Nonlinear Model Predictive Control for Induction Motor Drive

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1. Introduction

The induction motor (IM) is widely used in industry because of its well known advantages such as simple construction, less maintenance, reliability and low cost. However, it is highly nonlinear, multivariable, time-varying system and, contrary to DC motor, requires more complex methods of control. Therefore, this machine constitutes a theoretically challenging control problem.

One of the most important development in control area for induction motor has been field oriented control (FOC) established firstly by (Blaschke, 1972). However, the performance of this technique is affected by the motor parameter variations and unknown external disturbances. To improve the dynamic response and reduce the complexity of FOC methods, an extension amount of work has been done to find new methods, such as direct torque control (DTC), sliding mode and nonlinear control (Barut et al., 2005; Chen & Dunnigan, 2003; Chiasson, 1996; Marino et al. 1993).

Model based predictive control (MPC) is one of the most promising control methods for both linear and nonlinear systems. The MPC formulation integrates optimal control, multivariable control, and the use of future references. It can also handle constraints and nonlinear processes, which are frequently found in industry. However, the computation of the MPC requires some mathematical complexities, and in the way of implementing and tuning this kind of controller, the computation time of the MPC may be excessive for the sampling time required by the process. Therefore, several MPC implementations were done for slow processes (Bordons & Camacho, 1998; Garica et al., 1989; Richalet, 1993). However, the explicit formulation of MPC allows its implementation in fast linear systems (Bemporad et al. 2002).

A review of fast method for implementing MPC can be found in (Camacho & Bordons, 2004). In case of nonlinear systems, where the mathematical packages are available in research control community, and thanks to the advancement of signal processing technology for control techniques, it becomes easy to implement these control schemes. Many works have been developed in nonlinear model predictive control (NMPC) theory (Ping, 1996; Chen et al., 1999; Siller-Alcala, 2001; Feng et al., 2002). A nonlinear PID model predictive controller developed in (Chen et al., 1999), for nonlinear control process, can improve some desirable features, such as, robustness to parameters variations and external disturbance rejection. The idea is to develop a nonlinear disturbance observer, and by

embedding the nonlinear model predictive control law in the observer structure, it allows to express the disturbance observer through a PID control action. The NMPC have been implemented in induction motor drive with good performance (Hedjar et al., 2000; Hadjar et al. 2003; Maaziz et al., 2000; Merabet et al., 2006; Correa et al., 2007; Nemec et al., 2007). However, in these works, the load torque is taken as a known quantity to achieve accurately the desired performance, which is not always true in the majority of the industrial applications. Therefore, an observer for load torque is more than necessary for high performance drive. The design of such observer must not be complicated and well integrated in the control loop.

This chapter presents a nonlinear PID model predictive controller (NMPC PID) application to induction motor drive, where the load torque is considered as an unknown disturbance. A load torque observer is derived from the model predictive control law and integrated in the control strategy as PID speed controller. This strategy unlike other techniques for load torque observation (Marino et al., 1998; Marino et al., 2002; Hong & Nam, 1998; Du & Brdys, 1993), where the observer is an external part from the controller, allows integrating the observer into the model predictive controller to design a nonlinear PID model predictive controller, which improves the drive performance. It will be shown that the controller can be implemented with a limited set of computation and its integration in the closed loop scheme does not affect the system stability. In the development of the control scheme, it is assumed that all the machine states are measured. In fact a part of the state, the rotor flux, is not easily measurable and it is costly to use speed sensor. In literature, many techniques exist for state estimation (Jansen et al., 1994; Leonhard, 2001). A continuous nonlinear state observer based on the observation errors is used in this work to estimate the state variables. The coupling between the observer and the controller is analyzed, where the global stability of the whole system is proved using the Lyapunov stability. For this reason, a continuous version of NMPC is used in this work.

The rest of the chapter is organized as follows. In section 2, the induction motor model is defined by a nonlinear state space model. In section 3, the NMPC control law is developed for IM drive with an analysis of the closed loop system stability. In section 4, the load torque is considered as a disturbance variable in the machine model, and a NMPC PID control is applied to IM drive. Then, the coupling between the controller and the state observer is discussed in section 5, where the global stability of the whole system is proven theoretically. In section 6, simulation results are given to show the effectiveness of the proposed control strategy.

2. Induction motor modeling

The stator fixed (a-β) reference frame is chosen to represent the model of the motor. Under the assumption of linearity of the magnetic circuit, the nonlinear continuous time model of the IM is expressed as

$$\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}) + \mathbf{g_1}(\mathbf{x})\mathbf{u}(t) \tag{1}$$

where

$$\mathbf{x} = \begin{bmatrix} i_{s\alpha} & i_{s\beta} & \phi_{r\alpha} & \phi_{r\beta} & \omega \end{bmatrix}^T, \mathbf{u} = \begin{bmatrix} u_{s\alpha} & u_{s\beta} \end{bmatrix}^T$$

The state **x** belongs to the set $\Omega = \left\{ \mathbf{x} \in \Re^5 : \phi_{r\alpha}^2 + \phi_{r\beta}^2 \neq 0 \right\}$.

Vector function **f(x)** and constant matrix **g₁(x)** are defined as follows.

$$\mathbf{f(x)} = \begin{bmatrix} -\gamma i_{s\alpha} + \dfrac{K}{T_r}\phi_{r\alpha} + pK\omega\phi_{r\beta} \\[2mm] -\gamma i_{s\beta} + \dfrac{K}{T_r}\phi_{r\beta} - pK\omega\phi_{r\alpha} \\[2mm] \dfrac{L_m}{T_r}i_{s\alpha} - \dfrac{1}{T_r}\phi_{r\alpha} - p\omega\phi_{r\beta} \\[2mm] \dfrac{L_m}{T_r}i_{s\beta} - \dfrac{1}{T_r}\phi_{r\beta} + p\omega\phi_{r\alpha} \\[2mm] \dfrac{pL_m}{JL_r}\left(\phi_{r\alpha}i_{s\beta} - \phi_{r\beta}i_{s\alpha}\right) - \dfrac{f_r}{J}\omega - \dfrac{T_L}{J} \end{bmatrix} \qquad \mathbf{g_1} = \begin{bmatrix} g_{11}\, g_{12} \end{bmatrix} = \begin{bmatrix} \dfrac{1}{\sigma L_s} & 0 & 0 & 0 & 0 \\[2mm] 0 & \dfrac{1}{\sigma L_s} & 0 & 0 & 0 \end{bmatrix}^T$$

where

$$\sigma = 1 - \frac{L_m^2}{L_s L_r}\,;\; K = \frac{L_m}{\sigma L_s L_r}\,;\; \gamma = \frac{1}{\sigma L_s}\left(R_s + \frac{R_r L_m^2}{L_r^2}\right)$$

The outputs to be controlled are

$$\mathbf{y = h(x)} = \begin{bmatrix} \omega \\ \phi_r^2 = \phi_{r\alpha}^2 + \phi_{r\beta}^2 \end{bmatrix} \qquad (2)$$

f(x) and **h(x)** are assumed to be continuously differentiable a sufficient number of time. $i_{s\alpha}$, $i_{s\beta}$ denote stator currents, $\phi_{r\alpha}$, $\phi_{r\beta}$ rotor fluxes, ω rotor speed, $u_{s\alpha}$, $u_{s\beta}$ stator voltages, R_s, R_r stator and rotor resistances, L_s, L_r, L_m stator, rotor and mutual inductances, p number of poles pair, J inertia of the machine, f_r friction coefficient, $T_r = L_r/R_r$ rotor time constant, σ leakage coefficient and T_L load torque.

3. Nonlinear model predictive control

Nonlinear model predictive control (NMPC) algorithm belongs to the family of optimal control strategies, where the cost function is defined over a future horizon

$$\Im(\mathbf{x},\mathbf{u}) = \frac{1}{2}\int_0^{\tau_r} \left(\mathbf{y}(t+\tau) - \mathbf{y_r}(t+\tau)\right)^T \left(\mathbf{y}(t+\tau) - \mathbf{y_r}(t+\tau)\right)d\tau \qquad (3)$$

where τ_r is the prediction time, $\mathbf{y}(t+\tau)$ a τ-step ahead prediction of the system output and $\mathbf{y_r}(t+\tau)$ the future reference trajectory. The control weighting term is not included in the cost function (3). However, the control effort can be achieved by adjusting prediction time. More details about how to limit the control effort can be found in (Chen et al., 1999).

The objective of model predictive control is to compute the control $\mathbf{u}(t)$ in such a way the future plant output $\mathbf{y}(t+\tau)$ is driven close to $\mathbf{y_r}(t+\tau)$. This is accomplished by minimizing $\Im$.

