Mechanical state variable estimation of drive system with elastic coupling using optimised feed-forward neural networks

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Abstract. The paper deals with the application of the feed-forward and cascade-forward neural networks to mechanical state variable estimation of the drive system with elastic coupling. The learning procedure of neural estimators is described and the influence of the input vector size and neural network structure to the accuracy of state variable estimation is investigated. The quality of state estimation by neural estimators of different types is tested and compared. The simple optimisation procedure is proposed. Optimised neural estimators of the torsional torque and the load machine speed are tested in the open-loop and closed-loop control structure of the drive system with elastic joint, with additional feedbacks from the shaft torque and the difference between the motor and the load speeds. It is shown that torsional vibrations of the two-mass system are damped effectively using the closed-loop control structure with additional feedbacks obtained from the developed neural estimators. The simulation results are confirmed by laboratory experiments.

Key words: electrical drive, estimation techniques, neural networks, two-mass system, vibration suppression.

1. Introduction

Modern industrial drives are required to present relatively high dynamical performance. They have to achieve the reference signal with fast dynamics and to minimize the intermediate phases. Typically, when the industrial drive is designed, the elasticity of the shaft is neglected. In the case of the standard drive such an assumption is reasonable; however, there is a large group of drives, like: rolling-mill drives, conveyer belt or cage host drives, modern servo-drives, robot-arm or even computer disc drives, where the characteristic features of the mechanical part have to be included in the analysis [1–4].

A lot of control methods have been developed in order to suppress the torsional vibrations in the drive systems with elastic couplings. One basic concept relies on the modification of the speed controller parameters setting as presented in [5]. This method can slightly improve the damping ability of the drive, but the system dynamics decreases at the same time. The next solution is based on the application of digital filters [3]. It is commonly applied, when the resonant frequency of the system excides hundreds of hertz. However, it also reduces the drive system dynamical performance. The more advanced approaches are based on the application of the additional feedback from a selected state variable. In [6] nine different control structures with one additional feedback are presented and compared. The design method of the control structure relies on the pole-placement method. The most advanced control structures, which allowed free setting of the system dynamics are based on the application of the additional feedbacks from all state variables. These can be the classical control structure with two additional feedbacks [6] or a state control structure [7].

In all control structures which use additional feedbacks from mechanical state variables, the information on these signals is required. Except of the driven motor speed, all these state variables, like the load machine speed, torsional torque or their derivatives, are hardly or even non-measurable ones. In many applications the Luenberger observers are applied for the non-measurable state variables estimation. In the case of the linear, well identified system, with small value of measurement noises, this estimator can ensure good accuracy of reconstructed variables. However, if the system has high value of parameter and measurement noises the performance of Luenberger observer is non-satisfactory. Contrary to the Luenberger observer, the Kalman filter can ensure much better results of mechanical variable estimation in the presence of noises [8, 9]. It results from the fact that Kalman filter algorithm relies directly on the parameter and measurement noises. But this solution has some drawbacks also: to ensure the proper work of Kalman filter there is a need to set the state and measurement covariance matrices correctly, which is a quite difficult task. Moreover, the algorithm is computationally complicated and requires a fast microprocessor, which in turn raises the total cost of the application [9].

Recently much research has been devoted to the issue of the artificial neural networks (NN). They have been applied in different industrial branches, including electrical drives, for the state variables estimation, control and diagnostic purposes [10, 11]. The big advantage of the NN is the ability of non-linear function mapping. The neural estimators do not need a mathematical model of the system, only the training data are required. The next advantage of NN is the possibility of data generalisation: this means the ability of representation areas not included in the training process.

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The NN estimator can be designed to be more robust to parameter and measurement noises than the Luenberger observer. In comparison to the Kalman filter, the NN estimator requires less computational time, which decreases the implementation cost. Additionally, in the case of special microprocessor structure (FPGA), the time necessary to run one loop of the NN algorithm can be drastically reduced due to the fact that NN allows parallel data processing in contrast to the Kalman filter, whose algorithm is sequential. That means further cost reduction in the case of NN application.

This paper deals with the application of the neural networks to mechanical state variable estimation of the drive system with elastic joint. The learning procedure of neural estimators is described and the influence of the input vector size and neural network structure to the accuracy of state variable estimation is investigated. The quality of state estimation by feed-forward and cascade-forward neural networks is tested and compared. The simple NN optimisation procedure is proposed, which not only reduces the number of neural connections in the structure (zeroing chosen weight factors, what simplifies the practical realisation of the neural estimators), but also improves the estimation accuracy. Next the optimised neural estimators of the torsional torque and the load machine speed are tested in the open-loop and closed-loop control structure of the drive system with elastic joint, with additional feedbacks from the shaft torque and the difference between the motor and the load speeds. The simulation results are confirmed by laboratory experiments.

