Speed Sensorless Neuro-Fuzzy Controller for Brush type DC Machines

Ferenc FARKAS, Sándor HALÁSZ, István KÁDÁR

Budapest University of Technology and Economics,
Department of Electric Power Engineering
1111 Budapest, Egry József u. 18., Hungary
E-mail: ikadar@eik.bme.hu

Abstract: A speed sensorless neuro-fuzzy controller is proposed for brush type DC motors. The actual speed of the DC machine is estimated using a feed-forward neural network. The inputs of the neural network are the armature current and voltage of the DC machine and their changes in time. Because DC machines are usually fed by 4-quadrant chopper, the measured armature voltage and current contains higher order harmonics, which have reduced value on the output of the neural network. Since the fuzzy controller is a robust system, which tolerates the noisy input to some degree, the observed speed signal is fed to a PI like fuzzy controller. The output of the fuzzy controller is the current reference for the PWM servo system. The proposed neuro-fuzzy controller is robust to the change of load, inertia and speed reference.

Keywords: Speed sensorless control, neuro-fuzzy controller, brush type DC motor

1 Introduction

In most servo systems the speed information is usually obtained from a shaft encoder. The precision of the shaft encoder influences the smoothness of the measured speed, especially in the lower speed range [6]. In order to avoid this drawback, one may use a higher precision shaft encoder, which however, increases the overall price of the DC drive. In order to avoid shaft encoder at all, the speed of the brush type DC motor is estimated from the motor induced voltage U_e. One classical way for brush type DC motor with constant flux is shown in Fig.1 where the rotor speed is estimated by measuring the induced voltage. The voltage equation of the DC motor circuit is

$$U = U_e + I \cdot R \tag{1}$$

where I represents the armature current and R the armature resistance. The potential difference in the bridge is half of the induced voltage, which is proportional to the rotor speed. The factor K depends on the flux (excitation) and the motor construction. The speed of the DC motor is controlled by changing the U_d voltage.

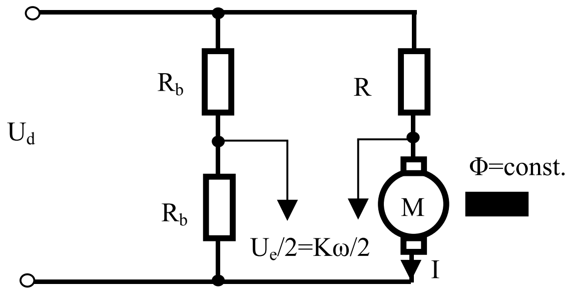

Fig.1. Estimating rotor speed at constant flux

The presented rotor speed estimation has two shortcomings: the flux must be constant and the U_d voltage cannot be changed abruptly, otherwise another term appears in equation (1), namely the change of current. The first shortcoming can be avoided using DC servomotor with permanent magnet, in which case the flux is constant. However, the second shortcoming it makes impossible to use this method in modern PWM servo systems, where the motor voltage has square-wave form with 2 or 3 values, namely $\{-U_d,+U_d\}$ or $\{-U_d,0,+U_d\}$. The chopping frequency of the PWM system is 10kHz-50kHz. The voltage equation of the armature circuit in this case is

$$u = u_e + i \cdot R + L\frac{di}{dt} \tag{2}$$

where R, L are the armature resistance and inductance, respectively. Lowercase letters in equation (2) indicate that using PWM servo system the instantaneous values of current and voltage should be considered. Reordering equation (2) and taking into account that $u_e = K\omega$ the following relation is obtained:

$$K\omega = u - i \cdot R - L\frac{di}{dt} \tag{3}$$

Thus, from equation (3) the rotor speed can be estimated. However, measuring of u and i is not an easy task when using 4 quadrant chopper amplifier. In the next section a feed-forward neural network is shown, which is trained to approximate equation (3).

