DIAGNOSTIC OF ROTATING MACHINERY WITH MAGNETIC BEARINGS & RIGID ROTOR

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ABSTRACT

A magnetic suspension system for bearing single axis consists of displacement and two current sensors, two opposite coils, two amplifiers, and suspended mass. Such unstable open-loop magnetic bearing system is stabilized by a microprocessor control system. The proposed diagnostic system should detect deterioration or failure of above mentioned system and indicate the failure component.

A diagnostic algorithm consists of four tests. 1) Test of measurement system which we are using the observer bank in. It allows us to detect any failure in the system. 2) Test which recognizes whether the failure is in measurement system or in other components. Having a failure is in measurement system the previous test indicates which sensor is failure. 3) Identification of state and control matrices in their physical form. Identification of open-loop matrices is realized by Markov parameters model detected by the ERA algorithm. 4) Localization of failure by inspection of state and control matrices.

INTRODUCTION

A rotating rotor has high kinetic energy which is approximately proportional to its mass and to square of the angular velocity. A such energy during emergency, for example after shut-up of the electric power supply to the magnetic bearings, can destroy all rotating machinery and be hazardous for people. To avoid such case the backup bearings are build-in and the additional source of power (usually accumulator) is joined to the energy power system.

Beside the emergency case there are other faults as a result of exploitation and of local damages. Such faults do not cause the catastrophic shut-up but gradually deteriorate performance of the system, what can finally lead to its damage. In the paper we consider detection an isolation of such faults since they are important in the case of the bearing system.

A fault detection and isolation in complex and controlled systems is considered in many papers and books, for example, in [1], [2]. Methods of fault detection can be divided into two groups [2]: methods basing on the analysis of process signals and methods basing on the analysis of connections among process signals.

In the first group the statistic or spectral analysis of signal is carried out to detect faults. These methods are simple so we have not to know the process model. On the second hand the quantity of diagnostic information in the single signal is small. Moreover, the information is unreliable because of many causes which influence on the process signal.

In the second group of methods we use quantitative or qualitative models of the systems describing connections among process signals. This approach is particularly useful in the case of multi-inputs and multi-outputs control systems (MIMO). The most popular are analytical models. Differences between signals from analytical model and measured signals are called the residua. To generate residua we use linear and nonlinear physics equations, state observer or Kalman filter models of process, parity equations of input-output models, or identified models.

A linearized analytical model of the magnetic bearing is available. Moreover, the identification method of magnetic bearing parameters was described in the [3]. The identification method of the open-loop system parameters will be used as a part of the diagnostic system. Another part will be devoted diagnostics of sensors. The tests which allow isolate different faults will be described. Due to the digital microprocessors and digital controllers have built-in diagnostic tests we omit their diagnostics.

PLANT MODEL AND CONTROL LAW

The dynamic equations of particular coils should be coupled with the model suspended rotor mass to implement the voltage control scheme. Finally, for each magnetic bearing axis we have the following model of the open-loop system [4]:

$$\dot{\mathbf{x}} = \mathbf{A}_c\mathbf{x} + \mathbf{B}_c\mathbf{u}, \quad \mathbf{y} = \mathbf{C}\mathbf{x} \tag{1}$$

where:

$\mathbf{x} = \begin{bmatrix} X = x & \dot{x} & i_1 & i_2 \end{bmatrix}^T$, $\mathbf{u} = \begin{bmatrix} u_1, & u_2 \end{bmatrix}^T$,

$\mathbf{y} = \begin{bmatrix} x & i_1 & i_2 \end{bmatrix}^T$

$$\mathbf{A_c} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ \nu_1 & 0 & \nu_{21} & -\nu_{22} \\ 0 & -\nu_{31} & -\nu_{41} & 0 \\ 0 & \nu_{32} & 0 & -\nu_{42} \end{bmatrix}, \quad \mathbf{B_c} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ \nu_{51} & 0 \\ 0 & \nu_{52} \end{bmatrix},$$

$$\mathbf{C} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \tag{2}$$

and: x-rotor displacement from the point located at the bearing center to the operation point, u – coil voltages, i – coil currents, and ν - coefficients designed from system parameters.