The relative degree of the output, defined to be the number of times of output differentiation until the control input appears, is $r_1=2$ for speed output and $r_2=2$ for flux output. Taylor series expansion (5) can be used for the prediction of the machine outputs in the moving time frame. The differentiation of the outputs with respect to time is repeated r times.

$$y_i(t+\tau) = h_i(\mathbf{x}) + \tau L_{\mathbf{f}} h_i(\mathbf{x}) + \frac{\tau^2}{2!} L_{\mathbf{f}}^2 h_i(\mathbf{x}) + \dots + \frac{\tau^{r_i}}{r_i!} L_{\mathbf{f}}^{r_i} h_i(\mathbf{x}) + \frac{\tau^{r_i}}{r_i!} L_{\mathbf{g}} L_{\mathbf{f}}^{(r_i-1)} h_i(\mathbf{x}) \mathbf{u}(t) \quad (4)$$

The predicted output $\mathbf{y}(t+\tau)$ is carried out from (4)

$$\mathbf{y}(t+\tau) = \overline{\mathbf{T}}(\tau)\mathbf{Y}(t) \quad (5)$$

where

$$\begin{cases} \overline{\mathbf{T}}(\tau) = \left[I_{2\times 2} \quad \tau I_{2\times 2} \quad \tau^2\!\big/\!2\, I_{2\times 2} \right] \\ I_{2\times 2} : \text{Identity matrix} \end{cases}$$

The outputs differentiations are given in matrix form as

$$\mathbf{Y}(t) = \begin{bmatrix} \mathbf{y}(t) \\ \dot{\mathbf{y}}(t) \\ \ddot{\mathbf{y}}(t) \end{bmatrix} = \begin{bmatrix} \mathbf{h}(\mathbf{x}) \\ L_{\mathbf{f}}\mathbf{h}(\mathbf{x}) \\ L_{\mathbf{f}}^2\mathbf{h}(\mathbf{x}) \end{bmatrix} + \begin{bmatrix} 0_{2\times 1} \\ 0_{2\times 1} \\ \mathbf{G}_1(\mathbf{x})u(t) \end{bmatrix} \quad (6)$$

where

$$L_{\mathbf{f}}^i \mathbf{h}(\mathbf{x}) = \left[L_{\mathbf{f}}^i h_1(\mathbf{x}) \quad L_{\mathbf{f}}^i h_2(\mathbf{x}) \right]^T, (i=0,1,2)$$

$$\mathbf{G}_1(\mathbf{x}) = \begin{bmatrix} L_{g_{11}} L_{\mathbf{f}} h_1(\mathbf{x}) & L_{g_{12}} L_{\mathbf{f}} h_1(\mathbf{x}) \\ L_{g_{11}} L_{\mathbf{f}} h_2(\mathbf{x}) & L_{g_{12}} L_{\mathbf{f}} h_2(\mathbf{x}) \end{bmatrix} \quad (7)$$

A similar computation is used to find the predicted reference $\mathbf{y}_r(t+\tau)$

$$\mathbf{y}_r(t+\tau) = \overline{\mathbf{T}}(\tau)\mathbf{Y}_r(t) \quad (8)$$

where

$$\begin{cases} \mathbf{Y}_r(t) = \left[\mathbf{y}_r(t) \ \dot{\mathbf{y}}_r(t) \ \ddot{\mathbf{y}}_r(t) \right]^T \\ \mathbf{y}_r(t) = \left[\omega_{ref} \ \phi_{ref}^2 \right]^T \end{cases}$$

Using (7) and (8), the cost function (3) can be simplified as

$$\Im(\mathbf{x},\mathbf{u}) = \frac{1}{2}\left(\mathbf{Y}(t) - \mathbf{Y}_r(t)\right)^T \overline{\Pi}\left(\mathbf{Y}(t) - \mathbf{Y}_r(t)\right) \quad (9)$$

where

$$\bar{\mathbf{\Pi}} = \int_0^{\tau_r} \bar{\mathbf{T}}(\tau)^T \bar{\mathbf{T}}(\tau) d\tau = \begin{bmatrix} \tau_r I_{2\times 2} & \dfrac{\tau_r^2}{2} I_{2\times 2} & \vdots & \dfrac{\tau_r^3}{6} I_{2\times 2} \\ \dfrac{\tau_r^2}{2} I_{2\times 2} & \dfrac{\tau_r^3}{3} I_{2\times 2} & \vdots & \dfrac{\tau_r^4}{8} I_{2\times 2} \\ \cdots & \cdots & \cdots & \cdots \\ \dfrac{\tau_r^3}{6} I_{2\times 2} & \dfrac{\tau_r^4}{8} I_{2\times 2} & \vdots & \dfrac{\tau_r^5}{20} I_{2\times 2} \end{bmatrix}$$

$$= \begin{bmatrix} \bar{\mathbf{\Pi}}_1 & \bar{\mathbf{\Pi}}_2 \\ \bar{\mathbf{\Pi}}_2^T & \bar{\mathbf{\Pi}}_3 \end{bmatrix}$$

The optimal control is carried out by making $\partial\Im/\partial u = 0$

$$\mathbf{u}(t) = -\mathbf{G}_1(\mathbf{x})^{-1} [\bar{\mathbf{\Pi}}_3^{-1} \bar{\mathbf{\Pi}}_2^T \quad I_{2\times 2}] \mathbf{M} \tag{10}$$

where

$$\begin{cases} \mathbf{M} = \begin{bmatrix} \mathbf{h}(\mathbf{x}) \\ L_{\mathbf{f}}\mathbf{h}(\mathbf{x}) \\ L_{\mathbf{f}}^2\mathbf{h}(\mathbf{x}) \end{bmatrix} - \begin{bmatrix} \mathbf{y_r}(t) \\ \dot{\mathbf{y}}_{\mathbf{r}}(t) \\ \ddot{\mathbf{y}}_{\mathbf{r}}(t) \end{bmatrix} \\ \det[\mathbf{G}_1(\mathbf{x})] = -\dfrac{2pL_m^2}{J\sigma^2 L_s^2 L_r T_r} \left(\phi_{r\alpha}^2 + \phi_{r\beta}^2\right) \end{cases}$$

The conditions $\{\phi_{r\alpha}(0), \phi_{r\beta}(0)\} \neq 0$ and the set $\Omega\{\phi_{r\alpha}^2 + \phi_{r\beta}^2 \neq 0\}$ allow $\mathbf{G}_1$ to be invertible. The singularity of this matrix occurs only at the start up of the motor, which can be avoided by putting initial conditions of the state observer different from zero. Let the optimal control (10) is developed as:

$$\mathbf{u}(t) = -\mathbf{G}_1(\mathbf{x})^{-1} \left(\sum_{i=0}^{2} \mathbf{K}_i \left(L_{\mathbf{f}}^i \mathbf{h}(\mathbf{x}) - \mathbf{y}_{\mathbf{r}}^{[i]}(t) \right) \right) \tag{11}$$

where

$$\mathbf{K}_0 = K_0 * I_{2\times 2}; \mathbf{K}_1 = K_1 * I_{2\times 2}; \mathbf{K}_2 = I_{2\times 2}; \left(K_0 = 10/3\tau_r^2 ; K_1 = 5/2\tau_r \right)$$

4. Nonlinear PID predictive control

In the development of the NMPC, the load torque is taken as a known parameter and its values are used in the control law computation. In case, where the load torque is considered as an unknown disturbance, the nonlinear model of motor with the disturbance variable is given by

$$\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}) + \mathbf{g_1}(\mathbf{x})\mathbf{u}(t) + \mathbf{g_2}(\mathbf{x})T_L(t) \tag{12}$$

where

$$\mathbf{g_2} = [g_{21}] = \begin{bmatrix} 0 & 0 & 0 & 0 & -\dfrac{1}{J} \end{bmatrix}^T$$

The function $\mathbf{f}(\mathbf{x})$ in (12) is similar to the one in (1), but without the term $(-T_L/J)$.
We assume that the load torque follows this condition

$$\dot{T}_L(t) = 0 \tag{13}$$

Note that the assumption (13) does not necessarily mean a constant load torque, but that the changing rate of the load in every sampling interval should be far slower than the motor electromagnetic process. In reality this is often the case.

On the basis of equations (12), (13) and (9) it can be shown, in a manner similar to (10), that the optimal control becomes

$$\mathbf{u}(t) = -\mathbf{G_1}(\mathbf{x})^{-1} \left\{ [\, \overline{\mathbf{\Pi}}_\mathbf{3}^{-1}\overline{\mathbf{\Pi}}_\mathbf{2}^T \quad I_{2\times 2} \,]\, \mathbf{M} + [\overline{\mathbf{\Pi}}_\mathbf{3}^{-1}\overline{\mathbf{\Pi}}_\mathbf{2}^T \quad I_{2\times 2}]\, \mathbf{G_2}(\mathbf{x})T_L(t) \right\} \tag{14}$$

where

$$\mathbf{G_2}(\mathbf{x}) = \begin{bmatrix} 0 & 0 & L_{g_{21}}h_1(\mathbf{x}) & 0 & L_{g_{21}}L_\mathbf{f}h_1(\mathbf{x}) & 0 \end{bmatrix}^T$$

The optimal NMPC PID proposed in (Chen et al., 1999) has been developed for the same output and disturbance relative degrees. However, in the motor model (12), the disturbance relative degree is lower than the output one, which can be seen in the forms of $\mathbf{G_1}(\mathbf{x})$ and $\mathbf{G_2}(\mathbf{x})$. The same method is used in this work, to prove that even in this case a NMPC PID controller can be applied to induction motor drive.

