Parameter Estimator for Twin Rotor MIMO System based on DREM Procedure

Nikita Shopa[1][a], Dmitry Bazylev[1][b], Sergey Vrazhevsky[1,2][c] and Artem Kremlev[1][d]

[1] *Faculty of Control Systems and Robotics, ITMO University, St. Petersburg, Russia*

[2] *The Laboratory "Control of Complex Systems", Institute for Problems in Mechanical Engineering of the Russian Academy of Sciences (IPME RAS), St. Petersburg, Russia*

Keywords: Parameter Identification, Nonlinear Systems, Multi-channel Systems, Linear Regression.

Abstract: The paper deals with a problem of parameter identification for a model of Twin Rotor MIMO System laboratory bench, which is described by a nonlinear multi-channel system with cross-couplings. The chosen method is based on the Dynamic Regressor Extention and Mixing (DREM) procedure that guarantees monotonic convergence of the estimations even in case of multiple related parameters simultaneously identification. Results are verified by computer simulation.

1 INTRODUCTION

Parameter uncertainties is an anticipated problem in the practice area of control. Model-based control algorithms, including adaptive control techniques, require to improve estimation approaches. One of the modern approaches that ensure fast estimation convergence with high-quality transients is developed in (Aranovskiy et al., 2016). This paper (Aranovskiy et al., 2016) describes the so-called Dynamic Regressor Extention and Mixing (DREM) procedure which is synthesized in two steps. The first is an additional filtering data process that extends the standard linear regression model. In the second step, an extended regressor model is transformed in a way it became possible to apply standard estimation techniques independently for each unknown parameter. This new property ensures faster transients without overshooting, unlike the classical gradient method (Aranovskiy et al., 2016). Another important property of DREM is a possibility to avoid the persistency of excitation (PE) condition, which is one of the main restrictions for identification and adaptive control theories. Instead of PE condition, DREM procedure requires not square-integrable condition satisfaction.

Result (Aranovskiy et al., 2016) demonstrates high quality in wide area of practical and theoretical tasks. Besides the original idea of using linear stable dynamic operators to obtain an extended regressor, modifications have been proposed that construct extended regressor using time-delay operators (Bazylev et al., 2018a). DREM procedure was successfully applied in the task of multi-harmonic disturbances identification and to ensure the stability of quantized systems in (Dobriborsci et al., 2019a). In the research (Bobtsov et al., 2017), DREM approach is extended to the problem of position estimation as a state observer, which significantly improves an application area of the method. In practice, there are solutions of sensorless control algorithms applied to a motor control based on DREM in (Bazylev et al., 2018b).Some rubust properties against measurement noises were demonstrated in (Bobtsov et al., 2017) and (Bazylev et al., 2018b).

Current research deals with a problem of parameter identification of laboratory platform named Twin Rotor MIMO System (TRMS). The platform realises the dynamics of rotary-wing aircraft in two planes - pitch and yaw. It has complex nonlinear dynamics with cross-coupling and parametrical uncertainties which reduce the tracking accuracy of the closed-loop system. There are researches dealing with a problem of TRMS modelling including parameter identification task (see, for example, (Rahideh et al., 2008)), however, this researches keep identification problem apart from the control task. As soon as parametrical uncertainties can appear during the technical plant

[a] https://orcid.org/0000-0001-7518-6346
[b] https://orcid.org/0000-0003-4416-5731
[c] https://orcid.org/0000-0001-9725-5330
[d] https://orcid.org/0000-0002-7024-3126

Shopa, N., Bazylev, D., Vrazhevsky, S. and Kremlev, A.
Parameter Estimator for Twin Rotor MIMO System based on DREM Procedure.
DOI: 10.5220/0009875506890694
In *Proceedings of the 17th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2020)*, pages 689-694
ISBN: 978-989-758-442-8

functioning, current research proposes a more convenient way to deal with it. Another motivation of testing DREM approach on TRMS platform is to examine accuracy of identification in case of parallel identification of parameters of two separate subsystems of the same plant with cross reactions.

