

APPLICATION OF NEURAL NETWORK MODEL FOR PARAMETERS IDENTIFICATION OF NON-LINEAR DYNAMIC SYSTEM

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Abstract: A method for identification of parameters of a non-linear dynamic system, such as an induction motor with saturation effect taken into account, is presented in this paper. Adaptive identifier with structure similar to model of the system performs identification. This identifier can be regarded as a special neural network, therefore its adaptation is based on the gradient descent method and Back-Propagation well known in the neural networks theory. Parameters of electromagnetic subsystems were derived from the values of synaptic weights of the estimator after its adaptation. Testing was performed with simulations taking into account noise in measured quantities. Deviations of identified parameters in case of electrical parameters of the system were up to 1% of real values. Parameters of non-linear magnetizing curve were identified with deviations up to 6 % of real values. Identifier was able to follow sudden changes of rotor resistance, load torque and moment of inertia.

Key words: *Neural networks, non-linear dynamic systems, induction machines, identification*

Received: October 19, 2012

Revised and accepted: February 25, 2013

1. Introduction

Identification has been studied for decades from a variety of viewpoints and research communities, such as statistical regression-estimation, signal processing-filtering, and control engineering-adaptive control. When a priori information about the rules that govern a system either do not exist or are too complex, identification techniques are used to build a model by only observing input-output data. Then, the system is called a 'black box' since the internal behavior is unknown. On the

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contrary, in technical practice we often meet with the case that the system does not behave just like a 'black box', but we have some a priori information about it. In many physical systems our knowledge of mechanical or electrical laws allow us to formulate a model which is the fundamental tool for studying and analysis its properties. However, no matter how deep our physical insight, the parameters of any model present inaccuracies.

In case of induction motor identification, it is possible to assume that some parameters are known, the magnetizing curve is linear, identified motor is at standstill or rotary speed of motor is constant during some time period. Above assumptions simplify identification, but at the same time they limit the number of identifiable parameters or they can be used only in special working modes of the motor. Our aim was to develop an identification procedure of all induction motor parameters, if possible, with non-linear friction [1–3] and saturation effect taken into account [4–8]. An inspiration for handling such a complex system may be found in the artificial neural networks applications, where a complex system is divided into small units - neurons operating according to local-defined rules. If rules are properly designed, network produces required global effect, although operation of each neuron is strictly local. Though the whole network may be strongly non-linear, operating rules of each neuron may be very simple. Proposed identifier of induction motor is based on the same principle. The identifier is constructed as a model of the motor with all above non-linearities incorporated. The identifier is properly divided into neurons. Parameters are replaced with adaptive weights and whole identifier works as a network of several neurons, each of them operating according to local-defined rules. Using stator voltages and rotary speed as inputs and stator currents as demanded outputs, identifier adapts its weights with use of the well-known gradient descent method [9]. The deviations of demanded and actual outputs of identifier are transferred to inner neurons with use of the Back-Propagation algorithm [3]. Many non-linearities and feedbacks influence only input signals of neurons, therefore neurons themselves are linear and their adaptive rules are very simple. Proposed identifier identifies stator and rotor resistances, leakage inductances and course of non-linear magnetizing curve. Testing of the identifier was performed with simulations. To make testing conditions somewhat more similar to reality, Gaussian noise was added to signals supposed to be measured from motor. Structure of the identifier is similar to model of motor in $\alpha\beta$ frame of reference [11]. As a consequence of this transformation, quantities of motor do oscillate and contain more information for the purpose of identification.

2. Model of Induction Motor

The two phase electrical equations of an induction motor in an arbitrary frame rotating at a speed ω_a are given by [6]:

$$\bar{U}_S = R_S \bar{I}_S + \frac{d\bar{\psi}_S}{dt} + j \cdot p_p \omega_a \bar{\psi}_S \quad (1)$$

$$\bar{U}_R = \bar{0} = R_R \bar{I}_R + \frac{d\bar{\psi}_R}{dt} + j \cdot p_p (\omega_a - \omega) \cdot \bar{\psi}_R, \quad (2)$$

where

$$\bar{\psi}_S = L_{\sigma S} \bar{I}_S + \bar{\psi}_m \text{ and } \bar{\psi}_R = L_{\sigma R} \bar{I}_R + \bar{\psi}_m \quad (3)$$

$$\bar{\psi}_m = \bar{F}(\bar{I}_m) \text{ and } \bar{I}_m = \bar{I}_S + \bar{I}_R \quad (4)$$

$$m = \frac{3}{2} p_p I_m [\bar{\psi}_S^* \cdot \bar{I}_S] \quad (5)$$

Symbol * denotes conjugate vector.

