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Experimental Study of Artificial Neural Network as a Rotor Resistance Estimator in the Indirect Vector Control of an Induction Motor

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***Abstract*— This paper presents a rotor resistance estimator based on an artificial neural network (ANN) used in the indirect vector control (IVC) of an induction motor (IM). Attention is focused on the dynamic performance of ANN rotor estimator, which gives superior performance over the fuzzy logic based rotor estimator reported in technical literature. The simulation was done using a 20 HP induction motor. The same ANN rotor estimator was proved with other IM having different rated powers. The use of the same ANN was possible because the scaling and descaling (normalization) of the input and output of ANN was property done for each motor. The ANN training was done offline using the Levenberg-Marquardt algorithm. The neuronal network is a three-layer network; the first layer has fourteen neurons, the hidden layer has five neurons and the output layer has only one neuron because the unique output signal is the rotor resistance value.**

***Index Terms*— Induction motor vector control, rotor resistance estimation, artificial neural network**

I. INTRODUCTION

Vector control or field-oriented control is the most popular method of obtaining high performance in induction motor drives. There are essentially two general methods of vector control. One, called the direct or feedback method, and the other, the indirect or feed forward method. Indirect vector-controlled (IVC) induction motor (IM) drives used in high-performance systems are very popular in industrial applications due to their relative simple configuration, as compared to the direct method which require flux and torque estimators [1]-[2]. IVC eliminates the need for a flux model but require an accurate measurement of shaft position in order to determine the precise location of the rotor flux space vector or phasor. In an IVC induction motor drive, the flux, torque, and slip commands are calculated from the IM variables based on machine's parameters. It is desirable that these parameters match the actual parameters of the machine at all operating conditions to achieve decoupling control of the machine. The control performance is thus sensitive to the system parameters, in particular to the rotor resistance which changes significantly with temperature and skin effect. The estimation of rotor resistance is done in order to update its value into the control and keep the IVC tuned.

The estimation of rotor resistance in an IVC induction motor drive has been subject of several research works [3]-[7]. Despite all these efforts, rotor resistance estimation remains a difficult problem. In this paper, a rotor resistance estimator based on artificial neural networks (ANN) is presented. The ANN simulation results are compared with the ones obtained by a fuzzy logic estimator presented in the literature. The effectiveness of the proposed rotor resistance estimator for a 20 hp IM is then demonstrated by simulation. The use of the ANN rotor estimation for other rated power IM is also shown.

II. IVC USING AN ANN ROTOR RESISTANCE ESTIMATOR

Figure 1 shows IVC scheme with an ANN rotor resistance estimator.

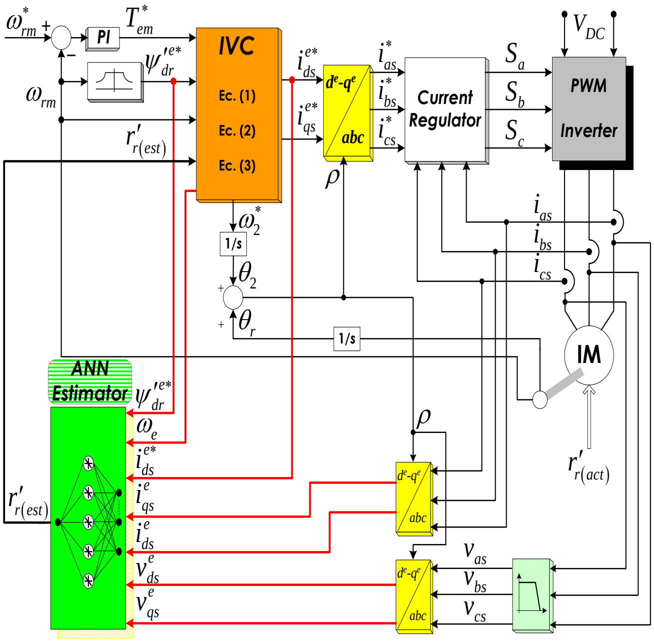

Fig.1. Indirect vector-controlled IM drive with an ANN rotor resistance estimator.

