Robust Control of an Electrical Drive using Adaptive Fuzzy Logic Control Structure with Sliding-Mode Compensator

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Abstract—**In the paper a robust control system with the fuzzy adaptive controller and the additional compensator is presented. A model reference adaptive control system (MRAC) is applied to a drive system with changeable parameters. The speed controller is based on the neuro-fuzzy network. The additional compensator relaying on the sliding-mode theory is used to improve the dynamical characteristics of the drive system. The proposed control structure is investigated in simulation and experimental tests.**

Keywords — **motion control, fuzzy control, adaptive control.**

I. INTRODUCTION

Recently much research has been devoted to the robust control systems, where the fuzzy logic, neural network and sliding-mode based controllers are applied.

The fuzzy logic control has been successfully applied in different industrial applications as it can ensure much better dynamical performance of the controlled object than linear controllers. However, the common opinion that the fuzzy controller can be constructed easily and fast, is true only for relatively simple plants. More complex objects require a huge amount of fuzzy rules which make the design process and the analysis of those controllers very complicated [1]-[3].

The sliding mode control is robust to plant uncertainties and insensitive to external disturbances. It is widely used to obtain good dynamic performance of controlled systems. However, the chattering phenomena due to the finite speed of the switching devices can affect the system behaviour significantly. Additionally, the sliding control requires the knowledge of mathematical model of the system with bounded uncertainties [4]-[5].

Another method, popular in recent years, is based on fuzzy neural network. In paper [6] the comparison between the mentioned methods is presented. It is proved that both methods ensure good characteristics, yet the fuzzy neural network requires less control effort. Fuzzy neural networks combine the capability of fuzzy reasoning and the ability of neural networks learning from processes [6]-[11]. On the other hand, the combination of the fuzzy control base design and the sliding mode control causes the reduction of the fuzzy rules significantly. The adaptive fuzzy sliding controller is able to ensure very good dynamical performance of different industrial objects including electrical drives.

In this paper the combined solution, using a robust control system with the fuzzy adaptive controller and the additional sliding-mode based compensator is presented. A model reference adaptive control system (MRAC) is applied to a drive system with changeable parameters. The speed controller is based on the neuro-fuzzy network. The additional compensator relaying on the sliding-mode theory is used to improve the dynamical characteristics of the drive system, in the case of large load torque or parameter changes. The proposed control structure was investigated in simulation and experimental tests.

The paper is divided into five sections. After a short introduction the mathematical model of the drive system is described. Then the structure of the adaptive fuzzy controller and the compensator system is presented. In the fourth section simulation results of the system with changeable moment of inertia are presented. In the next section the short description of the laboratory set-up with selected experimental results is included.

II. MATHEMATICAL MODEL OF THE DRIVE SYSTEM

A typical electrical drive system is composed of a power converter-fed motor coupled to a mechanical system, a microprocessor-based system controller, current speed and/or positions sensors used as feedback signals. Typically, cascade control structure containing two major control loops is used. The inner control loop performs a motor torque regulation and consists of the power converter, electromagnetic part of the motor, current sensor and respective current or torque controller. Therefore, this control loop is designed to provide sufficiently fast torque control, so it can be approximated by an equivalent first order term. If this control is ensured, the driven machine could be AC or DC motor, with no difference in the outer control loop. The outer loop consists of the mechanical part of the motor, speed sensor, speed controller, and is cascaded to the inner loop. It provides speed control according to the reference value.

The mechanical part of the drive includes such nonlinearities as friction, backlash, finite stiffness of the shaft, unbalance between the motor and the load machine. In this paper the following model of the mechanical part of the system is considered (Fig. 1):

$$T_m \frac{d\omega_m}{dt} = m_e - m_L - m_f \tag{1}$$

where T_m – mechanical time constant of the drive (including motor and load), ω_m – motor speed, m_e– electromagnetic torque, m_f – nonlinear friction torque, m_L – load torque.

