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Optimized model based control for an outer rotor surface permanent magnet machine with temperature influence

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Summary

This paper presents the optimization of a model based control for a Surface Permanent Magnet Synchronous Machine. Model Predictive Control and Field Oriented Control methods are considered. The thermal and the saturation effects on the model parameters are captured. Based on the results of MOTORCAD software, functional dependencies of armature resistance, inductance, flux linkage and core loss vs. stator current, operating frequency, magnet and winding temperature are created and then used in the control model. Furthermore, the paper highlights how the thermal model enhances the Model Predictive Control performance regarding the parameter variation as a function of temperature.

Keywords: Control System, Efficiency, Prediction, Simulation, Synchronous Motor.

1 Introduction

The increase of the computational power has brought the electrical drive system into a better spotlight, showing an increase of popularity in the automotive area. Beside the electromagnetic machine design, the controller parameter optimization is an important issue for an efficient drive-train. For this optimization, information about the non-linear machine characteristics and thermal behavior is essential. An outer rotor surface permanent magnet synchronous machine (SPMSM) used in an in-wheel application is under the study. Many control techniques have been developed for the permanent magnet synchronous machine due to its high efficiency. Classical cascaded PI controllers used in FOC (field oriented control), or DTC (direct torque control) have proved good performance. The linear quadratic regulator (LQR) control method is used to minimize the undesired deviations under some constraints at a minimum cost. This control method can be used for linear differential equations. Model predictive control (MPC) is an advanced method used for the minimization of the cost function as in the case of LQR. Compared to LQR method, MPC can handle the non-linearities of the plant in order to find the minimum cost.
As it was aforementioned, in order to create a more realistic simulation, there is a need of a thermal model of the machine. Considering the mechanical, electrical and thermal part of the motor, it is possible to create an optimization of the energy consumption while using the machine at its highest potential.
The controlled systems have often nonlinearities leading to difficulties for the PI controller to work at its highest potential. For increasing the efficiency of the drive system, nonlinear control methods have been developed. These control techniques involve: neural networks, feedback linearization, feedforward, fuzzy logic, genetic algorithm and so on. Most of them are considered intelligent control systems because of the artificial intelligence involved in the process of learning. Model predictive control (MPC) is a

model based control technique which has become recently known for its application to electrical drives. The computational power of the electronic devices has given the chance for this method to be used in optimization problems which involve electrical machines and drives.
The MPC strategies used for the control of the surface permanent magnet synchronous machine are discussed in the next sections.

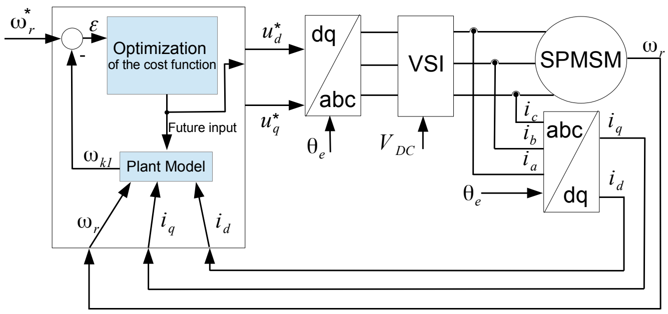
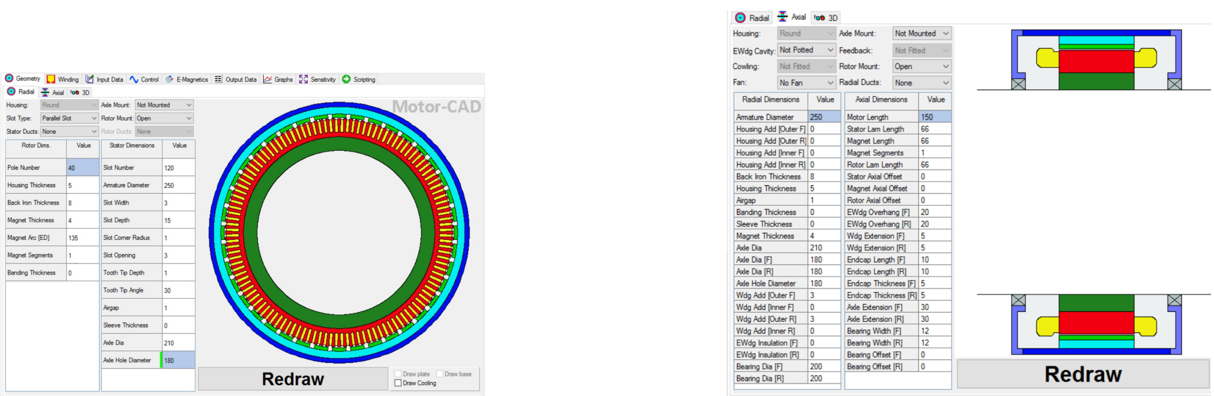


