Adaptive Fault Detection and Isolation for DC Motor Input and Sensors

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Keywords: Fault Detection, Fault Isolation, DC Motor, Identification, Adaptive System.

Abstract: The paper is devoted to the development of an adaptive approach to the fault detection and isolation of input and sensor failures of armature-controlled direct current motors. The proposed detection method is based on the full state Luenberger observer. Isolation scheme uses the directional residual set and relationships between fault directions and residual vector. Adaptability is provided by dynamic regressor extension and mixing approach for online estimation of parameters. Proposed scheme allows to isolate following faults: unaccounted load acting on the rotor, input voltage disturbance, failures of velocity and current sensors. Simulation results confirm performance of the proposed approach.

1 INTRODUCTION

The development of technologies leads to use of process automation systems in various fields of human activity: industrial manufacturing, autonomous cars and aircrafts, HVAC, etc. These systems typically have a complex structure that includes interconnected sensors, actuators and passive elements. Failures of system parts may cause sufficient consequences. Therefore, timely fault detection and isolation is of particular importance, especially for safety-critical systems. Such function allows to increase reliability, perform predictive maintenance, effective reconfiguration and quick failure elimination. According to Wunnenberg (1990) faults can be classified as follows: com- ponent fault (deviation of a plant parameters from its nominal values); sensor fault (sensor measurement doesn't corresponds to real physical value); actuator fault (deviation of control signals from the desired values).

The most common methods of fault detection are observer based approaches, parity relations, parameter identification based algorithms and machine learning approaches (Chen & Patton, 1999). Parity relation methods rely on hardware or temporal redundancy. Hardware duplication is effective and does not require system model but demands additional financial costs for adding sensor and maintenance (Ray & Luck, 1991). Another drawback of a sensor duplication is a confines imposed by technological restrictions. Temporal redundancy requires accurate plant model, but doesn't need additional hardware devices. Both approaches have a good performance for sensor faults detection in linear systems and are applicable for DC motors.

Observer based approaches use difference between estimated and measured state variables (residual) for fault detection. Isolation problem can be solved with structured and directional residual sets or fault detection filters (Patton & Chen, 1997). The structured set method is based on synthesis of specific residual generator sensitive for only one or all-but-one corresponding fault. The main idea of directional generators set is changing of residual signals in only one direction that corresponds to the specific fault in a residual space. Fault direction filters approaches use special procedures of observer synthesis to make it sensitive to the specific failures. Mentioned above methods are effective for actuator and sensor fault detection and isolation (Chung & Speyer, 1998).

Problem of robustness with respect to the parametric uncertainties, disturbances, noises and

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Kolesnik, N., Margun, A., Kremlev, A. and Zhivitskii, A.
Adaptive Fault Detection and Isolation for DC Motor Input and Sensors.
DOI: 10.5220/0011336700003271
In *Proceedings of the 19th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2022)*, pages 703-710
ISBN: 978-989-758-585-2; ISSN: 2184-2809

additive nonlinearities can be solved with the use of unknown input observers (Chen, Patton & Zhang). However, the synthesis procedure for these algorithms has solution only for a class of linear systems with sufficient limitations on plant matrices. Model of DC motor with measured velocity or current doesn't satisfy the necessary conditions (Wunnenberg, 1990).

Identification approaches use online parameters estimation algorithms (for example, gradient descent or least squares). These methods provide detection and isolation of component faults on the base of deviation between nominal and estimated parameters (Isermann, 1997).

Last researches propose to use artificial intelligence and neural networks to detect and isolate faults. In (Santos et all, 2018) the fault detection and classification schemes are proposed. The fault is detected by a classical Luenberger observer. The classification is based on a representation which combines the subctrative clustering algorithm with an adaptation of particle swarm clustering. DC motor fault detection, isolation and identification based on a neural networks approach is presented in (Adouni, Abid & Sbita, 2016). However, this method requires a lot of computational power and don't guarantee results. Experimental researches of fault detection and diagnosis methods for DC motor drives are analyzed in (Isermann, 2006).