I_S, I_R, I_m	stator, rotor and magnetizing currents
U_S, U_R	stator and rotor voltages
ψ_S, ψ_R, ψ_m	stator, rotor and mutual fluxes
p_p	number of the pole pairs
ω_a	angular speed
ω	mechanical angular speed
m	torque
$L_{\sigma S}, L_{\sigma R}$	leakage inductances of stator and rotor
R_S, R_R	stator and rotor resistance

Tab. I Used symbols.

In stator coordinate system [11] $\alpha\beta$ frame of reference $\omega_a=0$. Based on (1), we obtain:

$$\bar{U}_S = R_S \bar{I}_S + \frac{d\bar{\psi}_S}{dt} \quad (6)$$

$$\bar{U}_R = \bar{0} = R_R \bar{I}_R + \frac{d\bar{\psi}_R}{dt} - j \cdot p_p \cdot \omega \cdot \bar{\psi}_R \quad (7)$$

and the transformation of three-phases stator voltages into stationary α, β reference frame is by [11]:

$$u_{\alpha 1} = \frac{1}{3} (2u_a - u_b - u_c) \text{ and } u_{\beta 1} = \frac{1}{\sqrt{3}} (u_b - u_c). \quad (8)$$

From (6) and (7) follows that

$$\frac{d\bar{\psi}_S}{dt} = \bar{U}_S - R_S \bar{I}_S \text{ and } \frac{d\bar{\psi}_R}{dt} = -R_R \bar{I}_R + j \cdot p_p \cdot \omega \cdot \bar{\psi}_R \quad (9)$$

and in component form

$$\begin{bmatrix} \frac{d\psi_{\alpha 1}}{dt} \\ \frac{d\psi_{\beta 1}}{dt} \end{bmatrix} = \begin{bmatrix} u_{\alpha 1} \\ u_{\beta 1} \end{bmatrix} - R_S \begin{bmatrix} i_{\alpha 1} \\ i_{\beta 1} \end{bmatrix}$$

$$\begin{bmatrix} \frac{d\psi_{\alpha 2}}{dt} \\ \frac{d\psi_{\beta 2}}{dt} \end{bmatrix} = -R_R \begin{bmatrix} i_{\alpha 2} \\ i_{\beta 2} \end{bmatrix} + p_p \cdot \omega \begin{bmatrix} -\psi_{\beta 2} \\ \psi_{\alpha 2} \end{bmatrix}$$

From equation (3):

$$\bar{I}_S = \frac{\bar{\psi}_S - \bar{\psi}_m}{L_{\sigma S}} \text{ and } \bar{I}_R = \frac{\bar{\psi}_R - \bar{\psi}_m}{L_{\sigma R}} \quad (10)$$

According to [4], where authors considered controlled induction motor, the vector version of the saturation function in (3) is defined as $\bar{F} : \mathfrak{R}^2 \rightarrow \mathfrak{R}^2$ such that $\|\bar{\psi}_m\| = f(\|\bar{I}_m\|)$ and $\psi_{\alpha m}/\psi_{\beta m} = i_{\alpha m}/i_{\beta m}$. Function $f : \mathfrak{R} \rightarrow \mathfrak{R}$ is a scalar saturation function that only affects the magnitude of the mutual flux $\bar{\psi}_m$ so that $\bar{\psi}_m$ and \bar{I}_m have the same angle. According to [10] the time constant T_{mg} , of leeway of flux after magnetizing current in dynamo sheets, is not zero, but approximately 0.016 ms.

