Cascaded Nonlinear Adaptive Predictive Control based Adaptive Flux Observer of Induction Motor

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ABSTRACT
This paper present a new advanced control algorithm based on continuous minimization of predicted tracking errors, to achieve torque, rotor speed and rotor flux amplitude tracking objectives. This algorithm called a new Adaptive Nonlinear Predictive Control to induction motor drive uses a combination of the adaptive observer for rotor flux and Cascaded Nonlinear Predictive Control technique. The variables to be controlled are the rotor speed and the rotor flux norm, required to implement the predictive control algorithm is estimated by flux observer. The parameters identified adaptively are stator and rotor resistance which vary with motor temperature using the adaptive rotor flux observer. A stability of the proposed adaptive flux observer will be proved by the Lyapunov's theorem. Simulations are carried out in order to show the effectiveness of the drive and the robustness to parameters variations.

Keywords
Cascaded Nonlinear Predictive Control, Nonlinear Control, Induction Motors, Adaptive Flux Observer.

1. INTRODUCTION
For over fifty years, DC motors have been widely used in variable speed drives applications principally due to their fast torque response, high precision of regulation and the possibility to use these motors in whichever mode of operation [1]. However DC motors with drawbacks of spark, corrosion and necessity of maintenance, this motor has been replaced by AC induction motors (IMs)[2].Induction motors (IMs) are widely used in many industrial applications due to their mechanical robustness and low cost [1,2]. However, it is known that the control of induction motors is relatively difficult compared to other kinds of motors, such as DC motors and synchronous motors due to their coupled and nonlinear model [1-4].

To solve this problem and achieve high performance, field-oriented control (FOC) schemes have been proposed by F. Blaschke in 1972 [4]. This method can provide at least the same performance from an inverter-driven induction motor as is obtainable from a separately excited DC motor [5].
To improve the Field Oriented Control, in the last years, many strategies have been studied to control induction motor. [7] Among recent studies on input-output linearization, in [8] has proposed a controller designed to track torque and rotor flux references, in [9] have developed an input-output decoupling controller which decouples the regulation of the rotor speed and the rotor flux norm.

The predictive control method is traditionally used for industrial process control and a large number of implementation algorithms have been presented in literature such as extended prediction self adaptive control, generalized predictive control and unified predictive control [10], the basic idea of GPC presented by Clarke et al. 1987 in [11].Predictive Algorithms have already been used for controlling industrial plants, as related in [12] the author present a novel algorithm called Generalized Predictive Control (GPC) is shown to be particularly effective for the self-tuning control of industrial processes. In [13] is proposed a control approach where the direct power control is combined with predictive selection of a voltage-vector of inverters. In [14], the use of low-frequency predictive current control is proposed for a single-phase cascaded H-bridge multilevel rectifier.

Various proposals have been made for the use of predictive algorithms to control electric motors, especially induction motors (IM). The majority of these algorithms involve vector control algorithms and independent strategies to control the rotor flux and speed [15]. A model-based predictive control of rotor flux and speed of a vector-controlled induction motor is presented in [16], a state space approach is employed for modelling a rotor-flux oriented induction motor. Generalized predictive control of linear systems has received considerable attention in the last decade due to its robustness with respect to parameters variations. Much effort has been done to extend GPC to nonlinear system [17].

The classical GPC had been developed with linear plant for prediction model which leads to a formulation that can be solved analytically if the process is defined by a nonlinear model, [18] the use of linear model predictor becomes impractical, and the design of nonlinear predictor and nonlinear algorithm for optimization are necessary [19]. A nonlinear generalized predictive control (NGPC) of induction motor drive is presented in [20]; the predictive control algorithm is implemented using a model of the motor in fixed stator reference frame. The task of the controller is to track the desired speed and flux profiles. Rotor flux information required to implement the predictive control algorithm is estimated using Kalman Filter algorithm.

This paper is organized as follows. The mathematical model of the induction motor is developed in Section 3, while Section 4 describes a Cascaded Nonlinear Predictive Control scheme to simultaneous control of the electromagnetic torque, the norm of rotor flux and rotor speed, (Kalman filter used for the estimation of rotor flux).

