Adaptive nonlinear observer augmented by radial basis neural network for a nonlinear sensorless control of an induction machine

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Abstract: This paper presents adaptive neural network nonlinear observer associated with a sensor less nonlinear feedback linearisation controller for induction machine. The proposed observer is used to estimate the mechanical speed using the stator currents measurements and the supplied input voltages; whereas the load torque (unknown disturbance) is estimated using online radial basis neural network function approximation. The stability of the proposed controller-observer is achieved using Lyapunov function. Hence, simulation results have been performed under MATLAB/Simulink shows clearly the performance of the proposed algorithm.

Keywords: sensorless control; neural network observer; adaptive observer; load torque estimation; induction machine; feedback linearisation control; mechanical speed estimation; radial basis function approximation; field oriented control; FOC.


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1 Introduction

Recently induction motors have been used for industrial applications due to their sample constructions; ruggedness low cost and reliability, since induction motor (IM) is highly nonlinear and coupled multivariable system where it requires more complex methods to control, hence these machines constitute theoretically challenging control problems (Merabet, 2012). A field oriented control technique is used to achieve high speed control performance in industrial applications. However this technique is affected by external disturbance and parameter uncertainties. Therefore many studies have been made on motor in order to enhance the performance under these uncertainties such as sliding mode control, predictive control (Orlowska-Kowalska and Dybkowski, 2012; Merabet, 2012; Chen and Dunnigan, 1999; Chiasson, 1996; Marino et al., 1993; Oscar et al., 2012), and exact feedback linearisation (Bentaallah et al., 2008) to improve the dynamic and response and reduce the complexity of the field oriented control. However these techniques need more sensors to be placed in order to estimate the unmeasured states such as mechanical speed and position where their sensors are more expensive than the machine itself. Hence researches on the control of induction machines are dealing with sensor less solution. Where this control strategy uses less sensors and make the system less expensive and avoid sensor failures problems.

Thus, in recent years researchers are interested in using neural network for control and identification of nonlinear dynamic systems due to its accurate approximation of a wide range of nonlinear functions. The main advantages of the neural network especially in identification of nonlinear dynamics that they do not require any mathematical descriptions of the induction machine.
In Abolfazl and Farzan (2005), an adaptive neural fuzzy network is adopted to estimate the mechanical speed of the induction machine using a MLP neural network associated with the classical field oriented control, the results are fairly good but the authors have not applied a robust nonlinear control. In Mechrane et al. (2012) and Abolfazl and Khoei (2015) model reference adaptive systems is used to estimate the speed by augmenting the adaptive part with a neural network; where simulations obtained shows a good performance, however the authors do not take into account the use of a nonlinear controller as well as the effect of load torque to enhance the performance of the machine. In Bensalem et al. (2008), a $H_{\infty}$ controller combined with field oriented control of an induction machine, the speed is estimated using a neural network estimator by considering only the stator voltages and currents as measured states. The simulation results obtained show a good performance of the proposed controller at the absence of load torque (unknown disturbance). In Abbas et al. (2015), a nonlinear adaptive feedback linearisation controller augmented by neural network associated with a linear observers to estimate the rotor flux is used the results are good but the authors takes the speed as measured. In Iqbal and Khan (2010) and Brandstetter (2014), a MRAC observer is proposed to estimate the unmeasured mechanical speed combined with the classical field oriented control. super twisting sliding mode observer for sensor less sliding mode control in (2011) is used to estimate the mechanical speed and flux. The use of an adaptive observer to estimate the load torque in Tarek and Omari (2011) and Cherifi et al. (2012) associated with the classical field oriented control proposed by Blaschke (1972). In Basha and Suryakalavathi (2013) a neural network reference model observer is used to estimate the rotor flux in the field oriented control with an adaptive mechanism that can estimate the speed of the machine. In Mechrane et al. (2012) an adaptive observer augmented by neural network using the technique of reference model to estimate the speed, flux and rotor resistance variations that affects the field oriented control performance.

