Multilayer Neural Network Verification of Mutual Inductance Choice in Sensorless Induction Motor Vector Control System

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Abstract: Squirrel-cage induction motor (IM) is the most frequently used electric machine in modern controlled electromotor drives. In this paper is analyzed IM sensorless vector control system based on MRAS (Model Reference Adaptive System) theory. It is especially important get knowledge of the IM rotor time constant incorporated into observer (Fig. 1.). In this constant is incorporated IM mutual inductance L_m. The characteristic of the observed IM is varying of mutual inductance L_m at lower frequency of supply voltage due to saturation effect in iron. In this paper accuracy of the mutual inductance L_m in the observer of induction motor vector control is verified by using feedforward static four layer artificial neural network (ANN).

Key-Words: Induction motor, vector control, observer, neural network, speed estimation

1 Introduction

In induction motor vector control systems is widely researched rotor speed estimation using measured stator currents and voltages. However, most of proposed sensorless vector control systems have problem based on IM parameter changes due to saturation in iron and thermal changes of stator and rotor resistance.

In this paper is analyzed IM sensorless vector control system based on MRAS theory. This control system is based on the fact that rotor flux vector can be estimated in two ways: using voltage and current model [3]. The minimization of the difference between value and angle of that two flux vectors is achieved by the adaptive control theory.

There are in reference [6] a review of existing IM estimation techniques that are based on online and offline parameter estimation techniques. IM inductances estimation is based on a-priori knowledge of the magnetizing curve or without it. If IM inductances are estimated using magnetizing curve then that estimation technique satisfies sufficient good in steady state as well as in transient state. Inductance estimation techniques that do not require magnetizing curve are sufficiently good in steady state, while during transient show some limitations [6]. This paper is based on knowledge of the magnetizing curve, and calculation method of saturation in iron is verified by measurement [4].

Analyzed induction motor is pervious to the saturation impact of the main magnetic circuit at the lower supply frequencies [4]. The mutual inductance as a parameter is incorporated into observer of rotor flux vector and rotor speed (in the next text observer only) (Fig. 1.). Changes of mutual inductance value due to saturation in iron strongly depend on quality of rotor speed control and system stability. Multilayer static ANN is incorporated in control system for verification of mutual inductance accuracy that there is as a parameter in observer. This ANN is based on using files being accommodated by calculated components of currents and voltages vectors taking into account main magnetic circuit saturation. The trained neural network, in this way, is sensitive to estimation error of mutual inductance that is present in observer as an important parameter. This sensitivity is noticed in difference between actual rotor speed and ANN estimated speed. By changing different values of mutual inductance in observer of vector control system could be concluded about accuracy of their selection. That method of mutual inductance choice is not mentioned in [6].

2 Rotor speed estimation in vector control system - MRAS

The analyzed vector control system shown in Fig. 1 is based on voltage model [3]:

$$\frac{d\overline{\psi}_s^v}{dt} = \overline{u}_s - \hat{R}_s\overline{i}_s - j\omega_s^*\overline{\psi}_s^v + \frac{L_m}{L_r}\frac{\overline{\psi}_r^c - \overline{\psi}_r^v}{T_c}, \quad (1)$$

$$\overline{\psi}_r^v = \frac{L_r}{L_m}\left(\overline{\psi}_s^v - \sigma L_s\overline{i}_s\right), \quad (2)$$

and current model:

$$\psi_{rd}^c = L_m i_{sd}^* . \qquad (3)$$

The input values in these equations are besides IM parameters also stator voltage vector $\overline{u}_s$, stator current vector $\overline{i}_s$ and observer gain $1/T_c$. The used signs indicate: „c" – current model, „v" – voltage model, „*"- reference value, „∧"- estimated value.