In Section 5 we present a new advanced control algorithm based on continuous minimization of predicted tracking errors, to achieve load torque, rotor speed and rotor flux amplitude tracking objectives. This algorithm called a new Adaptive Cascaded Nonlinear Predictive Control uses a combination of the adaptive observer for rotor flux and Cascaded Nonlinear Predictive Control. Finally, the performance of the proposed drive control system is verified by simulation.

2. NONLINEAR INDUCTION MOTOR MODEL

The induction motor consists of three-phase stator windings and a rotor with short cut windings. Since the torque produced is a function of the difference between the mechanical speed and the angular speed of the supplied stator voltage, this results in a nonlinear model. To reduce the complexity of a three-phase model, an equivalent two-phase representation is chosen [5]. For the FOC this two-phase model is usually transformed in a rotating (d,q) reference frame [9]. This transformation is a source of problems but usually the FOC approach does not allow control the model in a stator fixed (α,β) reference frame. Using nonlinear feedback allows to contorted the model in the stator fixed (α,β) reference frame avoiding the transformation in a rotating reference frame. The complete model in stator fixed (α,β) reference frame can is written form for a control in speed and flux [7-10]:

$$S=\begin{cases}\dot{x}=f(x)+g_1.u(t)\\ y=\begin{bmatrix}h_1(x)\\ h_2(x)\end{bmatrix}=\begin{bmatrix}\Omega\\ \varphi_{r\alpha}^2+\varphi_{r\beta}^2\end{bmatrix}\end{cases} \quad (1)$$

Where $x=[I_{s\alpha}\ I_{s\beta}\ \varphi_{r\alpha}\ \varphi_{r\beta}\ \Omega]^T$; $u=[u_{s\alpha}\ u_{s\beta}]^T$

$$f(x)=\begin{bmatrix}-\gamma I_{s\alpha}+\frac{K}{Tr}\varphi_{r\alpha}+p\Omega K\varphi_{r\beta}\\ -\gamma I_{s\beta}-p\Omega K\varphi_{r\alpha}+\frac{K}{Tr}\varphi_{r\beta}\\ \frac{M}{Tr}I_{s\alpha}-\frac{1}{Tr}\varphi_{r\alpha}-p\Omega\varphi_{r\beta}\\ \frac{M}{Tr}I_{s\beta}+p\Omega\varphi_{r\alpha}-\frac{1}{Tr}\varphi_{r\beta}\\ p\frac{M}{JL_r}(\varphi_{r\alpha}I_{s\beta}-\varphi_{r\beta}I_{s\alpha})-\frac{1}{J}(T_L+f)\end{bmatrix}$$

$$g_1=\begin{bmatrix}\frac{1}{\sigma LS} & 0 & 0 & 0 & 0\\ 0 & \frac{1}{\sigma LS} & 0 & 0 & 0\end{bmatrix}$$

$$Tr=\frac{L_r}{R_r},\ \sigma=1-\frac{M^2}{L_sL_r},\ K=\frac{M}{\sigma L_sL_r},\ \gamma=\frac{Rs}{\sigma L_s}+\frac{R_rM^2}{\sigma L_sL_r^2}$$

$I_{s\alpha}$, $I_{s\beta}$ is denote the stator currents, $\varphi_{s\alpha}$, $\varphi_{s\beta}$ the rotor fluxes, usα , usβ the stator voltages, Ls , Lr the stator and rotor inductance, Rs , Rr the stator and rotor resistance, J the inertia of the machine, M the mutual inductance, f the friction coefficient, p the poles pair number, T_L the load torque, and finally Tr is the rotor time constant [17].

3. CASCADED NONLINEAR PREDICTIVE CONTROL OF INDUCTION MOTOR

The objective of this structure is to simultaneous control of the electromagnetic torque, the norm of rotor flux and rotor speed using the cascaded structure decomposed into two sub-systems in a cascaded form as shown in Fig.1.