From (12), we get

$$\mathbf{g_2}(\mathbf{x})T_L(t) = \dot{\mathbf{x}}(t) - \mathbf{f}(\mathbf{x}) - \mathbf{g_1}(\mathbf{x})\mathbf{u}(t) \tag{15}$$

An initial disturbance observer is given by

$$\dot{\hat{T}}_L(t) = -\mathbf{l}(\mathbf{x})\mathbf{g_2}(\mathbf{x})\hat{T}_L(t) + \mathbf{l}(\mathbf{x})\left\{\dot{\mathbf{x}}(t) - \mathbf{f}(\mathbf{x}) - \mathbf{g_1}(\mathbf{x})\mathbf{u}(t)\right\} \tag{16}$$

In (16), $\mathbf{l}(\mathbf{x}) \in \Re^5$ is a gain vector to be designed.
The error of the disturbance observer is

$$e_{T_L}(t) = T_L(t) - \hat{T}_L(t) \tag{17}$$

Then, the error dynamic is governed by

$$\dot{e}_{T_L}(t) + \mathbf{l}(x)\mathbf{g_2}(x)e_{T_L}(t) = 0 \tag{18}$$

It can be shown that the observer is exponentially stable when

$$\mathbf{l}(\mathbf{x})\mathbf{g_2}(\mathbf{x}) = c, \ \ c > 0 \tag{19}$$

The disturbance (load torque) T_L is replaced by its estimated value in the control law given by (14); which then becomes

$$\mathbf{u}(t) = -\mathbf{G_1}(\mathbf{x})^{-1}\left\{ [\ \bar{\mathbf{\Pi}}_\mathbf{3}^{-1}\bar{\mathbf{\Pi}}_\mathbf{2}^T \quad I_{2\times2}]\ \mathbf{M} \ + [\bar{\mathbf{\Pi}}_\mathbf{3}^{-1}\bar{\mathbf{\Pi}}_\mathbf{2}^T \quad I_{2\times2}]\ \mathbf{G_2}(\mathbf{x})\hat{T}_L(t)\right\} \tag{20}$$

Substituting (20) into (16) yields

$$\begin{aligned}\dot{\hat{T}}_L &= \mathbf{l}(\dot{\mathbf{x}} - \mathbf{f}) - \mathbf{lg_2}\hat{T}_L - \mathbf{lg_1}\mathbf{u} \\ &= \mathbf{l}(\dot{\mathbf{x}} - \mathbf{f}) - \mathbf{lg_2}\hat{T}_L + \mathbf{lg_1}\left(\mathbf{G_1}^{-1}\left\{ [\bar{\mathbf{\Pi}}_\mathbf{3}^{-1}\bar{\mathbf{\Pi}}_\mathbf{2}^T \quad I_{2\times2}]\mathbf{M} + [\bar{\mathbf{\Pi}}_\mathbf{3}^{-1}\bar{\mathbf{\Pi}}_\mathbf{2}^T \quad I_{2\times2}]\mathbf{G_2}\hat{T}_L]\right\} \ \right)\end{aligned} \tag{21}$$

Based on the definition of $\mathbf{G_2}(\mathbf{x})$, (14) and the condition (19), let's define (see B6)

$$\mathbf{l}(\mathbf{x}) = p_0\left(\frac{\partial L_\mathbf{f}h_1(\mathbf{x})}{\partial \mathbf{x}} + K_1\frac{\partial h_1}{\partial x}\right), \ \ p_0 \neq 0 \text{ is a constant} \tag{22}$$

Substituting $\mathbf{l}(\mathbf{x})$ into (21), and using Lie derivatives simplifications (see appendix B), we get a simple form for load torque disturbance estimator.

$$\dot{\hat{T}}_L = p_0\left\{(\ddot{\omega} - \ddot{\omega}_{ref}) + K_1(\dot{\omega} - \dot{\omega}_{ref}) + K_0(\omega - \omega_{ref})\right\} \tag{23}$$

Integrating (23), we get

$$\hat{T}_L = p_0\left(\dot{e}_\omega(t) + K_1 e_\omega(t) + K_0\int_0^t e_\omega(\tau)d\tau\right) \tag{24}$$

The structure of this observer is driven by three tunable parameters, where p_0 is an independent parameter and K_i (i=0, 1) depend on the controller prediction horizon τ_r. It can be seen that the load toque observer has a PID structure, where the information needed is the speed error. Compared to the work in (Marino et al., 1993), where the load torque is estimated only via speed error, the disturbance observer (24) contains an integral action, which allows the elimination of the steady state error and enhances the robustness of the control scheme with respect to model uncertainties and disturbances rejection.

5. Global stability analysis

Initially, the model predictive control law is carried out assuming all the states are known by measurement, which is not always true in the majority of industrial applications. In fact, the rotor flux is not easily measurable. Therefore, a state observer must be used to estimate it. However, the coupling between the nonlinear model predictive control and the observer must guarantee the global stability.

5.1 Nonlinear state observer

To estimate the state, several methods are possible such as the observers using the observation errors for correction, which are powerful and improve the results. To construct

an observer for the induction motor, written in (a, β) frame, the measurements of the stator voltages and currents are used in the design.

The real state, estimated state and observation errors are

$$
\begin{cases}
\mathbf{x} = \begin{bmatrix} i_{s\alpha} & i_{s\beta} & \phi_{r\alpha} & \phi_{r\beta} & \omega \end{bmatrix}^T \\
\hat{\mathbf{x}} = \begin{bmatrix} \hat{i}_{s\alpha} & \hat{i}_{s\beta} & \hat{\phi}_{r\alpha} & \hat{\phi}_{r\beta} & \hat{\omega} \end{bmatrix}^T \\
\tilde{\mathbf{x}} = \mathbf{x} - \hat{\mathbf{x}}
\end{cases}
\tag{25}
$$

The state observer, derived from the motor model (1) with stator current errors for correction, is defined by

$$
\dot{\hat{\mathbf{x}}} = \begin{bmatrix}
-\gamma \hat{i}_{s\alpha} + \dfrac{K}{T_r} \hat{\phi}_{r\alpha} + pK\hat{\omega}\, \hat{\phi}_{r\beta} \\[2mm]
-\gamma \hat{i}_{s\beta} + \dfrac{K}{T_r} \hat{\phi}_{r\beta} - pK\hat{\omega}\, \hat{\phi}_{r\alpha} \\[2mm]
\dfrac{L_m}{T_r} \hat{i}_{s\alpha} - \dfrac{1}{T_r} \hat{\phi}_{r\alpha} - p\hat{\omega}\, \hat{\phi}_{r\beta} \\[2mm]
\dfrac{L_m}{T_r} \hat{i}_{s\beta} - \dfrac{1}{T_r} \hat{\phi}_{r\beta} + p\hat{\omega}\, \hat{\phi}_{r\alpha} \\[2mm]
\dfrac{pL_m}{JL_r} \left(\hat{\phi}_{r\alpha} \hat{i}_{s\beta} - \hat{\phi}_{r\beta} \hat{i}_{s\alpha} \right) - \dfrac{f_r}{J} \hat{\omega} - \dfrac{1}{J} T_L
\end{bmatrix}
+ \begin{bmatrix}
\dfrac{1}{\sigma L_s} & 0 \\[2mm]
0 & \dfrac{1}{\sigma L_s} \\[2mm]
0 & 0 \\
0 & 0 \\
0 & 0
\end{bmatrix} \mathbf{u}
+ \begin{bmatrix}
k_1 & 0 \\[1mm]
0 & k_1 \\[1mm]
\dfrac{k_2}{T_r} & -p\hat{\omega}\, k_2 \\[2mm]
p\hat{\omega}\, k_2 & \dfrac{k_2}{T_r} \\[2mm]
k_3 & k_3
\end{bmatrix}
\begin{bmatrix} \tilde{i}_{s\alpha} \\ \tilde{i}_{s\beta} \end{bmatrix}
+ \begin{bmatrix} f_{ia} \\ f_{ib} \\ 0 \\ 0 \\ 0 \end{bmatrix}
\tag{26}
$$

$T_L = \hat{T}_L + e_{T_L}(t)$ and (f_{ia}, f_{ib}) are additional terms added in the observer structure, in order to establish the global stability of the whole system.

