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Influence of Covariance-Based ALS Methods in the Performance of Predictive Controllers with Rotor Current Estimation

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***Abstract*—The use of on-line rotor current estimators with predictive current controllers has been very recently stated in five-phase induction motor drives, where the closed-loop performance of the system is improved using sub-optimal estimators based on Kalman filters. In this work, the interest of using optimization methods in the definition of the Kalman filter, like the covariance technique, is analyzed. Obtained system performances using optimal and sub-optimal rotor current estimators are experimentally compared.**

***Index Terms*—Kalman filter, multiphase drives, optimal covariance estimation, predictive current control.**

I. Introduction

The interest in model predictive control like an alternative in power converters and drives to field oriented or direct torque controllers has been growing up in the last decade [1]. In the multiphase drives' research field the predictive current control (PCC) technique represents the most popular case study [2]. PCC uses a state-space representation of the drive to optimize the control action. The estimation of non-measurable state components, typically rotor currents, is a complex problem that has been recently solved using different methods for the on-line estimation of the rotor variables [3, 4]. These studies illustrate the benefits in using rotor current observers like Kalman filters (KF), although sub-optimal techniques were applied during the necessary tuning process of these observers.

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In this paper, a rotor current observer based on KF is included in the conventional PCC technique, being a remarkable contribution of the work the optimal design of the KF by means of a robust covariance estimation method. In [4] the KF gains are tuned based on trial and error strategies, using some prior expert knowledge or hypothesis about the noise. The proposed method is based on the estimation of true covariances in the control system, which has not been previously tested in the multiphase electrical drives' field. A five-phase induction machine (IM) is used as a case example, but the obtained results can be extrapolated to different electrical machines.

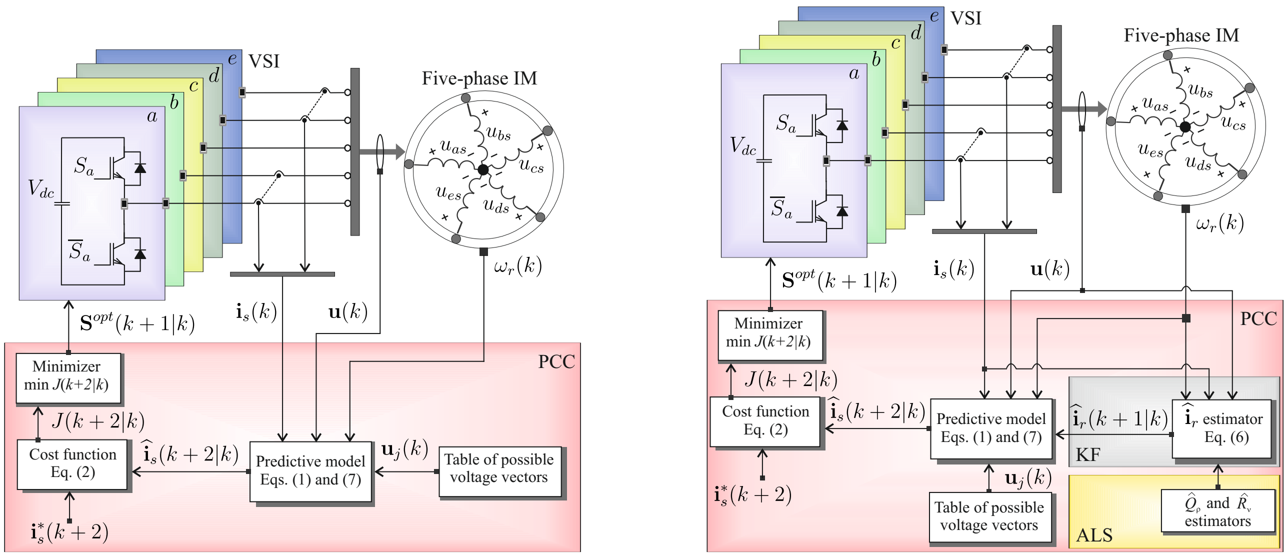
II. Predictive Current Control With Optimal Rotor Current Estimation