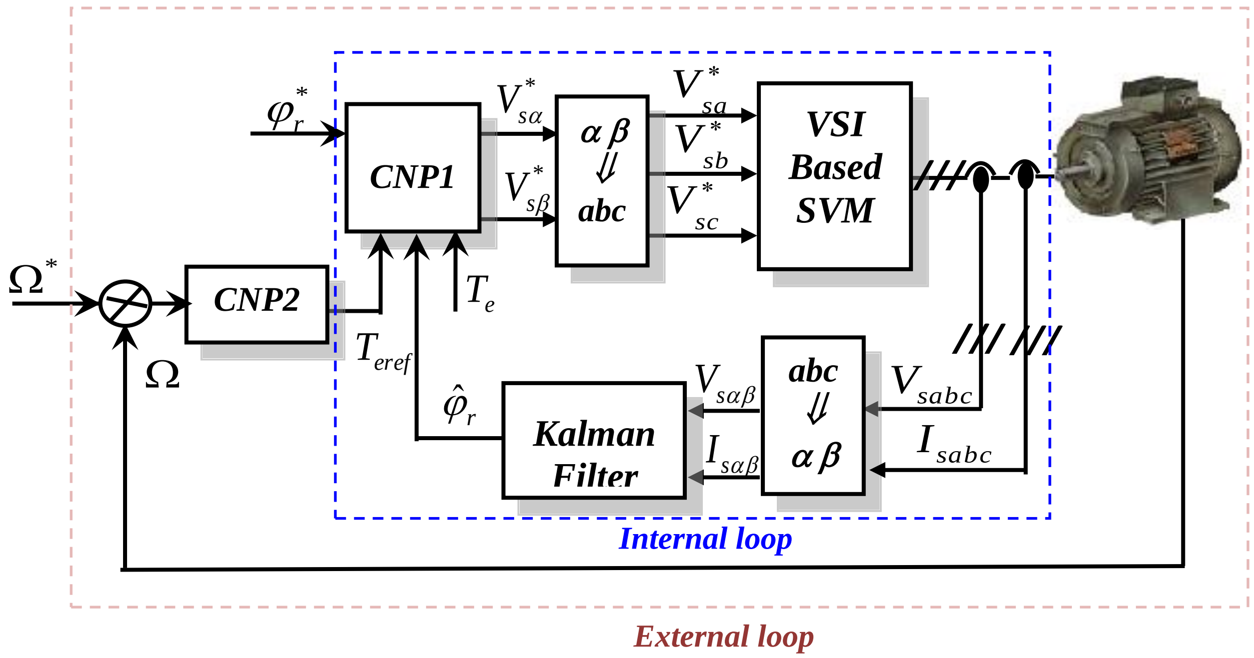

Fig 1: Nonlinear generalized predictive control structure

In this model the external load torque is considered to be a disturbance. Its amplitude is computed with an disturbance observer developed, from the mechanical equation of the induction motor [16,20].

The two loops of the cascaded structure imply the definition of two G.P.C. algorithms and consequently the minimization of two quadratic cost functions. It is also necessary to define two models, corresponding to the inner and external systems [23]. The external loop controls the speed. The internal loop controls the torque and flux.

Where U is the resulting control signal applied on the induction motor, w1 is the set point "followed" by y1, w2, is the inner signal coming from the minimization of G.P.C.1.

3.1 Internal loop controls the torque and rotor flux

Considering the electromagnetic torque and rotor flux modulus as outputs of the A.C. drive, the following equations can be derived, with y_1 as the torque and y_2 as the squared rotor flux modulus:

$$\begin{cases} y_1(x) = h_1(x) = \dfrac{pM}{L_r}(\varphi_{r\alpha} I_{s\beta} - \varphi_{r\beta} I_{s\alpha}) \\ y_2(x) = h_2(x) = \varphi_{r\alpha}^2 + \varphi_{r\beta}^2 = \varphi_r^2 \end{cases} \quad (2)$$

The derivatives Lie of the Electromagnetic torque and rotor Flux, are:

$$\begin{cases} y_1(x) = h_1(x) \\ \dot{y}_1(x) = L_f h_1(x) + L_{g1} h_1(x) V_{s\alpha}(t) + L_{g2} h_1(x) V_{s\beta}(t) \end{cases} \quad (3)$$

$$\begin{cases} y_2(t) = h_2(x) \\ \dot{y}_2(t) = L_f h_2(x) \\ \ddot{y}_2(t) = L_f^2 h_2(x) + L_{g1} L_f h_2(x) V_{s\alpha}(t) + L_{g2} L_f h_2(x) V_{s\beta}(t) \end{cases} \quad (4)$$