Let us denote

$$I_m = \|\bar{I}_m\| = \sqrt{I_{\alpha m}^2 + I_{\beta m}^2}. \quad (11)$$

Components of mutual flux may be written by [4] as follows:

$$\psi_{\alpha m} = i_{\alpha m} \frac{f(I_m)}{I_m} \quad \psi_{\beta m} = i_{\beta m} \frac{f(I_m)}{I_m}. \quad (12)$$

According to [10] the first order inertias with very small time constant T_{mg} were included into the model. Including by [10] the first-order inertias into (12):

$$\begin{aligned} \frac{d\psi_{\alpha m}}{dt} &= \frac{1}{T_{mg}} i_{\alpha m} \frac{f(I_m)}{I_m} - \frac{1}{T_{mg}} \psi_{\alpha m} \\ \frac{d\psi_{\beta m}}{dt} &= \frac{1}{T_{mg}} i_{\beta m} \frac{f(I_m)}{I_m} - \frac{1}{T_{mg}} \psi_{\beta m}. \end{aligned} \quad (13)$$

The mechanical equation can be expressed as:

$$m - m_L \cdot \text{sgn}(\omega) - m_f = J \frac{d\omega}{dt}, \quad (14)$$

where m , m_L and m_f are motor, load and friction torque and J is moment of inertia.

Substituting (2) into (5), we obtain:

$$m = \frac{3}{2} p_p [i_{\beta 1} \cdot \psi_{\alpha m} - i_{\alpha 1} \cdot \psi_{\beta m}]. \quad (15)$$

Fig. 1 shows transformation of three-phases stator voltages into stationary α, β reference frame by (8).

The discrete model of an induction motor with non-linear magnetic circuit is represented in Figs. 2–4, where symbol \square denotes numerical integrator. Fig. 2 and 3 shows discrete model of stator and rotor of an induction motor by (3), (4) and (9).

Fig. 4 shows discrete model of magnetizing subsystem of an induction motor by (10)–(13). Function g comprises non-linear magnetizing curve, the square root function and dividing by module of I_m .

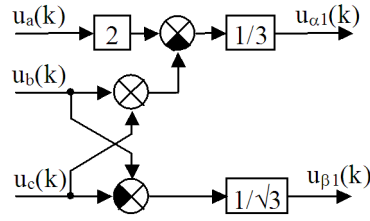


Fig. 1 Transformation of phase voltages into α, β frame of reference.

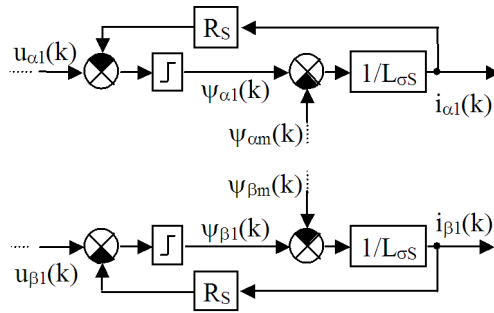


Fig. 2 Model of stator of an induction motor.

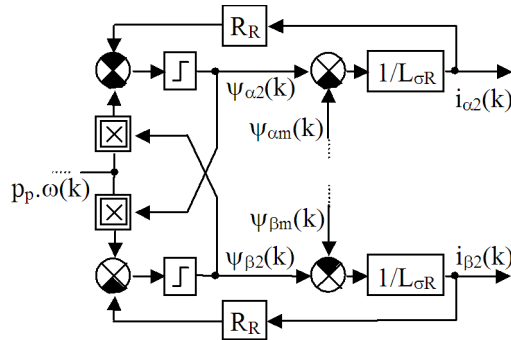


Fig. 3 Model of rotor of an induction motor.

3. Neural Identifier

General structure of the proposed identifier is shown in Fig. 5. Figs. 6–8 depict detailed structure of the identifier. After adaptation, identified parameters can be derived from particular weights of the identifier based on its similarity to identified motor's structure.

Symbol * denotes identified signals.

In case of ideal adaptation weights for neurons N1 and N2 by Fig. 6 is $w_1^{N1} = w_1^{N2} = -R_S$, and $w_O^{N1} = w_O^{N2} = 1/L_{\sigma S}$. The output o of the neuron N1 is determined by (17) and output of neuron N2 analogically.

