Method of Sensor Fault Identification Based on High-order Sliding Mode Observers

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Abstract: The problem of sensor fault identification in technical systems described by linear equations under the external disturbances is studied. To solve the problem, sliding mode observer is used which is constructed based on the reduced-order model of the original system. This model is sensitive to the faults and insensitive to the disturbances. It is shown that if some conditions are met, then sliding mode exists which allows obtaining exact estimation of the fault.

Keywords: Dynamic systems, Continuous-time, Sensors, Faults, Identification, Sliding mode observers.

1. INTRODUCTION

Various sensors are an integral part of almost any technical system. They are often the least reliable elements of the system, as a result of which, when faults appear in them, the sensors can provide distorted information about the state of the system, which will ultimately lead to erroneous responses of the control system. If the magnitude of the faults that have arisen can be estimated, this information can be used to correct the distortions and restore the normal operation of the control system.

Currently, sliding mode observers are actively used to estimate (identify) the magnitudes of the faults that have arisen [1-6]. In these paper, the problem of identification for various classes of systems and faults arising both in the dynamics and drives of the system and its sensors is solved. It is assumed that before identification, the localization problem is solved, determining which sensor is faulty. For concreteness, below we will assume that the distortion of sensor readings is described by an unknown function $d(t)$ that needs to be identified.

It should be noted that the problem of identifying sensor faults was considered in [2], where only an approximate solution was obtained, since the final expression contains the derivative $\dot{d}(t)$. The method proposed in [6] gives an exact solution due to the use of a special high-dimensional system, on the basis of which a sliding mode observer is constructed. In contrast to these methods, in the present work the sliding mode observer is constructed on the basis of a reduced-order model of the original system of low dimension, insensitive to disturbances, which does not contain the derivative $\dot{d}(t)$.

This work is a logical continuation of the article [5], where the problem of identifying sensor faults in technical systems was considered on the basis of sliding mode observers. From [1-5] and similar works it follows that the problem can be solved by imposing a number of conditions on the original system, which are far from always satisfied, which makes it impossible to solve the identification problem.

These conditions can be significantly weakened by using the so-called high-order sliding mode observers, considered in a number of articles [7, 8], which are based on the Levant differentiator [9]. To implement this idea, the paper poses and solves the problem of identifying sensor faults based on high-order sliding mode observers. The novelty of the paper is that, unlike known works, the identification procedure is not sensitive to external disturbances and is implemented without imposing a matching condition, which makes it possible to solve the identification problem for a wider class of systems.

To do this, we will first present the basic information about high-order sliding mode observers based on [7], since the approach of papers [8] imposes more restrictions on the original system.

2. PRELIMINARIES

Let us consider a class of systems described by equations

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) + L\rho(t), \\ y(t) &= Cx(t), \end{aligned} \qquad (1)$$

where $x(t) \in R^n$ and $u(t) \in R^m$ are the state and control vectors, $y(t) \in R$ is a scalar measurement;

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$A \in R^{n\times n}$, $B \in R^{n\times m}$, $L \in R^{n\times 1}$ and $C \in R^{1\times n}$ are known constant matrices; $\rho(t) \in R$ is an unknown scalar function of time describing the disturbances acting on the system. Note that to solve the problem under consideration, in [1-4] a matching condition was imposed on system (1), which is removed in [7-9]. Let us introduce several concepts from [7] necessary for further exposition.

Recall that the observability matrix of system (1) is called the matrix

$$P = \begin{pmatrix} C \\ CA \\ \vdots \\ CA^{n-1} \end{pmatrix}.$$

It is assumed that the pair (C, A) is observable, *i.e.* $\mathbf{rank}(P) = n$. It is known that in this case there exists a matrix K such that $\tilde{A} = A - KC$ will be stable. It is also assumed that system (1) is minimal-phase, *i.e.* the invariant zeros of the triple (A, C, L) have negative real parts. The latter means that the zeros of the transfer function of system (1) are stable.