The implementation of IVC is based in the following equations [2]:

$$i_{ds}^{*} = \psi_{dr}'^{e*} \frac{r_r' + L_r' p}{r_r' L_r'} \tag{1}$$

$$i_{qs}^{*} = \frac{2}{3}\frac{2}{P}\frac{L_r'}{L_m}\frac{T_{em}^{*}}{\psi_{dr}'^{e*}} \tag{2}$$

$$\omega_2^{*} = \omega_e - \omega_r = \frac{r_r'}{L_r'}\frac{i_{qs}^{e*}}{i_{ds}^{e*}} \tag{3}$$

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where r_r', L_r', L_m are the rotor resistance and the rotor and the magnetizing inductances respectively; T_{em}^*, $\psi_{dr}'^{e*}$ are the electromagnetic torque and rotor flux reference values respectively, i_{ds}^{e*}, i_{qs}^{e*} are the reference values of stator current d-q components in the synchronous reference frame; P is the number of pole pairs; $\omega_2^*, \omega_e, \omega_r$ are the slip (reference value), synchronous and rotor frequency respectively and p is the Laplace operator.

A. *ANN rotor estimator*

The rotor estimator shown in figure 1 is described in more detailed in figure 2. As it is observed in this figure, the ANN has fourteen inputs because each one of the seven input variables is entered to ANN together with a one-step time delayed variable value.

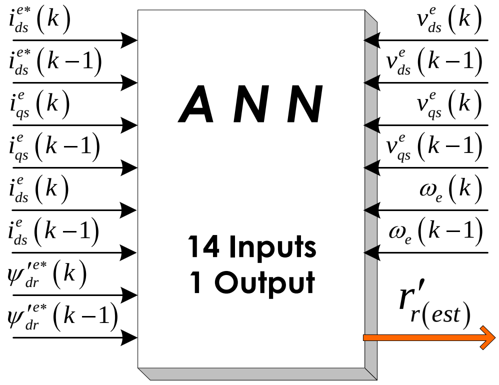

Fig.2. Input variables in ANN rotor resistance estimator.

Figure 3 shows the training method of the ANN. The input/output data patterns were generated from a system model based on fuzzy logic [5], [8]-[9]. The training was done considering both the starting and steady state operating condition of IM vector control. Three different values of rotor resistances were employed during the training procedure. The inputs of ANN rotor resistance estimator are: stator voltages and currents components in synchronous reference frame, reference stator flux, d-axis component stator reference current and synchronous electrical speed. Besides these seven inputs seven delayed inputs were also considered.

The neuronal network is a three-layer network; the first layer has fourteen neurons (or nodes), the hidden layer has five neurons and the output layer has only one neuron because the unique output signal is the rotor resistance value. The training procedure used was the back propagation algorithm and it was carried on using the Matlab/Simulink package. The input/output example data patterns are gathered from the simulated system because a system model is available as it can be seen in the top side of the figure 3. The network is initialized with random positive and negative weights to avoid saturation before training starts. With one input pattern, the output is calculated and compared with the desired output pattern. The weights are then changed until the error between the calculated pattern and the desired pattern is very small and acceptable. A similar training is done with all the patterns, in order to make them match. At this point, the network is said to have been trained satisfactorily.

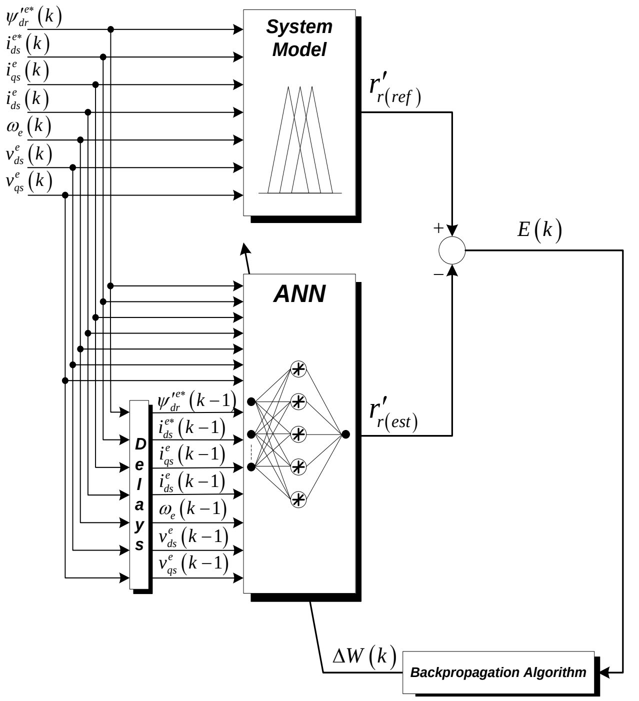

Fig.3. Training scheme of the ANN rotor resistance estimator.

