Application of Augmented Observer for Fault Diagnosis in Rotor Systems

Zhentao Wang, Rudolf Sebastian Schittenhelm, Matthias Borsdorf and Stephan Rinderknecht

***Abstract*—Observers are widely used to generate residuals for fault diagnosis processes. However the generated residuals are not only influenced by faults but also by disturbances and model uncertainties. In order to avoid false alarm and achieve a high fault detection rate disturbances and model uncertainties have to be considered in the fault detection and isolation (FDI) processes. In rotor systems the predominant disturbances and model uncertainties are forces excited by unbalances and gyroscopic effect which result in a rotary frequency dependent system behavior. The effect of unbalance forces and gyroscopic effect appear in a sinusoidal form with rotor rotary frequency. The disturbances and model uncertainties can be generally represented using unknown inputs and the signals of unknown inputs are sinusoidal. To take advantage of this characteristic of rotor systems augmented observers that account for sinusoidal unknown inputs are designed in this work. The augmented observer for sinusoidal signals can be used to estimate the distribution matrix of unknown inputs or to generate the residual for fault detection. In case that the faults (e.g. rotor disc wear) acting on the rotor are also sinusoidal, the augmented observer can be applied for fault isolation and identification. Different configurations of the observers are introduced in this paper according to their applications.**

***Index Terms*—fault detection, fault diagnosis, observers, rotors, unbalances, unknown inputs.**

I. Introduction

OBSERVERS based fault detection and isolation (FDI) methods are widely used in technical processes. The quality of the generated residuals determines the FDI performances, however the residuals are not only influenced by faults but also by disturbances and model uncertainties. In order to achieve better FDI performances disturbances and model uncertainties have to be attenuated or decoupled on the residuals i.e. the designed observers as residual generators have to be robust against disturbances and model uncertainties. In rotor systems unbalances are inevitable and their distributions on the rotor shaft can not be detected to full extent. Forces excited by unbalances in rotating shaft are major disturbances in rotor systems. In cases of rotor with large discs, the gyroscopic effect cannot be neglected and the system behavior varies dependent on the rotor rotary frequency. If a rotor model is built for a constant rotary frequency, the gyroscopic effect can be considered as model uncertainty [1]. Observers e.g. Luenberger observer and Kalman filter [2] designed on the basis of the constant linear time invariant (LTI) model are not applicable for other rotary frequencies. If the gyroscopic matrix is modeled, an observer dependent on the rotary frequency can be constructed. But the gyroscopic matrix is often not available or can not be modeled accurately. In these cases alternative methods have to be found to take the gyroscopic effect into account.

In the last decades model based FDI methods dealing with disturbances and model uncertainties have been widely investigated [3], [4]. Wantanabe and Himelblau introduced the idea of unknown inputs observer (UIO) in [5]. Since then, different authors further developed the method and methods to describe disturbances and model uncertainties as unknown inputs are investigated [6], [7]. The UIO is able to estimate the system states and outputs accurately despite the presence of unknown inputs. The generated residuals are thus decoupled from unknown inputs. Besides the UIO approach, other methods such as eigenstructure assignment [8], [9] and null space based methods [10], [11] are developed for FDI with the aim to decouple unknown inputs in residual generation processes. Besides the methods that decouple unknown inputs, methods to attenuate the influence of disturbances and model uncertainties and enhance the influence of faults on the residuals at the same time by means of optimization [12] e.g. using LMI [13] or genetic algorithm [14] are also investigated.

Most of the methods introduced above are designed under the assumption that no information about the unknown inputs is available. In rotor systems exited by unbalances, the predominant disturbances e.g. unbalance forces are sinusoidal with rotor rotary frequency. The influence of gyroscopic effect, which results in a rotary frequency dependent system behavior, also acts on the rotor system in a sinusoidal way [1]. Instead of describing the gyroscopic effect as a rotary frequency dependent term in the model, it can be considered as sinusoidal disturbance moments acting on the system [15]. Often the rotor rotary frequency can be measured, thus if the unbalance forces and gyroscopic effect are represented by unknown inputs, the unknown inputs are sinusoidal signals with known frequency. Augmented observers introduced in this paper utilize this characteristic of the unknown inputs and consider the influences of unknown inputs in the observer structure [16]. It can be used both for the FDI purpose and for the estimation of the unknown input distribution matrix.

In section II the structure of the augmented observer which account for the effect of sinusoidal unknown inputs is introduced. Different configurations of the augmented observer for the purpose of fault detection and for fault isolation and identification are presented in section III. In section IV a method using augmented observer to estimate unknown inputs distribution matrix, which represents how the disturbances and model uncertainties influence the system, is introduced. The accuracy of the estimates dependent on the sensor number is discussed. In order to test the functionality of the augmented observer, we apply the observer both on the basis of simulation and on the basis of measurements of

Manuscript received July 21, 2012; revised January 31, 2013.

