Experimental Evaluation of Braided EKF for Sensorless Control of Induction Motors

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Abstract—Temperature- and frequency-dependent variations of the rotor ($R_s'$) and stator ($R_s$) resistances pose a challenge in the accurate estimation of flux and velocity in the sensorless control of induction motors (IMs) over a wide speed range. Solutions have been sought to the problem by signal injection and/or by the use of different algorithms for the different parameters and states of the same motor. In this paper, a novel Extended-Kalman-Filter (EKF)-based estimation technique is developed for the solution of the problem based on the consecutive operation of two EKF algorithms at every time step. The proposed “braided” EKF technique is experimentally tested under challenging parameter and load variations in a wide speed range, including low speed. The results demonstrate a significantly increased accuracy in the estimation of $R_s$ and $R_s'$, as well as load torque, flux, and velocity in transient and steady state, when compared with single EKFs or other approaches taken to estimate these parameters and states in the sensorless control of IMs. The improved results also motivate the utilization of the new estimation approach in combination with a variety of control methods which depend on accurate knowledge of a high number of parameters and states.

Index Terms—Braided Extended Kalman Filter (EKF), induction motors (IMs), load-torque estimation, rotor- and stator-resistance estimation, speed sensorless control.

I. INTRODUCTION

Induction-Motor (IM) parameters vary significantly with operating conditions. Besides, the load torque can vary from no load to full load and stator ($R_s$) and rotor ($R_s'$) resistances change with temperature and frequency, while inductances tend to saturate at high current levels. The effects of parameter and model uncertainties become even more relevant with speed sensorless control, calling for sophisticated methods for the estimation of flux and velocity. The benefits of sensorless control are the increased reliability of the overall system with the removal of mechanical sensors, thereby reducing sensor noise and drift effects as well as cost and size. However, to exploit the benefits of sensorless control, the developed estimation methods must achieve robustness against parameter and model uncertainties over a wide speed range. Parameters of particular concern in the sensorless control literature are the frequency-dependent $R_s'$, temperature-dependent $R_s$, and the load torque, all of which are very effective on the accurate estimation of flux and velocity.

To address the parameter-sensitivity problem in IM sensorless control, a variety of approaches have been proposed and problems have been reported; i.e., studies based on sliding-mode observers with [1] estimating the $R_s'$ and [2] estimating the $R_s$: studies on speed adaptive-flux observers as in [3], in which $R_s$ is also estimated, and in [4]–[7], which adjust the value of $R_s'$ in proportion to the estimated $R_s$. More recently, in [8], a Lyapunov-function-based flux and speed observer is developed, which can estimate $R_s$ but not $R_s'$, while in [9], a thermal-state estimation is performed to compensate for the parameter, hence, speed deviations due to heating.

There are also Extended-Kalman-Filter (EKF) applications in the literature for the sensorless control of IMs. Model uncertainties and nonlinearities inherent in IMs are well suited to the stochastic nature of EKFs [10]. With this method, it is possible to make the online estimation of states while performing the simultaneous identification of parameters in a relatively short time interval [11]–[13] by also taking system process and measurement noises directly into account. This is the reason why the EKF has found wide application in the sensorless control of IMs, in spite of its computational complexity. Among recent sensorless studies using EKF estimation for IMs, the authors in [14]–[16] estimate the flux and velocity, while Lee and Chen [17] use an adaptive flux observer in combination with a second-order KF for the same purpose. None of these studies estimate the load torque and rotor resistances, resulting in a performance that is sensitive to the variation of these parameters. In [14]–[16] and [18]–[20], which present reduced-order estimators, the velocity is estimated as a constant parameter, which gives rise to a significant estimation error in the velocity during the transient state, particularly under instantaneous load variations, although the performance is improved in the steady state. While the study in [18] and [19] are sensitive to rotor-resistance variations, the study in [20] also estimates the rotor resistance. However, the estimation of rotor resistance is performed by the injection of low-amplitude high-frequency signals into the flux reference in the direct vector control of IMs. This has caused fluctuations in the motor flux, torque, and speed. Finally, recent studies of the authors in [21] and [22], estimating the velocity via the consideration of the equation of motion in the EKF model, in addition to the estimation of rotor resistance and mechanical uncertainties, demonstrate
improved results over a wide speed range. However, the results are sensitive to the variations of stator resistance, indicating the necessity of an approach to estimate rotor resistance and stator resistance, simultaneously, as well as the load torque.