The contribution of this paper is to use a nonlinear controller based on the technique of an input output feedback linearisation (Shankar, 1999) to enhance the control performance of the induction machine in the field oriented control; where mechanical speed and rotor flux are controlled with a nonlinear controller that uses the currents as an input to the systems whereas the input voltages sources are used as output states to the stator currents of the machine. Based on that novel control strategy the machine will be controlled using only a proportional gains rather than proportional integrator gains as in the classical case. Since that the mechanical speed sensor is needed and due to its expensive cost as well as for the load torque (unknown disturbance ) which could be linear or nonlinear unknown input and has an effect on the control performance; than a novel adaptive neural network nonlinear observer is proposed to overcome this problem. Where the load torque is estimated using online neural network function approximations.

Finally the proposed adaptive neural network observer is tested using simulations on the reduced dynamical model of the induction machine to estimate the mechanical speed and the load torque (unknown disturbance), where the observer uses the stator current as measured states associated with a nonlinear feedback controller for the speed and rotor flux. A global stability analysis of the proposed method (controller-observer) has been established using Lyaponouv-based function.

This paper is organised as follows, we present in Section 2 the mathematical model of the induction machine (IM) with the orientation of the rotor flux. Section 3 describes the nonlinear feedback linearisation controller. Section 4 describes the adaptive neural
network nonlinear adaptive observer for mechanical speed and load torque estimation. Section 5 describes the global stability of the overall system. Section 6 shows the simulation results and we end up with a conclusion in Section 7.

2 The mathematical model of an induction motor

The induction motor model can be described in the synchronous frame with rotor flux aligned on the d axis such that \( \phi_{rq} = 0 \), by the following state equations:

\[
\dot{x} = f(x) + gu
\]

where the state vector \( x \) and the input vector \( u \) are defined as:

\[
x = [i_{sd}, i_{sq}, \phi_{rd}, \Omega]
\]

\[
u = [u_{sd}, u_{sq}]
\]

\[
f(x) = \begin{bmatrix}
-\gamma i_{sd} + K_c \phi_{rd} - \omega_s i_{sq} \\
-\gamma i_{sq} + \omega_s i_{sd} + K_p \phi_{rd}
\end{bmatrix}
\]

\[
\frac{M L_s}{\sigma L_s} \phi_{rd} i_{sq} - \frac{J_m}{J_m} \Omega - \frac{\tau_d}{J_m}
\]

The control input matrix is defined by:

\[
g = \begin{bmatrix}
\sqrt{\frac{\sigma}{T_c}} & 0 & 0 & 0 \\
0 & \frac{\sigma}{T_c} & 0 & 0
\end{bmatrix}^T
\]

where the parameters \( \sigma, \gamma, T_r \) are defined as:

\[
\sigma = 1 - \frac{M^2}{L_r L_s},
\]

\[
\gamma = \frac{R_s}{\sigma L_s} + \frac{R_r M^2}{\sigma L_s L_r}
\]

\[
T_r = \frac{L_r}{R_r}
\]

where \( \sigma \) is the scattering coefficient, \( T_r \) is the time constant of the rotor dynamics, \( J_m \) is the rotor inertia, \( f_m \) is the mechanical viscous damping, \( p \) is the number of pole pairs, \( \tau_d \) is the unknown external load torque which will be estimated as well.

The state variables \( i_{sd}, i_{sq}, \phi_{rd}, u_{sd}, u_{sq} \), are the stator currents, rotor flux linkages, stator terminal voltages respectively. and for the parameters \( L_s, L_r, M \) are the rotor, stator, mutual inductance, \( R_s, R_r \) are stator, rotor resistance respectively.

