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Robust nonlinear receding-horizon control of induction motors

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ABSTRACT

Nonlinear robust receding-horizon control is designed and applied to fifth-order model of induction motor in cascade structure. The controller is based on a finite horizon continuous time minimization of the predicted tracking errors and no online optimization is needed. The initial system is decomposed into two sub-systems (mechanical and electromagnetic sub-systems) in cascade form. An integral action is incorporated in external loop to increase the robustness of the controller with respect to unknown time-varying load torque and mechanical parameters uncertainties. The control uses only measurement of the rotor speed and stator currents. The rotor flux is estimated by Kalman filter. The proposed nonlinear controller permits to achieve asymptotic speed and flux tracking in presence of mechanical parameters uncertainties, unknown variable load torque and resistances variations. In addition, it assures asymptotic decoupling of the speed and flux subsystems. The controller is applied, via simulation, to a benchmark example.

1. Introduction

Induction machines are very attractive and widely used in many industrial applications owing to their size, low cost, simple structure and high reliability. Nevertheless, they represent a highly coupled and nonlinear multivariable system. Furthermore, the rotor flux is not usually measurable and there are uncertain critical parameters in addition to load torque, which is typically unknown in all electric drives. Thus, the induction motors constitute an important area of application for nonlinear robust control theory.

The field-oriented control technique has been widely used in industry for high performance induction motor drive because it gives control characteristics similar to separately excited DC motor. However, the performance is sensitive to the variation of motor parameters, especially the rotor time constant which varies with temperature [1–3]. To increase the performance of field-oriented control, much attention has been given to the possibility of identifying the changes in the motor parameters of an induction motor while the drive is in normal operation. Indeed, most of the proposed nonlinear control strategies use online rotor resistance estimator to achieve better tracking performance and to maintain the decoupling property. Indeed, authors in [4–6,35] have proposed a speed/torque and flux tracking adaptive controller without measurements of the rotor fluxes while adapting to both rotor resistance and unknown load torque. However, to ensure the convergence, the persistent excitation condition should be satisfied. It is stated in [7] that the persistent excitation condition is not satisfied when the electric torque is absent due to lack of currents. While in [9], authors have proposed an indirect field oriented control (IFOC) which guarantees global exponential speed-flux tracking but under the condition of constant value of load torque and rotor resistance. The load torque estimator was utilized in this control scheme. Also in [10], authors have proved the asymptotic stability of indirect field oriented control of induction motor in the presence of rotor resistance and load torque variations.

Moreover, the stator resistance may also vary up to 50% during motor operation. It becomes critical in low speed region [8]. Thus, both of stator and rotor resistances have been estimated online and the convergence is also under persistent excitation condition [7,8,17].

Many other researchers have designed nonlinear controllers for induction motors which are robust to mechanical parameters variations and load torque variations only [11–13]. A discrete-time sliding mode control has designed and applied to induction motor [14]. This control algorithm is robust to unknown load torque variations. However, the robustness of this algorithm to resistances variations has not been reported.

A predictive optimal control strategy has been proposed for the control of the flux and speed of an induction machine [15]. In this work, authors use a linearized model and good tracking performances have been obtained. The load torque is estimated and the robustness of this control scheme to resistances variation has not been mentioned.

Recently, artificial intelligence has been used to control the speed and rotor flux of induction motor [16]. Here also the robustness of the algorithm to resistances variations has not been reported.

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Consequently, for better performances, many authors have used online parameters estimation schemes, especially for unknown rotor resistance and load torque variations, which are available in the literature, and broadly classified in [18].

The proposed algorithm in this work does not need to estimate unknown mechanical parameters neither resistances variations nor load torque variations.

Nonlinear model predictive control (NMPC) of nonlinear systems has received considerable attention in the last years owing to its robustness with respect to parameter variations and allows the explicit consideration of state and input constraints [19]. Thus, the NMPC is evaluated implicitly online by solving a constrained optimization problem. A serious limitation in using NMPC is the presence of fast plant dynamics, which require high sampling frequencies that do not allow to perform the constrained nonlinear optimization problem online [19–21]. For the above reason, this kind of control scheme is usually applied to industrial processes characterized by a slow dynamics such as chemical processes. Consequently, the application of NMPC with online optimization to systems characterized by fast dynamics (like asynchronous machine), sounds like an unusual proposal. To avoid this, several offline nonlinear predictive laws have been developed in [22,23], where the one-step ahead predictive error is obtained by expanding the output signal and reference signal in a r_ith order Taylor series, where r_i is the relative degree of the ith output. Then, the continuous minimization of the predicted tracking errors is used to drive the control law.

This work examines the nonlinear receding-horizon control approach with integral action based on a finite horizon dynamic minimization of the tracking errors, to achieve torque and rotor flux amplitude tracking objectives. An extension to speed control is realized using a cascaded structure. This is a modified version of the Ping's method [22]. Note that the proposed approach in [22] cannot be applied to induction motor since the derivative of the control signal will appear in the cost function. The advantages of the proposed control law include good tracking performance and good robustness property with respect to mechanical parameters uncertainties, unknown and variable load torque and resistances variations. Moreover, the flux weakening operation has no effect on the speed behavior.