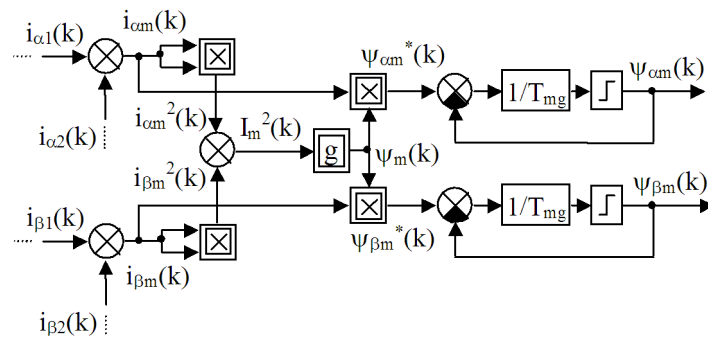


Fig. 4 Model of magnetizing subsystem.

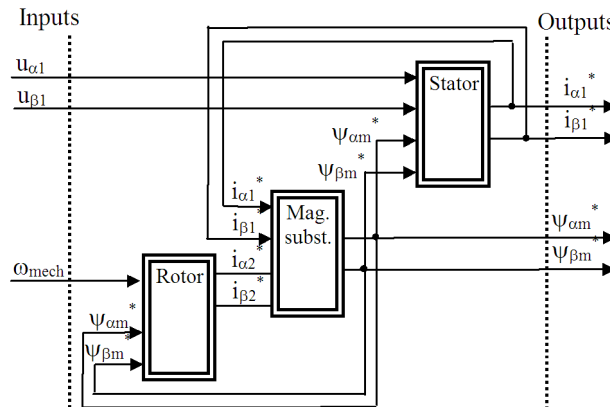


Fig. 5 General scheme of electromagnetic identifier.

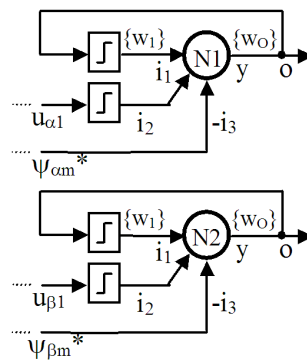


Fig. 6 Neural identifier of stator.

In case of ideal adaptation weights for neurons N3, N4, N5 and N6 is $w_O^{N4} = w_O^{N6} = 1/L_{\sigma R}$ and $w_1^{N3} = w_1^{N5} = -R_R$. The outputs of the neurons are determined analogically with the neuron N1.

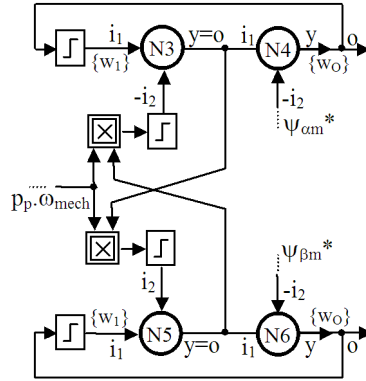


Fig. 7 Neural identifier of rotor.

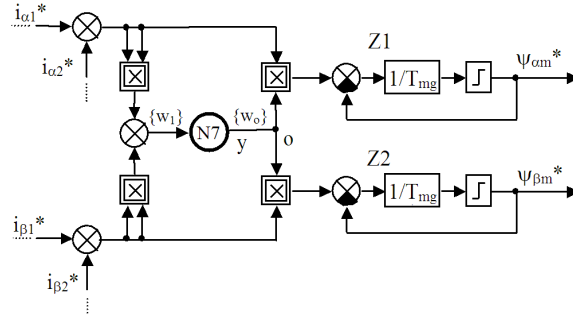


Fig. 8 Neural identifier of magnetizing subsystem.

Neural identifier of magnetizing subsystem is shown in Fig. 8. The neuron N7 represents the magnetizing curve. In case of ideal adaptation of weights for the neuron N7, $w_1^{N7} = -d$ and $w_0^{N7} = c$. Z1 and Z2 are first order inertias by (13).

4. Rules of adaptation

Identifiers of stator and rotor contain branches with identical parameters. During adaptation, however, signals in particular branches are different and their information value from identification point of view is different too. Therefore, adaptation of weights in one of the branches is usually slower and it may even stop at a certain level. It is useful to perform adaptation so that values of corresponding weights are bound somehow in order to preserve their similar values. In this case, this aim was achieved by averaging corresponding weights after each step of adaptation. This approach ensures identical values of corresponding weights in each step and, at the same time, the information value of signals in both branches is used for adaptation.