A five-phase IM drive with distributed windings equally displaced $\vartheta = 2\pi/5$ and powered by a five-phase two-level voltage source inverter (VSI) is used. A block diagram of the conventional PCC technique detailed in [2] is shown in Fig. 1(a) together with a schematic representation of the five-phase IM drive. This PCC controller utilizes a discrete model of the system, named predictive model, to predict (at time k) the future values (time $k+1$) of the machine's stator currents, $\widehat{\mathbf{i}}_s(k+1|k)$, for each possible stator voltage, $\mathbf{u}(k)$. Thus, the predictive model relies on the knowledge of some variables such as the measured stator currents $\mathbf{i}_s(k)$ and electrical speed $\omega_r(k)$, as it is shown in the following equation:

$$\widehat{\mathbf{i}}(k+1|k) = \mathbf{A}\,\mathbf{i}(k) + \mathbf{B}\,\mathbf{u}(k) \tag{1}$$

where $\mathbf{i} = (i_{\alpha s}, i_{\beta s}, i_{xs}, i_{ys}, i_{\alpha r}, i_{\beta r})$, $\mathbf{u} = (u_{\alpha s}, u_{\beta s}, u_{xs}, u_{ys})$, and $\mathbf{A}$ and $\mathbf{B}$ are matrices that depend on the electrical parameters of the machine and the sampling time T_s. Matrix $\mathbf{A}$ also depends on the actual value of $\omega_r(k)$, and it must be calculated every sampling time. A detailed explanation of the machine model is not included here for the sake of conciseness and can be found in [3]. It is worth stating that, according to the well-known vector space decomposition approach [4], the electromechanical energy conversion variables are mapped into the $\alpha-\beta$ subspace, meanwhile the current components in the $x-y$ subspace in the analyzed electrical machine are related to harmonic losses.

In conventional PCC the computation of the control signal takes a significant amount of time which is comparable with



(a) (b)

Fig. 1. Schematic diagram of the five-phase IM drive and blok diagram of (a) the conventional PCC technique applied in [2] for the regulation of five-phase IM drives, and (b) the proposed PCC technique that uses a KF-based optimum rotor current estimator.

T_s, so a second-step ahead prediction of the stator currents $\widehat{\mathbf{i}}_s(k+2|k)$ is required [3]. In the existing literature this term is obtained iteratively using the predictive model. Regarding the rotor quantities that appear in (1), most research works rely on aggregating all unmeasurable quantities into one term that is tracked, although the use of estimators for rotor quantities has been recently proposed in [4], at the expense of a remarkable increment of the computational cost of the implemented controller (by 36 % of the total). Once the second-step ahead prediction is obtained, an optimization process is applied every sampling period, where a cost function J is calculated for all 32 (2^5) possible stator voltages to obtain a desired reference trajectory $\mathbf{i}_s^*(k)$. The voltage vector that minimizes the cost function is selected and applied to the system during the next sampling period. The cost function can be defined in different ways, although the deviation between reference and predicted stator currents is normally used as follows:

$$J(k+2|k) = \parallel \widehat{\mathbf{e}}_{\alpha\beta} \parallel^2 + \lambda_{xy} \parallel \widehat{\mathbf{e}}_{xy} \parallel^2 \tag{2}$$

being $\widehat{\mathbf{e}}$ the second-step ahead predicted error computed as $\widehat{\mathbf{e}} = \mathbf{i}_s^*(k+2) - \widehat{\mathbf{i}}_s(k+2|k)$, and λ_{xy} a tuning parameter that allows to put more emphasis on $\alpha-\beta$ or $x-y$ subspaces [1, 5].