Rotor flux vector in *d,q* reference frame in observed vector control system is described by three vectors: rotor flux vector estimated using voltage model $\overline{\psi}_r^v$, rotor flux vector estimated using current model $\overline{\psi}_r^c$ and actual rotor flux vector $\overline{\psi}_r$. Rotor flux vector $\overline{\psi}_r$ resulting from simulation of vector controlled induction motor using Matlab package [5]. The base parameters of the simulated induction motor are: $P_n = 1,5$ [kW] (rated power), $M_n=10,5$ [Nm] (rated torque), $n_n=1391$ [r/min] (rated rotor speed), $L_m=0,4058$ [H] (unsaturated value of mutual inductance), $L_b=0,1838$ [H] (basic inductance).

d axis of the *d,q* reference frame is aligned to the rotor flux vector estimated by current model (Eq. (3)). In reference [3] is shown that in that situation rotor flux vectors being estimated by current model $\overline{\psi}_r^c$ and voltage model $\overline{\psi}_r^v$ are equal to actual rotor flux vector $\overline{\psi}_r$ at steady state. Under this condition it is possible to estimate the rotor speed by equation [1]:

$$\frac{d\hat{\omega}}{dt} = \frac{K_\omega}{T_\omega} \psi_{rq}^v , \qquad (4)$$

which presents PI controller with rotor flux component ψ_{rq}^v.

Rotor flux and speed estimation in observer (Fig. 1.) is based on well know (measured or calculated) stator voltage and current vectors (Eq. (1)-(4)).
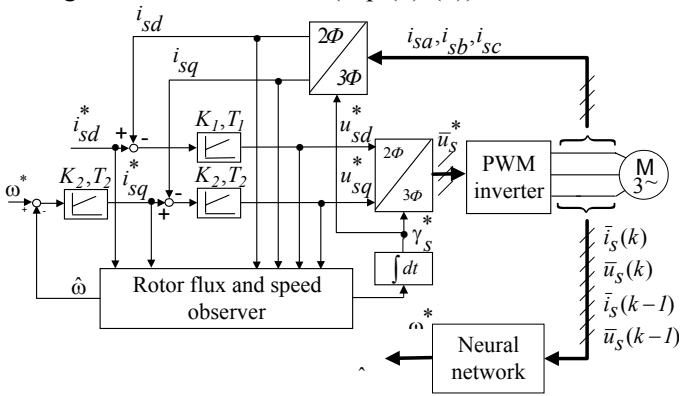

Figure 1. Sensorless vector control system

The researches were shown that saturation of mutual inductance L_m can strongly influence to the validity of rotor speed estimation. The observed IM has significant saturation effect in iron. Unsaturated value of mutual inductance L_m in analyzed observer (then mutual inductance L_m estimation error is about 200%, certainly taking into account saturation in iron) results with wrong rotor speed estimation, and system becomes unstable. Otherwise, if the estimation of mutual inductance is better, then the control system will be stable. It was shown that if estimation error of mutual inductance is less than 5 % then actual rotor speed ω and rotor speed estimated by observer $\hat{\omega}$ can satisfactory coincide. This fact can be assigned to mould of PI rotor speed controller that always minimizes difference between reference rotor speed and estimated rotor speed. If that relative estimation error of mutual inductance becomes higher then the control system becomes useless. To reach a solution for estimation of the mutual inductance value L_m in control system is introduced an ANN. The ANN was trained with a goal to estimate rotor speed taking into account saturation effect in iron according to the reference [4]. The method described in reference [4], is not possible directly implement, in this research stage, for on line work because it contains more logical *if-then* statements and branch statements. For IM rotor speed estimation in this paper is proposed four layer feedforward static ANN which structure is 8-9-7-1 (8 neurons in first hidden layer, 9 neurons in second hidden layer, 7 neurons in third hidden layer and one neuron in output layer) [1,5]. The activation function in hidden layers is tansigmoid function, and in output layer is a linear function. The selected ANN in this way was obtained by trial and error procedure [1]. At 8 first hidden neurons is connected 8 input signals (components of IM stator currents and voltages all expressed in the stationary *α,β* reference frame in k^{th} and $(k-1)^{th}$ simulation step; $i_{s\alpha}(k)$, $i_{s\alpha}(k-1)$, $i_{s\beta}(k)$, $i_{s\beta}(k-1)$, $u_{s\alpha}(k)$, $u_{s\alpha}(k-1)$, $u_{s\beta}(k)$, $u_{s\beta}(k-1)$). The ANN output value is rotor speed in k^{th} simulation step $\omega(k)$. Topology of the proposed ANN is shown in Fig. 2.
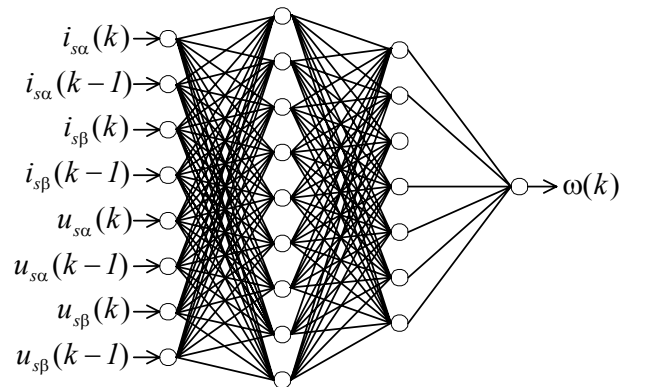