2. Mathematical model of the drive system and applied control structure

In the paper the commonly-used mathematical model of the drive system with elastic coupling is considered. The system is described by the following state equation (in per unit system):

$$\frac{d\omega_1(t)}{dt} = \frac{1}{T_1}(m_e(t) - m_s(t) - m_f(t)) \tag{1}$$

$$\frac{d\omega_2(t)}{dt} = \frac{1}{T_2}(m_s(t) - m_L(t) - m_f(t)) \tag{2}$$

$$\frac{dm_{SD}(t)}{dt} = \frac{1}{T_C}(\omega_1(t) - \omega_2(t)) \tag{3}$$

$$m_S = \begin{cases} \left(m_{SD}(t) - \frac{\varepsilon}{2}sgn(m_{SD}(t))\right) & \text{for } abs(m_{SD}) > \frac{\varepsilon}{2} \\ 0 & \text{for } m_{SD} \le \frac{\varepsilon}{2} \end{cases} \tag{4}$$

where: ω_1, ω_2 – motor and load speeds; m_e, m_{SD}, m_S, m_L, m_f – motor, shaft (before backlash), shaft, disturbance and nonlinear friction torques; T_1, T_2 – mechanical time constant of the motor, and load machine; T_c – stiffness time constant; ε – the width of the backlash.
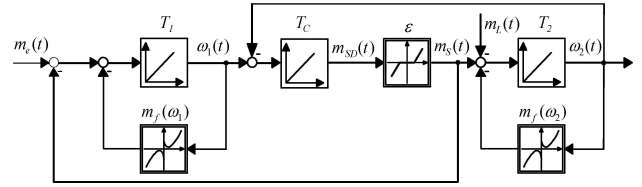

Fig. 1. The block diagram of the nonlinear two-mass system

In Fig. 1 the block diagram of the nonlinear two-mass system is presented. The classical cascade control structure of such system 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 the PI controller typically adjusted according to the symmetry criterion or pole placement method [6], neglecting the nonlinear phenomena occurring in the two-mass system (nonlinear friction torques and backlash).

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 [6]. In this paper the following feedback state variables are chosen: the shaft torque and the difference between the motor and the load speed, as shown in Fig. 2.
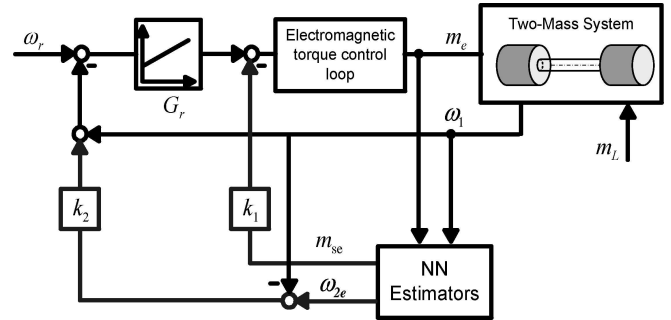

Fig. 2. The block diagram of the control structure

Parameters of the control structures are setting using the following equations (neglecting non-linear elements) [6]:

$$K_I = \omega_0^4 T_1 T_2 T_c \tag{5}$$

$$K_P = 4\xi_r \omega_0^3 T_1 T_2 T_c \tag{6}$$

$$k_2 = \left(\omega_0^2 T_2 T_c\right)^{-1} - 1 \tag{7}$$

$$k_1 = T_1 T_2^{-1} \left(4\xi_r^2 - k_2\right)(1 + k_2)^{-1} - 1 \tag{8}$$

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 part of the PI controller with the following transfer function:

$$G_r = K_p + \frac{K_I}{s}.$$ (9)

The direct feedbacks from the shaft torque and load speed are very difficult in the industrial application. Therefore, in many papers different methods for non-measurable variable reconstructions have been considered [7–9]. Usually the Luenberger observer or Kalman filter are applied. However, the presence of the nonlinear elements makes the application of those methods much more complicated. The linearization of the system in every point of the work becomes necessary. As a result, the control algorithm becomes more complicated and the application of a faster microprocessor becomes necessary. Due to those factors in this paper the NN estimators are applied to reconstruct the non-measurable variables of the non-linear two-mass system.