Studies achieving the simultaneous estimation of \( R_s \) and \( R'_r \) in the sensorless control of IMs are only few; in fact, Faiz and Sharifian [23] state that simultaneous estimation of \( R_s \) and \( R'_r \) gives rise to instability in the speed sensorless case. As a solution, Zhen and Xu [24] present a model-reference adaptive system based on three models, of which one is used for the estimation of the rotor time constant via high-frequency signal injection and the other two models are used interchangeably by enabling the stator-resistance estimation only during short intervals, during which the rotor speed has reached the steady state. In studies such as [25] and [26], the speed and rotor flux are estimated as well as the stator resistance and rotor resistance by injecting high-frequency signals into the flux and magnetizing current commands. However, in [25], the algorithm identifying the resistances (used in a feedback linearization controller) is applicable only when the sensorless-speed-control system is in steady state and not when the load torque is varying largely or when the speed command is being changed, as also stated by the authors. On the other hand, in [26], it is stated that the proposed drive can compete with a speed-sensor-equipped drive only if accuracy in steady state is not essential and operation under high loads is not a requirement. Recently, Edelbaher et al. [27] presented a sensorless-control scheme using an open-loop estimator to calculate \( R'_r \) and a model reference adaptation for \( R_s \). However, the performance of the parameter estimation is not demonstrated and only evaluated indirectly via the estimated velocity and flux. The above listed studies, to the authors’ best knowledge, are among the most significant reported IM sensorless-control studies estimating \( R_s \) and \( R'_r \) simultaneously as the two most effective parameters on estimation and control performance; however, the results require either signal injection [28] or design of different algorithms based on the velocity range or based on the parameters and states to be estimated, \( R_s \) or \( R'_r \).

The major contribution of this paper is the development of an EKF-based novel observer approach, which achieves the simultaneous estimation of \( R_s \) and \( R'_r \), and hence, the accurate estimation of flux, torque, and velocity for the speed sensorless control of IMs without the need for signal injection or algorithm changes as in most previous studies. The observer involves the consecutive use of two EKF algorithms at every time step by what could be called a “braided” technique. The two EKF algorithms have exactly the same configuration and are derived based on the same extended model except for one state; i.e., \( R_s \) in one replaced by \( R'_r \) in the other. Persistency of excitation required for parameter convergence in the steady state and provided by signal injection in most previous methods is thus fulfilled by the system noise (or modeling error), which is inherently taken into account in all EKFs. The braided EKF technique exploits this characteristic as well as the fast convergence property of EKFs. The proposed approach also offers a solution against the well-known decreased-estimation-accuracy problem faced when a high number of states and parameters are to be estimated with a single EKF, as noted in [29]. The fast convergence rate and high estimation accuracy demonstrated in the experimental results indicate that the proposed technique can address the challenge of \( R_s \) and \( R'_r \) estimation in the sensorless control of IMs and improve estimation of flux and velocity over a wide speed range, both in transient and steady state.

This paper is organized as follows. After a discussion of previous literature on sensorless estimation and control in Section I, Section II proceeds with the derivation of the extended models for the new EKF algorithm. Next, the development of the multiple-model braided EKF is introduced in Section III, which is followed by experimental results presented for various scenarios in Section IV. Finally, the conclusions and the future directions are discussed in Section V.

II. EXTENDED MATHEMATICAL MODELS FOR BRAIDED EKF

Sensorless schemes developed for IMs require the estimation of rotor-flux components, \( \psi_{r\alpha} \), \( \psi_{r\beta} \), angular velocity, \( \omega_m \), and stator-current components \( i_{sa} \) and \( i_{sb} \), which are also measured as output. However, as aforementioned in Section I, the accurate estimation of these states is very much dependent on how well the system parameters are known, particularly the rotor \( (R'_r) \) and stator \( (R_s) \) resistances over a wide speed range. To this purpose, in this paper, two extended models are developed: One which is developed for the estimation of the rotor resistance \( R'_r \) and the other for the stator resistance \( R_s \), with an additional set of estimated states which are the same in both models. The extended models to be used in the development of the two EKF algorithms can be given (as referred to the stator stationary frame) in the following general form:

\[
\dot{x}_{ei}(t) = f_{x_{ei}}(x_{ei}(t), u_{ei}(t)) + w_{ei}(t) \\
= A_{x_{ei}}(x_{ei}(t)) \dot{x}_{ei}(t) + B_{x_{ei}}u_{ei}(t) + w_{ei}(t)
\]

\[
\tilde{z}(t) = h_{x_{ei}}(x_{ei}(t)) + w_{ei2}(t) \quad \text{(measurement equation)}
\]

\[
\dot{x}_{ei}(t) = f_{x_{ei}}(x_{ei}(t), u_{ei}(t)) + w_{ei}(t)
\]

where \( i = 1, 2 \), extended state vector \( x_{ei} \) is representing the estimated states, \( f_{x_{ei}} \) is the nonlinear function of the states and inputs, \( A_{x_{ei}} \) is the system matrix, \( u_{ei} \) is the control-input vector, \( B_{x_{ei}} \) is the input matrix, \( w_{ei} \) is the process noise, \( h_{x_{ei}} \) is the function of the outputs, \( H_{x_{ei}} \) is the measurement matrix, and \( w_{ei2} \) is the measurement noise. Based on the general form in (1) and (2), the detailed matrix representation of the two IM models are given below.

Model 1: Extended model of IM derived for the estimation of \( R_s \) (model—\( R_s \)), in (3) and (4), shown at the bottom of the next page.

Model 2: Extended model of IM derived for the estimation of \( R'_r \) (model—\( R'_r \)), in (5) and (6), shown at the bottom of p. 4, where \( p_h \) is the number of pole pairs, \( L_\sigma = \sigma L_s \) is the stator transient inductance, \( \sigma = 1 - \frac{L_m}{L_s} \) is the leakage or coupling factor, \( L_s, R_s \) are the stator inductance and resistance, respectively, \( L'_r, R'_r \) are the rotor inductance and resistance, referred to the stator side, respectively, \( v_{\alpha \alpha}, v_{\beta \beta} \) are the stator stationary axis components of stator voltages, \( i_{\alpha \alpha}, i_{\beta \beta} \) are the
stator stationary axis components of stator currents, $\psi_{ta}$, $\psi_{tb}$ are the stator stationary axis components of rotor flux, $J_L$ is the total inertia of the IM and load, and $\omega_m$ is the angular velocity. As can be seen from (3)–(6), the only difference between the two extended vectors, $\xi_{e1}$ and $\xi_{e2}$, are the constant states $R_s$ and $\omega_m$, respectively. $i_{sa}$ and $i_{sb}$ are the measured variables in both algorithms. The load torque and stator or rotor resistances are assumed to have a slow variation with time and, therefore, are taken into consideration as constant parameters.

III. DEVELOPMENT OF THE BRAIDED EKF ALGORITHM

In this section, the two EKF algorithms used in the braided EKF technique will be derived using the extended model in (3)–(6). For nonlinear problems, such as the one in consideration, the KF method is not strictly applicable, since linearity plays an important role in its derivation and performance as an optimal filter. The EKF technique attempts to overcome this difficulty by using a linearized approximation, where the linearization is performed about the current state estimate. This process requires the discretization of (3) and (4)—or (5) and (6)—as follows:

$$\begin{align*}
\dot{\xi}_{e1}(k + 1) &= f_e(\xi_{e1}(k), u_e(k)) + w_{11}(k) \\
\bar{Z}(k) &= H\bar{\xi}_{e1}(k) + w_{21}(k). 
\end{align*}$$

(7) (8)

The linearization of (7) and (8) is performed around the current estimated state vector $\bar{\xi}_{e1}(k)$ as well as the control-input vector $\bar{u}_e(k)$, taking into account the control-input quantization error $[12]$, as given as follows:

$$\begin{align*}
E_{e1}(k) &= \frac{\partial f_e(\xi_{e1}(k), u_e(k))}{\partial \xi_{e1}(k)}|_{\bar{\xi}_{e1}(k), \bar{u}_e(k)} \\
E_{u1}(k) &= \frac{\partial f_e(\xi_{e1}(k), u_e(k))}{\partial u_e(k)}|_{\bar{\xi}_{e1}(k), \bar{u}_e(k)}. 
\end{align*}$$

(9) (10)