Figure 2. Topology of the 8-9-7-1 ANN for IM rotor speed estimation

Neural network works in any simulation step parallel with vector control system and ANN is independent about it.

3 ANN training and testing

ANN proposed in this paper was trained with the target of rotor speed estimation in the lower rotor speed region (lower supply voltages frequencies). In this region, for observed IM operating modes, saturation of main magnetic flux is important. ANN is trained with mutual inductance estimated without error in an equivalent way as in references [3, 4]. The batch training is performed by using backpropagation algorithm described in [2]. For training process where chosen four reference rotor speed values: $\omega^* = 0,02$ [p.u.], $\omega^* = 0,03$ [p.u.], $\omega^* = 0,08$ [p.u.], $\omega^* = 0,12$ [p.u.]. These rotor speed reference values cover region of stator voltage supply frequencies from 1 [Hz] to 10 [Hz] (rotor speed region from $0,02\omega_n$ to $0,2\omega_n$, ω_n-nominal rotor speed value). For each of mentioned reference rotor speed values active step load and step unload was applied (Fig. 3.). In order to achieve rapider static torque-speed characteristic rotor flux has constant value $\Psi_r = 1,2\Psi_{rn}$. This value is set indirectly by d component of stator current i_{ds}^* (Fig. 1.).
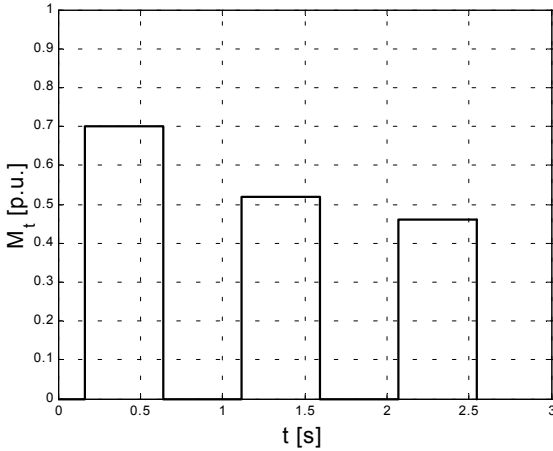

Figure 3. Time step load torques

Thus, four files were given containing input-output data for ANN batch training. The ANN training using Matlab package (Neural Network Toolbox) and with PC $1,3$ [GHz] computer processor continues about 11 hours, and mean square error in 500th training epochs is $5 \cdot 10^{-6}$. Checking the validity of ANN rotor speed estimation is realized by comparison ANN estimated speed with actual rotor speed for four above-mentioned IM operating modes. Actual rotor speed and ANN estimated rotor speed for rotor speed reference value $\omega^* = 0,03$ [p.u.] by step load torques (Fig. 3.) are shown in Fig. 4.
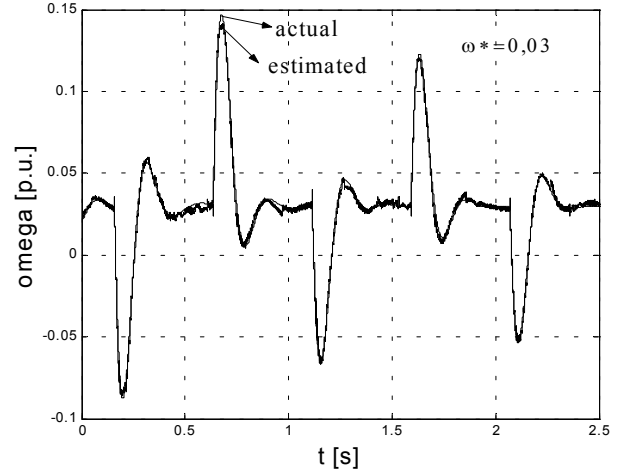

Figure 4. Actual rotor speed and ANN estimated rotor speed by step load torques; $\omega^* = 0,03$ [p.u.]