3 Nonlinear feedback linearisation controller

Mainly feedback linearisation uses a state transformation that enable us to express the system in a new coordinate system that made it linear so that a state linearisation in
the new coordinates is achieved; theoretical background and procedures for finding such transformation and controller can be found in Shankar (1999), Khalil et al. (2008), Orlowska-Kowalska and Dybkowski (2012) and 2010 (2010), and in order to achieve these transformation the following notation is used for the Lie derivatives of a function $h(x)$:

$$
\dot{h}(x) = \frac{\partial h}{\partial x} \dot{x}
$$

where the derivative of the output along the vector field $f(x)$ and $g$ are defined iteratively as:

$$
L_f h(x) = L_{i-1} f h
$$

$$
L_g h(x) = L_{i-1} g h
$$

3.1 The stator currents control

The stator input voltages are controlled using the stator current equations given by:

$$
f(x) = \begin{bmatrix}
-\gamma \tilde{i}_{sd} + \frac{K}{L_s} \dot{\phi}_{rd} - \omega \tilde{i}_{sq} \\
-\gamma \tilde{i}_{sq} + \omega \tilde{i}_{sd} + K_p \tilde{\phi}_{rd}
\end{bmatrix}
$$

The control input matrix is given by:

$$
g = \begin{bmatrix}
\frac{1}{\sigma L_s} & 0 \\
0 & \frac{1}{\sigma L_s}
\end{bmatrix}
$$

Than the output vector is defined as:

$$
h(x) = \begin{bmatrix}
\hat{h}_1(x) \\
\hat{h}_2(x)
\end{bmatrix} = \begin{bmatrix}
\hat{i}_{sd} \\
\hat{i}_{sq}
\end{bmatrix}
$$

Then to obtain the control vector $u_{sd}$ and $u_{sq}$, equation (12) has to be differentiated as follows:

$$
\begin{bmatrix}
\dot{\hat{h}}_1 \\
\dot{\hat{h}}_2
\end{bmatrix} = \begin{bmatrix}
L_f \hat{h}_1 + L_g \hat{h}_1 u_{sd} \\
L_f \hat{h}_2 + L_g \hat{h}_2 u_{sq}
\end{bmatrix}
$$

Therefore; the control law is constructed from equation (13) as:

$$
\begin{bmatrix}
u_{sd} \\
u_{sq}
\end{bmatrix} = \begin{bmatrix}
L_g \hat{h}_1 & 0 \\
0 & L_g \hat{h}_2
\end{bmatrix}^{-1} \begin{bmatrix}
V_1 - L_f \hat{h}_1 \\
V_2 - L_f \hat{h}_2
\end{bmatrix}
$$

where

$$
L_f \hat{h}_1 = -\gamma \tilde{i}_{sd} + \frac{K_c}{L_c} \dot{\phi}_{rd} - \tilde{\Omega} \tilde{\omega} \tilde{i}_{sd}
$$

$$
L_f \hat{h}_2 = -\gamma \tilde{i}_{sq} + \tilde{\omega} \tilde{i}_{sd} + K_p \tilde{\phi}_{rd}
$$

$$
L_g \hat{h}_1 = L_g \hat{h}_2 = \frac{1}{\sigma L_s}
$$
3.2 The speed and rotor flux control

To control the speed and rotor flux the following state equations are used:

\[ f(x) = \begin{bmatrix} -\frac{1}{T_r} \dot{\phi}_{rd} \\ -\frac{f_m}{J_m} \hat{\Omega} - \frac{\dot{\tau}_d}{J_m} \end{bmatrix} \]  
(18)

The control input matrix is defined by:

\[ g = \begin{bmatrix} \frac{M}{T_r} & 0 \\ 0 & \frac{pM}{x_s J_m} \phi_{rd} \end{bmatrix} \]  
(19)

The output vector is:

\[ h(x) = \begin{bmatrix} \dot{h}_3(x) \\ \dot{h}_4(x) \end{bmatrix} = \begin{bmatrix} \dot{\phi}_{rd} \\ \hat{\Omega} \end{bmatrix} \]  
(20)

The control vectors \( h_{1r} \) and \( h_{2r} \), which are the input references of the stator currents, will be obtained by applying differentiating equation (20):

\[ \begin{bmatrix} \dot{h}_3 \\ \dot{h}_4 \end{bmatrix} = \begin{bmatrix} L_f \dot{h}_3 + L_{g1} \dot{h}_3 h_{1r} \\ L_f \dot{h}_4 + L_{g2} \dot{h}_2 h_{2r} \end{bmatrix} \]  
(21)

