Model Predictive Control for Deadbeat Performance of Induction Motor Drives

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Abstract: - The paper presents a design methodology based on model predictive control (MPC) to assure deadbeat performance of both current and speed loops in vector-controlled induction motor drives. Two controllers are independently designed for both loops where the controller parameters are adapted to cope with load changes over a wide range of operation. The performance is compared to that of PI controllers designed based on particle swarm optimization (PSO) and adaptive neuro-fuzzy inference systems (ANFIS). The comparison study shows superior performance of the MPC design.

Key-Words: - Model predictive control, vector control, induction motor drives, deadbeat performance.

1 Introduction

Model predictive control (MPC) is an advanced method of process control that has been used in industry for chemical plants and oil refineries since the 1980's. In recent years it has also been used in power system balancing models [1]. Model predictive controllers rely on dynamic models of the process, most often linear empirical models obtained by system identification. In other words, MPC systems rely on the idea of obtaining control values for process inputs by solving an optimization problem online. The problem is usually formulated with the help of a process model and continuous measurements [2].The main advantage of MPC is the fact that it allows the current timeslot to be optimized, while keeping future time slots in account. A finite time-horizon is optimized, whereas the current time slot only is implemented. MPC has the ability to anticipate future events and can carry out control actions accordingly taking full advantage of the power available in today's computer hardware in an automatic control context [3].

In its basic form, MPC is closely related to linear quadratic optimal control; however, MPC can be applied to linear time varying (LTV) systems. In [4], both uncertain time-varying parameter and bounded additive disturbance are explicitly taken into account in the MPC formulation. Robust stability and constraint satisfaction are guaranteed by computing a positively invariant set containing the measured state at each sampling instant. A decentralized hierarchical MPC approach is proposed in [5] for a LTV system to prove its ability in navigation under obstacle avoidance conditions.MPC has shown high competency in a variety of fields; it is a well-established industrial standard for controlling constrained multivariable processes. Two nonlinear model predictive control methods are implemented and compared in [6] on a laboratory three tank system. In [7], two different chemical processes are simulated in HYSYS software and a complete procedure for applying MPC control is carried out for each one including system identification, controller design, and parameter tuning.

Moreover, MPC is applied in power system load frequency control for the enhancement of power system dynamic performance subject to several disturbances; the system is evaluated in [8]. The effectiveness of the proposed controller is validated upon a comparison with a fuzzy logic controller. In [9], another MPC-based load frequency controller of a multi-area power system in the presence of wind turbines is introduced. In such a system, each local area controller is designed independently so that stability of the overall closed loop system is guaranteed. On the other hand, MPC has been employed in many applications of electrical drive systems, including but not limited to, speed control of DC motors [10], position control of DC servomotors [11], torque ripple reduction of brushless DC motors [12], speed and direct torque control of permanent magnet synchronous motors (PMSM) [13, 14], and torque control of induction motors [15, 16]. Recently, renewable energy sources have been also controlled by implementing MPC. The energy required for air conditioning as well as basic living appliances can be predicted and minimized using MPC [17]. MPC is also applied to grid-tied photovoltaic storage system yielding satisfactory real-time dynamic response [18]. Advantages of MPC in such a case include smoother power output while respecting and maintaining the functional requirements of the storage units and power converters.

Fuzzy logic control and artificial neural networks are combined with MPC to enhance its performance. A neural network controller is applied to the optimal MPC of constrained nonlinear systems by minimizing a control-relevant cost function [19]. In [20], a fuzzy MPC approach is introduced to design a control system for a highly nonlinear process system. A fuzzy decision making agent is superimposed on MPC, and results are compared to those obtained from conventional MPC [21]. Comparing MPC to conventional PID controllers, it should be noted that MPC is a relatively more complex regulator, especially in the present of constraints. Moreover, it takes more time for on-line calculations when the constraints intervene. Parameters of MPC are designed based on successive iterations, where no mathematical forms have been developed yet to determine the best configuration of the parameters. A large volume of literature considers performance comparison between MPC and conventional PID control, where the results usually point out to noticeable MPC superiority [22, 23].

This paper presents a design methodology of a MPC scheme for vector-controlled induction motor drives. The design objective is to maintain deadbeat performance for both inner current loop and outer control loop. The design process and system modelling are carried out in Matlab/Simulink environment. The performance of the proposed controller is compared to that of an adaptive PI controller designed previously in [24] using particle swarm optimization (PSO) and adaptive neuro-fuzzy inference systems (ANFIS). Both qualitative comparison (via time domain step response) and qualitative comparison (via certain performance indices) are used to evaluate the behaviours of both controllers. Results show distinct superiority in favour of the proposed MPC.