2 Estimating the armature voltage in case of PWM

There is no use to measure the instantaneous armature voltage which, as was mentioned already, is varying between $\{-U_d,+U_d\}$ or $\{-U_d,0,+U_d\}$, depending on the applied modulation technique, symmetrical or cyclical, respectively. It is more appropriate to estimate the so-called *instantaneous-average* armature voltage. It is instantaneous in the sense that changing the current reference of the current controller abruptly the average armature voltage should change abruptly, as well. But it is also an average value, because for a given current reference (in steady state) the estimated armature voltage has an almost constant value with "noise" and not an impulse-like signal. There are two ways to estimate the armature voltage: either calculating the armature voltage from the switch on/off time of the chopper or measuring the integrated armature voltage using ADC. Further these two techniques will be presented briefly.

2.1 Calculating the instantaneous-average armature voltage

When discrete current controller is implemented with symmetrical modulation technique using a DSP (Digital Signal Processing) the instantaneous-average armature voltage u_a can be calculated using the following relation (considering ideal switches in the chopper – see Fig.2.):

$$u_a = \frac{t_1 \cdot U_d + t_2 \cdot (-U_d)}{t_1 + t_2} \tag{4}$$

where t_1 is the time during which the armature voltage is $+U_d$ and t_2 is the time when the armature voltage is set to $-U_d$. Thus, at a carrier frequency of 20 kHz, the instantaneous-average armature voltage should be calculated in every 50 μs using equation (4), where t_1 and t_2 can be obtained using a timer with a clock frequency of at least 10 times higher then the carrier frequency. (In order to reduce the fluctuation, the average of the last 10 calculated values is given to the input of the neural network.)

The presented method has the advantage that there is no need to measure the armature voltage directly. However, the exact schedule of switching of the chopper transistors is needed.

2.2 Measuring the instantaneous-average armature voltage

Using a 20 kHz 4 quadrant chopper with symmetrical modulation technique the armature voltage varies between $\{-U_d,+U_d\}$, and it's average value might change in every 50 μs. Taking into account that the control cycle time is in order of 100 μs, the instantaneous-average voltage should be measured in such way that its fluctuation be minimal in one hand but an abrupt change in load or reference be followed as well. Using RC integration circuit (filter) the average armature voltage can be obtained by hardware. An important question is, what value should be selected for R_v and C_v, or more importantly what time-constant of the R_vC_v circuit needed?

As it can be seen in Fig. 2., the armature voltage varies between $\{-U_d,+U_d\}$. There must be made a compromise of requirements when the armature voltage is measured in steady state and in transient state. In steady state (the upper diagram in Fig. 2.) the armature voltage variation can be seen as a noisy DC voltage. Thus, this variation has to be filtered as much as possible. However, in transient state (the lower diagram of Fig. 2.) the measured voltage should follow the armature voltage as quickly as possible. The voltage on the capacitance C_v is changing by

$$U_C(t) = U_d(1 - e^{-\frac{t}{T_{RC}}}) \tag{5}$$

from where the R_vC_v time-constant can be calculated as

$$T_{RC} = -\frac{t}{\ln\left[1 - \frac{U_C(t)}{U_d}\right]} \tag{6}$$

Taking into account that the control cycle time is in order of 100 μs let the variation of the steady-state voltage at 50% duty cycle be 10% of U_d, that is, $U_C(50\mu s)=0.1U_d$ – results that the time-constant of the R_vC_v circuit should be set to T_{RC}=0.5 ms.

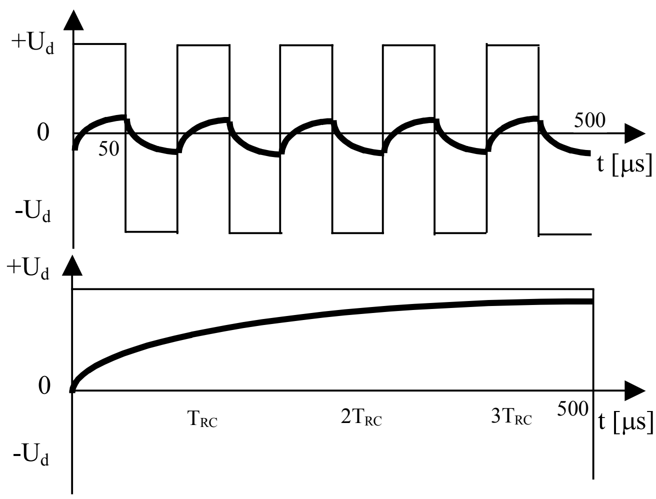

Fig. 2. Armature voltage (real with thin and measured with thick line)