B. *System model based on fuzzy logic*

Figure 4 shows the system model used in the training procedure of ANN. The difference between the functions

$$F_{est} = -i_{ds}^{e*}\psi_{dr}'^{e*}\omega_e \tag{4}$$

$$F_{act} = \frac{L_r'}{L_M}\left[\left(i_{qs}^e v_{ds}^e - i_{ds}^e v_{qs}^e\right) + \left(i_{qs}^{e\,2} + i_{ds}^{e\,2}\right)L_s\sigma\omega_e\right] \tag{5}$$

reflects the variation of rotor resistance [5], [8]-[9]. The superscript * means reference values instead of measured values.

The system model shown in figure 4 is used in [9] as rotor resistance estimator. In the present paper this scheme is used as model in the training procedure of an ANN. The simulating results show that the rotor resistance based on ANN has a better dynamic performance than the rotor resistance estimator shown in [9] (figure 4) even when different rated power of IM are used with the same ANN estimator. In this case only one training procedure was needed. The use of the same ANN was possible for different motors because the scaling and descaling (normalization) of the ANN input and output was properly done for each motor. The error $E_F(k)$ between F_{est} and F_{act} and its time variation $\Delta E_F(k)$ are then calculated as:

$$E_F(k) = F_{est}(k) - F_{act}(k) \tag{6}$$

$$\Delta E_F(k) = E_F(k) - E_F(k-1) \tag{7}$$

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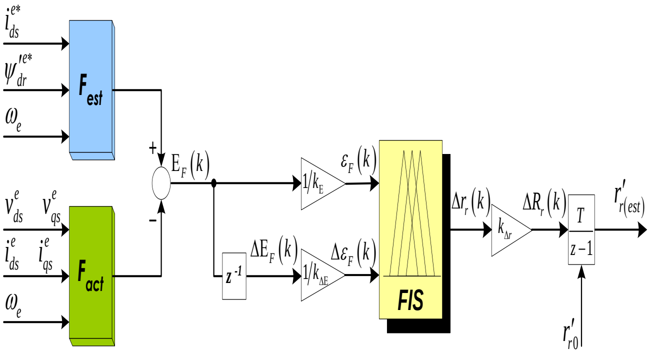


Fig. 4. System model based on fuzzy logic.

These variables are used as input for the estimator based on fuzzy logic. The internal structure of the fuzzy logic rotor resistance estimator is chosen similar to that of a fuzzy logic controller, which consists of three stages: fuzzification, inference, and defuzzification. The $\varepsilon_F(k)$ and $\Delta\varepsilon_F(k)$ fuzzification stage inputs signals are per unit (p.u.) signals computed from the actual $E_F(k)$ and $\Delta E_F(k)$ by dividing them by the respective gain factors k_E and Δk_E. The crisp variables $\varepsilon_F(k)$ and $\Delta\varepsilon_F(k)$ are converted into fuzzy variables ε_F and $\Delta\varepsilon_F$ using triangular membership functions.

In the second stage of the estimator, variables $\varepsilon_F(k)$ and $\Delta\varepsilon_F(k)$ are processed by an inference engine (block FIS in fig. 4) that executes 49 rules (7x7) as shown in table 1, where NL, NM, NS, ZE, PS, PM, PL correspond to Negative Large, Negative Medium, Negative short, Zero, Positive Short, Positive Medium, and Positive Large respectively.