Then the input current references are:

\[ \begin{bmatrix} h_{1r} \\ h_{2r} \end{bmatrix} = \begin{bmatrix} L_{g1} \dot{h}_3 & 0 \\ 0 & L_{g2} \dot{h}_4 \end{bmatrix}^{-1} \begin{bmatrix} V_3 - L_f \dot{h}_3 \\ V_4 - L_f \dot{h}_4 \end{bmatrix} \]  
(22)

where

\[ L_f \dot{h}_3 = -\frac{1}{T_r} \phi_{rd} \]  
(23)

\[ L_f \dot{h}_4 = -\frac{f_m}{J_m} \hat{\Omega} - \frac{1}{J_m} \dot{\tau}_d \]  
(24)

\[ L_{g1} \dot{h}_3 = \frac{1}{T_r} \]  
(25)

\[ L_{g2} \dot{h}_4 = \frac{pM}{x_s J_m} \phi_{rd} \]  
(26)

3.3 The tracking error equations

To track the reference trajectories \( h_1 \) to \( h_4 \), the variation \( V_1 \) up to \( V_4 \) are calculated as follows:

\[ \begin{cases} V_1 = \dot{h}_1 - k_{p1} (\dot{h}_1 - h_{1r}) \\ V_2 = \dot{h}_2 - k_{p2} (\dot{h}_2 - h_{2r}) \\ V_3 = \dot{h}_3 - k_{p3} (\dot{h}_3 - h_{3r}) \\ V_4 = \dot{h}_4 - k_{p4} (\dot{h}_4 - h_{4r}) \end{cases} \]  
(27)
Hence, the closed loop tracking errors are given by:

\[
\begin{bmatrix}
\dot{e}_1 \\
\dot{e}_2 \\
\dot{e}_3 \\
\dot{e}_4
\end{bmatrix} =
\begin{bmatrix}
-k_{p1}e_1 \\
-k_{p2}e_2 \\
-k_{p3}e_3 \\
-k_{p4}e_4
\end{bmatrix}
\] (28)

The exponential convergence of the tracking errors in equation (28) are guaranteed by an appropriate choice of the gains \(k_{p1}, k_{p2}, k_{p3}\) and \(k_{p4}\)

### 4 Adaptive nonlinear observer augmented by radial basis neural network

Let’s consider the following nonlinear system with the following structure:

\[
\begin{align*}
\dot{x} &= Ax + B_1 u + f(x, y, u) + B_2 \tau \\
y &= Cx
\end{align*}
\] (29)

where \(A \in \mathbb{R}^{n \times n}\) is the known matrix, \(B_1 \in \mathbb{R}^{n \times m_1}\) and \(u \in \mathbb{R}^{m_1}\) are a known input matrix and \(B_2 \in \mathbb{R}^n\) is a known input vector, whereas \(C \in \mathbb{R}^{p \times n}\) is the output matrix, \(f(x, y, u) : \mathbb{R}^n \times \mathbb{R}^1 \rightarrow \mathbb{R}^n\) is a partially unknown function, \(\tau \in L_{\infty}\) represent the unmodelled dynamics or unknown disturbance. In order to complete the description of the observer the following assumptions are used:

**Assumption 1:** The pair \((A, C)\) is observable.

**Assumption 2:** The function \(\hat{\tau}(t) = \hat{W}^T \delta(\bar{x})\), unknown disturbance will be estimated using an online neural network function approximation.

**Assumption 3:** The weights \(W\) is bounded \(\dot{W} = 0\).

**Assumption 4:** The finite time convergence of the unknown dynamics is guaranteed using an online update law for neural network function approximation weights.