The relative degree of system (1) for the variable $\rho(t)$ is a number n_1 such that

$$CA^j L = 0, \quad j = 1, 2, ..., n_1 - 2, \quad CA^{n_1 - 1} L \neq 0.$$

It is known that $n_1 \leq n$ and by the corresponding coordinate transformation, the system can be reduced to the form

$$\begin{aligned} \dot{x}_1(t) &= A_{11}x_1(t) + A_{12}x_2(t) + B_1u(t) + L_1\rho(t), \\ \dot{x}_2(t) &= A_{21}x_1(t) + A_{22}x_2(t) + B_2u(t), \\ y(t) &= C_1x_1(t), \end{aligned} \tag{2}$$

where $A_{11} \in R^{n_1 \times n_1}$, $A_{12} \in R^{n_1 \times (n-n_1)}$, $L_1 \in R^{n_1 \times 1}$, and $C_1 \in R^{1\times n_1}$, while

$$A_{11} = \begin{pmatrix} 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \\ \beta_1 & \beta_2 & \dots & \beta_{n_1} \end{pmatrix}, \quad A_{12} = \begin{pmatrix} 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 \\ \beta_{n_1+1} & \beta_{n_1+2} & \dots & \beta_n \end{pmatrix},$$

$$L_1 = (\ 0 \quad \dots \quad 0 \quad q\ )^T, \quad q \neq 0,$$

where $\beta_1, ..., \beta_n$ are some constants; if $n_1 = n$, the subsystem with the vector x_2 is absent.

Let us first consider the case $n_1 = n$, assuming that the unknown function $\rho(t)$ is bounded together with its p derivatives: $\rho(t) \leq \rho_0$, $\rho^{(i)}(t) \leq \rho_0$, $i = 1, 2, ..., p$. In addition, it is assumed that the p-th derivative satisfies the Lipschitz condition with constant ρ_1, *i.e.* $|\rho^{(p)}(t) - \rho^{(p)}(t')| \leq \rho_1 |t - t'|$.

To estimate the value of the function, two observers are constructed, the first of which is a standard Luenberger observer of full order:

$$\dot{z}(t) = Az(t) + Bu(t) + K(y(t) - Cz(t)), \quad z \in R^n, \tag{3}$$

K is the feedback gain matrix. The second is a sliding mode observer of high order [9], which has the following form:

$$\begin{aligned} \dot{v}_1 &= w_1 = -\alpha_{n+p+1}M^{1/(n+p+1)} |v_1 - y + Cz|^{(n+p)/(n+p+1)} \mathbf{sign}(v_1 - y + Cz) + v_2, \\ \dot{v}_2 &= w_2 = -\alpha_{n+p}M^{1/(n+p)} |v_2 - w_1|^{(n+p-1)/(n+p)} \mathbf{sign}(v_2 - w_1) + v_3, \\ &\vdots \\ \dot{v}_n &= w_n = -\alpha_{p+2}M^{1/(p+2)} |v_n - w_{n-1}|^{(p+1)/(p+2)} \mathbf{sign}(v_n - w_{n-1}) + v_{n-1}, \\ &\vdots \\ \dot{v}_{n+p} &= w_{n+p} = -\alpha_2 M^{1/2} |v_{n+p-1} - w_{n+p-2}|^{1/2} \mathbf{sign}(v_{n+p-1} - w_{n+p-2}) + v_{n+p}, \\ \dot{v}_{n+p+1} &= -\alpha_1 M \mathbf{sign}(v_{n+p+1} - w_{n+p}), \end{aligned} \tag{4}$$

where M is a sufficiently large constant, the constants α_i are chosen sufficiently large according to the recommendations of [9]; in particular, it is proposed there $\alpha_1 = 1.1$, $\alpha_2 = 1.5$, $\alpha_3 = 2$, $\alpha_4 = 3$, $\alpha_5 = 5$, $\alpha_6 = 8$.