5.2 Control scheme based on state observer

The process states are used in the predictive control law design. However, in case of the IM, the states are estimated by (26). Including this observer in the control scheme allows defining the outputs (2) by

$$
\begin{cases}
\hat{h}_1 = \hat{\omega} \\
\hat{h}_2 = \hat{\phi}_{r\alpha}^2 + \hat{\phi}_{r\beta}^2
\end{cases}
\tag{27}
$$

The relative degrees are $r_1 = 2$ and $r_2 = 2$. Then, the first Lie derivatives of $\hat{h}_1$ and $\hat{h}_2$ are obtained by

$$
\begin{cases}
\dot{\hat{h}}_1 = L_{\hat{\mathbf{f}}} \hat{h}_1 \\
\dot{\hat{h}}_2 = L_{\hat{\mathbf{f}}} \hat{h}_2
\end{cases}
\tag{28}
$$

In (28), $\hat{\mathbf{f}}$ is the function of the motor model expressed with estimated states. Since $\dot{\hat{h}}_1$ and $\dot{\hat{h}}_2$ are not functions of the control inputs, one should derive them once again. However,

they contain terms which are functions of currents. The differentiation of those terms introduces terms of flux, which are unknown. To overcome this problem, auxiliary outputs are introduced (Chenafa et al., 2005; Van Raumer, 1994) as

$$
\begin{cases}
L_{\hat{f}}\hat{h}_1 = \hat{h}_{11} - \dfrac{f_r}{J}\hat{h}_1 - \dfrac{T_L}{J} \\[3mm]
L_{\hat{f}}\hat{h}_2 = -\dfrac{2}{T_r}\hat{h}_2 + \hat{h}_{21} + \Delta
\end{cases}
\tag{29}
$$

where

$$
\hat{h}_{11} = \frac{pL_m}{JL_r}(\hat{\phi}_{r\alpha}\hat{i}_{s\beta} - \hat{\phi}_{r\beta}\hat{i}_{s\alpha})
$$

$$
\hat{h}_{21} = \frac{2L_m}{T_r}(\hat{\phi}_{r\alpha}\hat{i}_{s\alpha} + \hat{\phi}_{r\beta}\hat{i}_{s\beta})
$$

$$
\Delta = 2\left(\frac{k_2}{T_r}\hat{\phi}_{r\alpha} + k_2 p\hat{\omega}\hat{\phi}_{r\beta}\right)\tilde{i}_{s\alpha} + 2\left(\frac{k_2}{T_r}\hat{\phi}_{r\beta} - k_2 p\hat{\omega}\hat{\phi}_{r\alpha}\right)\tilde{i}_{s\beta}
$$

The derivatives of $\hat{h}_{11}$ and $\hat{h}_{21}$ are given by

$$
\begin{cases}
\dot{\hat{h}}_{11} = L_{\hat{f}}\hat{h}_{11} + L_{g_{11}}\hat{h}_{11}u_{s\alpha} + L_{g_{12}}\hat{h}_{11}u_{s\beta} \\[2mm]
\dot{\hat{h}}_{21} = L_{\hat{f}}\hat{h}_{21} + L_{g_{11}}\hat{h}_{21}u_{s\alpha} + L_{g_{12}}\hat{h}_{21}u_{s\beta}
\end{cases}
\tag{30}
$$

where

$$
L_{\mathbf{f}}\hat{h}_{11} = f(\hat{i}_{s\alpha},\hat{i}_{s\beta},\hat{\phi}_{r\alpha},\hat{\phi}_{r\beta},i_{s\alpha},i_{s\beta},\omega);
$$

$$
L_{g_{11}}\hat{h}_{11} = -\frac{pL_m}{J\sigma L_s L_r}\hat{\phi}_{r\beta}; \quad L_{g_{12}}\hat{h}_{11} = \frac{pL_m}{J\sigma L_s L_r}\hat{\phi}_{r\alpha}
$$

$$
L_{\mathbf{f}}\hat{h}_{21} = f(\hat{i}_{s\alpha},\hat{i}_{s\beta},\hat{\phi}_{r\alpha},\hat{\phi}_{r\beta},i_{s\alpha},i_{s\beta},\omega);
$$

$$
L_{g_{11}}\hat{h}_{21} = \frac{2L_m}{\sigma L_s T_r}\hat{\phi}_{r\alpha}; \quad L_{g_{12}}\hat{h}_{21} = \frac{2L_m}{\sigma L_s T_r}\hat{\phi}_{r\beta}
$$

This leads to

$$
\begin{bmatrix}
\dot{\hat{h}}_1 \\[2mm]
\dot{\hat{h}}_{11} \\[2mm]
\dot{\hat{h}}_2 \\[2mm]
\dot{\hat{h}}_{21}
\end{bmatrix}
=
\begin{bmatrix}
\hat{h}_{11} - \dfrac{f_r}{J}\hat{h}_1 - \dfrac{T_L}{J} \\[3mm]
L_{\hat{f}}\hat{h}_{11} + L_{g_{11}}\hat{h}_{11}u_{s\alpha} + L_{g_{12}}\hat{h}_{11}u_{s\beta} \\[3mm]
-\dfrac{2}{T_r}\hat{h}_2 + \hat{h}_{21} + \Delta \\[3mm]
L_{\hat{f}}\hat{h}_{21} + L_{g_{11}}\hat{h}_{21}u_{s\alpha} + L_{g_{12}}\hat{h}_{21}u_{s\beta}
\end{bmatrix}
\tag{31}
$$

The errors between the desired trajectories of the outputs and the estimated outputs are

$$\begin{cases} e_1 = \hat{h}_1 - h_{1r} \\ e_2 = \hat{h}_{11} - h_{11r} \\ e_3 = \hat{h}_2 - h_{2r} \\ e_4 = \hat{h}_{21} - h_{21r} \end{cases} \tag{32}$$

Using (31), (32), the estimated states and the auxiliary outputs, the predictive control law (11), developed above through the cost function (3) minimization, becomes

$$\begin{bmatrix} u_{s\alpha} \\ u_{s\beta} \end{bmatrix} = \begin{bmatrix} L_{g_{11}}\hat{h}_{11} & L_{g_{12}}\hat{h}_{11} \\ L_{g_{11}}\hat{h}_{21} & L_{g_{12}}\hat{h}_{21} \end{bmatrix}^{-1} \begin{bmatrix} -L_{\hat{f}}\hat{h}_{11} - e_1 - K_1 e_2 + \dot{h}_{11r} \\ -L_{\hat{f}}\hat{h}_{21} - e_3 - K_1 e_4 + \dot{h}_{21r} \end{bmatrix} \tag{33}$$

The decoupling matrix in (33) is the same as in (7), since $L_{g_{1i}}\hat{h}_{11} = L_{g_{1i}}L_{\hat{f}}\hat{h}_1$ and $L_{g_{1i}}\hat{h}_{21} = L_{g_{1i}}L_{\hat{f}}\hat{h}_2$; $i = 1, 2$

From (31), (32) and (33), we get the error dynamic as

$$\begin{bmatrix} \dot{e}_1 \\ \dot{e}_2 \\ \dot{e}_3 \\ \dot{e}_4 \end{bmatrix} = \begin{bmatrix} \hat{h}_{11} - \dfrac{f_r}{J}\hat{h}_1 - \dfrac{T_L}{J} - \dot{h}_{1r} \\ -K_1 e_2 - e_1 \\ -\dfrac{2}{T_r}\hat{h}_2 + \hat{h}_{21} + \Delta - \dot{h}_{2r} \\ -K_1 e_4 - e_3 \end{bmatrix} \tag{34}$$

The references h_{1r} and h_{2r} and their derivatives are considered known.

In order to have (34) under the form given in (35) below, to use it in Lyapunov candidate, the references h_{11r} and h_{21r} must be defined as in (36)

$$\begin{bmatrix} \dot{e}_1 \\ \dot{e}_2 \\ \dot{e}_3 \\ \dot{e}_4 \end{bmatrix} = \begin{bmatrix} -K_0 e_1 + e_2 \\ -K_1 e_2 - e_1 \\ -K_0 e_3 + e_4 + \Delta \\ -K_1 e_4 - e_3 \end{bmatrix} \tag{35}$$

$$\begin{cases} h_{11r} = \dfrac{f_r}{J}\hat{h}_1 + \dot{h}_{1r} - K_0 e_1 + \dfrac{T_L}{J} \\ h_{21r} = \dfrac{2}{T_r}\hat{h}_2 + \dot{h}_{2r} - K_0 e_3 \end{cases} \tag{36}$$

An appropriate choice of K_0, K_1 ensures the exponential convergence of the tracking errors.

We now consider all the elements together in order to build a nonlinear model predictive control law based on state observer.

The functions V_1 and V_2, given by (37) and (38) below, are chosen to create a Lyapunov function candidate for the entire system (process, observer and controller); where γ_2 is a positive constant.

$$V_1 = \frac{\tilde{i}_{s\alpha}^2 + \tilde{i}_{s\beta}^2}{2} + \frac{\tilde{\phi}_{r\alpha}^2 + \tilde{\phi}_{r\beta}^2}{2\gamma_2} \tag{37}$$

$$V_2 = \frac{e_1^2 + e_2^2 + e_3^2 + e_4^2 + e_5^2}{2} \tag{38}$$

where, $e_5 = e_{T_L}$, represents the load torque observation error driven by the equation (18).
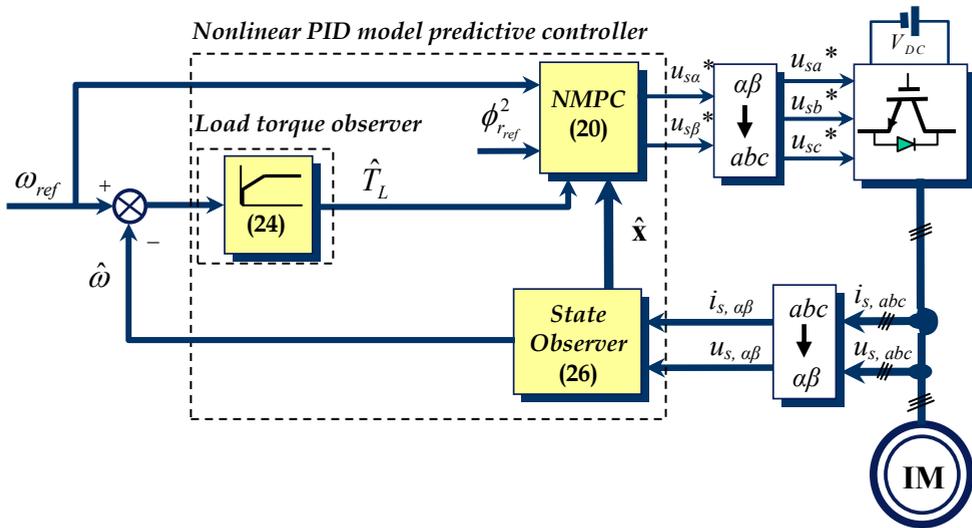
Fig. 1. Block diagram of the proposed nonlinear predictive sensorless control system.

