NEURAL SPEED ESTIMATOR FOR THE INDUCTION MOTOR DRIVE

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SUMMARY

Artificial neural networks are recently showing good promise for application in power electronics and motion control system. They have been applied mainly in control of converters and drives. Sensorless control of the induction motor drives requires knowledge of the instantaneous value of the rotor speed. Various methods of the rotor speed estimation were recently used, based on the mathematical models of the induction machine, on non-linear phenomena of the motor and based on neural networks. This paper deals with utilisation of artificial neural networks (ANN) for observing an induction motor drive variables. The observing is realised utilising several quasi-single estimators, number of those is equal to number of observed variables. The observers are based on feed-forward neural network and on cascade-forward backpropagation ANN, respectively. The structure of the neural network is analogues to the mathematical model of an induction motor. Stator currents and stator voltages of the induction motor are inputs of the neural network. Estimation is based on off-line learning principle using backpropagation algorithm with Levenberg-Marquardt algorithm. The simulation using Matlab with Simulink realises the application results. Rotor flux, torque and angular speed of an induction motor are estimated. Changes in the rotor resistor do not influence the quality of observing.

The results of simulated experiments indicate that a neural network can be an alternative way to other estimation methods.

Keywords: *artificial neural network, control system, estimation techniques, an induction motor, off-line mode*

1. INTRODUCTION

The neural network observer design starts from an analogy between the known model of the induction motor and structure of the observer. The induction motor is described in the rotating system *x*, *y* by the set of equations:

$$i_{1x}=\frac{1}{\sigma L_1}\psi_{1x}-\frac{L_h}{\sigma L_1 L_2}\psi_{2x} \tag{1}$$

$$i_{1y}=\frac{1}{\sigma L_1}\psi_{1y}-\frac{L_h}{\sigma L_1 L_2}\psi_{2y} \tag{2}$$

$$i_{2x}=\frac{1}{\sigma L_2}\psi_{2x}-\frac{L_h}{\sigma L_1 L_2}\psi_{1x} \tag{3}$$

$$i_{2y}=\frac{1}{\sigma L_2}\psi_{2y}-\frac{L_h}{\sigma L_1 L_2}\psi_{1y} \tag{4}$$

$$\frac{d\psi_{1x}}{dt}=u_{1x}-R_1 i_{1x}+\omega_k\psi_{1y} \tag{5}$$

$$\frac{d\psi_{1y}}{dt}=u_{1y}-R_1 i_{1y}-\omega_k\psi_{1x} \tag{6}$$

$$\frac{d\psi_{2x}}{dt}=u_{2x}-R_2 i_{2x}+(\omega_k-\omega)\psi_{2y} \tag{7}$$

$$\frac{d\psi_{2y}}{dt}=u_{2y}-R_2 i_{2y}-(\omega_k-\omega)\psi_{2x} \tag{8}$$

The motor torque is described using the stator variables:

$$\begin{aligned} t&=\frac{3p}{2}Im\left(\psi_{1x}-j\psi_{1y}\right)\left(i_{1x}+ji_{1y}\right)\\ t&=\frac{3p}{2}\left(\psi_{1x}i_{1y}-\psi_{1y}i_{1x}\right)\end{aligned} \tag{9}$$

The mechanical dynamics of the motor and load systems is described by:

$$J\frac{d\omega}{dt}=t-t_l \tag{10}$$

where:

i_{1x}, i_{1y}, (i_{2x}, i_{2y})	- *x, y* components of stator (rotor) current vector
Ψ_{1x}, Ψ_{1y}, Ψ_{2x}, Ψ_{2y}	- *x, y* components of stator (rotor) magnetic flux vector
ω_k, ω	- synchronous (mechanical) angular speed
R_1, R_2	- stator (rotor) winding resistance
L_1, L_2, L_h	- stator, rotor and main inductance
σ	- leakage factor
p	- number of poles
t_l	- load torque

Estimators were designed for the following IM motor:

P_N=3 kW, U_N=220 V, I_N=6.9 A, n_N= 1420 rpm, J_N=0.1 kg.m2, R1=1.81 Ω, R2=1.91 Ω, $L1_N$=$L2_N$=0.00885 H, Lh_N=0.184 H, p_p=2, σ=0.0897

