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Extended Kalman filters in the control structure of two-mass drive system

K. SZABAT, T. ORLOWSKA-KOWALSKA*, and K.P. DYRCZ

Electrical Engineering Faculty, Wroclaw University of Technology, 13 Grunwaldzki Square, 50-377 Wrocław, Poland

Abstract. The paper deals with the application of the extended Kalman filters in the control structure of a two-mass drive system. In the first step only linear extended Kalman filter was used for the estimation of mechanical state variables of the drive including load torque value. The estimation algorithm showed good robustness to mechanical parameters variations. For the system with some parameters changing in the wide range, simultaneous estimation of the state variables and chosen system parameters is required. For this reason the non-linear extended Kalman filter, which estimates simultaneously state variables and mechanical parameters of the two-mass drive system, was developed. Parameters of covariance matrices of used Kalman filters were set using the genetic algorithm. Both proposed estimators were investigated in simulation and experimental tests, in the open-loop operation and in the state-feedback control system of the two-mass system.

Key words: Kalman filtering, two-mass system, torsional vibration, electrical drives.

1. Introduction

In some industrial applications like the rolling mill drives, the mechanical part of the system has very low resonant frequency, because of a long shaft between the motor and the load machine. So, especially in the drive systems with high performance speed and torque regulation, the motor speed is different from the load speed during transients. The speed difference results in the coupling shaft stresses, which influences this mechanical coupling in a negative way. Additionally, speed oscillations cause decrease in the quality of the rolling material and can influence the stability of the control system [1–4]. Some methods of solving this problem are reported in technical papers. The most advanced techniques, ensuring very good performance of the system, are based on special control structures with additional feedbacks from such state variables as torsional torque, load speed and/or disturbance torque. But the direct feedbacks from these signals are very often impossible, because additional measurements of these mechanical variables are difficult, cost effective and reduce the system reliability. Thus special systems for estimation of these variables are necessary, as state observers or state filters [5–8].

In the industrial plants parameters of the system can also change. The parameter which can change in the wide range in the drive systems is the load side inertia. To ensure desired characteristics of the drive system there is a need to estimate the changeable parameters and to retune the control structure parameters.

2. The mathematical model of the drive

In the paper the commonly-used model of the drive system with the resilient coupling is considered. The system is described by the following state equation (in per unit system), with nonlinear friction neglected:

$$\frac{d}{dt}\begin{bmatrix}\omega_1(t)\\ \omega_2(t)\\ \Gamma_s(t)\end{bmatrix} = \begin{bmatrix}0 & 0 & -\frac{1}{T_1}\\ 0 & 0 & \frac{1}{T_2}\\ \frac{1}{T_c} & -\frac{1}{T_c} & 0\end{bmatrix}\begin{bmatrix}\omega_1(t)\\ \omega_2(t)\\ \Gamma_s(t)\end{bmatrix} + \begin{bmatrix}\frac{1}{T_1}\\ 0\\ 0\end{bmatrix}[\Gamma_e] + \begin{bmatrix}0\\ -\frac{1}{T_2}\\ 0\end{bmatrix}[\Gamma_L] \tag{1}$$

where: ω_1 – motor speed, ω_2 – load speed, Γ_e – motor torque, Γ_s – shaft (torsional) torque, Γ_L – disturbance torque, T_1 – mechanical time constant of the motor, T_2 – mechanical time constant of the load machine, T_c – stiffness time constant. Parameters of the analysed system are following: $T_1 = 203$ ms, $T_2 = 203$ ms, $T_c = 2.6$ ms.

The electromagnetic torque of the motor is used as a control input of the system and the angular speed of the motor is taken as the output value. Hence, results of this research can be applied to any kind of the electrical motor with high performance electromagnetic torque control.

3. Utilized control structure

The considered speed control of the drive system has the most widely used cascade structure, with additional feedbacks from the shaft torque and load side speed, shown in Fig. 1.

The classical cascade control structure consists of two major control loops: the inner control loop encloses the current controller, the power converter and the electromagnetic part of the motor. It is designed to provide sufficiently fast torque regulation and very often is approximated by a first order filter. The PI current controller is usually adjusted according to the well known modulus criterion. The outer control loop includes: the mechanical part of the drive, the speed sensor and

*e-mail: teresa.orlowska-kowalska@pwr.wroc.pl

the PI controller typically adjusted according to the symmetry criterion or poles placement method [2].

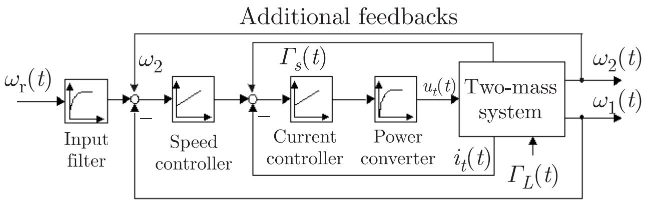


Fig. 1. The PI control structure with additional feedbacks

The classical structure works well only for some inertia ratio (T_2/T_1) of the two-mass system. In the case of low mechanical time constant of the load machine, transients of the system are not proper. To improve the dynamical characteristics of the drive, the modification of the cascade structure is necessary. It is obtained by insertion of additional feedbacks from selected state variables to the control structure [2,3]. In this paper the following feedback state variables were chosen: the shaft torque and the difference between the motor and the load speed, as in Fig. 1. The parameters of the control structures were set using the following equations:

$$K_I = \omega_0^4 T_1 T_2 T_c \tag{2}$$

$$K_P = 4\xi_r \omega_0^3 T_1 T_2 T_c \tag{3}$$

$$k_2 = \left(\omega_0^2 T_2 T_c\right)^{-1} - 1 \tag{4}$$

$$k_1 = T_1 T_2^{-1}\left(4\xi_r^2 - k_2\right)(1 + k_2)^{-1} - 1 \tag{5}$$

where: ω_0 – the required resonant frequency of the system, ξ_r – the required value of the damping coefficient, k_1, k_2 – feedback coefficients, K_I, K_P – the integral and the proportional parts of the PI controller with the following transfer function:

$$G_r = K_p + K_I/s. \tag{6}$$

In the industrial applications the direct measurements of the shaft torque and load speed are very difficult. For that reason, in this paper, the Kalman filter is used to provide the information about non-measurable state variables. Additionally, in the case of nonlinear Kalman filter also the time constant of the load side is estimated and used to on-line retuning the control structure parameters according to Eqs. (2)–(5).