The resulting EKF algorithm can be given with the following recursive relations [12]:

$$\begin{align*}
\bar{N}_e(k) &= E_{e1}(k)P_e(k)E_{e1}^T(k) \\
&+ E_{u1}(k)D_uE_{u1}^T(k) + Q_e, \\
\bar{P}_e(k + 1) &= \bar{N}_e(k) - \bar{N}_e(k)H_e^T \\
&\times (D_e + H_e\bar{N}_e(k)H_e^T)^{-1}H_e\bar{N}_e(k) \\
\bar{\xi}_{e1}(k + 1) &= \bar{f}_{e1}(\bar{\xi}_{e1}(k), \bar{u}_e(t(k)) + P_e(k + 1) \\
&\times H_eD_e^{-1}(\bar{Z}(k) - H_e\bar{\xi}_{e1}(k)).
\end{align*}$$

(11a) (11b) (11c)

where $Q_e$ is the covariance matrix of the system noise, namely, model error, $D_e$ is the covariance matrix of the output noise, namely, measurement noise, $P_e$ is the covariance matrix of the control input noise ($u_{sa}$ and $u_{sb}$), namely, input noise, and...
\( P_i, N_i \) are the covariance matrix of state estimation error and extrapolation error, respectively.

The algorithm involves two main stages: prediction and filtering. In the prediction stage, the next predicted states \( \hat{X}_{i+1}(k+1) \) and predicted state-error covariance matrices, \( P_i(k+1) \) and \( N_i(k+1) \), are processed, whilst in the filtering stage, the next estimated states \( \hat{X}_{e,k+1} \), obtained as the sum of the next predicted states and the correction term [second term in (11c)], are calculated.

The flowchart of the braided EKF algorithm is shown in Fig. 1, demonstrating the consecutive use of the two EKF algorithms; thus, while one algorithm estimates \( R_s \) and the other, \( R'_t \), both algorithms also estimate load torque, velocity, flux, and current components as the common states. After the initialization of the states, the algorithms are run by switching them on and off consecutively and at each time step. The final values of \( P_i(k+1) \) and \( N_i(k+1) \) calculated for one EKF algorithm at the end of each switching period are passed over to the next EKF algorithm as the initial values of the covariances and states. The resistance \( R_s \) or \( R'_t \) estimated during the previous period is also passed on to the next EKF algorithm and is assumed to be constant in the new EKF model throughout the whole switching period.

IV. EXPERIMENTAL RESULTS AND OBSERVATIONS

In this section, the performance of the braided EKF will be evaluated against the single EKF algorithms designed for \( R'_t \) estimation (EKF – \( R'_t \)) and \( R_s \) estimation (EKF – \( R_s \)). The experimental setup used for the sensorless-estimation tests is shown in Fig. 2. The IM under consideration is three phase, eight pole, and 3 HP/2.238 kW, with its specification details given in Table I(a). The EKF algorithm and all analog signals are developed and processed on a Power PC-based DS1104 Controller Board, offering a four-channel, 16-b (multiplexed) ADC and four 12-b ADC units. The controller board processes floating-point operations at a rate of 250 MHz. A torque transducer rated at 50 N·m and an encoder with 3600 counts/rev are also used for the verification of the load torque and velocity estimation and, hence, for the performance evaluation of the braided EKF. The phase voltages and currents are measured with high band voltage and current sensors from LEM Inc.

The load is generated through a dc machine operating in generator mode coupled to the IM. An array resistor connected to the armature terminals of the dc machine is used to vary the load torque applied to the IM based on the relationship as \( t_L = k_t \omega/R \), where \( k_t \) is the torque constant of the dc machine, \( \omega \) is angular velocity, and \( R \) is the total resistance (switched array + armature). The value of the resistance is adjusted to 7.8 \( \Omega \) to generate a load torque \( t_L \) of 20.73 N·m at approximately 819 rev/m. The parameters for the IM and dc generator used in the experiments are listed in Tables I(a) and (b).