In the defuzzification stage, a crisp value for the output variable $\Delta r_r(k)$ is obtained by the height method. The calculated value of the incremental resistance $\Delta R_r(k)$ is then obtained by multiplying $\Delta r_r(k)$ by the gain factor $k_{\Delta r}$. The value of estimated rotor resistance is then obtained by integrating the output signal:

$$r'_{r(est)} = R_r(k-1) + k_{\Delta r}\Delta r_r(k) \qquad (8)$$

Note that the rated value of rotor resistance is taken as inicial value for this integral.

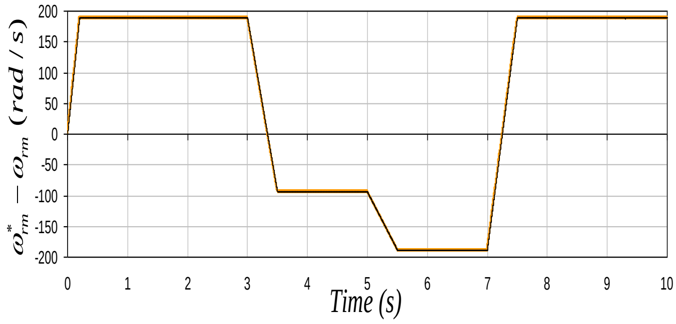
The estimate valor $r'_{r(est)}$ is used in the slip calculator (equation 3) and rotor flux (d-component stator current) estimator to ensure the correct field orientation operation of the drive.

Table1. Rule base for rotor resistance determination.

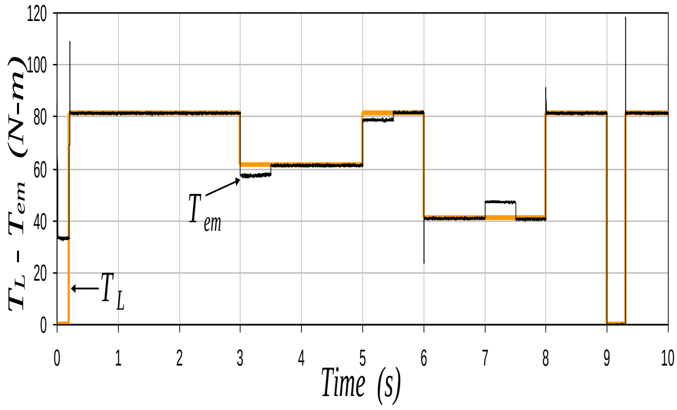
ε_F \ $\Delta\varepsilon_F$	NL	NM	NS	ZE	PS	PM	PL
NL	NL	NM	NS	NL	PS	PM	PL
NM	NL	NM	NS	NM	PS	PM	PL
NS	NL	NM	NS	NS	PS	PM	PL
ZE	NL	NM	NS	ZE	PS	PM	PL
PS	NL	NM	NS	PS	PS	PM	PL
PM	NL	NM	NS	PM	PS	PM	PL
PL	NL	NM	NS	PL	PS	PM	PL

III. SIMULATION RESULTS

The simulation was done using the Matlab/Simulink package. Figure 5 shows the simulated transient response of both fuzzy logic based and ANN based rotor resistance estimator using 20 hp rated power motor drive (see appendix). The transient variation of reference and actual speed, and electromagnetic and load torque are shown in the figures 5 (a) and (b) respectively. Figures 5 (c), (e), (g), and (i) show the rotor flux responses when speed and torque vary as they are shown in figure 5 (a) and (b). The responses of fuzzy logic based and ANN based rotor resistance estimator for keeping the actual rotor resistance constant are observed in the figures 5 (d) and (f) respectively. The response of both estimators, when the actual rotor resistance varies, is shown in figures 5 (h) and (j). Regardless the ANN was training for the 20 hp rated power IM using the rotor resistance fuzzy logic based estimator as system model, the reached performance of ANN rotor resistance estimator is much better than fuzzy logic based estimator as it can be observed in figure 5. Figure 5 shows the influence of rotor resistance estimation on the IVC performance (see rotor flux response); from this figure it is clear that when the estimation of rotor resistance is improved, the vector control detuning due to rotor resistance mismatch is almost eliminated.