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a rotor test rig in section VI. The results are discussed in the section before a conclusion is made in section VII.

II. Design of augmented observer

A. Rotor model

In this work we consider a class of rotor systems with the state space representation:

$$\begin{aligned} \dot{x} &= A(\Omega)x + Bu + \tilde{E}\tilde{d} \\ y &= Cx, \end{aligned} \tag{1}$$

where x denotes the system states, u the control input, y the sensor signals and $\tilde{d}$ the disturbances, i.e. unbalance forces working on the rotor. $A(\Omega)$, B, C, $\tilde{E}$ are system matrices with appropriate dimensions, where $A(\Omega)$ is dependent on the rotor rotary frequency Ω because of gyroscopic effect. The model (1) is controllable and observable for whole rotary frequency range.

The major focus of this work is to detect input faults (e.g. rotor disc wear) that is influenced by the gyroscopic effect and periodical with the rotor rotary frequency. These faults are not simply distinguishable from the influences of gyroscopic effect and unbalance forces. The system under the consideration of faults reads:

$$\begin{aligned} \dot{x} &= A(\Omega)x + Bu + \tilde{E}\tilde{d} + Ff \\ y &= Cx, \end{aligned} \tag{2}$$

where f is the faults to be detected and F is its input matrix. It has to be pointed out that the augmented observers introduced in this work are also applicable for FDI of output faults and multiplicative faults. Multiplicative faults can be transformed into additive faults [12]. Output faults e.g. sensor faults are not influenced by gyroscopic effect and are often simple to be separated from the influence of unknown inputs in frequency domain. Thus the detection of output faults are not explicitly presented in this paper.

For the FDI processes some limitations of the model are considered according to the knowledge of the rotor system:

- The unbalances cannot be detected to full extent, thus the disturbance term $\tilde{E}\tilde{d}$ in equation (1) is supposed to be unknown.
- If a physical model for the rotor is available, the gyroscopic effect can be modeled as in equation (1). If the model is to be identified, the gyroscopic effect is hard to identify because of its dependence on rotary frequency. Without loss of generality, it is assumed that gyroscopic effect is not modeled and only models at specific rotor rotary frequencies are assumed to be available.
- The rotor rotary frequency is supposed to be measured.

The design of the augmented observer is based on a model of non-rotating rotor

$$\begin{aligned} \dot{x} &= Ax + Bu + Ff \\ y &= Cx \end{aligned} \tag{3}$$

with $A = A(0)$. Since unbalance forces and gyroscopic effect only appear in rotating rotor, the model of non-rotating rotor is simple to be identified or simple to be built physically. Thereby, the gyroscopic effect and unbalance forces are not included in the model, for FDI purpose they can be represented together using unknown inputs d with their distribution matrix E [15], [1]. The model is then extended to

$$\begin{aligned} \dot{x} &= Ax + Bu + Ed + Ff \\ y &= Cx. \end{aligned} \tag{4}$$

For the design of augmented observer, the distribution matrix E of unknown inputs has to be modeled or estimated. The knowledge about the amplitudes and phases of unknown inputs d is not necessary, while the frequency of the unknown inputs i.e. the rotor rotary frequency has to be known.

B. Augmented state space model and observer

The augmented observer introduced in this work and in [16] is based on the idea of disturbance observer [17], [18], which introduces extra states in the system model to describe the influences and behavior of disturbances. If the disturbances can be described using a disturbance model:

$$\begin{aligned} \dot{x}_d &= A_d x_d \\ d &= C_d x_d, \end{aligned} \tag{5}$$

the augmented structure of the system reads

$$\begin{aligned} \dot{x}_B &= \begin{bmatrix} A & EC_d \\ 0 & A_d \end{bmatrix} x_B + \begin{bmatrix} B \\ 0 \end{bmatrix} u \\ y &= \begin{bmatrix} C & 0 \end{bmatrix} x_B = C_B x_B, \end{aligned} \tag{6}$$

with the augmented system states vector

$$x_B = \begin{bmatrix} x \\ x_d \end{bmatrix}. \tag{7}$$

The matrices A_d and C_d are respective matrices for the disturbance model and the matrix E describes how the disturbances influence the plant. If the augmented model is used for unknown inputs, the matrix E is set to unknown input distribution matrix.

