Abstract—This paper deals with the experimental realization of a sensorless interior permanent-magnet synchronous motor drive. The motor has been specifically designed to get a wide flux-weakening region, to minimize the drive power rating in spite of a wide speed range. Position and angular speed of the rotor are obtained through an extended Kalman filter. The estimation algorithm requires neither the knowledge of the mechanical parameters, nor the initial rotor position. In the paper, particular emphasis is placed on control algorithms, which are complicated by the motor anisotropy and which have been specifically studied to enhance the overall system performance.

Index Terms—AC motor drives, flux weakening, interior permanent-magnet (IPM) synchronous motor drives, sensorless drives.

NOMENCLATURE

- \( x \): System state vector.
- \( x_e \): Estimated state vector.
- \( u \): System input vector.
- \( y \): System output vector.
- \( F \): Jacobian of system state functional.
- \( K \): Kalman gain matrix.
- \( P \): State error covariance matrix.
- \( Q \): Model noise covariance matrix.
- \( R \): Measurement noise covariance matrix.
- \( i_s \): Stator current vector.
- \( R_s \): Stator resistance.
- \( L_{daq} \): Stator direct, quadrature inductance.
- \( N_{mg} \): Permanent-magnet (PM) flux linkage.
- \( T_c \): Sampling period.
- \( p \): Motor pole pairs.
- \( \omega_{me}, \dot{\omega}_{me} \): Electrical rotor speed, position.
- \( \omega_{e}, \dot{\omega}_{e} \): Estimated electrical speed, position.
- \( \omega_m \): Mechanical speed.

Subscripts and Superscripts

- \( d, q \): Synchronous frame quantities.
- \( \alpha, \beta \): Stationary frame quantities.

I. INTRODUCTION

Several industrial and automotive applications call for drives operating above the motor base speed, in the so-called flux-weakening (FW) region. For permanent-magnet synchronous motors (PMSMs), this reflects in a particular rotor design, with internal PM (IPM) placement. Buried magnets create a rotor anisotropy, which in turn yields several advantages, as extended flux-weakening range, high torque-to-ampere and torque-to-volume ratios [1], [2]. A simple manufacture should also assure a cost-effective end product. Compared to conventional induction motors or surface-mounted PM motors, IPM motors require a more complex drive control. A bright idea for effective operations in the flux-weakening region is reported in [3], in which an external voltage loop is used to calibrate the FW action. The same principle has been exploited in [4], where an IPM motor drive has been applied to an electrical scooter, to minimize the drive power rating in spite of a wide speed range. The demand of inexpensive and reliable drives now pushes applied research toward the elimination of mechanical sensors [5]–[8]. The next challenge for IPM drives is, thus, their reliable and robust sensorless control. Since an IPM motor behaves like a salient-pole machine, stator inductances are functions of the rotor position. Former speed and position observers were based on this feature. The inductance can be obtained by monitoring the stator voltages and currents, and the inductance variations can be used to estimate the rotor position and speed [9], [10].

A promising rule is played by extended Kalman filter (EKF) techniques, for their ability to perform state estimation for nonlinear systems, with inherent robustness against parameters variation. The theoretical aspects of EKF technique have been deeply investigated in the literature [11]–[14]. There are also application examples [14], [15], in which well-known pitfalls, such as the starting from unknown rotor position and the filter matrices tuning have been successfully fixed. It comes out that the residual weakness of sensorless control resides in the low-speed range, in which noise and inverter nonideality still play a harmful role.

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This paper presents the extension of the EKF-based sensorless technique to IPM synchronous motor drives, for FW-oriented applications. The implicit idea is to exploit the excellent properties of EKF at high speed, that is, far from standstill critical neighboring.

The task is not trivial, since the rotor anisotropy complicates the mathematical model. In Section II, a short review of IPM motor structure is given. Section III recalls the EKF fundamentals, and the innovative application to a synchronous rotating reference frame. Section IV presents the hardware structure. Experimental results, obtained on a laboratory prototype, are reported in Section V. Conclusive remarks close the paper.