It is worth noting that using cyclical modulation technique the fluctuation of the armature voltage and current is much less than in case of symmetrical modulation technique. The armature voltage is changed only between –Ud, 0 or 0, +Ud with a frequency equal to the double of the chopping carrier frequency used by the modulation, thus the armature current fluctuation is much less.

3 Estimating the speed using neural network

From equation (3) the rotor speed can be obtained by measuring the armature voltage, armature current and the derivative of the armature current. Because the armature voltage is varying between $\{-U_d,+U_d\}$, the armature current also has fluctuation. Thus, before calculating the change of armature current it should be filtered (we are not interested in the derivative of the fluctuation, only in the trend of the change of the armature current). Experience shows that much better results can be achieved if the derivative of the armature voltage is also supplied to the neural network (in the same way as the armature current). The time-constant of the R_iC_i circuit for the derivative of armature voltage and current is calculated on the bases of equation (6). Thus, the neural network has four inputs: $u, \frac{du}{dt}, i, \frac{di}{dt}$ while the output is the estimated rotor speed ω.

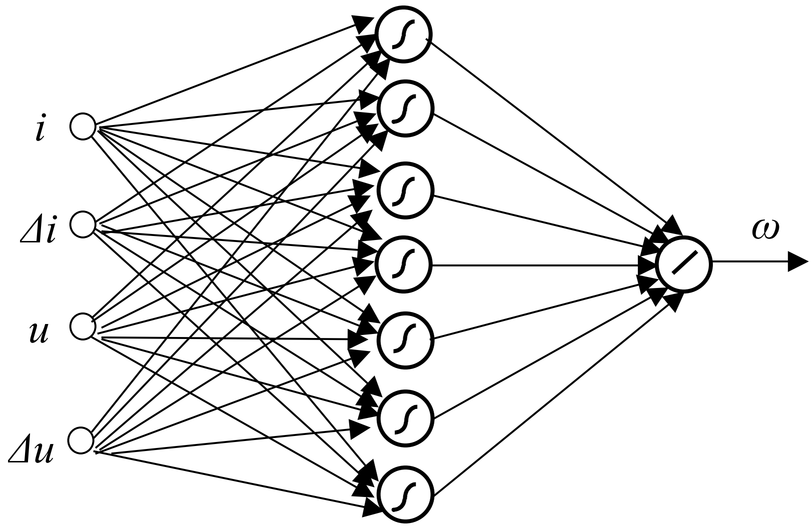

Fig. 3. The structure of the neural network used

The applied neural network is a multilayer feed-forward network with 7 hidden neurons with tan-sigmoid transfer function and 1 output neuron with linear transfer function as it can be seen in Fig. 3. Each neuron has weights and a bias, not shown in the picture.

The neural network training can be made more efficient if certain preprocessing steps are performed on the network inputs and targets (see User's Guide of MATLAB Neural Network Toolbox). The simplest preprocessing technique is the MIN-MAX scaling, when the inputs and targets are scaled so they always fall into a specified range, for example [-1, +1]. The following relation is used to preprocess the inputs and targets:

$$P_N = 2 \cdot \frac{P - MIN}{MAX - MIN} - 1 \tag{7}$$

where P is the original and P_N is the normalized value.

The trained neural network estimate the motor speed in the range of [-1, +1], thus, it must be postprocessed in order to obtain the corresponding value:

$$P = 0.5 \cdot \frac{P_N + 1}{MAX - MIN} + MIN \tag{8}$$

However, postprocessing is eliminated when the output of the neural network is the input of the fuzzy controller, which has normalized inputs and outputs. The neural network is trained with input/target pair obtained from the DC machine step response. Different speed references can be included in the training set. After training, the neural network is able to estimate the speed very well not only for the speed values, which were included into the training set.