(a) Reference and actual speed variation



(b) Electromagnetic and load torque variation

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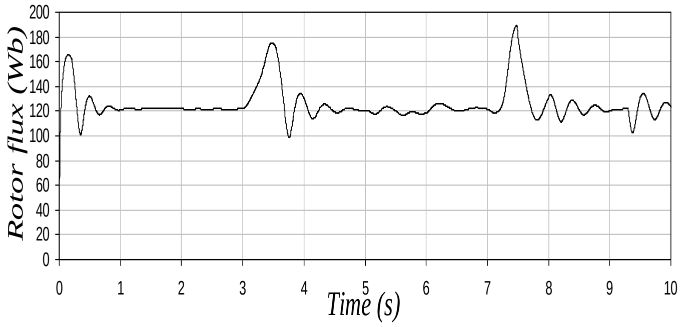
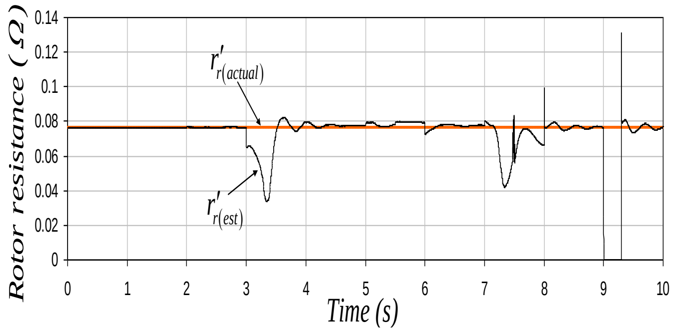
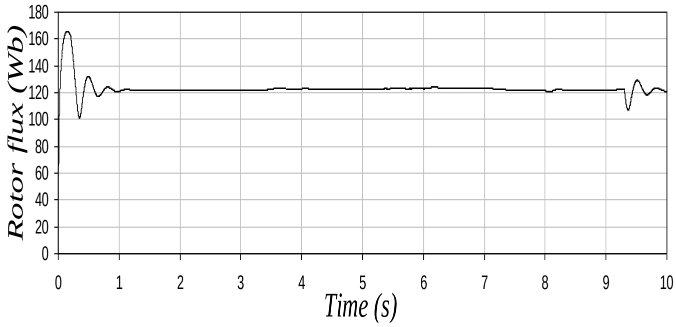


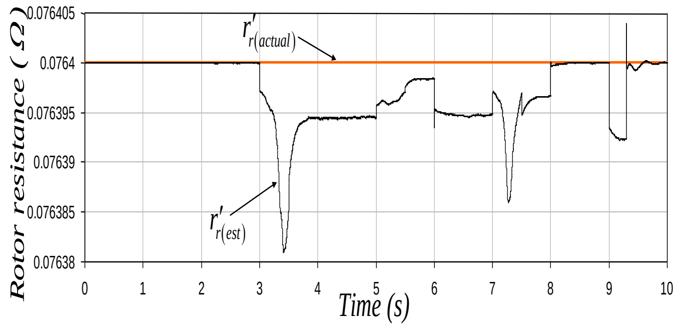
(c) Rotor flux response at constant rotor resistance of fuzzy logic based rotor resistance estimator



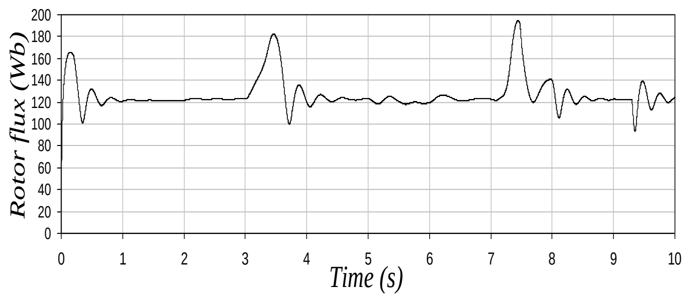
(d) Response of fuzzy logic based rotor resistance estimator