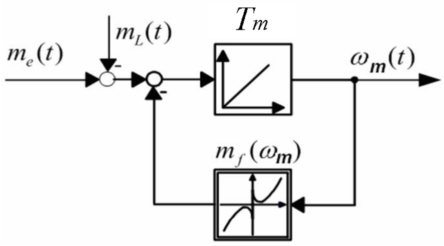

Fig. 1. The block diagram of the one-mass system

III. Adaptive Control Structure

The model reference adaptive control structure with the on-line tuning fuzzy controller and additional compensator is proposed for the drive system with a changeable mechanical time constant and unknown friction torque. The general diagram of the system is presented in Fig.2.

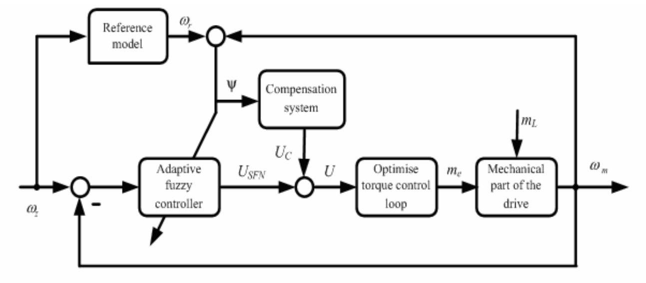

Fig. 2. Structure of the adaptive control system

The neuro-fuzzy controller [4] is tuned so that the actual drive output can follow the output of the reference model. The tracking error is used as the tuning signal. The reference model was chosen as a standard second order term [4]:

$$G_m(s) = \frac{\omega_n^2}{s^2 + 2\zeta\omega_n s + \omega_n^2} \tag{2}$$

where ζ is a damping ratio and ω_n is a resonant frequency.

The supervised gradient descent algorithm is used to tune the parameters $w_1, ..., w_M$ of the 4th layer of the neuro-fuzzy structure presented in Fig. 5, to obtain the minimizing the cost function like:

$$J(k) = \frac{1}{2}(\omega_m - \omega_r)^2 = \frac{1}{2}e_m^2 \tag{3}$$

Parameter adaptation is obtained using the following expression:

$$w_j(k+1) = w_j(k) - \gamma \frac{\partial J(k)}{\partial w_j(k)} \tag{4}$$

The chain rule is used then:

$$\frac{\partial J(k)}{\partial w_j(k)} = \frac{\partial J(k)}{\partial \omega}\frac{\partial \omega_{12}}{\partial \Delta u}\frac{\partial \Delta u}{\partial w_j} \tag{5}$$

where

$$\frac{\partial J(k)}{\partial \omega} = -(\omega_m - \omega_r) = -e_m \tag{6}$$

and

$$\frac{\partial \Delta u(k)}{\partial w_j} = O_{Nj}^3 \,, \tag{7}$$

with O_{Nj}^3 - the normalized firing strength of *j-th* rule.

Expression (6) involves computation of the gradient of ω_m with respect to the Δu output of the controller which is the change of the reference electromagnetic torque Δm_e. The exact calculation of this gradient cannot be determined due to the uncertainty of the plant and nonlinear friction characteristic. However, it can be assumed that the change of the drive speed with respect to the motor torque or current is a monotonic increasing process. Thus, this gradient can be approximated by some positive constant values. Owing to the nature of gradient descent search only the sign of the gradient is critical to the iterative algorithm convergence. So the adaptation law of the controller parameters can be written:

$$w_j(k+1) = w_j(k) + \gamma e_m O_{Nj}^3 \tag{8}$$

where e_m – error between model response ω_m and actual speed of the drive system ω_m, γ– learning rate.

However, the learning speed of the above algorithm is usually not satisfactory due to the slow convergence. To overcome this weakness, a modified algorithm based on local gradient PD control is used [10]:

$$w_j(k+1) = w_j(k) + O_{Nj}^3\left(k_p e_m(k) + k_d \Delta e_m(k)\right) \tag{9}$$

Comparing (9) to (8), one can see that k_p is equivalent to the learning rate γ. The derivative term is used to suppress a large gradient rate.

The output signal of the adaptive neuro-fuzzy controller is supported with the additional compensator, which starts operation when the relatively big error e_m occurs. So the output of control structure is the combination of the fuzzy controller output and a compensator output:

$$U = U_{SFN} + U_C \,. \tag{10}$$

The neuro-fuzzy controller has the structure described in detail in [6]-[7]. The block diagram of the applied compensator is shown in Fig. 3.