The article is organized as follows. Section 2 describes the mathematical model of TRMS. Section 3 considers DREM implementation for TRMS. Computer modelling results are shown and discussed in Section 4.

2 TWIN ROTOR MIMO SYSTEM MODEL

"Twin Rotor MIMO System" laboratory platform is a helicopter-like setup designed for testing various control approaches. The structure of TRMS is shown on fig.1.

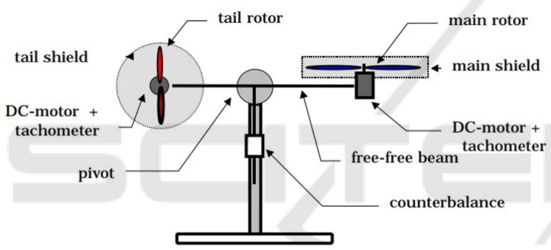

Figure 1: The structure of Twin Ritir MIMO System.

TRMS dynamics include nonlinearities, cross-reactions, and parametrical uncertainties. There are two known basic mathematical models of TRMS (Feedback Instruments, 1998), (Feedback Instruments, 2006). In the first paper, experimental approximations for nonlinear functions of electrical circuits and aerodynamic forces influence are proposed. This model also considers well-described mass and weight parameters information. The model in (Feedback Instruments, 2006) gives cross-couplings definitions and nonlinear aerodynamic forces function descriptions instead of approximations in (Feedback Instruments, 1998). Most of the papers dealing with TRMS are usually based on one of them. For example, in (Huang, 2011) authors use the first model to construct a new robust control scheme. In (Rahideh and Shaheed, 2009) a robust model predictive control algorithm is developed in accordance with the second model. In (Rahideh et al., 2008) an empirical modelling approach is compared with the model from (Feedback Instruments, 2006) and the high quality of the obtained models is shown. In this paper, the first TRMS model is used. The model there is not based on an experimental approximation which makes research of identification approaches more logical. It should be noted, that despite the differences between the descriptions in (Feedback Instruments, 1998) and (Feedback Instruments, 2006), both models are based on the same physical principles and correlate with each other well. We assume that the results given in the current research can be reproduced with respect to (Feedback Instruments, 2006) without significant changes.

The full dynamical model of TRMS is defined by

$$\begin{cases} J_1\ddot{\alpha} = M_1 - M_{B1} - M_{FG} - M_G, \\ J_2\ddot{\beta} = M_2 - M_{B2} - M_R, \end{cases} \tag{1}$$

where J_1 and J_2 are inertia moments; $M_1(\tau_1)$ and $M_2(\tau_2)$ are moments of control influence for both pitch (produced by the main motor) and yaw (tail motor) subsystems; $M_{B1}(\dot{\alpha})$, $M_{B2}(\dot{\beta})$ are friction forces moments; $M_{FG}(\alpha)$ is a gravity moment; $M_G(\tau,\alpha,\dot{\beta})$ and $M_R(\tau_1)$ are cross-reactions; $\tau_1(u_1)$ and $\tau_2(u_2)$ are torque moments of DC motors and u_1, u_2 are voltage levels on DC motor terminals. All functions are specified as follows:

$$\begin{aligned} M_1 &= a_1\tau_1^2 + b_1\tau_1, \\ M_2 &= a_2\tau_2^2 + b_2\tau_2, \\ M_{B1} &= B_1\dot{\alpha}, \\ M_{B2} &= B_2\dot{\beta}, \\ M_{FG} &= M_g\sin(\alpha), \\ M_G &= K_g M_1\dot{\beta}\cos(\alpha), \\ M_R &= \frac{k_c(T_0 s + 1)}{T_p s + 1}\tau_1, \\ \tau_1 &= \frac{k_1}{T_{11}s + T_{20}}u_1, \\ \tau_2 &= \frac{k_1}{T_{21}s + T_{20}}u_2. \end{aligned}$$

The first equation of (1) describes the plant dynamic in the vertical plane and the second equation of (1) does the same for the horizontal plane. It should be noted that the TRMS platform realizes output control only and signals $\dot{\alpha}$ and $\dot{\beta}$ are unknown which is important for identification approaches as well. Numerical values of plant parameters are in accordance with documentation (Feedback Instruments, 2006) and shown in Table 1. However, while there are parameters that are determined with high accuracy, there also exist parameters needed to be clarified. Friction force moment coefficients B_1 and B_2 belong to a set of uncertain parameters. This is caused by the fact that friction forces momentum coefficients can be changed by tuning mechanical parts of TRMS platform and changed during functioning. From another side, gravity moment parameters, as well as control functions parameters, are known, because mass, weight and electrical parameters of TRMS can be measured and evaluated accurately.