The initial values of the \( P_i \) and \( Q_i \) in the EKF algorithms are found by trial-and-error to achieve a rapid initial convergence as well as the desired transient- and steady-state performance.
Tables 1A and 1B provide the rated values and parameters of the IM and DC machine used in the experiments. For model-1 (EKF - $R_e$),

$$P_1 = \text{diag}\left\{ 1[A^2] \ 1[A^2] \ 1[(V \cdot s)^2] \ 1[(V \cdot s)^2] \times 1 \left[ \text{rad/s}^2 \right] \ 1[\text{N} \cdot \text{m}^2] \ 1[\text{rad}] \right\}$$

$$Q_1 = \text{diag}\left\{ 10^{-8}[A^2] \ 10^{-8}[A^2] \ 4 \times 10^{-17} [(V \cdot s)^2] \times 4 \times 10^{-17} [(V \cdot s)^2] \ 10^{-14} \left[ \text{rad/s}^2 \right] \times 10^{-15} \left[ (\text{N} \cdot \text{m})^2 \right] \ 10^{-16} [\text{rad}] \right\}.$$  

For model-2 (EKF - $R'_e$),

$$P_2 = \text{diag}\left\{ 1[A^2] \ 1[A^2] \ 1[(V \cdot s)^2] \ 1[(V \cdot s)^2] \times 1 \left[ \text{rad/s}^2 \right] \ 1[\text{N} \cdot \text{m}^2] \ 1[\text{rad}] \right\}$$

$$Q_2 = \text{diag}\left\{ 1.5 \times 10^{-11}[A^2] \ 1.5 \times 10^{-11}[A^2] \times 0 \left[ (V \cdot s)^2 \right] \times 0 \left[ (V \cdot s)^2 \right] \times 1.1 \times 10^{-15} \left[ \text{rad/s}^2 \right] \times 7 \times 10^{-15} \left[ (\text{N} \cdot \text{m})^2 \right] \ 10^{-6} [\text{rad}] \right\}.$$  

Fig. 1. Flowchart of the braided EKF algorithm.

Fig. 2. Schematic representation of the experimental setup.

Table 1A

<table>
<thead>
<tr>
<th>TABLE 1A</th>
<th>RATED VALUES AND PARAMETERS OF THE IM USED IN THE EXPERIMENTS</th>
</tr>
</thead>
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<tr>
<td>( P )</td>
<td>( V )</td>
</tr>
<tr>
<td>[kW]</td>
<td>[Hz]</td>
</tr>
<tr>
<td>2.238</td>
<td>60</td>
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Table 1B

<table>
<thead>
<tr>
<th>TABLE 1B</th>
<th>RATED VALUES AND PARAMETERS OF THE DC MACHINE USED IN THE EXPERIMENTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>( P )</td>
<td>( V )</td>
</tr>
<tr>
<td>[kW]</td>
<td>[V]</td>
</tr>
<tr>
<td>3</td>
<td>125</td>
</tr>
</tbody>
</table>

Note: \( J_L \) = total inertia in the experimental test-bed.
For both models

$$D_x = \text{diag} \left\{ 2.6 \times 10^{-4}[A^2], 2.6 \times 10^{-4}[A^2] \right\}$$

$$D_u = \text{diag} \left\{ 2.3 \times 10^{-5}[V^2], 2.3 \times 10^{-5}[V^2] \right\}.$$  

For a realistic evaluation, the performance of the IM is tested in open-loop with pulsewidth-modulated input voltages and currents, as shown in Fig. 3. The EKF algorithms take as input the transformed components of the current and voltage. The following is a generalized description of this transformation:

$$x_a = x_a; \quad x_b = \frac{1}{\sqrt{3}}(x_b - x_c)$$

where $x$ is the $i$ and $v$ for current and voltage, respectively.

Fig. 3 shows the transformed current and voltage at 60 Hz and 230 V for a $t_L$ of approximately 21.06 N·m.

To test the performance of the braided EKF against the conventional EKF – $R_s$ and EKF – $R'_s$ algorithms, five scenarios are developed, which impose challenging $R_s$, $R'_s$, load torque, and velocity variations on the motor in the high- and low-speed range. All algorithms are started with initial parameter and state estimations of zero. The sampling period for all algorithms is $T_{\text{sample}} = 110$ [$\mu$s].

The resulting performances are presented with the variations of $n_m$ and $\eta_m$, $t_{\text{ind}}$ and $t_L$, $\psi_{\text{rot}}$, $\psi_{\text{r,}}$, $R'_s$, $R_s$, $e_{i_a}$, and $e_{i_b}$, $e_{n_m} = n_m - \hat{n}_m$, and $e_{t_{\text{ind}}} = t_{\text{ind}} - t_L$, namely, the measured and estimated velocity, the induced torque as obtained from the torque meter and estimated load torque, the estimated $\alpha$ and $\beta$ components of the rotor flux, estimated rotor resistance, estimated stator resistance, estimation errors in ($i_a$) and ($i_b$), and estimation errors of velocity and load torque, respectively.