2 Problem Formulation

The deadbeat response is characterized in control systems by zero steady-state error, fast transient response, and maximum overshoot within ±2%. Deadbeat response is greatly desirable in high performance applications of induction motor drives. Nevertheless, maintaining the deadbeat response constantly is a challenging task due to the variation in loading conditions. One more difficulty arises from the change in system parameters that is associated with load variation. Since MPC can optimize the control scheme over timeslots, this feature could be employed to maintain certain targeted performance of the controlled system.

The present work aims at developing MPC-based controllers for a vector-controlled induction motor drive to maintain deadbeat performance for both inner and outer loops. The stator and rotor resistances denote the most significant varying parameters of the current loop [25]. The resistance value changes with loading as a result of the associated change in current magnitude. On the other hand, the shaft moment of inertia and coefficient of viscous friction designate the main noteworthy parameters, which vary with mechanical loading in the speed loop [26]. The operating region of the current loop covers stator and rotor resistances varying between 50% and 150% of the nominal value [27]. Similarly, the moment of inertia of the motor shaft changes between 100% and 300% of the rated value, while the coefficient of friction is considered to vary from 50% to 200% of the normal value [27].

The design of the MPC controllers is based on maintaining deadbeat characteristics for the time-domain step response of current and speed loops through forming and solving an on-line optimization problem at each control cycle. The procedure that is followed to guarantee such deadbeat characteristics is described in details in Section 4. The proposed MPC scheme is compared to an adaptive controller based on PSO and ANFIS techniques [24].

3 Induction Motor Dynamic Model

The dynamic model of an induction motor can be represented by a set of highly nonlinear differential equations. In order to develop the model, linear magnetic circuit and identical mutual inductances are assumed, and iron losses are neglected [28]. The equivalent circuits of a three-phase symmetrical induction motor in d-q reference frame are shown in Fig. 1. The nonlinear dynamic model in synchronous reference frame is given in [29-32] as follows:

$$\frac{di_{ds}}{dt} = -\gamma i_{ds} + \eta \mu \lambda_{dr} + \omega_s i_{qs} + \omega_r \mu \lambda_{qr} + \frac{1}{\sigma L_s} v_{ds} \quad (1)$$

$$\frac{di_{qs}}{dt} = -\gamma i_{qs} - \omega_r \mu \lambda_{dr} - \omega_s i_{ds} + \eta \mu \lambda_{qr} + \frac{1}{\sigma L_s} v_{qs} \quad (2)$$

$$\frac{d\lambda_{dr}}{dt} = \eta L_m i_{ds} - \eta \lambda_{dr} + \omega_{sl} \lambda_{qr} \quad (3)$$

$$\frac{d\lambda_{qr}}{dt} = \eta L_m i_{qs} - \eta \lambda_{qr} - \omega_{sl} \lambda_{dr} \quad (4)$$

$$T_e = \frac{3 P L_m}{4 L_r} (i_{qs} \lambda_{dr} - i_{ds} \lambda_{qr}) \quad (5)$$

$$T_e - T_L = \frac{2}{P} (J \frac{d\omega_r}{dt} + B \omega_r) \quad (6)$$

$$\eta = \frac{R_r}{L_r}, \ \sigma = 1 - \frac{L_m^2}{L_s L_r}, \ \mu = \frac{L_m}{\sigma L_s L_r}, \quad (7)$$

$$\gamma = \frac{1}{\sigma L_s} (R_s + \frac{L_m^2}{L_r^2} R_r), \text{ and } \ \omega_{sl} = \omega_s - \omega_r$$

Where:

v_{ds} and v_{qs}: Stator voltages in d-q reference frame.
i_{ds} and i_{qs} : Stator currents in d-q reference frame.
λ_{dr} and λ_{qr}: Rotor flux linkages in d-q ref. frame.
T_e : Electromagnetic torque.
T_L : Load or disturbance torque.
P : Number of poles.
ω_s : Stator angular frequency (rad/sec).
ω_r : Rotor electrical speed (rad/sec).
ω_{sl} : Slip angular frequency.
R_r and R_s: Rotor and stator resistance referred to the stator.
L_r and L_s: Rotor and stator inductance referred to the stator.
L_m: Mutual inductance referred to the stator.
J: Moment of inertia.
B: Coefficient of frictions.