Since dx/dt can be simply estimated from rotor displacement x the state feedback control law is as follows:

$$\mathbf{u} = -\mathbf{F}\mathbf{x}\,. \tag{3}$$

Different control methods can be applied to implement the above state feedback control laws. In [5] the pole-placement method was used to obtain the controller gain matrix **F**. The LQR method is described for example in [6]. The deadbeat predictive control method [7] can also be used to obtain the gain matrix.

FAULT LIST

We assume that each of the axes in the single radial magnetic bearing is controlled independently and the rotor mass is reduced to the magnetic bearing plane. The plant consists of two electromagnetic coils, two amplifiers, and rotor as a point mass. The measurement system has a displacement sensor and two sensors of the coils currents. We will limit the discrimination of the faults to this parts of the control system. In such case the list of faults is as in Tab.1, where faults are denoted by f_k, for k=1÷8.

As faults we can consider the external excitations: rotor unbalance, displacement sensor's run-out, denoted as f_k, for k=9, 10. These faults can be isolated by identification method [4].

We can establish values of above faults f_k for which the diagnostic system generates the following actions: warning signal, alarm signal, counteraction to the external excitations, system reconfiguration, and the others.

Tab.1. List of faults for single axis of magnetic bearings

f_k	Discription of faults
f_1	Fault of displacement sensor
f_2	Fault of 1 coil current sensor
f_3	Fault of 2 coil current sensor
f_4	Fault of 1 amplifier
f_5	Fault of 2 amplifier
f_6	Rotor mass change
f_7	Fault of 1 coil
f_8	Fault of 2 coil
f_9	Unbalance
f_{10}	Displacement sensor run-out

Profoundness of diagnostics depends on the needs of a user. For example, when we have found an amplifier is failed we can need to isolate failure deeper inside the amplifier. Since amplifier is a complex electronic device in the place of faults f_3, f_4 we have many other faults connected with different components of the amplifier.

FAULT MODELS

The faults change the model parameters from their nominal values as follows:

$$\underline{\mathbf{A}}_\mathbf{c} = \mathbf{A_c} + \Delta\mathbf{A_c}, \quad \underline{\mathbf{B}}_\mathbf{c} = \mathbf{B_c} + \Delta\mathbf{B_c}, \quad \underline{\mathbf{C}} = \mathbf{C} + \Delta\mathbf{C}. \tag{4}$$

Analyzing the state and measurement equations we can notice that in our case the information about faults f_1, f_2, f_3 is in matrix $\Delta\mathbf{C}$, about faults f_4, f_5, in matrix $\Delta\mathbf{B_c}$, and about faults f_6, f_7, f_8 in matrix $\Delta\mathbf{A_c}$. Faults f_9, f_{10} are connected with unbalance $\mathbf{w}$(t), and sensor run-out $\mathbf{p}_r$(t), respectively. In the correctly working system those external excitations should be reduced, and they are considered as faults. Taking into account the model with faults we have:

$$\begin{aligned} \mathbf{x}(k+1) &= \underline{\mathbf{A}}\mathbf{x}(k) + \underline{\mathbf{B}}\mathbf{u}(k) + \mathbf{B}_d\mathbf{w}(k), \\ \mathbf{y}(k) &= \underline{\mathbf{C}}\mathbf{x}(k) + \mathbf{C}_p\mathbf{p}_r(k). \end{aligned} \tag{5}$$

Output vector $\mathbf{y}$(k) can be expressed as a function of vectors: control $\mathbf{u}$(k), unbalance $\mathbf{w}(k)$, and sensor runout $\mathbf{p}_r(k)$

$$\mathbf{y}(k)=\underline{\mathbf{C}}\underline{\mathbf{A}}^{\mathbf{k}}\mathbf{x}(0)+\sum_{i=1}^{s}\mathbf{Y}_i\mathbf{u}(k-i)+\sum_{i=1}^{s}\mathbf{Y}_{wi}\mathbf{w}(k-i)+\mathbf{C}_p\mathbf{p}_r \tag{6}$$

where the first component describes the transient signal, while:

$$\mathbf{Y}_i=\underline{\mathbf{C}}\underline{\mathbf{A}}^{i-1}\underline{\mathbf{B}},\quad \mathbf{Y}_{wi}=\underline{\mathbf{C}}\underline{\mathbf{A}}^{i-1}\mathbf{B}_d,\quad \mathbf{Y}_{ri}=\underline{\mathbf{C}},$$
$$i=1,\ 2,\ 3,\ \ldots,\ s$$

are Markov parameters of: the system, external excitations, and signal run-out.