A. Influence of Rotor Current in Prediction

As commented before, the predictive model given by (1) cannot be used for producing predictions if rotor currents are not measurable (as it is the normal case) unless some estimation of rotor currents is provided. PCC methods have overcome this problem by aggregating all non-measurable terms in one factor that is later tracked and updated ($\mathbf{G}$). For this purpose, the stator current vector is divided into a measurable part, $\mathbf{i}_s = (i_{\alpha s}, i_{\beta s}, i_{xs}, i_{ys})$, and a non-measured part, $\mathbf{i}_r = (i_{\alpha r}, i_{\beta r})$, and the predictive model takes the following form:

$$\widehat{\mathbf{i}}_s(k+1|k) = \bar{\mathbf{A}}\,\mathbf{i}_s(k) + \bar{\mathbf{B}}\,\mathbf{u}(k) + \widehat{\mathbf{G}}(k|k) \tag{3}$$

with appropriate $\bar{\mathbf{A}}$ and $\bar{\mathbf{B}}$ matrices obtained from (1) using elemental algebra. The $\widehat{\mathbf{G}}(k|k)$ term is approximated holding its previous value $\widehat{\mathbf{G}}(k-1|k)$ computed at time k, using past values of measured variables:

$$\widehat{\mathbf{G}}(k-1|k) = \mathbf{i}_s(k) - \bar{\mathbf{A}}\,\mathbf{i}_s(k-1) - \bar{\mathbf{B}}\,\mathbf{u}(k-1) \tag{4}$$

B. Rotor Current Estimator Based on Kalman Filter

Instead of using the tracking and updating technique proposed in conventional PCC methods, a KF is used in [4] as it is shown in Fig. 1(b), where the $\widehat{Q}_\rho$ and $\widehat{R}_\nu$ estimators block were not taken into account. The rotor currents ($\widehat{\mathbf{i}}_r$) are estimated every sampling time using the measured rotor speed ω_r, stator phase currents $\mathbf{i}_s$ and stator phase voltages $\mathbf{u}$. Considering uncorrelated processes and zero-mean Gaussian measurement noises, the machine's model (1) can be written as follows:

$$\begin{aligned} \widehat{\mathbf{i}}(k+1|k) &= \mathbf{A}\,\mathbf{i}(k) + \mathbf{B}\,\mathbf{u}(k) + \mathbf{H}\,\rho(k) \\ \mathbf{i}_s(k) &= \mathbf{C}\,\mathbf{i}(k) + \nu(k) \end{aligned} \tag{5}$$

being $\rho(k)$ the disturbance vector (process noise), $\nu(k)$ the measurement noise, and $\mathbf{H}$ the noise weight matrix.

Dividing the current vector in two parts, $\mathbf{i}_{\alpha\beta s} = (i_{\alpha s}, i_{\beta s})$ and $\mathbf{i}_{\alpha\beta r} = (i_{\alpha r}, i_{\beta r})$, the dynamic of the reduced-order rotor current estimator can be defined in the following way:

$$\begin{aligned} \widehat{\mathbf{i}}_{\alpha\beta r}(k+1|k) &= (\mathbf{A}_{22} - \mathbf{K}(k)\,\mathbf{A}_{12})\,\widehat{\mathbf{i}}_{\alpha\beta r}(k) \\ &+ \mathbf{K}(k)\,\widehat{\mathbf{i}}_{\alpha\beta s}(k+1|k) \\ &+ (\mathbf{A}_{21} - \mathbf{K}(k)\,\mathbf{A}_{11})\,\mathbf{i}_{\alpha\beta s}(k) \\ &+ (\mathbf{B}_2 - \mathbf{K}(k)\,\mathbf{B}_1)\,\mathbf{u}_{\alpha\beta}(k) \end{aligned} \tag{6}$$

where $\mathbf{K}(k)$ represents the KF gain matrix and $\mathbf{u}_{\alpha\beta} = (u_{\alpha s}, u_{\beta s})$. This estimation of rotor currents can now be used to produce the second-step ahead prediction for the stator current as:

$$\begin{aligned}\widehat{\mathbf{i}}_{\alpha\beta s}(k+2|k) =& \mathbf{A}_{11}\,\widehat{\mathbf{i}}_{\alpha\beta s}(k+1|k) + \mathbf{A}_{12}\,\widehat{\mathbf{i}}_{\alpha\beta r}(k+1|k) \\ &+ \mathbf{B}_1\mathbf{u}_{\alpha\beta}(k+1)\end{aligned} \quad (7)$$