In vector control, the rotor flux in the q-axis is set equal to zero (λ_{qr}= 0 and $p\lambda_{qr}$= 0). Therefore, Equations (1) through (4) of the mathematical model become,

$$\frac{di_{ds}}{dt} = -\gamma i_{ds} + \eta \mu \lambda_{dr} + \omega_s i_{qs} + \frac{1}{\sigma L_s} v_{ds} \quad (8)$$

$$\frac{di_{qs}}{dt} = -\gamma i_{qs} - \omega_r \mu \lambda_{dr} - \omega_s i_{ds} + \frac{1}{\sigma L_s} v_{qs} \quad (9)$$

$$\frac{d\lambda_{dr}}{dt} = \eta L_m i_{ds} - \eta \lambda_{dr} \quad (10)$$

$$0 = \eta L_m i_{qs} - \omega_{sl} \lambda_{dr} \quad (11)$$

If the d-axis rotor flux, λ_{dr}, is kept constant, the generated torque will be linearly proportional to i_{qs}. Therefore, the rate of change of d-axis rotor flux, $p\lambda_{dr}$, becomes zero; Equations (10) and (11) yield,

$$\omega_{sl} = \eta \frac{i_{qs}}{i_{ds}} \quad (12)$$

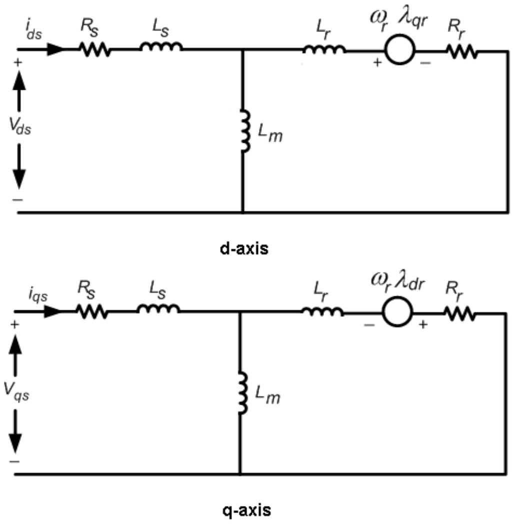


Fig.1 The equivalent circuit of IM in d-q reference frame

4 Model Predictive Control

Model Predictive Control (MPC) is an advanced control technique that has been proved to efficiently control a wide range of applications in industry including unstable systems, multi-input multi-output (MIMO) systems, systems with delay, constrained and hybrid systems [2].

Unlike most control algorithms, MPC has the ability to predict the future response of the plant. At each control interval, MPC attempts to predict future plant behaviour through an on-line optimization process, which maximizes the tracking performance while satisfying constraints [3]. Fig. 2 shows a simple block diagram describing the MPC.

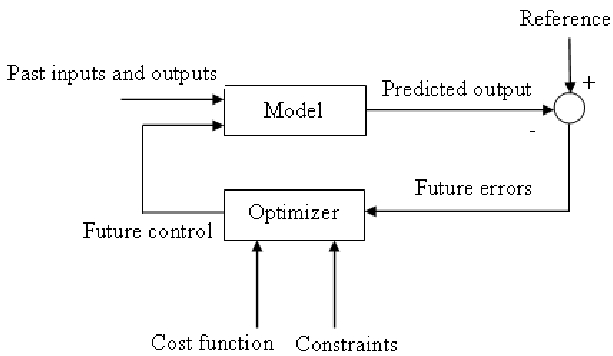


Fig. 2 A simple block diagram describing MPC

MPC is characterized by the following strategy which is represented in Fig. 3:

Step 1: An explicit model is used to predict the process output along a future time horizon. Predicted outputs $\hat{y}(t+k),\ k=1,\ ...,\ N$ for the prediction horizon are calculated at each instant t depending on the past inputs and outputs as well as the future control signal $u(t+k),\ \ k=0,\ ...,\ N-1$.

