Adaptive control of induction motor with unknown motor resistance

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Abstract
In this paper, a new approach for induction motor rotor resistance variation estimate is presented by using adaptive neural networks. Indeed, the proposed neural networks are endowed with adaptive rules that allow them to estimate the true values of the necessary nonlinear state feedbacks for the input-output feedback linearization control of an induction motor. A comparison between the nonlinear state feedbacks provided by neural networks and those calculated through the nominal model of the induction motor with nominal parameters allows us to estimate the variation in the rotor resistance.

Key words: Induction motor; Neural networks; Feedback linearization; estimator of rotor resistance; Adaptive nonlinear rules.

1. Introduction

For reasons of the weak cost, reduced mass, hardiness and simple construction, the induction motor plays the main role in electrical practices. However, with a greatly nonlinear model and with time varying parameters, the control was very difficult to be achieved, what oriented the research toward the combination of several techniques to control the induction motor behavior.

The use of classical approaches as the field oriented control [1 and 2] and the feedback linearization control [3, 4 and 5] showed their insufficiency against the parametric variation. Typically, to assure an adaptive control for the induction motor we must find a solution for the
rotor flux modulus that is non available to the direct measure as well as for the problem of the parametric variation in particular the rotor resistance.

For that, several solutions treating the problem of rotor flux estimate and parameters identification has been proposed for both field oriented control [6, 7, 8 and 9] and feedback linearization control [10, 11, 12 and 13]. While these approaches give satisfactory performances the resulting control laws are very complicated and require an enormous mathematical development.

To avoid the classical estimator’s constraints we can resort to neural networks that proved great approximation capacities [14]. Where we can note that for classical feedback linearization control the performances are bound to the precision with which are estimated the necessary nonlinear state feedbacks to generate the corresponding control laws. Therefore, two neural networks endowed with non-linear adaptive rules are proposed to estimate those nonlinear state feedbacks [15]. The introduction of such networks in the control schema ensured an adaptive control for the induction motor in all operating conditions if we suppose that the rotor flux modulus and its position are available. However the accurate determination of this flux is one of essential challenges in the control of the induction motor. Therefore it is necessary to establish an estimator for the rotor flux modulus.

Therefore to complete the approach developed in [15] in this paper, the proposed neural networks outputs are exploited to identify the rotor resistance and thereafter to establish an estimator for the rotor flux. For that we can assume that the necessary non-linear reactions for the feedback linearization control can be estimated by neural networks that by induction motor mathematical model. Thanks to the adaptive rules, the proposed neural networks can give the true values of the wished nonlinear state feedbacks whose parametric variations are considered. While with the mathematical model when the parameters variation is unknown we can only have the nominal values for these state feedbacks corresponding to the nominal parameters of induction motor. Therefore we can conclude that the difference between the two estimated values comes of the parameters variation effect (rotor resistance). From a simple comparison between the two estimated values we can deduct the rotor resistance variation. Thereafter the found resistance is used in the mathematical equations of rotor flux to estimate its module.
2. Feedback linearization control of induction motor

The dynamics of the induction motor in a stationary frame can be expressed by:

\[ \dot{x} = F(x) + g(x)V_s \] (1)

Where \( x \) and \( V_s \) respectively the state vector and the input vector given by:

\[ x = [I_a, I_b, \Phi_a, \Phi_b, \omega] \]
\[ V_s = [V_a, V_b] \] (2)

\( F \) and \( g \) are given by:

\[
F(x) = \\
\begin{bmatrix}
-\gamma I_a + \alpha \beta \Phi_a + w_r \Phi_b \\
-\gamma I_q - w_r \Phi_a + \alpha \beta \Phi_b \\
\alpha M I_a - \alpha \Phi_a - w_r \Phi_b \\
\alpha M I_b + w_r \Phi_a - \alpha \Phi_b \\
\mu (\Phi_a I_b - \Phi_b I_a) - \frac{T_L}{J}
\end{bmatrix}
\] (3)

\[
g(x) = \\
\begin{bmatrix}
1 \\
0 \\
0 \\
0 \\
0
\end{bmatrix}
\] (4)

