



Article Application of Multilayer Observer for a Drive System with Flexibility

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Abstract: This paper proposes a new estimation algorithm based on the Luenberger observer methodology and multilayer concept. The proposed multi-layer Luenberger observer (MLO) is implemented in the control structure designated for a two-mass system. Two types of aggregation mechanism are evaluated in the paper. The MLO ensures better estimation quality of the mechanical state variables: motor speed, shaft torque, load speed and load torque, as compared to the classical single observer. The more accurate estimated states, the more precise closed-loop control is guaranteed. MLO is designated for the system where initial conditions of the plant are not known or the state variables can change rapidly (load torque in the considered case). The estimation algorithm and control strategy is evaluated through simulation and experimental tests. The obtained results confirm efficiency of the proposed MLO.

Keywords: torsional vibration; state estimation; multi-layer observer; servo system

1. Introduction

Technological progress of industrial servo drives has influenced the modern industry significantly [1–5]. Better characteristics of servo-systems can increase the productivity of technological lines, which is obtained by designing systems with faster responses of the speed/position. There are two general ways of modification the standard drive resulting in better dynamics. The first one is to use lighter structures with smaller inertia, while the increase of gains of industrial controllers can be treated as a second option. However, both options may excite torsional vibrations, limiting the efficiency of modern servo-drives [6–8].

The torsional vibrations have been evident in novel drives for a few decades. Originally, this phenomenon had been described in traditional big drives used in industry, such as rolling-mill drives, conveyer-belt drives and machines used in textile and paper industries [9–11]. Large inertias of motor and load machines and long couplings create a visible model of the so called two-mass system. The first mass refers to the inertia of the driving motor, whereas the second mass represents the inertia of the load machine, and the long shaft acts as a flexible connection. During transients, the speed of the driving motor is different from the speed of the load machine. The driving (motor) torque goes through the shaft with some inertia. Nowadays, a similar problem is recognized also in modern applications, i.e., deep space antenna drives, wind mills, robot arm drive, servo-drives, and even in MEMS (micro electromechanical systems) [12–15].

In order to suppress torsional vibrations, different approaches have been proposed over the years. The simplest structure is based on a classical PI controller. Because the closed-loop structure is fourth order and there are only two control coefficients, performances of the classical system are limited [16,17]. The characteristics of the drive can be improved by inserting additional feedback(s) from one of the state variable(s) to the close-loop control structure. In [18], nine possible feedbacks were analysed. It was shown that all possibilities can be divided into three main frameworks with identical properties. The



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Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). simulation and experimental results confirm the theoretical work. Another popular option, mentioned in the literature, is based on the application of the disturbance observer(s), which allows one to damp vibrations successfully in two- and three-mass systems [19,20]. In [21,22], a control structure based on forced dynamic control has been investigated. It allows one to shift the system closed-loop poles independently, and, at the same time, to successfully reject the disturbances coming from the load torque. A similar problem has been considered in [23], where a state controller with independent location of the poles and cancelation of the load torque effect (based on zeros analysis in disturbance transfer function) has been proposed.

In recent years, the model predictive control (MPC) has also become popular in the topic of electrical drives. This control methodology is based on the shifted time window, where the future behaviour of the plant is predicted based on the model of the plant. In order to find the optimal strategy, a special procedure based on the defined cost function is applied. When setting the present working point, all system state variables should be measured or estimated. The properties of MPC strategy for the two- and three- mass system were described in [24–28] under different operation conditions. Besides good performances of the drive, the MPC ensures successful limitation, not only of the driving torque, but also of other variables. Limitation of the shaft torque is especially important, because it increases the reliability of the whole system.

For drive systems with changeable mechanical parameters, selection of adaptive control strategy is preferable, e.g., as in paper [28], where indirect adaptive control is implemented. In the system, the changeable parameter is the load time inertia. In order to estimate its variation, the nonlinear extended Kalman Filter is implemented. Then, on the basis of the estimated value, the parameters of the control structure are retuned in order to ensure the assumed location of the system closed-loop poles. Alternative control approaches used in order to suppress mechanical oscillations can also be found in the literature [29–34].

All advanced control structures, mentioned in the literature, require the knowledge of the present value of the system states and parameters. Because the direct measurements of all states are not possible in most of cases (due to the cost, difficulty and reliability of the system), there is a need to apply special estimation techniques [29,35–43]. Usually, only the driving torque and motor speeds are assumed to be available.

