as a pole with a determined imaginary part (relationship with natural frequency) and real part (relationship with damping).

Development of a reliable and efficient solution of the proposed method may bring numerous benefits to simplified rotating machinery monitoring systems. A parametric model-based system identification approach allows to detect and recognize malfunctions significantly easier than in case of a nonparametric signal-based method providing symptoms recommended for automatic diagnostic, e.g. pole placement on a complex plain. New approach is proposed due to the following advantages: (i) increased resolution in the frequency domain allows to detect slight frequency changes occurring in case of a rub or cracked rotors, (ii) decreased capacity required for storage of frequency data, (iii) possibility of dual representation of identified system in the form of a nonparametric model and parametric model.

5. CASE STUDY

Long-term monitoring of time-invariant frequency and damping components provides sufficient data sets to detect statistically significant deviation from the mean initial values assumed as the reference normal operating condition. A possible diagnostics approach is to collect the time-invariant frequency and damping components on a complex plain and follow their trends. The advantage of this approach is the semi-physical interpretation of poles placement indicating potential malfunctions. The paper considers only transient conditions for bearing-rotor systems, e.g. steam turbines, turbo charges, engine crank-shafts. However, the conclusions and developed method is applicable to other rotating machinery equipped with rolling bearings and data represented, i.e. displacement, velocity or acceleration measurements.

Currently, computational models are very common and useful in order to provide a reliable, relatively quick and cheap solutions for real world problems. However, those kinds of simulations usually have some kind of implemented uncertainty and inaccuracy resulting from used assumptions and simplifications within the process of model creation. Therefore, there is still a need for model validation. Usually, models are validated by a comparison of simulated data to experimental results from well-known operating points and that is why authors used a test rig in order to obtain experimental data needed for model validation. Due to the fact, that considered machinery is subjected to the largest stress and fatigue under transient operational conditions rather in the steady-state, this paper focuses only on transient conditions.

5.1. Experimental validation

The RK-4 Rotor test rig [2] used in this study was manufactured by Bently Nevada is shown in the Figure 4. The experimental rotor-bearing system consists of speed controller, electric motor, speed controller transducer, elastic coupling, phase-maker transducer (once per turn), laterally rigid with pivoting brass oil bearing, steel shaft, four proximity eddy current transducers mounted in XY orthogonal configuration respectively, rotor disk of mass 0.8 kg with some unbalance, four radial spring supporting system, oil (T-10) lubricated bearing and four-port oil supply. The motor provides the experimental test rig with rotation torque that allows for a rotordynamic investigation. A flexible motor coupling connects the motor to the shaft, allowing for small axial and radial movement of the shaft. The test stand also comes with an adjustable base which allows for axial movement of system components to achieve different system configurations. The base of the test rig allows for axial flexibility of the location of the disk and the hydrodynamic bearing making it possible for a vertical Y axis and a horizontal X axis orientation. A disk is mounted on a defined location on the shaft near the middle of the bearing span of a bushing and the considered bearing. Two types of sensors are used in this experiment to monitor position change of the rotor. One is a pair of eddy current position probes located near the disk, oriented vertically and horizontally. Data from these probes are collected using an DSPi (Dynamic Signal Processing Instrument) and a computer. The other is a pair of variable reluctance probes located on a sensor ring on the bearing.

5.2. Numerical validation

The exact rotor model consists of 17 nodes and 16 rotor sections and has been tuned to the measurements of a test rig. This test rig consists of a flexible rotor supported by a single sliding/hydrodynamic bearing characterized by physical. The model provides only qualitative accuracy which is essential to understand placement of eigenvalues' trajectories during transient operating conditions. The simulation provides a basis for diagnostic algorithm development. In order to simplify the analysis of eigenvalues' patterns, the analysis was carried out using the reduced model, where the sliding bearing is massless, and only hydrodynamic bearing and the disk have mass. Due to those simplifications, the sliding bearing can be represented as a rigid support and will not be consider in further simulations. Figure 5 shows the discrete representation of simplified model used for numerical calculations.

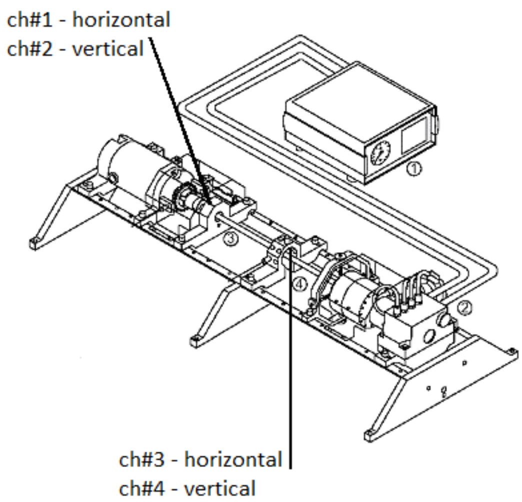

Fig. 4. R4 ROTOR KIT [2] with:1-oil pump assembly, 2-oil bearing assembly, 3-rotor kit shaft with oil bearing journal, 4-preload frame.