With \( I_a \) and \( I_b \) the stator currents, \( V_a \) and \( V_b \) the stator voltages, \( \Phi_a \) and \( \Phi_b \) the rotor flux, \( \omega \) the rotor speed, \( T_L \) the load torque, \( J \) the moment of inertia, \( R_s \) and \( L_s \) the stator resistance and inductance, \( R_r \) and \( L_r \) the rotor resistance and inductance, \( M \) the magnetizing inductance and

\[ \beta = M/(\sigma L_r), \quad \mu = M/(J L_r), \quad \gamma = \alpha M \beta + R_s / \sigma, \quad \sigma = L_s (1 - M^2/(L_s L_r)), \quad \alpha = \frac{R_r}{L_r}. \]

In operating conditions, the induction motor rotor resistance is a time varying parameter. If \( R_{rn} \) is the nominal value of \( R_r \) and \( \tilde{R}_r = R_r - R_{rn} \) the unknown variation in rotor resistance, \( \alpha \) (the inverse of rotor time constant) can be rewritten as follows:

\[ \alpha = (1 + \rho) \kappa_n \] (5)
Where:
\[
\alpha_a = \frac{R_a}{L_a} \\
\rho = \frac{R}{R_n}
\] (6)

To control the IM, we need to express its dynamic in the rotating frame (d, q) that turns with an appropriate speed (\(\omega_a\)). According to the new frame, the state variables \((I_d, I_q, \Phi_d, \Phi_q)\) and the control inputs \((V_d, V_q)\) can be obtained through the following coordinate transformation:

\[
\begin{bmatrix}
    x_d \\
    x_q
\end{bmatrix} = \begin{bmatrix}
    \cos(\theta_a) & \sin(\theta_a) \\
    -\sin(\theta_a) & \cos(\theta_a)
\end{bmatrix}\begin{bmatrix}
    x_a \\
    x_b
\end{bmatrix}
\] (7)

Where:
\[
\theta_a(t) = \arctan\left(\frac{\Phi_a}{\Phi_d}\right)
\] (8)

\((x_a, x_b)\) and \((x_d, x_q)\) are respectively the vectors components according to the old and the new referential frame.

If \(\omega_f\) and \(\Phi_f\) are the desired signals for the controlled outputs of the induction motor that are in this paper the rotor speed \(\omega_r\) and the square of the rotor flux modulus \(\Phi = \Phi_r^2\) [10].

Considering the tracking errors definite as follow:

\[
\begin{align*}
\ddot{\omega}_r &= \omega_r - \omega_f \\
\ddot{\Phi} &= \Phi_r - \Phi_f \\
\ddot{\Phi}_q &= \Phi_q
\end{align*}
\] (9)

The rotor flux modulus is given by:

\[
\Phi_r = \sqrt{\Phi_d^2 + \Phi_q^2}
\] (10)

For the induction motor only \(I_a, I_b\) and \(\omega_r\) are directly available for measure. Our goal is to design the dynamic compensation:
\[
\begin{bmatrix}
V_a \\
V_b
\end{bmatrix}
= \begin{bmatrix}
\cos(\theta_a) & -\sin(\theta_a) \\
\sin(\theta_a) & \cos(\theta_a)
\end{bmatrix}
\begin{bmatrix}
V_d \\
V_q
\end{bmatrix}
\] (11)

Where \( V_d, V_q \) and \( \omega_b \) are chosen so that for any initial condition of \( I_a, I_b, \Phi_a, \Phi_b \) and \( \omega_r \), we have:

\[
\lim_{t \to \infty} \omega_b(t) = 0
\] (12)

\[
\lim_{t \to \infty} \Phi(t) = 0
\] (13)

What implies that:

\[
\lim_{t \to \infty} \left[ \Phi^2_r(t) - \Phi_f(t) \right] = \lim_{t \to \infty} \Phi(t) = 0
\] (14)

Therefore, if the control objectives are attained we have:

\[
\lim_{t \to \infty} \Phi_r(t) = |\Phi_d(t)|
\] (15)