3. Basic structures of neural state estimators and training procedure

In order to work properly, the NN estimators require a suitable choice of the learning signals. The appropriate selection of learning vectors can ensure good data generalization. It means that NN estimators can reconstruct even the states not taken into consideration during the learning procedure correctly. The learning vectors should change in a wide range and include all specific cases of the system work (reverse work, different load torque level). As was shown in [12], the NN estimators possess the best accuracy when the input vector is defined in the following way:

$$W = [\omega_1(k), \omega_1(k-1), \omega_1(k-2), m_e(k),$$
$$m_e(k-1), m_e(k-2)].$$ (10)

The factor k stands for the actual sampling period. So the NN estimators were supplied by the actual and delayed by one and two samples of the electromagnetic torque and motor speed. For this research two types of the NN are selected:

– feed-forward neural networks;
– cascade-forward neural networks.

In order to get the learning signals, the control structure presented in Fig. 1 with direct feedbacks from the shaft torque and load speed is used in simulations. The main parameters of the analysed system are following: $T_1 = 203$ ms, $T_2 = 203$ ms, $T_c = 2.6$ ms. The obtained signals are presented in Fig. 3.

In the paper the following initial structure of the NN is selected for both state variable estimators, after comparing different NN configurations, taking into account the quality of state variable estimation as well as simplicity of the practical realization (the total number of neurons):

$$\{NN\} = \{6\text{-}8\text{-}1\}$$ (11)

which means: 6 inputs, 8 neurons in hidden layer, 1 output.

For the hidden layer the nonlinear tangensoidal activation functions are applied. As the output function of the NN estimators the linear activation functions are selected. The back-propagation learning method is used to train the NN systems. After the training process the quality performance of the designed NN estimators is checked using the test signals presented in Fig. 4 (obtained in simulation of the control structure with directly measured state variables).
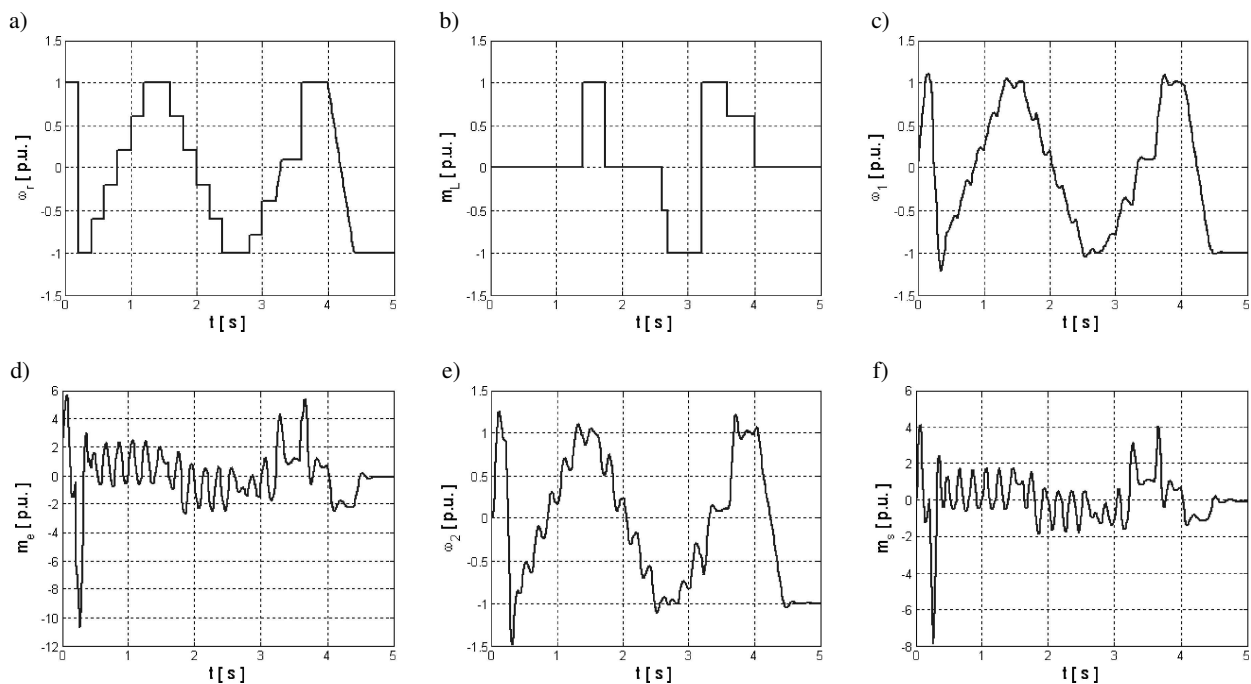