In the literature, there is a big variety of different estimation algorithms which can be implemented in order to reconstruct the states (as well as parameters) of two-mass drive systems. In general, they can be divided into two main frameworks [29,35–41]. The first one includes the algebraic estimation techniques, among which the simplest are based on the disturbance observer approach [19,20]. Relying on one differential equation (motor speed relationship), the shaft torque is calculated. The main advantage of this methodology is simplicity of this estimator and independence to the changes of shaft and load parameters. However, only the shaft torque can be estimated in this way.

The next approach is connected to the classical Luenberger observer algorithm [35], in which the other states of the system are reconstructed by using the driving torque and motor speed. Usually, only shaft torque, load speed and load torque are estimated. However, in some cases, additional variables, such as the first and the second derivative of the disturbance (load) torque are also reconstructed. The relatively simple structure and analytical tuning methodology are the main advantages of the Luenberger observer; its dynamic properties depend on the location observer closed-loop poles. However, the selection of the poles' location is not a trivial task, since it influences the characteristics of the observer significantly.

In order to improve the properties of the observer working under different conditions, the system with a changeable poles' location is proposed in [35]. The additional fuzzy system detects the present states of the plant and changes the location of the poles, improving the properties of the closed-loop control structure in this way.

The next algebraic estimation technique is based on the Kalman filter theory. This algorithm improves the robustness of the system in presence of the process and measurement noises. The application of extended Kalman filter EKF, is shown in [29]. The state vector of the two-mass system (motor speed, shaft torque and load speed) is extended by load torque and mechanical time constant of the load. The present values of the parameters allow one to retune the control structure coefficient in order to obtain the desired location of the system closed-loop poles. An additional adaptation mechanism is proposed in order to improve efficiency of EKF. In [23], the EKF is applied in order to identify the present parameters of the drive, i.e., the stiffness time constant of the shaft and mechanical time constant of the load machine. In recent years, the application of the unscented Kalman filter has been gaining attention from the control community, for example [36].

A different estimation technique used for the two-mass system is the moving horizon estimator. It can improve the system work through the implementation of the moving time window, which makes the system more robust to the measurement noises [37].

The second main group of the estimation techniques encompasses all solutions based on an artificial intelligence method. The most popular group of estimators is based on artificial neural networks (ANN). In [38–40], different structures of ANN are proposed and analysed. The authors report good properties of such system. In order to implement the ANN, the training data recorded from the plant is required. On the one hand, this is a disadvantage, because the data saved in different operation conditions are not always available. On the other hand, real data allow one to model the real plant with additional nonlinearities. In the literature, systems based on fuzzy logic are also proposed. However, despite the good results, these estimators are not popular in industry.

In all the described methods, the problem of non-zero conditions of the plant is not considered. The initial conditions in two-mass drives disturb the work of the estimator and influence the properties of the closed-loop control structure. Twisting the mechanical shaft between the motor and load machine can influence the drive performance negatively. However, there are limited works in which this problem is stated. In conference papers, basic considerations referring to the problem were shown in [41,42], in which the multi-layer observer MLO was implemented to improve covariance.

The main goal of the present paper is to discuss issues related to applying a multilayer observer in the control structure for the two-mass mechanical system. The considered MLO allows one to shorten the convergence time of the system states, so that the distortions resulting from the improper values of the initial conditions can be reduced. Contrary to the conference papers [41,42], where the basic studies are presented, the paper contains a detailed analysis of MLO and includes extended studies under different conditions. Additionally, the performances of the system under load torque changes are investigated. Two aggregations algorithms inside MLO are investigated in the paper. The new method, which takes into account the probability of certain initial states, is presented.

The paper is divided into five sections. In the introduction, the topic of control and state estimation in drive systems with flexible coupling is presented. Then the mathematical model of the drive system with flexibility is described. Next, the advanced control structure with PI controller supported by additional feedbacks from shaft torque and difference between the motor and load speeds as well as load torque is presented. The Luenberger observer is described later, and its features are stressed. Then, the concept of a multilayer estimator is introduced. The aggregation algorithm used in MLO is presented. Simulation and experimental results showing the properties of the considered system are included.