The expansion of the same r^{th} order Taylor series of the motor outputs y(t+T) with (r_1=1 and r_2=2) in matrix form is the following :

$$\begin{cases} y_1(t+T) = y_1(t) + T\dot{y}_1(t) \\ y_2(t+T) = y_2(t) + T\dot{y}_2(t) + \dfrac{T^2}{2}\ddot{y}_2(t) \end{cases} \quad (5)$$

Using the matrix form, the predicted output is rewritten as:

$$y(t+T) = \Pi(Y(t) + G(x)u(t))^T \quad (6)$$

Where

$$\Pi = \begin{bmatrix} I_{2\times2} & T_r * I_{2\times2} & (T_r^2/2) * I_{2\times2} \end{bmatrix}$$

$$Y(t) = \begin{bmatrix} h_1(x) & h_2(x) & L_f h_1(x) & L_f h_2(x) & 0 & L_f^2 h_2(x) \end{bmatrix}^t$$

$$G(x) = \begin{bmatrix} 0 & 0 & L_{g_1} h(x) & 0 & 0 & L_{g_1} L_f h(x) \\ 0 & 0 & L_{g_2} h(x) & 0 & 0 & L_{g_2} L_f h(x) \end{bmatrix}^t$$

Similarly, *Yr*(t+T) may be expanded in a same r^{th} order Taylor series:

$$\begin{cases} y_{r1}(t+T) = y_{r1}(t) + T\dot{y}_{r1}(t) \\ y_{r2}(t+T) = y_{r2}(t) + T\dot{y}_{r2}(t) + \dfrac{T^2}{2}\ddot{y}_{r2}(t) \end{cases} \quad (7)$$

The predicted reference trajectory using matrix form as:

$$y_r(t+T) = \Pi Y_r(t) \quad (8)$$

Where

$$Y(t) = \begin{bmatrix} y_{r1}(t) & y_{r2}(t) & \dot{y}_{r1}(t) & \dot{y}_{r2}(t) & 0 & \ddot{y}_{r2}(t) \end{bmatrix}^t$$

For the internal loop the control objective is the tracking of y_1 and y_2 to desired reference signals y_{r1} and y_{r2}, along the interval [t; t + T], That is, the tracking error is defined by:

$$\begin{vmatrix} e_1(t+T) \\ e_2(t+T) \end{vmatrix} = \begin{vmatrix} y_1(t+T) \\ y_2(t+T) \end{vmatrix} - \begin{vmatrix} y_{r1}(t+T) \\ y_{r2}(t+T) \end{vmatrix} \quad (9)$$

The cost function to be minimised is then:

$$J_1 = \frac{1}{2}[Y(t) + G(t)u(t) - Y_r(t)]^t\, \overline{\Pi}\, [Y(t) + G(t)u(t) - Y_r(t)] \quad (10)$$

Where

$$\overline{\Pi} = \int_0^T \Pi^t \Pi \, dT$$

The minimization of J with respect to *u(t)*, by setting $\frac{\partial J_1}{\partial t} = 0$, yield s to an optimal predictive control law:

$$u(t) = (G^t(x)\Pi G(x))^{-1} G^t(x)\Pi(Y_r(t) - Y(t)) \quad (11)$$

Differentiating the output y_1, one time and the output y_2 twice and by using the above control equation, we can show that the tracking errors dynamics are:

For the torque:

$$\dot{e}_{y_1}(t) + \frac{3}{2T} e_{y_1}(t) = 0 \quad (12)$$

For the flux:

$$\ddot{e}_{y_2}(t) + \frac{5}{2T}\dot{e}_{y_2}(t) + \frac{10}{3T^2} e_{y_2}(t) = 0 \quad (13)$$

The above dynamics equations are linear and time invariant. Therefore, the proposed technique leads to feedback linearization and we can easily verify the asymptotic stability of the tracking errors dynamics of the overall system.