Fig. 3. Transients of the learning signals: reference speed (a) load torque (b) motor speed (c), electromagnetic torque (d) load speed (e) shaft torque (f)
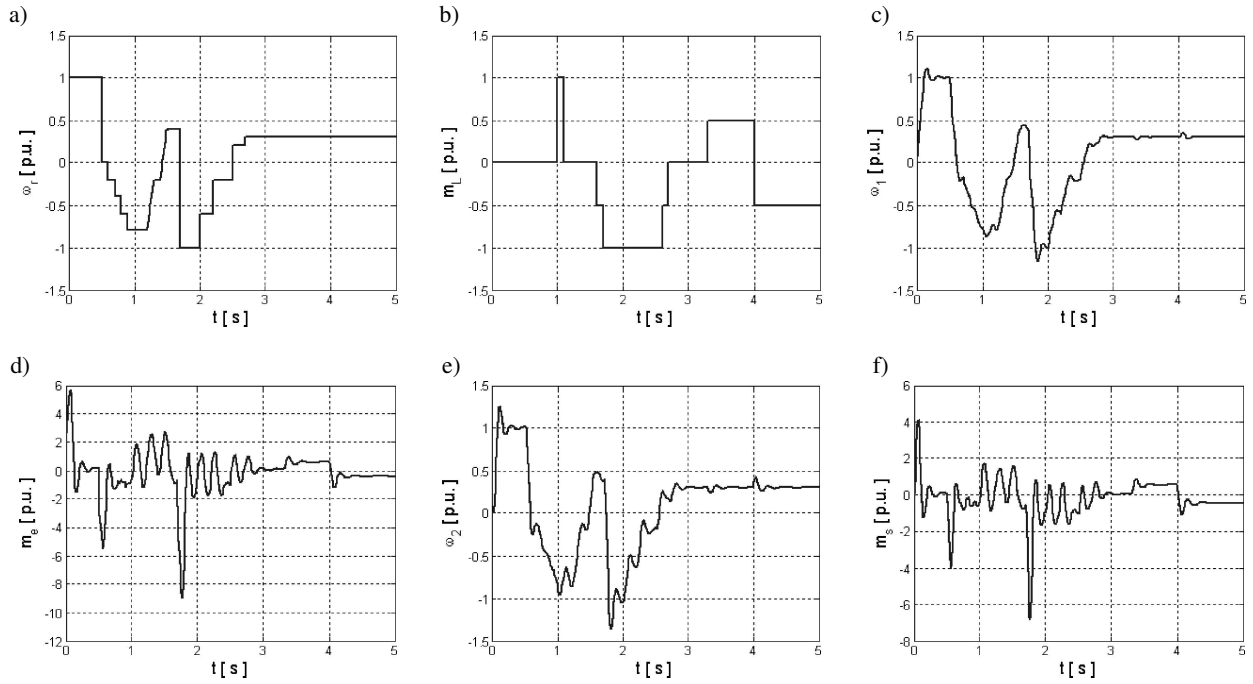
Fig. 4. Transients of the testing signals: reference speed (a) load torque (b) motor speed (c), electromagnetic torque (d) load speed (e) shaft torque (f)
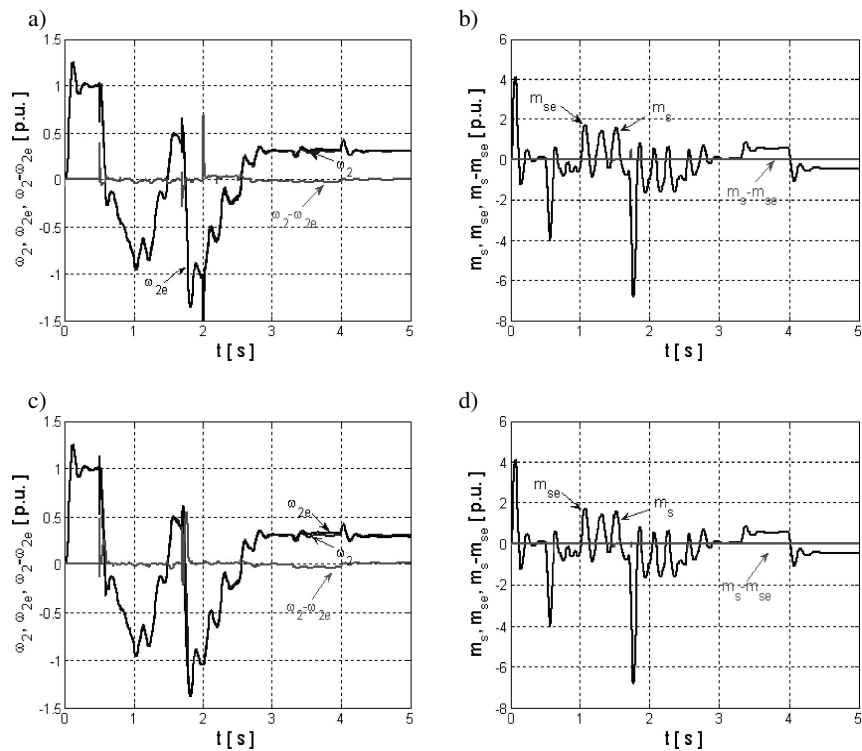

