

DISCRETE LINEAR PREDICTIVE CONTROL OF PERMANENT MAGNET SYNCHRONOUS MOTOR (PMSM)

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ABSTRACT

This paper presents a discrete linear predictive control (DLPC). This strategy is applied to permanent magnet synchronous motor (PMSM) for monitoring the speed at trajectory and rejection of disturbance. The predictive control law is obtained by using a cost function and a Taylor series to perform prediction in a finite horizon. No information on the external disturbances and uncertainty parameters are necessary to ensure the robustness of the proposed strategy. Furthermore, in order to maintain the current phase within the saturation we used a cascade structure with a block anti-windup. Simulation results demonstrated the stability, robustness and effectiveness of control strategy proposed for the trajectory tracking and disturbance rejection of torque.

Keywords: *Discrete Linear Predictive Control (DLPC) – Model Predictive Control (MPC) , Permanent Magnet Synchronous Motor (PMSM)*

1. INTRODUCTION

The PMSM has been gradually replacing DC and induction motors in a wide range of drive applications such as: robotic actuators, computer disk drives, domestic applications, automotive and renewable energy conversion systems. Despite its advantages, such as high efficiency, high power density and high torque to current ratio, the PMSM remains complicated and difficult to control when good transient performance under all operating conditions is desired. This is due to the fact that the PMSM is a nonlinear, multivariable, time varying system subjected to unknown disturbances and variable parameters.

Over the past decades, various robust control techniques have been developed in order to improve the performances of the PMSM in the presence external disturbances.

However, the widely used approach consists in using linear control theory with the disturbance estimate [5]-[6]. In [7], the robustness is ensured by using H_∞ control theory.

Disturbance observers which rely on time delay control approach have been reported in [8]. In [9], an observer is designed based on a Lyapunov function, to deduce the voltage disturbance caused

by uncertainties. To take into account nonlinearities of the PMSM, different approaches have been adopted such as nonlinear control [6] and the sliding mode control.

The main objective in the control of a PMSM is to design a robust controller for rotor speed trajectory tracking while regulating the d-axis current, in the presence of varying parameters and unknown load torque. Discrete time model predictive control (DTMPC) for nonlinear dynamic processes can improve some desirable features, such as robustness which can be handled using the internal model control (IMC) [12]-[13]. More detailed literature review on the robustness features of DTMPC for nonlinear systems can be found in [14]. However, it is still quite hard to adopt this strategy for nonlinear systems having fast dynamics such as electrical machines; as it requires heavy online computation.

In order to apply MPC to fast nonlinear systems, many approaches have been proposed [15]-[19]. In [15] and [16], an optimal predictive control for a continuous time system is developed. Chen et al. [17] has proposed a NGPC based on Taylor series expansion to a certain order for Multi-Input Multi-Output (MIMO) systems. The control order is taken to be different from zero to analyze the stability of the closed loop system when the input relative

degree is higher than four. Robust nonlinear predictive control for a SISO system is introduced in [18], where the external disturbance is estimated and compensated in the control law. In [19] the robust NGPC is extended to MIMO systems.

Nowadays, the MPC has been successfully applied for control of power electronics converters and electric drives.

Hedjar et al [20]-[21] have designed a cascaded NGPC based on Taylor series expansion for an induction motor (IM). It is to be noted that NGPC based on Taylor series expansion can't remove completely the steady state error under unknown disturbances. In [22]-[23], the robustness of the classical NGPC is improved by modifying its cost function. This strategy has proved to be effective when applied to the speed control of the PMSM [24]. However, the d-axis current regulation is not guaranteed when the electrical parameters vary.

The MPC of a PMSM with unknown load torque based on linear plant models has been investigated in [25], where the decoupling method of current and voltage is used to obtain a linear model. In [26], the General predictive control (GPC) has been employed to generate the required torque to implement the DTC technique. Constrained MPC of PMSM is studied in [27].