Since we use the unknown inputs to represent unbalance forces and gyroscopic effect, their signals are sinusoidal with same frequency and different amplitudes and phase angles i.e.

$$x_B = \begin{bmatrix} \delta_1 \sin(\Omega t + \theta_1) \\ \delta_2 \sin(\Omega t + \theta_2) \\ \vdots \end{bmatrix}, \tag{8}$$

where Ω is the frequency of the unknown inputs and $\delta_1, \delta_2, \dots$ and $\theta_1, \theta_2, \dots$ are the amplitude and phase angles of the unknown inputs. Two different structures can be used for the disturbance model. If the disturbance states vector x_d in equation (5) is written as

$$x_d = \begin{bmatrix} d \\ \dot{d} \end{bmatrix}, \tag{9}$$

a disturbance model can be built as

$$\begin{aligned} \dot{x}_d &= \underbrace{\begin{bmatrix} 0 & I \\ -\Omega^2 I & 0 \end{bmatrix}}_{A_d} x_d \\ d &= \underbrace{\begin{bmatrix} I & 0 \end{bmatrix}}_{C_d} x_d. \end{aligned} \tag{10}$$

Another option for disturbance model uses a complementary vector of unknown inputs

$$\hat{d} = \begin{bmatrix} \delta_1 \cos(\Omega t + \theta_1) \\ \delta_2 \cos(\Omega t + \theta_2) \\ \vdots \end{bmatrix}. \tag{11}$$

If the disturbance states vector is set as

$$x_d = \begin{bmatrix} d \\ \hat{d} \end{bmatrix}, \tag{12}$$

the disturbance model is then in the form of

$$\begin{aligned} \dot{x}_d &= \underbrace{\begin{bmatrix} 0 & -\Omega I \\ \Omega I & 0 \end{bmatrix}}_{A_d} x_d \\ d &= \underbrace{\begin{bmatrix} I & 0 \end{bmatrix}}_{C_d} x_d. \end{aligned} \tag{13}$$

On the basis of the augmented system model in equation (6), observers (e.g. Luenberger observer) can be designed. The observers are called augmented observer in this paper. Both of the disturbance models can be applied to the augmented model and the augmented system has to be observable. The structure of an augmented observer is presented in Fig. 1, where $\hat{y}$ is the observed outputs vector K is the feedback term of the observer and r is the residual vector.

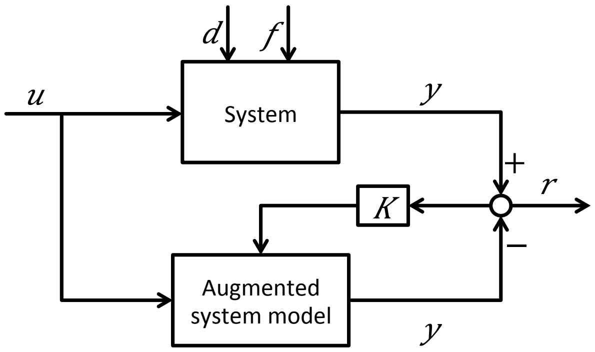

Fig. 1. Scheme of augmented observer

C. Observability of augmented observer

Both of the disturbance models (10) and (13) have the same output matrix C_d. Applying the matrix C_d to equation (6), the augmented system model reads

$$\begin{aligned} \dot{x}_B &= \underbrace{\begin{bmatrix} A & \begin{bmatrix} E & 0 \end{bmatrix} \\ 0 & A_d \end{bmatrix}}_{A_B} x_B + \underbrace{\begin{bmatrix} B \\ 0 \end{bmatrix}}_{B_B} u \\ y &= \begin{bmatrix} C & 0 \end{bmatrix} x_B = C_B x_B, \end{aligned} \tag{14}$$

Lemma II.1. *If (A, C) is an observable pair and E is of full column rank, equation* (14) *is observable only if*

$$\operatorname{rank}(E) \leq \operatorname{rank}(C), \tag{15}$$

i.e. $\operatorname{rank}(E)$ *must be equal to or smaller than the number of linearly independent measurements.*

Proof: Assume that $\operatorname{rank}(A) = n$ and $\operatorname{rank}(E) = p$, according to the observability criterion of Hautus [19] the system (14) is observable if and only if

$$\operatorname{rank} \begin{pmatrix} \lambda_i I - A_B \\ C_B \end{pmatrix} = n + 2p \tag{16}$$

for all eigenvalues λ_i of $A_B \in \mathbb{R}^{(n+2p)\times(n+2p)}$. The system matrix A_B with

$$\det(\lambda_i I - A_B) = \det(\lambda_i I - A) \cdot \det(\lambda_i I - A_d) \tag{17}$$

has at least p pairs of eigenvalues at $\lambda_i = \pm i\Omega$ for $\det(\lambda_i I - A_d) = 0$. Thus in case of $\lambda_i = \pm i\Omega$, $\lambda_i I - A_B$ will be row rank deficient with $\operatorname{rank}(\pm i\Omega I - A_B) \leq n+p$. Thus $\operatorname{rank}(C)$ must be greater than or equal to $\operatorname{rank}(E) = p$, in order to satisfy condition (16). ■

According to Lemma II.1 the augmented observer can often not be applied in systems with large number of disturbances, the applicability is limited by the available sensor number. In order to apply augmented observer, there must be at least so many sensors available as the number of the considered unknown inputs; otherwise the rank of matrix E has to be reduced. One possible method to reduce the rank of matrix E is to use the technique of singular value decomposition. The matrix E can be reduced as a set of singular vectors corresponding to the most significant singular values [3], [15].