Table 1: Twin Rotor MIMO System Parameters.

Parameter	Value
J_1	0.068 $[kg \cdot m^2]$
J_2	0.02 $[kg \cdot m^2]$
B_1	0.006 $[H \cdot m \cdot s/rad]$
B_2	0.1 $[H \cdot m \cdot s/rad]$
a_1	0.0135 $[n/a]$
b_1	0.0924 $[n/a]$
a_2	0.02 $[n/a]$
b_2	0.09 $[n/a]$
M_g	0.32 $[H \cdot m]$
K_g	0.05 $[s/rad]$
k_1	1.1 $[n/a]$
k_2	0.8 $[n/a]$
T_{11}	1.1 $[n/a]$
T_{10}	1 $[n/a]$
T_{21}	1 $[n/a]$
T_{20}	1 $[n/a]$

3 PROBLEM STATEMENT

The task is to identify unknown parameters of a nonlinear MIMO plant and to ensure an asymptotic convergence of identification errors to zero. Define a goal

$$\begin{aligned} \lim_{t\to\infty} \|\tilde{q_p}\| = 0, \\ \lim_{t\to\infty} \|\tilde{q_y}\| = 0, \end{aligned} \tag{2}$$

where $\tilde{q}_p = \hat{q}_p - q_p$, $\tilde{q}_y = \hat{q}_y - q_y$ are identification errors, $q_p = [J_1; B_1]^T$ and $q_y = [J_2; B_2]^T$ are vectors of unknown parameters of the plant (1), $\hat{q}_p = [\hat{J_1}; \hat{B_1}]^T$ and $\hat{q}_y = [\hat{J_2}; \hat{B_2}]^T$ are estimates of q_p and q_y respectively.

In the current research, we define the following set of TRMS parameters which need to be estimated: B_1, B_2, J_1, J_2. The motivation of choosing the parameters is explained by the idea that friction forces coefficients need to be estimated to improve the accuracy of model-based control algorithms while inertia moments values are known and can be used to determine the accuracy of the identification method itself.

4 PARAMETER IDENTIFICATION METHOD

Rewrite equation (1) in a convenient form

$$\begin{cases} M_1 - M_{FG} - M_G = J_1\ddot{\alpha} + M_{B1}, \\ M_2 - M_R = J_2\ddot{\beta} + M_{B2}. \end{cases} \tag{3}$$

Since signals $\dot{\alpha}$, $\ddot{\alpha}$, $\dot{\beta}$, $\ddot{\beta}$ can't be measured, it is possible to apply a stable linear filter $F(s) = \frac{a}{(s+a)^2}$ with the parameter $a > 0$ to the model (3), which makes possible to reproduce unknown signals and construct a standard linear regression model. Otherwise, DREM technique could be applied immediately. Applying $F(s)$, we get

$$\begin{cases} \frac{a}{(s+a)^2}[M_1 - M_{FG} - M_G] = J_1 \frac{as^2}{(s+a)^2}[\alpha] + B_1 \frac{as}{(s+a)^2}[\alpha], \\ \frac{a}{(s+a)^2}[M_2 - M_R] = J_2 \frac{as^2}{(s+a)^2}[\beta] + B_2 \frac{as}{(s+a)^2}[\beta]. \end{cases}$$