The KF gain matrix is calculated at each sampling time in a recursive manner using an estimation of two covariance matrices of the noises called $\widehat{Q}_\rho$ and $\widehat{R}_\nu$. These covariances are defined as the expected values of the disturbance and the measurement noise as $Q_\rho = \mathrm{cov}(\rho) = \mathrm{E}\{\rho \cdot \rho^T\}$ and $R_\nu = \mathrm{cov}(\nu) = \mathrm{E}\{\nu \cdot \nu^T\}$, being the KF gain matrix obtained using the following steps:

$$\mathbf{\Gamma}(k) = \varphi(k) - \varphi(k)\cdot\mathbf{C}^T(\mathbf{C}\cdot\varphi(k)\cdot\mathbf{C}^T + \widehat{R}_\nu)^{-1}\cdot\mathbf{C}\cdot\varphi(k) \quad (8)$$

$$\mathbf{K}(k) = \mathbf{\Gamma}(k)\cdot\mathbf{C}^T\;\widehat{R}_\nu^{-1} \quad (9)$$

$$\varphi(k+1) = \mathbf{A}\,\mathbf{\Gamma}(k)\cdot\mathbf{A}^T + \mathbf{H}\,\widehat{Q}_\rho\cdot\mathbf{H}^T \quad (10)$$

This completes the required relations for the state estimation, where the minimum estimation errors depends on $\mathbf{K}(k)$ and it is guaranteed if the estimated noise covariances and the initial condition of the state covariance ($\varphi(0)$) are known. Notice that the interest of using KF in the context of the stator current prediction and PCC is presented in [4], where the KF was hardly tuned using initial values, but the obtained experimental results encouraged future research towards establishing the KF as a tool of choice for the definition of predictive controllers in electrical drives.

C. Proposed optimization procedure

The KF optimal implementation is difficult due to the lack of information about the noises. The use of an optimal estimation using KF requires the estimation of $\widehat{Q}_\rho$ and $\widehat{R}_\nu$, which can be done through Bayesian, maximum likelihood, covariance matching or correlation techniques. Bayesian and maximum likelihood are complex and require much data. Covariance matching uses the residuals of the state estimation problem, but it provides biased estimates of the true covariances, resulting in a non optimal KF tuning. In [6] the Autocovariance Least Squares method (ALS) is proposed to provide unbiased estimates with the lowest variance, guaranteeing optimal KF tuning. The ALS method is done off-line based on data gathered from closed-loop operation. The positive semi-definiteness of the covariance estimation is guaranteed by adding constraints to the ALS problem. Note that without this method, and given the current level of sophistication of the predictive control methods, the use of KF is incomplete, following the Bellman optimality principle. Furthermore, the KF algorithm computational cost is the same whereas the system performance improves.

The initial estimation of disturbance covariances ($\widehat{Q}_{\rho 0}$ and $\widehat{R}_{\nu 0}$) can be obtained from the residuals of the estimator using (11) and (12), as it is stated in [7]. Then, by solving the optimization problem (13) the estimated covariances ($\widehat{Q}_\rho$ and $\widehat{R}_\nu$) are obtained. The first term in (13) is the residues norm, the second term is the constraint penalization term, the term $|\cdot|$ denotes the determinant of the matrix, $\mathscr{A}$ and $\widehat{b}$ are defined in [6] as Eqs. (11) and (12), respectively, and μ is the barrier parameter for the semi-definite constraint ($Q_\rho \geq 0$ and $R_\nu \geq 0$). By using a Newton-based optimization procedure, the covariances are obtained after a predefined number of iterations (n) or when the results converge as shown in Fig. 2.