This paper is devoted to the actuator and sensor adaptive fault detection and isolation for armature controlled direct current motors. Unknown input observers don't exist in the cases of sensor and actuator faults occurring in mechanical and electrical parts (equations for its synthesis have no solution (Wunnenberg, 1990)). Proposed research describes easy for computation and application method of fault detection and isolation. The Motor is assumed to be equipped with a velocity and current sensor. Fault detection is based on full order state observer. Isolation algorithm is provided by online parameters identification with the use of dynamic regressor extension and mixing. The proposed approach is an adaptive extension of previous authors' research (Margun, Kremlev & Vlasov, 2021; Nguev, Vlasov, Margun & Kirsanova, 2021;Margun,) where DREM is used for components fault detection and isolation. Simulation results confirm performance of the proposed approach.

The paper is organized as follows. Section II describes a mathematical model of the motor under faults and problem statement. General detection and isolation scheme, algorithms of observers calculation and residual directions are shown in Section III. Simulation results are shown in Section V.

2 PROBLEM STATEMENT

Consider a model of DC motor. Its dynamic is described by equations

$$L\frac{di}{dt} + Ri = u - E_b, \qquad J\dot{\omega} = M - M_f, \tag{1}$$

where L is an inductance, R is an armature resistance, i is a current, u is an input voltage, E_b is a back electromagnetic force, ω is a rotor angular velocity, J is a rotor and load inertia, M is a motor torque, M_f is a friction momentum,

$$E_b = k_b\phi\omega, \qquad M = k_m\phi i, \qquad M_f = k_f\omega, \tag{2}$$

where k_b, k_m and k_f are constants, ϕ is a magnetic flux assumed to be constant.

If motor is equipped with a velocity and current sensor then the dynamic in state space representation takes the form:

$$\begin{cases} \dot{x} = Ax + Bu, \\ y = Cx, \end{cases} \tag{3}$$

where

$$x = \begin{bmatrix} \omega \\ i \end{bmatrix}, A = \begin{bmatrix} -\frac{k_f}{J} & \frac{k_m\phi}{J} \\ -\frac{k_b\phi}{L} & -\frac{R}{L} \end{bmatrix} = \begin{bmatrix} a_1 & a_2 \\ a_3 & a_4 \end{bmatrix}, B = \begin{bmatrix} 0 \\ \frac{1}{L} \end{bmatrix}, C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

Consider the model (3) under following faults: external torque applied to the rotor (this failure can be caused by wear-out of bearing or any unaccounted load); input voltage disturbanc; velocity sensor fault; current sensor fault. Torque and voltage are classified as actuator faults because of they are directly acting on state vector derivatives.

A motor model under the above faults is described by equations

$$\begin{cases} \dot{x} = Ax + Bu + \begin{bmatrix} \frac{1}{J} & 0 \\ 0 & \frac{1}{L} \end{bmatrix} \begin{bmatrix} f_{a1} \\ f_{a2} \end{bmatrix}, \\ y = Cx + \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} f_{s1} \\ f_{s2} \end{bmatrix}, \end{cases} \quad (4)$$

where f_{a1} is a torque fault, f_{a2} is a voltage fault, f_{s1} is a velocity sensor fault, f_{s2} is a current sensor fault signals assumed to be unknown.

The goal of the research is to develop an adaptive scheme for actuator and sensor faults detection and isolation that remains operability under uncertain or non-stationary parameters. First, consider the case of known motor parameters. Next, an adaptive modification is proposed for the case of parametric uncertainties.

3 FAULT DETECTION AND ISOLATION SCHEME

The basis of the proposed approach is the use of bank of full order Luenberger state observers for fault detection (Clark, 1979):

$$\begin{cases} \dot{\hat{x}} = A\hat{x} + Bu + K(y - \hat{y}), \\ \hat{y} = C\hat{x}, \end{cases} \quad (5)$$

where $\hat{x}$ is an estimate of state vector, $K = \begin{bmatrix} k_1 & k_2 \\ k_3 & k_4 \end{bmatrix}$ an observer design matrix specific for i-th fault.