II. IPM SYNCHRONOUS MOTOR

Interior PMSMs give excellent performance in terms of torque-to-ampere and torque-to-volume ratios, minimizing both the inverter cost and the drive dimensions. The simple construction and mechanical robustness make them ideal for high-speed applications. The most suitable motor structure considers an anisotropic rotor, with a fairly reduced PM flux. Fig. 1 shows two pole pitches of the motor used in the experimental setup.

A commercial 24-slot induction motor stator has been used, with a single-layer winding. Motor design has been carried out by a finite-element analysis (FEA) tool, which has also provided a first rough parameters identification. They have been validated by a batch of measurements, carried out on the prototype. The motor data are reported in Appendix A.

Let us place the direct \( (d) \) axis on PM flux direction, while quadrature \( (q) \) axis leads \( d \) axis by \( \pi/2 \) electrical degrees. Fig. 2 reports the flux paths, produced by the PM only and by \( q \)-axis current, respectively.

As stated before, buried magnets yield different paths for \( d \) and \( q \) axes. In particular, the quadrature path runs mostly in the stator and rotor iron and, thus, the quadrature inductance \( L_q \) is higher than \( L_d \), and it is also more subjected to saturation than \( L_d \). Direct and quadrature flux linkages as functions of currents for the IPM motor of Fig. 2 are reported in Fig. 3.

The curves represented in Fig. 3 put into evidence that \( L_d \) can be roughly kept constant in the motor model, while \( L_q \) saturation cannot be neglected at all. Actually, the \( L_d \) behavior is worth closer analysis. Fig. 2(a) shows that the PM flux saturates the iron ribs in the rotor. Let us consider \( i_q = 0 \). When \( i_d \) is negative, its contribution to the flux in the iron ribs is concordant to the PM flux, and the ribs remain saturated, yielding a constant \( L_d \) (Fig. 3). When \( i_d \) is positive, the related flux through the iron ribs weakens the flux produced by the PM, resulting in a partial iron desaturation and a subsequent \( L_d \) increase. For greater values of \( i_d \), the iron ribs are again directly saturated, by the direct current \( i_d \) itself, and \( L_d \) again experiences a linear behavior. Tests with different levels of \( i_d \) and \( i_q \) currents have revealed a fairly low magnetic cross coupling between the \( d \) and \( q \) axes, which will be neglected in the following. The effect of this simplification will be ascribed to the model imperfection.

III. EKF DESIGN CONSIDERATIONS

The motor model can be derived both in a stationary orthogonal reference frame \( \alpha, \beta \), fixed to the stator, or in a synchronous reference frame \( d, q \), fixed to the rotor flux. Usually, the EKF algorithm for a PMSM is derived for the former representation [12]–[14]. In the following, some considerations on this crucial choice are developed. Advantages and drawbacks of each solution are depicted.

For both models, the so-called infinite inertia hypothesis will be assumed. This is the same as neglecting the influence of speed variations within the time step \( T_c \) in the model itself. The robustness of the EKF convergence to approximate load equations has already been documented in [14]. When not otherwise specified, inductances will be considered independent from currents, i.e., saturation effects will be neglected. Actually, a precise mathematical model should consider either apparent \( (\Delta N/I) \) and differential \( (d\Delta/dI) \) inductances, which could both be derived from the curves of Fig. 3. The complexity would be unbearable. It has been chosen to ascribe this imperfection to the model and exploit the EKF robustness to get a good state estimation, in spite of the model approximations.
A. IPM Motor Stationary Model

The two axes currents \(i_a, i_b\), the rotor electrical position \(\theta_{me}\), and speed \(\\omega_{me}\) can be selected as system state variables. With the above assumptions, the two IPM motor voltage equations and the two load dynamic equations can be rearranged in a canonical state-space form as shown by (1), at the bottom of the page, where

\[
\begin{align*}
L_1(\theta_{me}) &= \frac{L_d - L_q}{2} \sin(2\theta_{me}) \\
L_2(\theta_{me}) &= \frac{L_d - L_q}{2} \cos(2\theta_{me}) \\
B_1(\theta_{me}) &= -L_1(\theta_{me})(L_d - L_q) \\
B_2(\theta_{me}) &= L_2(\theta_{me})(L_d + L_q) + \frac{(L_d - L_q)^2}{2} \\
C_1(\theta_{me}) &= L_2(\theta_{me})(L_d + L_q) - \frac{(L_d - L_q)^2}{2} \\
C_2(\theta_{me}) &= L_1(\theta_{me})(L_d + L_q) \\
D_1(\theta_{me}) &= \frac{L_d + L_q}{2} - L_2(\theta_{me}) \\
D_2(\theta_{me}) &= \frac{L_d + L_q}{2} + L_2(\theta_{me}).
\end{align*}
\]