2. Mathematical Model of the Plant and Control Structure

The driving motor can be coupled to the load machine with long (elastic) joint. During start-up, reversal, etc., the motor speed/position are different from the load speed/position.

Widely, a model named two-mass system is utilised to describe dynamics of the plant [18]. It is established on state-equation presented below (in p.u. values):

$$\frac{d}{dt} \begin{bmatrix} \omega_1(t) \\ \omega_2(t) \\ m_s(t) \end{bmatrix} = \begin{bmatrix} 0 & 0 & \frac{-1}{T_1} \\ 0 & 0 & \frac{1}{T_2} \\ \frac{1}{T_c} & \frac{-1}{T_c} & 0 \end{bmatrix} \begin{bmatrix} \omega_1(t) \\ \omega_2(t) \\ m_s(t) \end{bmatrix} + \begin{bmatrix} \frac{1}{T_1} \\ 0 \\ 0 \end{bmatrix} [m_e] + \begin{bmatrix} 0 \\ \frac{-1}{T_2} \\ 0 \end{bmatrix} [m_L]$$
(1)

where: ω_1 , ω_2 —the speeds of driving motor and load machine, respectively, m_e , m_s , m_L —the driving (electromagnetic), shaft (torsional) and load (disturbance) torques, T_1 , T_2 —the mechanical time constant of the driving motor and load machine, T_c elasticity coefficient.

The mathematical model Equation (1) is described in a per unit system, with the help of the following equations:

$$\omega_1 = \frac{\Omega_1}{\Omega_N}, \omega_2 = \frac{\Omega_2}{\Omega_N}, \ m_e = \frac{M_e}{M_N}, \ m_s = \frac{M_s}{M_N}, \ m_L = \frac{M_L}{M_N}$$
(2)

where: Ω_N —nominal speed of the motor, Ω_1 , Ω_2 —motor and load speeds, M_N —nominal torque of the motor, M_e , M_s , M_L —electromagnetic, shaft and load torques. The mechanical time constant of the motor— T_1 , the load machine— T_2 and stiffness time constant are given as:

$$T_1 = \frac{\Omega_N J_1}{M_N}, \ T_2 = \frac{\Omega_N J_2}{M_N}, \ T_C = \frac{M_N}{K_c \Omega_N}$$
(3)

where: J_1 —inertia of the motor, J_2 —inertia of the load machine, K_c —stiffness coefficient.

In Figure 1, an illustrative block draft of the two-mass system is presented. The left mass is referred to the inertia of the driving motor, while the second mass imitates the inertia of the load machines. The electromagnetic torque is transmitted from the driving motor to the load machine through a mechanical shaft.



Figure 1. Block diagram of the mechanical two-mass drive system.

The issues considered in the paper are connected with non-zero values of the system states. This is illustratively conveyed in Figure 1. In the considered object, two additional, non-equal forces are operating on the load machine. This leads to a twist of the shaft. Non-zeros initial conditions resulting from the twist can worsen the performance of the drive system, especially during the start-up. Thus, additional vibrations can be excited in the system. It should be stated that the twist of the mechanical coupling can be caused by additional phenomena, e.g., position control by friction forces. The initial non-zero conditions can be referred to the starting twist of the shaft. However, in this paper, an additional case is also considered, resulting from rapid change of the load torque, and creating new conditions of the system.

The advanced control structure is implemented in the paper in order to suppress mechanical vibrations. It utilises the classical PI controller supported by two additional feedbacks (from shaft torque and difference between system speeds) [18]. The block diagram of the analysed control structure is presented in Figure 2.



Figure 2. Block diagram of the analysed control structure.

Coefficients evident in the control structure are determined using a poles-placement approach [18] according to the equations below:

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

$$k_p = 4\xi_r \omega_0^3 T_1 T_2 T_c \tag{5}$$

$$k_2 = \left(\omega_0^2 T_2 T_c\right)^{-1} - 1 \tag{6}$$

$$k_1 = T_1 T_2^{-1} \left(4\xi_r^2 - k_2 \right) \left(1 + k_2 \right)^{-1} - 1 \tag{7}$$

where: ω_0 —the desired frequency of the system closed-loop poles, ζ_r —damping coefficient, k_1 , k_2 , k_i , k_p —coefficients of the control structure. The transfer function of the speed controller is given by:

$$G_r = k_p + \frac{k_i}{s} \tag{8}$$

The conferred mathematical equations secure the location of the system closed-loop poles in every desired position, which means that the dynamics of the system can be set openly in linear range of operation. Moreover, in order to reduce the effect of the load torque on the drive system, the additional feedback from this variable is used here:

$$k_L = T_c k_i (1 + k_2) + 1 + k_1 \tag{9}$$

The complete neglecting of the load torque effect is not possible due to the rank of the system [33]. However, this feedback increases the drive performance in a visible way.

