Sensorless Cascaded-Model Predictive Control
applied to a Doubly Fed Induction Machine

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Abstract—This paper proposes a sensorless cascaded model predictive control strategy applied to a doubly-fed induction machine. This technique is based on an improved stator flux estimator, and an extended Kalman filter to control encoder-less and independently the electromagnetic torque and the reactive power of the machine. The purpose of employing a model predictive-based control, is to achieve fast dynamic response and upgrading it with a modulation stage to mitigate the control variables ripple. The introduced control technique might be considered for adjustable speed application such as wind energy conversion systems.

Index Terms—Doubly fed induction machine (DFIM), two-level voltage source inverter (2L-VSI), extended Kalman filter (EKF), cascade model predictive control (C-MPC),

I. INTRODUCTION

The Doubly Fed Induction Machine (DFIM) has been widely adopted in modern wind energy conversion systems due to the capability of controlling independently the electromagnetic torque, and the reactive power [1], finding it in other fixed frequency variable speed applications such as hydro-power pumping and generation [2], and electric vehicles [3]. So far, the field of high-performance DFIM drives has been mainly controlled by two milestones of control algorithm: direct torque control (DTC) [4], and field-oriented control (FOC) [5]. The former is a widely control technique which takes advantage of the discrete feature of power converters and it includes hysteresis band and comparators for the switching state commutation; the switching frequency results to be variable according to the operating point and the hysteresis band, and this aspect is unfavorable due to the possibility of creating resonance issues, it can cause unwelcome harmonic content making the signal filtering design arduous, moreover, the higher switching losses restrict the application of hysteresis control to low power users [4], [6]. The latter mentioned control algorithm consists of adopting linear proportional-integral controllers (PI) to calculate the needed actuating variables, and even though they assure good result at steady-state, performance degradation might be found for time-varying references, especially at high frequencies making the aforementioned controllers unsuitable in some applications [6]; furthermore the gains tuning can be insidious especially when the system results to be non-linear multiple-input-multiple-output. Model Predictive Control (MPC) technique are becoming the new trend of investigation among the power electronics and electric drives research community due to their inherent dynamic performance, and the disposability of powerful digital controllers to implement such a high demanding computational algorithms. The term MPC covers a wide variety of control techniques [7]. The Finite-Set MPC introduced in [6], is based on a selection-criteria by the minimization of an objective function to select the best feasible voltage vector among the switching states of the power converter, in order to fulfil the desired control. These algorithms easily deal with non-linear systems, taking into account the digital nature of power converters, handling multiple-input-multiple-output systems, as well as including constrains. The objective function can be defined in a way to optimize multiple variables prioritizing their importance by means of weighting factors usually tuned by trial and error procedure. The tuning of weighting factors is the most demanding aspect of scalar cost function-based Model Predictive Control which want to be avoid; in [8] the effort of the weighting factor selection has been avoided by decoupling the control variables considering two cascade cost functions to optimize the individually. Nevertheless, this strategy is still affected by having unwanted non-constant switching frequency and high ripples.

In order to tackle the non-constant switching frequency issue,
in [12] a further stage has been introduced to calculate the
duty cycle of the previous selected optimum vectors, in order
to fulfill constant switching frequency, and visible improvement
can be observed on the state variables ripple. This paper proposes
an alternative to the method exploited in Riccio et al.
(2018) by considering two cascade objective functions as in
Vodola et al. (2019), but introducing a different duty cycle cal-
culation criteria; this paper proposes a Modulated and Cascade
Model Predictive Control (C-MPC) strategy which consists on
two sequential objective functions, which operate to control
the desired variables, without the need of defining weighting
factors. In the first objective function, two optimum voltage
vectors are selected among the eight feasible configurations of
a two-level voltage source inverter (2L-VSI), to optimize the
first cost function, defined to track the first control variable
which will be one of the current components represented in
the synchronous reference frame. In the second stage, the two
selected voltage vectors and the zero vector are used in a
second cost function, created to control the second control
variable, whose values are used to calculate the duty cycle of
each selected vector. The technique to calculate the duty
cycles has been introduced in [10], and it will be carried out
in this paper to a DFIM for operations around the synchronous
speed.

Since the DFIM mathematical model will be reported into the
stator flux oriented synchronous reference frame, the stator
flux vector quantities such as magnitude, rotating speed, and
angle have to be calculated from the available current and voltage
measures. An improved stator flux estimation technique
which does not need a full-order DFIM model addressing
the DC offset issues, has been previously investigated on a
Squirrel Cage Induction Machine [13], and it will be carried out
to the DFIM studied in this paper to decrease the overall
computational load.