To design the state observer we add and subtract the component $\mathbf{Gy}(t)$ to the first equation in (5):

$$\begin{gathered}\mathbf{x}(k+1)=\\ =(\underline{\mathbf{A}}+\mathbf{G}\underline{\mathbf{C}})\mathbf{x}(k)+\underline{\mathbf{B}}\mathbf{u}(k)+\mathbf{B}_d\mathbf{w}(k)+\mathbf{GC}_p\mathbf{p}_r(k)-\mathbf{Gy}(k),\\ \mathbf{y}(k)=\underline{\mathbf{C}}\mathbf{x}(k)+\mathbf{C}_p\mathbf{p}_r(k).\end{gathered} \tag{7}$$

where $\mathbf{G}$ is the observer gain matrix.

We assume that control signal $\mathbf{u}(k)$ is a sum of persistent pseudo-random signal $\mathbf{r}(k)$ and of feedback signal $\mathbf{u}_f(k)$ as follows:

$$\begin{gathered}\mathbf{u}(k)=\mathbf{u}_f(k)+\mathbf{r}(k),\\ \mathbf{u}_f(k)=-\mathbf{F}\hat{\mathbf{x}}(k).\end{gathered} \tag{8}$$

Introducing equations (8) into equations (7) we obtain the observer/controller model of the closed-loop system in the form:

$$\begin{gathered}\hat{\mathbf{x}}(k+1)=\underline{\bar{\mathbf{A}}}\hat{\mathbf{x}}(k)+\underline{\bar{\mathbf{B}}}\begin{bmatrix}\mathbf{u}(k)\\ \mathbf{y}(k)\end{bmatrix}+\mathbf{GC}_p\mathbf{p}_r(k)+\mathbf{B}_d\mathbf{w}(k),\\ \mathbf{y}_u(k)=\begin{bmatrix}\hat{\mathbf{y}}(k)\\ \mathbf{u}_f(k)\end{bmatrix}=\underline{\bar{\mathbf{C}}}\hat{\mathbf{x}}(k)+\mathbf{C}_r\mathbf{p}_r,\end{gathered} \tag{9}$$

where:

$$\underline{\bar{\mathbf{A}}}=\underline{\mathbf{A}}+\mathbf{G}\underline{\mathbf{C}},\quad \underline{\bar{\mathbf{B}}}=\begin{bmatrix}\underline{\mathbf{B}} & -\mathbf{G}\end{bmatrix},\quad \underline{\bar{\mathbf{C}}}=\begin{bmatrix}\underline{\mathbf{C}}\\ -\mathbf{F}\end{bmatrix},\quad \mathbf{C}_r=\begin{bmatrix}\mathbf{C}_p\\ \mathbf{0}\end{bmatrix}.$$

To reduce the estimation time we introduce the deadbeat observer where matrix **G,** fulfills the condition: $(\underline{\bar{\mathbf{A}}})^i=(\underline{\mathbf{A}}+\mathbf{G}\underline{\mathbf{C}})^i=\mathbf{0}$, for: *i≥p*.

In this case the output signal can be expressed by reduced number of Markov parameters of observer/controller model:

$$\mathbf{y}_u(k)=\sum_{i=1}^{p}\bar{\mathbf{Y}}_i\mathbf{v}(k-i)+\sum_{i=1}^{p}\bar{\mathbf{Y}}_{wi}\mathbf{w}(k-i)+\sum_{i=0}^{p}\bar{\mathbf{Y}}_{ri}\mathbf{p}_r(k-i),\quad \text{for } k\ge p, \tag{10}$$