III. Augmented observer for FDI

The augmented system vector x_B can therefore be observed with a designed augmented observer under the condition that the augmented system is observable. In the considered scenario the system vector x and disturbance states vector x_d are observed and E describes the influence of disturbance states vector x_d on real system vector x (see augmented system model in equation (6)). Thus, theoretically the estimated system states vector x is accurate under the influences of the unknown inputs. The generated residuals

$$r = y - \hat{y} \tag{18}$$

would be zero under the influence of unknown inputs since there is no difference between the estimated observer outputs $\hat{y}$ and the system outputs y. Hence, the unknown inputs have no impacts on the residuals ideally, in real systems their impacts on the residuals will be strongly attenuated . Faults with the input matrix $F \neq E$ will be detected easily, because the deviation of the residuals by faults is reasonably higher than the deviation of the residuals by unknown inputs. A major class of the faults in rotor systems, like rotor disc wear, show a sinusoidal oscillation. An augmented system model with the structure

$$\begin{aligned} \dot{x}_B &= \begin{bmatrix} A & \begin{bmatrix} E & F \end{bmatrix} C_d \\ 0 & A_d \end{bmatrix} x_B + \begin{bmatrix} B \\ 0 \end{bmatrix} u \\ y &= C_B x_B \end{aligned} \tag{19}$$

can be designed for fault isolation and identification. The augmented states vector x_B is extended to include the respective sinusoidal fault f. An augmented observer based on model (19) enables the direct observation of the sinusoidal fault f. Observed fault signals can be used to accomplish fault isolation and identification.

IV. Estimation of the Unknown Input Distribution Matrix Using Augmented Observer

Information about the disturbances and model uncertainties might be insufficient or not available. In such a case the unknown input distribution matrix E has to be estimated by means of measurements. In rotor systems the augmented observer is applicable to estimate the distribution matrix E of the sinusoidal unknown inputs.

For the estimation of the matrix E an augmented system model is used:

$$\begin{aligned} \begin{bmatrix} \dot{x} \\ \dot{x}_{d_1} \end{bmatrix} &= \begin{bmatrix} A & \begin{bmatrix} H & 0 \end{bmatrix} \\ 0 & A_{d_1} \end{bmatrix} \begin{bmatrix} x \\ x_{d_1} \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} u \\ y &= \begin{bmatrix} C & 0 \end{bmatrix} \begin{bmatrix} x \\ x_{d_1} \end{bmatrix}. \end{aligned} \tag{20}$$

The disturbance model (10) or (13) can be used for A_{d_1}.

Observability of the augmented system (20) is affected by the choice of matrix H. In ideal case (i.e. there are enough sensors available to fulfill the observability condition) the matrix H can be set to $H = I$. Comparing to the system model (14) the disturbance vector reads

$$d_1 := Ed = \begin{bmatrix} H & 0 \end{bmatrix} x_{d_1}. \tag{21}$$

If an augmented observer is applied to (20), the disturbance vector d_1 can be estimated directly. The estimated vectors $d_1(k)$ for discrete time steps k are the result of a mapping of unknown inputs $d(k)$ by matrix E. The distribution matrix E can then be estimated as a vector space in which all the vectors $d_1(k)$ lie.

The observability condition $\mathrm{rank}(C) \geq \mathrm{rank}(A)$ for $H = I$ is in many cases not fulfilled for rotor systems with high system order. Thus the matrix H has to be chosen properly, so that the equation (20) is observable and the estimation of E is as accurate as possible. Note that the frequency range of unknown inputs is limited from 0 to maximal rotor rotary frequency. In the state space representation of the rotor system the eigenforms corresponding to eigenvalues with negative imaginary parts (i.e. negative eigenfrequencies) are not excited significantly, they can be neglected without introducing too much error. The modes corresponding to eigenfrequencies that are much higher than the maximum rotary frequency usually have less influence than the low frequency ones on the system outputs. Thus influences of the high frequency modes can often also be neglected. Thus the matrix H can be chosen as

$$H = \begin{bmatrix} e_1, & e_2, & \cdots, & e_q \end{bmatrix}, \tag{22}$$

with $q \leq \mathrm{rank}(C)$ and $e_1, e_2, \cdots, e_q$ are eigenvectors corresponding to the eigenvalues with low positive imaginary parts.