Residual signal is chosen as the difference between sensor measurements $y(t)$ (4) and observer output $\hat{y}(t)$ (5):

$$r = y - \hat{y} = C(x - \hat{x}) = Ce = y - C\hat{x}, \quad (6)$$

where $e(t)$ is a state estimation error.

The dynamic of considered faults residual is described by equations:

$$\begin{cases} \dot{e} = (A - KC)e + l_i f_i, \\ r = Ce, \end{cases} \quad (7)$$

where vector l_i defines fault direction in two-dimensional residual space, f_i is an i-th fault signal.

It is necessary to develop a K synthesis algorithm for each considered faults. The matrix should satisfy following condition to provide isolability property (Chen & Patton, 1999):

1) $rank[l_i; (A - KC)l_i] = 1$ to provide unidirectional residual for faults in residual space;
2) *(A − KC)* should be stable to provide stability of the observer;
3) all vectors Cl_i should be linearly independent for faults separability.

Additionally, mutual faults are separable if above conditions are satisfied for all occurred failures.

Hence, it is necessary to design observer synthesis algorithm for each of failures and develop an isolation scheme on the base of residual signals (fig. 1). Let's analyze motor behavior under actuator and sensor faults.

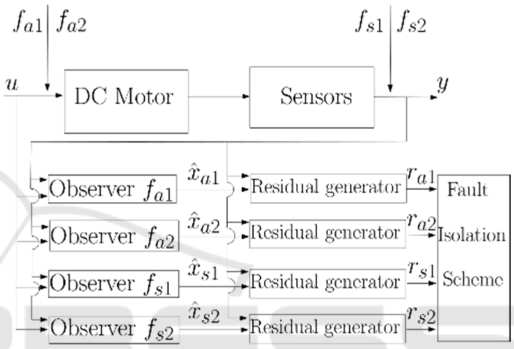

Figure 1: Fault detection and isolation scheme.

3.1 Torque Fault Detection

Some unaccounted force acting on the rotation of mechanical parts causes torque fault. Error dynamic takes the form

$$\dot{e} = (A - KC)e + l_{a1} f_{a1}, \quad l_{a1}^T = \begin{bmatrix} \frac{1}{J} & 0 \end{bmatrix} = \begin{bmatrix} l_1 & 0 \end{bmatrix}, \quad (8)$$

where f_{a1} is an external force momentum acting on rotor.

Consider condition 1:

$$rank\left[l_{a1}; (A - KC)l_{a1}\right] = rank \begin{bmatrix} \frac{1}{J} & (a_1 - k_1)l_1 \\ 0 & (a_3 - k_3)l_1 \end{bmatrix} = 1 \quad (9)$$

It holds if we choose $k_3 = a_3$:

$$rank \begin{bmatrix} \frac{1}{J} & (a_1 - k_1)l_1 \\ 0 & 0 \end{bmatrix} = 1 \quad (10)$$

Consider condition 2. Characteristic polynomial of error model (8) takes the form:

$$p_{a1} = \det(sI - (A - KC)) = s^2 + ms + n, \quad (11)$$

where s is a complex variable,

$$\begin{aligned} m &= k_1 - a_1 - a_4 + k_4, \\ n &= k_1 a_4 - a_1 a_4 + k_1 k_4 - a_1 k_4 - k_2 k_3 + a_2 k_3 + a_3 k_2 - a_2 a_3. \end{aligned} \quad (12)$$

Characteristic polynomial doesn't depend on k_2, because of $k_2 k_3 = a_3 k_2$ and $a_2 k_3 = a_2 a_3$. So we can define $k_2 = 0$. One can choose positive n, m to provide desired observer behaviour and complete K calculation by solution of equations (12) with respect to the k_1, k_4 with known k_2, k_3 and n, m chosen by the designer.