where: $\mathbf{y}_u(k)=\begin{bmatrix}\mathbf{y}(k)\\ \mathbf{u}_f(k)\end{bmatrix}$, $\mathbf{v}(k-i)=\begin{bmatrix}\mathbf{u}(k-i)\\ \mathbf{y}(k-i)\end{bmatrix}$,

$$\bar{\mathbf{Y}}_i=\underline{\bar{\mathbf{C}}}\underline{\bar{\mathbf{A}}}^{i-1}\underline{\bar{\mathbf{B}}},\quad \bar{\mathbf{Y}}_{wi}=\underline{\bar{\mathbf{C}}}\underline{\bar{\mathbf{A}}}^{i-1}\mathbf{B}_d,\quad \bar{\mathbf{Y}}_{r0}=\mathbf{C}_r,$$
$$\bar{\mathbf{Y}}_{ri}=\underline{\bar{\mathbf{C}}}\underline{\bar{\mathbf{A}}}^{i-1}\mathbf{GC}_r,\quad i=1,\ 2,\ \ldots p.$$

Identified Markov parameters (particularly first of them) will be used in diagnostic tests.

ISOLATION OF FAILED SENSOR

Omitting external excitations we have the model of the system with faults:

$$\begin{gathered}\mathbf{x}(k+1)=(\mathbf{A}+\Delta\mathbf{A})\mathbf{x}(k)+(\mathbf{B}+\Delta\mathbf{B})\mathbf{u}(k),\\ \mathbf{y}(k)=(\mathbf{C}+\Delta\mathbf{C})\mathbf{x}(k)=\mathbf{Cx}(k)+\mathbf{y}_F(k),\end{gathered} \tag{11}$$

where: $\mathbf{y}(k)$ is real measured signal and $\mathbf{y}_F(k)$, is signal generated by sensor faults.

To isolate sensor fault we use the method IFD – Instrument Fault Detection [1] with residua generated by the observer bank. We denote that $\hat{\mathbf{x}}(k)$ is estimated state vector, so the estimation error is: $\boldsymbol{\varepsilon}(k)=\mathbf{x}(k)-\hat{\mathbf{x}}(k)$. For observer gain matrix **L** it leads to the following estimation error equation:

$$\dot{\boldsymbol{\varepsilon}}=[\mathbf{A}\text{ - }\mathbf{LC}]\boldsymbol{\varepsilon}+[\Delta\mathbf{A}\text{ - }\mathbf{L}\Delta\mathbf{C}]\mathbf{x}+\Delta\mathbf{Bu}-\mathbf{Ly}_F. \tag{12}$$

It means that all faults: $\Delta\mathbf{A}$, $\Delta\mathbf{B}$, $\Delta\mathbf{C}$ influence on the estimation error. Such approach allows to detect faults in the system but not to isolate them. The situation is much simple if only the sensor is failed. Then we can isolate such sensor by the observer bank. So we have to design a test to separate the diagnostics of measurement system from the other faults. Identification of Markov parameters will be used to separate faults $\Delta\mathbf{C}$ from $\Delta\mathbf{A}$, $\Delta\mathbf{B}$.

DIAGNOSTIC TABLES

A diagnostic table written in the binary matrix form shows dependences among diagnostic signals and different faults. The table enables the isolation of particular faults. In the binary matrix the columns are connected with faults, while rows with diagnostic signals. When a fault influences on a diagnostic signal we put value *true* (integer 1) in the proper place of the matrix. In opposite case we put *false* (zero).

The residua from the observer bank and the residua obtained during identification of the open-loop system parameters will be diagnostic signals. First three diagnostic signals are generated by the observer bank of the measurement system:

$$s_1(t)=r_1(t),\quad s_2(t)=r_2(t),\quad s_3(t)=r_3(t). \tag{13}$$

where *r(t)* are signals designed to isolate faults of particular sensors. Unfortunately, if there are faults in other components of system they influence above diagnostic signals. Therefore, these signals are functions of faults connected with sensors, amplifiers and coils as follows:

$$\begin{aligned} s_1 &= s_1(f_1, f_4, f_5, f_6, f_7, f_8), \\ s_2 &= s_2(f_2, f_4, f_5, f_6, f_7, f_8), \\ s_3 &= s_3(f_3, f_4, f_5, f_6, f_7, f_8). \end{aligned} \tag{14}$$