(2)

(3)

(4)

(5)

(6)

(7)

(8)

(9)

It is worth recalling that, in practice, inductance \(L_q\) is sensible to saturation (Fig. 3) and, therefore, it would be in general a function of \(i_a, i_b\) and \(\theta_{me}\), with further model complication. The phase voltages \(u_a, u_b\) represent the system input, while \(i_a, i_b\) can be considered as the system output.

The influence of rotor position on the stator inductances complicates the Jacobian matrix of the system, which is an essential element in the prediction step of the EKF algorithm. The CPU time required for the four-by-four Jacobian matrix calculation could overwhelm the digital signal processor (DSP) time-sharing routine management. As a spot, the explicit expression of the Jacobian element \(F_{1,3}\) is given hereafter

\[
F_{1,3} = \frac{1}{L_d L_q} \left[ -B_2 i_a - B_1 i_b + D_1 L_{mq} \sin(\theta_{me}) \\
+ L_1 L_{mq} \cos(\theta_{me}) \right]
\]

(10)

and symbols are defined by (2)–(9). It can be proved that no modification occurs to the innovation step respect to the isotropic case, described for example in [14]. As a design hint, it has been found that the amount of floating-point operations (FLOPS) in the EKF prediction step for the IPM motor is almost triple the case of the isotropic motor.

B. IPM Motor Synchronous Model

In order to obviate the large computing time requested by the EKF algorithm in the stationary reference frame, and to simplify the formal expression of the equations, the impact of a coordinates transformation has been evaluated. Then, the whole EKF algorithm has been rewritten in the synchronous frame and the new state vector becomes \(x = [\dot{i}_d \dot{i}_q \omega_{me} \dot{\theta}_{me}]^T\). The system state equations are as follows:

\[
\dot{x} = f(x(t), x(t) + Gu(t))
\]

(11)

\[
y(t) = Hx(t)
\]

where \(u = [u_d u_q]^T\) and \(y = [\dot{i}_d \dot{i}_q]^T\) are the input and output vectors, respectively. The system state matrices are defined as

\[
H = \begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0
\end{bmatrix}
\]

(12)

\[
f(x(t)) = \begin{bmatrix}
-\frac{L_d}{L_d} & \omega_{me} & \frac{L_d}{L_d} & 0 & 0 \\
-\frac{L_q}{L_q} & \frac{L_d}{L_d} & -\frac{L_q}{L_q} & 0 & 0 \\
0 & 0 & 0 & 0 & 1
\end{bmatrix}
\]

(13)

\[
G = \begin{bmatrix}
\frac{1}{L_d} & 0 & 0 & 0 & \frac{1}{L_q}
\end{bmatrix}^T.
\]

(14)

Although a remarkable change in algorithm syntax, these equations appear greatly simpler than those expressed by (1). The choice of the input vector \(u\) is worth a deeper insight. In the proposed implementation, the measurement of the phase voltages is replaced by the reference space-vector modulation (SVM) signals. The actual \(dq\) voltage reference delivered by current control may be altered by SVM saturation and dead-time routines. Therefore, the use of corrected quantities in the \(dq\) frame implies an additional inverse \(dq/\alpha\beta\) transformation, operated on voltage references directly derived from definitive SVM timings.

C. Extended Kalman Filter Equations

The extended Kalman filter is an optimal estimator in the least-square sense for estimating the states of dynamic nonlinear systems. It consists of two main parts, namely, the prediction step and the innovation step. The former performs a state estimation based on the best available motor model, while the latter filters and corrects the predicted state by measuring the actual motor phase currents.