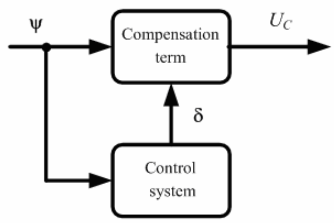

Fig. 3. The block diagram of the compensating system

The compensating system has two primary blocks: the compensator term and the block which controls it. The output signal of the compensation system δ is switched between two values, γ and -γ, depending on the value of the error sign ψ. The input signal $\boldsymbol{\Psi}$ of the compensator is composed of the error between the reference model and the object and its first derivative:

$$\boldsymbol{\Psi} = \left[\Psi,\ \dot{\Psi}\right]^T . \tag{11}$$

The output of the compensation system is described by the following formula:

$$U_S = \gamma\delta(t)\,\mathrm{sgn}(\boldsymbol{\Psi}^T \mathbf{P}_v \mathbf{B}_t), \tag{12}$$

where:

$$\dot{\delta}(t) = \lambda\left|\boldsymbol{\Psi}^T \mathbf{P}_v \mathbf{B}_t\right| . \tag{13}$$

Coefficients λ and γ in (12), (13) are positive scalars. The vector $\mathbf{B_t}$ is composed in the following way:

$$\mathbf{B_t} = [0 \quad B_{pn}]^T \tag{14}$$

where B_{pn} is inversely proportional to the drive inertia.

The $\mathbf{P_V}$ is symmetrical, positive defined matrix which fulfills the Lapunov equation:

$$\boldsymbol{\Lambda}^T \mathbf{P}_v + \mathbf{P}_v \boldsymbol{\Lambda} = -\mathbf{Q} \tag{15}$$

where $\boldsymbol{\Lambda}$ is defined in the following way:

$$\boldsymbol{\Lambda} = \begin{bmatrix} 0 & 1 \\ -k_1 & -k_2 \end{bmatrix} \tag{16}$$

The coefficient k_1 and k_2 are positive scalars.

In some special cases, when $t \to \infty$, the value of $\dot{\delta}$ can reach very large value. Therefore in the real system the equation (13) is replaced by the following formula:

$$\dot{\delta}(t) = I\lambda\left|\boldsymbol{\Psi}^T \mathbf{P}_v \mathbf{B}_t\right| \tag{17}$$

where I is the initialization (switching) function for the compensation term. This function can be formulated in different ways [2]. In this paper the switching function was described as follows:

$$I = 1 - U_{fuz}, \tag{18}$$

where U_{fuz} is the nonlinear fuzzy function.

IV. Simulation Results

The quality of reference speed tuning strictly depends on k_d and k_p parameters of the adaptive law (9). For the bigger value of these parameters, the faster decrease of the tracking error is obtained. However, too large value of adaptation coefficients introduces the high-frequency oscillations into the system states. Also the parameters of the compensation system have big influence on dynamical performances of the drive. In order to select the optimal value of all parameters the following procedure was applied. In the first step, parameters k_d and k_p of the adaptation law were tuned in order to get the best dynamical characteristic of the system. In the second step the parameters of the compensation system were set in the way which improved performance of the system. In all tests presented below the initial controller parameters were set to zero. This means that the system could be totally unknown.

In Fig. 4 transients of the system with 9-rules neuro-fuzzy controller are demonstrated for the resonant frequency of the reference model set to ω_n=40s^{-1}. The system is disturbed with changeable load torque presented in Fig. 4h. In this particular case the mechanical time constant of the drive system has nominal value T_m=0.203s. In Fig. 4a the reference, motor and load speeds are presented for 1the first 10s of the system work. The system starts with the controller weights set to zeros (Fig.4d). It means that the parameters of the drive are unknown. Despite this, the initial tracking error is very small and is decreasing continually (Fig. 4g). In Fig. 4b the fragment of the system speeds are shown. It is clear that even in the first period of the work the motor speed covers the reference signal almost perfectly. In Fig. 4c the electromagnetic torque is presented and in Fig. 4e and Fig. 4f the control signals produced by the neuro-fuzzy controller and compensating system are shown, respectively. The compensation system supports the neuro-fuzzy controller only when the tracking error excides selected value. Its signal is switched on and off by a supervisory fuzzy system.