Fig. 5. Transients of the real and estimated state variables: load speeds and estimation error (a,c) shaft torques and estimation error (b,d) for the feed-forward NN (a,b) and the cascade-forward NN (c,d)

Next the reconstruction accuracy of the non-measurable state variables (load speeds and shaft torque) for feed-forward NN estimators is checked. The real and estimated transients of the load speed and its estimation error are demonstrated in Fig. 5a. In the steady state condition the estimation error of the load speed equals almost zero. The big, quickly eliminated estimation errors appear, when the speed reference value

rapidly changes its direction. In Fig. 5b the real and estimated shaft torques and its estimation error are presented. The estimation accuracy of the shaft torque is much better than for the load speed. The estimated shaft torque transient covers its real value almost perfectly.

Next the performances of the NN cascade-forward estimators are investigated. In Fig. 5c the real and estimated tran-

sients of the load speeds are presented. The estimation errors are a bit bigger than for the feed-forward NN tested before. The rapid change of the reference value causes bigger estimation errors. In Fig. 5d the real and estimated shaft torques and their error are shown. Similarly as in the previous case, the reconstructed transient covers its real value without visible difference.

4. Optimisation of neural estimators

Because the feed-forward NN estimators present better performances than the cascade-forward NN systems, they are selected for the optimisation procedure. This procedure should improve the estimation quality of those estimators and minimise the number of required neural connections in the structure (zeroing of chosen weight factors).

The applied optimisation algorithm can be presented as follows:

1. Calculation of the total reconstruction error of the tested NN.
2. Every internal connection between weights is neglected (only one at a time) and the state estimation errors are determined.
3. The errors of all cases are compared and the network which has the smallest error is selected to the next step of the procedure.
4. The chosen estimator is learned again.

5. The procedure is repeated, starting from the step 1.
6. The optimisation process is stopped when there is no possibility to obtain a smaller estimation error.

In Fig. 6 transients of the optimised NN estimators based on feed-forward networks are presented.

The optimization procedure improves the characteristics of the NN estimators. As can be seen from the comparison of transients in Fig. 5a and Fig. 6a, the dynamical errors of the load speed estimate significantly decrease. Also the estimation accuracy increases in the steady state condition. The estimated transient covers its real value thoroughly. In Fig. 6b the real and estimated shaft torques and their estimation errors are presented. There is no visible error between the real and estimated values of the shaft torque.

In order to shown the efficiency of the applied optimization procedure, the estimation errors of different NN systems are calculated, using the following formula:

$$\Delta_j = \frac{\sum\limits_{i=1}^{N} |x_j - \hat{x}_{je}|}{N} * 100\% \qquad (12)$$

where: x_j – real value, $\hat{x}_{je}$ – estimated value, N – number of samples.

In Fig. 7 the estimation errors calculated using the Eq. (12), for the feed-forward, cascade-forward and the optimized feed-forward NN estimators are presented.
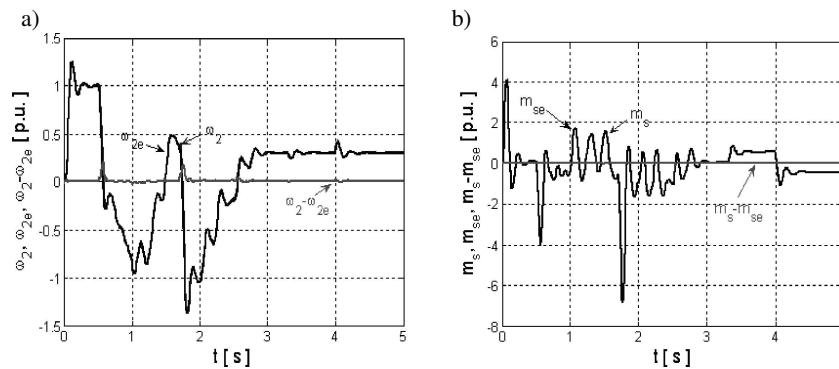