Now, for achieving the dynamic compensation (11), considering the tracking errors vectors \( e_{t1} \) and \( e_{t2} \) and those of the filtered errors \( e_{f1} \) and \( e_{f2} \) for the controlled outputs \( \omega_r \) and \( \Phi_r \):

\[
\begin{bmatrix}
e_{t1} \\
e_{t2}
\end{bmatrix} = \begin{bmatrix}
e_{11} & e_{12} \\
e_{21} & e_{22}
\end{bmatrix} = \begin{bmatrix}\Phi - \Phi_f \\
\Phi - \Phi_f\end{bmatrix}
\] (16)

\[
\begin{bmatrix}
e_{f1} \\
e_{f2}
\end{bmatrix} = \begin{bmatrix}k_f & k_f \\
k_f & k_f
\end{bmatrix} \begin{bmatrix}e_{11} \\
e_{12}
\end{bmatrix}
\] (17)

The dynamics of the filtered error can be expressed as follow [15]:

\[
\begin{bmatrix}
\dot{e}_{f1} \\
\dot{e}_{f2}
\end{bmatrix} = \begin{bmatrix}f_1(x) + k_1 e_{21} \Phi_f \\
f_2(x) + k_2 e_{22} \Phi_f
\end{bmatrix} + G \dot{f}_s
\] (18)

With:
\[ [G] = \begin{bmatrix} \frac{2aM}{\delta L_s} \Phi_d & \frac{2aM}{\delta L_s} \Phi_q \\ -\frac{\mu}{\delta L_s} \Phi_q & \frac{\mu}{\delta L_s} \Phi_d \end{bmatrix} \] (19)

\[ f_1(x) = (4a^2 + 2a^2 \beta M)(\Phi_q^2 + \Phi_d^2) + 2aM\omega_r (\Phi_d I_q - \Phi_q I_d) - (6a^2 M + 2a\gamma M)(\Phi_d I_d + \Phi_q I_q) + 2a^2 M^2 (I_q^2 + I_d^2) \] (20)

\[ f_2(x) = -\mu \beta \omega_r (\Phi_q^2 + \Phi_d^2) - \mu (\alpha + \gamma)(\Phi_d I_q - \Phi_q I_d) - \mu \omega_r (\Phi_d I_d + \Phi_q I_q) \] (21)

\[ U_s = \begin{bmatrix} V_d \\ V_q \end{bmatrix} \] (22)

While considering (18), the control laws can be valued as follows [16]:

\[ U_s = [G]^{-1} \begin{bmatrix} -f_1(x) - k_1 e_{21} + \ddot{\varphi}_f + v_{f1} \\ -f_2(x) - k_2 e_{22} + \dot{\vartheta}_f + v_{f2} \end{bmatrix} \] (23)

\[ \begin{bmatrix} v_{f1} \\ v_{f2} \end{bmatrix} = \begin{bmatrix} -k_f e_{f1} \\ -k_v e_{f2} \end{bmatrix} \] (24)

3. Adaptive neural control of induction motor

Now instead of (21) and (22) let us consider two neural networks to estimate \( f_1 \) and \( f_2 \). Supposing that there are ideal parameters allowing them to estimate the exact values (ideal) of \( f_1 \) and \( f_2 \) such that:

\[ \begin{cases} f_1(x_1) = w_1^T \sigma_1(w_{c1}^T x_1) \\ f_2(x_2) = w_2^T \sigma_2(w_{c2}^T x_2) \end{cases} \] (25)
Furthermore, if we only have the estimated values of neural network parameters, we will only have the estimated values of \( f_1 \) and \( f_2 \) that can be expressed by:

\[
\begin{align*}
\hat{f}_1(x_i) &= \hat{w}_i^T \sigma_j(\hat{w}_{ci}^T x_i) \\
\hat{f}_2(x_2) &= \hat{w}_2^T \sigma_2(\hat{w}_{ci2}^T x_2)
\end{align*}
\]  
\hspace{1cm} (26)

The input vectors for these networks are chosen among the measurable states; in this paper those inputs are selected as follows:

\[
x_i = x_2 = [I_d \ I_q]^T 
\]  
\hspace{1cm} (27)

In (25) and (26) \( \sigma_j \) is a sigmoid function, \( w_i \) and \( w_{ci} \), \( \hat{w}_i \) and \( \hat{w}_{ci} \) are respectively the ideal and estimated parameters of the selected neural networks.