In this paper, the DLPC based on the Taylor series expansion is revised to enhance the robustness in controlling a PMSM, which is a nonlinear system with fast dynamics. A novel performance index is proposed and the controller is developed under the assumption that there is no disturbance and no mismatched parameters. A cascade structure for the controller is adopted. This structure allows directly limiting the magnitude of the armature phase current by using saturation blocks. However, when the control saturates, the closed loop performances deteriorate significantly; resulting in a high overshoot and a long settling time. This is due to the fact that the DLPC contains an integral action. The windup phenomenon occurs, especially, when large set-point changes are made. To suppress this undesired effect, known as integrator windup, an anti-windup compensator based on the well known conditional integral method is used.

Linearization and/or high-frequency switching based nonlinear speed control techniques, such as feedback linearization control and sliding mode control, have been implemented for the PMSM drives [4][17]. However, it is more efficient to use a nonlinear control method that is based on minimizing a cost function and allows one to

tradeoff between the control accuracy and control effort.

2. MODEL OF THE PMSM

The dynamic model of a typical surface-mounted PMSM can be described in the well known (d-q) frame through the park transformation as follows [1][3]:

$$\begin{aligned} \frac{di_{sd}}{dt} &= -\frac{R_s}{L_d} i_{sd} + \frac{L_q}{L_d} p\Omega i_{sq} + \frac{u_{sd}}{L_d} \\ \frac{di_{sq}}{dt} &= -\frac{R_s}{L_q} i_{sq} - \frac{L_d}{L_q} p\Omega i_{sd} - \frac{\Phi_f}{L_q} p\Omega + \frac{u_{sq}}{L_d} \\ T_e &= \frac{3p}{2} (\Phi_f i_{sq} + (L_d - L_q) i_{sd} i_{sq}) \end{aligned} \quad (1)$$

$$J \frac{d\Omega}{dt} + f\Omega = T_e - T_L$$

$$\frac{d\Omega}{dt} = \frac{3p}{2J} (\Phi_f i_{sq} + (L_d - L_q) i_{sd} i_{sq}) - \frac{f}{J} \Omega + \frac{T_L}{J}$$

Where

u_{sd}, u_{sq} Direct-and quadratic-axis stator voltages

i_{sd}, i_{sq} Direct-and quadratic-axis stator currents

L_d, L_q Direct -and quadratic-axis inductance

p Number of poles

R_s Stator resistance

Φ_f Flux of linkage

Ω Electrical rotor speed

ω Mechanical rotor speed ($\omega = p\Omega$)

f Viscous friction coefficient

J Moment of Inertia

T_e Electromagnetic Torque

T_L Load Torque

3. PRINCIPLE OF THE DLPC

3.1 Case of SISO process

In this article, we will design a so-called discrete linear predictive control [5], [7]. To do this, we assume that the process is monovariable and there are no constraints to be respected. Figure1 illustrates the basic idea of predictive control. The predictive control is based on a priori knowledge of the process through a model that

provides predictions of changes in future outings. This prediction is then compared to the desired output of a finite horizon, called the prediction horizon N_p . The computer then determines the optimal sequence of controls to minimize the difference between the predicted output and the reference but only the first component is actually implemented. At the next sampling instant, the prediction horizon and not a slip of the optimization problem is repeated and so on. Therefore, this control strategy is called receding horizon control.

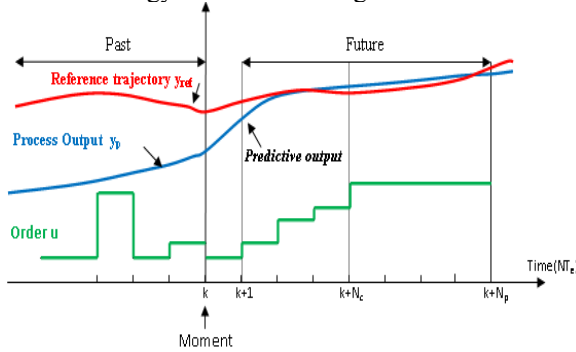


Fig. 1: principle of the Model Predictive Control

The objective of continuing reference trajectory is formulated in terms of minimization of a criterion of optimization over a finite prediction slippery. We then bring back the following optimization problem:

$$\min_{u(k) \dots u(k+N_c-1)} \mathfrak{J} = \sum_{j=k+1}^{j=k+N_p} (y_{ref}(j) - y_p(j))^2 + \sum_{j=k+1}^{j=k+N_c} (u(j-1) - u(j-2))^2 \gamma (u(j-1) - u(j-2)) \quad (2)$$

Where γ is a positive parameter, which penalizes the variation of the order.

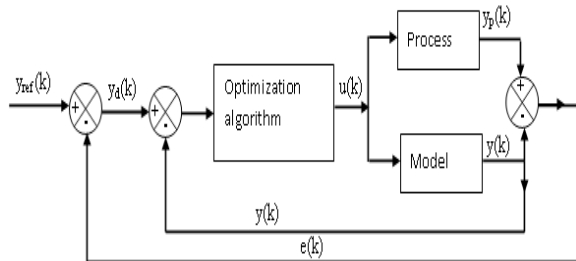


Fig. 2: Structure of the control by the internal model

From the expression (1), we note that the optimization problem is written based on the reference trajectory and the output of the process in the future. As for the reference trajectory, it is

assumed to be known about the prediction horizon. By cons, on the output of the process, we only have measurements at the present time. Therefore, there must be a command structure for assessing the future outputs y_p over the prediction horizon N_p .

Generally, to solve this problem, we use the structure for internal model control (IMC), whose block diagram is shown in Figure 2. Besides being easy to implement, it provides the robustness of the control in the presence of parametric uncertainties and disturbances on the output.

$$y_d(k) = y_{ref}(k) - e(k) \quad (3)$$

$$y_d(k) = y_{ref}(k) - y_p(k) + y(k) \quad (4)$$

Which implies :

$$y_d(k) - y(k) = y_{ref}(k) - y_p(k) \quad (5)$$

Substituting the above expression in the formula optimization criterion given by (1), we obtain:

$$\mathfrak{J} = \sum_{j=k+1}^{j=k+N_p} (y_d(j) - y(j))^2 + \quad (6)$$

$$\sum_{j=k+1}^{j=k+N_c} (u(j-1) - u(j-2))^2 \gamma (u(j-1) - u(j-2))$$

Therefore, having the objective of continuing reference trajectory by the output of the process means that we want the output from the model to follow the desired signal y_d . In addition, the continuing trajectory is ensured even if the output of the model is different from the process. For the realization of the order by the internal model [3], we take $e(j)$ equal to $e(k)$ over the entire prediction horizon N_p , that is to say:

$$e(j) = e(k) \quad \forall j \in [k+1 \quad k+N_p] \quad (7)$$

Thus, knowing $y_{ref}(j)$ of the prediction horizon, simply use the equation (3) to predict $y_d(j)$ of the prediction horizon.

3.2 Case of MIMO process

According to the above, the problem of predictive control monovariable, without constraints, amounts to a quadratic optimization problem. To generalize the control strategy for multivariable processes, simply change the performance criteria as follows [8]:

$$\mathfrak{J} = \sum_{j=k+1}^{j=k+N_p} (y_d(j) - y(j)) Q (y_d(j) - y(j)) + \sum_{j=k+1}^{j=k+N_c} (u(j-1) - u(j-2))^2 R (u(j-1) - u(j-2)) \quad (8)$$

where

Q and R are weighting matrixes, respectively, output and control. They are positive definite. In general, the predictive control is based on the following:

➤ A reference trajectory in the future: it represents the desired behavior of the process. His determination is very important because it represents the specifications (dynamic performance, stability) of the process in closed loop.