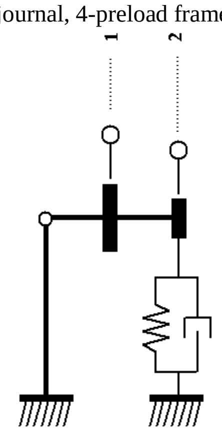

Fig. 5. Simplified rotor-bearing model discrete representation: 1 – rotor disk, 2 – hydrodynamic bearing.

5.3 Conclusions

Preliminary research based on analytical, numerical and laboratory model [2] provided promising results 4. The analytical solution provided preliminary insight into a linearized diagnostic model. The numerical simulations allowed the prediction of rotor behavior in the case of considered malfunctions that have been simulated on the test-rig and others not included for physical experiment. Transient operating conditions were simulated. During identification experiments ARX(2,1,1) model was used. The model parameters were transformed into zeros/poles representation of a dynamic system. As the input to ARX model the phase signal was assumed of the amplitude that equals one. Relative vibrations of shaft at hydrodynamic bearing [4] in horizontal and vertical direction were assumed as the ARX model output. As a result of identification several sets of ARX model parameters were obtained for each type of fault rotor condition. Next, the model parameters were transformed to zero/pole representation (Eq.

10,11). The identification procedure was repeated several times for each simulating case of malfunction to asset dispersion in population.

The method procedure can be defined as follows: (i) the model is represented by a transfer function with arbitrary assumed orders of numerators and denominators, (ii) identification is performed separately in a vertical and horizontal plain of the rotor axis, (iii) system is considered as a finite-degree and number of conjugate poles corresponding to the number of vibration modes to be trunked to the most essential ones, (iv) malfunctions affect models' parameters in result of significant physical/geometrical nonlinearities and structural changes, e.g. nonlinear stiffness, turbulent oil flow through restrictions, looseness, wear.

Table 2. Average poles placement based on simulation (mean value ± standard deviation)

Operating conditions	Direction	Average damping [Hz]	Average frequency [Hz]
Reference	horizontal	-7.011 ± 1.231	44.034 ± 0.899
	vertical	-6.466 ± 1.435	43.515 ± 1.329
Rub	horizontal	-1.167 ± 0.455	45.339 ± 0.324
	vertical	-0.891 ± 0.187	45.786 ± 0.486
Looseness	horizontal	-0.730 ± 0.362	41.016 ± 1.148
	vertical	-0.544 ± 0.239	40.775 ± 1.347

In the investigated case, the looseness condition causes a significant drop of average natural frequency; from 44.03 Hz to 41.02 Hz and from 43.52 Hz to 40.76 Hz for the horizontal and the vertical direction respectively. The average decay ratio also decreased from -7.01 to -0.73 for horizontal direction and from -6.47 to -0.54 for vertical direction (Figure 3). The second part of the conducted test was intended to show the influence of the rub condition on the bearing stability and stiffness. The average natural frequencies in horizontal and vertical direction changed from 44.03 Hz to 45.34 Hz and from 43.52 Hz to 45.79 Hz respectively. The average decay ratio decreased from -7.01 to -1.17 for the horizontal direction and from -6.47 to -0.89 in the vertical direction.

Table 3. Average poles placement based on experiment (mean value ± standard deviation)

Operating conditions	Direction	Average damping ratio [Hz]	Average frequency [Hz]
Reference	horizontal	-9.047 ± 1.054	44.024 ± 0.755
	vertical	-12.223 ± 1.615	42.711 ± 3.662
Looseness	horizontal	-0.805 ± 0.055	38.883 ± 0.169
	vertical	-0.786 ± 0.215	38.249 ± 0.346
Rub	horizontal	-1.113 ± 0.347	46.372 ± 1.113
	vertical	-0.748 ± 0.251	47.015 ± 0.947

Table 2 and Table 3 show that both malfunctions can be easily detected and isolated based on the poles placement. The proposed method allows to identify typical malfunctions – the looseness conditions and the condition of rub. One can detect the first one by observation of drop of average natural frequency of considered system about 2-5 Hz (5-10 %) and drop of the damping ratio by about 5-7 (40-50 %). The other one appears by increase of natural frequency by about 2-3 Hz (5-7%) and decrease of damping ration by about 5-6 (40-45 %). One could also observe the behavior or confidence ellipses in time since they can indicate the quality of diagnostic process, the smaller the ellipses, the more accurate analysis is. If ellipses would increase it means, that the quality decreases.

Due to the fact that only simplified model of a rotor-bearing system was used, obtained results from the simulations and conducted measurements differ in poles locations. The initial assumption was that the model is supposed to provide only qualitative accuracy which is essential to understand the location of poles for considered malfunctions. Therefore, the simulation provides only a basis for development of diagnostic algorithm. The observation of trend of poles location may give a better insight of malfunction development over operational time.