The rotor angle and the rotor speed signals are essential to
be either measured or estimated to make the modulated and
C-MPC strategy effective. The most adopted solution is the
installation of an optical encoder on the shaft of the DFIM
[9]; this solution is inclined to mechanical failure, limitations
on machine size, electromagnetic interference, cost reliability,
and mounting; these aspects deteriorate the reliability of the
system creating a single point of failure. As the DFIM presents
rotor windings accessible for measurements, according to [11],
the system state can be fully observed, hence, a sensorless
control strategy will be implemented to estimate the rotor
angle and speed to avoid the usage of an encoder signal and its
related issues. However, sensorless control techniques require
electrical measurements and accurate mathematical models to
achieve a good estimate. System uncertainties, measurement
noise, and parameters variations affect the goodness of the
estimation. Furthermore, the observability of the state of the
system has to be guaranteed in the whole speed operation
range. The Extended Kalman Filter (EKF) is a well-established
state observer which deals non-linear systems which addresses
the aforementioned issues and it will be used in this paper
to make the control algorithm encoder-less as it has been
implemented in [12].

The paper is structured as follow: section II describes the
considered DFIM model; section III describes how the EKF
has been implemented to estimate the state of the system;
section IV presents the C-MPC; the results of simulation and conclusions are given in the section V.

II. DOUBLY-FED INDUCTION MACHINE MODEL

For the DFIM drive configuration adopted in this paper,
the rotor windings are fed by a 2L-VSI, while the stator
windings are connected to the grid through an autotransformer;
the measured variables are the the rotor currents, the stator
voltages, and the stator currents. Using the well-known space
vector representation, the DFIM dynamic model is given in the
“dq” synchronous reference frame rotating at the synchronous
speed superimposed by the frequency of the stator voltage
given by the grid. The DFIM mathematical model is described
as follow:

\[
\begin{align*}
\dot{\psi}_s &= \frac{d}{dt}\psi_s = \frac{4}{\pi}\psi_{ldq} + j\omega_s \psi_{ldq} \\
\dot{\psi}_r &= \frac{d}{dt}\psi_r = \frac{4}{\pi}\psi_{ldq} + j\omega_d \psi_{ldq} \\
\dot{\psi}_{ldq} &= L_s \psi_{rdq} + L_m \psi_{rdq} \\
\dot{\psi}_{rdq} &= L_s \psi_{ldq} + L_m \psi_{ldq} \\
J \frac{d\omega_r}{dt} &= \frac{3}{2} \left( \psi_{rdq} - \psi_{rdq} \right) - T_L
\end{align*}
\]

In (1), \(\hat{\psi}_{sldq}, \hat{\psi}_{rldq}, \hat{\psi}_{rdq}, \hat{\psi}_{rdq}\) are the stator and rotor voltages,
and the stator and rotor currents, represented into the syn-
chronous reference frame “dq” rotating at \(\omega_s\). It is important
to highlight that the stator voltages and currents are not
considered as control variables as they are superimposed by the
grid connection as shown in fig. 2, hence the only manipulated
variable in order to manipulate to the system state is the rotor
voltage vector. The stator and the rotor fluxes are \(\psi_{sldq}, \psi_{rldq}\)
respectively. The term \(\omega_r\) represents the slip speed calculated
as the difference between the synchronous speed and the rotor
electrical speed \(\omega_e\). The stator and rotor resistance are \(R_s\) and
\(R_r\), while the stator, rotor and the magnetizing inductances
are represented respectively by the symbols \(L_s\), \(L_r\) and \(L_m\).
The term \(T_L\) is the torque load, \(p\) is the pole pairs and \(\theta_r\) is the rotor
angle. Once the \(d\)-axis of the synchronous reference frame has
been aligned along the stator flux vector, the electromagnetic
torque and the reactive power can be expressed as follows:

\[
T_{erm} = -\frac{3p}{2L_s} \left( \psi_{sldq} \right)^2 L_m i_{rdq}
\]

\[
Q_s = \frac{3\omega_s}{2L_s} \left( \psi_{sldq} \right)^2 \left( L_m i_{rdq} \right)
\]