The next diagnostic signals are obtained from identification procedure. Using the ERA algorithm we calculate real matrices of the open-loop system. They are compared with nominal matrices by introduction of array division in the form:

$$\mathbf{A_p} = \frac{\mathbf{A_{Ce}} - \mathbf{A_C}}{\mathbf{A_C}} \cdot 100\%, \qquad \mathbf{B_p} = \frac{\mathbf{B_{Ce}} - \mathbf{B_C}}{\mathbf{B_C}} \cdot 100\%, \tag{15}$$

Array division is a division of respective matrices elements. Elements of matrices $\mathbf{A}_c$, $\mathbf{B}_c$ are shown in equation (2). The elements of matrices $\mathbf{A}_{ce}$, $\mathbf{B}_{ce}$ are estimated in identification procedure. So, we have the following matrix indicators of faults:

$$\mathbf{A}_p = \begin{bmatrix} 0 & 1 & 0 & 0 \\ v_{p1} & 0 & v_{p21} & -v_{p22} \\ 0 & -v_{p31} & -v_{p41} & 0 \\ 0 & v_{p32} & 0 & -v_{p42} \end{bmatrix}, \mathbf{B}_p = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ v_{p51} & 0 \\ 0 & v_{p52} \end{bmatrix}, \tag{16}$$

Analyzing physical parameters of the system we can notice that elements of above matrices are generated by different faults according to the following relations:

$$\begin{gathered} v_{p1} = v_{p1}(f_6, f_7, f_8), \quad v_{p21} = v_{p21}(f_6, f_7, f_8), \\ v_{p22} = v_{p22}(f_6, f_7, f_8), \; v_{p31} = v_{p31}(f_7), \quad v_{p32} = v_{p32}(f_8), \\ v_{p41} = v_{p41}(f_7), \quad v_{p42} = v_{p42}(f_8), \\ v_{p51} = v_{p51}(f_4), \quad v_{p52} = v_{p52}(f_5). \end{gathered} \tag{17}$$

The information about the same faults is contained in a few diagnostic signals. Thus, we can reduce the list of diagnostic signals as follows:

$$\begin{gathered} s_4(f_4) = v_{p51}, \quad s_5(f_5) = v_{p52}, \quad s_6(f_6, f_7, f_8) = v_{p1}, \\ s_7(f_7) = v_{p31}, \quad s_8(f_8) = v_{p32}. \end{gathered} \tag{20}$$

As it results from identification method these functions are valid for normally working sensors. In real situation we have to take into account the failure of sensors. Then, above diagnostic signals are functions of the following faults:

$$\begin{gathered} s_4 = s_4(f_1, f_2, f_3, f_4), \quad s_5 = s_5(f_1, f_2, f_3, f_5), \\ s_6 = s_6(f_1, f_2, f_3, f_6, f_7, f_8), \\ s_7 = s_7(f_1, f_2, f_3, f_7), \quad s_8 = s_8(f_1, f_2, f_3, f_8). \end{gathered} \tag{21}$$

The full binary matrix has the form shown in the Tab. 2. The matrix is fulfilled by logic values 1 (*true*). We omitted and replaced by blank the logic values 0 (*false*) to make the table clearer. As a limit for values *true* we assumed 5% changes in the physical parameters which lead to system instability.

Tab.2. Binary diagnostic matrix for single axis of magnetic bearing.

S/F	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8
s_1	1			1	1	1	1	1
s_2		1		1	1	1	1	1
s_3			1	1	1	1	1	1
s_4	1	1	1	1				
s_5	1	1	1		1			
s_6	1	1	1			1	1	1
s_7	1	1	1				1	
s_8	1	1	1					1

As an example we consider the electromagnetic coils. The coil fault can be a result of short circuit between parts of coils. It reduces the number of active coils. As a result it changes the coefficient of displacement stiffness, coefficient of current stiffness, inductivity, and resistance. During a computer simulation we can find the limit number of failed coils causing the closed-loop system instability (for fixed control law). If total number of failed coils cross the 5% of the limit number then corresponding values of elements in matrix indicators should show appearance of the fault.