In this work, the EKF code originally developed for a sensorless surface-mounted PM motor [14] has been modified to
extend the EKF to the IPM motor. For a fully digital implementation, the system model (11) has been discretized every $kT_c$, by a rectangular approximation

$$\begin{align*}
x_{k+1} &= F_{d}(x_k, x_{k-1}) + G u_k + v_k \\
y_k &= H x_k + \mu_k.
\end{align*}$$

According to the EKF theory, the model (15) also includes a statistical description of inaccuracies. As usual, in the absence of more precise system knowledge, both model and measurement disturbances have been described by the zero-mean Gaussian random vectors $v_k$ and $\mu_k$, whose variance matrices are $Q$ and $R$, respectively. The discretized system matrix $F_d$ is derived from (13) as follows:

$$F_d(x_k) = 1 + T_c f(x(kT_c)).$$

At time $t_k = kT_c$ the optimal state estimate $x_{e|k|k}$ and the estimation error covariance matrix $P_{k|k}$ are obtained through a simplified version of the EKF algorithm [15], summarized in Table I.

<table>
<thead>
<tr>
<th>TABLE I</th>
<th>EKF ALGORITHM</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Prediction step</strong></td>
<td></td>
</tr>
<tr>
<td>$x_{e</td>
<td>k</td>
</tr>
<tr>
<td>$P_{k</td>
<td>k-1} = P_{k-1</td>
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<tr>
<td><strong>Innovation step</strong></td>
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<tr>
<td>$x_{e</td>
<td>k</td>
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<tr>
<td>$P_{k</td>
<td>k} = P_{k</td>
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<td><strong>Kalman gain</strong></td>
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<tr>
<td>$K_k = P_{k</td>
<td>k-1} H' (H P_{k</td>
</tr>
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</table>

The prediction of the state covariance requires the online computation of the Jacobian matrix $F$, defined as

$$F_{k-1} = \frac{\partial f(x(t)) x(t)}{\partial x} |_{x=x_{e|k-1|k-1}}.$$ (17)

For the sake of completeness, the explicit calculation of (17) is drawn in Appendix B. The main disadvantage of the synchronous model resides in the innovation step of the EKF algorithm, where predicted and actual currents are compared. Opposite to the stationary frame case, the measured quantities need to undergo a coordinate transformation, in which the estimated electrical position itself is used. In the presence of uncertainties in the model, this may yield a constant error in the position estimate. It has been found that the EKF algorithm shows the greatest sensibility to mismatch.

By an offline comparison between estimated and measured position, for different levels of the $i_q$ current, such sensibility has been exploited to get a fine tuning of the relation $L_q(i_q)$, which is used instead of a constant $L_q$ value in (15). Fig. 4 shows the steady-state error between the estimated and actual position ($\theta_{me} - \theta_{me_{true}}$), as a function of time, at no load and after a step of 50% of rated torque. Case (a) in Fig. 4 refers to a constant $L_q$ in the model and (b) uses online $L_q(i_q)$ retrieval from a memory lookup table (LUT). Even if (15) remains a simplified model, the use of $L_q(i_q)$ yields an effective abatement of the steady-state position error estimate.

IV. DRIVE STRUCTURE

The experimental IPM motor drive designed for this work featured a wide flux-weakening region. As a counterpart, the presence of both reluctance and PM torque requires involved control strategies, to guarantee effective drive operations at all conditions. The block schematic of the complete drive structure is reported in Fig. 5.

The specific target of this work was the test of EKF behavior at high speed. A smooth transition from the constant torque to the flux-weakening region is guaranteed by an external voltage closed-loop regulation, as depicted in Fig. 5. The phase voltage amplitude is compared with a limit, proportional to the dc-link voltage. As mentioned before, accurate dead-time compensation allows the use of reference voltages instead of the actual ones. When the limit is exceeded, the error is integrated and a proper flux-weakening action is triggered, through the delivery of an additional direct current component $i_{d,q}$ (Fig. 5). The choice of the voltage limit $K_v$ has to be harmonized with that of the integral gain $K_i$, which in turn must preserve the overall system stability. It is worth noting that the greater $K_v$, the closer