Fig. 6. Transients of real and estimated state variables: load speeds and its estimation error (a), shaft torques and its estimation error (b) for the optimized feed-forward NN
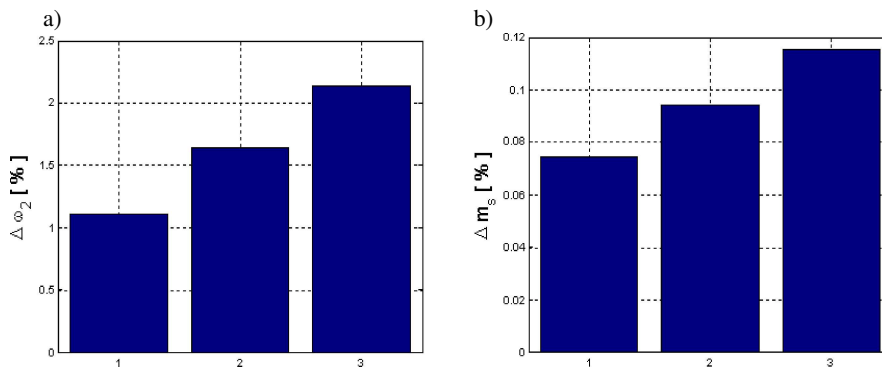

Fig. 7. Estimation errors of the load speed (a) and shaft torque (b) calculated using Eq. (12), for the optimized feed-forward (1), non-optimized feed-forward (2) and cascade-forward (3) NN estimators

The following conclusions result from the analysis of the Fig. 5–7. The cascade-forward NN estimators present the worst dynamical and steady-state performance; their estimation errors, calculated according (12), are about 2.2% for the load speed and about 0.118% for the shaft torque. The application of the feed-forward type NN systems decreases the estimation error to the values 1.6% and 0.095% for load speed and shaft torque, respectively. The optimized feed-forward NN estimators have the best characteristics. Their estimation errors are about 1.1% for the load speed and 0.075% for the shaft torque.

5. Simulation tests in the closed-loop operation

Next the NN estimators are tested in the closed-loop control structure (shown in Fig. 2). The information about the motor speed and electromagnetic torque comes directly from the measurement sensors. The load speed and the shaft torque signals are provided by the NN estimators. In Fig. 8 transients of such two-mass system are presented. The assumed resonant frequency of the system is $\omega_0 = 40$ s^{-1} and the damping coefficient is $\xi_r = 0.7$. The drive system is working under reverse condition. The applied load torque transient is presented in Fig. 8e.

As can be concluded from Fig. 8, the motor and load speeds have the desired shapes. The estimation errors of the load speed and shaft torque are very small. The presented transient of the real and estimated variables are almost identical.

6. Experimental results

The theoretical considerations are confirmed experimentally. The laboratory set-up, presented in Fig. 9 is composed of a motor driven by a static converter. The motor is coupled to a load machine by an elastic shaft (a steel shaft of 5 mm diameter and 600 mm length). The motors have the nominal power of 500 W each. The speed and position of both motors are measured by incremental encoders (36000 pulses per rotation). There is no shaft torque sensor on the laboratory set-up. Therefore, in order to check the estimated shaft torque shape, the Kalman filter is applied [9]. The mechanical system has a natural frequency of approximately 9.5 Hz. The control and estimation algorithms are implemented with a digital signal processor using the dSPACE software.

In the analysed system the direct feedback from the motor speed and the electromagnetic torque (motor current) is realised. The additional feedbacks – form the load side speed and the torsional torque – come from NN estimators.