To derive adaptation rules for all neurons, the gradient descent method and Back-Propagation algorithm were used. Let there be objective function $E = \frac{1}{2}e^2$, where e – is the deviation between required and actual output of the neuron.

For deviation and error function of neuron N1

$$e^{N1} = i_{\alpha 1} - o^{N1} \quad E^{N1} = \frac{1}{2} (e^{N1})^2 \quad (16)$$

$$o^{N1} = w_O^{N1} (w_1^{N1} \cdot i_1^{N1} + 1 \cdot i_2^{N1} - 1 \cdot i_3^{N1}) = w_O^{N1} \cdot y^{N1}. \quad (17)$$

According to the gradient descent algorithm for weights adaptation of neuron N1

$$\frac{dw_O^{N1}}{dt} = -\eta_O^{N1} \frac{\partial E^{N1}}{\partial w_O^{N1}} = \eta_O^{N1} \cdot e^{N1} \cdot y^{N1} \quad (18)$$

$$\frac{dw_1^{N1}}{dt} = -\eta_1^{N1} \frac{\partial E^{N1}}{\partial w_1^{N1}} = \eta_1^{N1} \cdot e^{N1} \cdot w_O^{N1} \cdot i_1^{N1}, \quad (19)$$

where i_n is n -th input of the neuron and η is the rate of the adaptation.

Analogically for neuron N2

$$e^{N2} = i_{\beta 1} - o^{N2}$$

$$\frac{dw_O^{N2}}{dt} = \eta_O^{N2} e^{N2} y^{N2} \quad \text{and} \quad \frac{dw_1^{N2}}{dt} = \eta_1^{N2} e^{N2} w_O^{N2} i_1^{N2}. \quad (20)$$

For neurons N4 and N6

$$o^{N4} = w_O^{N4} (1 \cdot i_1^{N4} - 1 \cdot i_2^{N4}) = w_O^{N4} \cdot y^{N4}. \quad (21)$$

If e^{N4} would be known then

$$E^{N4} = \frac{1}{2} (e^{N4})^2 \quad (22)$$

$$\frac{dw_O^{N4}}{dt} = -\eta_O^{N4} \frac{\partial E^{N4}}{\partial w_O^{N4}} = \eta_O^{N4} \cdot e^{N4} \cdot y^{N4}. \quad (23)$$

In order to derive adaptation rule we can consider the Z1 inertia with a very small time constant to have almost the same effect as non-inertia element with gain 1. Neuron N4 affects the operation of neuron N1, therefore:

$$o^{N1} \cong w_O^{N1} (w_1^{N1} \cdot i_1^{N1} + i_2^{N1} - o^{N7} (o^{N4} + o^{N1})) \quad (24)$$

$$e^{N1} = r^{N1} - o^{N1} \quad (25)$$

$$\frac{dw_O^{N4}}{dt} = -\eta_O^{N4} \frac{\partial E^{N1}}{\partial w_O^{N4}} = \eta_O^{N4} e^{N1} w_O^{N1} (-o^{N7} y^{N4}). \quad (26)$$

From (23) and (26) follows that

$$e^{N4} = -e^{N1} w_O^{N1} o^{N7}. \quad (27)$$

Analogically

$$e^{N6} = -e^{N2} w_O^{N2} o^{N7} \quad \text{and} \quad \frac{dw_O^{N6}}{dt} = \eta_O^{N6} e^{N6} y^{N6}. \quad (28)$$

For neurons N3 a N5

$$o^{N3} = w_1^{N3} \cdot i_1^{N3} - 1 \cdot i_2^{N3}. \quad (29)$$

If e^{N3} would be known then

$$E^{N3} = \frac{1}{2} (e^{N3})^2 \quad (30)$$

$$\frac{dw_1^{N3}}{dt} = -\eta_1^{N3} \frac{\partial E^{N3}}{\partial w_1^{N3}} = \eta_O^{N3} \cdot e^{N3} \cdot i_1^{N3}. \quad (31)$$