The Lyapunov function and its derivative are respectively

$$V = V_1 + V_2 \tag{39}$$

$$
\begin{aligned}
\dot{V} = &\left(-K_0 e_1^2 - K_1 e_2^2 - K_0 e_3^2 - K_1 e_4^2 - c e_5^2\right) - (\gamma + k_1)\left(\tilde{i}_{s\alpha}^2 + \tilde{i}_{s\beta}^2\right) - \frac{1}{T_r \gamma_2}\left(\tilde{\phi}_{r\alpha}^2 + \tilde{\phi}_{r\beta}^2\right) + \\
&p\hat{\omega}\left(K - \frac{k_2}{\gamma_2}\right)\left(\tilde{i}_{s\alpha}\tilde{\phi}_{r\beta} - \tilde{i}_{s\beta}\tilde{\phi}_{r\alpha}\right) + \left(\frac{K}{T_r} + \frac{L_m}{T_r \gamma_2} - \frac{k_2}{T_r \gamma_2}\right)\left(\tilde{i}_{s\alpha}\tilde{\phi}_{r\alpha} + \tilde{i}_{s\beta}\tilde{\phi}_{r\beta}\right) - \left(f_{ia}\tilde{i}_{s\alpha} + f_{ib}\tilde{i}_{s\beta}\right) + \Delta e_3
\end{aligned}
\tag{40}
$$

The following conditions form a sufficient set ensuring $\dot{V} < 0$

$$
\begin{cases}
k_2 = K\gamma_2 \\
-[f_{ia}\tilde{i}_{s\alpha} + f_{ib}\tilde{i}_{s\beta}] + \Delta e_3 = 0
\end{cases}
\tag{41}
$$

Replacing Δ by its value leads to the following equation

$$\left[f_{ia}\tilde{i}_{s\alpha} + f_{ib}\tilde{i}_{s\beta} \right] = 2\left(\frac{k_2}{T_r}\hat{\phi}_{r\alpha} + k_2 p\hat{\omega}\hat{\phi}_{r\beta} \right)\tilde{i}_{s\alpha}e_3 + 2\left(\frac{k_2}{T_r}\hat{\phi}_{r\beta} - k_2 p\hat{\omega}\hat{\phi}_{r\alpha} \right)\tilde{i}_{s\beta}e_3 \qquad (42)$$

Equation (42) is satisfied if f_{ia} and f_{ib} are chosen as

$$\begin{cases} f_{ia} = 2\left(\dfrac{k_2}{T_r}\hat{\phi}_{r\alpha} + k_2 p\hat{\omega}\hat{\phi}_{r\beta} \right)e_3 \\[3mm] f_{ib} = 2\left(\dfrac{k_2}{T_r}\hat{\phi}_{r\beta} - k_2 p\hat{\omega}\hat{\phi}_{r\alpha} \right)e_3 \end{cases} \qquad (43)$$

V is then a Lyapunov candidate function for the overall system, formed by the process, the observer and the controller. Hence, the whole process is stable and the convergence is exponential.

6. Simulation results and discussion

In order to test all cases of IM operations, smooth references are taken for reversal speed and low speed. The results are compared with those of the standard FOC controller. The load torque disturbance is estimated by the observer (24) discussed above, which is combined with NMPC to create NMPC PID controller. The 1.1 kW induction motor (appendix D), which is fed by a SVPWM inverter switching frequency of 10 kHz, run with a sample time of 10 μs. The voltage input is given from the controller at the sample time T_s = 100 μs. The tuning parameters are the prediction time τ_r, the disturbance observer gain p_0 and (k_1, k_2, k_3) the gains of the state observer. All parameters are chosen by trial and error in order to achieve a successful tracking performance. The most important are (τ_r= 10*T_s, p_0=-0.001), which are used in all tests.

Figures 2 and 3 present the results for rotor speed and rotor flux norm tracking responses for the NMPC PID controller and for the well-known Field Oriented Controller (FOC). Figure 4 shows the components of the stator voltage and current. It can be seen that the choice of the prediction time τ_r has satisfied the tracking performance and the constraints on the signal control to be inside the saturation limits. Figure 5 gives the estimated load torque for different conditions of speed reference in the case of the proposed controller. As shown, the tracking performance is satisfactory achieved and the effect of the load torque disturbance on the speed is rapidly eliminated compared with the FOC strategy. Figures 6 to 8 present the proposed NMPC PID tracking performances for low speed operation. These results are also compared to those obtained by the FOC. As shown, the tracking performance is satisfactory achieved even at low speed.

In order to check the sensitivity of the controller and the state observer with respect to the parametric variations of the machine, these parameters are varied as shown in figure 9. It is to be noted that the motor model is affected by these variations, while the controller and the state observer are carried out with the nominal values of the machine parameters. The same values of tunable parameters (τ_r, p_0, k_1, k_2, k_3) have been used to show the influence of the parameters variations on the controller performance.
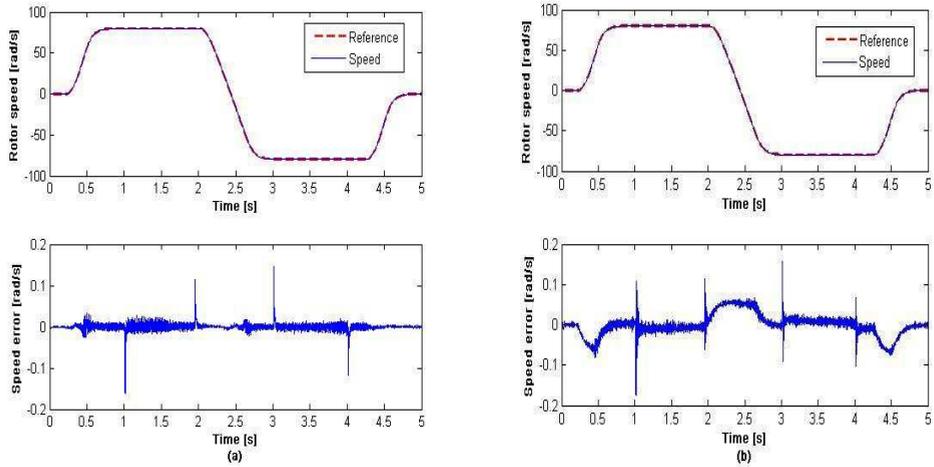
Fig. 2. Speed tracking performances - (a) proposed NMPC PID Controller, and (b) Field Oriented Controller (FOC).
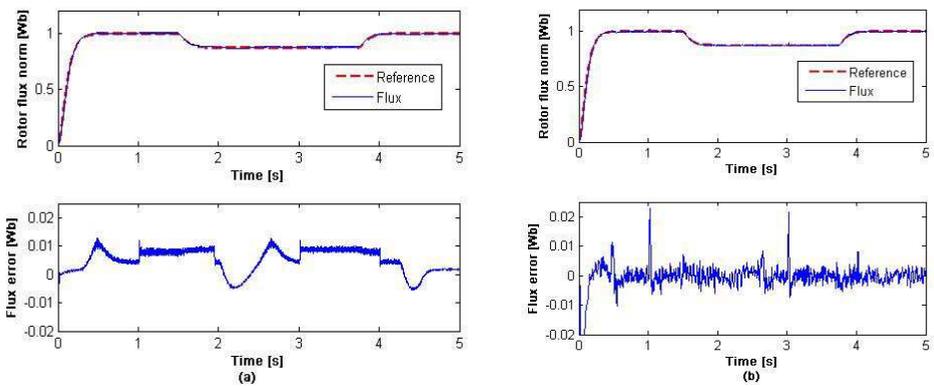