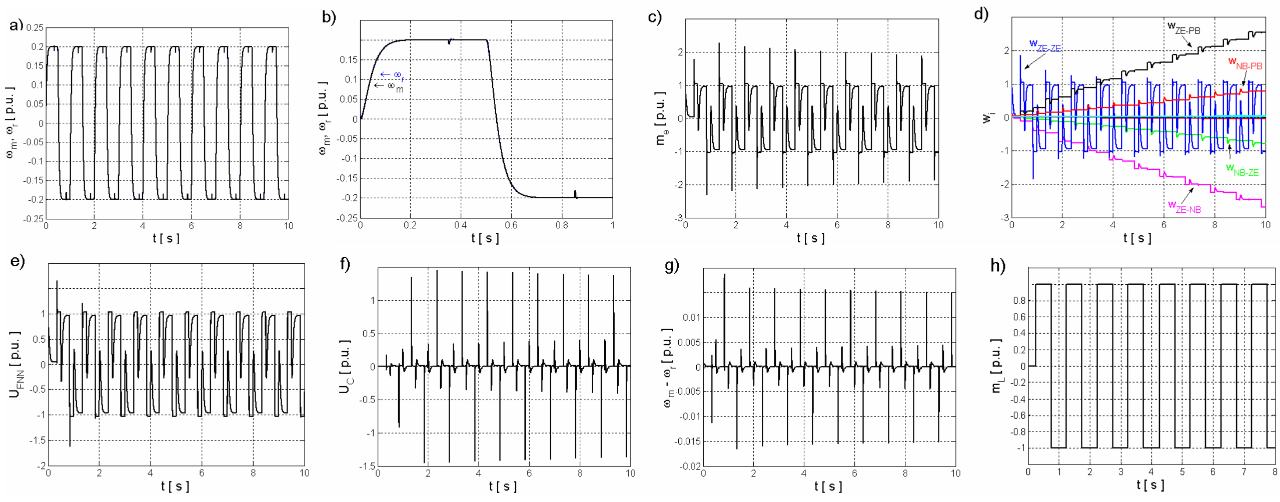

Fig. 4. Transients of the system with nominal parameters: motor and reference speed (a,b), electromagnetic torque (c), selected controller weights (d), control signals generated by fuzzy con-troller (e) and compensator (f), tracking error (g), load torque (h)

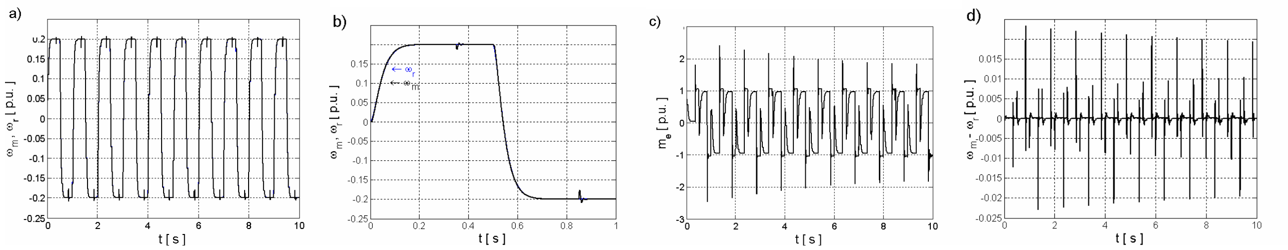

Fig. 5. Transients of the system with nominal parameters, without compensator: motor and reference speed (a,b), electromagnetic torque (c), tracking error (d)

In order to show the advantages of the proposed sliding-mode compensator, in the next step the control structure without such a system was investigated. In Fig.5 the selected transients of the system working in the same conditions as above are shown. (T_m=203ms). In Fig.5a,b the system speed are demonstrated. As can be concluded from the Fig.5d, the tracking error is 25% bigger in this case than before (compare Fig.4g and Fig.5d). The forced electromagnetic torque is demonstrated in Fig.5c.Next the proposed control system (neuro-fuzzy controller with compensator) was tested in operation with rapid changeable time constant of the load machine. The applied load torque has the transient presented in Fig. 4h. In Fig. 6 the system transients are presented.