![Figure 4](image1)

**Fig. 4.** (a) Position error due to $L_q$ saturation. (b) LUT compensation.

![Figure 5](image2)

**Fig. 5.** IPM motor sensorless drive block schematic.
the voltage limit to the inverter saturation. If this is the case, a prompt flux-weakening action is required. Of course, this calls for higher values of \( K_{iu} \), whose upper limit is yet imposed by system stability. In this work, it was set at \( K_{iu} = 0.51 \). As a simple rule of thumb, it is reasonable to choose \( K_{iu} \) so that in the presence of the maximum input error the maximum flux-weakening component \( I_N \) is delivered within a fixed time. This time is preferably much larger (20–30 times) than the \( i_d \) rise time \( t_{ri} \), to maintain a good separation between the voltage and the current control loops dynamic. Since the amplitude of the maximum undistorted voltage (before entering the hexagonal saturation) for an SVM inverter is \( U_{dc}/\sqrt{3} \), the integral gain can be calculated as

\[
K_{iu} = \frac{I_{df,N}}{30t_{ri} \left(1/\sqrt{3} - K_v\right) U_{dc}}. \tag{18}
\]

Several simulation results have confirmed that if \( K_{iu} \) is chosen sensibly smaller than (18), the voltage loop is no longer able to follow the transient voltage produced by the current control, and inverter saturation occurs. Conversely, if the voltage loop is too fast, instability due to system delays has been experienced.

Another crucial parameter is the maximum negative current \( i_{df,min} \), which limits the output of the integrator (Fig. 5). It is worth performing an adaptive limitation, according to the actual working point, by setting

\[
i_{df,min} = I_N - \bar{i}_{d,n} \tag{19}
\]

where \( I_N \) is the rated stator current and \( \bar{i}_{d,n} \) is the direct current that the current reference generator would give in absence of voltage limitation. Several experimental tests have highlighted that if a fixed limitation is chosen instead, instability may arise at load detaching during operation far above the base speed [4].

### A. Current Reference Generator

In the drive schematic of Fig. 5, the output of the proportional–integral (PI) speed regulator is the (signed) amplitude of the stator current space vector \( \vec{i}_s \). The well-known maximum torque per ampere strategy has been used to link the PI output to the torque production. For a given \( i_d, i_q \) pair and under the hypothesis of system linearity the electromagnetic torque is given by

\[
\tau = \frac{3}{2} \frac{\lambda_{mg}}{i_d} \left( L_q - L_d \right) i_d \tag{20}
\]

The direct current reference \( i_q^* \) is expressed as function of \( i_q^* \) and the current reference amplitude \( i_s^* \)

\[
i_q^* = -\sqrt{(i_{d})^2 - (i_{q})^2}. \tag{21}
\]

It is possible to determine the value of the reference \( i_q^* \) that maximizes the torque, by imposing

\[
\frac{\partial \tau}{\partial i_q^*} = 0 \tag{22}
\]

which yields

\[
i_q^* = \text{sign}(\tau) \sqrt{\left(\frac{2\lambda_{mg}}{L_q - L_d}\right)^2 - i_{d,q}^2 + \sqrt{i_{d,q}^4 + 8(i_{d,q}^*)^2}} \tag{23}
\]

where \( i_{d,q} = \lambda_{mg}/(L_q - L_d) \). It is soon evident that, in the presence of deep saturation of the \( q \) path, (21) and (23) are only rough and ready approximations of the correct \( d-q \) current references. They have been taken as the starting point for the on-the-field tuning of the drive. The IPM motor drive has been operated in current mode in a test bench capable of torque measurement. For each reference value of the stator current, the couple \( i_d, i_q \) which yields the maximum motor torque production has been selected. Fig. 6 shows the resulting \( d-q \) axes current references as a function of stator current amplitude.

The \( i_d, i_q \) references of Fig. 6 have been stored in an LUT, which has been used as an optimal current reference generator in the constant torque region.