Substitute moments descriptions and introduce new variables for (3)

$$g_p = \frac{a}{(s+a)^2}[a_1\tau_1^2 + b_1\tau_1 - M_g\sin(\alpha) - pK_gM_1\beta\cos(\alpha)]$$

$$g_y = \frac{a}{(s+a)^2}[a_2\tau_2^2 + b_2\tau_2 - \frac{k_c(T_0s+1)}{T_ps+1}\tau_1],$$

$$m_p = [\frac{as^2}{(s+a)^2}[\alpha]; \frac{as}{(s+a)^2}[\alpha]]^T,$$

$$m_y = [\frac{as^2}{(s+a)^2}[\beta]; \frac{as}{(s+a)^2}[\beta]]^T,$$

where functions m_p, m_y, g_p and g_y are the measurable. In accordance to the goal (2), vectors of unknown parameters are defined by $q_p = [J_1; B_1]^T$ and $q_y = [J_2; B_2]^T$ and, following the replacement before, we get the standard linear regression models

$$\begin{aligned} g_p = m_p^T q_p, \\ g_y = m_y^T q_y. \end{aligned} \tag{4}$$

At the current step of the model analysis, the DREM procedure can be applied in two steps.

4.1 Step 1

Applying a new filter satisfies the Hurwitz condition and defined by $H(s) = \frac{b}{(s+b)^2}$ with the parameter $b > 0$ to the regression model (4), we get a second set of linear regression models in the following form

$$\begin{aligned} \bar{g}_p = \bar{m}_p^T q_p, \\ \bar{g}_y = \bar{m}_y^T q_y, \end{aligned} \tag{5}$$

where $\bar{g}_p = H(s)g_p$, $\bar{g}_y = H(s)g_y$, $\bar{m}_p = H(s)m_p$, $\bar{m}_y = H(s)m_y$.

4.2 Step 2

Construct an extended linear regression model in the form

$$\begin{aligned} G_p &= M_p q_p, \\ G_y &= M_y q_y, \end{aligned} \tag{6}$$

where

$$G_p = \begin{bmatrix} g_p \\ \bar{g}_p \end{bmatrix}, M_p = \begin{bmatrix} m_{p1} & m_{p2} \\ \bar{m}_{p1} & \bar{m}_{p2} \end{bmatrix},$$
$$G_y = \begin{bmatrix} g_y \\ \bar{g}_y \end{bmatrix}, M_y = \begin{bmatrix} m_{y1} & m_{y2} \\ \bar{m}_{y1} & \bar{m}_{y2} \end{bmatrix}.$$

Multiplying (6) by adjoint matrices

$$adj\{M_p\} = \begin{bmatrix} \bar{m}_{p2} & -m_{p2} \\ -\bar{m}_{p1} & m_{p1} \end{bmatrix},$$
$$adj\{M_y\} = \begin{bmatrix} \bar{m}_{y2} & -m_{y2} \\ -\bar{m}_{y1} & m_{y1} \end{bmatrix},$$

model (6) takes the representation

$$adj\{M_p\} \begin{bmatrix} g_p \\ \bar{g}_p \end{bmatrix} = adj\{M_p\} \begin{bmatrix} m_{p1} & m_{p2} \\ \bar{m}_{p1} & \bar{m}_{p2} \end{bmatrix} \begin{bmatrix} J_1 \\ B_1 \end{bmatrix},$$
$$adj\{M_y\} \begin{bmatrix} g_y \\ \bar{g}_y \end{bmatrix} = adj\{M_y\} \begin{bmatrix} m_{y1} & m_{y2} \\ \bar{m}_{y1} & \bar{m}_{y2} \end{bmatrix} \begin{bmatrix} J_2 \\ B_2 \end{bmatrix}.$$