While using (23), (24), (25) and (26) the filtered errors dynamics can be written as follows [14 and 15]:

\[
\begin{align*}
\dot{e}_{f1} &= -k_e e_{f1} + \hat{w}_i^T (\hat{\sigma}_j - \tilde{\sigma}_j \hat{w}_{ci}^T x_i) + \hat{w}_i^T \tilde{\sigma}_j \hat{w}_{ci}^T x_i \\
\dot{e}_{f2} &= -k_e e_{f2} + \hat{w}_2^T (\hat{\sigma}_2 - \tilde{\sigma}_2 \hat{w}_{ci2}^T x_2) + \hat{w}_2^T \tilde{\sigma}_2 \hat{w}_{ci2}^T x_2
\end{align*}
\]  
\hspace{1cm} (28)

Following the filtered errors dynamics, the adaptive rules for the neural network parameters can be given as follow [14 and 15]:

\[
\begin{align*}
\dot{\hat{w}}_i &= -\Gamma_{wi} \left( \hat{\sigma}_j - \tilde{\sigma}_j \hat{w}_{ci}^T x_i \right) e_{f1} - \tau_j [e_{f1}] [\hat{w}_i] \\
\dot{\hat{w}}_{ci} &= -\Gamma_{wci} \left( x_i \hat{w}_i^T \tilde{\sigma}_j e_{f1} - \tau_j [e_{f1}] [\hat{w}_{ci}] \right) \\
\dot{\hat{w}}_2 &= -\Gamma_{w2} \left( \hat{\sigma}_2 - \tilde{\sigma}_2 \hat{w}_{ci2}^T x_2 \right) e_{f2} - \tau_j [e_{f2}] [\hat{w}_2] \\
\dot{\hat{w}}_{ci2} &= -\Gamma_{wci2} \left( x_2 \hat{w}_2^T \tilde{\sigma}_2 e_{f2} - \tau_j [e_{f2}] [\hat{w}_{ci2}] \right) 
\end{align*}
\]  
\hspace{1cm} (29)

Where \( \Gamma_{wi} \) and \( \Gamma_{wci} \) are positive definite matrixes, \( \tau_j \) and \( \tau_f \) are positive constants used to improve the adaptive rules convergence.
4. Neural estimator of the rotor resistance

From (1) the rotor flux components estimates can be given by:

\[
\begin{align*}
\hat{\Phi}_a &= a(MI_a - \hat{\Phi}_a) - \omega_r \hat{\Phi}_b \\
\hat{\Phi}_b &= a(MI_b - \hat{\Phi}_b) + \omega_r \hat{\Phi}_a
\end{align*}
\]  

(30)

It is obvious that the exact estimate of rotor flux depends on the rotor resistance value. Therefore, any imprecision in rotor resistance value causes the violation of the mentioned conditions in (13), (14) and (15) and therefore the dynamic compensation (11) will be affected. Therefore, while using only the previous results, in this section, we will try to establish a procedure to estimate the unknown variation in rotor resistance (5) and (6).

Moreover, we can note that the values of \( f_1 \) and \( f_2 \) in the control law (24) can be obtained by (20) and (21) as by the proposed neural networks through (26). The difference between the two approaches is that, in (20) and (21); we ignore the variation of motor parameters, only the nominal values of these parameters are known. Therefore, the rotor resistance variation \( \tilde{R}_r \) is not considered with absence of any estimator. So the values given by (20) and (21) don't reflect the true values of \( f_1 \) and \( f_2 \). Contrarily, with the proposed neural networks, any parametric variation in motor parameters is reflected in the state vector and therefore in the filtered errors (18). In this case, the adaptive rules (29) intervene to eliminate the parametric variation effect. This action allows modifying the neural networks behavior so that they have to their outputs the true values of \( f_1 \) and \( f_2 \).