4. The mathematical model of the Kalman filter

4.1. Mathematical model of the linear extended Kalman filter. According to the theory of Kalman filtering, it was assumed that a system is disturbed with Gaussian white noise, which represents process and measurement errors $(w(t),\ v(t))$ The system is thus described by Eq. (7):

$$\begin{aligned}\dot{\mathbf{x}}(t) &= \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{w}(t)\\ \mathbf{y}(t) &= \mathbf{C}\mathbf{x}(t) + \mathbf{v}(t)\end{aligned} \tag{7}$$

After discretization of Eq. (7) with T_s sampling step, the state estimation using Kalman filter algorithm is calculated:

$$\begin{aligned}\hat{\mathbf{x}}(k+1/k+1) &= \hat{\mathbf{x}}(k+1/k) + \mathbf{K}(k+1)\\ &\times\left[\mathbf{y}(k+1) - \mathbf{C}(k+1)\hat{\mathbf{x}}(k+1/k)\right]\end{aligned} \tag{8}$$

where the gain matrix is obtained by the following numerical procedure:

$$\mathbf{P}(k+1/k) = \mathbf{A}(k)\mathbf{P}(k/k)\mathbf{A}(k)^T + \mathbf{Q} \tag{9a}$$

$$\begin{aligned}\mathbf{K}(k+1) &= \mathbf{P}(k+1/k)\mathbf{C}(k+1)^T\\ &\times\left[\mathbf{C}(k+1)\mathbf{P}(k+1/k)\mathbf{C}(k+1)^T + \mathbf{R}\right]^{-1}\end{aligned} \tag{9b}$$

$$\begin{aligned}\mathbf{P}(k+1/k+1) &= \left[\mathbf{I} - \mathbf{K}(k+1)\mathbf{C}(k+1)\right]\\ &\times\mathbf{P}(k+1/k)\end{aligned} \tag{9c}$$

with state and measurement covariance matrices $\mathbf{Q}$ and $\mathbf{R}$.

In the case of the drive system with elastic joint, the state vector of the drive system (1) was extended by the load torque value, to obtain the estimation of all mechanical state variables of the system:

$$\mathbf{x} = [\omega_1\ \omega_2\ \Gamma_s\ \Gamma_L]^T. \tag{10}$$

The motor electromagnetic torque and speed were used as input and output variables, respectively

$$\mathbf{u} = \Gamma_e, \quad \mathbf{y} = \omega_1. \tag{11}$$

Thus the state, control and output matrices of this Linear Extended Kalman Filter (LEKF) are following:

$$\mathbf{A} = \begin{bmatrix} 0 & 0 & -\frac{1}{T_1} & 0\\ 0 & 0 & \frac{1}{T_2} & -\frac{1}{T_2}\\ \frac{1}{T_c} & -\frac{1}{T_c} & 0 & 0\\ 0 & 0 & 0 & 0\end{bmatrix},\ \mathbf{B} = \begin{bmatrix}\frac{1}{T_1}\\ 0\\ 0\\ 0\end{bmatrix},\ \mathbf{C} = \begin{bmatrix}1\\ 0\\ 0\\ 0\end{bmatrix}^T. \tag{12}$$

The covariance matrices $\mathbf{Q}$ and $\mathbf{R}$ were determined using the genetic algorithm (GA) with the following cost function:

$$F = \min\prod_{i=1}^{3} F_i\left(e_{\Gamma_s}, e_{\omega_2}, e_{\Gamma_L}\right), \tag{13}$$

where:

$$F_{1\ for\ T_2=T_{2n}} = \left\{\sum_1^n\left(|\Gamma_s - \Gamma_{se}|\right) * \sum_1^n\left(|\omega_2 - \omega_{2e}|\right) * \sum_1^n\left(|\Gamma_L - \Gamma_{Le}|\right)\right\}, \tag{14}$$

$$F_{2\ for\ T_2=0.5T_{2n}} = \left\{\sum_1^n\left(|\Gamma_s - \Gamma_{se}|\right) * \sum_1^n\left(|\omega_2 - \omega_{2e}|\right) * \sum_1^n\left(|\Gamma_L - \Gamma_{Le}|\right)\right\}, \tag{15}$$

$$F_3\ for\ T_2 = 2T_{2n} = \left\{\sum_1^n\left(|\Gamma_s - \Gamma_{se}|\right) * \sum_1^n\left(|\omega_2 - \omega_{2e}|\right) * \sum_1^n\left(|\Gamma_L - \Gamma_{Le}|\right)\right\}. \tag{16}$$

So the main attention was focused in the best estimation of all variables for different values of the mechanical time constant of the load machine.

4.2. Mathematical model of the nonlinear extended Kalman filter. In the presence of the time-varying load machine inertia, there is a need to extend the state vector (10) with the additional element $1/T_2$:

$$\mathbf{x}_R(t) = \left[\omega_1(t)\ \omega_2(t)\ \Gamma_s(t)\ \Gamma_L(t)\ \frac{1}{T_2}(t)\right]^T. \tag{17}$$

where T_2 denotes the time constant of the load side inertia. The extended state equation can be rewritten in the following form:

$$\dot{\mathbf{x}}_R(t) = \mathbf{A}_R\left(\frac{1}{T_2}(t)\right)\mathbf{x}_R(t) + \mathbf{B}_R\mathbf{u}(t) + \mathbf{w}(t) = f_R(\mathbf{x}_R(t), \mathbf{u}(t)) + \mathbf{w}(t) \tag{18a}$$

$$\mathbf{y}_R(t) = \mathbf{C}_R\mathbf{x}_R(t) + \mathbf{v}(t) \tag{18b}$$

where the matrices of the system are defined as follows:

$$\mathbf{A}_R\left(\frac{1}{T_2}(t)\right) = \begin{bmatrix} 0 & 0 & -\frac{1}{T_1} & 0 & 0 \\ 0 & 0 & \frac{1}{T_2}(t) & -\frac{1}{T_2}(t) & 0 \\ \frac{1}{T_c} & -\frac{1}{T_c} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix},$$

$$\mathbf{B}_R = \begin{bmatrix} \frac{1}{T_1} \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \ \mathbf{C}_R = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}^T. \tag{19}$$

The matrix $\mathbf{A_R}$ depends on the changeable parameter T_2. It means that in every calculation step this matrix must be updated due to the estimated value of T_2. As in the case of the LEKF, the input and the output vectors of the nonlinear estimator are as in Eq. (11).