After the following calculations

$$adj\{M_p\}G_p = \begin{bmatrix} \bar{m}_{p2}g_p - m_{p2}\bar{g}_p \\ m_{p1}\bar{g}_p - \bar{m}_{p1}g_p \end{bmatrix},$$
$$adj\{M_p\}M_p = \begin{bmatrix} \bar{m}_{p2}m_{p1} - m_{p2}\bar{m}_{p1} & 0 \\ 0 & \bar{m}_{p2}m_{p1} - m_{p2}\bar{m}_{p1} \end{bmatrix},$$
$$adj\{M_y\}G_y = \begin{bmatrix} \bar{m}_{y2}g_y - m_{y2}\bar{g}_y \\ m_{y1}\bar{g}_y - \bar{m}_{y1}g_y \end{bmatrix},$$
$$adj\{M_y\}M_y = \begin{bmatrix} \bar{m}_{y2}m_{y1} - m_{y2}\bar{m}_{y1} & 0 \\ 0 & \bar{m}_{y2}m_{y1} - m_{y2}\bar{m}_{y1} \end{bmatrix},$$

we get a set of separate independent regression models for each unknown parameter in both subsystems defined by

$$\begin{cases} \bar{m}_{p2}g_p - m_{p2}\bar{g}_p = (\bar{m}_{p2}m_{p1} - m_{p2}\bar{m}_{p1})J_1, \\ m_{p1}\bar{g}_p - \bar{m}_{p1}g_p = (\bar{m}_{p2}m_{p1} - m_{p2}\bar{m}_{p1})B_1, \\ \bar{m}_{y2}g_y - m_{y2}\bar{g}_y = (\bar{m}_{y2}m_{y1} - m_{y2}\bar{m}_{y1})J_2, \\ m_{y1}\bar{g}_y - \bar{m}_{y1}g_y = (\bar{m}_{y2}m_{y1} - m_{y2}\bar{m}_{y1})B_2. \end{cases} \tag{7}$$

The model (7) considers separate regression models for both TRMS subsystems with independent representation for each unknown parameter. A standard gradient method for a problem of multiple parameter estimation does not allow obtaining independent regression equations for each unknown parameter. That new property of DREM increases estimates convergence speed and transient accuracy (Aranovskiy et al., 2016). Rewrite

$$\begin{aligned} \varepsilon_{p1} &= \bar{m}_{p2}g_p - m_{p2}\bar{g}_p, \\ \varepsilon_{p2} &= m_{p1}\bar{g}_p - \bar{m}_{p1}g_p, \\ \varepsilon_{y1} &= \bar{m}_{y2}g_y - m_{y2}\bar{g}_y, \\ \varepsilon_{y2} &= m_{y1}\bar{g}_y - \bar{m}_{y1}g_y, \\ \varphi_p &= \bar{m}_{p2}m_{p1} - m_{p2}\bar{m}_{p1}, \\ \varphi_y &= \bar{m}_{y2}m_{y1} - m_{y2}\bar{m}_{y1}, \end{aligned}$$

and transform (7) in the set of scalar regressions

$$\begin{cases} \varepsilon_{p1} = \varphi_p q_{p1}, \\ \varepsilon_{p2} = \varphi_p q_{p2}, \\ \varepsilon_{y1} = \varphi_y q_{y1}, \\ \varepsilon_{y2} = \varphi_y q_{y2}, \end{cases}$$

where $q_{p1} = J_1$, $q_{p2} = B_1$, $q_{y1} = J_2$, $q_{y2} = B_2$ are unknown parameters which need to be determined. Introduce scalar gradient estimators as follows

$$\begin{cases} \dot{\hat{q}}_{p1} = \gamma_{p1}(\varepsilon_{p1}\varphi_p - \varphi_p^2\hat{q}_{p1}), \\ \dot{\hat{q}}_{p2} = \gamma_{p2}(\varepsilon_{p2}\varphi_p - \varphi_p^2\hat{q}_{p2}), \\ \dot{\hat{q}}_{y1} = \gamma_{y1}(\varepsilon_{y1}\varphi_y - \varphi_y^2\hat{q}_{y1}), \\ \dot{\hat{q}}_{y2} = \gamma_{y2}(\varepsilon_{y2}\varphi_y - \varphi_y^2\hat{q}_{y2}), \end{cases} \tag{8}$$

where $\gamma_{p1} > 0$, $\gamma_{p2} > 0$, $\gamma_{y1} > 0$, $\gamma_{y2} > 0$ are adaptation coefficients.

A convergence of estimates in (8) is ensured by the proof of the following proposition (in accordance with (Aranovskiy et al., 2016)).