2. DESIGN OF ROTOR FLUX

The rotor magnetic fluxes are not measurable simply. One of possible solutions consists in utilisation of the ANN as an observer.
The design starts from realisation of the representation described by equations:

$$\psi_{2x} = \frac{\sigma L_1 L_2}{L_h}\left(\frac{1}{\sigma L_1}\psi_{1x} - i_{1x}\right) \tag{11}$$

$$\psi_{2y} = \frac{\sigma L_1 L_2}{L_h}\left(\frac{1}{\sigma L_1}\psi_{1y} - i_{1y}\right) \tag{12}$$

The equations were obtained simply by expressing the both rotor flux components from the equations (1) and (2). The ANN presents a certain analogy of the real model of the induction motor. From the equations (11) and (12) it follows, the both components of the stator current and stator flux will present the inputs into the ANN. The stator flux components can be computed or observed by the stator flux observers.

The neural network realises the time-independent representation. It means that the rotor flux is observed from the known values of variables in the k-th step in the same time instant.

The ANN realises a relatively simple representation where the motor parameters present the network weights. For this reason it is not necessary to use any hidden layer or any other transfer function than a linear one. For the learning, the Levenberg-Marquardt algorithm was used.

In the Fig. 1 and Fig. 2 there are shown courses of both components of the rotor fluxes and the absolute error, i.e. the difference between the observed fluxes obtained from the ANN and the fluxes got from the mathematical model of induction motor. The courses are valid for a direct connection to the supply with nominal values of the voltage, load torque and stator (rotor) resistance. Due to a relatively small error between the fluxes the courses coincide what is seen in the figures.

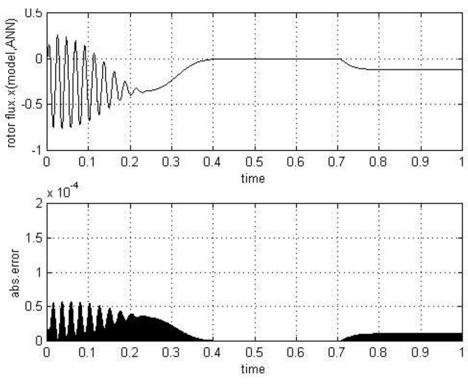

Fig. 1 Course of the flux component ψ_{2x} and the absolute error

The maximum absolute error occurs during transient state (the starting of the induction motor or during time of performance of the disturbance to the system - the load torque applied in time of 0.7 s) what is seen in the figures. The similar outcomes also are valid at observing of other variables.

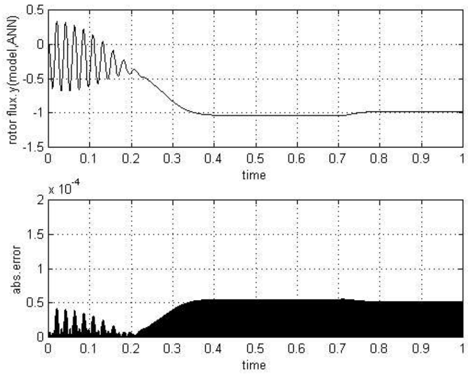

Fig. 2 Course of the flux component ψ_{2y} and the absolute error

3. DESIGN OF TORQUE ESTIMATOR

The motor torque presents a typical variable that causes difficulties at its measuring. It is measured usually by a torque sensor working on principle of a tensometer. The sensor material has an accurately defined boundary of elastic deformation exceeding of which leads to plastic deformation of the material and this causes consequentially a damage of the sensor. This is reason for using the torque observer.

Its design starts from the equation (9) for torque calculation. Using the equations (1) and (2) one gets:

$$\begin{aligned} t = {} & \frac{3p}{2}\psi_{1x}\left(\frac{1}{\sigma L_1}\psi_{1y} - \frac{L_h}{\sigma L_1 L_2}\psi_{2y}\right) - \dots \\ & \dots - \frac{3p}{2}\psi_{1y}\left(\frac{1}{\sigma L_1}\psi_{1x} - \frac{L_h}{\sigma L_1 L_2}\psi_{2x}\right) \end{aligned} \tag{13}$$

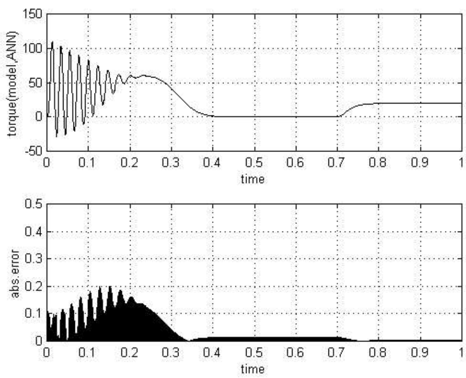

Fig. 3 Courses of the torque and absolute error

The ANN should realise the equation and thus to observe the torque knowing the stator and rotor fluxes. The networks again realises representation independent from time, i.e. the torque in the k-th step is calculated from known observed or calculated values of the stator and rotor fluxes in the k-th step, respectively.