Step 2: Sequence of future control signals is computed to optimize a performance criterion by minimizing a cost function. The cost function to be minimized is generally a weighted sum of square predicted errors and square future control values.

$$J(N_1,\ N_2,\ N_u)=\sum_{j=N_1}^{N_2}\beta(j)\left[\hat{y}(k+j)-w(k+j)\right]^2 + \sum_{j=1}^{N_u}\lambda(j)\left[u(k+j-1)\right]^2 \tag{13}$$

Where N_1, N_2 are the lower and upper prediction horizons over the output, N_u is the control horizon, β(j), λ(j) are weighting factors. The control horizon permits to decrease the number of calculated future control according to the relation: $\Delta u(k+j)=0$ for $j \geq Nu.w(k+j)$ represents the reference trajectory over the future horizon N. Constraints over the control signal, the outputs and the control signal changing can be added to the cost function:

$$\begin{aligned} u_{\min} &\le u(k) \le u_{\max} \\ \Delta u_{\min} &\le \Delta u(k) \le \Delta u_{\max} \\ y_{\min} &\le y(k) \le y_{\max} \end{aligned} \tag{14}$$

Step 3: The current control signal $u(t)$ is transferred to the plant. At the next instant, $y(t+1)$ is measured and step 1 is repeated according to the receding horizon strategy to calculate $u(t+1)$. Thus, at each instant, the horizon is moved towards the future keeping the same length.

MPC can be tuned easily apart from the fact that it handles constraints properly. Constraints can be either on the output of the controlled processes (control variable) or on the control signals that are inputs to the process (manipulated variables). The constraints are in the form of saturation characteristics, e.g., valves with a finite range of adjustment, control surface with limited deflection angles, etc. Input constraints also appear in the form of rate constraints: valves and other actuators with limited slew rates.

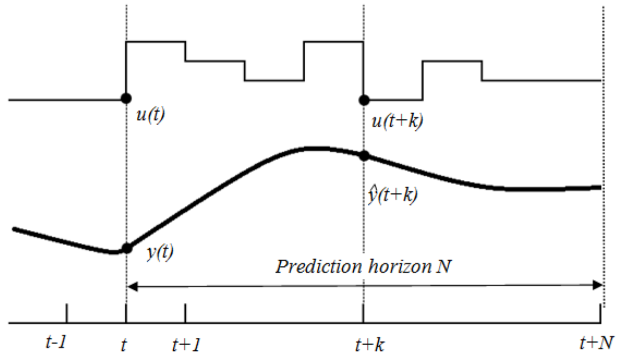


Fig.3 Strategy of Model Predictive Control

5 Simulation Results

The performance of the proposed MPC current and speed controllers is extensively studied through simulation under different operating conditions. The performance is always compared to that of the adaptive PI controllers presented in [24]. The range of system parameter change is assumed to be 50% to 150% of rated value for the stator and rotor resistances, R_s and R_r, which influence the performance of the inner current loop. The parameters which mostly impact the response of the outer speed loop – the moment of inertia, J, and friction coefficient, B – are assumed to vary from 100% to 300% and 50% to 200% of rated values, respectively. Since the response of the inner current loop is inherently much faster than the dynamics of the outer speed loop, inner loop parameters are not likely to affect the outer loop performance. In other words, in the present cascade control system, the inner loop could be considered as a unity-gain block when analyzing the outer loop performance according to dynamic time scale separation. It should be mentioned that controller development is carried out using the Model Predictive Control Toolbox™ of MATLAB; MPC uses a fixed model structure, but allows the model parameters to evolve with time.

Numerous simulation cases are carried out covering the whole range of parameters in order to study system performance under different loading conditions. Quantitative comparison between MPC and adaptive PI controllers are achieved by plotting the time-domain step responses on the same graph. A sample set of test cases are given in Figs. 4 through 6. The step response of the inner current loop is shown in Fig. 4 at nominal R_s and three different values of R_r. Whereas, Fig. 5 shows the step response of the inner loop at nominal R_r and three different values of R_s. It is clear from Figs. 4 and 5 that the performance of the proposed MPC controller usually outperforms that of the adaptive PI controller. The only exception is the case when R_r is nominal and Rs equals 50% of its nominal value, Fig. 5(a). Another noteworthy observation in Figs. 4 and 5 is related to how the response changes as the system load increases. Comparing the step responses of Figs. 4(a), 4(b), and 4(c) under adaptive PI controller, it is noticed that the response becomes more sluggish as the value of R_r increases, i.e., as system load increases. However, in the same three plots, no much change is observed in response under the proposed MPC controller. The same observation is still true when comparing the responses of Fig. 5. Conclusively, when either R_s or R_r increases keeping the other resistor constant, the response becomes more sluggish under the adaptive PI controller only, but not the proposed MPC controller. To assure the robustness of MPC controller for the current loop, the design parameters are kept unchanged in all cases. The following design parameters are used: control interval = 0.001s, prediction horizon = 10, control horizon =2, minimum constraints on manipulated variables = 0, maximum constraints on manipulated variables = 5, maximum down rate = –1000, maximum up rate = 1000, minimum constraint on output variable = 0, maximum constraint on output variable = 1 and overall tuning factor = 0.8.