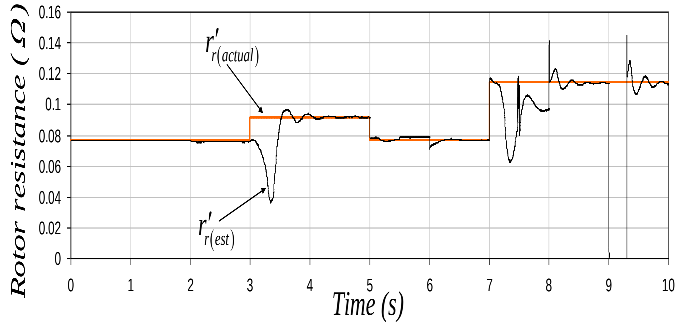
(e) Rotor flux response at constant rotor resistance of ANN based rotor resistance estimator



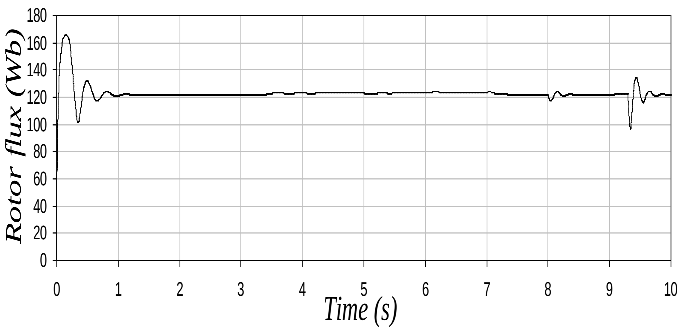
(f) Response of ANN based rotor resistance estimator



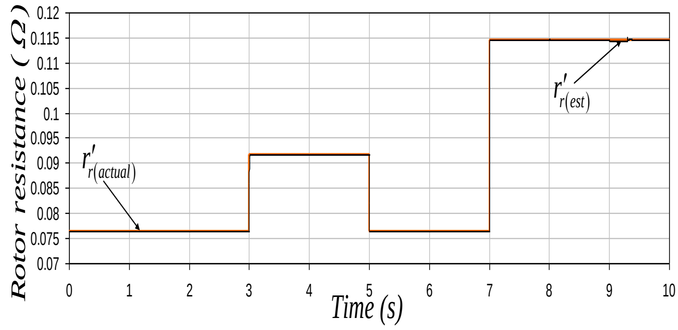
(g) Rotor flux response at variable rotor resistance of fuzzy logic based rotor resistance estimator



(h) Response of fuzzy logic based rotor resistance estimator



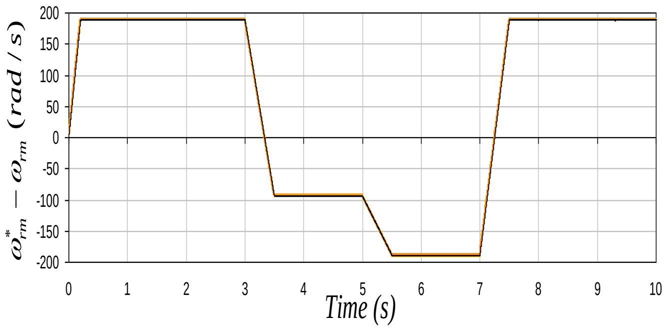
(i) Rotor flux response at variable rotor resistance of ANN based rotor resistance estimator



(f) Response of ANN based rotor resistance estimator

Fig. 5. Simulation transient response of fuzzy logic based and ANN based rotor resistance estimator for a 20 hp rated power IM

Figure 6 shows the transient responses of IVC and ANN based rotor resistance estimator using 100 hp rated power MI (see appendix). The same ANN can be used in the rotor resistance estimator by properly changing the scaling and descaling (normalization) of the input and output of ANN. As it is observed in this figure, an excellent performance of rotor estimator is obtained regardless that a different motor is used. This means that the ANN has a good generalization behavior.