After the discretization of Eq. (18) with T_s sampling step, the state estimation using Kalman filter algorithm is calculated:

$$\hat{\mathbf{x}}_R(k+1/k+1) = \hat{\mathbf{x}}_R(k+1/k) + \mathbf{K}(k+1) \times [\mathbf{y}_R(k+1) - \mathbf{C}_R(k+1)\hat{\mathbf{x}}_R(k+1/k)] \tag{20}$$

where the gain matrix $\mathbf{K}$ is obtained by the suitable numerical procedure. In the first step the predictor of the state vector is calculated:

$$\mathbf{P}(k+1/k) = \mathbf{F}_R(k)\mathbf{P}(k)\mathbf{F}_R(k)^T + \mathbf{Q} \tag{21}$$

where:

$$\mathbf{F}_R(k) = \left.\frac{\mathbf{f}_R(\mathbf{x}_R(k/k), \mathbf{u}(k), k)}{\partial \mathbf{x}_R(k/k)}\right|_{\mathbf{x}_R = \hat{\mathbf{x}}_R(k/k)}. \tag{22}$$

$\mathbf{F_R}$ is the state matrix of the system (18) after its linearization in the actual operation point, which must be updated in every calculation step:

$$\mathbf{F}_R = \begin{bmatrix} 1 & 0 & -\frac{1}{T_1}T_P & 0 & 0 \\ 0 & 1 & \frac{1}{T_2}(k)T_s & -\frac{1}{T_2}(k)T_s & T_s(\Gamma_s - \Gamma_L) \\ \frac{1}{T_c}T_s & -\frac{1}{T_c}T_s & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}. \tag{23}$$

The gain matrix of the Nonlinear Extended Kalman Filter (NEKF) and the covariance matrix of the state estimation error are calculated using the following equations:

$$\mathbf{K}(k+1) = \mathbf{P}(k+1/k)\mathbf{C}_R^T(k+1) \times \left[\mathbf{C}_R(k+1)\mathbf{P}(k+1/k)\mathbf{C}_R^T(k+1) + \mathbf{R}\right]^{-1} \tag{24}$$

$$\mathbf{P}(k+1/k+1) = [\mathbf{I} - \mathbf{K}(k+1)\ \mathbf{C}_R(k+1)]\ \mathbf{P}(k+1/k). \tag{25}$$

The covariance matrices $\mathbf{Q}$ and $\mathbf{R}$ were set using the genetic algorithm with the following cost function:

$$F = \min\left\{\left(\sum_1^n|\Gamma_s - \Gamma_{se}|\right) * \left(\sum_1^n|\omega_2 - \omega_{2e}|\right) * \left(\sum_1^n|\Gamma_L - \Gamma_{Le}|\right) * \left(\sum_1^n|T_2 - T_{2e}|\right)\right\}. \tag{26}$$

The cost function defined in this way ensures the optimal setting of covariance matrices $\mathbf{Q}$ and $\mathbf{R}$ for changeable time constant of the load machine.

5. Simulation results

5.1. The linear extended Kalman filter case. In simulation tests the estimation quality of all system state variables was investigated. The shaft torque and the load speed were taken for the closed-loop structure with the direct feedback from system state variables (Fig. 1). The electromagnetic torque and the motor speed, used as the input and output vectors of LEKF were disturbed with white noises, what is visible in Fig. 2.

The estimated components of the state vector (10) are presented in Fig. 3 and compared with the real drive variables. The biggest estimation errors exist in all states when the load torque is changed. The speed-up of the estimation errors decreasing can be obtained by increasing the values of the covariance matrix $\mathbf{Q}$. However, it increases the noise level of the estimation variables in the steady-state condition.

Next the linear Kalman filter was tested in the closed-loop control structure. The additional feedbacks from the shaft torque and load speed were provided by LEKF algorithm. The control structure parameters were set using Eqs. (2)–(5). In Fig. 4 the transients of the closed-loop system are presented. In Fig. 4a the small overshoot visible in the speed transients results from the assumed parameters of the control structure: resonant frequency $\omega_0 = 30\ \mathrm{s}^{-1}$ and damping factor $\xi_r = 0.7$. The step load torque was applied at the time $t = 1$ s. In Fig. 4b the electromagnetic, shaft and estimated load torques are demonstrated.

The closed loop-control structure with LEKF works in a proper way. The LEKF can ensure state variables estimation accuracy even in the case of changeable parameters of the system (see experimental results). However, the change of the system parameters requires retuning of the control structure parameter. Therefore the simultaneous estimation of the state variables and selected system parameters is desired.

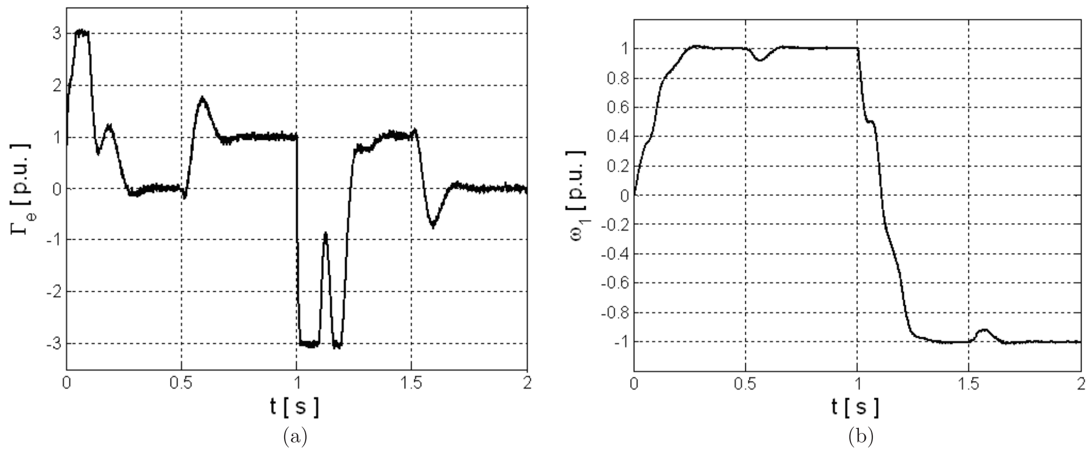


Fig. 2. Transients of the electromagnetic torque (a) and motor speed (b) used as input signals of LEKF