### B. Current Control

A proper current control can be achieved in the synchronous \( d-q \) coordinates system by conventional PI controllers. In this work, PI parameters have been tuned to get a bandwidth of approximately 600 Hz, with simultaneous two-phase current sampling at 7.2 kHz, which corresponds to \( T_c = 140 \mu s \). Sampling is triggered at the beginning of each SVM switching period, so that the measured signals are less affected by the ripple due to voltage modulation.

Particular care has been paid to the management of current regulators output and integral limitation. The SVM algorithm inherently constrains the produced voltage vector within a hexagonal boundary.

Antiwindup management is obtained by comparing the actual voltage references with the input errors. In the presence of saturation, the control freezes the integral action whenever the voltage reference and the input error have the same sign [4].

In the synchronous frame, the motor model presents coupling terms between \( d \) and \( q \) axes. These terms can be considered as disturbances that complicate the design of PI controllers and reduce the overall dynamic performances. A decoupling and feedforward algorithm has been implemented in the drive, as sketched in Fig. 7.
A precise decoupling action (blocks $\text{DC}_1$ and $\text{DC}_2$) has been obtained by including the $L_{dq}$ inductance saturation.

V. EXPERIMENTAL RESULTS

The EKF algorithm and the speed and current control loops, including the dead-time compensation, have been implemented on a TMS320C31 floating-point DSP, with 33.3-ns instruction cycle. All software procedures are written in C language, optimized for shortest execution time. Digital I/O management and switching pattern generation are handled by a slave fixed-point TMS320P14 DSP, with 160-ns instruction cycle, featuring six pulselength-modulation (PWM) channels, with 80-ns period resolution, and 16 individual bit-selectable I/O. Control software routines for the slave processor have been written in Assembly language, for a closer link with the embedded hardware peripherals. Phase currents have been measured by two parallel auto-calibrating 16-bit 10-μs A/D converters, while speed reference and dc-link bus voltage are measured by two 12-bit 3-μs A/D converters. From the software side, the first step was to accurately tune the current and speed PI regulators, by using a resolver as a position sensor. While maintaining the drive closed on measured quantities, a first batch of experiments was devoted to find out the range of values of $Q$ matrix that shorten the EKF convergence. A fine tuning of $Q$ and $R$ matrices was then obtained by minimizing the settling time of the speed control loop, with feedback closed on estimated quantities [15].

When implemented in the stationary reference frame, the EKF may exhibit a wrong convergence to the solution (−$\omega_1$, $\theta + \pi$). As found in [14], the wrong solution is maintained by the innovation step that continuously updates the estimate, compensating for the gap between the actual and predicted currents and voltages. A side advantage of the EKF implementation in the $d$–$q$ reference is that the wrong solution, also known as “slip condition,” does not fit the voltage equations of the model, thus preserving the system from a misleading convergence.

The correct operation of the sensorless drive in the flux-weakening region is documented in Fig. 8. It reports a no-load acceleration ramp, from 0.15 to 2.2 times the base speed $\Omega_B$.

The same figure also shows the $i_d$ current component generated by the current reference generator during the speed ramp. It is easy to recognize that the delivery of the flux-weakening component $i_{df}$ is triggered around the base speed $\Omega_B$. The $i_{df}$ component is added to the actual $i_d$ reference which, according to Fig. 6, is committed to getting the maximum motor torque production. At the end of the speed ramp the cancellation of the inertial torque acts as a load detaching. The amplitude of the current vector suddenly reduces, and less flux-weakening component is required, as is evident in the lower part of Fig. 8.

As mentioned earlier, the voltage loop is committed to avoid SVM saturation. Fig. 9 reports the phase voltage amplitude during an acceleration from 0 to 2.2 $\Omega_B$.

The steady-state fixed voltage limitation was moving along smoothly, without harmful effects on current control.

The last batch of measurements was carried out to investigate the drive response to different load conditions, in the flux-weakening region. Fig. 10 shows the speed and $i_q$ current behavior to a positive load step variation of 30% $T_B$, at 1.65 $\Omega_B$.