Since neuron N3 affects the neuron N4, it can be written:

$$\begin{aligned} o^{N4} &= w_O^{N4} (1 \cdot o^{N3} - 1 \cdot i_2^{N4}) \\ e^{N4} &= r^{N4} - o^{N4} \end{aligned} \quad (32)$$

$$\frac{dw_1^{N3}}{dt} = -\eta_1^{N3} \frac{\partial E^{N4}}{\partial w_1^{N3}} = -\eta_1^{N3} \cdot \frac{\partial E^{N4}}{\partial e^{N4}} \cdot \frac{\partial e^{N4}}{\partial w_1^{N3}} = \eta_1^{N3} \cdot e^{N4} \cdot w_O^{N4} \cdot i_1^{N3}. \quad (33)$$

From (31) and (33) follows that

$$e^{N3} = e^{N4} \cdot w_O^{N4}. \quad (34)$$

Analogically

$$e^{N5} = e^{N6} w_O^{N6} \text{ and } \frac{dw_1^{N5}}{dt} = \eta_O^{N5} e^{N5} i_1^{N5}. \quad (35)$$

For neuron N7

$$o^{N7} = w_O^{N7} \cdot \frac{1 - \exp(w_1^{N7} \cdot i_1^{N7})}{i_1^{N7}} = w_O^{N7} \cdot y^{N7}. \quad (36)$$

If e^{N7} would be known then

$$E^{N7} = \frac{1}{2} (e^{N7})^2 \quad (37)$$

$$\frac{dw_O^{N7}}{dt} = -\eta_O^{N7} \frac{\partial E^{N7}}{\partial w_O^{N7}} = \eta_O^{N7} \cdot e^{N7} \cdot y^{N7} \quad (38)$$

$$\frac{dw_1^{N7}}{dt} = -\eta_O^{N7} \frac{\partial E^{N7}}{\partial w_1^{N7}} = -\eta_O^{N7} e^{N7} w_O^{N7} \exp(w_1^{N7} i_1^{N7}). \quad (39)$$

Neuron N4 influences neurons N1 a N2. If for derivation of adaptive rules we substitute inertias Z1 a Z2 with simple gains 1 then following equations can be written:

$$o^{N1} = w_O^{N1} (w_1^{N1} \cdot i_1^{N1} + i_2^{N1} - o^{N7} \cdot (o^{N1} + o^{N4})) \quad (40)$$

$$o^{N2} = w_O^{N2} (w_1^{N2} \cdot i_1^{N2} + i_2^{N2} - o^{N7} \cdot (o^{N2} + o^{N6})) \quad (41)$$

$$e^{N1} = r^{N1} - o^{N1} \text{ and } e^{N2} = r^{N2} - o^{N2} \quad (42)$$

$$\begin{aligned}
 \frac{dw_O^{N7}}{dt} &= -\eta_O^{N7} \frac{\partial E^{N1}}{\partial w_O^{N7}} = -\eta_O^{N7} \frac{\partial E^{N1}}{\partial e^{N1}} \frac{\partial e^{N1}}{\partial o^{N7}} \frac{\partial o^{N7}}{\partial w_O^{N7}} = \\
 &= \eta_O^{N7} \cdot e^{N1} \cdot w_O^{N1} \cdot (- (o^{N1} + o^{N4})) \cdot y^{N7}
 \end{aligned} \tag{43}$$

$$\begin{aligned}
 \frac{dw_O^{N7}}{dt} &= -\eta_O^{N7} \frac{\partial E^{N2}}{\partial w_O^{N7}} = -\eta_O^{N7} \frac{\partial E^{N2}}{\partial e^{N2}} \frac{\partial e^{N2}}{\partial o^{N7}} \frac{\partial o^{N7}}{\partial w_O^{N7}} \\
 &= \eta_O^{N7} \cdot e^{N2} \cdot w_O^{N2} \cdot (- (o^{N2} + o^{N6})) \cdot y^{N7}.
 \end{aligned} \tag{44}$$