(a) Reference and actual speed variation

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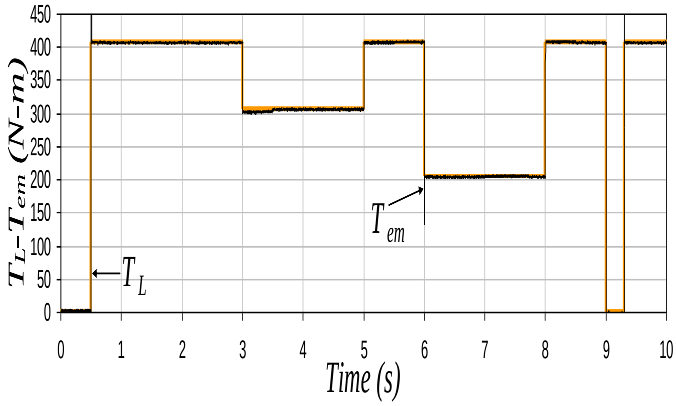
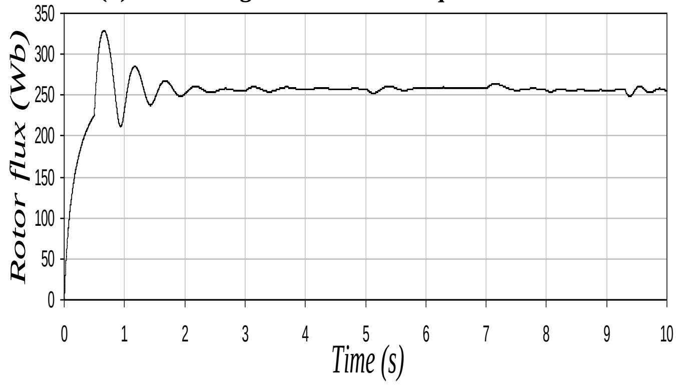
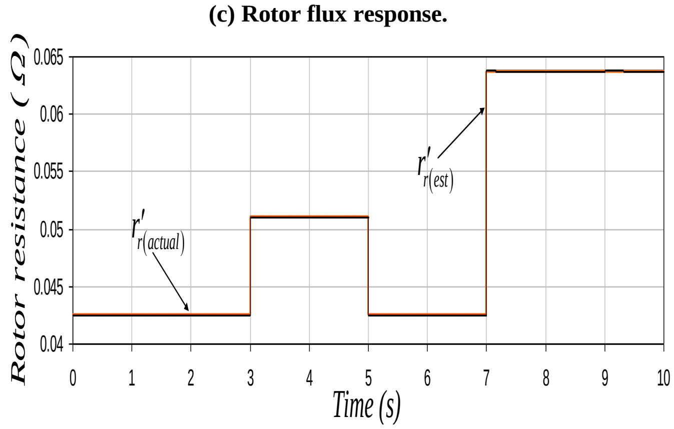


(b) Electromagnetic and load torque variation



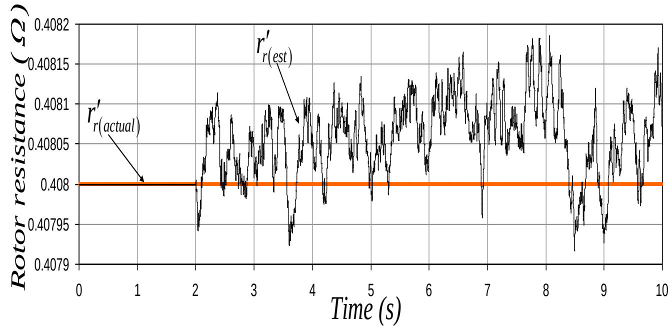
(c) Rotor flux response.



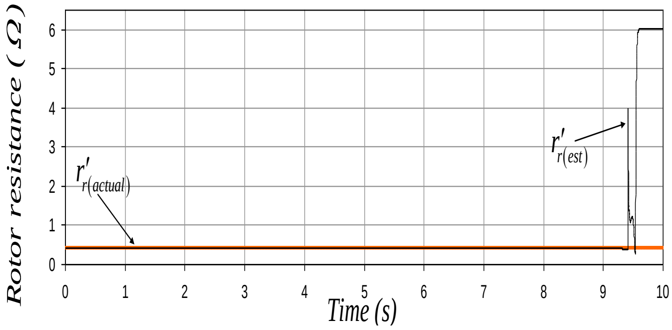
(d) Response of ANN based rotor resistance estimator

Fig. 6. Simulation transient response of ANN based rotor resistance estimator for a 100 hp rated power IM