Theorem [7]. The variable $\rho(t)$ can be estimated as

$$\hat{\rho}(t) = \frac{1}{q}(v_{n+1} - (b_1v_1 + b_2v_2 + ... + b_nv_n)), \tag{5}$$

where $b_1, b_2, ..., b_n$ are the coefficients of the characteristic equation of the matrix $A - KC$:

$$\det(A - KC - sI) = (-1)^n(s^n - b_ns^{n-1} - ... - b_1).$$

In [7] it is proved that under the restrictions imposed on system (1) and the corresponding choice of constants M and α_i the estimate (5) will be exact after the end of the transient process in a finite time. It is additionally shown that if the measurements contain noise with a maximum amplitude ε, then the magnitude of the error in estimating the function $\rho(t)$ is of the order of $\varepsilon^{(p+1)/(n+p+1)}$.

In the case of $n_1 < n$ under the same restrictions on the unknown function $\rho(t)$, its estimate can be obtained in a similar way by replacing the dimension n in formulas (4) and (5) with n_1.

In the simplest special case, when $n = 1$, system (1) has the form

$$\dot{x}(t) = ax(t) + bu(t) + q\rho(t),$$
$$y(t) = x(t)$$

and the unknown function $\rho(t)$ satisfies the Lipschitz condition, *i.e.* $p = 0$, we obtain:

$$\dot{z}(t) = az(t) + bu(t) + K(y(t) - z(t)),$$

$$\dot{v}_1 = w_1 = -1.5M^{1/2} | v_1 - y + z |^{1/2} \mathbf{sign}(v_1 - y + z) + v_2,$$
$$\dot{v}_2 = -1.1M\mathbf{sign}(v_2 - w_1).$$

Then, when $M > | l | \rho_0$, the estimate of the function $\rho(t)$ has the form

$$\hat{\rho}(t) = \frac{1}{q}(v_2 - (a - K)v_1), \quad K > | a |.$$

3. REDUCED-ORDER MODEL DESIGN

The requirement for scalarity of measurement in model (1) is a disadvantage of the approach [7], limiting the possibilities of its application. This disadvantage, however, can be overcome by analyzing not the original system, but its reduced (lower-dimensional) model, which can always be constructed in such a way as to be sensitive to the faults subject to evaluation. To present this idea, we consider a class of technical systems described by a linear model

$$\dot{x}(t) = Fx(t) + Gu(t) + L\rho(t),$$
$$y(t) = Hx(t) + \sum\nolimits_{j=1}^{l} D_i d_i(t). \tag{6}$$

Here $x(t) \in R^n$, $u(t) \in R^m$, $y(t) \in R^l$ are the state, control, and measurement vectors; $F \in R^{n\times n}$, $G \in R^{n\times m}$, $L \in R^{n\times q}$, and $H \in R^{l\times n}$ are known constant matrices; $\rho(t) \in R^c$ is an unknown function of time describing the disturbances acting on the system; $d_i(t) \in R$ is a function describing the faults in the *i*-th sensor: in their absence $d_i(t) = 0$, when a fault appears, $d_i(t)$ becomes an unknown function of time, $i = 1,2,...,l$; matrices D_1, …, D_l associate faults with the corresponding components of the measurement vector: $D_1 = (1 \;\; 0 \;\; ... \;\; 0)^{\mathbf{T}}$, …, $D_l = (0 \;\; 0 \;\; ... \;\; 1)^{\mathrm{T}}$. It is assumed that each function $d_i(t)w$ satisfies the Lipschitz condition with some constant.

For simplicity, we consider the case when faults are possible only in one sensor with the corresponding elements D and $d(t)$. It is required to estimate the function $d(t)$ without the assumption of minimal phase of system (6).

