Model Based Fault-Detection and -Diagnosis using Active Magnetic Bearings

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Abstract: This paper shows how model based fault detection and diagnosis can be integrated into the active magnetic bearing system. It describes two appropriate fault-detection methods on the example of centrifugal pumps in magnetic bearings and shows how typical fault states occurring on these pumps can be detected and diagnosed. Prior to the fault detection the modeling of the magnetic bearing system is described.
The investigated multi model method contains a bank of models representing the systems transfer behavior for the different fault. With this method the error between the outputs of the models and the output of the plant are provided as features for the fault diagnosis. A balancing filter is described helping to separate the different features more clearly.
Instead of computing the complete frequency behavior of the plant the transfer factor method uses the Goertzel algorithm to compute only significant discrete frequency points and provides the complex transfer factor as feature.
It is shown that fault detection and diagnosis could be integrated within AMB systems. Both methods are well suited to provide reliable information about the system state.

Keywords: Model Based Fault Identification, Modal System Representation, Elastic rotor, Active Magnetic Bearing, Centrifugal Pump

Introduction

Active magnetic bearings have many advantages compared to conventional roller bearings. One of them is the potential to integrate functions for fault-detection and fault-diagnosis within the mechatronic system. Since most magnetic bearing systems already provide information about the bearing-forces and the shaft displacements through current and displacement sensors, multiple possibilities for fault detection exist. Furthermore the commonly used digital controllers for AMBs have enough computational power to run fault diagnosis algorithms in parallel to the position control.

Often the process itself has an influence on the mechanical properties of the shaft. A running wheel of a centrifugal pump produces an axial load on the shaft, which depends on the hydraulic parameters of the pump process. If this load can be measured through the bearing loads, an analytic redundancy can be set up for fault diagnosis.

In certain cases the dynamical behavior of the shaft is influenced by fault states. A loosened shaft nut for example can influence the stiffness and damping properties of the shaft. Likewise fluid-structure-interaction within seal gaps of centrifugal pumps influence the dynamical properties of the shaft through inertia, damping and stiffness [1]. With the knowledge of the bearing forces as the (dominating) inputs of the dynamic system and the displacements as its outputs, the dynamic behavior of the shaft can be analyzed and therewith the different faults diagnosed.

Test rigs

Two test rigs of centrifugal pumps in magnetic bearings are available for the investigations. They differ in size and design. Test rig A is a smaller pump where the pump housing is placed between the two bearings. Within test rig B the rotor is designed as a cantilever arm. Fig. 1 and Fig. 2 show the test rigs, Table 1 gives their properties.

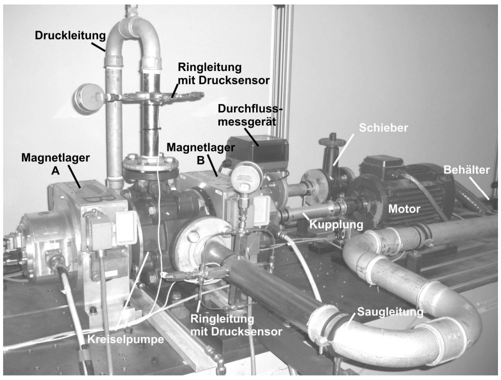

Fig. 1 - Test rig A

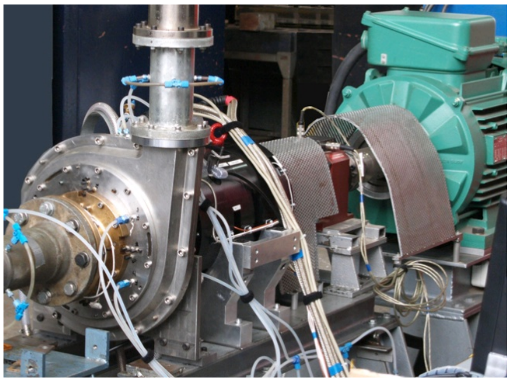

Fig. 2 - Test rig B

Table 1- Properties test rig A and test rig B

	Testrig A	Testrig B
Volumeflowrate	18[m³/h]	105 [m³/h]
Pressurehead	21 [m]	59 [m]
Engine Power	1,7 [kW]	24 [kW]
Nominal Speed	2500 [rpm]	2500 [rpm]
Radial Magnetic Force	800 [N]	1000 [N]
Axial Magnetic Force	2300 [N]	7000 [N] and 2000 [N]