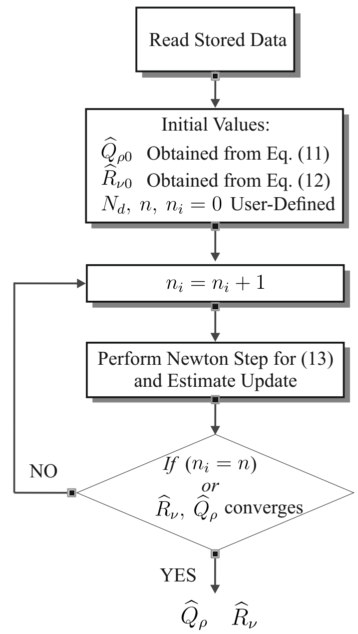


Fig. 2. ALS flow chart considering initial covariances ($Q_{\rho 0}$ and R_{nu0}) and number of data points (N_d).

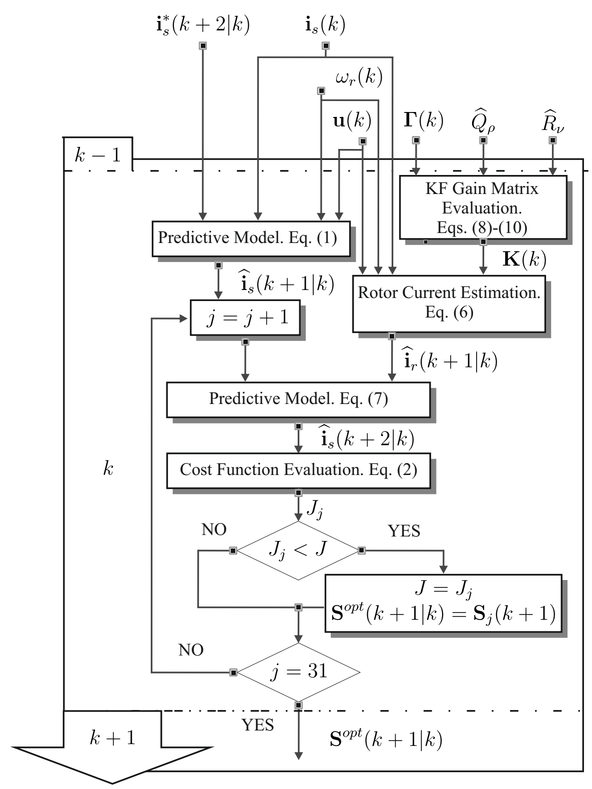


Fig. 3. Proposed PCC algorithm in a flow chart diagram.

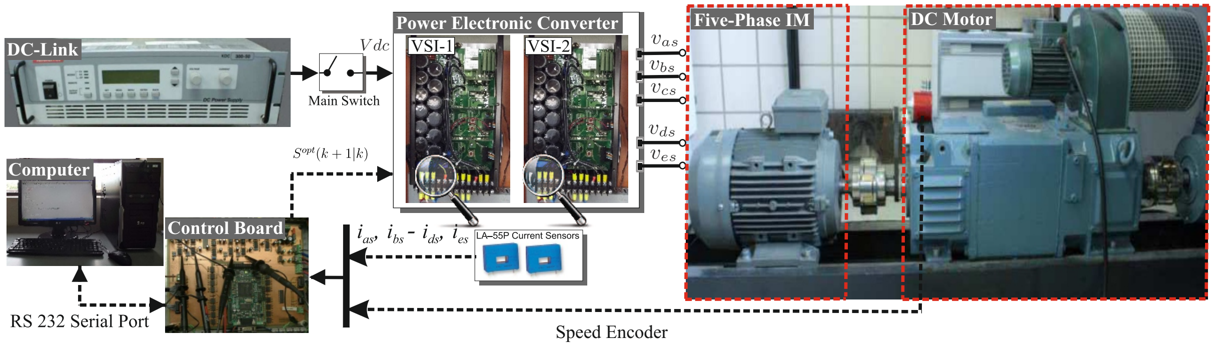


Fig. 4. Scheme of the experimental test rig.