**Assumption 5:** The signals \(y\) and \(u\) are measured signals, which is a common assumption in all observers.

Under the over mentioned assumptions, adaptive RBF neural network nonlinear observer is proposed to estimate the mechanical speed and unknown load torque of the machine which takes the following form:

\[
\begin{align*}
\dot{x} &= A\hat{x} + B_1 u + f(\hat{x}, y, u) + B_2 \hat{\tau} + L(y - C\hat{x}) \\
\dot{\tau} &= \hat{W}^T \delta(\bar{x}) \\
\dot{\hat{W}} &= \gamma \delta(\bar{x}) Fe
\end{align*}
\] (30)

where \(\hat{x}\) represents the estimated states, \(\delta(x) = \exp(-\|x-c\|^2/b^2)\) is the activation function with a positive scalar dimension \(b\) and centre vector \(c\) that has the same dimension as the vector \(x\), \(\hat{W}\) is the weights of the radial basis neural network function. \(\gamma\) is the gain of the adaptive law which has to be chosen adequately. \(L\) is the observer gain matrix...
where $A_c = A - LC$; $P$ and $Q$ are diagonal positive definite matrices that satisfy the following Lyapunov function,

$$A_c^T P + PA_c = -Q$$  \hspace{1cm} (31)

The gain $F$ is obtained using the following relation:

$$PB = CTF^T$$  \hspace{1cm} (32)

### 4.1 Mechanical speed and load torque estimation

Since the load torque is unknown and should be measured using sensors to compensate it, and since sensors are more expensive; therefore a good solution could be the use of the load torque observer. Hence the developed adaptive neural network nonlinear observer in equation (30) will be applied to a reduced order model of an induction machine, which is given by:

$$\dot{i}_{sq} = -\gamma i_{sq} + \hat{\omega}_s i_{sd} + K_p\hat{\Omega}\hat{\phi}_{rd} + \frac{1}{\sigma L_s} u_{sq}$$

$$\dot{\Omega} = \frac{pM}{L_s J_m} \hat{\phi}_{rd} i_{sq} - \frac{f_m}{J_m} \Omega - \frac{\tau_d}{J_m}$$  \hspace{1cm} (33)

The stator pulsation and rotor flux are estimated from the following state equations:

$$\dot{\hat{\theta}} = \hat{\omega}_s = \frac{M}{T_r} \hat{i}_{sq} + p\hat{\Omega}$$  \hspace{1cm} (34)

$$\dot{\hat{\phi}}_{rd} = \frac{M}{T_r} i_{sd} - \frac{\hat{\phi}_{rd}}{T_r}$$  \hspace{1cm} (35)

The following key points are used to construct the observer:

1. the stator current $i_{sq}$ is a measured state
2. the inputs to the observer are $u = [i_{sd}, \hat{\omega}_s, \hat{\phi}_{rd}, u_{sq}]$
3. the load torque $\tau$ is the unknown disturbance which will be estimated using neural network.

Using the structure of the adaptive observer (30) which is illustrated in Figure 1 as well; the reduced model (33) of the induction machine will be in compact form as:

$$\begin{bmatrix} \dot{i}_{sq} \\ \dot{\Omega} \end{bmatrix} = \begin{bmatrix} -\gamma & 1 \\ 0 & -\frac{f_m}{J_m} \end{bmatrix} \begin{bmatrix} i_{sq} \\ \Omega \end{bmatrix} + \begin{bmatrix} -\hat{\Omega} + \hat{\omega}_s i_{sd} + K_p\hat{\Omega}\hat{\phi}_{rd} \\ \frac{pM}{L_s J_m} \hat{\phi}_{rd} i_{sq} \end{bmatrix}$$

$$+ \begin{bmatrix} \frac{\sigma L_s}{\tau_d} \\ 0 \end{bmatrix} u_{sq} + \begin{bmatrix} \frac{0}{\sigma L_s} \\ \frac{0}{\tau_d} \end{bmatrix} t T \delta(e) + L(i_{sq} - \hat{i}_{sq})$$  \hspace{1cm} (36)

$$y = i_{sq}$$

According to observer structure (30); the system matrices $A$, $B_1$ and $B_2$ are defined by:

$$A = \begin{bmatrix} -\gamma & 1 \\ 0 & -\frac{f_m}{J_m} \end{bmatrix}; \quad B_1 = \begin{bmatrix} \frac{1}{\sigma L_s} \\ 0 \end{bmatrix}; \quad B_2 = \begin{bmatrix} 0 \\ -\frac{1}{\tau_d} \end{bmatrix}$$  \hspace{1cm} (37)
The known function $f(x, y, u)$ and the unknown disturbance (load torque) are defined by:

$$f(x, y, u) = \left[ -\hat{\Omega} + \hat{\omega}_s \hat{\phi}_{rd} + K_p \hat{\phi}_{rd} \hat{\phi}_{rd} \right]; \quad \hat{\tau} = \hat{W}^T \sigma(e)$$  

(38)

$L = \begin{bmatrix} L_1 & L_2 \end{bmatrix}^T$ is the observer gain that has to be chosen adequately to deliver the lyapunov matrix $P$, $\gamma$ is the gain of the neural network weights adaptive law.