Fig. 3. Flux norm tracking performances - (a) proposed NMPC PID Controller, and (b) Field Oriented Controller (FOC).
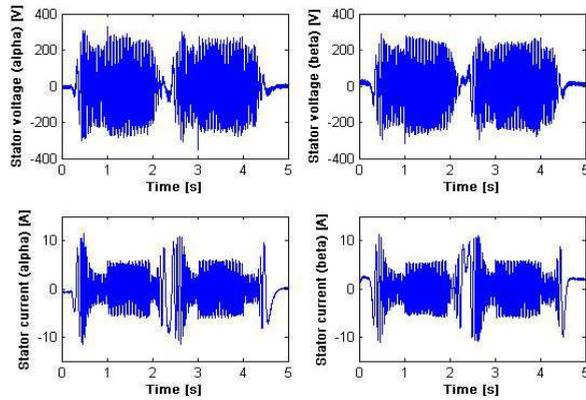
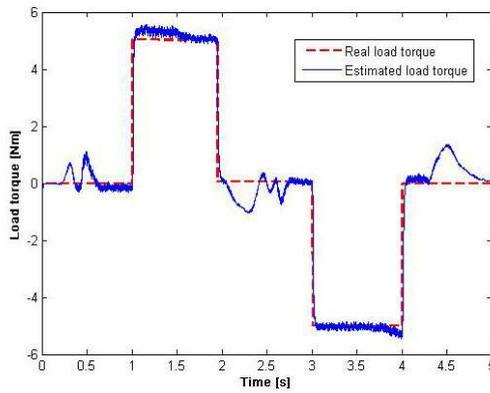Fig. 4. Stator voltage and current components with NMPC PID controller
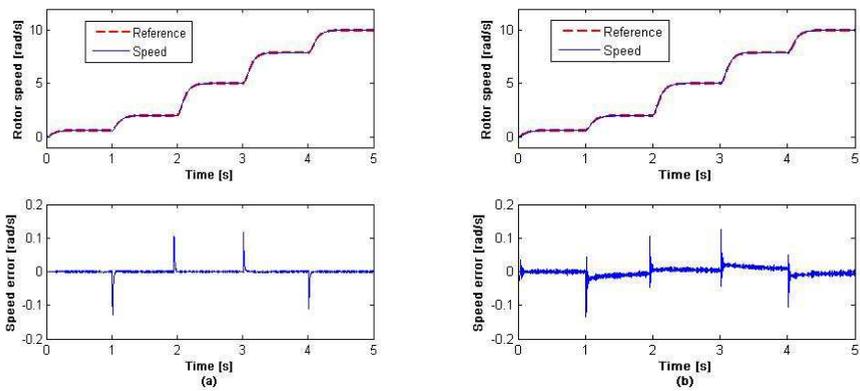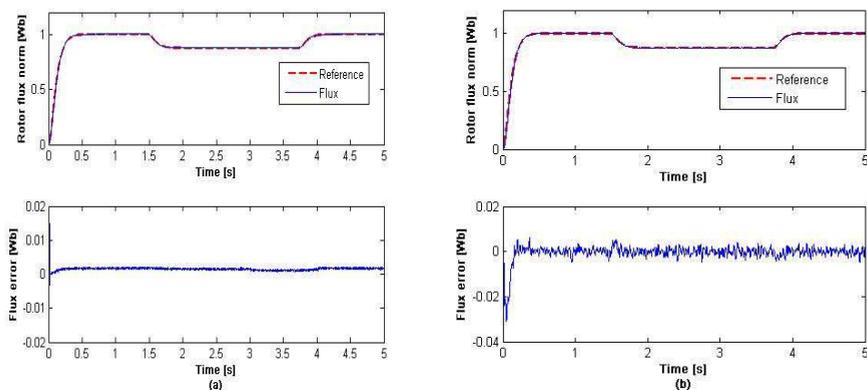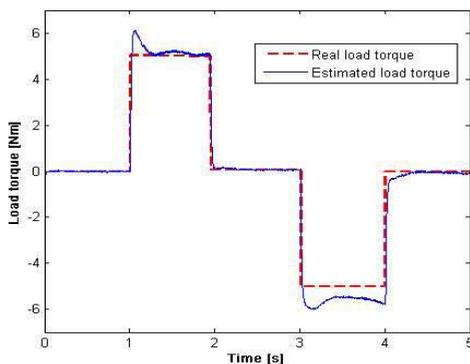

Fig. 5. Reference and estimated load torque

Fig. 6. Low speed tracking performances - (a) proposed NMPC PID Controller, and (b) Field Oriented Controller (FOC).

Fig. 7. Flux norm tracking performances for low speed operation - (a) proposed NMPC PID Controller, and (b) Field Oriented Controller (FOC).

Fig. 8. Reference and estimated load torque
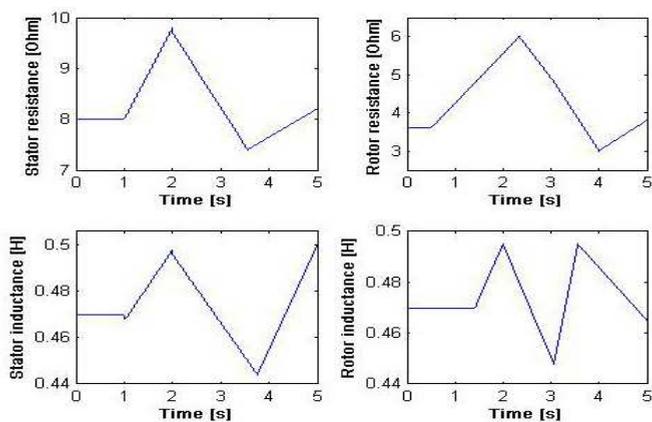
Fig. 9. Variation of machine parameters

Figure 10 gives the tracking responses for speed and flux norm in case of reversal speed. It can be seen that the speed and rotor flux are slightly influenced by the variations. However, the disturbance observation, in figure 11, is deteriorated by the variations. Although a deterioration of perturbation estimation is observed, the tracking of the mismatched model is achieved successfully, and the load torque variations are well rejected in speed response, which is the target application of the drive. Figure 12 gives the tracking responses for speed and flux norm in case of low speed. The speed and rotor flux responses are not affected by the parameters variations. The disturbance observation, shown in figure 13, is less affected than in first case. Although the load torque estimation is sensitive to the speed error, its rejection in speed response is achieved accurately.
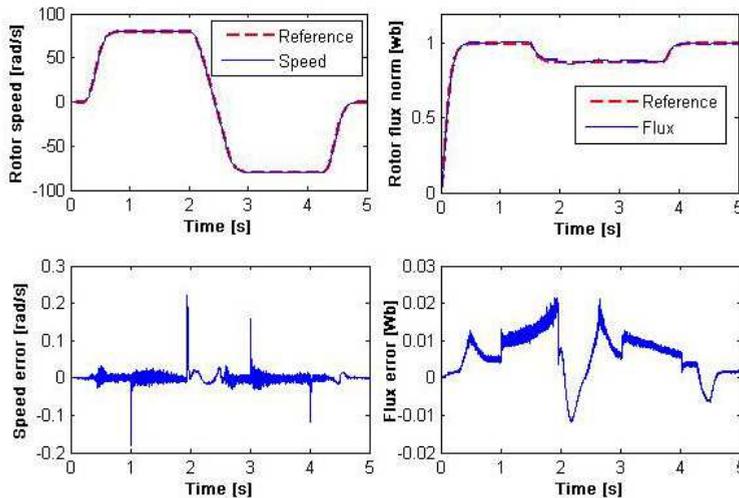
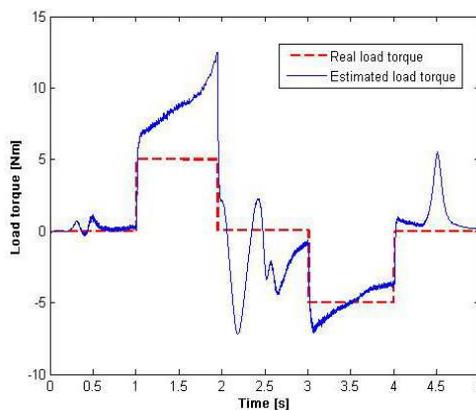Fig. 10. Speed and flux norm tracking performances under motor parameters variation.

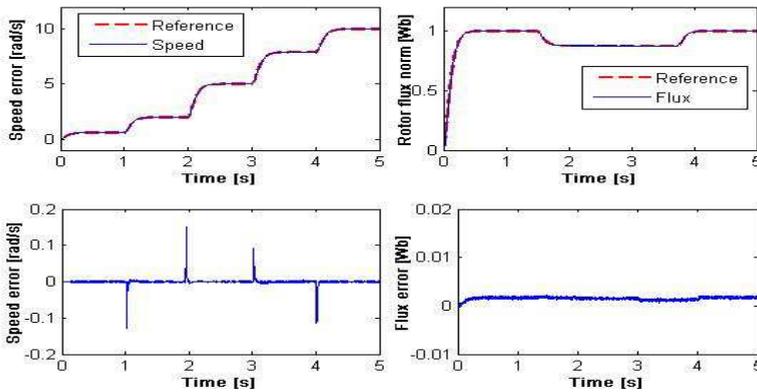Fig. 11. Reference and estimated load torque under motor parameters variation.

Fig. 12. Speed and flux norm tracking performances under motor parameters variation.
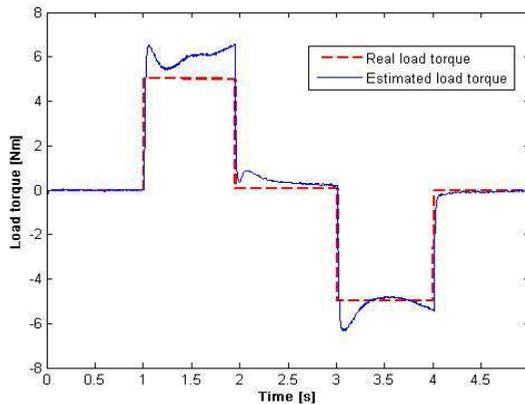

Fig. 13. Reference and estimated load torque under motor parameters variation.