➤ A model of the process to be controlled: it represents the evolution of the dynamic behavior of the process. It provides the prediction of the future outputs of the prediction horizon. In most cases, the model is linear and discrete.

➤ An optimization criterion in the future: it is also called performance criteria or cost function is the mathematical translation of the objectives of process control under the constraints of operation. In general, this criterion is quadratic, it is composed of two parts. The first part on the continued path is written based on the error between the output of the process and output of the model. The second part on the outcome of the penalty specifications (constraints) can be written according to the order of state variables and outputs of the process. In our case, it is given by (8).

➤ The solution method: it is an algorithm that provides the control sequence that allows the output of the process to continue the reference trajectory over a prediction. In our case, the derivative of the cost function with respect to the order is sufficient to develop the optimal control.

4. APPLICATION TO PMSM

The model of the system plays a central role in predictive control. Indeed, if the model is nonlinear, solving the optimization problem (5) must be done online, which may require significant computation time. Another disadvantage is the fact that finding a global optimum is not always guaranteed. To remedy this problem, we use the linear model obtained via the strategy of decoupling compensation while neglecting the reluctance torque.

Thus, from the objectives of the control equations and Park, the behavior of the motor can be represented by the following linear model:

$$\begin{cases} \dot{x} = Ax + Bv \\ y = Cx \end{cases} \quad (9)$$

The state matrices A, B input and compliance C are respectively given by:

$$A = \begin{bmatrix} -\frac{R_s}{L_{sd}} & 0 & 0 \\ 0 & -\frac{R_s}{L_{sq}} & -p\Phi_f \\ 0 & \frac{p}{J}\Phi_f & -\frac{f}{J} \end{bmatrix}; B = \begin{bmatrix} \frac{1}{L_{sd}} & 0 \\ 0 & \frac{1}{L_{sq}} \\ 0 & 0 \end{bmatrix};$$

$$C = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

The state vectors x and output y are respectively given by:

$$x = [i_{sd} \quad i_{sq} \quad \Omega]^T; \quad y = [i_{sd} \quad \Omega]^T$$

A new order is given by

$$v = \begin{bmatrix} v_d \\ v_q \end{bmatrix} = \begin{bmatrix} u_{sd} + p\Omega L_d i_{sq} \\ u_{sq} - p\Omega L_d i_{sd} \end{bmatrix} \quad (10)$$

In addition, for simplicity in developing the order, the linear model given by (6) must be written in discrete time as follows

$$\begin{cases} x(k+1) = A_d x(k) + B_d v(k) \\ y(k+1) = Cx(k+1) \end{cases} \quad (11)$$

$$\text{With } \begin{cases} A_d = e^{(A.T_s)} \\ B_d = A^{-1}(e^{(A.T_s)} - I_{3 \times 3})B \end{cases}$$

T_s is a sampling time.

By exploiting the above equations, the model prediction on the receding horizon N_p is given in the following vector form.

$$Y(k+1) = [y(k+1) \quad \dots \quad y(k+N_p)]^T \quad (12)$$

$$= \tilde{A}x(k) + \tilde{B}V(k)$$

$$\text{With } \tilde{A} = \begin{bmatrix} CA \\ CA^2 \\ \vdots \\ CA^{N_p} \end{bmatrix}; \quad V(k) = \begin{bmatrix} v(k) \\ v(k+1) \\ \vdots \\ v(k+N_p-1) \end{bmatrix}$$

$$\tilde{B} = \begin{bmatrix} CB & 0 & 0 & 0 \\ CAB & CB & 0 & 0 \\ \vdots & \dots & \dots & \dots \\ CA^{N_p-1}B & CA^{N_p-2}B & \dots & CB \end{bmatrix} \quad (13)$$