3.2 External loop controls the speed

The control objective of the external loop is the tracking of Ω(t) to a desired reference Ωr(t). A load torque is considered to be a disturbance. A mechanical dynamics model of the motor is described by the following equation:

$$\dot{\Omega}(t) = \frac{1}{J} y_1(t) - \frac{f}{J}\Omega(t) - \frac{f}{J} T_L \quad (14)$$

The expansion of the same r^{th} order Taylor series of the motor outputs y(t+ T)

$$\begin{cases} \Omega(t+T) = \Omega(t) + T\dot{\Omega}(t) \\ \Omega(t+T) = \Omega(t) + T(\dfrac{1}{J} y_1(t) - \dfrac{f}{J}\Omega(t) - \dfrac{f}{J} T_L) \end{cases} \quad (15)$$

Similarly, the prediction model for reference trajectory $y_r(t+T)$ can be presented by an expansion of the same r^{th} order Taylor series as.

$$\Omega_r(t+T) = \Omega_r(t) + T\dot{\Omega}_r(t) \quad (16)$$

The optimal predictive control law is abstained by, (15) et (16), and she given by:

$$T_e(t) = -\frac{J}{T}(\Omega(t)-\Omega_r(t)) + f_r\Omega(t) + J\dot{\Omega}_r(t) + C_r(t) \quad (17)$$

Substituting the law control (17) in the mechanical equation (14), the dynamic tracking error is given by:

$$\dot{e}_\Omega(t) + \frac{1}{\tau_r}(\Omega(t)-\Omega^*(t)) = 0 \quad (18)$$

The equation (19) allows controlling the speed by acting on the torque y_l.

$$J_2 = \frac{1}{2}\int_0^{T_\Omega}(\Omega(t+T_\Omega)-\Omega_r(t+T_\Omega))^t(\Omega(t+T_\Omega)-\Omega_r(t+T_\Omega))dT \quad (19)$$

4. ADAPTIVE FLUX OBSERVER

The parameters are updated only in a powering operation. Figure.2 shows a block diagram of the proposed flux observer with the parameter adaptive scheme.

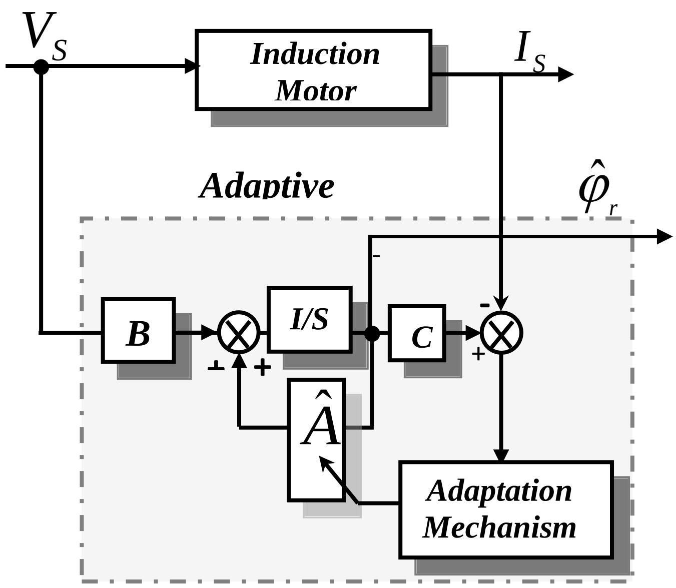

Fig 2: Block Diagram of Proposed Flux Observer

The full order state observer which estimates the stator current and the rotor flux is written by following equations [27]. The state observer, which estimates the stator current and the rotor flux together, is written as the following equation.

$$\begin{bmatrix}\dot{I}_s\\ \dot{\varphi}_r\end{bmatrix} = \begin{bmatrix}A_{11} & A_{12}\\ A_{21} & A_{22}\end{bmatrix}\begin{bmatrix}I_s\\ \varphi_r\end{bmatrix} + \begin{bmatrix}B_1\\ 0\end{bmatrix}V_s + G(\hat{I}_s - I_s) \quad (20)$$