Figure 1: Model Predictive Control for a SPM machine.

2 System model

2.1 Motor model

A detailed model of the outer rotor surface permanent magnet machine is developed in MOTORCAD software and the results are obtained in the complete torque-speed plane. The model is built in such a way that the thermal and saturation effects are included. Based on these results, the functional dependencies of motor parameter with temperature and stator current vector are established. The considered motor parameters are shown in Figs. 2b and 2a.



(a) Radial cross section.

(b) Axial cross section.

Figure 2: MOTORCAD model.

The armature resistance (R_a) is defined as a function of winding temperature (T_w) and electrical frequency (ω_e). The inductances (L_d, L_q) capture the saturation and the cross coupling effect of the machine as it is modeled based on I_d and I_q. The flux linkage (Ψ_{pm}) is defined based on permanent magnet temperature (T_{pm}).

$$R_a = f(T_w, \omega_r) \tag{1}$$

$$L_d = f(I_d, I_q) \tag{2}$$

$$L_q = f(I_d, I_q) \tag{3}$$

$$\Psi_{pm} = f(T_{pm}) \tag{4}$$

Similarly, the motor losses such as armature loss (P_a), core loss (P_c), permanent magnet loss (P_{pm}), and mechanical loss (P_{mech}) are modelled as functions of shaft speed (ω_r), armature resistance (R_a), stator current (I_s) and the temperatures of magnets (T_{pm}) and winging (T_w) as given below.

$$P_a = f(\omega_r, T_{w_r}) \tag{5}$$

$$P_c = f(\omega_r, T_{pm}) \tag{6}$$

$$P_{pm} = f(\omega_r, I_s) \tag{7}$$

$$P_{mech} = f(\omega_r) \tag{8}$$

2.2 Thermal model

A thermal model is built to estimate the winding temperature based on lumped parameter thermal networks using the distributed loss and capacitance (DLC) element as proposed in [1]. The network is solved by introducing the losses from the motor model and considering the effect of rotational speed on some of the boundary conditions. The thermal model is working in parallel with motor model to update the model parameters in the model based control.

2.3 MPC-overview

Model Predictive Control (MPC) has been used in research for more than 30 years. Nowadays, this control technique is applied to the electrical drives due to the increase of the computational power. Some advantages of this control technique is that it can include the nonlinearities, constraints and different variables into the cost function as it does not need a linear plant in order to find the optimal values [2]. The predicted output is compared with the reference value under the constraints and the optimal value represents the minimum error for a minimum effort. In order for the MPC to solve multi input - multi output (MIMO) problems, it is necessary to use weighting matrices as it is in the case of the LQR problem. These weighting matrices are used to penalize the state variables. The higher they are, the more penalized that signal is. The minimization of the predicted variable deviation from the reference one as a function of a minimum effort can be achieved through this control technique. This control strategy can be divided in four categories [3]:

- Optimal Switching Vector MPC (OSV-MPC)
- Optimal Switching Sequence MPC (OSS-MPC)
- Generalized Predictive Control (GPC)
- Explicit MPC (EMPC)

Although the vector control of electrical drives is most used in industry, MPC might have advantages over FOC or DTC due to the optimization process which includes an objective or cost function. The inclusion of the nonlinearities and constraints in the cost function allows one to control the machine under the constraints within an optimal solution area. OSV-MPC is simple and can be online optimized. The main disadvantage of this control strategy is the variable switching frequency which increases the total harmonic distortion (THD). Since 1970s, MPC has been used as an optimal control strategy for the process industry [4,5]. The progress of technology allowed MPC to be exploited in other industrial areas such as power electronics and electric drives [6–10]. FOC and DTC have proved good performance and dynamics during the decades, but for its simplicity and intuitive way of implementation, MPC might be a good competitor to vector control [6,10]. Despite its simplicity, some important aspects regarding the performance of an MPC must be solved [8,9]:

- Prediction model discretization
- Frequency spectrum shaping
- Cost function design
- Reduction of computational cost
- Increase of prediction and control horizon
- Stability and system performance design

MPC is a model based design, which requires all the state variables to be measured. The discretization of the model plays an important role in the prediction because of its deterministic nature. The quality of the prediction model has a high influence on the performance of MPC. As it was aforementioned, the discretization techniques as Euler or Taylor are very common in control design because of their simplicity. Several MPC strategies have been implemented to overcome the problem of high switching frequency [12–14].

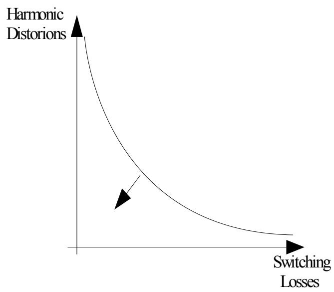


Figure 3: Fundamental trade-off between harmonic distortions and switching losses(frequency) [24](pp.67).

A fixed switching frequency means a lower harmonic distortion and leads to the removal or completely elimination of the filters in the system. The cost function design is another important aspect of MPC because system behavior is dictated by this function. The freedom of increasing the complexity of the cost function makes MPC such a good control strategy. Nevertheless, the increased number of variables in the cost function requires weighting factors because of their different order of magnitude. Without weighting factors, the minimization of objective function cannot be achieved. In order to solve this problem, one can work with the variables in per unit value [15]. The robustness of the system is an actual research subject. It is well known that a model based design has an issue when it comes to talk about perturbations. Due to its deterministic approach, one must be able to measure all variables and perturbations in order to offer a stability of the system. This can be achieved by introducing observers. In order to reduce the cost of the electrical drive and to increase its robustness, estimators are a good solution for an MPC.

There are several speed and position estimators for Synchronous machines based on:

- state observers
- back-emf
- flux linkage
- signal injection estimator with high frequency
- signal injection estimator with low frequency
- neural network, fuzzy logic or genetic algorithm

The sensitivity to parameter variation or uncertainty defines the robustness of the system. Another estimator is necessary for perturbation due to the predicted speed which involves the load torque. This can be accomplished using a model for an external load torque estimator as the case for a feedback-linearization technique [16]. MPC-based algorithms require high computational power which grows exponentially with the increase of the prediction horizon. In order to increase the performance of this algorithm, an increase of the length of the prediction horizon is recommended. In order to decrease the computational burden for a longer prediction horizon, some interesting strategies have been implemented. The sphere decoder has reduced the computational complexity allowing the use of longer prediction horizons [17–21]. Furthermore, a modified sphere decoder has succeeded in reducing even more the number of operations bringing the MPC closer to its highest potential [22]. The next figure represents the improvement of the modified sphere decoder.
The equation of the cost function for Model Predictive Control is as follows [3]:

$$J = \sum_{k+1}^{k+N_p} x^T Q x + \sum_{k+1}^{k+N_c} u^T R u \tag{9}$$

The equation (9) represents the cost function where Q and R are the weighting matrices with N_p as the prediction horizon and N_c representing the control horizon. x is the deviation of the predicted state vector from the reference one.