Topology. The test systems can be divided into three different levels as shown in Fig. 3. The hardware-level, with the pump in magnetic bearings, the user-level with the operator who wants to control and observe the system and the software level. The primary tasks of the software-level is to handle the control and observation requests from the operator, and to realize the position control for the magnetic bearings. It also provides further functionality for fault detection and -identification. It is executed on a real-time-controller, in order to ensure the necessary real-time capability.

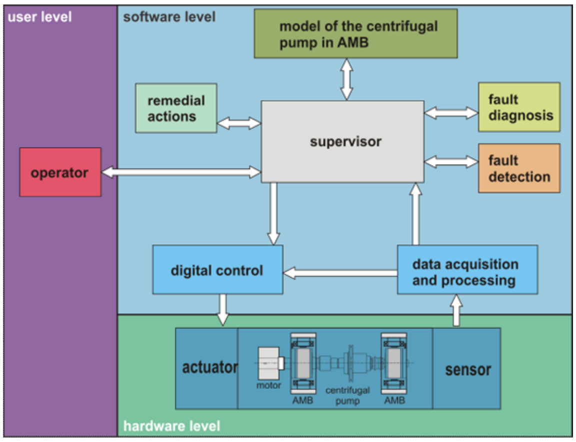

Fig. 3 - System topology

Modeling

The structure of the model, used to set up the model based fault identification is shown in the block diagram in Fig. 4. The overall model describes the dynamical properties of the hydro-mechatronical system, and considers the elastic pump shaft, the fluid-structure-interaction in the seals, the magnetic bearings with the digital position controller and the effects of the elastic substructure. The different parts of the model are described in the following.

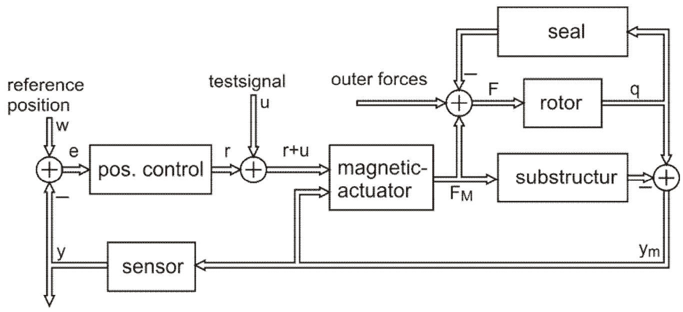

Fig. 4 - Model structure

Pump-shaft. Fig. 5 shows the pump-shaft of test rig A. It shows the wheel of the pump in the center and the ironing of the magnetic bearings on both sides. The rotordynamic model takes account of the elastic behavior of the shaft and the gyroscopic effects. It has four in- and outputs in the sensor and actuator-planes. The finite element model, shown in the state-space-form on the right, has 96 degrees of freedom. The dynamical behavior is mainly characterized by the first three natural frequencies of the elastic shaft. For 0 rpm they are 285 Hz, 640 Hz and 1015 Hz for test rig A and 301 Hz, 759 Hz and 1223 Hz for test rig B.

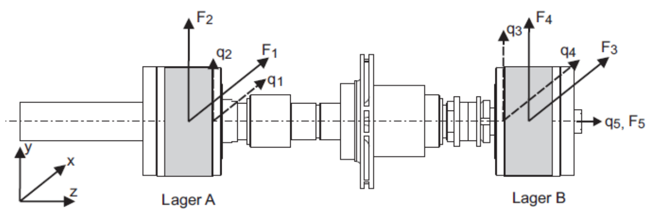

Fig. 5 – In- / outputs of the pump-shaft model test rig A

$$\overbrace{\begin{bmatrix}\dot{q}\\ \ddot{q}\end{bmatrix}}^{x} = \overbrace{\begin{bmatrix}0 & I\\ -M^{-1}K & -M^{-1}D\end{bmatrix}}^{A}\overbrace{\begin{bmatrix}q\\ \dot{q}\end{bmatrix}}^{x} + \overbrace{\begin{bmatrix}0\\ M^{-1}\end{bmatrix}}^{B}\overbrace{F}^{u}$$