This paper aims at the development of:

1. Asymptotically stable output feedback controller with speed-flux-tracking capability in the presence of unknown load torque.
2. Robustness of the closed loop algorithm against stator and rotor resistances variations.
3. Robustness of the closed loop algorithm against mechanical parameters uncertainties.
4. Less power consumption with regards to many proposed algorithms in [9,32–34].

The present contribution is an improvement of the previous work [24] in terms of the robustness of the nonlinear receding-horizon control algorithm against mechanical parameters uncertainties. Moreover, a global convergence and stability analysis of the closed-loop system have been investigated in this work.

The paper is organized as follows. After the mathematical model of the induction motor developed in Section 2, a brief overview of the optimal nonlinear receding-horizon control theory is presented in Section 3. In Section 4, the previous scheme is extended to speed control by a cascaded nonlinear control structure. Stability and robustness of the proposed algorithm are treated in this section. The rotor flux observer is presented in Section 5. Significant simulation results are given in Section 6 for the nominal and mismatched model of the induction motor with bounded and unknown time-varying load disturbance. The paper ends up with the concluding remarks and suggestions in Section 7.

2. Mathematical model

Assuming linear magnetic circuits, the dynamics of induction motor are given by the well-known fifth-order model, see for instance [1] for its derivation and modeling assumptions:

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

with $\mathbf{x} = [i_{s\alpha}\ i_{s\beta}\ \phi_{r\alpha}\ \phi_{r\beta}\ \Omega]^T;\ \mathbf{u} = [u_{s\alpha}\ u_{s\beta}]^T$

where $i_{s\alpha}, i_{s\beta}$: stator currents, $\phi_{r\alpha}, \phi_{r\beta}$: rotor fluxes, Ω: speed, $u_{s\alpha}, u_{s\beta}$: stator voltages.

Vector function $\mathbf{f}(\mathbf{x})$ and constant matrix $\mathbf{g}$ are defined as follows:

$$\mathbf{f}(\mathbf{x}) = \begin{bmatrix} -\gamma\ i_{s\alpha} + \frac{k}{T_r}\phi_{r\alpha} + p\Omega k\phi_{r\beta} \\ -\gamma\ i_{s\beta} + \frac{k}{T_r}\phi_{r\beta} - p\Omega k\phi_{r\alpha} \\ \frac{L_m}{T_r} i_{s\alpha} - \frac{1}{T_r}\phi_{r\alpha} - p\Omega\phi_{r\beta} \\ \frac{L_m}{T_r} i_{s\beta} - \frac{1}{T_r}\phi_{r\beta} + p\Omega\phi_{r\alpha} \\ p\frac{L_m}{JL_r}(\phi_{r\alpha}i_{s\beta} - \phi_{r\beta}i_{s\alpha}) - \frac{(T_L + f\Omega)}{J} \end{bmatrix},$$

$$\mathbf{g} = [g_1 \quad g_2] = \begin{bmatrix} \frac{1}{\sigma\ L_s} & 0 & 0 & 0 & 0 \\ 0 & \frac{1}{\sigma\ L_s} & 0 & 0 & 0 \end{bmatrix}^T$$

All required parameters above have the following meanings:

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

where L_s, L_r are stator and rotor inductances, L_m is the mutual inductance, R_s, R_r are stator and rotor resistances, $T_r = L_r/R_r$ is the rotor time constant, p is the pole pair number, J is the inertia of the machine, f is the friction coefficient, T_L is the load torque considered as an unknown disturbance.

Considering the torque and squared rotor flux modulus as outputs of the AC drive, the following equations can be derived, with y_1 as the torque and y_2 as the rotor flux norm:

$$\begin{cases} y_1 = h_1(\mathbf{x}) = p\frac{L_m}{L_r}(\varphi_{r\alpha}i_{s\beta} - \varphi_{r\beta}i_{s\alpha}) \\ y_2 = h_2(\mathbf{x}) = \varphi_{r\alpha}^2 + \varphi_{r\beta}^2 = \varphi_r^2 \end{cases} \tag{2}$$

3. Nonlinear receding-horizon law

In the receding-horizon control strategy, the following control problem is solved at each $t > 0$ and $\mathbf{x}(t)$:

$$\begin{aligned} Min_{u(t)} J(\mathbf{x}(t), t, \mathbf{u}(t)) &= \frac{1}{2}\int_t^{t+T} L(\tau)d\tau \\ &= Min_{u(t)} \frac{1}{2}\int_t^{t+T} [\mathbf{x}(\tau)^T\mathbf{Q}\mathbf{x}(\tau) + \mathbf{u}(\tau)^T\mathbf{R}\ \mathbf{u}(\tau)]d\tau \end{aligned} \tag{3}$$

subject to the Eq. (1) and $\mathbf{x}(t + T) = 0$ for some $T > 0$, where $\mathbf{Q}$ is positive definite matrix and $\mathbf{R}$ positive semi-definite matrix. To solve this nonlinear dynamic optimization problem with equality constraints is highly computationally intensive, and in many cases it is impossible to be performed within a reasonable time limit, especially for systems with extremely fast dynamics like induction motor. Furthermore, the global optimization solution cannot be guaranteed in each optimization procedure since; in general, it is a non-convex, constrained nonlinear optimization problem.