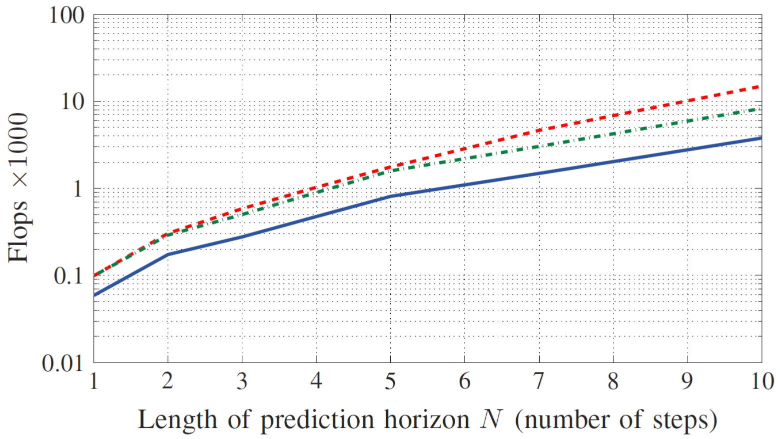


Figure 4: Maximum number of flops N_t as a function of the prediction horizon N as a resulting from the sphere decoder in [20] (dashed line), the sphere decoder in [21] (dash-dotted line), and the proposed algorithm (solid line) [22](pp.7).

3 Mathematical model of the PMSM in continuous and discrete form

In order to create the control architecture for a machine, one must first create a model of the actual machine. These equations which dictate the behavior of PMSM machine are given in the continuous form as follows:

$$u_d = Ri_d + \frac{d\psi_d(i_d, i_q)}{dt} - \omega_e\psi_q(i_d, i_q) \tag{10}$$

$$u_q = Ri_q + \frac{d\psi_q(i_d, i_q)}{dt} + \omega_e\psi_d(i_d, i_q) + \omega_e\psi_{pm} \tag{11}$$

$$T_e = \frac{3}{2}p[i_q\psi_d(i_d, i_q) - i_d\psi_q(i_d, i_q)] \tag{12}$$

$$\frac{d\omega_r}{dt} = \frac{1}{J}(T_e - B\omega_r - T_L) \tag{13}$$

The flux linkage on the direct and quadrature axes is strongly influenced by the inductances matrix. This matrix contains the differential self and mutual inductance. In order to create a more realistic simulation, it is important to take into consideration the cross-coupling and the saturation effects of the machine. To simplify the simulation, the mutual inductances are neglected and just the self inductances are taken into account as it is given in the following matrix:

$$\begin{bmatrix} L_{dd} & L_{dq} \\ L_{qd} & L_{qq} \end{bmatrix} \Rightarrow \begin{bmatrix} L_{dd} & 0 \\ 0 & L_{qq} \end{bmatrix} \tag{14}$$

Writing $\frac{dx}{dt} = \frac{x(k+1)-x(k)}{T_s}$, then the equations (10)-(13) will become in the discrete form as follows:

$$i_d(k+1) = \frac{T_s}{L_{dd}(i_d, i_q)}u_d(k) + i_d(k)(1 - \frac{T_sR}{L_{dd}(i_d, i_q)}) + \frac{T_s}{L_{dd}(i_d, i_q)}\omega_e(k)\psi_q(k) \tag{15}$$

$$i_q(k+1) = \frac{T_s}{L_{qq}(i_d, i_q)}u_q(k) + i_q(k)(1 - \frac{T_sR}{L_{qq}(i_d, i_q)}) - \frac{T_s}{L_{qq}(i_d, i_q)}\omega_e(k)\psi_d(k) - \frac{T_s}{L_{qq}(i_d, i_q)}\omega_e(k)\psi_{pm}(k) \tag{16}$$

$$T_e(k+1) = \frac{3}{2}p[\psi_{pm}i_q(k+1) + (L_{dd}(i_d, i_q) - L_{qq}(i_d, i_q))i_d(k+1)i_q(k+1)] \tag{17}$$

$$\omega_r(k+1) = \frac{T_s}{J}(T_e(k+1)) + w_r(k)(1 - \frac{T_s}{J}B) - \frac{T_s}{J}T_L(k+1) \tag{18}$$

The discrete equations of this machine are necessary for model predictive control due to its deterministic approach. The better the model is discretized, the smaller error will be.