$$\underbrace{\begin{bmatrix}q\\ \dot{q}\\ \ddot{q}\end{bmatrix}}_{y} = \underbrace{\begin{bmatrix}I & 0\\ 0 & I\\ -M^{-1}K & -M^{-1}D\end{bmatrix}}_{C}\underbrace{\begin{bmatrix}q\\ \dot{q}\end{bmatrix}}_{x} + \underbrace{\begin{bmatrix}0\\ 0\\ -M^{-1}\end{bmatrix}}_{D}\underbrace{F}_{u}$$

Fig. 6 - State space form of the pump-shaft FEM model

Magnetic bearings. The magnetic bearings have a standard eight pole stator. Each force direction (Fig. 5) is realized by a push-pull constellation of two electromagnetic circuits with bias current. The model of the magnetic bearings is derived by a linearization [2] which leads to the following equations (4x4-system).

$$\dot{I} = \frac{k_{SR}}{T_{SR}} \cdot I + \begin{bmatrix}\frac{1}{T_{SR}} & 0\end{bmatrix} \begin{bmatrix}I_{soll} & s\end{bmatrix}^T \tag{1}$$

$$F = k_i \cdot I + \begin{bmatrix}0 & k_s\end{bmatrix} \begin{bmatrix}I_{soll} & s\end{bmatrix}^T \tag{2}$$

Seal gap. The centrifugal pumps contain a seal gap (index SG) within their housing. It seperates the pressure side and the suction side. Caused by the fluid structure interaction within the gap, it influences the dynamical behavior of the system. The mass, damping and stiffness matrices [1] are obtained by an FEM-analysis [3] at the different operating points of the pump.

$$-\begin{bmatrix} F_{SG1} \\ F_{SG2} \end{bmatrix} = \begin{bmatrix} M_{SG} & m_{SG} \\ m_{SG} & M_{SG} \end{bmatrix} \begin{bmatrix} \ddot{q}_{SG1} \\ \ddot{q}_{SG2} \end{bmatrix} + \begin{bmatrix} D_{SG} & d_{SG} \\ d_{SG} & D_{SG} \end{bmatrix} \begin{bmatrix} \dot{q}_{SG1} \\ \dot{q}_{SG2} \end{bmatrix} + \begin{bmatrix} K_{SG} & k_{SG} \\ k_{SG} & K_{SG} \end{bmatrix} \begin{bmatrix} q_{SG1} \\ q_{SG2} \end{bmatrix} \quad (3)$$

Substructure. Especially on test rig A the substructure influences the system behavior. A FEM analysis of the bearings housing is conducted and the results are compared with the results of a modal analysis. The resulting parameters are implemented as follows:

$$\begin{bmatrix} q_{G1} \\ q_{G2} \end{bmatrix} = c_{sub} \begin{bmatrix} -sin(\frac{\pi}{4}) & 0 \\ cos(\frac{\pi}{4}) & 0 \end{bmatrix} \begin{bmatrix} \xi \\ \dot{\xi} \end{bmatrix} \quad (4)$$

$$\begin{bmatrix} \dot{\xi} \\ \ddot{\xi} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\omega_0^2 & -2\omega_0 D_{LG} \end{bmatrix} \begin{bmatrix} \xi \\ \dot{\xi} \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ -sin(\frac{\pi}{4}) & cos(\frac{\pi}{4}) \end{bmatrix} \begin{bmatrix} F_1 \\ F_2 \end{bmatrix} \quad (5)$$

Controller. The position control is realized by decentral PID controllers with additional lowpass-filters (C). The controller parameters are equal within one bearing plane, but slightly different parameters are used for the different bearings planes.

$$C = \begin{bmatrix} C_{11} & 0 & 0 & 0 \\ 0 & C_{22} & 0 & 0 \\ 0 & 0 & C_{33} & 0 \\ 0 & 0 & 0 & C_{44} \end{bmatrix} \quad (6)$$

Modal transformation and model reduction. The complete mathematical model of the mechatronic system is transferred to a modal state space form using right- and left-eigenvectors. The resulting system consists of 268 modal states and is truncated to 44 modal states.