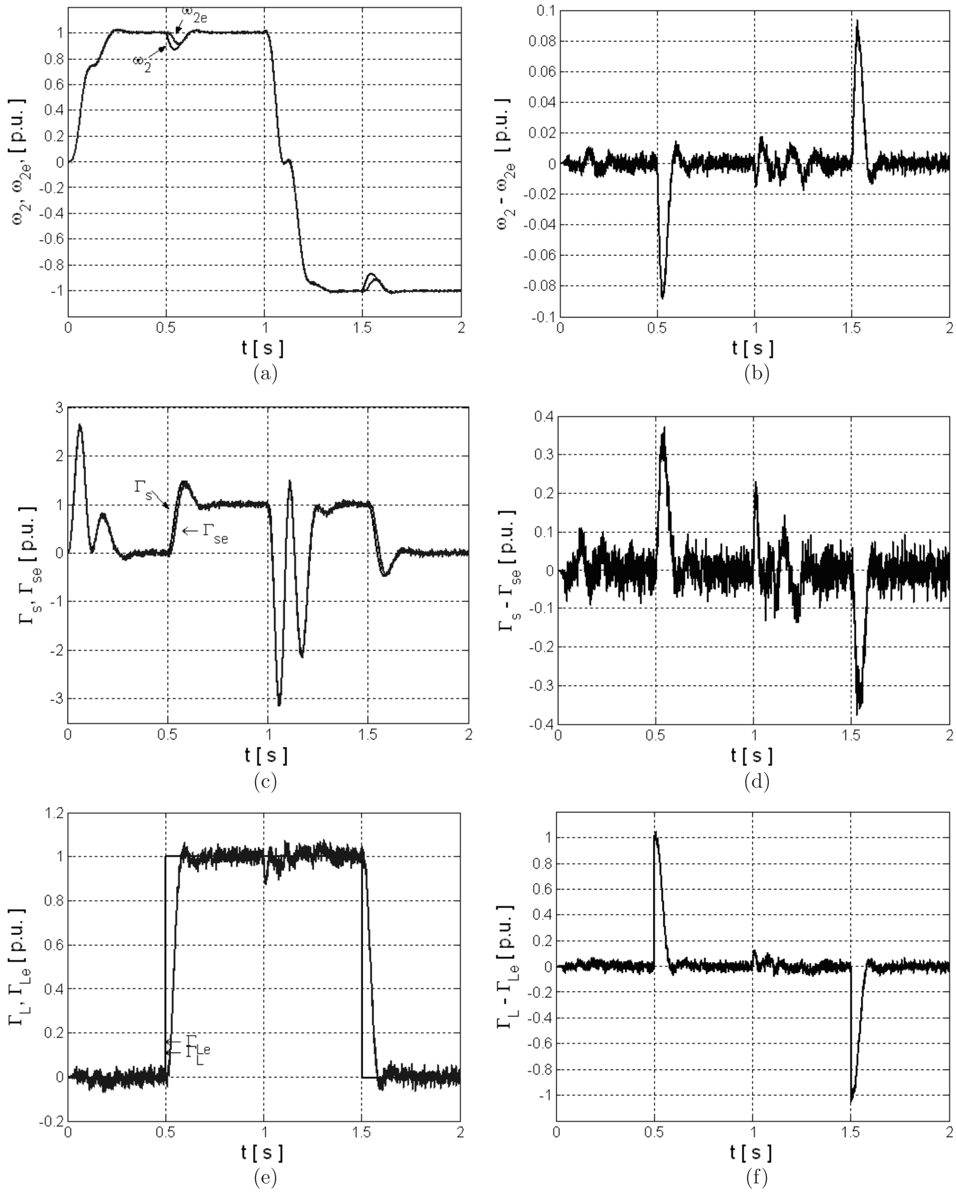


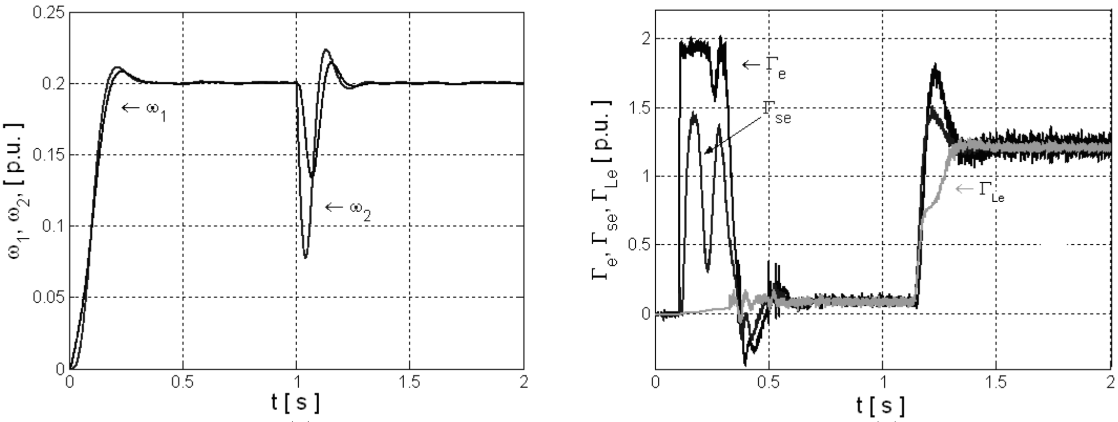
Fig. 3. Transients of the real and estimated variables and estimation errors: load speed (a,b), shaft torque (c,d) and load torque (e,f) – LEKF in the open-loop structure

5.2. The nonlinear extended Kalman filter case. The quality of the simultaneous estimation of all system state variables (17) was investigated. The input signals of the Kalman filter (electromagnetic torque and motor speed) were disturbed with additional measurement noises and supplied the NEKF. The drive system worked in the reverse condition with the electromagnetic torque limit was set to 3 in the considered case. In this test the state estimator working outside the control structure was tested. In Fig. 5 the electromagnetic torque and the motor speed used as the control and output signals for NEKF algorithm and in Fig. 6 the real end estimated variables are demonstrated.

The maximal value of the estimation error is about 0.02 for the load speed and about 0.15 for the shaft torque. Transients of all estimates contain high-frequency noises, which can be quite easy eliminated by the digital filtering. The biggest errors exist in transients of the load torque and time constant of the load machine. The change of the load torque causes the rise of the error of the load machine time constant and vice versa. The estimation of the time constant of the load machine is only possible when the motor speed is changing. This is why it is favorable to stop the estimation of T_2 when the motor speed is constant. It prevents changing the T_2 estimate during the rapid change of load torque.

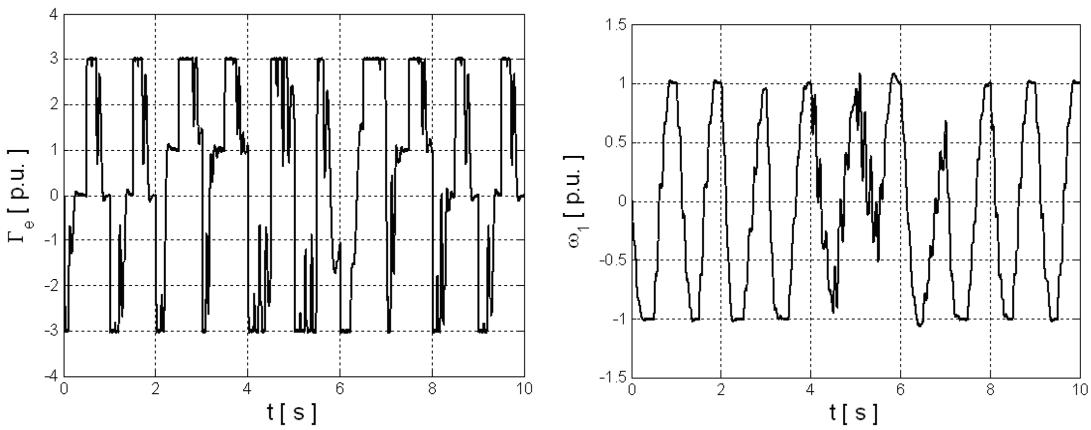
Next the closed-loop control structure was tested. The shaft torque and the load speed, provided by the NEKF were inserted to the control structure. The estimated value of the time constant of the motor was used to change the parameters of the control structure in accordance with the Eqs. (2)–(5).