Suppose that the control horizon is equal to the prediction, the cost function given by (7) becomes:

$$\begin{aligned} \mathfrak{J} &= \left(Y_d(k+1) - \tilde{A}x(k) - \tilde{B}V(k) \right)^T * \\ Q \left(Y_d(k+1) - \tilde{A}x(k) - \tilde{B}V(k) \right) & \quad (14) \\ + \Delta V(k)^T R \Delta V(k) \end{aligned}$$

$$\text{With } Y_d(k+1) = \begin{bmatrix} y_{ref}(k+1) - e(k) \\ \vdots \\ y_{ref}(k+N_p) - e(k) \end{bmatrix};$$

$$\Delta V(k) = V(k) - V(k-1) \quad (15)$$

The optimal solution is then obtained by derivation of the performance index (11) compared to control vector V(k). The calculation of the derivative of the cost function gives:

$$\begin{aligned} \frac{d\mathfrak{J}}{dV(k)} &= -2(\tilde{B})^T \tilde{Q} \left(Y_d(k+1) - \tilde{A}x(k) - \tilde{B}V(k) \right) \\ &+ 2 \left(\frac{d(\Delta V(k))}{dV(k)} \right)^T R \Delta V(k) \quad (16) \end{aligned}$$

$$\text{With } \tilde{Q} = \begin{bmatrix} Q & 0 & \dots & 0 \\ 0 & \ddots & \vdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & Q \end{bmatrix} \quad (17)$$

On the other hand we note that:

$$\left(\frac{d(\Delta V(k))}{dV(k)} \right)^T R = \begin{bmatrix} R & -R & 0 & \dots & 0 \\ 0 & R & -R & \ddots & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \dots & 0 & R & -R \\ 0 & 0 & 0 & 0 & R \end{bmatrix} \quad (18)$$

This leads to:

$$2 \left(\frac{d(\Delta V(k))}{dV(k)} \right)^T R \Delta V(k) = 2\tilde{R}V(k) - 2\hat{R}x(k-1) \quad (19)$$

$$\text{With } \tilde{R} = \begin{bmatrix} 2R & -R & \dots & \dots & 0 \\ -R & 2R & -R & \dots & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & 0 & -R & 2R & -R \\ 0 & 0 & 0 & -R & R \end{bmatrix}; \hat{R} = \begin{bmatrix} R \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad (20)$$

Ensuring the optimal solution minimizing the performance criterion on the horizon fleeing comes down to solving the following system of equations :

$$\begin{aligned} \frac{d\mathfrak{J}}{dV(k)} &= -2(\tilde{B})^T \tilde{Q} \left(Y_d(k+1) - \tilde{A}x(k) - \tilde{B}V(k) \right) \\ &+ 2\tilde{R}V(k) - 2\hat{R}x(k-1) = 0 \quad (21) \end{aligned}$$

From the above equation, we can show that the optimal control is expressed as follows:

$$V(k) = \left(\tilde{R} + \tilde{B}^T \tilde{Q} \tilde{B} \right)^{-1} \left[\tilde{B}^T \tilde{Q} Y_d(k+1) - \tilde{B}^T \tilde{Q} \tilde{A} x(k) + \hat{R} x(k-1) \right] \quad (22)$$

The optimization provides the analytical sequence future orders which only the first component will be effectively implemented on the system. The procedure is repeated again at the next sampling period according to the principle of receding horizon.