The information of the system state variables is necessary in order to implement the analysed control structure. In this paper the multi-layer estimator, based on the Luenberger observation theory, is proposed.

3. Single and Multi-Layer Observer

3.1. Luenberger observer

A linear dynamic system can be represented by following equation [35]:

$$\frac{d}{dt}\mathbf{x}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t)$$

$$\mathbf{y}(t) = \mathbf{C}\mathbf{x}(t)$$
 (10)

For system (10) the Luenberger observer can be presented through the following formula:

$$\frac{d}{dt}\hat{\mathbf{x}}(t) = \hat{\mathbf{Ax}}(t) + \mathbf{Bu}(t) + \mathbf{K}\left[\mathbf{y}(t) - \hat{\mathbf{y}}(t)\right]$$

$$\hat{\mathbf{y}}(t) = \hat{\mathbf{Cx}}(t)$$
(11)

The original state vector of the plant is extended by the load torque [35]:

$$\mathbf{x} = \begin{bmatrix} \omega_1 & \omega_2 & m_s & m_L \end{bmatrix}^T \tag{12}$$

The input variable of the system is motor torque; the motor speed is an output signal of the Luenberger observer:

$$\mathbf{u} = m_e, \ \mathbf{y} = \omega_1 \tag{13}$$

The matrices of the system (state, control and output matrices) are specified:

$$\mathbf{A} = \begin{bmatrix} 0 & 0 & -\frac{1}{T_1} & 0\\ 0 & 0 & \frac{1}{T_2} & -\frac{1}{T_2}\\ \frac{1}{T_c} & -\frac{1}{T_c} & 0 & 0\\ 0 & 0 & 0 & 0 \end{bmatrix}, \mathbf{B} = \begin{bmatrix} \frac{1}{T_1}\\ 0\\ 0\\ 0\\ 0 \end{bmatrix}, \mathbf{C} = \begin{bmatrix} 1\\ 0\\ 0\\ 0\\ 0 \end{bmatrix}^T$$
(14)

The coefficient matrix K of the observer is shown below:

$$\mathbf{K} = \begin{bmatrix} \frac{q_1}{T_1} & \frac{q_3}{T_2} & \frac{q_2}{T_c} & q_4 \end{bmatrix}$$
(15)

With the help of the pole-placement methodology, the correction gains of the observers can be calculated [35]:

$$q_1 = 4apT_1 \tag{16}$$

$$q_2 = \frac{T_1}{T_2} + 1 - T_1 T_c \left(4a^2 + 2\right) p^2 \tag{17}$$

$$q_3 = 4apT_1 \left(T_c T_2 p^2 - 1 \right)$$
(18)

$$q_4 = -T_1 T_2 T_c p^4 (19)$$

where: *p* and *a* are design parameters.

The above-presented Equations (16)–(19) allow one to locate the observer closed-loop poles in every desired position. The bigger the gains, the faster covariance is obtained. However, the values of these coefficients are limited by measurements noises. Thus, in practical applications, the observer poles are usually 2 to 5 times bigger than poles of closed loop structure. It should be underlined that no further mechanism exists in the classical observer which allows for faster speed convergence.

3.2. Multi-Layer Observer (MLO)

The classical (single) observer performance can be improved by applying the multilayer concept [43]. This system (MLO) is advanced principally for the plant where initial values of system states are unknown (load torque and shaft torque here) as well as with rapidly changing disturbances (load torque here). Additionally, it can be implemented for the drive with unknown/changeable values of the plant parameters (inertia of the load machine, stiffness coefficients). Different types of estimators can be utilised in the multi-layer concept, e.g., the Luenberger or sliding-mode observers and others [41–45].