4 Optimization of the MPC as a model based design

In order to see the performance of the MPC, an optimized control block for the PMSM has been designed by the use of Magnitude Optimum and Symmetrical Optimum criteria. The dynamics, spectral analysis and the problem of the steady state error for the MPC has been solved as well, showing zero error for a tracking problem. The equation of the cost function is given in (9), but there are more possibilities of writing this equation as follows:

- absolute value : $g = |\widehat{x}^*(k+1) - x^p(k+1)|$
- quadratic form : $g = (\widehat{x}^*(k+1) - x^p(k+1))^2$
- integral form : $g = \int_k^{k+1}(\widehat{x}^*(k+1) - x^p(k+1))$

The cost function consists of the predicted values and the estimated reference value and the purpose of MPC is to minimize the cost function under the constraints in such way so that the tracking will be possible with a minimum steady state error. All the enumerated cost function forms have advantages and disadvantages in the way of simplicity and computational performance. For simple problems where there is no more than one variable, one can obtain good results by the use of absolute value for the cost function. The quadratic form is the most used for cost function due to its performance and of its simplicity. The integral form could bring slightly better results than the quadratic form, but for a cost of an increased complexity in computation.

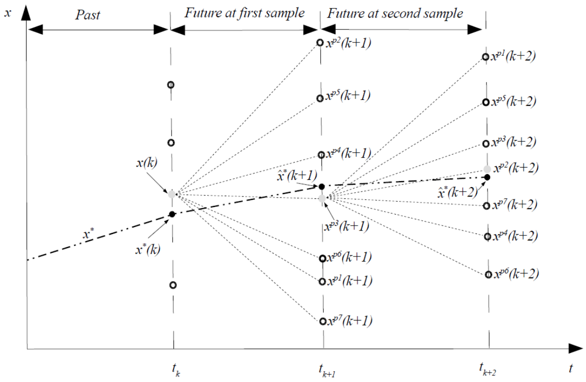


Figure 5: Model Predictive Control - Working principle.

The parameters of the machine at 25 °C are given in Table 1.

Table 1: Parameters of SPMSM

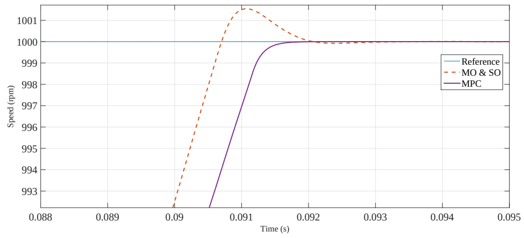
	Current (A)	Power (kW)	V_{DC} (V)	Resistance (Ω)
Peak	200	80	400	0.03459
Continuous	100	40	400	0.03459

The parameters of the PI controllers have been computed using Magnitude Optimum and Symmetrical Optimum criteria according to [23] for a switching frequency of 3 kHz and 10 kHz given in Tab. 2.

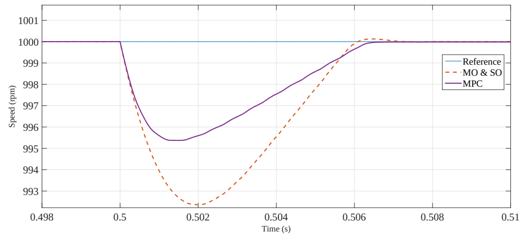
Table 2: Parameters of PI controllers

	$K_{p\omega_r}$	$K_{i\omega_r}$	K_{pi_d}	K_{ii_d}	K_{pi_q}	K_{ii_q}
3 kHz	193.965	$1.09 \cdot 10^5$	1.645	155.65	1.77	155.65
10 kHz	646.55	$1.21 \cdot 10^6$	5.482	518.85	5.91	518.85

In Fig. 6 the performance of both control methods are presented in a comparison. The machine has an overshoot of about 0.2% and a very small undershoot. In comparison to FOC, MPC has no overshoot or undershoot and its dynamics are similar to the vector control. Moreover, in the right part of the figure, one can see that the speed response at a load disturbance is faster for the MPC. Both control methods present a steady state error of zero.



(a) Step response for FOC (MO & SO) and MPC.

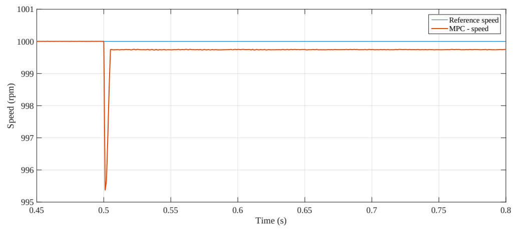


(b) Speed response at a load disturbance of 400 Nm.