In Fig. 10 transients of the closed-loop control structure are presented. The assumed values of resonant frequency is $\omega_0 = 45$ s^{-1} and the damping coefficient is $\xi_r = 1$. The system works under reverse condition. The reference value of the speed is set to 0.2 of the nominal speed (Fig. 10 a,c,e), to avoid the electromagnetic torque limitation. In Fig. 10a the motor and the load speed are presented. At the time $t = 1.5$ s the passive load torque is applied ($m_L = 0.8$ m_N). At that moment only small quickly damped estimation error of the load speed appears (Fig. 10c). The NN estimator of the shaft torque provides very good estimation accuracy.
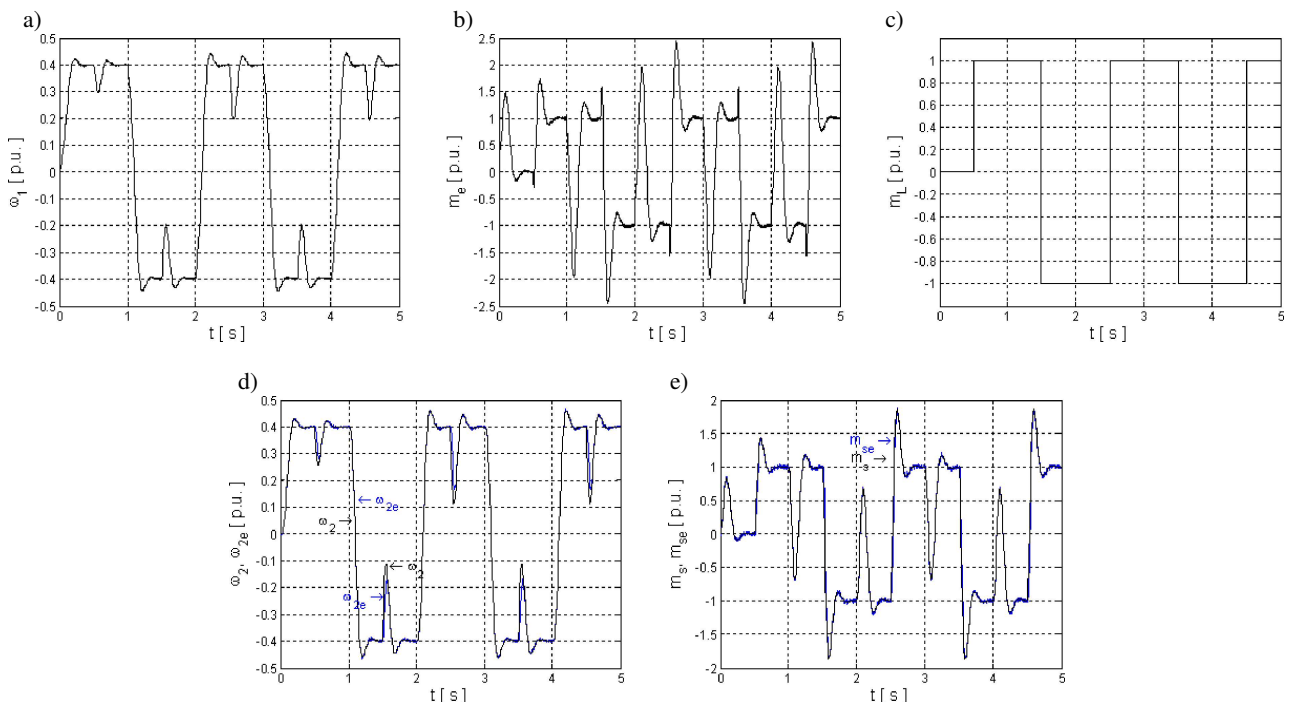