According to Gertler [2] the faults are detectable when all columns of binary matrix are different. If two columns differ only in one row the faults connected with these columns are weakly isolated. When all columns differ in two rows all faults are strongly isolated. It takes place when binary matrix is square and diagonal. In that case we are able to isolate multiple faults. Analyzing the Table 2 we can notice that all faults are strongly isolated except the f_6 fault because rotor mass change is weakly isolated.

DIAGNOSTIC SYSTEM

From the binary matrix (Tab.2) results that test of measurement system by observer bank is sufficient to detect faults in the system. A set of diagnostic signals s_1, s_2, s_3 reacts to all faults. To isolate fault we have to carry out the other tests. The isolation of all faults is available by the following tests.

1. Measurement system test by the observer bank.
2. Test separating faults of measurement system from faults in plant or actuators.
3. Identification of physical state matrix and physical control matrix.
4. The isolation of the faults.

Ad.1. Residua of measurement signals are generated on-line by the observer bank realized beside control loop. It can be realized by a microprocessor using parallel the measurement and control signals. Since that test is realized on-line it allows to emergency shut-down of the rotating machinery in the case of fast progression of the failure. The method of observer bank was checked in many industrial applications [1,2].

Ad.2. It is desired to have a test in which faults of the measurement system are distinguished from others faults. The test allows to avoid the identification procedure which consumes microprocessor time. In the case of sensor fault this test stops further tests. The previous test indicates which sensor is failed.

To check if the fault is in measurement system we can use observer/controller Markov parameters, particularly the first one which has the following form:

$$\bar{\mathbf{Y}}_1 = \underline{\bar{\mathbf{C}}}\underline{\bar{\mathbf{B}}} = \begin{bmatrix} \underline{\mathbf{C}}\underline{\mathbf{B}} & -\underline{\mathbf{C}}\mathbf{G} \\ -\mathbf{F}\underline{\mathbf{B}} & \mathbf{FG} \end{bmatrix}. \tag{22}$$

We can see that the diagnostic signal can be designed basing on elements of submatrix $\underline{\mathbf{C}}\mathbf{G}$ where observer gain matrix $\mathbf{G}$ is constant. Faults in measurement system cause changes in matrix $\mathbf{C}$. Submatrix $\underline{\mathbf{C}}\mathbf{G}$ has dimension 3×3. If matrix $\mathbf{C}$ has a similar form to diagonal then the best diagnostic signals can be designed from diagonal elements of the submatrix $\underline{\mathbf{C}}\mathbf{G}$.

To identify Markov parameters we are forced to excite the closed-loop system by additional signal $\mathbf{r}(t)$. Such test should be realized in an off-line regime. It means that the technological process of rotating machinery shoud be stopped to carry out test. Therefore, we can not resign from the observer bank because it does not disturb the technological process.

Ad.3. Above remarks apply to identification procedure of open-loop physical parameters. After identification we obtain matrix indicators. As it was mentioned the diagnostic signals are calculated from elements of the indicators. This test should be also realized in off-line regime.

Ad. 4. After above tests we are able to indicate faults. It can be noticed that after first two tests the binary matrix (Tab. 2) may be split into two simpler matrices (Tab.3, 4).

Tab.3. Diagnostic binary table for fault in measurement system.

S/F	f_1	f_2	f_3
s_1	1		
s_2		1	
s_3			1

Tab. 4. Diagnostic binary table for fault subset of plant and actuators.

S/F	f_4	f_5	f_6	f_7	f_8
s_4	1				
s_5		1			
s_6			1	1	1
s_7				1	
s_8					1

These matrices are almost diagonal and faults are strongly isolated with exception of rotor mass change.

COMPUTER SIMULATION AND CONCLUSSION

The following nominal parameters were used in computer simulation: $N_1=N_2=100$ - coil number in upper and lower electromagnetic coils, respectively, $R_1=R_2=1.5\ \Omega$ – coil resistance, $L_{s1}=L_{s2}=0.043$ H – leakage inductivity, $i_o=2$ A – operation point current, $A_{p1}=A_{p2}=400*10^{-6}$ m^2 – pole cross section area, $\mu=4\pi*10^{-7}$ – magnetic permeability, $k_{w1}= k_{w2}=30$ – amplifier gain.