Condition 3 is satisfied because we have only one fault direction vector.

3.2 Voltage Fault Detection

A voltage fault occurs due to some failure in electronic circuits and disturbances of input voltage (for example, the crash of the transistor in motor driver or influence of powerful non-stationary external magnetic field). Error dynamic takes the form

$$\begin{aligned} \dot{e} &= (A - KC)e + l_{a2} f_{a2}, \\ l_{a2}^T &= \begin{bmatrix} 0 & \frac{1}{L} \end{bmatrix} = \begin{bmatrix} 0 & l_2 \end{bmatrix}, \end{aligned} \quad (13)$$

where f_{a2} is an additive voltage applied to the motor input.

Consider condition 1:

$$rank\left[l_{a2}; (A - KC) l_{a2}\right] = rank \begin{bmatrix} 0 & (a_2 - k_2) l_2 \\ \frac{1}{L} & (a_4 - k_4) l_2 \end{bmatrix} = 1 \quad (14)$$

It holds if we choose $k_2 = a_2$:

$$rank \begin{bmatrix} 0 & 0 \\ \frac{1}{L} & (a_4 - k_4) l_2 \end{bmatrix} = 1 \quad (15)$$

Consider condition 2. Characteristic polynomial of error model (13) is the same as in for force fault case (12). It doesn't depend on k_3 because all terms with k_3 are rejected due to $k_2 = a_2$. So we can define $k_3 = 0$. In the same way as in previous subsection one can choose positive n, m to provide desired observer behaviour by pole placement procedure and complete K calculation by solution of equations (12) with respect to the k_1, k_4.

Condition 3 holds because residual directions l_{a1} and l_{a2} are orthogonal.

3.3 Velocity Sensor Fault Detection

This fault occurs due to mechanical or electronic failure in velocity sensor or its data channels. Multiply or stuck measurement value are the most common types of the failures. Taking into account (4), error dynamic takes the form

$$\begin{aligned} \dot{e} &= (A - KC)e + l_{s1} f_{s1}, \\ l_{s1} &= KC \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} k_1 \\ k_3 \end{bmatrix}, \end{aligned} \quad (16)$$

where f_{s1} is velocity sensor fault signal.

Residual directions l_{a1} and l_{a2} are basis vectors in two dimensional residual space. Therefore, it is impossible to build linearly independent l_{s1} with respect to l_{a1} and l_{a2} in the same time. Let us choose the following residual direction $l_{s1}^T = [k_1\ k_3] = [1\ \ 1]$. If the residual signal is along this direction, then this fault will be more likely. Moreover, we can provide mutual isolability with one of actuator faults.

Consider condition 1:

$$rank\left[l_{s1}; (A - KC) l_{s1}\right] = rank \begin{bmatrix} k_1 & (a_1 - k_1)k_1 + (a_2 - k_2)k_3 \\ k_3 & (a_3 - k_3)k_1 + (a_4 - k_4)k_3 \end{bmatrix} = 1 \quad (17)$$

It is impossible to design such k_2 and k_4 that the columns will be linearly dependent like in actuator faults case because one of observer poles will be equal to zero. Let rows will be linearly dependent to satisfy the condition. Therefore:

$$\frac{k_1}{k_3} = \frac{(a_1 - k_1)k_1 + (a_2 - k_2)k_3}{(a_3 - k_3)k_1 + (a_4 - k_4)k_3} \quad (18)$$

One can find k_2 as a solution of (18):

$$k_2 = \frac{a_1 k_1 k_3 + a_2 k_3^2 - a_3 k_1^2 - a_4 k_1 k_3 + k_1 k_3 k_4}{k_3^2} \quad (19)$$

The last coefficient k_4 is chosen to satisfy condition 2 with use of characteristic polynomial (12).

It is impossible to provide condition 3 for all simultaneous faults, but proposed scheme allows to isolate a velocity sensor fault with one of actuator faults.