It is worth nothing that the neural network is trained not only for steady state but for transient state as well (step response). Thus, the neural network can handle the abrupt change of speed reference and load, as well.

4 Considering flux control

When the rotor speed is modified by flux control, a new input has to be added to the neural network. This 5^{th} input is the excitation current. The neural network has to be trained with a training set, which includes the excitation current. At least two different excitation current values should be included in order to obtain good results. In this way the neural network will interpolate or even extrapolate for excitation currents different from the training set. The goodness of interpolation or extrapolation depends on the number of different excitation currents included in the training set. Choosing the right excitation current and speed reference values for training enhances the neural network response.

5 Adaptive fuzzy controller

For speed control PI-like fuzzy controller (FC) is used with inputs of error and change of error, where the error is the difference between the speed reference signal and the estimated rotor speed. The output of the controller is the current reference for the PWM servo system. The usage of the fuzzy controller has two advantages: 1.) the fuzzy controller has nonlinear transfer function, thus better controller can be obtained compared to the conventional PI controller [2]; 2.) the fuzzy controller is a robust system, which tolerates the noisy input to some degree.

An adaptive fuzzy controller is implemented in respect to the change of load torque. In every control cycle first the load is estimated then the membership functions of the FC are modified in respect to the evaluated load. The best estimation of the load can be achieved by computing the derivative of the speed and the armature current. However, the motor current and observed speed contains noises, therefore the load estimation is performed by integrating the motor current to filter out the noises. The load is computed by the following formula:

$$M_l = \frac{K\int_{\Delta t} i \cdot dt - J \cdot \Delta\omega}{T} - M_v \tag{9}$$

where J represents the inertia, M_v is the frictional torque and $\Delta\omega$ is the change of speed during $\Delta t = N \cdot T$ time, where N represents the number of samples considered to damp the noise of the motor current and fluctuation in the change of speed, while T is the speed control cycle time.

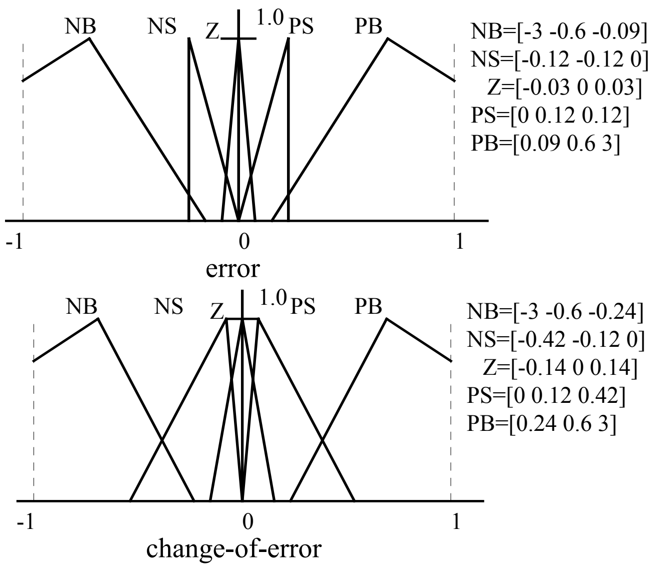

Fig. 4. The input membership functions of the fuzzy controller

By altering the position of the membership functions (see Fig. 4) in the input universe the influence of the change of load torque can be modified. First the effect of load torque variation to the system behaviour should be considered. When the load torque has the same direction as the motor torque, in order to eliminate any overshoot, the fuzzy input should be less sensitive to the error. Thus, the membership functions NS, PS of error are moved away from 0. On the contrary, when the load torque has opposite direction compared to the motor torque, the fuzzy input should be more sensitive to the error. Thus, the membership functions NS, PS of the error are moved towards 0.