Proposition 1. Consider the parametrized TRMS model (7). There exist parameters $\gamma_{p1} > 0$, $\gamma_{p2} > 0$, $\gamma_{y1} > 0$, $\gamma_{y2} > 0$ such that the adaptation law (8) satisfies the goal (2) and provides an exponential convergence of signals $\tilde{q}_p = \hat{q}_p - q_p$, $\tilde{q}_y = \hat{q}_y - q_y$ to 0 if the functions $\varphi_p(t)$, $\varphi_y(t)$ are persistently excited, $\varphi_p(t), \varphi_y(t) \in$ PE. If $\varphi_p(t)$, $\varphi_y(t)$ are not square integrable, $\varphi_p(t), \varphi_y(t) \notin \mathcal{L}_2$, then $\tilde{q}_p = \hat{q}_p - q_p$, $\tilde{q}_y = \hat{q}_y - q_y$ tend to 0 asymptotically.

Proof. Derivatives of $\tilde{q}_p$, $\tilde{q}_y$ in scalar form take a representation

$$\begin{aligned} \dot{\tilde{q}}_{p1} &= -\gamma_{p1}\varphi_p^2\tilde{q}_{p1}, \\ \dot{\tilde{q}}_{p2} &= -\gamma_{p2}\varphi_p^2\tilde{q}_{p2}, \\ \dot{\tilde{q}}_{y1} &= -\gamma_{y1}\varphi_y^2\tilde{q}_{y1}, \\ \dot{\tilde{q}}_{y2} &= -\gamma_{y2}\varphi_y^2\tilde{q}_{y2}. \end{aligned}$$

Solving equations above we immediately see that

$$\begin{cases} \tilde{q}_{p1} = e^{-\gamma_{p1}\int_0^t \varphi_p^2(s)ds}\tilde{q}_{p1}(0), \\ \tilde{q}_{p2} = e^{-\gamma_{p2}\int_0^t \varphi_p^2(s)ds}\tilde{q}_{p2}(0), \\ \tilde{q}_{y1} = e^{-\gamma_{y1}\int_0^t \varphi_y^2(s)ds}\tilde{q}_{y1}(0), \\ \tilde{q}_{y2} = e^{-\gamma_{y2}\int_0^t \varphi_y^2(s)ds}\tilde{q}_{y2}(0), \end{cases}$$

which completes the proof. ■

5 SIMULATION RESULTS

Computer simulation consists of two parts. First, the plant model is tested by generating input signals which ensure a diverse informative output of (1). Such behavior is reached by constructing a control system which consists of the plant (1) and a PID controller described by

$$u_1 = 5e_\alpha + 10\dot{e}_\alpha + 8\int_0^t e_\alpha(s)ds,$$
$$u_2 = 2e_\beta + 5\dot{e}_\beta + 0.5\int_0^t e_\beta(s)ds, \quad (9)$$

that provides tracking stability against following reference signals

$$\alpha_{ref} = 0.5\,\mathrm{sgn}(\sin(\pi t)), \beta_{ref} = 0.3\,\mathrm{sgn}(\sin(\pi t)).$$

PID controller parameters are chosen equal to the values presented in the official documentation of TRMS (Feedback Instruments, 2006). Reference signals are chosen to ensure the sustained excitation condition. Output and input signals are shown in fig. 2-3. Figures 4-5 show the results of the estimation of inertia moments (Fig. 4) and friction forces coefficients (Fig.5) with various parameter γ values which determines a convergence rate. The following parameters of gradient estimators and filters are chosen:

$$F(s) = \frac{10}{(s+10)^2}, H(s) = \frac{100}{(s+100)^2},$$
$$\gamma_{p1} = \gamma_{p2} = \gamma_{y1} = \gamma_{y2} = \{10; 100\}. \quad (10)$$

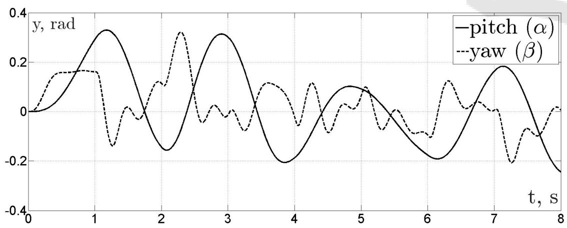

Figure 2: Output signals used for the identification.