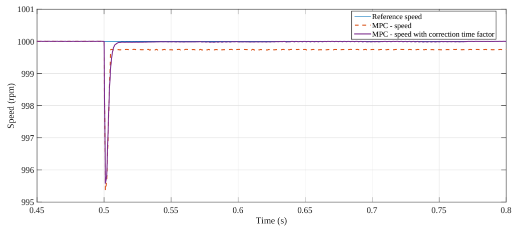
Figure 6: Optimized MPC in a comparison with an optimized FOC (MO & SO) for a 10 kHz switching frequency.

One of the research subjects for the MPC is the minimization of the steady state error. The lack of the integrator block for the new control strategy leads to a steady state error even if it is small. To overcome this problem, one must see the parts of the MPC block divided in two parts: current loop and speed loop. Similar to the vector control, in order to overcome this problem, the sample time for the current loop must be smaller than the sample time for the speed loop. Considering the aforementioned statement, the sample time of the speed loop will become $T_{w_r} = 150T_s$. With the new sample time for the speed loop, the equation (18) will become:

$$\omega_r(k+1) = \frac{T_{w_r}}{J}(T_e(k+1)) + w_r(k)(1 - \frac{T_{w_r}}{J}B) - \frac{T_{w_r}}{J}T_L(k+1) \tag{19}$$



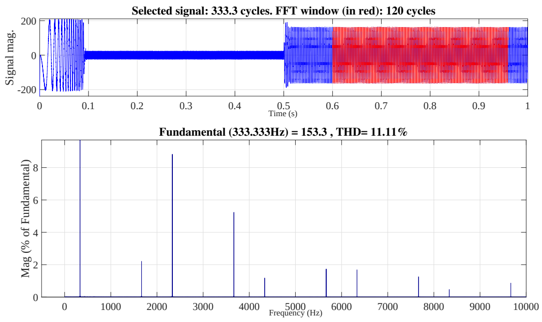
(a) Steady state error of 0.03% at a load disturbance.



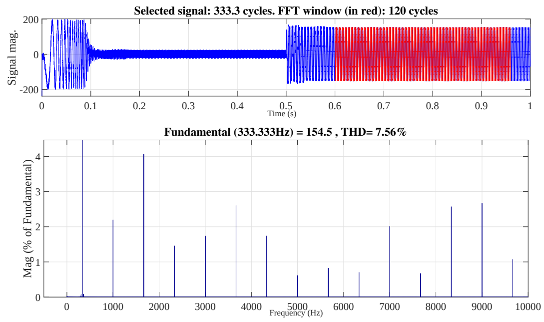
(b) Steady state error 0% at a load disturbance.

Figure 7: The correction of the steady state error.

Figure 7 shows the improvement of the MPC block regarding the steady state error when a load is applied to the machine. With the corrected speed loop, the MPC strategy can be used in a comparison with FOC as it was given in figure 7.



(a) Spectral Analysis for FOC.



(b) Spectral Analysis for MPC.

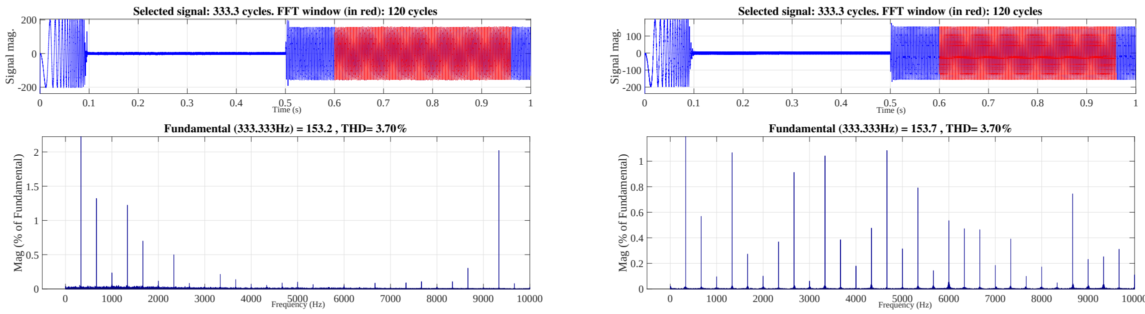
Figure 8: Spectral Analysis at 3kHz for FOC and MPC.