3.4 Current Sensor Fault Detection

Reasons for current sensor faults are the same as for velocity sensor. Error dynamic is described by equations

$$\dot{e} = (A - KC)e + l_{s2} f_{s2},$$
$$l_{s2} = KC \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} k_2 \\ k_4 \end{bmatrix}, \quad (20)$$

where f_{s2} is a velocity sensor fault signal. Choose fault direction as $l_{s2}^T = [k_2 \;\; k_4] = [2 \;\; -1]$. This direction is isolable from one of previous faults (condition 3 is partially satisfied). Consider condition 1:

$$rank\left[l_{s2}; (A - KC) l_{s2}\right] = rank \begin{bmatrix} k_2 & (a_1 - k_1)k_2 + (a_2 - k_2)k_4 \\ k_4 & (a_3 - k_3)k_2 + (a_4 - k_4)k_4 \end{bmatrix} = 1 \quad (21)$$

Similarly to previous subsection:

$$\frac{k_2}{k_4} = \frac{(a_1 - k_1)k_2 + (a_2 - k_2)k_4}{(a_3 - k_3)k_2 + (a_4 - k_4)k_4} \quad (22)$$

Therefore, k_3 is a solution of (22):

$$k_3 = \frac{a_3 k_2^2 + a_4 k_2 k_4 - a_1 k_2 k_4 - a_2 k_4^2 + k_1 k_2 k_4}{k_2^2} \quad (23)$$

The last coefficient k_1 is chosen to satisfy condition 2 with use of the characteristic polynomial (12).

3.5 Fault Isolation Scheme

Faults directions in residual space are illustrated in figure 2.

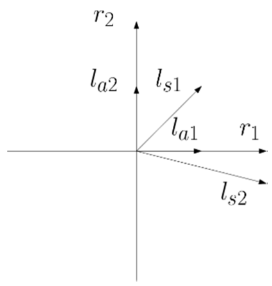

Figure 2: Fault directions in residual space.

However, it is impossible to provide explicit separation of all simultaneous faults because two of its directions define basis of two dimensional residual space. But we can propose a scheme that allows faults detection and isolation with the use of directional relationship similarly to (Chen et all, 1996).

Introduce directional relationship Z between residual vector r and fault direction l_i

$$C_i = \frac{\left|l_i^T r\right|}{\left\|l_i^T\right\|_2 \left\|r\right\|_2}. \quad (24)$$

Coefficient Z_i denotes normalized value of residual projection on the i-th fault direction. If $Z_i > Z_j$ then fault i is more likely then j. The most likely fault corresponds to $max(C_i)$, $i = \{l_{a1}, l_{a2}, l_{s1}, l_{s2}\}$.

Robustness with respect to the noises can be provided by use of threshold:

$$r = \begin{cases} r, if\ |r| \geq Threshold, \\ 0, if\ |r| < Threshold, \end{cases} \quad (25)$$

Problem of insensitivity to parametric uncertainties can be overcome with the use of identification algorithms. However, observer matrix becomes depending on estimates of plant parameters to perform all necessary detection conditions.

It should be noted, condition 3 is not satisfied for all possible mutual faults. Hence, proposed scheme may lead to isolation errors in cases of multiple faults. For example, two simultaneous actuator failures can cause increasing of the residual vector in sensor fault direction. However, such situation is unlikely in practice and detection algorithm remains its performance.

4 ADAPTIVE MODIFICATION

Combine proposed method with the method of dynamic regressor extension and mixing (DREM) (Aranovskiy, Bobtsov, Ortega & Pyrkin, 2016; Aranovskiy, Belov, Ortega, Barabanov & Bobtsov, 2019) for online estimation of parameters to ensure FDI operability under uncertainties and non-stationarity.