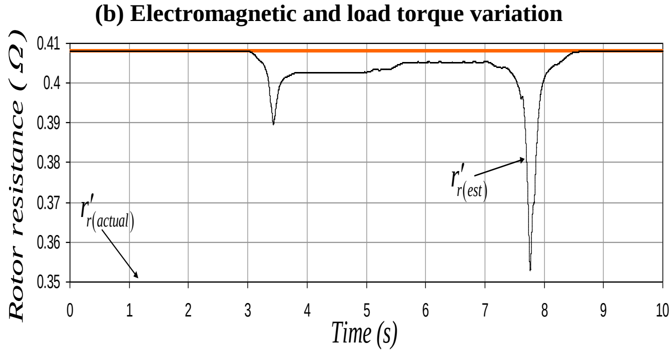
Figure 7 shows the steady-state ANN rotor resistance estimation response considering a 5 hp rated power IM drive (see appendix). In figure 7 (a) rated speed and electromagnetic torque is considered. In figure 7 (b) the rotor speeds is kept constant and equal to rated rotor speed, while load torque varies in the same rate shown in figure 5 (b). The estimation of rotor resistance is lost at 9.3 s, when the load torque varies from zero to rated value instantaneously. Figure 7 (c) shows the response when the electromagnetic torque is equal to its rated value and the rotor speed varies as in figure 5 (a). In figure 7 (d) the rotor speed and electromagnetic torque varies at the same time, again the estimation fails at 9.3 s when the load torque varies from zero to rated value.



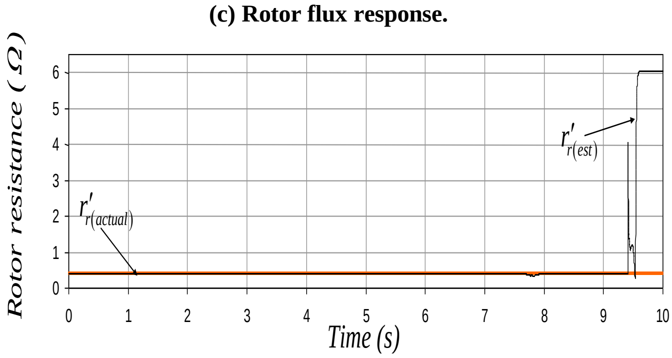
(a) Reference and actual speed variation



(b) Electromagnetic and load torque variation



(c) Rotor flux response.



(d) Response of ANN based rotor resistance estimator

Fig. 7. Simulation transient response of ANN based rotor resistance estimator for a 5 hp rated power IM

IV. CONCLUSION

This paper has presented an ANN based rotor resistance estimator used to update its value in indirect-vector control of induction motor drives. Base on obtained results, the proposed estimator has much better dynamic performance than fuzzy based rotor resistance estimator presented in the technical literature though the training of ANN was done using this fuzzy based estimator as system model. In this case the use of the Neural Networks is better than conventional

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controllers, such as stability and reliability; this kind of neural estimator is more robust than the fuzzy logic estimator performance whit the same parameters of the cage induction motor. Using an ANN with this data was improved velocity, flux and torque according to the behavior of the rotor resistance estimator. The obtained simulation results show that the ANN based estimator can be extended to other IM getting an acceptable performance, even in dynamic conditions.

APPENDIX

Induction motor parameters

20 hp, 60 Hz, 220 V, 1750 r/min, $r_s = 0.1062\ \Omega$, $r_r' = 0.0764\ \Omega$, $x_m = 5.834\ \Omega$, $x_{ls} = x_{lr} = 0.2145\ \Omega$, $J = 2.8\ kgm^2$.

100 hp, 60 Hz, 460 V, $r_s = 0.0425\ \Omega$, $r_r' = 0.0425\ \Omega$, $x_m = 8.51\ \Omega$, $x_{ls} = x_{lr} = 0.284\ \Omega$, $J = 2.0\ kgm^2$.

5 hp, 60 Hz, 230 V, $r_s = 0.531\ \Omega$, $r_r' = 0.408\ \Omega$, $x_m = 31.931\ \Omega$, $x_{ls} = x_{lr} = 0.95\ \Omega$, $J = 0.1\ kgm^2$.

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