In Fig. 8 a comparison has been made between FOC and MPC regarding the total harmonic distortion (THD). As it is seen, the THD for the MPC block is lower than the THD for FOC with almost the same number of commutations. The comparison for 10 kHz and 3kHz for FOC and MPC is given in the following table. One must remember that the MPC in this case has a variable switching frequency.

Table 3: Data for FOC and MPC at different frequencies

	THD (FOC)	THD (MPC)	Number of switches - FOC	Number of switches - MPC
3 kHz	11.11%	7.56%	3000	2980
10 kHz	3.7%	3.7%	10000	8000

With the results given in the Tab. 3, one can see that the MPC block has been well optimized and although the lack of the modulator block in this control strategy is present, it is possible to achieve the same THD of the currents as the FOC with a PWM, but with less number of switches.
The comparison between FOC and MPC at 10 kHz switching frequency for vector control is given in the following figure.



(a) Spectral Analysis for FOC.

(b) Spectral Analysis for MPC.

Figure 9: Spectral Analysis at 10 kHz for FOC and MPC.

5 MPC with temperature influence

Model Predictive Control is a model based design which depends very much on the accuracy of the machine model. The variation of the parameters due to perturbations and temperature plays a major role in the performance of this control strategy. The actual thermal model of the SPMSM acts as an observer for the MPC. The coupling of the thermal model based on the results from MOTORCAD with the electro-mechanical model in MATLAB/Simulink is given in Fig. 10.
The variation of the inductances, resistance and permanent magnet flux linkage at different temperature values are given in the next table.

Table 4: The parameters of the machine at different temperature values.

	I_s	L_d	L_q	R_s	ψ_{pm}	T_L
T_1=25°C	153.7	$3.655 \cdot 10^{-4}$	$3.94 \cdot 10^{-4}$	0.03459	0.0870	400
T_2=52.4°C	153.7	$3.266 \cdot 10^{-4}$	$3.77 \cdot 10^{-4}$	0.03820	0.0827	400
$\varepsilon = \lvert\frac{x(T_1)-x(T_2)}{x(T_1)} \cdot 100\rvert$	0 %	10.64 %	4.31 %	10.43 %	4.94 %	0 %

According to Tab. 4, in 700 seconds the temperature changed from T_1=25°C to T_2=52.4°C with a change for L_d of 10.64 % and for L_q of 4.31 %. The increase of the stator resistance and the decrease of the permanent magnet flux leads to a steady state error, even though the MPC block has been optimized for fixed values of the machine parameters. The thermal model uses a sample time of 1 second while the sample time of the MPC block is of $1 \cdot 10^{-5}$. In order to connect the two blocks, it was necessary to synchronize them with a rate transition block. The machine parameters are updated every second with the information given from the thermal model simulating the temperature influence on the winding resistance, inductances and the permanent magnet flux linkage. Without any update in the MPC block with the new values of the machine parameters as a function of temperature and currents, one can see in the following figure the increase of the steady state error due to the uncertainties.
In order to overcome the problem of the steady state error, the MPC block has been updated every second with the new values of the machine parameters. As it is given in figure 11, the steady state error is zero as it was in the case with fixed values.