Two layers can be distinguished in the considered MLO. Some (minimum two) of the classical observers are placed onto the first layer. They are calculated distinctly by the system states. The difference between them lies in different initial values of the system states. However, it should be stressed that the concept of MLO relies on the analysis of estimation errors of all single observers, not on "guessing" the initial values of the plant. The output of the MLO (system states) is computed based on estimation errors and additional aggregation mechanism located in the second layer. Firstly, the weights α_n , which relay on distance between states in particular single observer and real values, are calculated. Then, with the help of the aggregation mechanism, using α_n , the output of the MLO is computed, defined as follows:

$$\mathbf{x} = \alpha_1 \mathbf{x}_1 + \alpha_2 \mathbf{x}_2 + \dots + \alpha_n \mathbf{x}_n \tag{20}$$

where α_n is the weight of the n-observer. The parameter α_n is computed in two steps. Firstly, the following formula is used:

$$\alpha^{i} = \gamma \left(\int \left| \omega_{1}^{i} - \omega_{1e}^{i} \right| dt \right)^{-1} \tag{21}$$

where γ is a learning coefficient.

The following relationship is evident in Equation (21): a larger integral of estimate error results in a smaller value of α^{i} .

Normalization procedure is applied in the next step:

$$\alpha_i = \frac{\alpha^i}{\sum\limits_{i=1}^n \alpha^i}$$
(22)

In order to satisfy the given condition.

$$\alpha_1 + \alpha_2 + \dots + \alpha_n = 1 \tag{23}$$

The fundamental concept of the MLO can be described as follows. At least two observers have to be implemented in the first layer. The values of the initial conditions of the plant are placed oppositely into single observers. Next, the errors of each observer are analysed. The closer the particular system is to the real states, the smaller the value Equation (22) obtained (due to inverse correlation in Equation (21)). Thus, it affects the output of the MLO more significantly. The applied aggregation system connects signals from single observers taking into account weights α .

The described multi-layer concept can also be applied to the case of rapid changes of the external torque. In order to increase the effectiveness of the MLO, the following modification is proposed. Namely, the forgetting factor is introduced to the system in order to obtain an identical value of weights α after finite time. It is realised with the help of the formula presented below:

$$\alpha^{i}(k+1) = \gamma \left(\int \left(\left| \omega_{1}^{i} - \omega_{1e}^{i} \right| - \beta \alpha^{i}(k) \right) dt \right)^{-1}$$
(24)

where β can be treated as a forgetting factor.

The learning coefficient and forgetting factor have been selected experimentally for the presented studies. The large values of these parameters are limited by the stability problem of the system and gaining measurement noises evident in the plant; small values affect the estimation quality of the MLO.

The described algorithm is suggested for the plant where the initial conditions and disturbances are totally unknown. In this case, the initial values of all α are identical. However, there are some cases in which the initial states can be predicted with some probability. The observer in which more probable initial states are specified has a bigger initial coefficient α as compared to others. Thus, this algorithm is also tested in the paper.

The schematic block diagram of the multilayer observer is shown in Figure 3. In the paper system with three single observers is implemented.



Figure 3. Block diagram of the multilayer observer.

4. Simulation Results

In this section, simulation results showing features of the MLO are presented. For the investigation, a system with three single observers placed in the first layer was selected. The study is divided into two main parts. Firstly, the multilayer observer working in the open-loop control structure is tested. Next, properties of the closed-loop system are analysed. The simulation results were obtained with the help of Matlab-Simulink 2020 software.

The control structure presented in Figure 2 was investigated. In the first part, the feedbacks for the control structure were taken directly from the plant (the transients are shown on Figure 4). This created an ideal situation and the obtained transients will be used for further analysis. The gains of the control structure were set with the help of Equations (2)–(6), in order to get the following values of $\omega_0 = 30 \text{ s}^{-1}$ and $\zeta_r = 0.7$. The initial conditions of the plant were set as follows: $m_s = m_L = 1.0$. Then, at the time $t_1 = 1 \text{ s}$, the load torque changed quickly to the new value equal 1.6. The signals of the motor speed and driving torque were disturbed by noises (at the input of multilayer observer). On account of the estimation error of the driving motor speed Equation (24) three weights α were computed. Finally, in the second layer, all system states were calculated on the basis of incoming signal from the first layer and weights α .



Figure 4. Transients of system states: driving motor and load machine speeds (**a**), electromagnetic (driving), shaft (torsional) and load (disturbance) torques (**b**), for the system working in closed-loop structure with direct information from state variables–simulation.