$$\widehat{Q}_{\rho 0} = \text{cov}\{\mathbf{i}(k+1|k) - \mathbf{A}\,\widehat{\mathbf{i}}(k|k-1) - \mathbf{B}\,\mathbf{u}(k) - \mathbf{H}\,\rho(k|k-1)\} \tag{11}$$

$$\widehat{R}_{\nu 0} = \text{cov}\{\mathbf{i}_s(k) - \mathbf{C}\,\mathbf{i}(k|k-1)\,\mathbf{I}\,\rho(k|k-1)\} \tag{12}$$

$$\min_{\substack{Q_\rho \\ R_\nu}} \left\| \mathscr{A} \begin{bmatrix} (Q_\rho)_s \\ (R_\nu)_s \end{bmatrix} - \widehat{b} \right\|_2^2 - \mu \log \begin{vmatrix} Q_\rho & 0 \\ 0 & R_\nu \end{vmatrix} \tag{13}$$

Note that $\widehat{Q}_\rho$ and $\widehat{R}_\nu$ are constant values during the proposed PCC algorithm. To make things clearer, a flow chart of the proposed PCC control algorithm is presented in Fig. 3.

In general, tuning parameters of the predictive controllers is not easy as many studies focusing on this area have shown [5, 8]. Although the use of KF improves the modeling of complex electrical systems and consequently the better performance of the PCC controller, the optimal parameters of the filter was still a problem to be solved, and the proposed method covers this part of the problem by an optimal estimation of $\widehat{Q}_\rho$ and $\widehat{R}_\nu$. The contribution of this paper analyzes the obtained improvement when this optimal rotor current estimator is applied.

III. Experimental Results

To validate the proposed control method, an experimental evaluation has been conducted. A diagram of the test rig is shown in Fig. 4. The principal element is a three pairs of poles five-phase IM whose nominal parameters have been experimentally determined as $R_s = 19.45\ \Omega$, $R_r = 6.77\ \Omega$, $L_{ls} = 100.7$ mH, $L_{lr} = 38.06$ mH, $M = 656.5$ mH, $\omega_n = 1,000$ rpm and $P_n = 1$ kW. Two 2-level three-phase power converters from Semikron (SKS22F) are used to drive the five-phase IM, where the DC-link voltage is set to 300 V using a DC power supply system. The control system is based on a MSK28335 board and a TMS320F28335 DSP, being the rotor mechanical measured using a GHM510296R/2500 digital encoder and the eQEP peripheral of the DSP. A DC motor is also used to introduce a variable load torque in the system.