A set of states vectors $x_{d_1}(k)$ for discrete time steps k can be observed using an observer on the basis of the augmented system model and the disturbance vectors $d_1(k)$ can be calculated as

$$d_1(k) := Ed(k) \approx \begin{bmatrix} H & 0 \end{bmatrix} x_{d_1}(k). \tag{23}$$

The solution $E = H$ is mathematically possible for this problem, but for the FDI purpose it is practically not applicable. Otherwise part of the faults would be represented by the unknown inputs and can thus not be detected. In order to achieve a high fault detection rate, the matrix E is to be estimated with fewer columns. For state space control a matrix E with fewer columns means less computing time and thus is also advantageous.

For N time steps of a measurement, a set M of vectors $d_1(k)$ is calculated:

$$M = \begin{bmatrix} d_1(1), & d_1(2), & \cdots, & d_1(N) \end{bmatrix}. \tag{24}$$

Using singular value decomposition M is decomposed as

$$M = U \begin{bmatrix} \mathrm{diag}(\sigma_1, \sigma_2, \cdots, \sigma_n), & 0 \end{bmatrix} V^T. \tag{25}$$

The matrices U and V are left and right singular matrices and $\sigma_1, \sigma_2, \cdots, \sigma_n$ are the singular values with $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_n$. The desired low rank approximation of E is obtained by keeping a few of the most significant singular values [3] i.e.:

$$E = U \left[\mathrm{diag}(\sigma_1, \sigma_2, \cdots, \sigma_p) \right], \tag{26}$$

with $p \leq n$ and $\sigma_1 \gg \sigma_{p+1} \geq \sigma_n$.

V. Test Rig

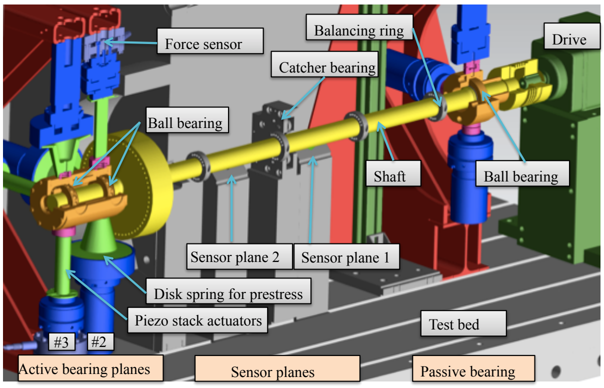

Fig. 2. Rotor test rig

The augmented observer is tested on a rotor test rig at the Institute for Mechatronic Systems in Mechanical Engineering at the Technische Universität Darmstadt. Fig. 2 shows a cutaway view of the test rig. The main part of the test rig is a rotor, which has scaled similarity to medium-sized low pressure engine shafts. The rotor has a length of about 1100mm, a main diameter of 35mm and a maximum rotational speed of 300Hz. Two out of the three bearings of the test rig are equipped with piezo stack actuators to influence the rotor vibrations. Due to the bearing configuration with 3 bearings the alignment of the bearings was given a high priority during buildup of the test rig. Since piezo stack actuator only push and not pull, the actuators are prestressed with about 7kN by disk springs with a low stiffness compared to the actuator stiffness. One piezo of each active bearing is horizontal and one is vertical, the springs are located on the opposite side of each actuator. The actuators have a maximal displacement of 120μm and a blocking force F_{block} of 14kN. Voltages from 0 to 1000 Volts can be applied. We choose a offset voltage of 500 Volts to enable positive and negative input signals. To avoid torsional or bending forces on the actuators modified axial bearings are implemented between the bearing cup and the piezo stack actuators, see Fig. 3. For high dynamic amplification of the control output modified E-481 amplifiers from Physik Instrumente are chosen.

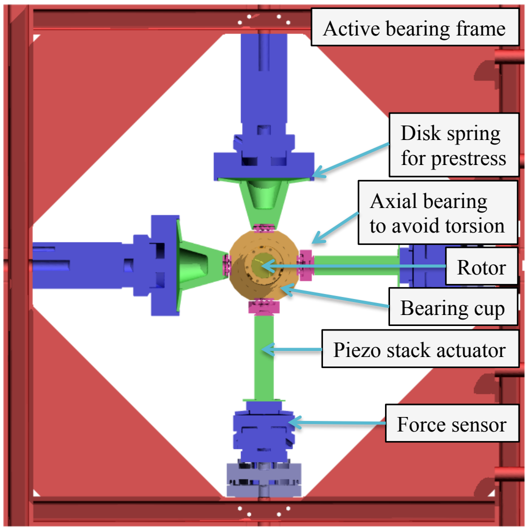

Fig. 3. Active bearing configuration

Most of the vibrations in the system are caused by unbalance of the rotor and have the same frequency as the rotation. Implemented sensors to evaluate rotor vibrations are eddy current displacement sensors to measure radial displacement of the rotor shaft and force transducers in the bearings in a position where the applied forces are about the same as in the actuators. For data acquisition from the force transducer an analog amplifier and a 3.3kHz first order analog low pass filter is used.