The initial parameters of multilayer observers were as follows: $m_s = m_L = 2$ (in first observer), $m_s = m_L = 0$ (in second observer), $m_s = m_L = -2$ (in third observer). The initial values of three α coefficients were set to 1/3 (Figure 5a). Based on speed estimation error

Equation (22), values of α coefficients were modified during work. Because the real value of internal states is located between the second and the third observer (α_2 and α_3 obtain the biggest values), these systems influence the output significantly. Estimation errors transients of all variables in single- as well as multi-layer estimators are presented in Figure 5b–f. Due to the forgetting factor β , all coefficients α obtained the value of 1/3 after 0.5 s.



Figure 5. Transients of the observer's weights α (**a**) and estimation errors for: motor (**b**) and load speeds (**c**), shaft (**d**) and load torques (**e**) and fragments of load torque (**f**) for multilayer observer working in open-loop system, first version–simulation.

At the time $t_2 = 1$ s, the disturbance torque changed its value to 1.6. In order to expedite the estimation process, the present value of the load torque changed in two systems to 2 and -2, respectively. This generates a similar situation as during start-up (unknown value of the system state). Moreover, in this case, the multilayer observer ensures good

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estimation quality. The estimation error of MLO is much smaller in comparison to a single observer. Due to the rapid changes in the value of load torque in two single observers, the small error in load torque is visible (Figure 5f black line). In order to compensate it, an alternative solution is proposed.

The changes of the load torque values in particular observers results in step-changing transients of load torque generated by MLO. Because this variable directly influences the control signal by coefficient k_{L_i} it can generate additional stresses to the system. In order to neglect this effect, the following procedure is proposed. It is assumed that a single observer with a non-modified value of the load torque has a bigger influence on MLO. It was obtained by changing its coefficient to big values $\alpha_2 = 0.98$. Two other coefficients were set to 0.01. Additionally, the learning coefficient γ was also decreased for 10 ms. The changes of coefficients are presented in Figure 5g. This methodology allows one to ensure the continuous estimate of the load torque, which is especially visible by comparing Figure 5f with Figure 6f. The other estimation errors of particular states are shown in Figure 6b–e.

After, the features of the considered control structure working with different types of observers was tested. The parameters of the control structure, as well as the plant, were identical ($\omega_0 = 30 \text{ s}^{-1}$ and $\zeta_r = 0.7$, $m_s = m_L = 1.0$) as for transients presented in Figure 4. This allows one to compare those transients ('ideal case') with those presented in Figure 7.

Firstly, a two-mass drive system working with classical (single) observer was tested. The parameters of the internal value in the considered observer were set to zero. Thus, there was a difference between the initial conditions in the plant and the observer. The motor and load speed, as well as driving, shaft and load torque, are shown in Figure 7a,b.

The considered system was working in a stable way (Figure 7a,b). However, there were significant differences between the ideal and considered case. Firstly, in the system working with the classical observer, a drop of two speeds could be observed in the first few milliseconds. The remarkable overshoot and bigger settling time than in the 'ideal case' (Figure 4) could be observed in this case. The reaction to the application of the load torque (at t = 1 s) was also slower. The existing overshoot was also bigger than in the 'ideal case'.

Next the system with a multilayer observer (first case) was analysed. After changes of the disturbance torque, the initial values of the load torque were set to initial conditions. This eliminated the difference between the real and estimated values of system states quickly. The transients of the system are shown in Figure 7c,d.

The following remarks can be concluded on the basis on Figure 7c,d. The application of the multilayer observer eliminates drop from both speeds. Moreover, overshoot in velocities is almost the same as in the 'ideal case'. At the moment of changing of the load torque the internal values are set to its initial conditions (different from real one). This generates estimation errors in the load torque, which results in a quickly generated large value of the driving torque (Figure 7d). It is also visible in the transients of the driving motor speed. The overshoot in the motor speed is smaller than in Figure 6a, but bigger than in the 'ideal case'.

The performance of the system during changes of the load torque can be improved by a modification of the standard algorithm. It was assumed that conditions of the load torque in one observer were more likely to be real. Therefore, this value was not changed and had greater weight α at this moment. This situation was also assumed during the start-up. The transients, which illustrate this case, are shown in Figure 7e,f.