As it can be observed from the previous formulas, reactive
power is directly related to the \(d\)-axis current, and electromag-
netic torque can be driven by controlling the \(q\)-axis current
component. Readjusting the equations given in (1), the
following rotor voltage expressions can be derived as described
in (5) and (6), and they will be used to build the control
strategy. The term $|\dot{\psi}_{s\alpha\beta}|$ is the stator flux magnitude, while $\sigma$ is the leakage coefficient calculated as:

$$\sigma = L_r - \frac{L_m^2}{L_s}$$  \hspace{1cm} (4)

$$v_{r_d} = R_r i_{r_d} - R_{sr} i_{sr} - \omega_s L_r i_{r_q} + \frac{L_m}{L_s} \frac{d}{dt} |\dot{\psi}_{s\alpha\beta}|$$  \hspace{1cm} (5)

$$v_{r_q} = R_r i_{r_q} + \omega_s L_r i_{r_d} + \frac{L_m}{L_s} \frac{d}{dt} |\dot{\psi}_{s\alpha\beta}|$$  \hspace{1cm} (6)

III. EXTENDED KALMAN FILTER IMPLEMENTATION

The Extended Kalman Filter (EKF) is a well-established state observer which handles non-linear systems, and it has been implemented in this work to evaluate the DFIM required variables for the feedback control loop such as the mechanical speed, the rotor angle and the rotor currents. To design the EKF, the state-space model of the DFIM is given as follow:

$$\begin{align*}
x'(t) &= f(x(t), u(t)) + w \\
y(t) &= h(x(t)) + v
\end{align*}$$  \hspace{1cm} (7)

The stator and the rotor voltage vectors are the input $u(t)$ of the state-space defined in (7) projected in the stator reference frame $\alpha\beta_s$, and the rotor reference frame $\alpha\beta_r$ respectively. The output vector $y(t)$ contains the measurements of the stator and rotor currents components again represented in the stator and rotor reference frames respectively. The state vector $x(t)$ consists of the stator and rotor currents in the synchronous reference frame “dq”, the rotor rotational speed $\omega_r$, the rotor angle $\theta_r$ and the load torque $T_L$. The input, output and state vectors components are listed in (8).

$$\begin{align*}
u(t) &= [V_{s\alpha}, V_{s\beta}, V_{r\alpha}, V_{r\beta}]^T \\
y(t) &= [I_{s\alpha}, I_{s\beta}, I_{r\alpha}, I_{r\beta}]^T \\
x(t) &= [I_{s\alpha}, I_{s\beta}, I_{r\alpha}, I_{r\beta}, \omega_r, \theta_r, T_L]^T
\end{align*}$$  \hspace{1cm} (8)

The term $x(t)$ is the derivative of the state vector with respect to time. The state transformation function $f$ might be derived from (1) according to the notation given in (7) as described in [11]. The state-space defined in (7) has been discretized by the Euler approximation where $x_{k+1}$ represents the state at the next sample time $T_s$, and $x_k$ represents the state at the actual sample time:

$$\frac{dx(t)}{dt} = \frac{x_{k+1} - x_k}{T_s}$$  \hspace{1cm} (9)

The function $h$ represents the inverse Park transformation where $\theta_s$ and $\theta_{sl}$ are the stator angle, and the slip angle respectively.

$$h(x(t)) = \begin{bmatrix}
I_{s\alpha} \cos(\theta_s) - I_{s\beta} \sin(\theta_s) \\
I_{s\alpha} \sin(\theta_s) + I_{s\beta} \cos(\theta_s) \\
I_{r\alpha} \cos(\theta_{sl}) - I_{r\beta} \sin(\theta_{sl}) \\
I_{r\alpha} \sin(\theta_{sl}) + I_{r\beta} \cos(\theta_{sl})
\end{bmatrix}$$  \hspace{1cm} (10)

The process and the measurement noises $w$ and $v$ are also included, assumed as random variables with zero mean and $Q$ and $R$ constant covariance matrices defined as follows and tuned according to the guidance given in [14].

$$\begin{align*}
Q &= \text{diag} [0.01, 0.01, 0.01, 0.01, 5e - 4, 0.5, 5e - 4] \\
R &= \text{diag} [0.01, 0.01, 0.01, 0.01]
\end{align*}$$  \hspace{1cm} (11)

The matrix $Q$ indicates the accuracy of the system model: the higher the values of the elements of $Q$, the less accurate is the system model, leading the Kalman filter calculation relying more on the actual measurements than the system estimate. The matrix $R$ represents how the measurements are affected by noise: the higher the elements of $R$, the less confident are the feedback signals. The state estimation is obtained in two steps: a priori prediction estimates and a posteriori estimation, as it has been explained in [11] and [12] and illustrated in fig. 1.