Because the load torque and the time constant of the motor are coupled, they are not estimated at the same time. The estimation of the time constant of the load machine is only activated when the control error is bigger than 0.5 (this value depends on a particular application). In this time the estimation of the load torque is terminated. The last estimated value of Γ_L is given to the NEKF. In the case of the start-up, the value of the load torque is assumed to be zero. The estimation of T_2 is stopped, when the value of the control error drops to 0.01 and then the estimation of Γ_L is activated. The value of the time constant T_2 utilized in the NEKF algorithm is set to the previously estimated value. In Fig. 7 the transients of such adaptive control system are presented.



(a) (b)

Fig. 4. Transients of motor and load speeds (a), electromagnetic, estimated shaft and load torques (b) for the closed loop system with state variables estimated by LEKF



(a) (b)

Fig. 5. Transients of the electromagnetic torque (a) and the motor speed (b) used as input signals of NEKF

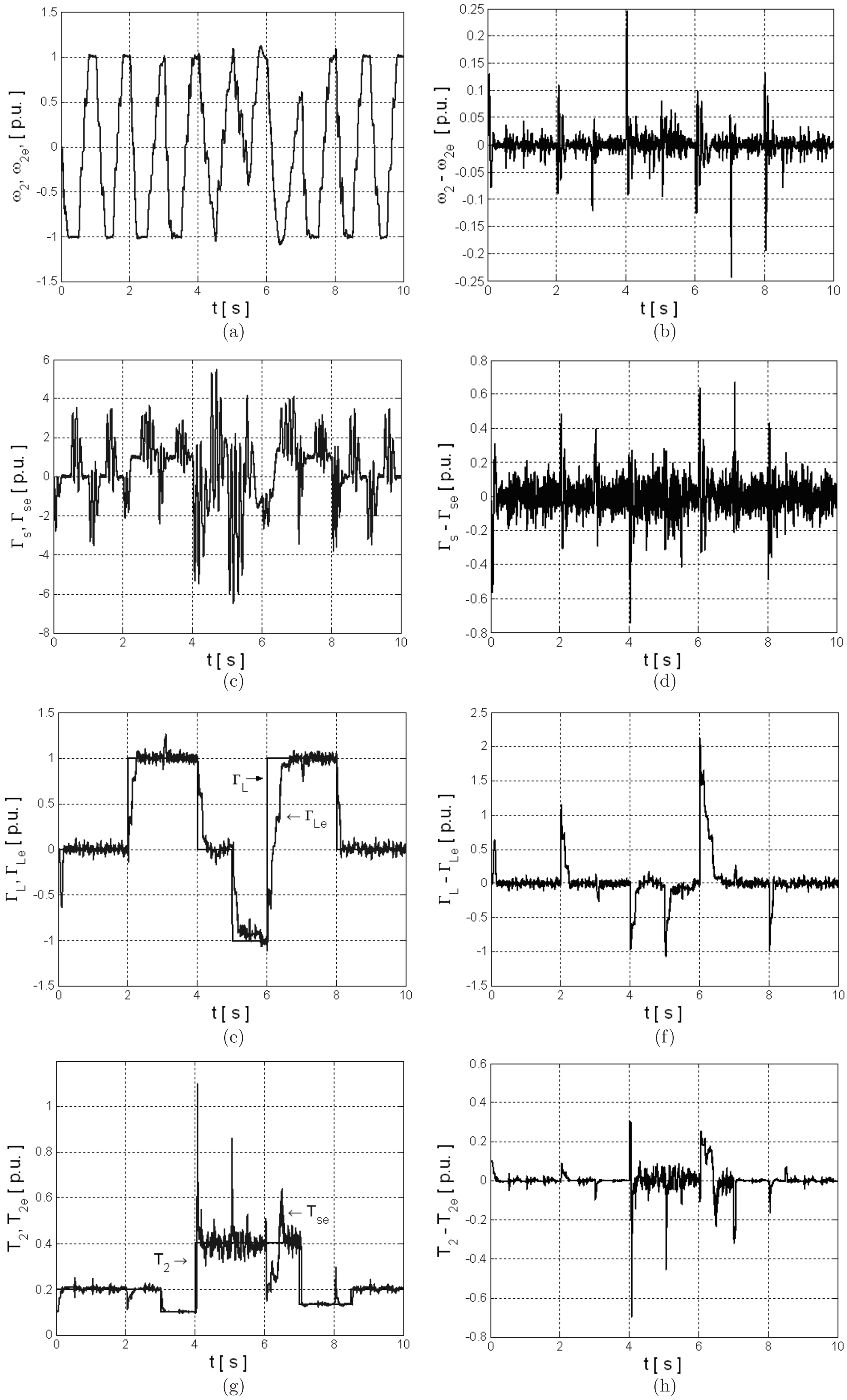


Fig. 6. Transients of the real and estimated state variables and their estimation errors: load speed (a,b), shaft torque (c,d), load torque (e,f) and time constant of the load side (g,h)