4.1 Plant Parameterization

It is necessary to transform (3) to the autoregressive model for use of DREM. Rewrite plant (3) in transfer function representation. Transfer functions with current and velocity outputs take the form:

$$W_i(s) = \frac{s\omega_1 + \omega_2}{s^2 + s\omega_3 + \omega_4}, \quad (26)$$

$$W_\omega(s) = \frac{\omega_5}{s^2 + s\omega_3 + \omega_4}, \quad (27)$$

where

$$\omega_1 = \frac{1}{L},\ \omega_2 = \frac{k_f}{LJ},\ \omega_3 = \frac{Lk_f + RJ}{LJ},$$
$$\omega_4 = \frac{Rk_f + k_b k_m \phi}{LJ},\ k_5 = \frac{k_m \phi}{LJ}.$$

There are unmeasured derivatives of *i(t)* and *ω(t)* that prevents transformation to the autoregressive model.

Rewrite (26), (27) as differential equations:

$$\begin{aligned} s^2 i(t) &= -\omega_3 si(t) - \omega_4 i(t) + \omega_1 su(t) + \omega_2 u(t), \\ s^2 \omega(t) &= -\omega_3 si(t) - \omega_4 i(t) + \omega_1 su(t) + \omega_2 u(t), \end{aligned} \tag{28}$$

Apply second order stable linear filter with characteristic polynomial $\Lambda(s) = s^2 + 2s + 1$ to the left and right parts of (28) according to Ioannou & Sun (2012):

$$\begin{aligned} \frac{s^2}{\Lambda(s)} i &= -\frac{\omega_3 s}{\Lambda(s)} i - \frac{\omega_4}{\Lambda(s)} i + \frac{\omega_1 s}{\Lambda(s)} u + \frac{\omega_2}{\Lambda(s)} u, \\ \frac{s^2}{\Lambda(s)} \omega &= -\frac{\omega_3 s}{\Lambda(s)} i - \frac{\omega_4}{\Lambda(s)} i + \frac{\omega_1 s}{\Lambda(s)} u + \frac{\omega_2}{\Lambda(s)} u, \end{aligned} \tag{29}$$

Coefficients λ_0, λ_1 do not affect convergence time, but appropriate choice allows to filter measurement noises.

Equations (29) can be represented in desired form with measured signals:

$$\begin{aligned} y_{fi} &= q_i^T \eta_i, \\ y_{f\omega} &= q_\omega^T \eta_\omega, \end{aligned} \tag{30}$$

where

$$y_{fi} = \frac{s^2}{s^2 + \lambda_1 s + \lambda_0} i,\ y_{f\omega} = \frac{s^2}{s^2 + \lambda_1 s + \lambda_0} \omega,$$
$$q_i^T = \left[-\frac{s}{s^2 + \lambda_1 s + \lambda_0} i; -\frac{1}{s^2 + \lambda_1 s + \lambda_0} i; \right.$$
$$\left. \frac{s}{s^2 + \lambda_1 s + \lambda_0} u; -\frac{1}{s^2 + \lambda_1 s + \lambda_0} u \right] =$$
$$= \left[q_{i1}^1; q_{i2}^1; q_{i3}^1; q_{i4}^1 \right],$$

$$\eta_i^T = [\omega_1; \omega_2; \omega_3; \omega_4] = [\eta_1; \eta_2; \eta_3; \eta_4], \tag{31}$$

$$q_\omega^T = \left[-\frac{s}{s^2 + \lambda_1 s + \lambda_0} \omega(t); -\frac{1}{s^2 + \lambda_1 s + \lambda_0} \omega(t); \right.$$
$$\left. \frac{1}{s^2 + \lambda_1 s + \lambda_0} u(t) \right] = \left[q_{\omega 1}^1; q_{\omega 2}^1; q_{\omega 3}^1 \right],$$
$$\eta_\omega^T = [\omega_5; \omega_3; \omega_4] = [\eta_5; \eta_3; \eta_4].$$

and η_i, η_ω are transfer function unknown parameters vectors to be identified.

4.2 Identification Algorithm

Let us use DREM method for DC motor parameters online identification (Aranovskiy et all, 2016). This approach provides independent estimation of plant parameters and convergence speed tuning.