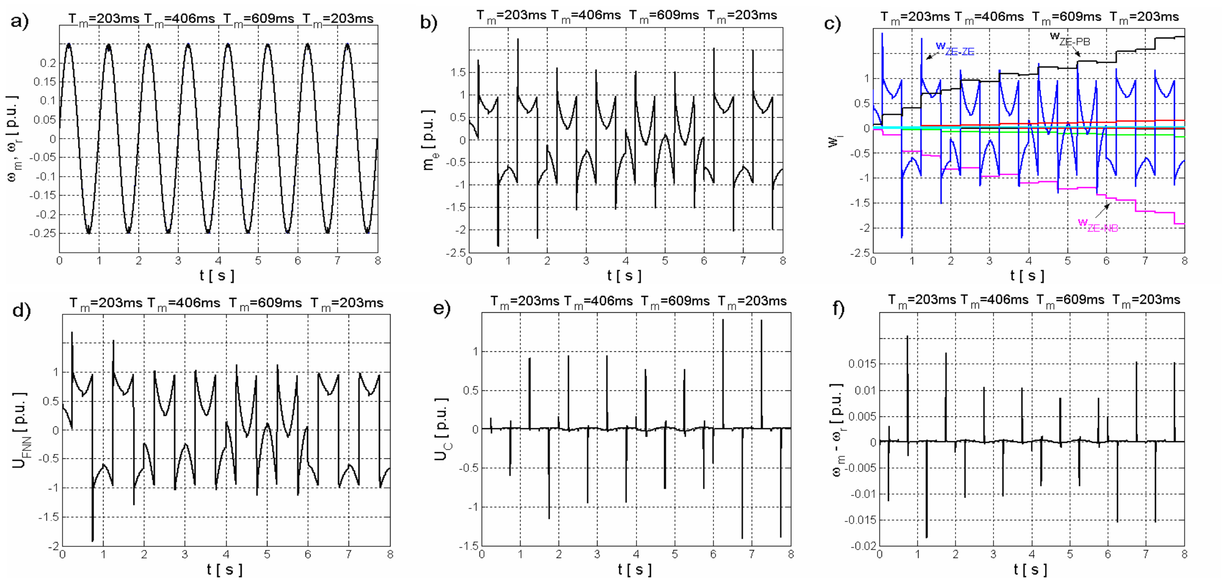

Fig. 6. Transients of the system with changeable mechanical time constant: motor and reference speed (a), electromagnetic torque (b), selected controller weights (c), control signals generated by fuzzy controller (d) and compensator (e), tracking error (f)