Where

$$V_s = \begin{bmatrix}V_{s\alpha} & V_{s\beta}\end{bmatrix}^T, I_s = \begin{bmatrix}I_{s\alpha} & I_{s\beta}\end{bmatrix}^T, \varphi_r = \begin{bmatrix}\varphi_{r\alpha} & \varphi_{r\beta}\end{bmatrix}^T$$

$$A_{11} = -\left(\frac{R_s}{\sigma.L_s} + \frac{1-\sigma}{\sigma.T_r}\right)I = a_{r11}I$$

$$A_{12} = \frac{M}{\sigma.L_s.L_r}\left(\left(\frac{1}{T_r}\right)I - \Omega J\right) = a_{r12}I + a_{112}J$$

$$A_{21} = \frac{M}{T_r}I = a_{r21}I \quad , A_{22} = -\left(\frac{1}{T_r}\right)I + \Omega J = a_{r22}I + a_{122}J$$

$$B_1 = \left(\frac{1}{\sigma.L_s}\right)I = b_1 I \quad , I = \begin{bmatrix}1 & 0\\ 0 & 1\end{bmatrix} \quad J = \begin{bmatrix}0 & -1\\ 1 & 0\end{bmatrix}$$

$$G = \begin{bmatrix}g_1 & g_2 & g_3 & g_4\\ -g_2 & g_1 & -g_4 & g_3\end{bmatrix}^T$$

$$g_1 = (k-1)(-a_{r11} - a_{r22}), g_2 = (k-1)(-a_{i22})$$
$$g_3 = (k-1)(ca_{r11} - a_{r21}) + (k-1)(-a_{r11} - a_{r22})$$
$$g_4 = c(k-1)(-a_{r22}) \quad , c = -\frac{\sigma L_s L_r}{M}$$

k is the proportional constant

4.1 Rotor Flux Observer with Parameter Adaptation

The Influence of the parameter variations on the flux estimation will be investigated in this section. We propose the addition of a parameter adaptive scheme to the flux observer described by equation (20) in order to solve the problem of the parameter variations. We propose the following update law [28]:

$$\begin{cases}\dot{\hat{R}}_s = \lambda_1(e_{is\alpha}\hat{I}_{s\alpha} + e_{is\beta}\hat{I}_{s\beta})\\ \dot{\hat{R}}_r = -\lambda_2\left\{e_{is\alpha}(\hat{\varphi}_{s\alpha} - M\hat{I}_{s\alpha}) + e_{is\beta}(\hat{\varphi}_{s\beta} - M\hat{I}_{s\beta})\right\}\\ e_{is\alpha} = (\hat{I}_{s\alpha} - I_{s\alpha}), \quad e_{is\beta} = (\hat{I}_{s\beta} - I_{s\beta})\end{cases} \quad (21)$$

4.2 Stability of Flux Observer

A stability of the proposed flux observer with the parameter adaptation scheme is proved by the Lyapunov's theorem. For the simplification of the proof, the induction motor and the observer are expressed by [28, 29].

$$\begin{bmatrix}\dot{\hat{I}}_s\\ \dot{\hat{\varphi}}_r\end{bmatrix} = \begin{bmatrix}a_{r11} & a_{r12} + a_{112}\\ a_{r21} & a_{r22} + ja_{122}\end{bmatrix}\begin{bmatrix}\hat{I}_s\\ \hat{\varphi}_r\end{bmatrix} + \begin{bmatrix}B_1\\ 0\end{bmatrix}V_s \quad (22)$$

$$\dot{x} = (A + \Delta A)\hat{x} + bV_s$$

Where ΔA is an error matrix caused by the parameter variation. An error equation can be expressed by:

$$\dot{e} = (A(x-\hat{x}) - \Delta A\hat{x}) = (Ae - \Delta A\hat{x}) \quad (23)$$

We define a following Lyapunov's function candidate:

$$V = e * e + \frac{(\Delta R_s)^2}{\lambda_1 \sigma L_s} + \frac{(\Delta R_r)^2 (1/L_2)^2 M}{\lambda_2 \sigma} \quad (24)$$

Computing the time derivative of V and using equation (24) gives following equation:

$$\dot{V} = e * (A^* + A)e \qquad (25)$$

Equation (25) is negative-semi; because the matrix A is negative we can be proved the stability of observer.