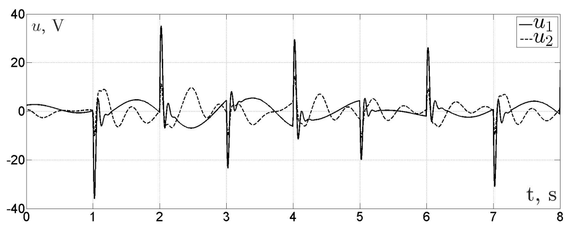

Figure 3: Input signals used for the identification.

In practice, a closed-loop system in tracking mode usually provides less variability of input and output signals reasoned by physical constraints on signal

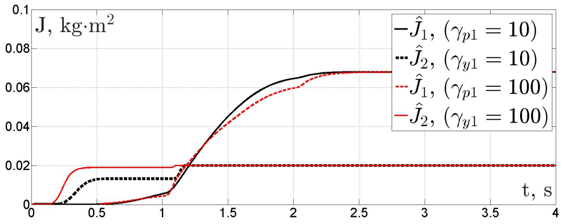

Figure 4: Inertia moments estimation results.

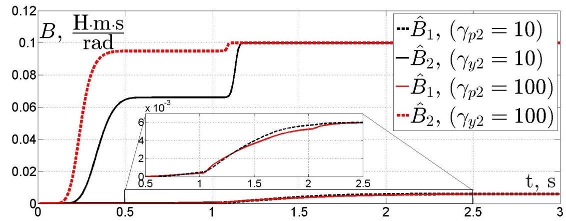

Figure 5: Friction forces estimation results.

magnitudes and specific control requirements. Following practical relevance, DREM is tested on control system which consists of the plant (1) and a PID controller (9) with the following reference signals

$$\alpha_{ref} = 0.5\sin(0.5t), \beta_{ref} = 0.2\sin(0.3t).$$

Output and input signals are shown in fig. 6-7. Fig. 8 shows the results of the estimation of inertia moments and friction forces coefficients with the following parameters of gradient estimators and filters:

$$F(s) = \frac{10}{(s+10)^2}, H(s) = \frac{100}{(s+100)^2},$$
$$\gamma_{p1} = \gamma_{p2} = \gamma_{y1} = \gamma_{y2} = 1000.$$

The graphics show that estimation rate and convergance can be ensured in case of relatively low measured signal magnitudes by increasing adaptation parameter γ.

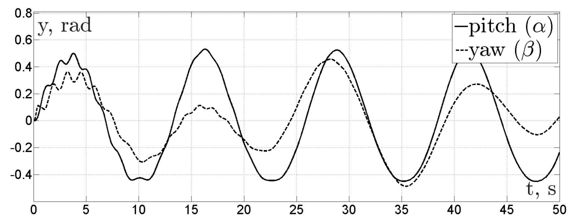

Figure 6: Output signals used for the identification in the closed-loop system.

Fig. 9 demonstrates the dependence of the DREM convergence rate on the adaptation coefficient value under conditions of the first computer simulation. Comparing with analogues, such as the least-square technique, DREM identification system guarantee monotonic convergence of estimates and can be tuned to provide faster transients.

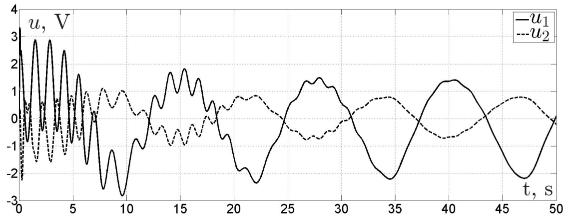

Figure 7: Intput signals used for the identification in the closed-loop system.