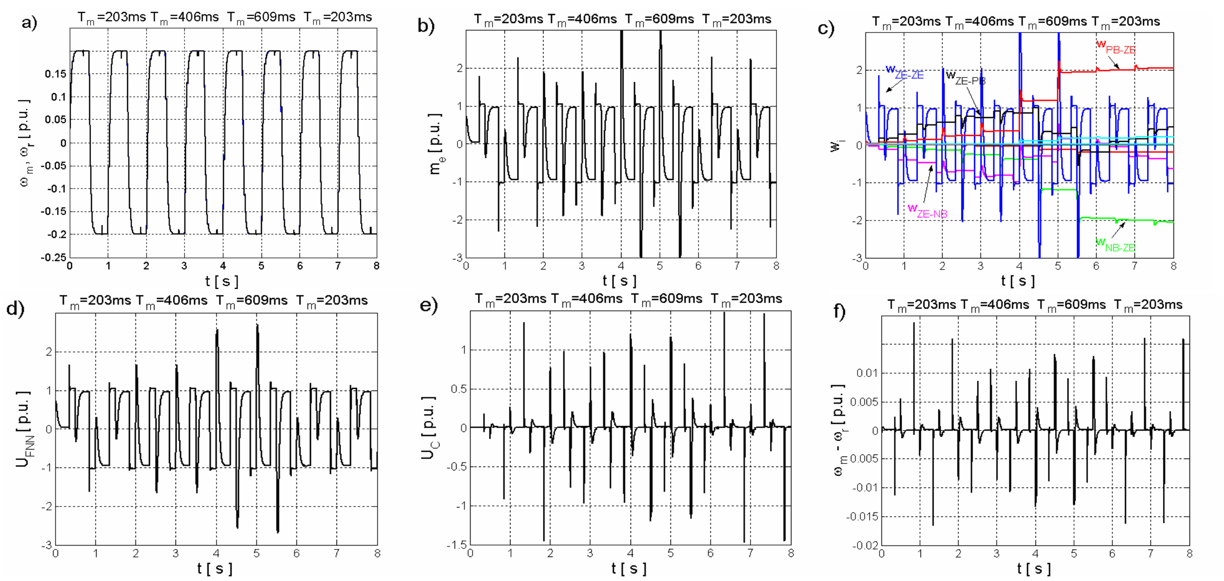

Fig. 7. Transients of the system with changeable mechanical time constant: motor and reference speed (a), electromagnetic torque (b), selected controller weights (c), control signals generated by neuro-fuzzy controller (d) and compensator (e), tracking error (f)

The initial time constant of the load machine T_m is set to 203ms. Then at the time t_2=2s the value of the T_m is changed to 406ms, next at the time t_3=4s load inertia is varied to T_m=609ms and finally it decreases to the value T_m=203ms at the time t_4=6s. The controller starts operation with no knowledge about the controlled plant, i.e. the initial values its output functions are set to zero (Fig. 6c). Despite this, the tracking error between the load and the reference speeds is small for the whole time of the work. In Fig. 7b the electromagnetic torque is shown. It has the biggest value when mechanical time constant T_m=609ms. The output weights are shown in Fig. 6c. The characteristic shape has the weight of the rule zero-zero. It is very similar to the electromagnetic torque transient. The control signals produced by the fuzzy controller and the compensator are shown in Fig. 6d and Fig. 6f respectively.Then the performance of the drive for the sinusoidal type of the reference signal and drive inertia changes was investigated. In this case the reference model was replaced with the transfer function $G_M(s)=1$. In Fig. 7 the system transients are shown.

The program of the drive inertia changes is similar as in the previous case. Despite of parameter changes, the system works in the proper way. The motor speed covers the reference signal almost perfectly. The biggest tracking error appears when the system is disturbed by the rapid load torque changes. The main part of the control signal is produced by fuzzy controller (Fig.7d). The compensation system supports the main controller only in the cases when tracking error reaches big values. The output functions of the fuzzy controller are shown in Fig. 7c. The system starts work with initial parameters set to zero. During the work the weight functions change (Fig.7c) in order to ensure the minimum tracking error.

V. Experimental Results

The experimental set-up is established to check the efficiency of the proposed controller in real conditions, including measurements noise, variations in plant parameters (mechanical time constant, friction) and load torque changes. This set-up, presented in Fig.8, is composed of a DC motor driven by a four-quadrant chopper. The motor is coupled to a load machine by stiff shafts. The load machine is also a DC motor. The two motors have the nominal power of 500W each. The speed and position of the motor are measured by incremental encoders (4096 pulses per rotation). The control algorithm is implemented in the digital signal processor DS1102 using the dSPACE software.

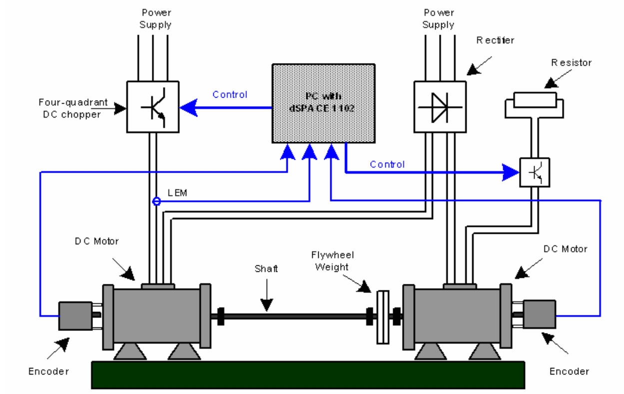

Fig.8. Schematic diagram of the experimental set-up

A number of experiments is carried out to check the performance of the proposed control structure with adaptive tuning of neuro-fuzzy controller's parameters. The nominal value of time constant of the load machine is 203ms. The applied controller has 9 rules as in the simulation study. In Fig. 9 the system transients with different reference signals are presented. In Fig. 9a the reference and motor speeds for the resonant frequency set to 20s^{-1} are demonstrated. As in simulation study, the system is disturbed by load torque changes. The difference between the reference and the drive speeds is very small. In Fig. 9d the transient of the electromagnetic torque is shown.