Analyzing the arrangement of poles in the case of looseness conditions, it is possible to infer the following conclusions. A system model is stable; all the poles are on the left complex semi-plane. A decreased stability margin is clearly visible as far as the displacement of poles towards to the right of a complex plane. Due to the introduction of high-valued backlash during the mounting of hydrodynamic bearings upon the foundation (the mounting rail), a marked decrease of the damping to zero (approx. –0.4 [1/s]) was observed. The natural frequency also decreased from 260 rad/s up to 240 rad/s. High amplitude vibration in the system is generated at lower natural frequencies. The system has lost its anisotropy in the horizontal and vertical directions (Fig. 4). In the consequence of looseness similar natural frequencies may be registered both in vertical and horizontal directions.

6. SUMMARY

As a result of intensive laboratory and numerical experiments the parametric approach based on ARX model was proposed. Selected aspects of testing methods for rotating machines under transient operating conditions were discussed in the paper. A mathematical model of the rotating machine was also utilized to verify physical test result [3].

The proposed diagnostic method allows for setting the thresholds corresponding to normal and malfunctioned conditions evaluated by maintenance or service provider staff. It allows to classify the malfunctioned machinery to one of a few predefined defects based on eigenvalues patterns which are represented and visualize on a complex plain. The malfunctions are assigned to specific poles patterns based on historical data (previously collected data sets and calculated trends of parameters change) and experts' recommendations. When current poles pattern is out of the reference specification a fault isolation procedure has been initialized to detect malfunctions, i.e. identify where is the problem, and what caused the problem.

The presented method of malfunction risk assessment based on eigenvalue patterns shows that group of basic malfunctions, i.e. rub and looseness can be detected while the machine is operating. The detection is related to the change of poles location – natural frequency and damping ratio. The presented method confirms the idea, that relatively unskilled operators or maintenance stuff could monitor the change in poles placement patterns and make a meaningful decision regarding the health of the machine. Of course, it is not possible to exchange the skilled engineers, they knowledge and expertise will still be necessary in order to periodically verify the thresholds and to make a detailed diagnosis regarding the actual state of the machinery.

The paper considers only transient conditions for bearing-rotor systems, e.g. steam turbines, turbo charges, engine crank-shafts. However, the conclusions and developed method is applicable to other rotating machinery equipped with rolling bearings and data represented, i.e. displacement, velocity or acceleration measurements.

Summarized, parametric model approach provides increase of frequency resolution, elimination of disturbances, and easier stability recognition. It was shown that parameters of AR/ARX and similar models can be applied in early warning diagnostic solutions. Introduced aspect of continuously developing machinery diagnostics regarding parametric approach is a first step to design in the future fully model-based diagnostic method. This diagnostic is a very common within a few last years, however practical solutions are difficult to apply and not present in industry.

NOMENCLATURE

$i = \sqrt{-1}$ – imaginary unit,
t, i – continuous and discrete time domains,
s, z – Laplace and Z transformation operator,
Ω - rotating speed [1/s],
L - total rotor length [m] or length of the journal [m],
x, y - lateral motion coordinates [m],
z - coordinate along the shaft axis [m],
θ, ϕ - dx/dz and dy/dz coordinates in angular motion [rad],
Z, φ - complex translational and rotational vibrations [m],
n - the number of degrees of freedom [-],
$w_{(nx1)}$ - response vector of translational and rotational vibrations,
$u_{(nx1)}$ - excitation vector of translational and rotational vibrations,
$M_{(nxn)}$ - inertia matrix of translational and rotational vibration,
$G_{(nxn)}$ - gyroscopic matrix of translational and rotational vibrations,
$D_{(nxn)}$ - external damping matrix of translational and rotational vibrations,
$K_{(nxn)}$ - stiffness matrix of translational and rotational vibrations,
$K_{s(nxn)}$ - support stiffness matrix of translational and rotational vibrations,
d - damping coefficient of a fluid film [N·s/m],
k_0 - stiffness coefficients of a fluid film [N/m],
c - bearing clearance [m],
μ - dynamic viscosity [Pa·s],
θ - current angular position of the journal center [rad],
h - dimensional oil gap (oil film thickness) [m],
R - journal radius [m],
f(.) - nonlinear function [N],
m - mass [kg],
I_T, I_P – transverse and polar inertia moment [kg·m2],
I - area moment [m4],
l - length of shaft section [m],
d - diameter of shaft section [m],
ρ - density [kg/m3],
E - Young's modulus,
F_x,F_y - bearing forces [N],
x, y - current position of journal center [m],
x_0, y_0 - linearized position of journal center [m],
Abbreviations
FFT - Fast Fourier Transformation
ARX - Auto Regressive with eXogenous input
STFT - Short Time Fourier Transform
WT – Wavelet Transform
EMD - Empirical Mode Decomposition
IMF – Intrinsic Mode Function

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