It can be seen that the disturbance observation is influenced by transitions in speed response. Furthermore, the use of the state observer may influence on the system response. Therefore, a more powerful state observer can improve the controlled system performance.

An improvement can be achieved by introduction of an on-line parameters identification, which leads to the adaptive techniques (Marino et al., 1998; Van Raumer, 1994), which is beyond the scope of this chapter.

7. Conclusion

An application of nonlinear PID model predictive control algorithm to induction motor drive is presented in this chapter. First, the nonlinear model predictive control law has been carried out from the nonlinear state model of the machine by minimizing a cost function. Even though the control weighting term is not included in the cost function, the tracking

performance is achieved accurately. The computation of the model predictive control law is easy and does not need an online optimization. It has been shown that the stability of the closed loop system under this controller is guaranteed. Then, the load torque is considered as an unknown disturbance variable in the state model of the machine, and it is estimated by an observer. This observer, derived from the nonlinear model predictive control law, is simplified to a PID speed controller. The integration of the load torque observer in the model predictive control law allows enhancing the performance of the motor drive under machine parameter variations and unknown disturbance. The combination between the NMPC and disturbance observer forms the NMPC PID controller. In this application, it has been noticed that the tuning of the NMPC PID controller parameters is easier compared with the standard FOC method.

A state observer is integrated in the control scheme. The global stability of the whole system is theoretically proved using the Lyapunov technique. Therefore, the coupling between the nonlinear model predictive controller and the state observer guarantees the global stability.

The obtained results show the effectiveness of the proposed control strategy regarding trajectory tracking, sensitivity to the induction motor parameters variations and disturbance rejection.

8. Appendices

8.1 Lie derivatives of the process outputs

The following notation is used for the Lie derivative of state function $h_j(\mathbf{x})$ along a vector field $\mathbf{f(x)}$.

$$L_{\mathbf{f}}h_j = \frac{\partial h_j}{\partial \mathbf{x}}\mathbf{f(x)} = \sum_{i=1}^{n}\frac{\partial h_j}{\partial x_i}f_i(\mathbf{x}) \tag{A1}$$

Iteratively, we have

$$L_{\mathbf{f}}^k h_j = L_{\mathbf{f}}(L_{\mathbf{f}}^{(k-1)}h_j) \; ; \; L_{\mathbf{g}}L_{\mathbf{f}}h_j = \frac{\partial L_{\mathbf{f}}h_j}{\partial \mathbf{x}}\mathbf{g(x)} \tag{A2}$$

$$L_{\mathbf{f}}h_1(\mathbf{x}) = \frac{pL_m}{JL_r}\left(\phi_{r\alpha}i_{s\beta} - \phi_{r\beta}i_{s\alpha}\right) - \frac{f_r}{J}\omega - \frac{1}{J}T_L \tag{A3}$$

$$L_{\mathbf{f}}^2 h_1(\mathbf{x}) = \frac{pL_m}{JL_r}\left(\gamma + \frac{1}{T_r} + \frac{f_r}{J}\right)\left(\phi_{r\beta}i_{s\alpha} - \phi_{r\beta}i_{s\alpha}\right) - \frac{p^2 L_m K}{JL_r}\left(\phi_{r\alpha}^2 + \phi_{r\beta}^2\right) - \frac{p^2 L_m}{JL_r}\omega\left(\phi_{r\alpha}i_{s\alpha} + \phi_{r\beta}i_{s\beta}\right) + \frac{f_r^2}{J^2}\omega + \frac{f_r}{J^2}T_L \tag{A4}$$

$$L_{g_{11}}L_{\mathbf{f}}h_1(\mathbf{x}) = -\frac{pL_m}{J\sigma L_s L_r}\phi_{r\beta} \tag{A5}$$

$$L_{g_{12}}L_{\mathbf{f}}h_1(\mathbf{x}) = \frac{pL_m}{J\sigma L_s L_r}\phi_{r\alpha} \tag{A6}$$

$$L_{\mathbf{f}}h_2(\mathbf{x}) = \frac{2L_m}{T_r}\left(\phi_{r\alpha}i_{s\alpha} + \phi_{r\beta}i_{s\beta}\right) - \frac{2}{T_r}\left(\phi_{r\alpha}^2 + \phi_{r\beta}^2\right) \tag{A7}$$

$$L_{\mathbf{f}}^2 h_2(\mathbf{x}) = -\frac{2L_m}{T_r}\left(\gamma + \frac{3}{T_r}\right)\left(\phi_{r\alpha}i_{s\alpha} + \phi_{r\beta}i_{s\beta}\right) - \frac{2pL_m}{T_r}\omega\left(\phi_{r\beta}i_{s\alpha} - \phi_{r\beta}i_{s\alpha}\right) + \frac{4 + 2L_m K}{T_r^2}\left(\phi_{r\alpha}^2 + \phi_{r\beta}^2\right) + \frac{2L_m^2}{T_r^2}\left(i_{r\alpha}^2 + i_{r\beta}^2\right) \tag{A8}$$

$$L_{g_{11}}L_{\mathbf{f}}h_2(\mathbf{x}) = \frac{2L_m}{\sigma L_s T_r}\phi_{r\alpha} \tag{A9}$$

$$L_{g_{12}}L_{\mathbf{f}}h_2(\mathbf{x}) = \frac{2L_m}{\sigma L_s T_r}\phi_{r\beta} \tag{A10}$$

$$L_{g_{21}}h_1(\mathbf{x}) = -\frac{1}{J} \tag{A11}$$

$$L_{g_{21}}L_{\mathbf{f}}h_1(\mathbf{x}) = \frac{f_r}{J^2} \tag{A12}$$

8.2 Simplification of Lie derivatives according l(x)

Using the Lie notations (A1, A2) and output differentiations, in (4) and (6), with $\mathbf{l}(\mathbf{x})$, defined by (22), we have

$$L_{g_{11}}L_f h_1(x) = \frac{\partial L_f h_1(x)}{\partial x}g_{11}(x) = \frac{1}{p_0}l(x)g_{11}(x) \tag{B1}$$

$$L_{g_{12}}L_f h_1(x) = \frac{\partial L_f h_1(x)}{\partial x}g_{12}(x) = \frac{1}{p_0}l(x)g_{12}(x) \tag{B2}$$

$$L_{g_{21}}L_f h_1(x) = \frac{\partial L_f h_1(x)}{\partial x}g_{21}(x) = \frac{1}{p_0}l(x)g_{21}(x) - K_1 L_{g_{21}}h_1(x) \tag{B3}$$

$$L_f^2 h_1(x) = \frac{\partial L_f h_1(x)}{\partial x}f(x) = \frac{1}{p_0}l(x)f(x) - K_1 L_f h_1(x) \tag{B4}$$

$$l(x)\dot{x} = p_0\left(\frac{\partial L_f h_1(x)}{\partial x}\frac{\partial x}{\partial t} + K_1\frac{\partial h_1}{\partial x}\frac{\partial x}{\partial t}\right)$$
$$= p_0\left(\ddot{\omega}(t) + K_1\dot{\omega}(t)\right) \tag{B5}$$

$$\mathbf{l}(\mathbf{x})g_2(x) = p_0\left(\frac{\partial L_{\mathbf{f}}h_1(\mathbf{x})}{\partial \mathbf{x}}g_{21} + K_1\frac{\partial h_1}{\partial x}g_{21}\right) = p_0\left(L_{g_{21}}L_{\mathbf{f}}h_1(\mathbf{x}) + K_1 L_{g_{21}}h_1(\mathbf{x})\right) = p_0\left(\frac{f_r}{J^2} - K_1\frac{1}{J}\right) = c \tag{B6}$$