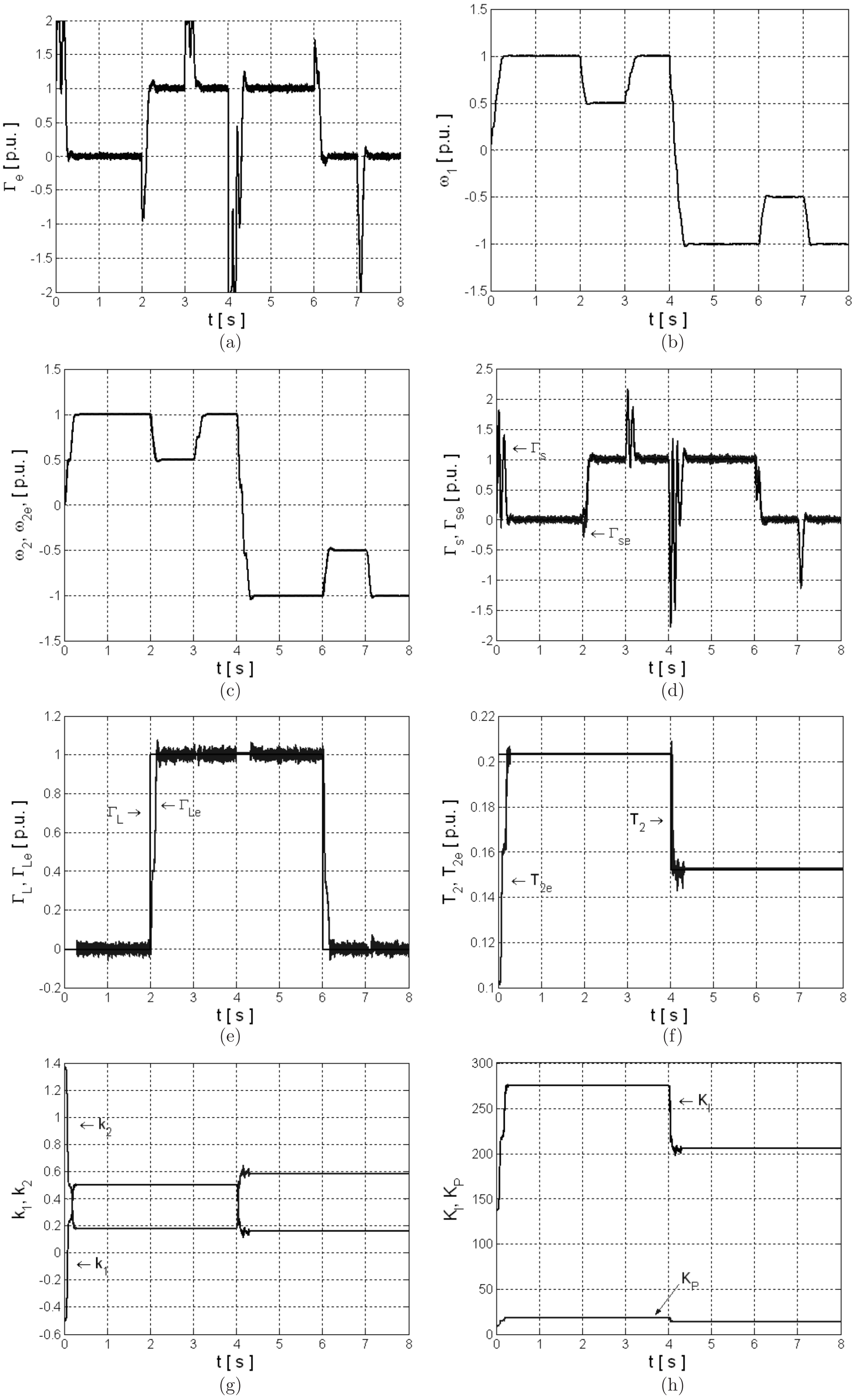


Fig. 7. Transients of the real and estimated variables: electromagnetic torque (a), motor speed (b), load speed (c), shaft torque (d), load torque (e), and time constant of the load side (f), control structure parameters (g,h) for the closed-loop drive system with NEKF

Transients of the electromagnetic torque and motor speed, demonstrated in Fig. 7a, are used as the input and output signals of the NEKF. The estimation errors of load speed and shaft torque, presented in Figs. 7c,d, are very small and they do not affect the behavior of the closed-loop structure. Next, in Figs. 7e,f transients of the real and estimated load torque and the load machine time constant are demonstrated. According to the utilized adaptation process, during the start-up of the system only the estimation of the time constant T_2 is active. During this time the assumed value of the load torque was set to zero. When the control error decreased to the value of 0.01, the estimation of the time constant T_2 was stopped and the estimation of the load torque was activated. A similar situation was repeated at the time $t = 4$ s. The application of the adaptation process is clearly visible in the transient of the estimated load torque (Fig. 7e). In Figs. 7g,h transients of the control structure parameters k_1, k_2 and K_p, K_I are presented.

6. Experimental results

6.1. General remarks. All theoretical considerations were confirmed experimentally. The laboratory set-up, presented in Fig. 8, is composed of a motor driven by a static converter. The motor was coupled to a load machine by an elastic shaft (a steel shaft of 5 mm diameter and 600 mm length). The motors had the nominal power of 500 W each. The speed and position of both motors were measured by incremental encoders (5000 pulses per rotation). The mechanical system had a natural frequency a approximately 9.5 Hz. The control and estimation algorithms were implemented by a digital signal processor using the dSPACE software.

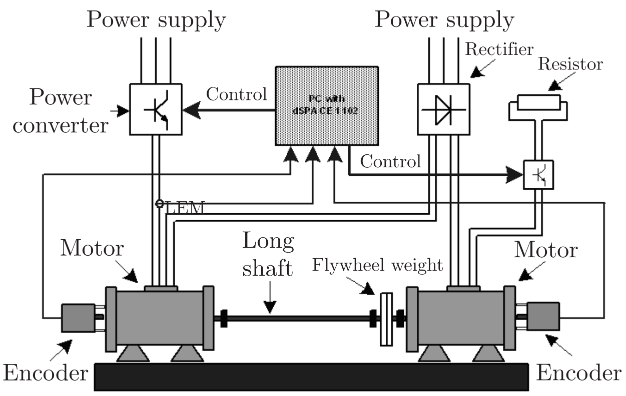


Fig. 8. Schematic diagram of the experimental set-up

6.2. The linear extended Kalman filter case. The linear Kalman filter was tested first in an open-loop structure. In Fig. 9 the actual and estimated load speeds were shown with respect to decreasing (a), nominal (b), and increasing (c) moment of the load inertia.

It was clearly shown that despite of parameter changes the estimation algorithm worked properly. Only small errors appeared during the start-up, but they were reduced very fast.

Then the linear Kalman filter (LEKF) was tested in the closed-loop structure with additional feedbacks from shaft torque and load speed, as presented in Fig. 1. The control structure parameters were tuned using following equations (2)–(5). The assumed value of the resonant frequency and damping coefficient were set to $\omega_0 = 30$ s^{-1} and $\xi_r = 0.7$, as in simulation tests. In Fig. 10 transients of the system states variables working without (a,b) and with passive load torque (c,d) are shown.

As can be seen from the presented experimental results, the linear Kalman filter works properly in the open- and closed loop system. It is robust to parameter variation of the mechanical parameters of the drive.

6.3. The nonlinear extended Kalman filter case. In the following section the experimental results of the application of the quasi-adaptive control structure is shown. Parameters of the control structure $K_I,\ K_P,\ k_1$ and k_2 were changed on-line according to the estimated values of mechanical parameters of the two-mass drive system. The utilized adaptation procedure was described in the previous section. According to this adaptation procedure during the start-up of the drive system, the load torque was set to zero. However, this assumption leads to the rise of the error of the estimated load machine time constant. The estimated value of this parameter was about 6% bigger than the nominal value. This error was created by omitting the friction torque. To decrease the estimation errors also the friction torque was taken into consideration. During the start-up the assumed value of the load torque is not zero but its value depends on the actual motor speed and linear friction coefficient. In Fig. 11 transients of the considered system with NEKF are presented.