From a comparison of (38) and (43), (38) and (44) follows that error signal of neuron N7 can be defined in two ways:

$$e^{N7} = -e^{N1} \cdot w_O^{N1} \cdot (o^{N1} + o^{N4}) \tag{45}$$

$$e^{N7} = -e^{N2} \cdot w_O^{N2} \cdot (o^{N2} + o^{N6}). \tag{46}$$

5. Identification of electromagnetic parameters

According to [10] the time constant of leeway of flux after magnetizing current is approximately 0.016 ms, therefore the time constant of magnetizing circuit was considered to be $T_{mg*} = 0.016$ ms. Other parameters of a squirrel-cage induction motor used in the simulation were: $m_L = 0$ Nm, $b = 0$ Nms, $U_z = 190$ V, $f = 50$ Hz, $R_S = 0.181 \Omega$, $R_R = 0.161 \Omega$, $J = 0.11$ kgm², $p_p = 2$, $L_{\sigma S} = 0.00183$ H, $L_{\sigma R} = 0.00183$ H, $\|\bar{\psi}_m\| = c \left(1 - e^{-d\|\bar{I}_m\|}\right)$, $c = 0.32$ Wb, $d = 0.2$.

Considered was motor loaded with friction with various components [11] and passive load torque. Measured signals of motor, i.e. stator voltages and currents and rotary speed, were simulated with Gaussian noise added. Parameters of induction motor may vary in time and they can considerably affect the quality of control. Therefore, it is desirable in many cases to use the on-line identification of the rotor resistance [3], [12–15] which varies with temperature of motor. Though its change is continuous, the sudden change of resistance value was considered in testing in order to investigate behavior of the identifier. As the proposed identifier does not identify the time constant of magnetizing circuit, it must be assumed that exact value of this time constant is not known. Therefore, robustness of the identifier is tested with respect to inaccurate value of time-constant in the identifier.

Conditions of simulations

- Loaded motor ($b = 0.1$ Nms, $M_L = 5$ Nm)
- Noisy input signals of identifier
- Non-linear magnetizing curve of motor and identifier
- Inaccurate magnetizing time constant of identifier $T_{mg*} = 0.000024$ s, i.e. 150 % of accurate value used in model of motor
- Sudden change of rotor resistance to 0.19Ω , i.e. 118 % of original value after 2000 periods

- 5 filters added to identifier to filter noisy inputs
- Noise: stator currents noise max. ± 5 A, stator voltages noise max. ± 2 V, speed noise max. ± 2 rad.s $^{-1}$
- Steps for adaptation of weights were constant and they were tuned experimentally
- Initial values of weights were chose to be of same scale and sign as expected identified values

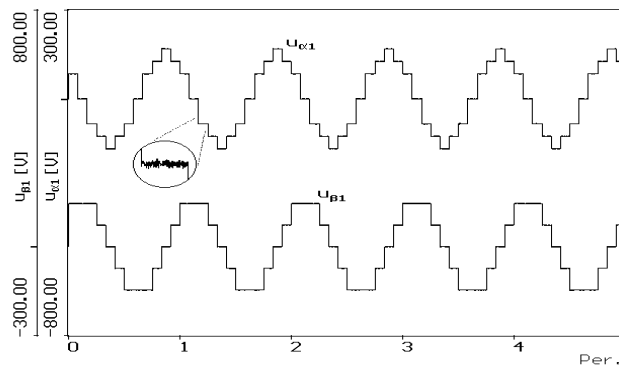


Fig. 9 Stator voltages of the motor.

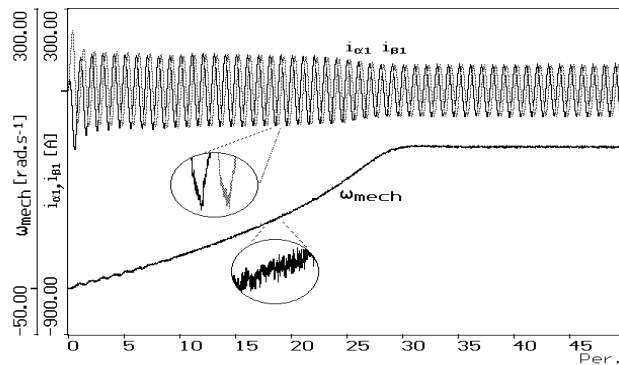


Fig. 10 The training set of the identifier contains 50 periods of stator voltages, currents and rotary speed of the motor.