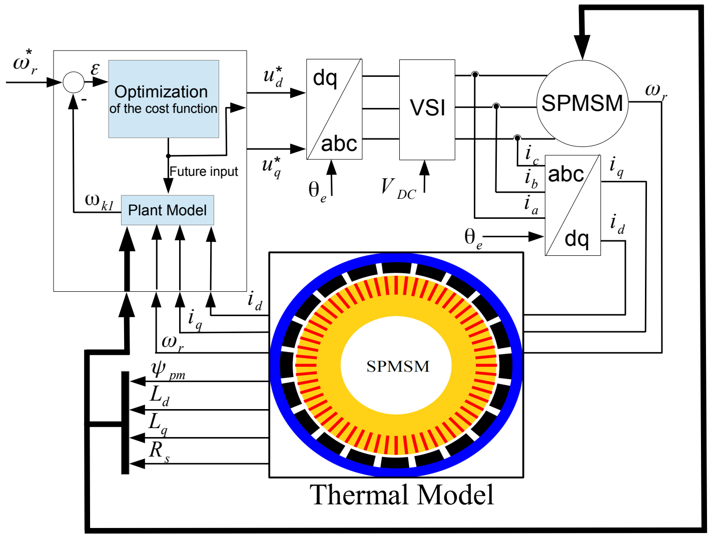
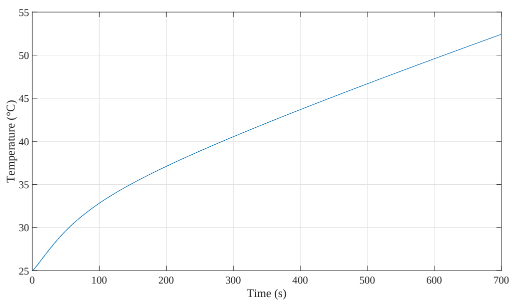
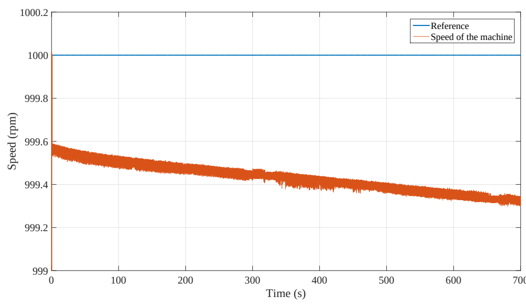


Figure 10: Model Predictive Control for a SPMSM machine with thermal influence.

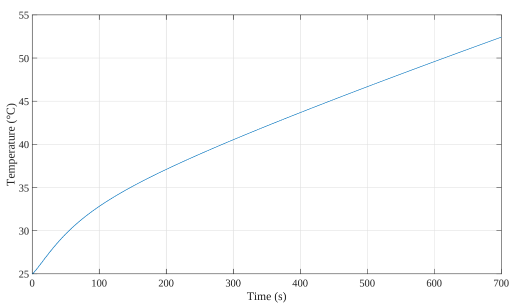


(a) The evolution of winding temperature.



(b) Speed error due to the parameter variation at a load disturbance of 400 Nm.

Figure 11: MPC without the Thermal Model - speed error.



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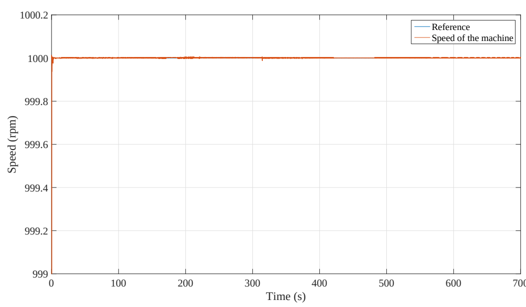

(b) Speed error due to the parameter variation at a load disturbance of 400 Nm.

Figure 12: MPC with the Thermal Model - speed error.

6 Conclusion

In this paper, a model based design with temperature influence has been achieved. The Model Predictive Control has been optimized through its weighting factors in order to achieve a zero steady state error and the dynamics comparable with an optimized Field Oriented Control. A spectral analysis has been done in comparison with the optimized vector control showing that Model Predictive Control could achieve the same Total Harmonic Distortion with less commutations of the transistor leading to smaller losses in the inverter. Moreover, the deterministic nature of this control method needs with accuracy the values of the parameters in order to obtain a zero steady state error when a load disturbance is applied, hence the thermal model played an important role to this control strategy. Due to the variation of the machine parameters as a function of temperature, thermal model assured an update of the MPC block every second with the actual parameter values in order to eliminate the steady state error at a load disturbance. A prediction horizon of one step has been used for the actual control strategy. The flexibility of this control technique offers the possibility to control the d and q axis as a decoupled model and moreover it allows more constraints to be included in the cost function. This method proves to be a good competitor to vector control due to the lower losses in the inverter and comparable dynamics with an optimized FOC. Furthermore, the increase of the computational power offers the possibility of a better exploitation of the MPC. The accelerated pace of technology allows more complex and intelligent control strategies to be applied in the electrical field, offering a possibility of the electrical drive system to be used at its maximum potential in the automotive field.

Acknowledgment

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12