The representation presented by the equation (12) is again non-linear and this is reason for an advantageous utilisation of the ANN. For the observer the cascade feed-forward ANN with one hidden layer and tansigmoid transfer function was used.

The ANN has been learned off-line by the Levenberg-Marquardt algorithm. In the fact this is a non-parametric identification in which the network inputs and outputs have been obtained from the mathematical model of the induction motor.

The algorithm for the torque observing has been verified by simulation. The Fig. 3 shows courses of the torque and an absolute error at direct connection of the induction motor to the supply with nominal values of the voltage, load torque and stator (rotor) resistance.

4. DESIGN OF ANGULAR SPEED ESTIMATOR

For the sensorless drives without a speed sensor the information about the speed can be obtained indirectly, e.g. from the observer or estimator.

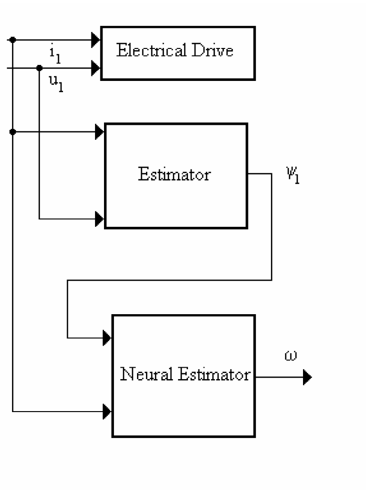

Fig. 4 Neural networks structure estimation of angular speed

Analogically with the structure of induction motor the design of the neural observer starts from the motion equation (9).

From it, the angular speed is expressed as:

$$\omega = \frac{1}{J}\int (t - t_l)dt + \omega_0 \tag{14}$$

At realisation of the equation (14) the inputs to the networks are values of the torque t (got from the ANN torque observer), load torque t_l and the previous value of the speed ω_0 in the (k-1)th step. The ANN torque and rotor magnetic flux estimators are included in block neural estimator in Fig.4.

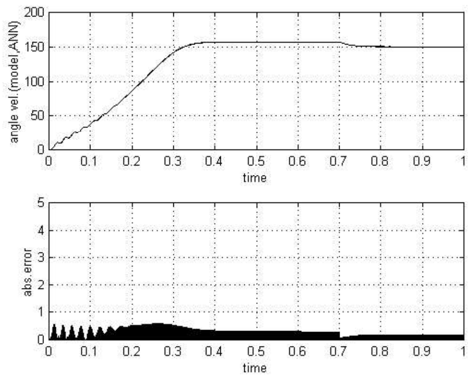

Fig. 5 Courses of the angular speed ω and absolute error

Similarly, like above, the cascade feed-forward network with one hidden layer and tansigmoid transfer function was used that has been learned by the Levenberg-Marquardt algorithm. The inputs and outputs for the learning procedure were obtained from the mathematical model of the induction motor.

The Fig. 5 shows courses of the angular speed and an absolute error at direct connection of the induction motor to the supply.

5. CONCLUSIONS

The observers based on the ANN presented in the paper are based on utilisation of the feed-forward and a cascade feed-forward network learned off-line by the Levenberg-Marquardt algorithm. Feed-forward neural network estimators were tested but the better results were obtained by cascade feed-forward network estimators.

The neural estimator requires off-line training. The results from simulation show a stability and precision both in the steady and transient states. The control system is robust against the change of the rotor resistance.

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BIOGRAPHY

Martin Borbel' (Ing.) received the MSc degree at the Technical University of Košice, at the Department of Electrical Drives of the FEI. He is PhD. student at the Department of Electrical Drives of the Faculty of Electrical Engineering and Informatics at Technical University of Košice. He deals with application of neural networks in Electrical Drives.

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