Tab. II contains values of identified parameters after 8000 periods, i.e. 160 repetition of the training set.

In spite of noise, but with respect to the fact that simulations performed testing, identified parameters are rather accurate. A larger deviation -4.9950 % occurred when identifying steepness of magnetizing curve d , which may be caused by quick transition of motor into the saturated part of the magnetizing curve and consequent

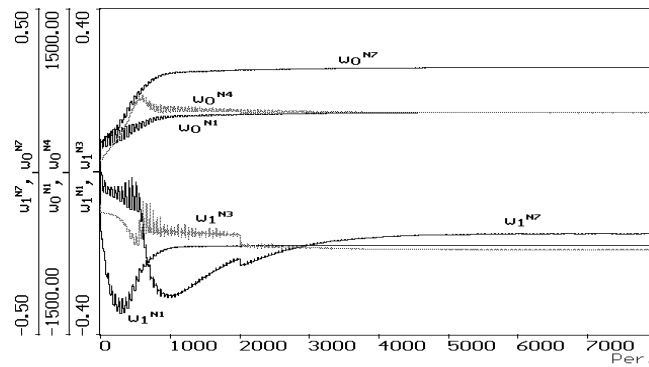


Fig. 11 Adaptation of weights.

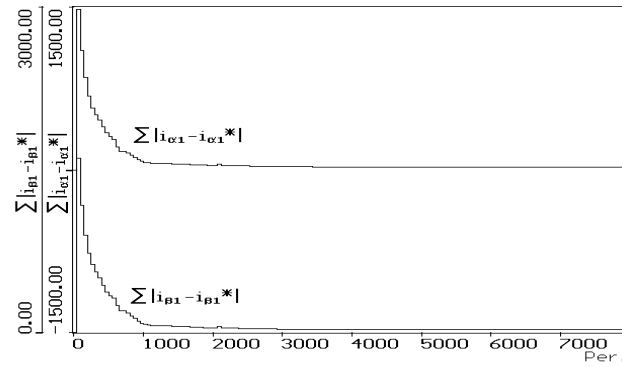


Fig. 12 Average absolute deviations of $N1$ and $N2$ outputs during adaptation.

Parameter	Identified Value	Real Value	Deviation
R_S	0.18088 Ω	0.181 Ω	-0.0663 %
R_R	0.19138 Ω	0.190 Ω	0.7263 %
$L_{\sigma S}$	0.0018279 H	0.00183 H	-0.1156 %
$L_{\sigma R}$	0.0018279 H	0.00183 H	-0.1156 %
d	0.19001	0.2	-4.9950 %
c	0.32018	0.32 Wb	0.0180 %

Tab. II Identified electromagnetic parameters.

lack of information about non-saturated part of the curve. As can be seen in Fig. 11, reaction of w_1^{N3} weight of the identifier on changed value of rotor resistance was very fast with respect to the dynamic of the whole adaptation process. Noise of measured signals enriches the frequency spectrum of input signals of the identifier, which may help identification but, at the same time, it may endanger its stability.

Similar results were obtained with $T_{mg}^*=0.000012$ s, i.e. 75 % of value used in motor model.

6. Conclusion

Deviations of identified parameters in case of electrical parameters of induction motor were up to 1% of real values. Parameters of non-linear magnetizing curve were identified with deviations up to 6 %. The identifier was able to follow sudden changes of rotor resistance, load torque and moment of inertia. All testing was performed with simulations, with a rather strong noise added to quantities, which would be measured from motor in the real application. The proposed identifier contains 7 neurons, most of which are linear. Therefore, adaptation rules are very simple. Identification lasts several thousands of periods of stator voltage, which means several hundreds repetitions of training set. As all repeated training sets were the same, it is possible to generate just a single training set from motor's quantities and repeat it. Adaptation of neurons was done with constant steps whose values were found experimentally. It is probable, therefore, that with optimized steps varying during adaptation the identification process may be much faster.

Acknowledgement

This work was supported by the Slovak Research and Development Agency under the contract No. APVV-0185-10 and R&D operational program Center of excellence of power electronics systems and materials for their components No. OPVaV-2008/2.1/01-SORO, ITMS 26220120003 funded by European Regional Development Fund (ERDF).

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