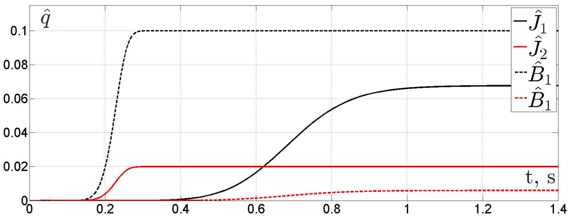

Figure 8: Unknown parameters estimation results in the closed-loop system.

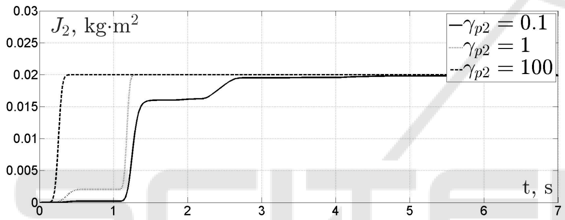

Figure 9: Estimation results under different adaptation coefficients.

6 CONCLUSION

The paper resolves a parameter identification problem for a Twin Rotor MIMO System laboratory platform. The DREM procedure is used for constructing an identification algorithm and results are verified by computer simulation. Unlike the analogues such as classical gradient method, least squares method or modern identification approaches such as (Dobriborsci et al., 2019b), The DREM procedure ensures monotonic convergence even in case of multiple related parameters simultaneously identification. Graphics demonstrate the high accuracy of identification and fast transients that can be improved by tuning adaptation coefficients. Futher research will analyse the DREM performance and applicability in the task of parameter estimation of discrete systems.

ACKNOWLEDGEMENTS

This work was financially supported by Government of Russian Federation (Grant 08-08). This work was supported by the Ministry of Science and Higher Education of Russian Federation, goszadanie no. 2019-0898.

REFERENCES

Aranovskiy, S., Bobtsov, A., Ortega, R., and Pyrkin, A. (2016). Performance enhancement of parameter estimators via dynamic regressor extension and mixing. volume 62, pages 3546–3550. IEEE.

Bazylev, D., Pyrkin, A., and Bobtsov, A. (2018a). Position and speed observer for PMSM with unknown stator resistance. In *2018 European Control Conference (ECC)*, pages 1613–1618. IEEE.

Bazylev, D., Vukosavic, S., Bobtsov, A., Pyrkin, A., Stankovic, A., and Ortega, R. (2018b). Sensorless control of PM synchronous motors with a robust nonlinear observer. In *2018 IEEE Industrial Cyber-Physical Systems (ICPS)*, pages 304–309. IEEE.

Bobtsov, A., Bazylev, D., Pyrkin, A., Aranovskiy, S., and Ortega, R. (2017). A robust nonlinear position observer for synchronous motors with relaxed excitation conditions. *International Journal of Control*, 90(4):813–824.

Dobriborsci, D., Kolyubin, S., Karashaeva, F., and Bobtsov, A. (2019a). Output adaptive switching controller design with DREM-based multi-harmonic disturbance cancellation. volume 52, pages 263–268. Elsevier.

Dobriborsci, D., Margun, A., and Kolyubin, S. (2019b). Tracking controller with harmonic disturbance cancellation. In *2019 18th European Control Conference (ECC)*, pages 1110–1115. IEEE.

Feedback Instruments, L. (1998). System advanced teaching manual 1 (33-007-4m5). *Feedback Instruments Ltd, Crowborough, UK.*

Feedback Instruments, L. (2006). Twin rotor MIMO system control experiments 33-949s. *Feedback Instruments Ltd, Crowborough, UK.*

Huang, L. (2011). An approach for robust control of a twin-rotor multiple input multiple output system. In *2011 IEEE International Conference on Robotics and Automation*, pages 4423–4428. IEEE.

Rahideh, A., Shaheed, M., and Huijberts, H. (2008). Dynamic modelling of a TRMS using analytical and empirical approaches. *Control Engineering Practice*, 16(3):241–259.

Rahideh, A. and Shaheed, M. H. (2009). Robust model predictive control of a twin rotor MIMO system. In *2009 IEEE International Conference on Mechatronics*, pages 1–6. IEEE.