Figure 6 shows the step-response of the outer speed loop at nominal *B* and different values of *J*. The plots indicate that the performance under the proposed MPC controller is evidently superior to that of the adaptive PI controller. Similarly, to assure the robustness of MPC controller for the speed loop, the design parameters are also kept unchanged in all cases. The design parameters of the speed controller are identical to those of current loop except for control interval and maximum constraints on manipulated variables, where their values are 0.01 s and 1, respectively.

Simulation cases show that the coefficient of friction, B, has minor impact on system performance. At rated inertia, J, the change of B produces time-domain response curves of the speed loop which are almost identical. For the whole range of B variation, system response always has deadbeat behaviour. These results agree with those obtained in reference [24].

Qualitative comparison of MPC and adaptive PI controllers is also carried out having regard to certain computable performance indices. The indices include the rise time, t_r, settling time, t_s, integral absolute error, *IAE*, and integral time-weighted absolute error, *ITAE*. The integral errors, *IAE* and *ITAE*, are measures to assess how far the actual response is from a desired ideal response, where both depend on the time integration of an error function. Large errors contribute more to *IAE*, whereas *ITAE* penalizes more the error which occurs late in time. In other words, *IAE* and *ITAE* reflect the transient and steady-state characteristics of the system, respectively. Mathematical expressions to compute *IAE* and *ITAE* are given as

$$IAE = \int_{t=0}^{\infty} |e(t)| dt \tag{15}$$

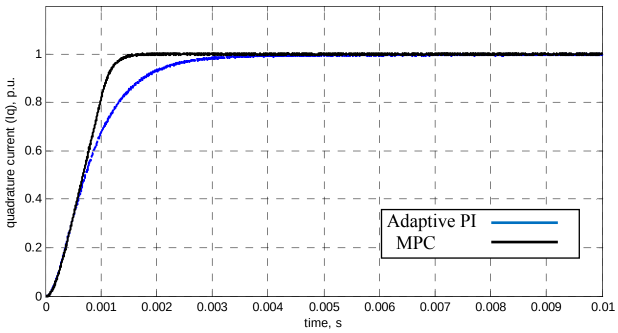
$$ITAE = \int_{t=0}^{\infty} t \times |e(t)| dt \tag{16}$$

where, *e(t)* is the time-domain error function. The performance indices used for quantitative comparison between the MPC and adaptive PI controllers are given under different test conditions in Tables 1 through 3. The rise time is always better with MPC controller except for the first entry of Table 2, where R_r is 50%. The settling time shows that the MPC controller is always favourable, which denotes faster response than that of the adaptive PI controller. The integral absolute error, *IAE*, is always less for MPC controller than adaptive PI controller with one exception at R_r equals 50%, second entry of Table 2. However, with respect to *ITAE*, MPC controller is always better except for first two entries of Table 1, where R_s is 50% and 100%. Therefore, both qualitative and quantitative comparisons show that the performance of the MPC controller is superior to that of the adaptive PI controller.

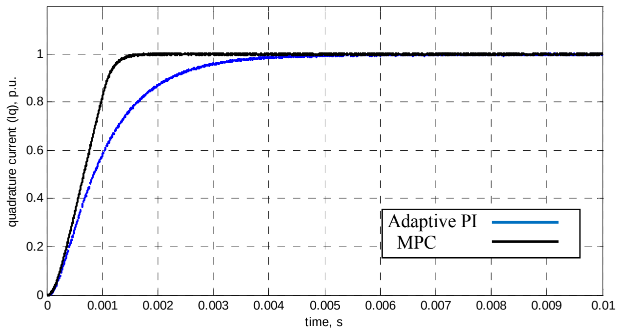
As pointed out earlier, the coefficient of friction, *B*, has negligible effect on performance indices of the outer loop. System performance measures shown in Table 3 correspond to the given values of *J* and any value of *B* within the considered range from 50% to 200% of rated value.