Finally, as it can be seen in Fig. 4 and Fig. 5, the nonlinearity in the fuzzy controller is introduced by the appropriate distribution and shape of the input and output membership functions.

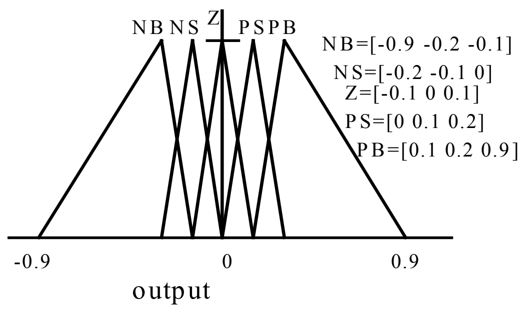

Fig. 5. The output membership functions of the fuzzy controller

6 Simulation results

Simulation results were obtained using MATLAB Simulink program. The neural network was trained in batch mode with Levenberg-Marquardt algorithm. Training set was obtained using step response of the DC motor with positive to negative load. The obtained result in Fig.6 shows a small overshoot of speed.

7 Experimental results

The experimental plant consists of two identical permanent magnet DC motors that are joined together by a clutch as it is shown in Fig. 7. One of them is the controlled motor and the other one is used as a load. Both DC motors are driven separately by two identical PWM servo amplifiers containing analogue PI controllers for the current loop as well as a four-quadrant chopper with 22 kHz chopping frequency and symmetrical modulation technique. The fuzzy controller and with the neural network are implemented in the same personal computer. The control program receives the armature current and voltage samples at every 400 μs. The shaft position of the motor is obtained from optical encoder (ROD426) through encoder control card (EB3005) and is used only to obtain the target for the neural network training set. The DC servomotor parameters are shown in Table 1.