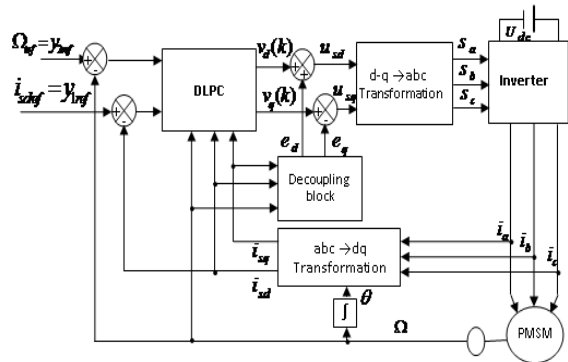


Figure3 : simulation scheme of DLPC controller

5. SIMULATION RESULTS

5.1 PMSM parameter's

TABLE I : PARAMETERS OF PMSM

parameter	value
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Maximal voltage of food	300 v
Maximal speed	3000 tr/s to 150 Hz
Nominal Torque ;T _n	14.2 N.ms
R _s	0.4578 Ω
Number of pair poles :p	4
L _d	3.34 mH
L _q	3.58 mH
The moment of inertia J	0.001469 kg.m2s
Coefficient of friction viscous f	0.0003035 Nm/Rad/s
Flux of linqage Φ _f	0.171

5.2 Simulation parameter's

Note that when the discrete linear predictive control (DLPC) is capable of giving good results, it is always with good choice of the prediction horizon N_p and the matrixes Q and R, considered as important parameters of the synthesis. In our case, we chose:

$$R = \begin{bmatrix} 1 & 0 \\ 0 & 20000 \end{bmatrix}; Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

N_c=5; N_p=200 ; T_s=0.00005s; λ = 0.01

5.3 Results

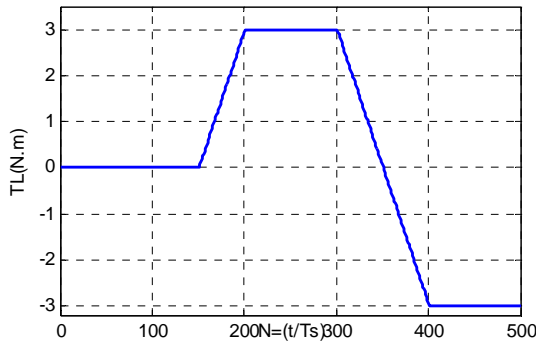


Fig. 4: Trajectory of the Load Torque

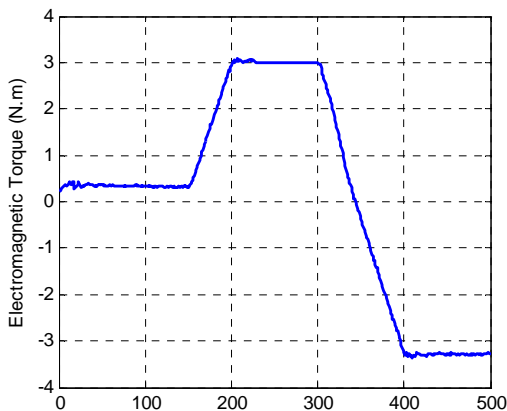


Fig. 5 : Response of electromagnetic torque

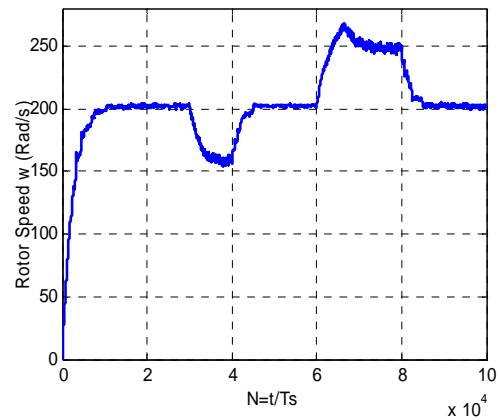


Fig. 6: speed response due to disturbance torque

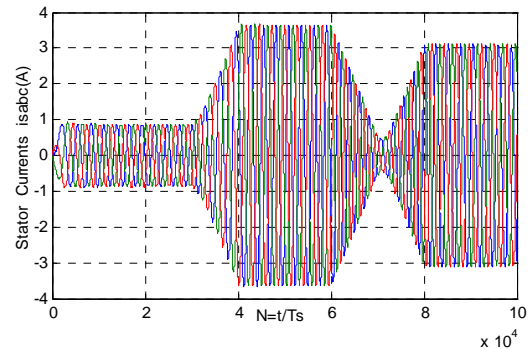


Fig. 7: Stator currents i_{sabc}

The figures (4 to 7) show the performance of controller (DLPC) with respect to the rejection of disturbances due to load torque variation. (W_{ref}=200 Rad/s)