8.3 Lie derivatives of the auxiliary outputs

$$\hat{h}_{11} = \frac{pL_m}{JL_r}(\hat{\phi}_{r\alpha}\hat{i}_{s\beta} - \hat{\phi}_{r\beta}\hat{i}_{s\alpha}) \tag{C1}$$

$$L_{\hat{f}}\hat{h}_{11} = \frac{pL_m}{JL_r}[(\gamma + \frac{1}{T_r} + k_1)(\hat{i}_{s\alpha}\hat{\phi}_{r\beta} - \hat{i}_{s\beta}\hat{\phi}_{r\alpha}) - p\hat{\omega}(\hat{i}_{s\alpha}\hat{\phi}_{r\alpha} + \hat{i}_{s\beta}\hat{\phi}_{r\beta}) - pK\hat{\omega}(\hat{\phi}_{r\alpha}^2 + \hat{\phi}_{r\beta}^2)$$
$$-k_1(i_{s\alpha}\hat{\phi}_{r\beta} - i_{s\beta}\hat{\phi}_{r\alpha}) + \frac{k_2}{T_r}(i_{s\alpha}\hat{i}_{s\beta} - i_{s\beta}\hat{i}_{s\alpha}) - pk_2\hat{\omega}(i_{s\alpha}\hat{i}_{s\alpha} - i_{s\beta}\hat{i}_{s\beta}) + pk_2\hat{\omega}(\hat{i}_{s\alpha}^2 + \hat{i}_{s\beta}^2) - \hat{\phi}_{r\beta}f_{ia} + \hat{\phi}_{r\alpha}f_{ib}] \tag{C2}$$

$$\hat{h}_{21} = \frac{2L_m}{T_r}\left(\hat{\phi}_{r\alpha}\hat{i}_{s\alpha} + \hat{\phi}_{r\beta}\hat{i}_{s\beta}\right) \tag{C3}$$

$$L_{\hat{f}}\hat{h}_{21} = \frac{2L_m}{T_r}[(\frac{L_m}{T_r} - \frac{k_2}{T_r})(\hat{i}_{s\alpha}^2 + \hat{i}_{s\beta}^2) - (\gamma + \frac{1}{T_r} + k_1)(\hat{i}_{s\alpha}\hat{\phi}_{r\beta} + \hat{i}_{s\beta}\hat{\phi}_{r\alpha}) - p\hat{\omega}(\hat{i}_{s\alpha}\hat{\phi}_{r\alpha} - \hat{i}_{s\beta}\hat{\phi}_{r\beta}) + \frac{k_2}{T_r}(i_{s\alpha}\hat{i}_{s\alpha} + i_{s\beta}\hat{i}_{s\beta})$$
$$+ pK\hat{\omega}(i_{s\alpha}\hat{i}_{s\beta} - i_{s\beta}\hat{i}_{s\alpha}) + \frac{K}{T_r}(\hat{\phi}_{r\alpha}^2 + \hat{\phi}_{r\beta}^2) + k_1(i_{s\alpha}\hat{\phi}_{r\alpha} + i_{s\beta}\hat{\phi}_{r\beta}) + \hat{\phi}_{r\alpha}f_{ia} + \hat{\phi}_{r\beta}f_{ib}] \tag{C4}$$

8.4 Induction machine characteristics

The plant under control is a small induction motor 1.1 kW, with the following parameters

ω_{nom} = 73.3 rad/s, $\phi_{r\alpha\beta}$ = 1.14 Wb, T_{nom} = 7 Nm, R_s = 8.0 Ω, R_r = 3.6 Ω, L_s = 0.47 H, L_r = 0.47 H, L_m = 0.44 H, p = 2, f_r = 0.04 Nms, J = 0.06 kgm²

9. References

Barut, M.; Bogosyan, S.; Gokasan, M. (2005). Speed sensorless direct torque control of IM's with rotor resistance estimation. *Energy Conversion and Management*, 46, pp. 335-349.

Bemporad, A.; Morari, M.; Dua, V.; Pistikopoulous, E.N. (2002). The explicit linear quadratic regulator for constrained systems *Automatica*, 38 (1), pp. 3-20.

Blaschke, F. (1972). The principle of field orientation as applied to the new transvector closed loop system for rotating field machines. *Siemens Rev.*, 39 (5), pp. 217-220.

Bordons, C.; Camacho, E.F. (1998). A generalized predictive controller for a wide class of industrial processes. *IEEE Transactions on Control Systems Technology*, 6 (3), pp. 372-387.

Camacho, E.F.; Bordons, C. (2004). Model Predictive Control, 2nd edition, Springer.

Chen, F.; Dunnigan, M.W. (2003). A new non-linear sliding-mode for an induction motor machine incorporating a sliding-mode flux observer. *International Journal of Robust and Nonlinear Control*, 14, pp. 463-486.

Chen, W.H.; Balance, D.J.; Gawthrop P.J. (2003). Optimal control of nonlinear systems: a predictive control approach. *Automatica*, 39 (4), pp. 633-641.

Chen, W.H.; Balance, D.J.; Gawthrop, P.J.; Gribble, J.J.; O'Reilly J. (1999). Nonlinear PID predictive controller. *IEE Proceedings Control Theory Application*; 146 (6), pp. 603-611.

Chenafa, M.; Mansouri, A.; Bouhenna, A.; Etien, E.; Belaidi, A. & Denai, M.A. (2005). Global stability of linearizing control with a new robust nonlinear observer of the

induction motor. *International Journal of Applied Mathematics and Computer Sciences*, 15 (2), pp. 235-243.

Chiasson, J. (1996). Nonlinear controllers for an induction motor. *Control Engineering Practice*, 4 (7), pp. 977-990.

Correa, P.; Pacas, M.; Rodriguez, J. (2007). Predictive Torque Control for Inverter Fed Induction Machines. *IEEE Transactions on Industrial Electronics*, 45 (2), pp. 1073-1079.

Du, T.; Brdys, M.A. (1993). Shaft speed, load torque and rotor flux estimation of induction motor drive using an extended Luenberger observer. 6th IEEE International Conference on Electrical Machines and Drives, pp. 179-184.

Feng, W.; O'Reilly, J.; Balance D.J. (2002). MIMO nonlinear PID predictive controller. *IEE Proceedings Control Theory Application*, 149 (3), pp. 203-208.

Garcia, C. E.; Prett, D.M., Morari, M. (1989). Model predictive control: theory and practice- a survey. *Automatica*, 3, pp. 335-348.

Hedjar, R.; Toumi, R.; Boucher, P.; Dumur D. (2003). Two cascaded nonlinear predictive control of induction motor. Proceedings of the IEEE Conference on Control Application, Istanbul, Turkey; 1, pp. 458-463.

Hedjar, R.; Toumi, R.; Boucher, P.; Dumur, D. (2000). Cascaded nonlinear predictive control of induction motor. Proceedings of the IEEE Conference on Control Applications, Anchorage, Alaska, USA, pp. 698-703.

Hong, K.; Nam, K. (1998). A load torque compensation scheme under the speed measurement delay. *IEEE Transactions on Industrial Electronics*, 45 (2), 283-290.

Jansen, L.P.; Lorenz, D.W. Novotny (1994). Observer-based direct field orientation: analysis and comparison of alternatives methods. *IEEE Transactions on Industry Applications*, 30 (4), pp. 945-953.

Leonhard, W. (2001). Control of Electrical Drives. 3rd Edition, Spinger-Verlag: Berlin.

Maaziz, M.K.; Boucher, P.; Dumur, D. (2000). A new control strategy for induction motor based on non-linear predictive control and feedback linearization. *International Journal of Adaptive Control and Signal Processing*, 14, pp. 313-329.

Marino, R.; Peresada, S.; Tomei, P. (1998). Adaptive output feedback control of current-feed induction motors with uncertain rotor resistance and load torque. *Automatica*, 34 (5), pp. 617-624.

Marino, R.; Peresada, S.; Valigi, P. (1993). Adaptive input-output linearizing control of induction motors. *IEEE Transactions on Automatic Control*, 38 (2), pp. 208-221.

Marino, R.; Tomei, P.; Verrelli, C.M. (2002). An adaptive controller for speed-sensorless current-feed induction motors with unkown load torque. Proceedings of the 7th International Conference on control, Automation, Robotics and Vision, Singapore, pp. 1658-1663.

Merabet, A.; Ouhrouche, M.; Bui, R.T. (2006). Nonlinear predictive control with disturbance observer for induction motor drive. Proceedings of IEEE International Symposium on Industrial Electronics, Montreal, Canada.

Nemec, M.; Nedeljkovic D.; Ambrozic; V. (2007). Predictive Torque Control of Induction Machines Using Immediate Flux Control. *IEEE Transactions on Industrial Electronics*, 54 (4), pp. 2009-2017.

Ping L. (1996). Optimal predictive control of continuous nonlinear systems. *International Journal of Control*; 63 (1), pp. 633-649.

Richalet, J. (1993). Industrial applications of model based predictive control. *Automatica*, 29 (5), pp. 1251-1274.

Siller-Alcalá, I.I. (2001). Generalized predictive control for nonlinear systems with unstable zero dynamics. *Journal of the Mexican Society of Instrumentation and Development*, 5 (3), pp. 146-151.

Van Raumer, T. (1994). Nonlinear adaptive control of induction machine. PhD thesis (in French), LAG, Grenoble, France.
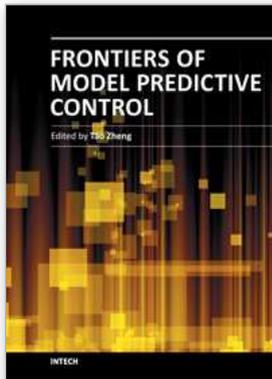
Frontiers of Model Predictive Control

Edited by Prof. Tao Zheng

Model Predictive Control (MPC) usually refers to a class of control algorithms in which a dynamic process model is used to predict and optimize process performance, but it is can also be seen as a term denoting a natural control strategy that matches the human thought form most closely. Half a century after its birth, it has been widely accepted in many engineering fields and has brought much benefit to us. The purpose of the book is to show the recent advancements of MPC to the readers, both in theory and in engineering. The idea was to offer guidance to researchers and engineers who are interested in the frontiers of MPC. The examples provided in the first part of this exciting collection will help you comprehend some typical boundaries in theoretical research of MPC. In the second part of the book, some excellent applications of MPC in modern engineering field are presented. With the rapid development of modeling and computational technology, we believe that MPC will remain as energetic in the future.

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