5. SIMULATION RESULTS

In this we present a series of simulations in the presence of variations in rotor, stator resistances and load torque, for Cascaded Nonlinear Predictive control CNPC used Adaptive flux observer used for the estimation of rotor flux variations rotor and stator resistances. The induction motor is fed by two level inverter based on space vector modulation technique.

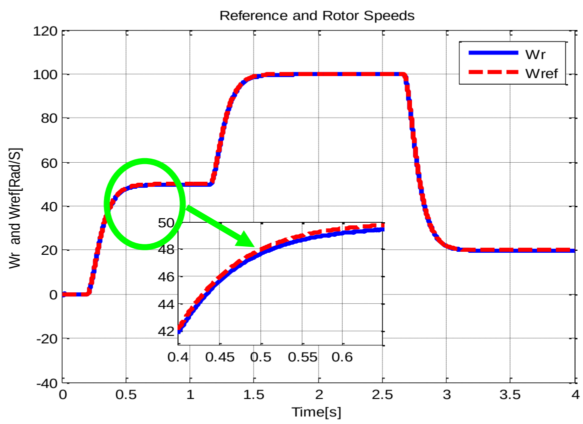

Fig 3: Reference and Rotor speed

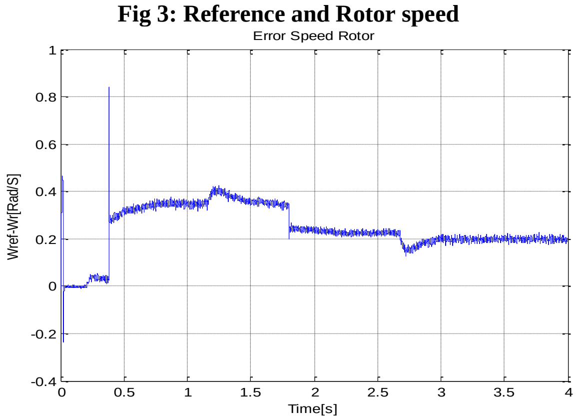

Fig 4: Rotor speed tracking error

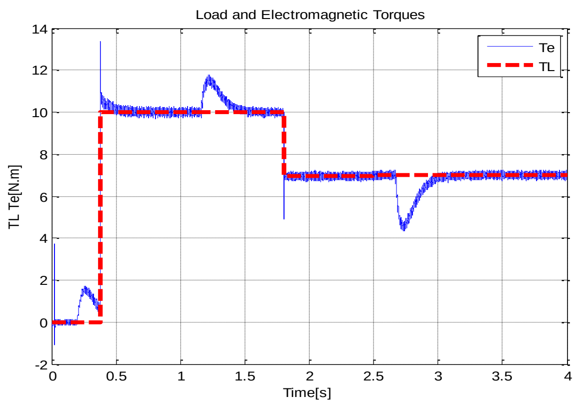

Fig 5: Load and electromagnetic torques

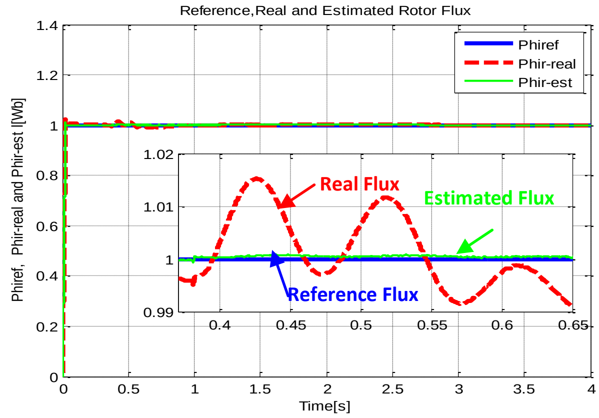

Fig 6: Reference, Real and Estimated Rotor flux.