A reduced model of system (6), insensitive to disturbances, is described by the equation

$$\dot{x}_*(t) = F_* x_*(t) + G_* u(t) + J_* Hx(t);$$
$$y_*(t) = H_* x_*(t), \tag{7}$$

where $x_* \in R^k$ is the state vector of dimension $k < n$, the matrix F_* and H_* of the dimensions $k \times k$ and $1 \times k$, respectively, have the canonical form

$$F_* = \begin{pmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ 0 & 0 & 0 & \ldots & 0 \\ \ldots & \ldots & \ldots & \ddots & \ldots \\ 0 & 0 & 0 & \cdots & 0 \end{pmatrix}, \quad H_* = (\; 1 \;\; 0 \;\; 0 \;\; \cdots \;\; 0 \;). \tag{8}$$

In contrast to system (6) and the observer constructed below, model (7) is a virtual object; in fact, it is a part of system (6). The term $J_* Hx(t)$ is used instead of $J_* y(t)$ to be able to take into account sensor faults.

Note that to apply the methods of works [1-5] to system (7), it is necessary to fulfill the condition $\mathbf{rank}(H_* J_* D) = \mathbf{rank}(J_* D)$ or equality $PJ_* D = (QH_*)^T$ for some matrix Q and a symmetric positive definite matrix P. The first, in particular, means that the fault should be included only in the first equation of system (7), which forms its output $y_*(t)$, the second is also restrictive, which makes it impossible to apply these methods in many cases. The approach described in the previous section does not imply the use of these restrictions.

Recall [5] that constant matrices J_* and G_* are determined based on the solution of the equation

$$(N \;\; -J_{*1} \;\; ... \;\; -J_{*k} \;)(V^{(k)} \;\; B^{(k)}) = 0, \tag{9}$$

where

$$V^{(k)} = \begin{pmatrix} D^0 HF^k \\ HF^{k-1} \\ \vdots \\ H \end{pmatrix}, \; B^{(k)} = \begin{pmatrix} D^0 HL & D^0 HFL & D^0 HF^2 L & \ldots & D^0 HF^{k-1} L \\ 0 & HL & HFL & \ldots & HF^{k-2} L \\ 0 & 0 & HL & \ldots & HF^{k-3} L \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ 0 & 0 & 0 & \ldots & 0 \end{pmatrix}.$$

Solving equation (9) with the minimum dimension k, starting with $k = 1$, we determine the row $(N \;\; -J_{*1} \;\; ... \;\; -J_{*k})$. Next, from the relations

$$R_* = ND^0, \quad \Phi_1 = R_* H, \quad \Phi_1 F = \Phi_2 + J_{*1} H,$$

$$\Phi_i F = \Phi_{i+1} + J_{*i} H, \quad i = \overline{2, k-1}, \quad \Phi_k F = J_{*k} H, \tag{10}$$

where D^0 is the matrix of maximum rank such that $D^0D=0$, the rows of the auxiliary matrix Φ are determined and the matrix $G_*=\Phi G$ is found. Since $y(t)=Hx(t)+Dd(t)$, then in model (7) the term $J_*Hx(t)$ is replaced by $J_*y(t)-J_*Dd(t)$. For simplicity, we assume that the vector $J_*D\neq 0$ contains only one non-zero component equal to q.

4. SOLUTION OF THE PROBLEM

Comparing model (7) with systems (1) and (2), we can conclude that model (7) with matrices $A=F_*$, $B=(G_*\ \ J_*)$, $L=-J_*D$, $C=H_*$ and variables $u(t):=\begin{pmatrix} u(t) \\ y(t) \end{pmatrix}$, $y(t):=y_*(t)$, and $\rho(t):=d(t)$, can be used as system (1), for which the problem of estimating an unknown function is solved.

It is easy to verify that the observability matrix of the model (7) is the identity matrix, so the model is observable. We will assume that the matrix J_*D satisfies the following condition: the complex frequency s, at which the rank of the Rosenbrock matrix

$$R=\begin{pmatrix} sI-F_* & J_*D \\ H_* & 0 \end{pmatrix}$$

becomes smaller $k+1$, has a negative real part, *i.e*. system (7) is minimally phase.