Fault states

Typical fault states occurring on centrifugal pumps like dry-run, wear and loosened shaft nut have been investigated. These faults can be described as multiplicative faults which are characterized by a change of at least one of the systems physical parameters e.g. mass, damping and stiffness. Hence the systems modal parameters change. One way to display the modal parameters is the frequency response function. Fig. 7 shows the systems reference state and a dry run. In comparison to the reference state the physical parameters within the seal gap have changed due to the dry-run which leads to the different curves.

Multi-model-method for fault detections

This method consists of a bank of models representing the process sensitivity functions of the different system states. The principle structure is given in Fig. 8. The models, which take account of the complete bandwidth of the system up to 1000Hz, are computed in parallel to the plant. The features are obtained as the standard deviation of the output error between the plant and the models.

A good correlation between the output of the models and the plant within the features time signals is achieved if experimentally identified models of the different system states are used.

To identify the models a testsignal is applied to the testsignal input of the system as shown in Fig. 4. The parametric models are identified using the Subspace Identification Method via Principal Component Analysis. Based on the knowledge about the system gained during the mathematic modeling the identified models can be reduced to a relevant number of states.

For some fault states the resulting features do not separate properly and it is not possible to detect the current fault state reliably. In these cases the faults do not lead to a significant change of the modal parameters at the dominating modes.

Due to the systems principle lowpass characteristic the deviations within the lower frequency range have a higher amplitude level than the ones at higher frequencies and thus have more influence on the resulting feature (Fig. 7). In order to balance the amplitudes a balancing filter has been developed which leads to similar amplitudes within the whole frequency range and thus to a good separation of all the features is possible as shown in Fig. 9 [4].

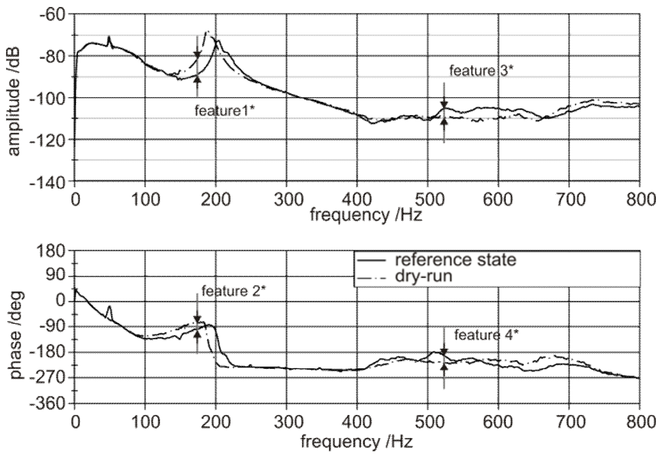

Fig. 7 - Frequency response function test rig A reference state and dry-run with significant features