Actual rotor speed is practically in agreement with the estimated speed (Fig. 4.). The similar results are given for rotor speed reference values $\omega^* = 0,02$ [p.u.], $\omega^* = 0,08$ [p.u.] and $\omega^* = 0,12$ [p.u.]. This good correspondence of actual and estimated rotor speed is expected since ANN was trained by four mentioned operating modes. It can be said that the ANN was „seen'' set of input-output data, and consequently gives expected good results.

For ANN testing is usually utilized so called test files with data at the ANN was not as an input values, i. e. data ANN has not „seen'' never before. For the ANN testing is selected operating mode with rotor speed reference $\omega^* = 0,06$ [p.u.] by step load torque from $M_{t1}=0$ to $M_{t2}=M_{tn}=0,65$ [p.u.] (nominal motor torque). Actual and estimated rotor speeds are shown in Fig. 5.
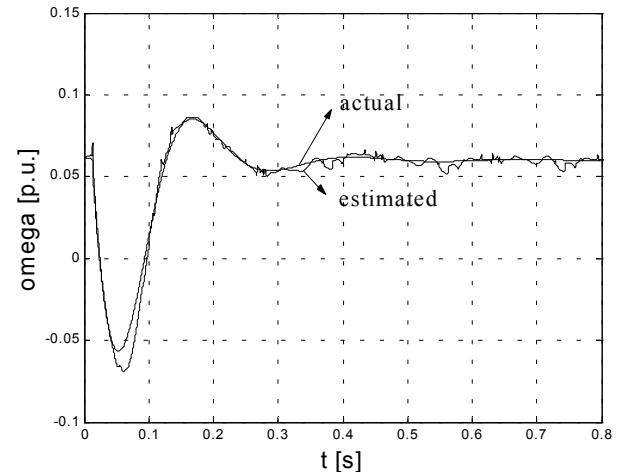

Figure 5. Actual and estimated IM rotor speeds: $\omega^* = 0,06$ [p.u.], $M_{t1}=0$, $M_{t2}=0,65$ [p.u.], $\hat{L}_m = L_m$

It is shown in Fig. 5. that actual rotor speed is in agreement with ANN estimated rotor speed; during transient state ($t<0,5$ [s]) difference is something higher than in steady state ($t>0,5$ [s]). The mean value of

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estimated rotor speed in steady state is *0,0594* [p.u.], and this is a tolerance *1* % from actual rotor speed.

From the theory of mathematical statistic is well known that mean value only do not describes in sufficient detail estimation of some values. It is necessary know standard deviation of an estimated value in steady state. Physically, it stands dissipation of samples around their mean values. It is calculated by equation [5]:

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(\omega(k)-\overline{\omega})^2} \ , \qquad (5)$$

where: *n* – number of analyzed samples of ANN estimated rotor speed (in observed case $n=4000$), $\omega(k)$ – ANN estimated rotor speed in k^{th} simulation sampled step, and $\overline{\omega}$ is mean value of the ANN estimated rotor speed at steady state. In the observed case standard deviation is $\sigma = 0,0019$.

Hence, it can be concluded on the base of mean value and standard deviation that the ANN in observed case very well estimates actual rotor speed. It is necessary again to notice that components of stator current and stator supply voltage in this operating mode be not including in training files.

The analyzed ANN is possible verify at rotor speeds that are not included in rotor speed region from *0,02* [p.u.] to *0,12* [p.u.]. The actual and estimated rotor speed are shown in Fig. 6. for rotor speed reference value $\omega^* = 0,2$ [p.u.], by step load torque from $M_{t1}=0$ to $M_{t2}=0,3$ [p.u.].
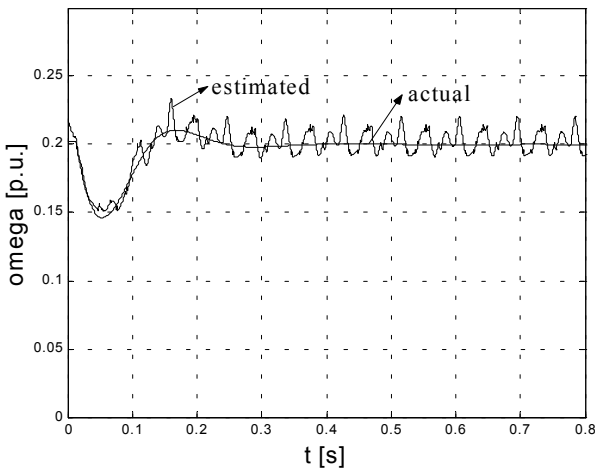