![EKF algorithm](Fig. 1: EKF algorithm)

The matrix $P_0$ represents the initial mean-state errors of the initial state $x_0$. The elements of $P_0$ affect the amplitude of the transient, leaving its duration and steady state performance unaffected. The following values have been selected for the current application based on the guidance given by [14].

$$\begin{align*}
x_0 &= [0.01, 0.01, 0.01, 0.01, 5e - 4, 0.5, 5e - 4]^T \\
P_0 &= \text{diag} [0.01, 0.01, 0.01, 0.01, 5e - 4, 0.01, 5e - 4]
\end{align*}$$  \hspace{1cm} (12)

The initial state $x_0$ and the initial covariance matrix $P_0$ start the procedure calculating the state a priori estimate $\hat{x}_{k+1}$, and the corresponding state error covariance matrix $P_{k+1}$ by means of the Jacobian of the function $f$ defined in (7) and the process covariance matrix $Q$. The Kalman gain is computed and the matrix $H$ is the system outputs matrix derived from (10). The previous calculated a priori state, is updated by means of the Kalman gain and the actual measurements $y$, $h(\hat{x}_{k+1})$ to obtain the a posteriori state $\hat{x}_k$. The a posteriori state error covariance matrix $P_k$ is also calculated and $I$ is the identity matrix.
IV. SENSORLESS AND MODULATED CASCADE-MODEL PREDICTIVE CONTROL

In this section the proposed control strategy is described in detail. Thanks to the rapid advancement of microcontrollers and microprocessors, nowadays complex algorithms can be executed real-time at low cost, giving to the MPC techniques the chance to be exploited both in industry and academia much easier than it could be done in the past. The concept of MPC algorithms is to evaluate the missing variables which are the stator flux vector, the rotor angle, and the rotor rotational speed; the prediction of the future system response to all the possible actuations and the current measurements through its mathematical model; the selection of the voltage vector which fulfil to the optimization criteria based on an objective function. The principal contrast between MPC and others consolidated control techniques is the pre-calculation of the system response and acting in advance to obtain the desired behaviour. The measurements needed are the the stator and rotor currents and voltages. The estimated quantities are the flux vector calculated according to [13], and the mechanical rotor position and speed, which are usually obtained by means of an optical encoder, but in this case the EKF algorithm as defined in III estimates the mentioned mechanical quantities. The stator flux estimation might have been relied on a full-order flux observer as it has been implemented in [15], but to keep the computational load lighter, an improved stator flux estimator scheme, based on the compensation of the DC offset, has been here adopted. The reference current components are calculated from the electromagnetic torque and reactive power which want to be tracked as described in (3) and (2). The easiest way of defining the cost function, is a scalar function which want to be tracked as described in (3) and (2). The control overall scheme is shown in Fig. 2.

The two selected vectors $V_{1,2}$ with the zero vector $V_{0,7}$, are used to evaluate the second stage cost function $g_d$ defined as $g_{d1}$, $g_{d2}$ and $g_{d0}$ for each of the mentioned vectors as follows:

$$ g_{d1} = \left( I_{r_d} - I_{r_d}^{k+1} \right)^2 $$

$$ g_{d2} = \left( I_{r_d} - I_{r_d}^{k+1} \right)^2 $$

$$ g_{d0} = \left( I_{r_d} - I_{r_d}^{k+1} \right)^2 $$

The two selected vectors $V_1,2$ with the zero vector $V_0,7$, are used to evaluate the second stage cost function $g_d$ defined as $g_{d1}$, $g_{d2}$ and $g_{d0}$ for each of the mentioned vectors as follows:

$$ g_{d1} = \left( I_{r_d} - I_{r_d}^{k+1} \right)^2 $$

$$ g_{d2} = \left( I_{r_d} - I_{r_d}^{k+1} \right)^2 $$

$$ g_{d0} = \left( I_{r_d} - I_{r_d}^{k+1} \right)^2 $$

In order to tackle the second difficulty of having non-constant switching frequency, the above expressions are used to calculate the duty cycles of the two selected active vectors and the null vector, in order to minimize the error of the d-current component, which is directly related to the reactive power which wants to be controlled. The duty cycles calculation outlined as an average value on the second stage cost function is shown as follows:

$$ d_1 = \frac{g_{d1}g_{d0}}{g_{d1}g_{d0} + g_{d1}g_{d0} + g_{d2}g_{d0}} $$

$$ d_2 = \frac{g_{d1}g_{d0}}{g_{d1}g_{d0} + g_{d1}g_{d0} + g_{d2}g_{d0}} $$

$$ d_0 = \frac{g_{d2}g_{d0}}{g_{d1}g_{d0} + g_{d1}g_{d0} + g_{d2}g_{d0}} $$

The overall rotor voltage vector signal $V_r$ given to control independently the electromagnetic torque and the reactive power is described as follows:

$$ V_r = V_1d_1 + V_2d_2 + V_0d_0 $$

The control overall scheme is shown in Fig. 2.