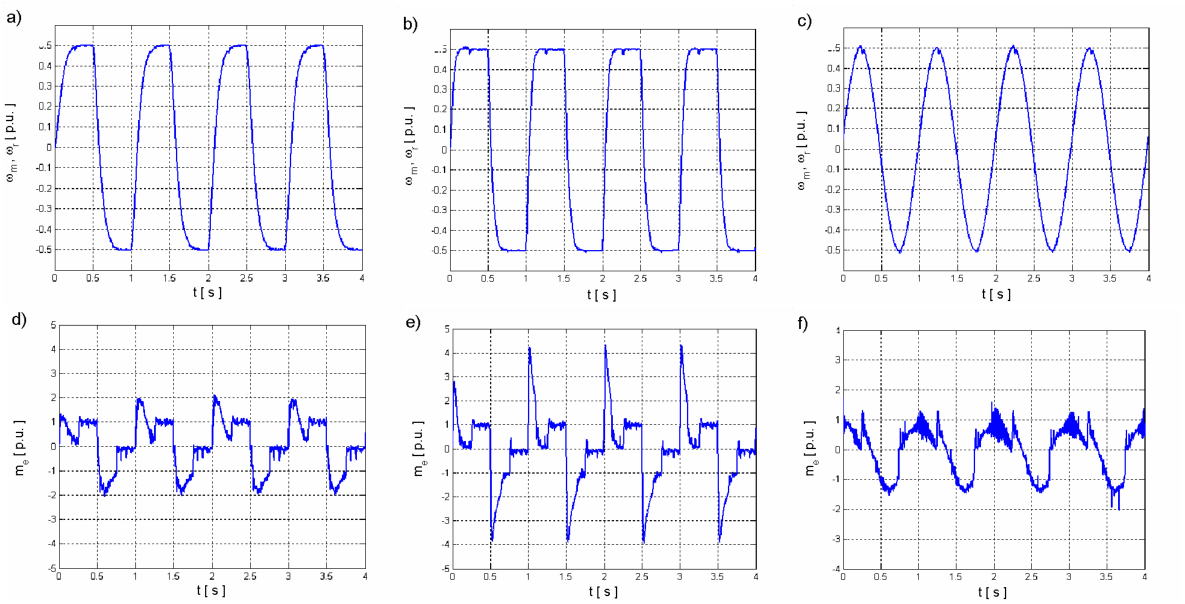

Fig. 9. Experimental transients of the system with nominal parameters: motor and reference speeds (a,b,c), electromagnetic torque (d,e,f), for resonant frequency ω_r=20s^{-1}(a,d), ω_r=40 s^{-1} (b,e), sinusoidal reference signal (c,f)

Next the control system was examined with the resonant frequency of the reference model set to $40s^{-1}$. The bigger resonant frequency of the speed reference means the harder conditions for the adaptation process. Still, the system works in a stable way. The system state transients are presented in Fig. 9c,d. There is no visible difference between the reference and the drive speeds. Then the control structure was examined for the sinusoidal reference signal. The transfer function of the reference model was set to 1 in this case. In Fig. 9e,f system transients are demonstrated. Even during the first period of the work the tracking error is almost eliminated. In the Fig. 9f the electromagnetic torque is demonstrated. The presented results confirmed the simulation work.

VI. CONSLUSION

In the paper the results of research concerning the application of the adaptive neuro-fuzzy controller with compensation system to a drive system is presented. The performances of the considered systems with different controllers are demonstrated by simulation and experimental results. The obtained results confirmed the efficiency of the proposed FNC adaptive scheme for control of a drive system without use of any qualitative knowledge about the plant parameters (the FNN parameters are initialized with null actions). It means, that an adaptive FN controller can deal with large range of parameters variations and external disturbance due to its on-line learning capability. It is shown that the additional compensator support the fuzzy controller and decrease the tracking error, especially in the case of sudden changes of the load torque or drive system parameters. The suitable design of the supervisory fuzzy system ensure the proper work of the whole control structure.

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