According to Margun et all (2021) and Nguev et all (2021), apply different stable linear filters to (30)

$$\begin{aligned} y_{fi}^2 &= \frac{\lambda_2}{s + \lambda_2} y_{fi} = \frac{\lambda_2}{s + \lambda_2} q^T \eta = q^{2T} \eta_i, \\ y_{fi}^3 &= q^{3T} \eta_i,\ y_{fi}^4 = q^{4T} \eta_i, \\ y_{f\omega}^2 &= q^{2T} \eta_\omega,\ y_{f\omega}^3 = q^{3T} \eta_\omega, \end{aligned} \tag{32}$$

where λ_i are unique positive constants. Algorithm for λ_i selection doesn't exists. However, there are following heuristics can be used: large differences between filter's parameters decrease convergence time; too large or small λ_i can sufficiently increase computation complexity; it is good practice to choose filters parameters that are ten times different.

Obtain an extended system which includes (30) and (32) in matrix representation:

$$Y_i = Q_i \eta_i,\ Y_\omega = Q_\omega \eta_\omega, \tag{33}$$

where $Y_i^T = [y_{fi}; y_{fi}^2; y_{fi}^3; y_{fi}^4]$, $Y_i^T = [y_{f\omega}; y_{f\omega}^2; y_{f\omega}^3]$

Multiply both equations (33) from the left by adjoint matrix of Q_i, Q_ω respectively. Yields

$$\begin{aligned} \xi_i &= diag\{\varphi_i\} \eta_i, \\ \xi_\omega &= diag\{\varphi_\omega\} \eta_\omega, \end{aligned} \tag{34}$$

where φ_i and φ_ω are determinants of matrices Q_i and Q_ω respectively.

Multiplication of (33) by adjoint matrix provides independent regressors for parameters estimation (one separate regressor for each unknown plant parameter). This allows to design an independent scalar identification algorithm for each parameter similar to the classical gradient descent approach with simplified tuning and fast convergence:

$$\dot{\hat{\eta}}_n = \gamma_n \left(\xi_n \varphi_n - \varphi_n^2 \hat{\eta}_m \right), \tag{35}$$

where $\gamma_n > 0$ is a design parameter that allow to tune the convergence speed, $\hat{\eta}_n$ is an estimate of the corresponding parameter n. Separate parameters identification and convergence speed tuning are main advantages of DREM. One parameter change doesn't influence on others parameters estimates. This fact provides the robustness of fault isolation in comparison with gradient descent and least squares approaches.

4.3 Adaptive Fault Detection and Isolation

To ensure the adaptability of fault isolation scheme it is necessary to combine it with a parameters identification algorithm. It should be noted, that the observer matrices depend on the identifier outputs. This leads to the fact that during transient processes the values of the observer matrices will have significant errors in comparison with the desired values. This may lead to false faults detections. We need to update values of observers matrices only after the end of identification algorithm transients to overcome this drawback. It can be performed with the use of sliding window:

$$if \ \frac{\int_{t-T}^{t}(\bar{\eta}(t) - \hat{\eta}(\tau)\, d\tau)}{T} \leq \Delta_1 \ \forall \eta, \ update\ K \qquad (36)$$

where $\bar{\eta} = \int_{t-T}^{T} \eta\,(\tau) d\tau / T$ is a mean value on period $(t\ -\ T;\ T)$, Δ_1 is a threshold value.

Moreover, detection scheme should be insensitive to the noises, small disturbances and deviations. This problem can be solved with a residual deadzone condition:

$$if \quad Z_i \leq \Delta_2 \quad Z_i = 0 \qquad (37)$$

5 SIMULATION RESULTS

Consider motor with following plant

Observers matrices $K_{a1}, K_{a2}, K_{s1}, K_{s2}$ are updated after parameters estimation transient time. Their initial values can be calculated for nominal plant. Characteristic polynomial for plants (26), (27) parameterization is $\Lambda(s) = s^2 + 2s + 1$. Parameters of DREM filters are chosen as follows: for current output transfer function $\lambda_2 = 0.1,\ \lambda_3 = 1,\ \lambda_4 = 10$; for velocity output transfer function $\lambda_3 = 0.1,\ \lambda_6 = 1$. Threshold values are $\Delta_1 = 0.05$, $\Delta_2 = 0.1$, all γ values equal to one, $u = 10\, sin(0.1t) + \sin(t)$ to satisfy the persistent excitation condition.