4 Conclusion

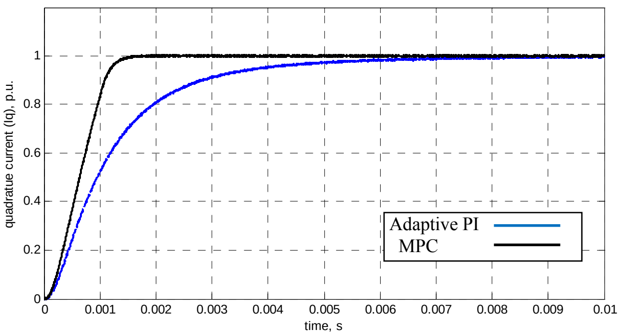
The paper presents a design methodology for current and speed controllers of vector-controlled induction motor drives based on MPC. The controllers maintain deadbeat response of both inner and outer loops of the cascaded control system. The time-domain response is compared with that of an adaptive PI controller designed based on PSO and ANFIS techniques. Certain performance indices are also selected to compare the characteristics of the two controllers. Both qualitative and quantitative comparisons show the superiority of MPC as in contrast with the adaptive PI scheme.



(a) $R_r = 50\%$

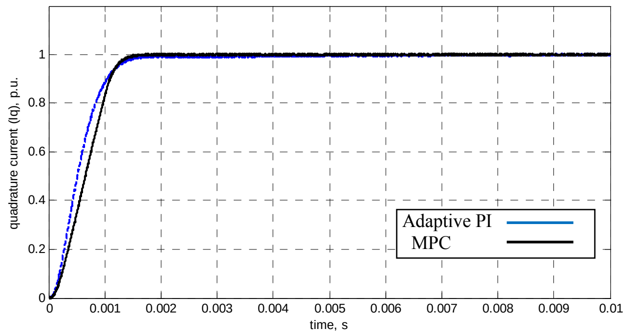


(b) $R_r = 100\%$

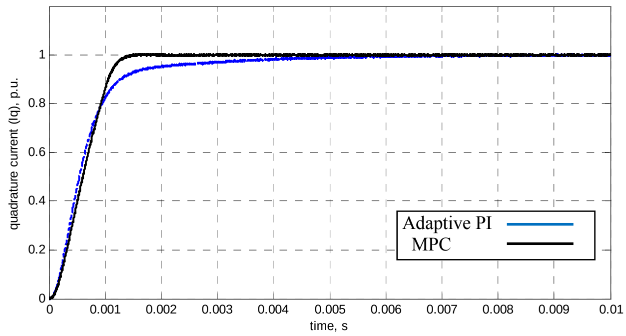


(c) $R_r = 150\%$

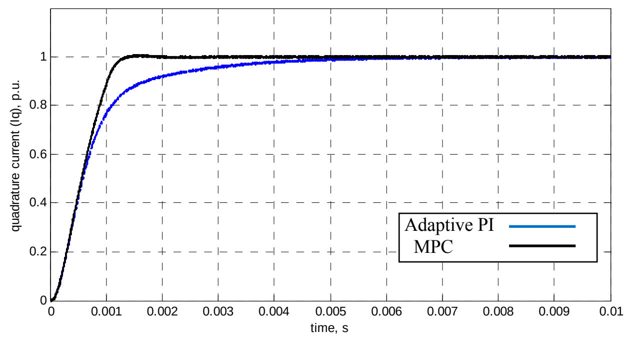
Fig. 4 Step response of quadrature current at nominal R_s with different R_r conditions



(a) $R_s = 50\%$



(b) $R_r = 100\%$



c) $R_r = 150\%$

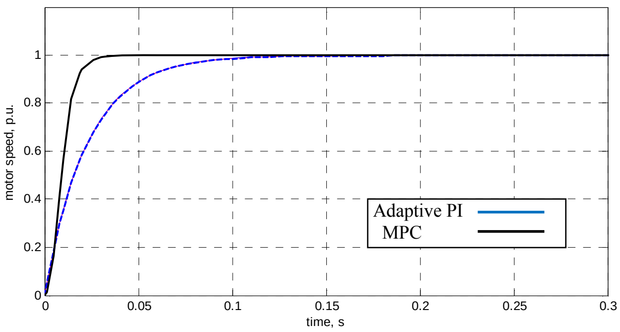
Fig. 5 Step response of quadrature current at nominal R_r with different R_s conditions