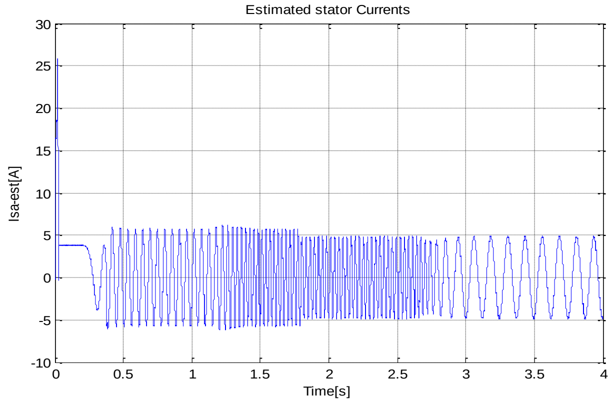

Fig 7: Stator Current

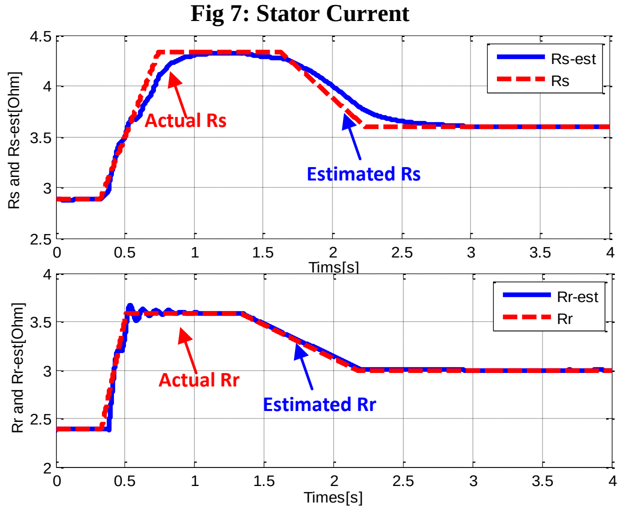

Fig 8: Actual and Estimated Stator and Rotor Resistances

The results of simulation are shown in figures (3 to 8). From these results as it may be observed, the rotor speed tracks the desired speed in spite of system uncertainties. Moreover, the speed tracking is not affected by the load torque change show figures 3 and 4, since the electromagnetic and load torque recovers the applied load torque value show figure.5.

As the figure show, the response of the flux is very good, because the real and estimate rotor flux rotor flux tracks the reference values adequately well (figure 6). That figure shows the satisfying induction motor working, the rotor flux is maintained in independently of the electromagnetic torque, because the load torque, rotor flux, stator resistance, and rotor resistance, are estimated at a time, and there variations, has been compensated show Figure.8. Those figures also show the estimated stator and rotor resistances on the same graph. Clearly, the adaptive observer is able to track bi-directional change in Rs and Rr adequately. The estimation error in the steady state is found to be less than ±2% in the steady-state.

Those figures show that currents are within acceptable limits where the rotor speed is decreasing a phase stator current waveform is sinusoidal; the peak current in transient state is required to accelerate the rotor to the desired speed show Figures 7.

From these simulation results we remark a good tracking performance is achieved, the above results demonstrate that the one step ahead Cascaded Nonlinear Predictive control based adaptive rotor flux observer has strong robustness properties in the presence of load torque and electrical parameters variations.

6. CONCLUSION

In this paper a new Cascaded Nonlinear Adaptive Predictive control, for speed and flux tracking of an induction motor is presented. It is based on a combination of a Cascaded Nonlinear Predictive Control and adaptive rotor flux observer. The rotor flux, stator and rotor resistances are estimated by adaptive observer, what can solve the control problem of induction machines in the presence of uncertainties in load torque and resistance parameters. The numerical simulations validate the performances of the proposed method and even in the unknown parameter case and achieve better speed and rotor flux tracking.

Various additional issues will be addressed in the future, including the Fuzzy logic or the Artificial Neural Network controller and to reduce the sampling time, and a robust predictive control sequence will be derived by solving a min-max problem which is subject to the model constraints.

7. APPENDIX

Motor parameter 230V, 1.5KW, 4 Poles, 1390 rpm $R_s = 2.89\Omega$, $R_r = 2.39\Omega$, Lr=0.225H, Lr=0.220H, $L_m = 0.214$H, J= 0.005 kg.m^2 f= 0.00014 N.m.s/rad

The prediction time is chosen as T=100*10-5 and p_0=-1.

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