V. SIMULATION RESULTS AND DISCUSSION

The proposed control strategy has been implemented by using the software “Matlab/Simulink”. The purpose is to show the reactive power and the electromagnetic torque control at constant speed, highlighting the d and q-current component tracking, and the fidelity of the estimated rotor angle and speed used to execute the algorithm and making it encoderless. The machine parameters used to run the simulations are shown in tab. I.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Symbol</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stator inductance</td>
<td>$L_s$</td>
<td>96.1</td>
<td>mH</td>
</tr>
<tr>
<td>Rotor Inductance</td>
<td>$L_r$</td>
<td>96.1</td>
<td>mH</td>
</tr>
<tr>
<td>Magnetizing Inductance</td>
<td>$L_{m}$</td>
<td>91.4</td>
<td>mH</td>
</tr>
<tr>
<td>Stator Resistance</td>
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<td>$\Omega$</td>
</tr>
<tr>
<td>Rotor Resistance</td>
<td>$R_r$</td>
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<td>Rated Torque</td>
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<td>rpm</td>
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<td>Pole Pairs</td>
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</tbody>
</table>

TABLE I: DFIM parameters
A. Reactive Power and Torque Control

The first simulation has been run as follows: at the beginning of the simulation the DFIM starts rotates at 1490 rpm by means of a prime mover with no control actions required on the electromagnetic torque and the reactive power; at the simulation time $t = 0.5$ s, the reactive power and the electromagnetic torque are controlled while the DFIM keeps rotating at constant speed 1490 rpm; at the simulation time $t = 1.5$ s, reactive power and the electromagnetic torque references change, and the corresponding step response curves are shown in Fig. 3 and 4 respectively. It can be observed, during first time lapse, the reactive power reference varies according to the stator voltage level 230 V connected to the grid through a transformer as shown in the scheme in Fig. 2, while the rotor windings are open circuit and consequently the rotor current components and the electromagnetic torque are zero.

The reactive power is controlled at 4 kVAR and then halved to 2 kVAR in order to reduce the resulting power factor when specific requirements from the grid side have to be met.

The electromagnetic torque provided by the machine goes from 25 Nm to 45 Nm and the corresponding d and q-current components tracking are shown in Fig. 5, and 6.

The speed estimation is shown in Fig. 7, and 8. The rotor angle is estimated by means of the EKF and the error between the estimated and the mechanical angle feedback signal is about 3.1 deg, as it is shown in Fig. 8. It can be observed how during the first time lapse ($0 < \text{time} < 0.5$ s) the state estimate is poor due to the fact that the current control is in open loop, making the system unobservable. When the current control is in close loop, the EKF provides a state estimate which allows to control successfully the wanted variables.
Another simulation has been run to show the effectiveness of the implemented control algorithm under a grid voltage dip. The stator voltage level drop to 80% the initial value of 230V for a time interval of 1 second. It can be seen how the control readily adapts the system to the new condition and track the torque and the reactive power. The control loop is close at the time \( t = 0.5s \); the electromagnetic torque reference is kept constant to \(-25Nm\) acting as a generator, while the reactive power is controlled at \(1kVAr\) sent to the grid. At the time \( t = 1.5s \), the reactive power reference changes its sign and \(1kVAr\) is absorbed from the grid. A stator voltage dip occurs at the time \( t = 2s \) to emulate a grid fault lasting 1s time; the phase stator currents \( I_{sa}, I_{sb}, I_{sc} \) are shown in figure 9. After a certain transient, the control acts in order to track the desired variables, as well as during the voltage dip the control variables are controlled. The reactive power and the electromagnetic torque tracking have been shown in fig. 10 and 11.

The DC-link has been set to \(100V\) to run the simulation. The rotor current components which correspond to the desired reactive power and electromagnetic torque according to (5) and (6) are plotted in fig. 12, and 13.
In this case the speed angle estimation calculated by the EKF is shown in fig. 14, while the rotor angle error results to have an average value of about $3.1^\circ$ as it has been obtained in the previous simulation.

![Fig. 14: Speed estimation.](image)

VI. CONCLUSIONS

This paper investigated on a different approach to implement a sensorless and modulated MPC. It presents a combination of cascaded model predictive control and extended Kalman filter-based sensorless control for doubly fed induction machines. The recent implementation of cascaded-MPC allows avoiding the calculation of weighting factors, and using a sequential optimization given by two separate cost functions instead; considering a modulation stage, a fixed switching frequency is achievable and it is always preferred to reduce the current ripple. The use of a sensorless approach enhances the robustness of the overall strategy bypassing the encoder-related issues, making the whole system more reliable making it suitable for new applications of predictive control into the aforementioned machine drive.

REFERENCES