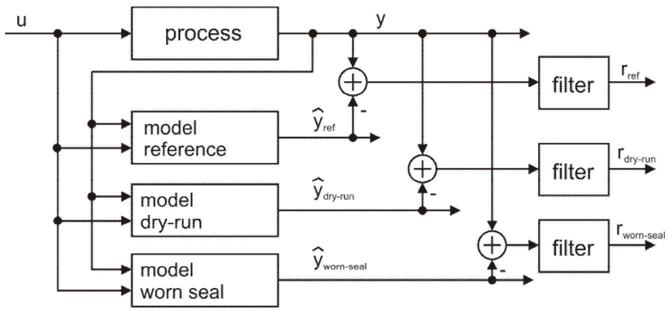

Fig. 8 - Multi-model-method

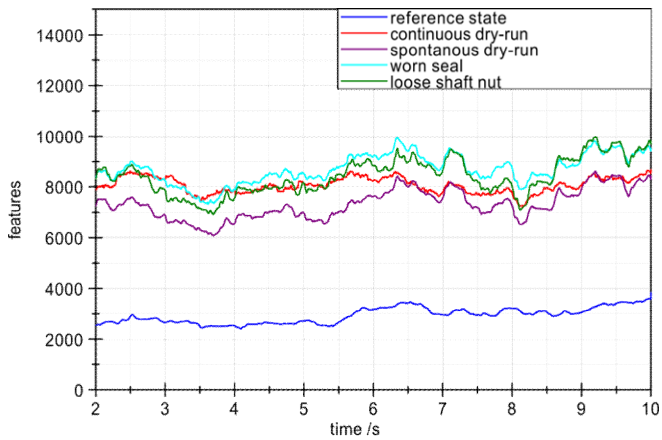

Fig. 9 – Symptom run of the multi-model-method; test rig A in reference state with balancing filter

Transfer-factor-estimation-method for fault detection

The parameter changes caused by the fault states lead to a different system response at certain frequencies. In comparison to the multi-model-method, which is based on the systems behavior within the bandwidth of the system, the idea behind this approach is to evaluate the changes at these significant frequency points. The feature consists of two complex transfer factors (Amplitude and phase). The approach has been investigated using two different algorithms, the LMS-(Least-Mean-Square) algorithm and the Goertzel algorithm [5]. Below the Goertzel algorithm is described as it leads to better results for the complex transfer factor.

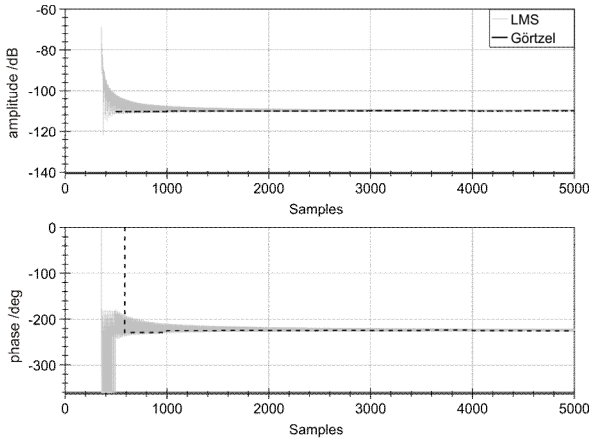

Fig. 10 - Response of Goertzel- and LMS-algorithm on a sudden change of system parameters

$$v[k] = x_f[k] + 2\cos\left(k\,{}^{2\pi}/_{N}\right)v[k-1] - v[k-2] \tag{7}$$

$$\underline{X_i}[k] = {}^{2}/_{N}\left(v[k] - \underline{W_n}^k v[k-1]\right) \tag{8}$$

Fig. 10 shows the result of the estimation of one complex transfer factor with the LMS- and the Goertzel algorithm on a sudden change within the parameters of the system. The Goertzel algorithm provides the first result after one block of 500 samples. The LMS is slower and has a higher variance within its result.

Conclusion

The paper shows how features for fault detection can be generated within magnetic bearing systems. The described methods are based on a change within the systems physical parameters e.g. mass, damping or stiffness, caused by the occurring fault. To detect the corresponding change of the modal parameters, the so called multi model method and the transfer-factor-estimation-method are used.

The multi-model-method is based on the analysis of the complete frequency range of the mechatronic system. To improve the results a balancing filter is implemented. The transfer-factor-estimation-method uses the Goertzel algorithm to analyze selected frequency points. A classification can be set up using confidence intervals [4] to achieve the fault detection and diagnosis.

It is shown on two different test rigs of centrifugal pumps in magnetic bearings that the methods allow for the reliable detection of faults typically occurring on centrifugal pumps. Both methods can be easily adopted on other mechatronic systems, and allow online fault diagnosis. In direct comparison the multi-model-method is more flexible to implement the detection of additional fault states, while the transfer-factor-estimation-method needs less computational power.

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