5 Global stability analysis

In this section the stability of the proposed method (observer-controller) will be proven. Lets consider the following Lyapunov candidate:

$$V = V_1 + V_2$$  

(39)
where \( V_1 \) and \( V_2 \) are the controllers and adaptive neural network nonlinear observer Lyapunov functions respectively, which are given by:

\[
V_1 = \frac{e_1^2}{2} + \frac{e_2^2}{2} + \frac{e_3^2}{2} + \frac{e_4^2}{2}
\]

\[
V_2 = \frac{e_o^2 P e_o}{2} + \frac{\tilde{W}^T P \tilde{W}}{2}
\]

where \( e_{1,2,3,4} \) are the errors between the nonlinear controller, \( e_o = x - \hat{x} \) is observer error, \( \tilde{W} = W - \hat{W} \) is the error of the estimated weights; thus differentiating equation (39) yields:

\[
\dot{V} = \dot{V}_1 + \dot{V}_2
\]

\[
\dot{V} = \dot{e}_1 e_1 + \dot{e}_2 e_2 + \dot{e}_3 e_3 + \dot{e}_4 e_4
+ \dot{e}_o^T P e_o + \frac{e_o^T P e_o}{2}
+ \tilde{W}^T \gamma^{-1} \tilde{W} + \tilde{W}^T \gamma^{-1} \tilde{W}
\]

The error of the observer is constructed from (30) as:

\[
\dot{e}_o = A_c e_o + B \tilde{W}^T \delta(e)
\]

\[
e_o^T = e_o^T A_c^T + \delta(e)^T \tilde{W} B^T
\]

Substituting equation (28) into (42) gives:

\[
\dot{V} = -k_p1 e_1^2 - k_p2 e_2^2 - k_p3 e_3^2 - k_p4 e_4^2
+ \dot{e}_o^T P e_o + \frac{e_o^T P e_o}{2}
+ \tilde{W}^T \gamma^{-1} \tilde{W} + \tilde{W}^T \gamma^{-1} \tilde{W}
\]

Substituting the error of the nonlinear observer found in equation (43) into (44) yields:

\[
\dot{V} = -k_p1 e_1^2 - k_p2 e_2^2 - k_p3 e_3^2 - k_p4 e_4^2
+ \frac{(e_o^T A_c^T + \delta(e)^T \tilde{W} B^T) P e_o}{2}
+ \frac{e_o^T P(A_c e_o + B \tilde{W}^T \delta(e))}{2}
- \frac{\tilde{W}^T \gamma^{-1} (\gamma \delta(e) e_o)}{2} - \frac{\tilde{W}^T (\gamma \delta(e) e_o) \gamma^{-1} \tilde{W}}{2}
\]

Adopting the update law of the radial basis neural network function of observer (30) into equation (45), and simplify gives:

\[
\dot{V} = -k_p1 e_1^2 - k_p2 e_2^2 - k_p3 e_3^2 - k_p4 e_4^2 - e_o^T Q e_o
\]

\[
\dot{V} \leq 0
\]

Therefore, the overall system controller-observer are stable in the sense of Lyapunov.
6 Simulations and results

Simulations have been performed with MATLAB-Simulink software. Using the induction motor parameters shown in Table 1, with the input references of the mechanical speed, rotor flux and the unknown load torque shown in Figure 3.