At the start-up, a small, quickly eliminated drop was visible in the motor speed. It resulted from the fact that the prediction of the initial conditions in one observer was not correct. Yet, the overshoot and settling time in both speeds were almost the same as in the previously considered case. The usefulness of prediction is visible during the application of the load torque, because the shapes of speeds are almost the same as in the 'ideal case'.



Figure 6. Transients of the observer's weights α (**a**) and estimation errors for: motor (**b**) and load speeds (**c**), shaft (**d**) and load torques (**e**) and fragments of load torque (**f**) for multilayer observer working in open-loop system, second version–simulation.



Figure 7. Transients of the system states: driving motor and load machine speeds (a,c,e), driving (electromagnetic), shaft and load (disturbance) torques (b,d,f), for the closed-loop system working with single observer (a,b) and multilayer observer–version 1 (c,d) and version 2 (e,f)–simulation.

5. Experimental Results

A laboratory stand, presented in Figure 8, was used to study the estimation algorithm. The main part of the experimental set-up consisted of two DC motors coupled by flexible joint (made of steel with following parameters: length 600 mm, diameter 5 mm). A power converter (H bridge structure) supplied the driving motor. The control of the load torque was possible by switching on and off the armature winding of the load machine to resistor. Incremental encoders (36,000 pulses per revolution) are used to measure both speeds (the measured load machine speed is to check the MLO quality). The nominal parameters of each motor were as follow: nominal power P = 500 W, nominal armature voltage $U_a = 220$ V, nominal armature current = 3.15 A, nominal speed $\Omega_N = 1450$ rev/min, armature resistance

 $R_a = 10.05 \Omega$, armature inductance $L_a = 0.8$ H, excitation current $I_e = 0.254$ A, excitation voltage $U_e = 220$ V, moment of inertia = 0.0044 kgm². The additional flywheel allows one to change the inertia of the load side. Moreover, the elasticity of the drive system can be modified by mounting a shaft with a different diameter. In the armature current control (driving torque) loop, a PI controller is implemented. This loop can be approximated by a first order term with an approximated time constant equal to 1 ms. The present value of the current was measured using an LEM transducer. The control algorithm was implemented with the help of a dSpace control desk. The obtained sampling time was equal to 0.5 ms (including speed and torque loops). The photograph of laboratory set-up is presented in Figure 9.



Figure 8. Laboratory set-up: schematic block diagram and real view.



Figure 9. Picture of laboratory set-up.

The drive is working with the following cycle. The initial conditions of all states are set to zero. At the time $t_1 = 0$ s, the reference value of system speed was changed to 0.2. Then the load torque was applied to the system at the time $t_2 = 0.5$ s (the rising time of load torque depends on DC motor parameters and has a value of 25 ms). Next, the reference command changes to zero at the time $t_3 = 1$ s. The cycle of work repeated after one second.

Firstly, the properties of the system working with classical observer is tested. It generates reference transients for the system with the MLO. Because there was no possibility to twist the shaft at zero speed, the following procedure was applied to check the control structure properties. Thus, different initial values were assumed in the single observers. In order to show the influence of the initial conditions more clearly, two cases were analysed. The initial conditions were set to $m_s = -2 m_L = -2$ (first case) as well as to $m_s = -5 m_L = -5$ (second case). The transients of system states are shown in Figure 10a,c,e,g (fist case) and Figure 10b,d,f,h (second case). The assumed value of the damping coefficient is 0.7.



Figure 10. Transients of the system states: motor and load speeds (**a**,**b**) and it's fragment (**c**,**d**), electromagnetic, estimated shaft and load torques (**e**,**f**), real and estimated load speed (**g**,**h**) for the system working in closed-loop structure with classical observers–case 1 (**a**,**c**,**e**,**g**) and case 2 (**b**,**d**,**f**,**h**)–experiment.

As can be expected, improper values of the initial condition affected properties of the system. At the start-up, both speeds exhibited a visible drop. Then, the overshoot in the load speed has a value ca. 70% (1-st case) and ca.110% (2-nd case, the overshoot is reduced

by limitation of the driving torque here). The reaction of the system to the application of load torque was also improper (slowly damped oscillations). The incorrect value of the system torque is visible in Figure 9e,f. It also caused a big estimation error in the load speed (Figure 9g,h).