In Figs. 11a,b transients of the motor speed, the real and estimated load speed are presented. Only a small error between the real and estimated speed exists during transients. In Fig. 11c the electromagnetic, estimated shaft and load torques are shown, and in Fig. 11d the transient of the estimated time constant T_2 is demonstrated. In the estimated value of T_2 the small overshoot exists. It can be eliminated completely by changing the value of the related element of the covariance matrix $\mathbf{Q}$. However it will slow down the estimation algorithm. In Figs. 11e,f changes of suitable feedback gain factors of the control structure as well as changes of parameters of the PI speed controller are presented according to actual value of the estimated time constant T_2 of the load machine.

7. Conclusions

In the paper the electrical drive system with elastic joint was considered. To calculate the control system parameters the classical pole-placement method was implemented. The performances of the control structure without additional feedback depend on the mechanical parameters of the considered drive, and are rather poor. In order to damp the torsional vibrations effectively the application of the additional feedbacks from selected state variables are necessary. However direct feedbacks from all states are very often impossible. For this reason application of different state variables estimators is recommended.

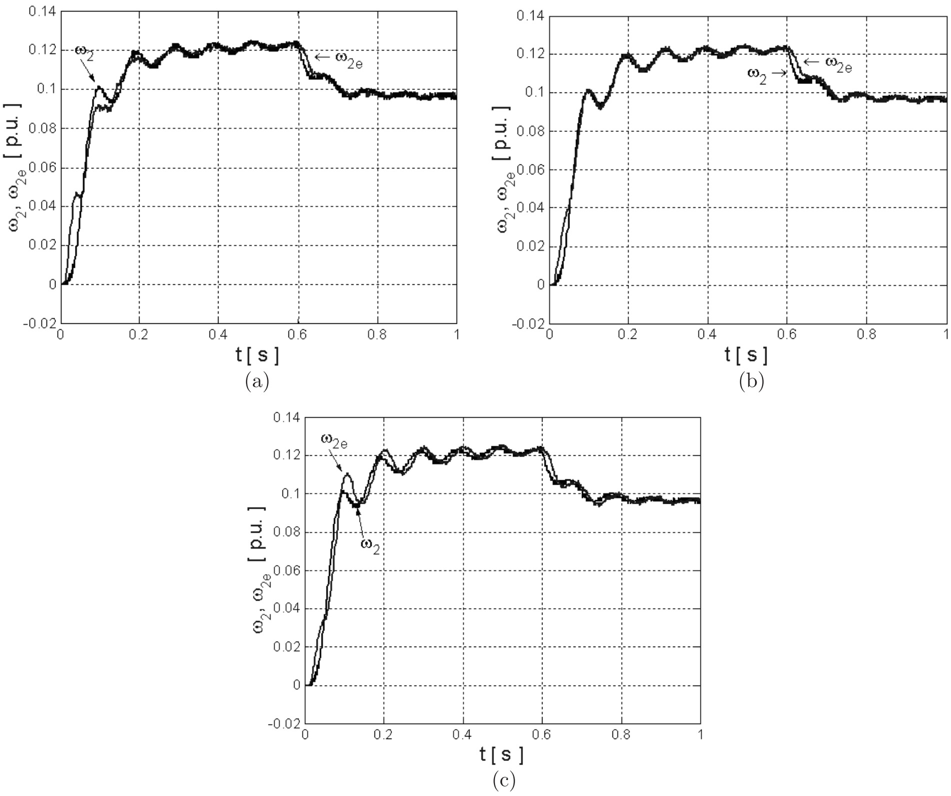


Fig. 9. Transients of real and estimated load speed for load inertia changes: a) 50%, b)100%, c) 200% of nominal value – LEKF in the open-loop structure

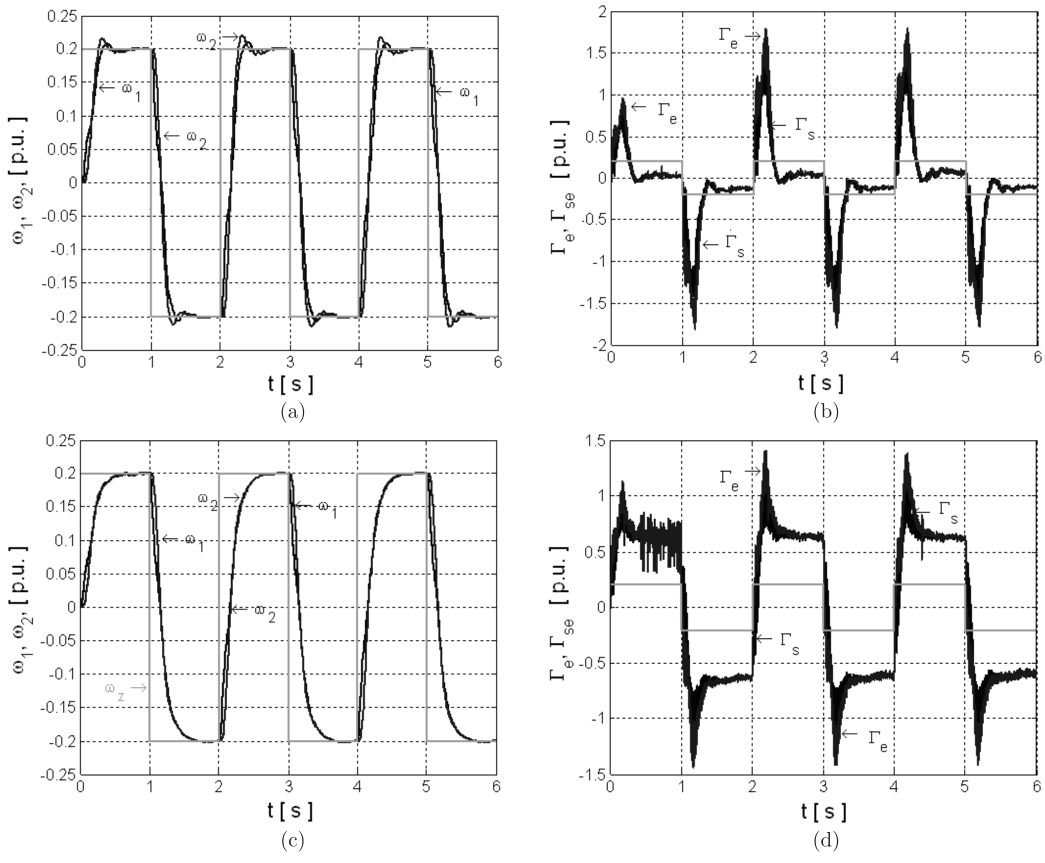


Fig. 10. Transients of the motor and load speed (a,c) and electromagnetical and shaft torque (b,d) in the closed-loop control structure using LEKF, without load torque (a,b) and with passive load torque (c,d)