Table 1 Parameters of the IM

<table>
<thead>
<tr>
<th>Designation</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rotor resistance</td>
<td>$R_r$</td>
<td>3.805 $\Omega$</td>
</tr>
<tr>
<td>Stator resistance</td>
<td>$R_s$</td>
<td>4.85 $\Omega$</td>
</tr>
<tr>
<td>Mutual inductance</td>
<td>$M$</td>
<td>0.258 H</td>
</tr>
<tr>
<td>Stator cyclic inductance</td>
<td>$L_s$</td>
<td>0.247 H</td>
</tr>
<tr>
<td>Rotor cyclic inductance</td>
<td>$L_r$</td>
<td>0.247 H</td>
</tr>
<tr>
<td>Rotor inertia</td>
<td>$J_m$</td>
<td>0.031 $Kg/m^3$</td>
</tr>
<tr>
<td>Pole pair</td>
<td>$p$</td>
<td>2</td>
</tr>
<tr>
<td>Viscous friction coefficient</td>
<td>$f_m$</td>
<td>0.008 N.m.s/rd</td>
</tr>
<tr>
<td>Mechanical power</td>
<td>$P_m$</td>
<td>15 KW</td>
</tr>
<tr>
<td>Nominal stator voltage</td>
<td>$V_s$</td>
<td>220 V</td>
</tr>
<tr>
<td>Nominal stator current</td>
<td>$I_s$</td>
<td>3.46 A</td>
</tr>
<tr>
<td>Nominal rotor current</td>
<td>$I_r$</td>
<td>6.31 A</td>
</tr>
<tr>
<td>Nominal speed</td>
<td>$\Omega_n$</td>
<td>1,500 rev/min</td>
</tr>
</tbody>
</table>

Figure 3 The input signal $u$ (see online version for colours)

6.1 The mechanical speed

We note from Figure 4 that the estimated mechanical speed follows its measured speed with a fast response, thus a good performance in state estimation of the observer.
Figure 4  The mechanical speed $\Omega$ (rad/s) (see online version for colours)

6.1.1 The mechanical speed errors

The speed error tracking is canceled; where at an abrupt variations of the load torque a peaks of about $\pm 0.1$ rad/s appears as shown in Figure 5 compared to Figure 6 that shows the effect of the load torque on the speed when no estimator of the torque is used. Where a peaks of about $\pm 1$ rad/s do appear when load torque is applied. Therefore a good performance is achieved using the proposed adaptive observer.

Figure 5  The mechanical speed error with the use of load torque estimation (see online version for colours)
6.2 Torque

We note that the drive torque follows the load torque when the speed is constant. During an increase or decrease in the speed, a difference of almost $\pm 5\ \text{N.m}$ appears between the two torques, as shown in Figure 7.

6.3 Load torque

The load torque (unknown disturbance) shown in Figure 8 is estimated using online radial basis neural network function approximation, the obtained results shows a rapid
convergence of the observed load torque; hence a good performance of the proposed observer for systems subjected to unknown dynamics (disturbance).

**Figure 8** The estimated load torque using neural network (see online version for colours)

![The Estimated Load Torque](image)

**6.4 The rotor flux**

We note a very good tracking, since the stator flux is controlled with a very fast response time with no overshoot in both transient and permanent regimes because it is unaffected by the change of speed as well as the load torque as shown in Figure 9, where we note that $\phi_{r,q} = 0\,\text{Wb}, \phi_{r,d} = 1\,\text{Wb}$ as stated by the field oriented control theory as well.

**Figure 9** The rotor flux (see online version for colours)

![The Rotor Flux](image)
6.5 The stator current

We note from Figure 10 that represents the estimated current; where the measured stator current converges to it is estimated current in a short period of time, and we note as well that the current is proportional to the load torque, which signify a good estimation performance.

Figure 10 The stator currents (see online version for colours)

7 Conclusions

In this paper, the input output feedback linearisation of the induction machine is applied with the orientation of the rotor flux, associated with a proposed adaptive radial basis function neural network nonlinear observer for mechanical speed and load torque (unknown disturbance) estimation; where the load torque is estimated using an online RBF function approximation. The global stability was established based on a chosen Lyapunov function for the overall system controller observers (adaptive neural network observer). Simulations results shows the effectiveness of the proposed method.

References


Adaptive nonlinear observer augmented by radial basis neural network