Four eddy current sensors in two sensor planes measure the radial displacement of the rotor shaft and four force sensors measure the forces at the active bearings. The sensors of each plane are positioned rectangular to each other and thus the whole orbit of the rotor can be measured. To avoid aliasing the signals from sensors are filtered with 4kHz first order analog low pass filters before digitalization. For data acquisition and output signal generation a dSpace ds1103 real time system is used.

The rotor can be considered a high-speed turning flexible rotor, since there are two natural bending eigenfrequencies, at about 110Hz and 240Hz, in the operating range up to 30Hz. A 5.1kW AC motor that is coupled to the shaft can accelerate or decelerate the rotor through the whole operating range within 30 seconds.

Because of the rotor disc the gyroscopic effect is not negligible. The dependence of the resonances on rotary speed is presented in Fig. 4. The points and crosses indicate the resonances of measured transfer functions at different rotary speeds.

For the purpose of FDI, a multiple inputs and multiple outputs (MIMO) model of the non-rotating rotor is identified. Since the unbalance forces and gyroscopic effect do not appear on non-rotating rotors, the rotor is only exited by control inputs during the identification process. The identification is simple comparing to the identification of a rotating rotor model. Sweep excitations of the control inputs are used for the identification. Using a subspace method, the model is identified with an order of 16.

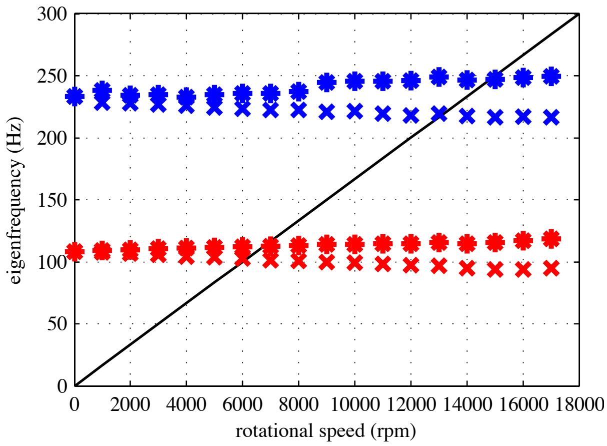

Fig. 4. Measured campbell diagram

VI. Application

A. Application of augmented observer for fault detection

The identified model for non-rotating rotor describes the system behavior without disturbances and model uncertainties. After balancing of the test rig, the residual unbalance still results in vibration of the rotor. The forces induced by residual unbalance is considered as disturbances on the test rig. As presented in section V, the gyroscopic effect is not negligible and is thus considered as model uncertainty. In order to achieve a higher FDI performance, the residual unbalance and gyroscopic effect have to be considered in the FDI process. As presented in section II we represent both disturbances and model uncertainties as unknown inputs and their distribution matrix are estimated by means of measurements of the test rig.

We use the augmented observer introduced in section IV to estimate the distribution matrix E of unknown inputs. Since 8 sensors are available and the identified state space model has an order of 16, only the eigenforms corresponding to the positive eigenfrequencies are considered in the estimation process, vibrations of the eigenforms corresponding to negative eigenfrequencies are neglected. Investigation shows that choice of the dimension of matrix E is dependent on the considered frequency range. If the rotor is running at a constant rotary frequency, an estimate of E with 2 columns is enough to represent the influences of the unknown inputs. In order to consider the influence of residual unbalance and gyroscopic effect for a large rotary frequency range, the matrix E has to be estimated with more columns. In this case measurements at different rotary frequencies in the considered range are needed. At each rotary frequency a matrix E_m with $(m = 1\ldots)$ is estimated using augmented observer to represent both gyroscopic effect and unbalances at this rotary frequency. According to equations (24), (25) and (26) the estimates of E_m are proportional to the amplitude of unknown inputs. Since the rotor excitations (i.e. unbalance forces) used for the estimation are proportional to Ω^2, the E_m are weighted with $1/\Omega^2$ and then combined in E_M with

$$E_M = \left[E_1^*, \quad E_2^*, \quad \ldots\right], \tag{27}$$

where matrices E_m^* are weighted matrices of E_m. Using the singular value decomposition technique presented in (25) and (26), E_M is approximated by a E-matrix with desired dimension; e.g. for a rotary speed range from 0rpm to 9000rpm, the matrix E has to be estimated with 6 columns.