Figure 6. Actual and estimated IM rotor speed: $\omega^* = 0,2$ [p.u.], $M_{t1}=0$, $M_{t2}=0,3$ [p.u.], $\hat{L}_m = L_m$

It is shown in Fig. 6 that mean value of actual rotor speed is practically in agreement with the mean value of estimated rotor speed. In the steady state mean value of the rotor speed is *0,2027* [p.u.]. This means that relative error is *1,35* %. Standard deviation is $\sigma = 0,0078$. In this case relative error and standard deviation are some higher than in operating mode shown in Fig. 5.

However, ANN estimated rotor speed could be reputed in this case as satisfactory good.

4 ANN verification of mutual inductance estimation accuracy

In reference [3] is demonstrated that rotor speed estimation accuracy by so called rotor flux and rotor speed observer depend about estimation accuracy of mutual inductance L_m. As a benchmark of validity of mutual inductance estimation in this paper is proposed ANN estimation. In order to show ANN application for this validity is selected operating mode with step load torques shown in Fig. 3. The response shown in Fig. 4 is accomplished with mutual inductance estimated without error. If mutual inductance estimation error is wittingly chosen at e. q. *5,2* % in steady state operating mode (actual $L_m=1,2963$ [p.u.], chosen $\hat{L}_m = 1,3635$ [p.u.]) then Fig. 7 show actual rotor speed, rotor speed estimated by observer and rotor speed estimated by ANN.
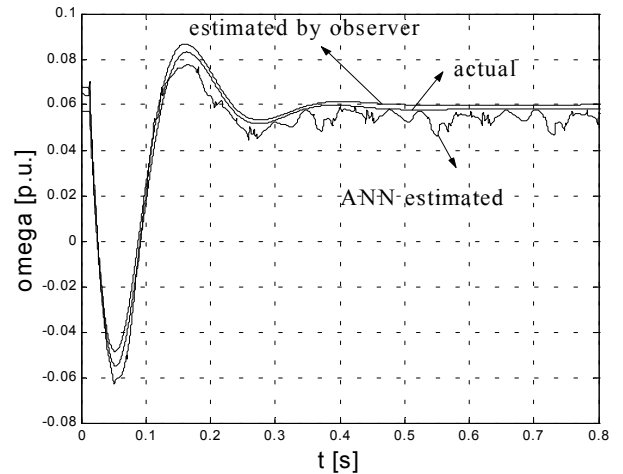

Figure 7. Actual rotor speed, rotor speed estimated by observer and ANN estimated speed; $\omega^* = 0,06$ [p.u.], $M_{t1}=0$, $M_{t2}=0,65$ [p.u.] (actual $L_m=1,2963$ [p.u.], chosen $\hat{L}_m = 1,3635$ [p.u.])

In the steady state operating mode (Fig. 7) by mutual inductance estimation error of *5,2* %, the difference of actual rotor speed and rotor speed estimated by observer is *3,2* %, as could be satisfactory result, because in IM control system that error is difficult perceive. However, proposed ANN gives mean estimated rotor speed in steady state of *0,0541*, with error of *9,8* %. Thereat, standard deviation is $\sigma = 0,0027$.