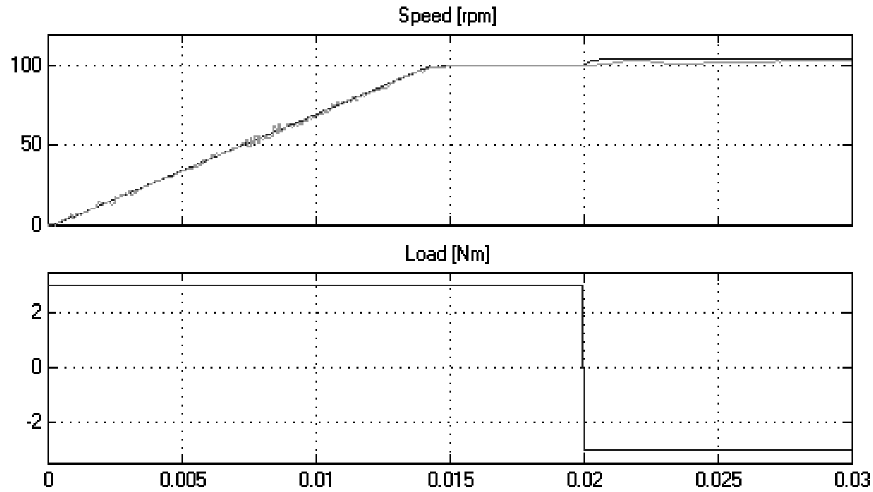

Fig. 6. Simulation result with change of load from +3 to –3 Nm

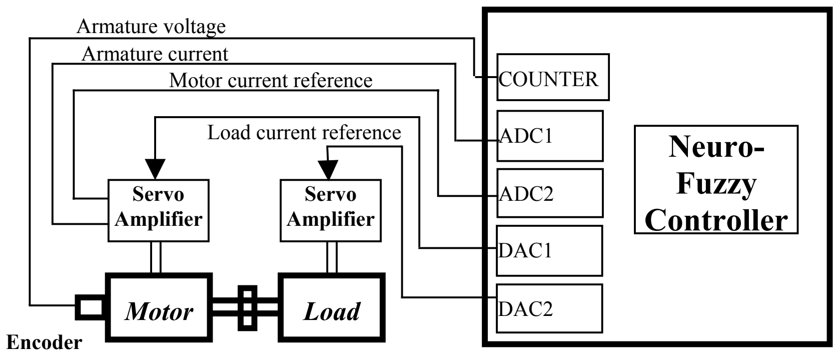

Fig. 7. Experimental plant for the neuro-fuzzy controller

The neural network was trained in batch mode with Levenberg-Marquardt algorithm using three sets of input/target pairs corresponding to samples obtained from three step responses of the reference speed signals: 4000, 5000 and 6000 rad/s. After the neural network was trained the encoder was unplugged and the fuzzy controller received the estimated speed signal from the neural network. The obtained results are shown in Fig. 8, Fig. 9. and Fig. 10. (w – rotor speed [rad/s], i – armature current [A], u – armature voltage [V]). These results testify to acceptable accuracy of speed in wide range.

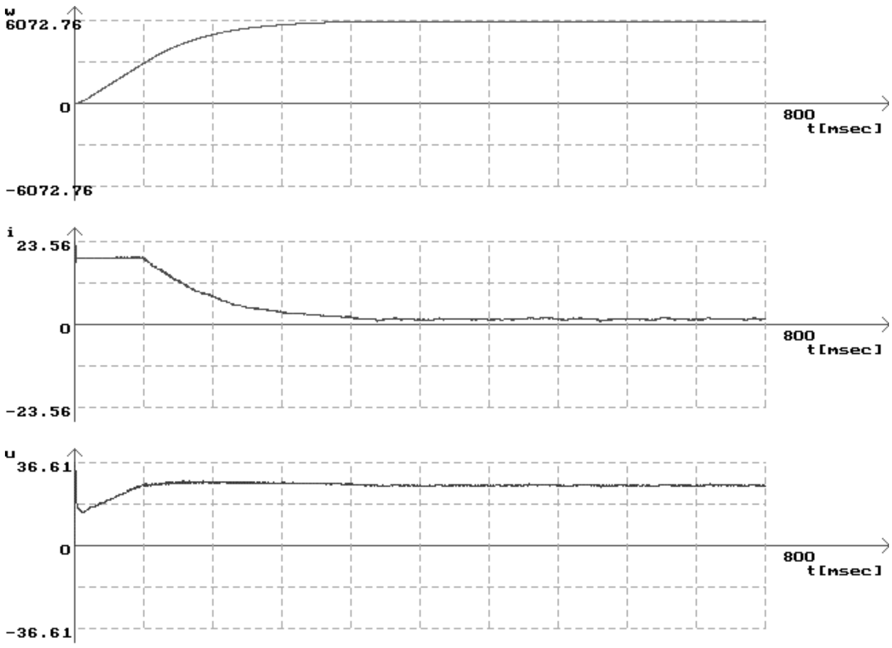

Fig.8. Step response of the neural-fuzzy controller (w_{ref}=6000rad/s)

Table 1. Parameters of the DC servomotor

Parameters	**Notation**	**Value**	**Unit**
Nominal torque	M_n	3	Nm
Nominal current	I_n	13	A
Maximal current	I_{max}	80	A
Speed domain	ω	0-2500	rpm
Frictional torque	M_f	0.113	Nm
Rotor inertia	J_n	0.00192	kgm^2
Torque coefficient	K_n	0.24	Nm/A
Armature	L_a	1.6	mH
Armature resistance	R_a	0.49	Ω