Although it is possible to represent the disturbances and model uncertainties for a large rotary frequency range, a matrix E with less columns is in general simple to handle and often result in better FDI performance. Considering matrix E as a vector space, the mapping of faults vector f on E is also decoupled from the residuals. Thus a matrix E with large dimension often result in reduced faults responses on the residuals.

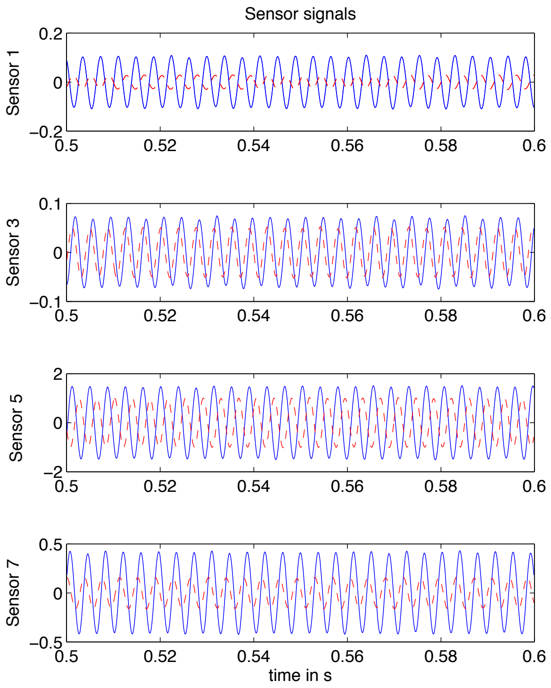

Fig. 5. Measured sensor signals, solid line: sensor signals without fault, dashed line: sensor signals with fault

As an example for FDI, an extra mass is brought to the rotor on the second balancing ring on the right hand side of Fig. 2. The induced unbalance by the mass equals 74gmm and it is considered as fault in this example. The identified model of non-rotating rotor is used as basis model for the FDI process and the fault is to be detected at a rotary speed of 15800rpm. The control inputs are not excited in both estimation of E and FDI process. The sampling frequency of the measurements is 10000Hz. The measurements are filtered by a digital low pass filter with cut off frequency at 800Hz. A 2-column unknown inputs distribution matrix E is estimated on the basis of measurements of the rotating rotor at 15800rpm in steady stats without faults.

The signals of the sensors on 4 sensor planes in horizontal direction are presented in figure 5. Sensor 1 and sensor 3 refer to the displacement sensors on sensor planes 1 and 2 in horizontal direction; sensor 5 and 7 refer to the force sensors collocated with actuators in horizontal direction, see Fig. 2. In this paper, the sensor signals and residuals are normalized values and are thus without unit. The signals of sensors in vertical direction are similar and are thus not presented here. It can be seen, that the fault (i.e. the extra mass) results in a phase shift and a reduced vibration amplitude at this frequency. Actually the fault enhances vibrations in most of the rotary frequency range and is thus not used in the balancing process. We consider the fault and rotary frequency as a kind of worst case for fault detection in order to show the functionality of the augmented observer for FDI application. At other rotary frequencies, where the fault enhances vibration, better FDI performance is achievable using augmented observer.

An augmented observer is built for fault detection. The feedback term K (see Fig. 1) of the observer is designed by means of pole placement and the poles are reallocated in a region which is 10 times faster than the poles of the identified system. The generated residuals corresponding to the horizontal sensors using the augmented observer are presented in Fig. 6. It can be seen that the influences of the unknown inputs on residuals are much smaller than these of the fault. The fault is then simple to be detected by monitoring the vibration amplitudes.

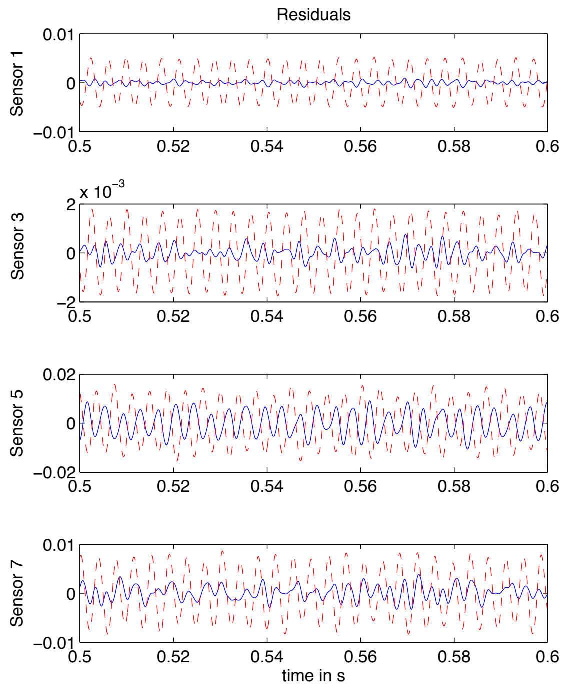

Fig. 6. Residuals generated by augmented observer, solid line: residuals without fault, dashed line: residuals with fault