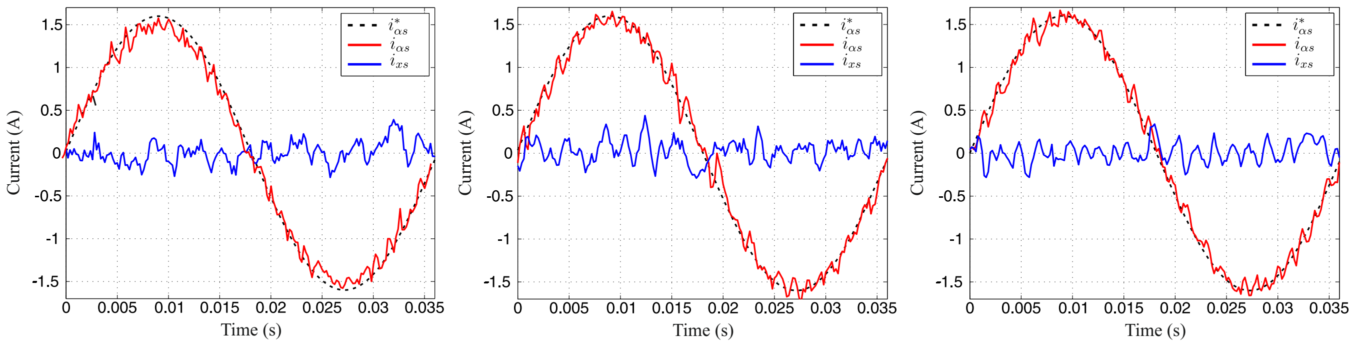
Different tests were carried out to validate the current controller performance using the conventional PCC method (C1), the PCC method with KF detailed in [4] (C2) and the PCC with the proposed optimum-KF (C3). A sampling frequency of 15 kHz and half of the nominal load are considered, as well as the cost function defined in (2) with $\lambda_{xy} = 0.1$ (the torque and flux production are promoted by the controller over the harmonic losses). Four figures of merit are used to compare the efficiency of the different rotor current estimators in terms of control performance and prediction accuracy. These are mean squared values of the current control error in α and x axis, defined in (14), the model prediction error in α axis (15), and a total harmonic distortion measurement (THD) of the stator phase (15).

TABLE I
Experimental results at different operating points

ω [rpm]	Figures of merit	C1	C2	C3
400	MSE$i^*_{\alpha s}$	0.1068	0.0972	0.0954
	MSE$\widehat{i}^*_{\alpha s}$	0.1468	0.1390	0.1382
	MSEi^*_{xs}	0.1217	0.1199	0.1176
	THD(%)	14.15	13.29	13.47
500	MSE$i^*_{\alpha s}$	0.1075	0.0950	0.0907
	MSE$\widehat{i}^*_{\alpha s}$	0.1411	0.1343	0.1267
	MSEi^*_{xs}	0.1284	0.1051	0.0963
	THD(%)	16.86	15.07	14.07
550	MSE$i^*_{\alpha s}$	0.1227	0.1044	0.0879
	MSE$\widehat{i}^*_{\alpha s}$	0.1526	0.1363	0.1247
	MSEi^*_{xs}	0.1408	0.1354	0.1260
	THD(%)	16.08	14.63	13.18
600	MSE$i^*_{\alpha s}$	0.1177	0.0924	0.0860
	MSE$\widehat{i}^*_{\alpha s}$	0.1469	0.1318	0.1234
	MSEi^*_{xs}	0.1435	0.1355	0.1203
	THD(%)	16.42	12.50	12.96
700	MSE$i^*_{\alpha s}$	0.1266	0.0875	0.0835
	MSE$\widehat{i}^*_{\alpha s}$	0.1579	0.1300	0.1285
	MSEi^*_{xs}	0.1524	0.1433	0.1430
	THD(%)	17.34	14.81	14.70

$$\text{MSE}i^*_{(\alpha,x)s} = \sqrt{\frac{\sum_{j=1}^{N}\left(i_{(\alpha,x)s}(j) - i^*_{(\alpha,x)s}(j)\right)^2}{N}} \tag{14}$$

$$\text{MSE}\widehat{i}_{\alpha s} = \sqrt{\frac{\sum_{j=1}^{N}\left(i_{\alpha s}(j) - \widehat{i}_{\alpha s}(j)\right)^2}{N}} \tag{15}$$



(a) (b) (c)

Fig. 5. Experimental comparison of obtained stator currents in α and x axis using (a) C1, (b) C2 and (c) C3 techniques at 550 rpm and half nominal torque load.

$$\mathrm{THD}\widehat{i_s} = \sqrt{\frac{\mathrm{MSE}\widehat{i}^2_{\alpha\beta s} + \mathrm{MSE}\widehat{i}^2_{xys}}{i_{\alpha s\; peak}/2}} \tag{16}$$