Remark. Let system (7) be minimally phase, *i.e*. some invariant zero $s=s_0$ of the triple $(F_*,H_*,-J_*D)$ has positive real part. This means that system (7) in the initial state $x_*(0)$ will be unstable under the function $d_0(t)=d_0\exp(js_0t)$ where $x_*(0)$ and d_0 satisfy the equation

$$\begin{pmatrix} s_0I-F_* & J_*D \\ H_* & 0 \end{pmatrix}\begin{pmatrix} e_0 \\ d_0 \end{pmatrix}=0 .$$

It follows from the last equation that this is possible only in very rare and practically impossible cases. This means that the minimally phase demand is of no practical importance.

Observer (3) in our case takes the form

$$\dot{z}(t)=F_*z(t)+G_*u(t)+J_*y(t)+K(R_*y-y_*),\quad z\in R^k . \qquad (11)$$

Equations (4) describing the sliding mode observer retain their form with the replacement of the expression v_1-y+Cz in the first equation by $v_1-y_*+H_*z$. The value of the number n_1 coincides with the number of the component of the state vector of the model (7), which includes the function $d(t)$.

Considering that the matrix K is a column $K=(k_1\ \ k_2\ \ ...\ \ k_k)^{\mathbf{T}}$, and F_* and H_* are given in the canonical form (8), the matrix $A-KC$ takes the form

$$F_*-KH_*=\begin{pmatrix} -k_1 & 1 & 0 & \cdots & 0 \\ -k_2 & 0 & 1 & \cdots & 0 \\ -k_3 & 0 & 0 & \dots & 0 \\ \dots & \dots & \dots & \ddots & \dots \\ -k_k & 0 & 0 & \cdots & 0 \end{pmatrix}.$$

Its characteristic equation has the form

$$\det(F_*-KH_*-sI)=(-1)^k(s^k+k_1s^{k-1}+...+k_k) . \qquad (12)$$

From here, by analogy with (5), we obtain a formula for estimating the function $d(t)$:

$$\hat{d}(t)=\frac{1}{q}(v_{k+1}+(k_kv_1+k_{k-1}v_2+...+k_1v_k)) . \qquad (13)$$

Algorithm.

Step 1. Solve equation (9) with minimal *k* and find the row $(N\ \ -J_{*1}\ \ ...\ \ -J_{*k})$.

Step 2. Calculate the row of the matrix Φ from (10) and $G_*=\Phi G$.

Step 3. Construct the reduced model (7) and verify is it minimally phase or not.

Step 4. Choose the gain matrix *K* and construct the observer (11).

Step 5. Construct the high order sliding mode observer (4) with $n=k$ and $p=0$.

Step 6. Obtain the characteristic equation (12).

Step 7. Estimate the fault according to (13).

Computational complexity of this algorithm is of the order of n^2.

5. EXAMPLE

Let us consider the linearized model of a three-tank object given in [5] and described by the equations

$$\dot{x}_1=-\gamma_1(x_1-x_2)+\gamma_2u_1,$$
$$\dot{x}_2=\gamma_1(x_1-x_2)-\gamma_3(x_2-x_3)+\gamma_4u_2,$$
$$\dot{x}_3=\gamma_3(x_2-x_3)-\gamma_5x_3,$$
$$y_1=x_1+d,\quad y_2=x_3,$$

where the coefficients $\gamma_1 \div \gamma_5$ depend on the design features of the object, $x_1 \div x_3$ are the liquid levels in the tanks. Unlike [5], we will assume that the levels in the first and third tanks are measured. For simplicity, we will assume $L = 0$, as well as $\gamma_1 = ... = \gamma_5 = 1$, which yields the following matrices:

$$F = \begin{pmatrix} -1 & 1 & 0 \\ 1 & -2 & 1 \\ 0 & 1 & -2 \end{pmatrix}, \quad G = \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{pmatrix}, \quad H = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix},$$

$$D = \begin{pmatrix} 1 \\ 0 \end{pmatrix}.$$

Let us consider a fault in the first sensor, for which $D^0 = (0 \quad 1)$. According to Step 1 of Algorithm, it is easy to verify that for $k = 1$ equation (9) has no solution, we will take $k = 2$:

$$\begin{pmatrix} N & -J_{*1} & -J_{*2} \end{pmatrix} \begin{pmatrix} 1 & -4 & 5 \\ -1 & 1 & 0 \\ 0 & 1 & -2 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix} = 0,$$

which yields $N = 1$, $J_{*1} = (0 \quad -4)$, $J_{*2} = (1 \quad -3)$. As a result,

$$R_* = (0 \quad 1), \quad \Phi = \begin{pmatrix} 0 & 0 & 1 \\ 0 & 1 & 2 \end{pmatrix}, \quad G_* = \Phi G = \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix},$$

$$D_* = -J_* D = \begin{pmatrix} 0 \\ -1 \end{pmatrix}, \quad q = -1.$$

According to Step 3 of Algorithm, model (7) takes the form

$$\begin{aligned} \dot{x}_{*1} &= x_{*2} - 4y_2, \\ \dot{x}_{*2} &= y_1 - 3y_2 + u_2 - d, \\ y_* &= x_{*1} = y_2. \end{aligned}$$

Let us consider the Rosenbrock matrix of this model:

$$R = \begin{pmatrix} s & -1 & 0 \\ 0 & s & 1 \\ 1 & 0 & 0 \end{pmatrix}.$$

It is easy to see that it is non-singular, *i.e.* the constructed model is minimally phase, *i.e.* means that the zeros of the transfer function of the reduced model are stable.

Since $J_* D = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$, then $n_1 = k = 2$; according to Step 4 of Algorithm, we take $K = \begin{pmatrix} 2 \\ 1 \end{pmatrix}$ and construct the Luenberger observer (10):

$$\begin{aligned} \dot{z}_1 &= z_2 - 4y_2 + 2(y_2 - y_*) = z_2 - 2y_2 - 2y_*, \\ \dot{z}_2 &= y_1 - 3y_2 + u_2 + (y_2 - y_*) = y_1 - 2y_2 - y_* + u_2, \\ y_* &= z_1. \end{aligned}$$

Since the function $d(t)$ satisfies the Lipschitz condition, we take $p = 0$. The sliding mode observer for $\alpha_1 = 1.1$, $\alpha_2 = 1.5$, $\alpha_3 = 2$, and $M = 0.5$ takes the form

$$\begin{aligned} \dot{v}_1 &= w_1 = -2M^{1/3} |v_1 - y_2 + z_{*1}|^{2/3} \, \mathbf{sign}(v_1 - y_2 + z_{*1}) + v_2, \\ \dot{v}_2 &= w_2 = -1{,}5M^{1/2} |v_2 - w_1|^{1/2} \, \mathbf{sign}(v_2 - w_1) + v_3, \\ \dot{v}_3 &= -1{,}1M \, \mathbf{sign}(v_3 - w_2), \\ M &> 2\left\| d_1(t) \right\|. \end{aligned}$$

We find the coefficients of the characteristic equation of the matrix $F_* - KH_*$:

$$F_* - KH_* = \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} - \begin{pmatrix} 2 \\ 1 \end{pmatrix} \begin{pmatrix} 1 & 0 \end{pmatrix} = \begin{pmatrix} -2 & 1 \\ -1 & 0 \end{pmatrix}.$$

Then, according to Step 6 of Algorithm, we obtain the characteristic equation:

$$\det(sI - (F_* - KH_*)) = \det \begin{pmatrix} s+2 & -1 \\ 1 & s \end{pmatrix} = s^2 + 2s + 1,$$

where $b_1 = -1, \; b_2 = -2$. As a result, the estimate of $d(t)$ takes the form

$$\hat{d}(t) = -(v_3 + v_1 + 2v_2).$$

Note that since the function describing the fault is included in the second equation, the identification methods considered in [1-4] are not applicable in this case.