Fig. 8. Simulated transients of motor speed (a), electromagnetic torque (b), and load torque (c), real and estimated load speeds (d), real and estimated shaft torques (e) for the closed-loop control structure with NN estimators
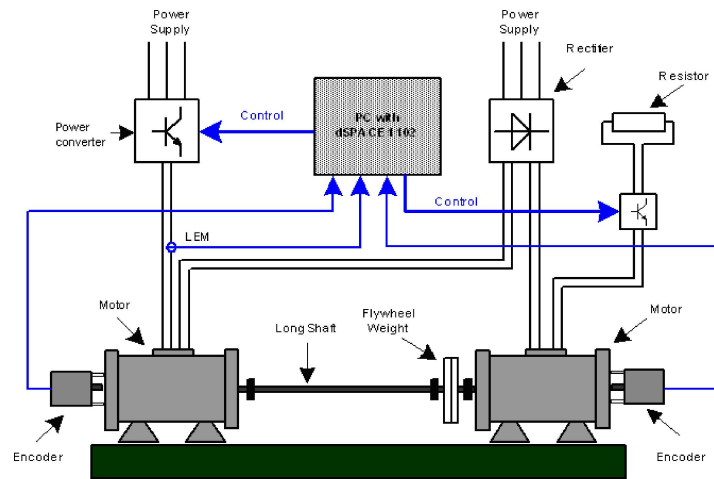
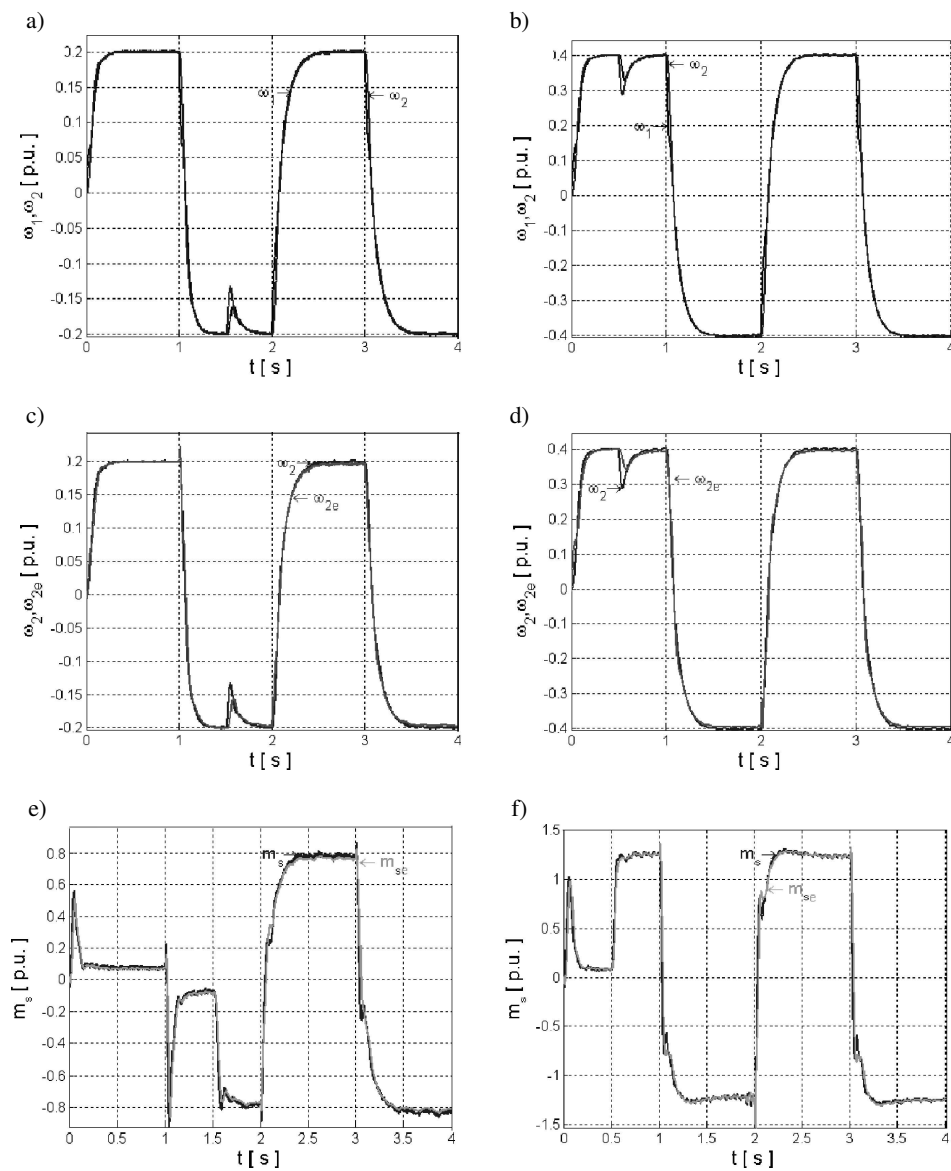Fig. 9. Schematic diagram of the experimental set-up

Fig. 10. Experimental transients of motor and load speeds (a,b), real and estimated load speed (c,d): real and estimated shaft torques (e,f) for different value of the reference speed

Then the system is tested for the bigger value of the reference speed, equal 0.4 [p.u]. The system transients are presented in Fig. 10 b,d,f. The control structure also works properly. The estimation errors of the load speed and shaft torque are small. The torsional vibrations in the two-mass drive systems are suppressed effectively using the control structure with two additional feedbacks obtained from properly trained and optimized NN estimators.

7. Conclusions

In the paper the issues related to the non-measurable variables estimation are presented.

The information about mathematical model of the drive system is not required in the design process of NN estimators. The suitable choice of training vector for the NN estimator is essential. Decision about topology of NN has significant influence to the precision of the state variables estimation. Two types of the NNs were tested and compared: the feed-forward and cascade-forward NN. The feed-forward NNs ensure better estimation accuracy than cascade-forward neural networks. The best estimation results were obtained after the application of the proposed optimization procedure of the feed-forward NN based state estimators for the drive system with elastic coupling. The experimental results have confirmed the good performance in the torsional vibration dumping of the proposed control structure of the drive system with suitably designed neural estimators of non-measurable feedback signals.

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