Table I and Fig. 5 summarize the obtained results in steady-state operation, where it is quantified the obtained improvement when the proposed rotor current estimator is used. It is observed that all mean squared values are improved (lower values) if the proposed optimum KF rotor current estimator (C3) is used. For instance, the obtained $\mathrm{MSE}i^*_{\alpha s}$ value at 550 rpm using C3 is reduced in 28.36 % and 15.80 % when it is compared with those obtained using C1 and C2, respectively. Similarly, the obtained $\mathrm{MSE}\widehat{i}_{\alpha s}$ value at 600 rpm is also reduced in 16.00 % and 6.37 % when C3 is employed instead of C1 and C2, respectively. Note that similar results are obtained at different operating points. Fig. 5 details the performance of the system using C1, C2 and C3 at 550 rpm, where the current tracking characteristics in α and x axis are plotted, showing that the closed-loop performance of the system using C3 technique offers better tracking characteristics than others. Regarding the harmonic content of the stator current, the obtained value is lower if the rotor current estimator is used, being C3 the best in most cases.

The dynamic performance using the C3 method is finally analyzed, and the obtained results are shown in Fig. 5. The q stator current reference (i^*_{qs}) is varied according to a step profile, while the d stator current reference is set to a constant value (i^*_{ds}=0.57 A); see Fig. 5 (upper plot). The measured stator currents in synchronous (d and q axis, upper plot of Fig. 5) and stationary ($\alpha - \beta - x - y$ axis, middle plot of Fig. 5) frames follow the impressed references, which confirms that the proposed controller works well at different mechanical speed and during transient states. Note that the outer speed controller is not used in the test and the mechanical speed is not regulated, hence it varies as it is shown in the lower plot of Fig. 5. It is also worth mentioning that a sampling frequency of 15 kHz (sampling time of about 67 μs) is used, which still enables the implementation of the KF-based rotor estimator in the C2 and C3 controllers. Note also that the proposed ALS method does not affect the computational cost (the proposed optimization procedure is performed off-line, prior to starting the normal operation of the multiphase drive).

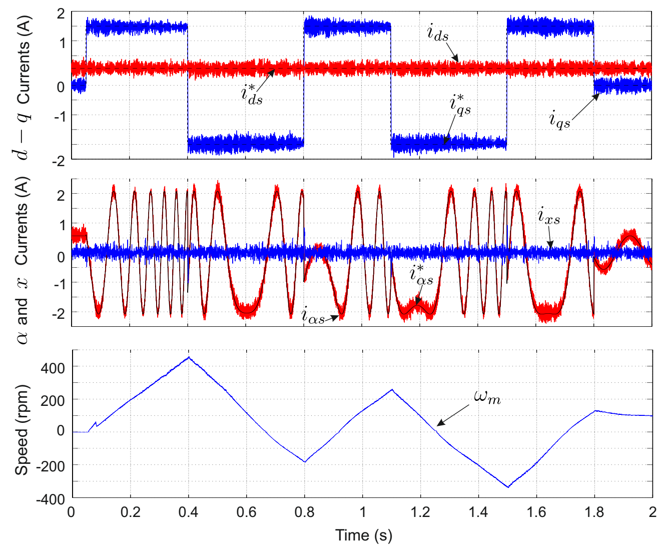


Fig. 6. Transient response using the C3 controller. From top to bottom: $d-q$ stator currents i_{ds} and i_{qs}, and their references i^*_{ds} and i^*_{qs}; α and x currents $i_{\alpha s}$ and i_{xs}, with the imposed reference $i^*_{\alpha s}$, and mechanical speed ω_m.

IV. Conclusion

This work addresses the application of KF in the design of rotor current observers when PCC methods are used in IM drives. In particular, a procedure for the design of an optimal KF is presented. Experimental results in a five-phase IM drive show the interest of the proposed procedure, which improves stator current prediction and tracking, comparing with other conventional or KF-based PCC methods. Notice that all the obtained conclusions for a particular case example based on five phase IM can be extended to different multiphase and conventional IM.

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