The transient is well recovered and the EKF maintains the convergence, also demonstrating excellent properties in this particular application.
VI. CONCLUSION

IPM drives are gaining widespread interest for their inherent flux-weakening capability. Thus, they can be used in applications where a reduced torque is needed above the base speed. In this range, the disadvantages commonly claimed for the EKF-based sensorless drives, among which is the poor robustness at low speed, are of minor relevance. On the other hand, the control of an IPM motor is more involved, since it features both PM and reluctance torque. The voltage equations are different from those of the surface-mounted PM motors. For IPM motors, the EKF applications presented in the literature are not straightforwardly applicable. This paper has given an insight into the different possible ways of implementation of an EKF-based sensorless drive for an IPM motor drive. The work implied an extensive theoretical approach, with a substantial differentiation from those existing in the literature. The most effective solution has been highlighted and tested on a laboratory prototype, realized for the purpose. The paper has reported both the mathematical background and the experimental results. The industrial manufacture of the prototype with a business partner is already under consideration.

APPENDIX A

MOTOR DATA AND PARAMETERS

The IPM motor prototype features neodymium–iron–boron (NeFeB) rare-earth magnets. The main parameters are reported in Table II.

The dc link was fixed at 370 V, monitored online to keep the SVM inverter gain constant.

APPENDIX B

CALCULATION OF THE JACOBIAN MATRIX $F$

At time $t_{k-1} = (k-1)T_c$, the Jacobian matrix $F$ is defined as in (17), reported here for ease of reference

$$F_{k-1} = \frac{\partial f(x(t))x(t)}{\partial x} \bigg|_{x=x_e[k-1]} = \frac{\partial x}{\partial x} \bigg|_{x=x_e[k-1]} = \begin{bmatrix} -R \cdot \omega_{me} L_q i_q + \frac{u_d}{L_d} & 0 \\ -\omega_{me} (L_d \cdot \omega_{me} L_q i_q + \frac{u_d}{L_d}) & \frac{R L_q}{L_q} + \frac{u_d}{L_q} \end{bmatrix} \cdot$$

From (13) and (14), it holds that

$$\dot{x} = \begin{bmatrix} \frac{R}{L_d} \cdot \omega_{me} L_q i_q + \frac{u_d}{L_d} \\ -\omega_{me} (L_d \cdot \omega_{me} L_q i_q + \frac{u_d}{L_d}) \\ \frac{R L_q}{L_q} + \frac{u_d}{L_q} \end{bmatrix}$$

$F$ is, therefore, a four-by-four matrix

$$F = \begin{bmatrix} F_{11} & F_{12} & F_{13} & 0 \\ F_{21} & F_{22} & F_{23} & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & F_{13} & 0 \end{bmatrix}$$

whose elements at time $t_{k-1} = (k-1)T_c$ can be derived as follows:

$$F_{11} = \frac{\partial}{\partial i_d} \left( \frac{di_d}{dt} \right) \bigg|_{x=x_e[k-1]} = \frac{R}{L_d}$$

$$F_{12} = \frac{\partial}{\partial i_q} \left( \frac{di_d}{dt} \right) \bigg|_{x=x_e[k-1]} = \frac{L_q \cdot \omega_{me} i_q}{L_d}$$

$$F_{13} = \frac{\partial}{\partial \omega_{me}} \left( \frac{di_d}{dt} \right) \bigg|_{x=x_e[k-1]} = \frac{L_q}{L_d} \cdot \omega_{me} i_q$$

$$F_{21} = \frac{\partial}{\partial i_q} \left( \frac{di_q}{dt} \right) \bigg|_{x=x_e[k-1]} = -\frac{R}{L_q}$$

$$F_{22} = \frac{\partial}{\partial \omega_{me}} \left( \frac{di_q}{dt} \right) \bigg|_{x=x_e[k-1]} = -\frac{L_d \cdot \omega_{me} i_q}{L_q}$$

$$F_{23} = \frac{\partial}{\partial \omega_{me}} \left( \frac{di_q}{dt} \right) \bigg|_{x=x_e[k-1]} = \frac{-L_d \cdot \omega_{me} i_q}{L_q} + \frac{\omega_{me} L_q i_q}{L_q}$$

$$F_{33} = \frac{\partial}{\partial \omega_{me}} \left( \frac{di_q}{dt} \right) \bigg|_{x=x_e[k-1]} = 1.$$

REFERENCES