It results that we are in a situation where the true values of \( f_1 \) and \( f_2 \) (while considering \( \tilde{R}_r \)) are given by the two neural network while (20) and (21) give only their nominal values (with nominal parameters of the motor). Then, we can use the difference between these two estimates to deduct the rotor resistance variation. In such a situation we can write:

\[
\hat{f}_2(x) = f_2(x, a_n) + \zeta_2(x, \tilde{R}_r) + \psi(\bar{w}_2, \bar{w}_{c2})
\]  

(31)

Where \( f_2(x, a_n) \) is obtained through (21) (with \( a = a_n \)), \( \zeta_2(x, \tilde{R}_r) \) expresses the influence of \( \tilde{R}_r \) in \( \hat{f}_1 \) and \( \psi(\bar{w}_2, \bar{w}_{c2}) \) corresponds to the estimate errors of the used neural networks.
While considering (21) and while using (5) \( \zeta(x, \tilde{R}_r) \) can be expressed by:

\[
\zeta(x, \tilde{R}_r) = f_2(x, \alpha) - f_2(x, \alpha_n)
\]
\[
= \hat{f}_2(x) - f_2(x, \alpha_n)
\]
\[
= -\rho y(x) + \Psi(\hat{w}_2, \hat{w}_c)
\]

(33)

Where:

\[
y(x) = -\mu_0 \left( 1 + \frac{M^2}{a L_r} \right) \Phi_d I_q
\]

(34)

With appropriated initial values for \( \Phi_d \) and \( I_q \), the rotor resistance variation \( \tilde{R}_r \) can be gotten as follow:

\[
\tilde{R}_r = \frac{\hat{f}_2(x) - f_2(x, \alpha_n)}{y(x)} R_n + \epsilon(\tilde{R}_r)
\]

(35)

\( \epsilon(\tilde{R}_r) \) expresses the effect of the neural networks estimate errors.

5. Simulation results

The parameters of the used induction motor are \( R_s=5.3 \Omega, R_r=3.3 \Omega, L_s=0.365H, L_r=0.375 \Omega, M=0.34H, J=0.0075 \text{ kg.m}^2, n_p=1, T_L=5.8 \text{ N.M}, \Omega_n=100\text{rad/s}, P_n=0.6kw \). The simulation test includes the following operating sequences:

- the machine is excited during the initial time interval 0-0.5s using a flux reference trajectory starting at \( \Phi_f=3.6 \times 10^{-3} \text{ Wb} \) and reaching the motor rated value of 1.16 Wb;
- The unloaded motor is required to track the speed reference trajectory, starting at \( t=0.5s \) from zero initial value and reaching the rated speed of 100 rad/s;
- At time \( t=1.5s \) a constant load torque, equal to the motor rated value of 5.8 Nm is applied;
- At time \( t=3s \) a steep of 100% of rotor resistance is applied.

The obtained results for rotor speed (Fig. 1), torque (Fig. 2) and rotor flux (Fig. 3) clearly prove the capacities of the proposed ANN to adapt with induction motor operating conditions. Furthermore, the rotor resistance variation is quickly compensated by the adaptive rules of ANN parameters.
In Fig. 4 we find the values of \( f_1 \) and \( f_2 \) that are estimated by the induction motor model and those estimated by neural networks. We can clearly see the difference between the two estimates. Indeed, it is the neural networks adaptive rules that created this difference. Where, the neural networks outputs are modified via these rules to consider the rotor resistance variation. Whereas the induction motor model can provide only the nominal values of the required functions when this variation is unknown. Fig. 5 shows the estimated rotor resistance while exploiting the difference between the two approximations. We can see that the estimate values correspond well to the true values of rotor resistance.

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Fig. 1 Rotor speed

Fig. 2 Torque

Fig. 3 Rotor flux modulus

Fig. 4 Estimated nonlinear state feedback \((f_1)\).  
--- \( f_1 \) estimated by neural network.  
---- \( f_1 \) estimated by induction motor model.

Fig. 5 Estimated and ideal rotor resistance.  
--- Estimated resistance.  
---- True (ideal) resistance.
5. CONCLUSION

The obtained results enable us to conclude that the proposed neural networks for the induction motor control ensures an adaptive control where the adaptive rules allow neural networks to adapt with all induction motor operating conditions. Furthermore, the proposed approach gives a satisfying estimate for rotor resistance variation. The estimated resistance is used to estimate the module of rotor flux and thus the control goals are reached.

REFERENCES