The following controls were used during the simulation: $u_1(t) = \sin(t)$, $u_2(t) = \sin(0.3t)$. The fault was modeled by the appearance of a signal $d(t) = 0.2\sin(\pi t / 2 - 2\boldsymbol{\pi})$ on the time interval of 4-8 s. The following initial conditions were used: $x_1(0) = 0.2$, $x_2(0) = 0.05$, $x_3(0) = 0.02$.

Figure **1** shows the graph of the estimate $\hat{d}(t)$, Figure **2** shows the graph of the identification error $\varepsilon(t) = d(t) - \hat{d}(t)$. It is clear from the figures that the constructed observers provide an exact estimate of the fault size after the end of the transient process in a finite time.

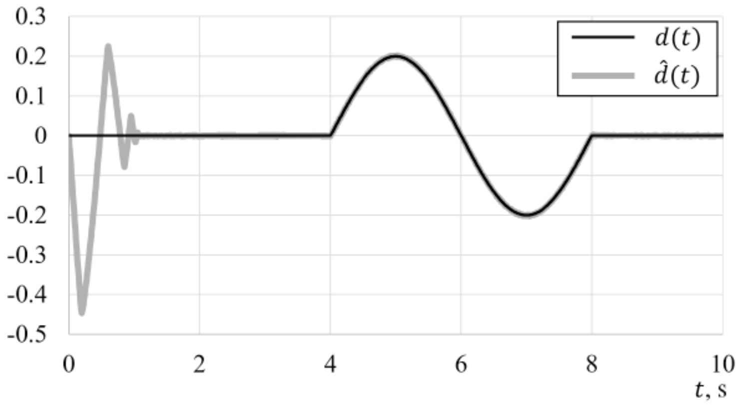

Figure 1: Function identification result.

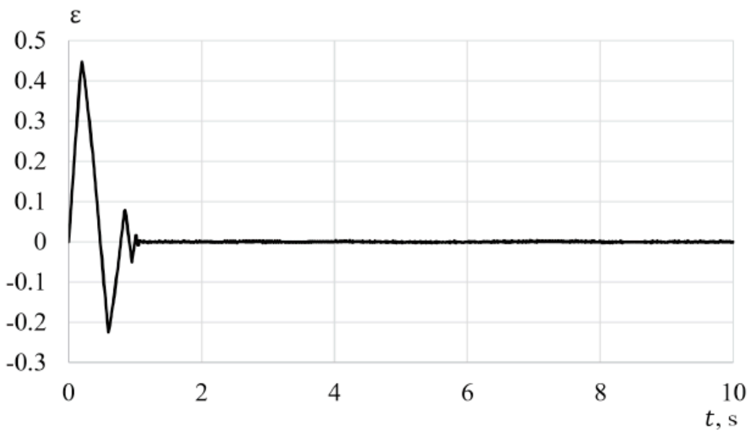

Figure 2: Function identification error

Simulation shows that the values $\alpha_1 = 1.1$, $\alpha_2 = 1.5$, $\alpha_3 = 2$, and $M = 0.5$ are suitable for our example. However, for another system, this choice can be unsuccessful, and other values should be chosen.

6. CONCLUSION

The paper states and solves the problem of constructing high-order sliding mode observers to identify sensor faults in technical systems described by linear models. The problem is solved based on a reduced (lower-dimensional) model of the original system that is insensitive to disturbances. This made it possible to reduce the complexity of the identification tools and loosen the restrictions imposed on the original system to solve the problem.

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CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interests.

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