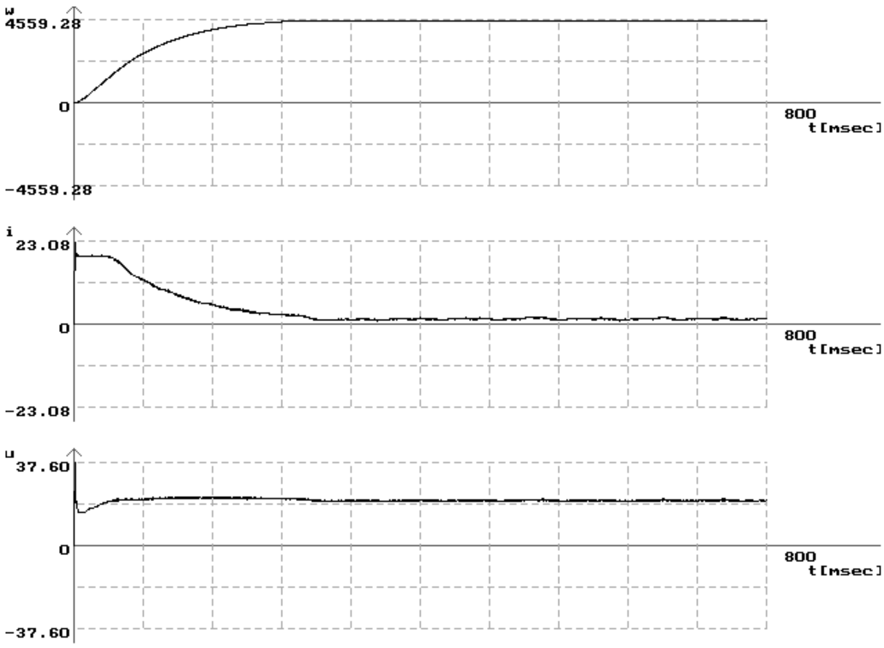

Fig.9. Step response of the neural-fuzzy controller (w_{ref}=4500rad/s)

Conclusions

In this paper a robust neuro-fuzzy speed control for brush type DC drive is presented. A neural network is used to estimate the rotor speed of the DC machine by measuring the armature current and voltage. The estimated speed is applied to the adaptive fuzzy controller, which provides robust control of the speed of DC drive. The results of the experiment on the real plant demonstrates that the neural network is able to estimate not only the speeds included in the training set, but it also is able to interpolate and extrapolate well. The proposed adaptive fuzzy controller shows robustness to the fluctuation of the estimated speed and to the variation of load torque.

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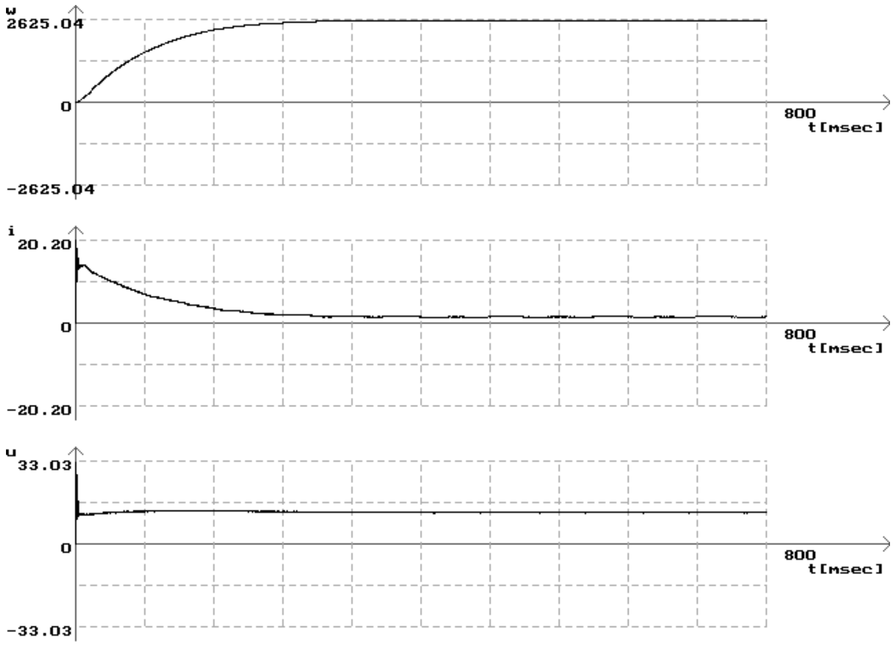

Fig.9. Step response of the neural-fuzzy controller (w_{ref}=2600rad/s)

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