Identification algorithm results are shown figure 3. Parameters estimate converges to the true value of six seconds. Observers matrices tend to the following values:

Figure 4 illustrates fault isolation algorithm output during external momentum acting on rotor shaft from 10 to 15 seconds. Fault signal is a constant that increases velocity. The largest value of directional relationships C_{a1} corresponds to the failure.

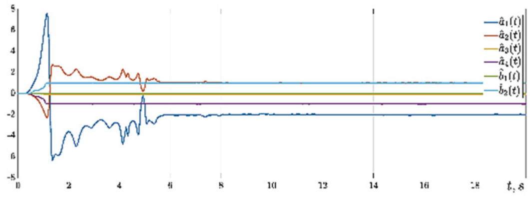

Figure 3: Plant parameters identification.

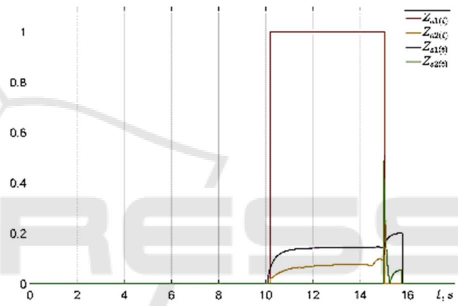

Figure 4: Directional relationships with force momentum fault from 10 to 15 seconds.

The case of voltage fault is illustrated in figure 5. The fault signal is an additional voltage applied to the motor input. The directional relationship allows to isolate this fault.

The case of sensor fault is illustrated in figure 6. The fault is a current sensor zero shift that may be caused by corruption of information bites. Proposed scheme allows to isolate this sensor fault.

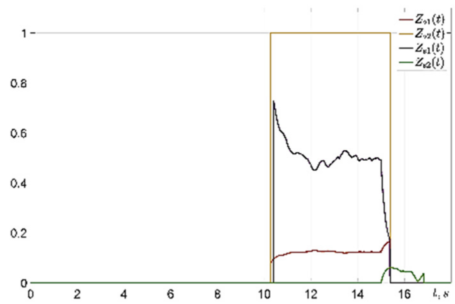

Figure 5: Directional relationships with voltage fault from 10 to 15 seconds.

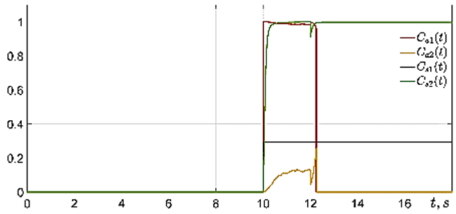

Figure 6: Directional relationships with current sensor fault since 10 seconds.

6 CONCLUSION

Actuator and sensor adaptive fault detection and isolation scheme for direct current motor is proposed. The motor is assumed to be equipped with velocity and current sensors. Detection algorithm is observer based. Isolation scheme uses directional relationship between residual and fault directions.

Adaptability is provided by DREM approach. Proposed solution allows to isolate torque fault, input voltage fault, velocity sensor fault and current sensor fault. Simplicity of observers and residual generators synthesis and its trivial computation are advantages of the scheme.

Robustness with respect to the noise is obtained by use of threshold. Insensitivity to uncertainties is provided by the DREM approach and switching techniques for the tracking of estimation end. Simulation results confirm the effectiveness of the proposed approach.

ACKNOWLEDGEMENTS

The work is supported by the Russian Science Foundation grant (project 19-19-00403).

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