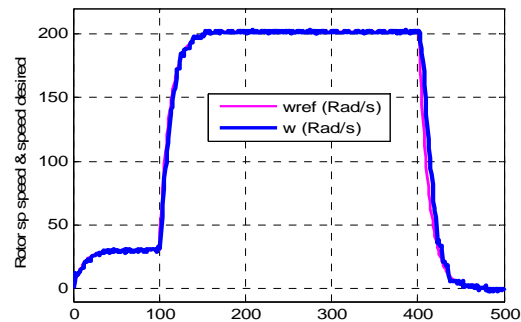


Fig. 8: Tracking trajectory of the rotor speed (T_L=0 N.m)

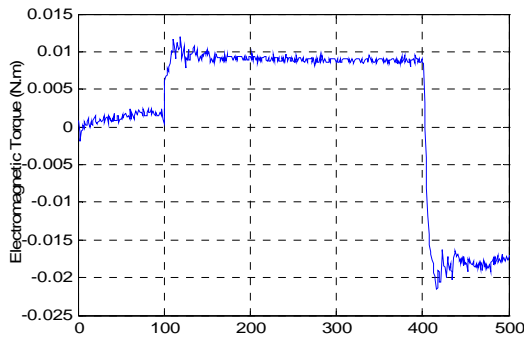


Fig. 9: Response of electromagnetic torque

The figures (8 and 9) show the system's ability to follow the trajectory imposed by the speed reference.

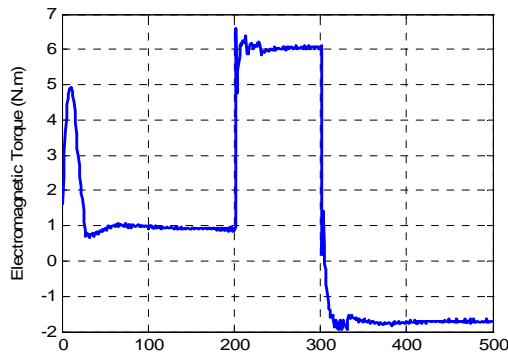


Fig. 10: Electromagnetic Torque ($T_L=6$ N.m at $t=0.2s$ and $T_L=-2Nm$ at $t=0.3s$)

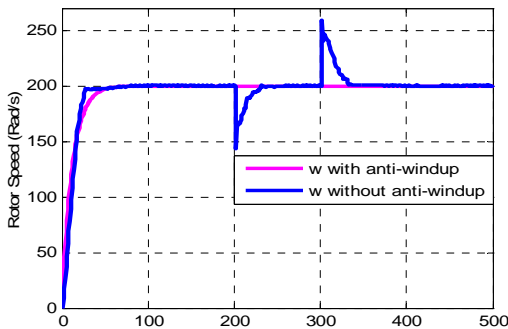


Fig. 11: Speed response with and without a block anti-windup.

CONCLUSION

In this paper we reviewed some control laws for the permanent magnet synchronous motor, namely the scalar control, vector control, the command input-output linearization, flatness control by the direct control of torque and receding horizon predictive control.

As for the scalar control and vector control, they are robust vis-à-vis the load torque and parameter uncertainty. This is particularly due to the integral contained in the control loop. However, it is known that these strategies do not provide good performance when tracking trajectories. The side of the non-linear control, namely the linearization and control the order by platitudes, they are ideal for the pursuit of trajectories. However, their performance depends strongly on the value of the load torque, which is assumed known, and parameters of the machine. We are thus led to combine the order non-linear adaptive algorithms or other methods of control to ensure robustness. On the receding horizon predictive control, it can provide good dynamic performance and static. However, it is difficult to implement for systems with fast dynamics, because it requires more computing power for real-time applications.

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