B. *Feasibility test of augmented observer for fault isolation*

Since the input matrix of the fault is not identified in the system model, fault isolation is not possible using augmented observer. To present the feasibility of the augmented observer for fault isolation and identification, a finite element model of a rotor presented in Fig. 7 is used. The residual unbalances are simulated as unbalances continuously distributed in both axial and circumferential directions. Two additional unbalances in point form are considered as faults. The first one is on the rotor disc (fault 1) and the second one is in the middle of the rotor (fault 2). 8 displacement sensors on 4 sensor planes are used for the measurement. The finite element model is reduced to 8 modes i.e. with order 16 in state space representation for the simulation. In the FDI process the rotor is simulated at 6000rpm.

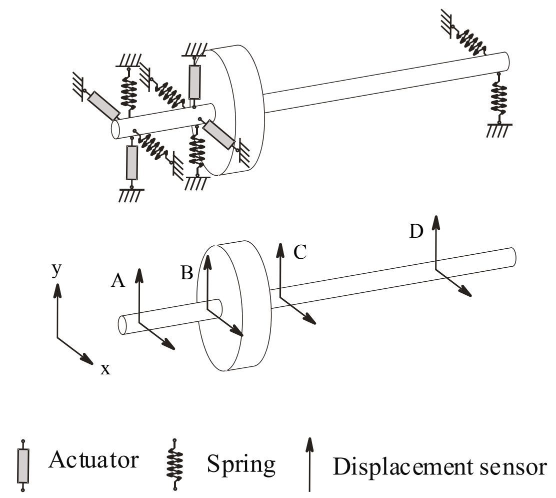

Fig. 7. Configuration of the rotor test rig

An augmented observer is constructed with the augmented model (19). The unknown input distribution matrix E is estimated by means of simulated signals. The time domain diagnosis is presented in Fig. 8. Fault 1 takes place at 10s and fault 2 takes place at 20s. The fault amplitude is understood as amplitude of unbalance forces and can be directly observed in the augmented system vector. Both faults are simply detectable and can be clearly separated. Even the unbalance forces are accurately estimated.

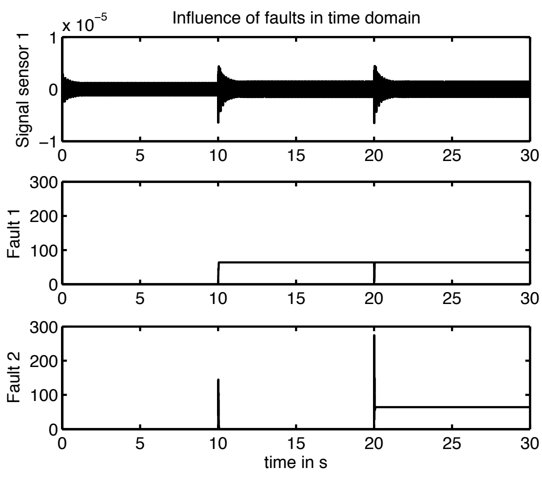

Fig. 8. Observed fault amplitude by means of augmented observer

VII. Conclusion

Design of augmented observers which considers sinusoidal disturbances is presented in this paper. It can be applied for the purpose of fault detection and isolation and for the estimation of unknown input distribution matrix in rotor systems. Two major problems are discussed in the FDI process of a rotor system, i.e. the gyroscopic effect and unbalance forces working on the shaft. Their influences on the rotor system can be considered together as unknown inputs working on the shaft. Since the unknown inputs are sinusoidal, their distribution matrix can be estimated using augmented observer. Applying the augmented observer a residual generator, the unknown inputs are observed and their impacts on the system are considered, thus robust FDI against unknown inputs is achieved.

As an example, an unbalance in a rotor test rig is considered as fault. Using the augmented observer for fault detection on the basis of an identified model of the non-rotating rotor achieves good result. Since the input matrix of faults is not identified in the model, the fault isolation was not possible on the basis of the identified model. The feasibility test of the augmented observer for fault isolation is thus done on the basis of simulation. In the future work, a model with fault input matrix is to be built and the application of the augmented observer for fault isolation will be tested on the test rig.

Acknowledgment

This paper is based on a research project in partnership with Rolls-Royce Deutschland Ltd & Co KG., supported by Deutsche Forschungsgemeinschaft (DFG) within the framework of the graduate college 1344, “Instationäre Systemmodellierung von Flugtriebwerken”.

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