Next, the system working with the MLO observer is tested. Following parameters are assumed in observers: $m_s = m_L = -11$ (first system), $m_s = m_L = -5$ (second system), $m_s = m_L = 1$ (third system). The average initial condition has a value of -5, identical as in classical observer (2-nd case). In the system tested first, all single observers have values of α set to 1/3 during the start-up. The moment the load torque is applied to the plant, the conditions of the load torque in single observers are reset to initial values. The transients of the plant are shown in Figure 11a–h.



Figure 11. Transients of the system states: motor and load speeds (**a**,**b**) and it's fragment (**c**,**d**), electromagnetic, estimated shaft and load torques (**e**,**f**), real and estimated load speed (**g**,**h**) for the system working in closed-loop structure with MLO–case 1 (**a**,**c**,**e**,**g**) and case 2 (**b**,**d**,**f**,**h**)–experiment.

The tested system was working correctly. A small drop of the driving torque and motor speed can be observer at start-up resulting from non-correct values of estimated states caused by wrong initial conditions. The shape of speed results from designing parameters. The moment the load torque was applied, the conditions in single observers are reset. This effect was visible in the estimated load torque by a large quickly eliminated pick value (at 2.5 s in Figure 11e). The application of the load torque caused a small drop in the motor speed, which was eliminated relatively slowly.

Then the second version of the algorithm was tested. During the start-up, the situation was identical to the the previously considered case. However, at the time when the load torque is applied to the system, only the values of the load torque in two observers are reset. The third observer follows the current value of estimated load torque and additionally it's α coefficient artificially increases (similarly as simulation study). The transients of this system are shown in Figure 11b,d,f,h.

The speeds of the system have the desired shapes. During the start-up, they were similar as in the previously discussed case. However, the reaction of the system to the changes of the load torque is better. The drop of the motor speed is smaller, which is the result of smaller estimation errors in all state variables. The negative pick in the load torque is not visible at the time $t_2 = 2.5$ s.

6. Conclusions

The paper investigates a novel estimation algorithm for a high-performance drive system with a flexible link. It is based on a PI controller supported by additional feedbacks from selected state variables (difference between the motor and load speeds as well as shaft torque). Because the states of the system are not measured, the implementation of the estimator is necessary. However, the classical observers are not effective enough for the non-zero initial condition of the plant, for example, the torsional torque resulting from the initial twist of the shaft.

In order to improve the performance of the drive in this case, a novel type of observer is implemented. The proposed MLO is based on three single observers and the design procedure is based on the classical Luenberger's observer theory. Correction coefficients of all observers are selected in order to shift the closed-loop poles in the required position. Thus, for this point, the observers are identical, yet the difference between them is visible in setting different initial values of states. In two observers, the initial value contains the minimal and maximal possible values of the particular state, while the initial value of the third observer is located in the middle between minimal and maximal values. In the paper the properties of the MLO were investigated under different conditions. On the basis of the obtained results, the properties of MLO can be specified.

The strong points of the system are as follows. Firstly, the MLO can significantly shorten the covariance time of all system states, which is particularly visible in the transients of the load torque, where the estimation errors are drastically reduced. Moreover, the improvement in other states is essential.

It should be underlined that the principle of work of the MLO does not rely on guessing the initial condition of the plant: the main point here is the analysis of distances between real and estimation errors in single observers. Then, drawing on the aggregation mechanism, the estimated states are calculated. The MLO observers can also be applied to a rapidly changeable load torque. In this case also a significant reduction of estimation is visible. The classical aggregation mechanism ensures that probability of different initial values is identical or unknown. However, in some cases, this probability can be calculated. If it is so, the learning coefficients set for different single observers can have various initial values, which can result in the improvement of the properties of the MLO.

The weak points of the MLO are high computational effort and certain complexity. Therefore, its use is suggested especially for a drive system working in applications where accuracy is a very important requirement. Moreover, in systems where safety reasons are one of the main points, the implementation of the MLO seems to be justified. It should also be stressed that, due to the continuous progress in microprocessor power, these drawbacks are not critical.

As has been shown in the paper, the application of MLO reduces the estimation error significantly as compared to single (classical) observers. This is also very important in closed-loop operation. As was shown through simulation and experimental study, the bigger the difference between the initial values of the plant and single observer is, the larger overshoots and oscillations occur. The use of the MLO allows one to improve the closed-loop significantly. Despite wrongly identified initial conditions, the transients of the system have desired shapes resulting from the design parameters.

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