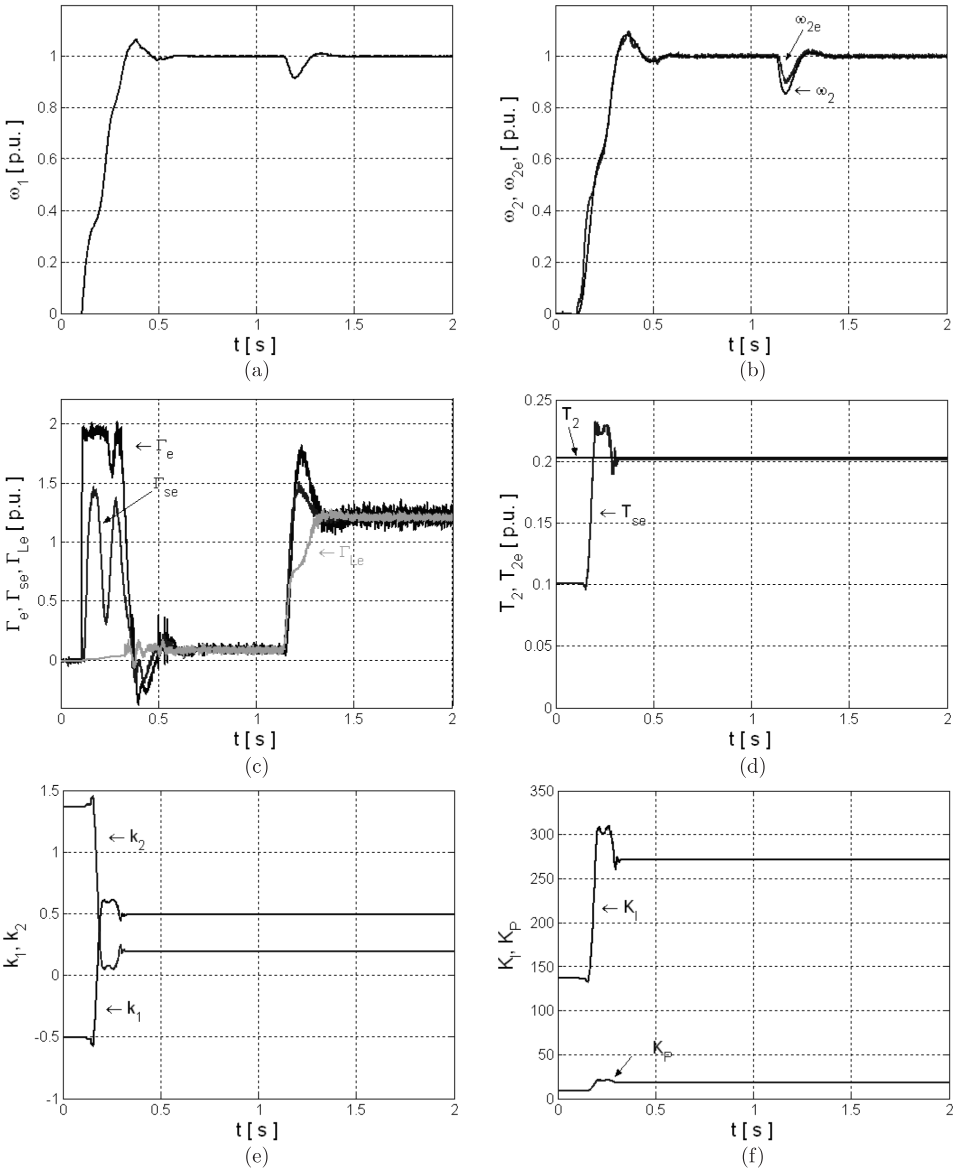


Fig. 11. Transients of: the motor speed (a), real and estimated load speeds (b), electromagnetic and estimated shaft and load torque (c) real and estimated time constant of the load side (d), control structure parameters (e,f) – NEKF in the closed-loop drive system

In the paper the application of linear and nonlinear extended Kalman filter was investigated. The utilised genetic algorithm ensures optimal setting of the covariance matrices $\mathbf{Q}$ and $\mathbf{R}$ elements, according to the defined cost function. The linear extended Kalman filters, used for the estimation of load speed, load and shaft torques, ensures good estimation accuracy even in the case of the changed parameters of the drive system. Only small, fast suppressed oscillations exist in the state transients.

However, when mechanical parameters of the system change in the wide range, (i.e. load side inertia), the control structure parameters have to be retuned. For that reason the estimation of changeable parameter is required. Because the load side inertia is coupled with the load torque, the simultaneous estimation of those variables is desired. The nonlinear extended Kalman filter was applied for the estimation of non-measurable mechanical variables and load side inertia. The estimated parameter was used for retuning the control structure parameters. The obtained adaptive control structure has ensured very good dynamical performance and estimation quality of the drive system with elastic joint.

References

[1] J.K. Ji and S.K. Sul, "DSP-based self tuning IP speed controller with load torque compensation for rolling mill DC drive", *IEEE Trans. on Industrial Electronics* 42 (4), 382–386 (1995).

[2] G. Zhang and J. Furusho, "Speed control of two-inertia system by PI/PID control", *IEEE Trans. on Industrial Electronics* 47 (3), 603–609 (2000).

[3] K. Sugiura and Y. Hori, "Vibration suppression in 2- and 3-mass system based on the feedback of imperfect derivative of

the estimated torsional torque", *IEEE Trans. on Ind. Electronics* 43 (1), 56–64 (1996).

[4] T. Orlowska-Kowalska and K. Szabat, "Optimisation of fuzzy logic speed controller for DC drive system with elastic joints", *IEEE Trans. on Industrial Applications* 40 (4), 1138–1144 (2004).

[5] J.K. Ji and S.K. Sul, "Kalman filter and LQ based speed controller for torsional vibration suppression in a 2-mass motor drive system", *IEEE Trans. on Ind. Electronics* 42 (6), 564–571 (1995).

[6] S. Beineke, F. Schütte, and H. Grotstollen, "Comparison of methods for state estimation and on-line identification in speed and position control loops", *Proc. on* 7^{th} *Confer. EPE'97* 3, 364–369 (1997).

[7] T. Orlowska-Kowalska and K. Szabat, "Sensitivity analysis of state variable estimators for two-mass drive system", *Proc. of* 10^{th} *Conf. EPE'03*, (2003).

[8] K. Szabat and T. Orlowska-Kowalska, "Application of different state variable estimators in the control structures of two-mass system", *Proc. of* 8^{th} *Intern. Conf. OPTIM'04*, (2004).