The simulation model was designed in Matlab-Simulink software. The controller was calculated for a linearized model. The controller was joined to the full nonlinear model including that part of system dynamics which was earlier omitted. For example the real model of amplifiers is in the form:

$$G_{w1} = \frac{k_{w1}}{T_{w1}s+1}, \quad G_{w2} = \frac{k_{w2}}{T_{w2}s+1} \tag{23}$$

In opposite to the linear model the nonlinear model is non-minimal phased. It is caused by delay in the system. The delay is caused by restriction of control signals. The transient process of the closed-loop system is similar in linear and nonlinear models (Fig. 1).

The nonlinear model was used for the further simulation. The simulation results are as follows:

1. System is sensitive for amplifier dynamics. It becomes unstable for: $T_{w1}>0.0005$ s, $T_{w2}>0.0005$. It means that amplifier band-pass should cross 2000 Hz. The system is also unstable for: $k_{w1}=<12.4$, $k_{w2}=<12.4$.

2. Coils failure in the form of active coil reduction cause changes in some elements of the state matrix. Under external load the coil faults influence in differ way on system stability. We assumed that system is unstable if one of electromagnets has all coils failed.

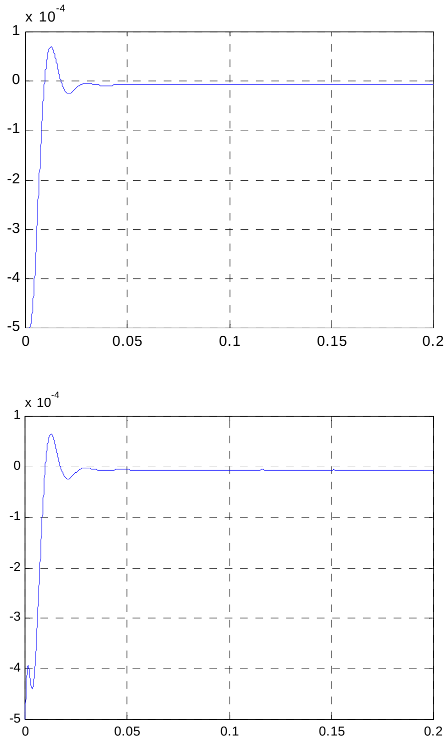
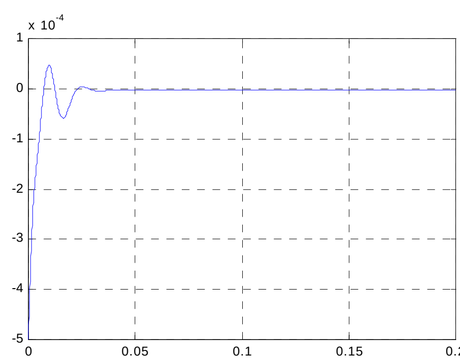


Fig.1. Answer to step input generated by linear model (uppert plot) and by nonlinear model (lower plot).



Rys.2. Step answers obtained from local observers gathered in observer bank. The observers are designed in order on signals: mass displacement, currents in upper coil and current in lower coil. Answers from different observers cover each others.

3. System is sensitive on sensors faults. The system is unstable if coefficient gain of displacement sensor is below 0.53 of nominal value. The system is even more sensitive in case of current sensors fault becoming unstable for sensor coefficient gain less than 0,72 of nominal value.
4. System is unstable for 60% loss of rotor mass.

In the next step the local observers were built. The every observer was driven by signal from one sensor. Output signals of closed loop system were calculated on basis of estimated states produced by particular observers. One of them is the displacement sensor. The transient process noticed by local observes is shown in Fig. 2.

After simulation the following conclusions can be made:

1. If bearings are not loaded then all three local observers repeated steady state values of the measured signals.
2. External forces, like gravity force, strongly influence on output signals of the observers. Their causes bias which should be compensated by the diagnostic system.
3. Due to fault in the system the measured and estimated signals sufficiently differ activating the decision function in the diagnostic system.

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