By the rotor reference speed of $\omega^* = 0,07$ [p.u.] and step load torque from $M_{t1}=0$ to $M_t=0,3$ [p.u.] with mutual inductance estimation error of *7,3%* ($\hat{L}_m = 1,3369$ [p.u.]) and without error ($\hat{L}_m = L_m = 1,2462$ [p.u.]) actual

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and estimated rotor speed are shown in Fig. 8. It is shown in Fig. 8 that actual rotor speed is in agreement with the rotor speed estimated by observer in steady state mode, even at remarkable mutual inductance estimation error. This effect can be assigned to rotor speed feedback that by PI rotor speed controller minimizes the difference between rotor speed reference value and rotor speed estimated by observer. However, the mean value of ANN estimated rotor speed in steady state in this case is *0,0678* (σ=*0,002*). This is relative error of *3,1%*. That relative error, although small, suggest that chosen mutual inductance $\hat{L}_m$ is not correct. If mutual inductance is estimated without error then the mean value of ANN estimated rotor speed in steady state is *0,0711* (Fig. 8 b)) (σ=*0,0016)*, which is relative error of *1,6%*.
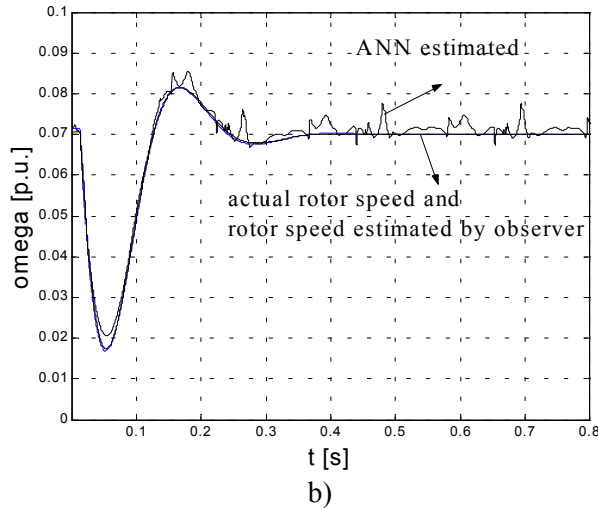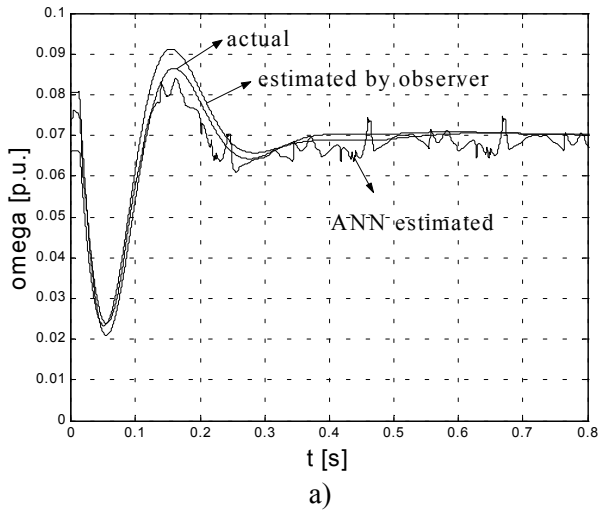

a)

b)

Figure 8. Actual rotor speed, rotor speed estimated by observer and ANN estimated rotor speed; $\omega^* = 0,07$ [p.u.], M_{t1}=*0*, M_{t2}=*0,3* [p.u.] a) $\hat{L}_m = 1,3369$ [p.u.] and b) $\hat{L}_m = L_m = 1,2462$ [p.u.]

So, it can be concluded that ANN is more sensible to mutual inductance values than analyzed observer. If

observer and ANN work parallel, then ANN can be utilized for validity of mutual inductance choice.

5 Conclusion

The analyzed vector control system is based on rotor speed estimation by solving an error in *q*- component of rotor flux. Estimation of rotor flux vector and rotor speed (rotor speed estimated by observer) strongly depend about observer gain $1/T_c$ and about accuracy of mutual inductance estimation $\hat{L}_m$.

As a benchmark of validity of mutual inductance estimation in this paper is proposed ANN estimation. That ANN works parallel with the observer and the ANN is independent about it. This ANN was trained using files accommodating calculated components of currents and voltages vectors taking into account main magnetic circuit saturation. If the estimation error of mutual inductance is small then actual rotor speed is practically in agreement with rotor speed estimated by observer. If these errors become relatively higher then the differences between actual rotor speed and ANN estimated speed become detectable higher. It can be concluded that ANN is more sensible in the open-loop for mutual inductance variations than the analyzed observer in the close-loop. If the ANN and observer work parallel, then the ANN can be employed for validation of mutual inductance estimation in IM vector control system.

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