Table 1: A comparison between results obtained by both MPC and Adaptive PI controllers under different R_r conditions

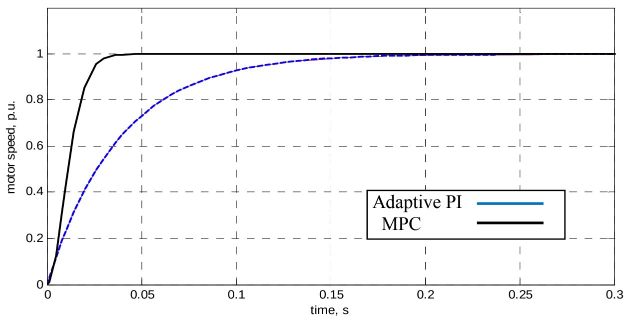
R_r	Controller	$t_r(ms)$	$t_s(ms)$	IAE	$ITAE$
50%	Adaptive PI	1.50	2.83	0.91×10^{-3}	7.36×10^{-7}
	MPC	0.86	1.37	0.69×10^{-3}	2.91×10^{-7}
100%	Adaptive PI	1.90	3.61	1.11×10^{-3}	1.03×10^{-6}
	MPC	0.86	1.36	0.68×10^{-3}	2.84×10^{-7}
150%	Adaptive PI	2.50	5.63	1.36×10^{-3}	1.84×10^{-6}
	MPC	0.85	1.34	0.66×10^{-3}	2.70×10^{-7}

Table 2: A comparison between results obtained by both MPC and Adaptive PI controllers under different R_s conditions

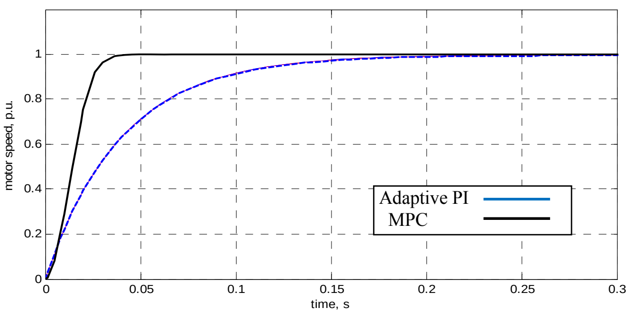
R_s	Controller	$t_r(ms)$	$t_s(ms)$	IAE	$ITAE$
50%	Adaptive PI	0.85	1.45	0.61×10^{-3}	3.64×10^{-7}
	MPC	0.86	1.33	0.66×10^{-3}	2.74×10^{-7}
100%	Adaptive PI	1.10	3.89	0.75×10^{-3}	6.83×10^{-7}
	MPC	0.84	1.28	0.63×10^{-3}	2.50×10^{-7}
150%	Adaptive PI	1.50	4.12	0.86×10^{-3}	8.41×10^{-7}
	MPC	0.82	1.22	0.59×10^{-3}	2.26×10^{-7}



(a) $J = 100\%$



(b) $J = 200\%$



(c) $J = 300\%$

Fig. 6 Step response of motor speed at nominal B with different J conditions

Table 3: A comparison between results obtained by both MPC and PI-PSO controllers under different J and (B = 50.. 200%)

J	Controller	$t_r(ms)$	$t_s(ms)$	IAE	$ITAE$
100%	Adaptive PI	50.0	90.0	0.023	0.0006
	MPC	14.6	25.8	0.005	1.69×10^{-5}
200%	Adaptive PI	83.7	150.0	0.038	0.0015
	MPC	18.0	30.0	0.007	3.99×10^{-5}
300%	Adaptive PI	88.6	161.0	0.041	0.0017
	MPC	19.5	32.8	0.010	6.66×10^{-5}

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Appendix A

Ratings and parameters of the induction motor

Output Power, P_o	4.6 kW
Voltage, V_{LL}	400V
Current, I_s	8.2 A
Frequency, f	50 Hz
Shaft Speed, N	1440 RPM
Number of Poles	4
Power Factor	0.85
Stator Resistance, R_s	0.624 Ω
Rotor Resistance, R_r	0.538 Ω
Rotor Inductance, L_r	0.138 H
Mag. Inductance, L_m	0.147 H
Stator Inductance, L_s	0.133 H
Moment of Inertia, J	0.0196 kg.m^2
Coeff. of friction, B	0.0087 N.m.sec/rad