A. Scenario I—Load-Torque and Stator-Resistance Variations for EKF – $R_s$ (Fig. 4)

This scenario aims to test the performance of EKF – $R_s$ under $R'_s$ and $R_s$ variations. To this purpose, while the IM is running at 849.5 rev/m under no-load and the switched array resistance of 7.8 $\Omega$ is connected to the armature, the field supply of the dc generator is switched on at $t = 1.8$ s; thus, the IM is loaded with 20.2 N·m at 817.2 rev/m, which also causes an increase in $R'_s$. To also test the algorithm under $R_s$ uncertainties, the following variations are given to $R_s$ at $t = 16.2$ s, $R_s$: $R_{\text{sn}} \rightarrow 2 \times R_{\text{sn}}$, at $t = 24.7$ s, $R_s$: $2 \times R_{\text{sn}} \rightarrow R_{\text{sn}}$. Finally, the scenario is switched back to its initial status at $t = 31.75$ s.

Inspecting the results, it can be seen that, due to the instantaneous switching effects created by the challenging variations, the maximum errors of $i_{\alpha}$ and $i_{\beta}$ jump to peak values of 3.1 mA; however, the errors of both currents remain within a band of ±2 mA. The estimated values of velocity and load torque also track their measured values quite closely with a reasonable relationship observed between the load-torque estimation error and that of the velocity. In the time interval of $0 \leq t \leq 16.2$ s and $31.75 \leq t \leq 40$ s in Fig. 4(c), it can be noted that the estimated rotor resistance $R'_s$ has demonstrated a variation in harmony with the rotor frequency and, consequently, with the load torque, as it has been stated in [22] and [30]. However, under the challenging $R_s$ variation, $R_s$: $R_{\text{sn}} \rightarrow 2 \times R_{\text{sn}}$ at $t = 16.2$ s, a considerable amount of error occurs in the estimated load torque and, consequently, in the estimated velocity and flux. The error is corrected at $t = 24.7$ s, when the $R_s$ value is switched back to its nominal value $R_{\text{sn}}$ used in the extended model. While the operation of the IM over a long duration is expected to cause a similar increase in the $R_s$ value even at high speeds, the temperature-dependent increase in $R_s$ is even more critical at
Fig. 4. Experimental results of EKF $- R'_r$ for load-torque and stator-resistance variations. (a) Variation of $n_m$ and $\hat{n}_m$. (b) Variation of $t_{\text{load}}$ and $\hat{\ell}_L$. (c) Variation of $\hat{\psi}_{\alpha}$. (d) Variation of $\hat{\psi}_{\beta}$. (e) Variation of $\hat{R}_r'$. (f) Variation of $e_{i_{\text{ref}}\alpha}$ and $e_{i_{\text{ref}}\beta}$. (g) Variation of $e_{n_m}$. (h) Variation of $e_{\ell_L}$.
Fig. 5. Experimental results of EKF – $R_s$ for load-torque and rotor-resistance variations. (a) Variation of $n_m$ and $\hat{n}_m$. (b) Variation of $t_{ind}$ and $\hat{t}_L$. (c) Variation of $\psi_{\alpha}$. (d) Variation of $\psi_{\beta}$. (e) Variation of $\hat{R}_s$. (f) Variation of $e_{i_{\alpha}}$ and $e_{i_{\beta}}$. (g) Variation of $e_{\psi_{m}}$. (h) Variation of $e_{t_L}$. 
Fig. 6. Experimental results of braided EKF for load-torque variations at constant velocity. (a) Variation of $n_m$ and $\hat{n}_m$. (b) Variation of $t_{ind}$ and $\hat{t}_L$. (c) Variation of $\hat{R}_r$. (d) Variation of $\hat{R}_s$. (e) Variation of $\hat{\psi}_m$. (f) Variation of $\hat{\psi}_d$. (g) Variation of $e_{n_m}$. (h) Variation of $e_{\psi}$. 
Fig. 7. Experimental results of braided EKF for steady state with incorrect $R_s(0^+) = 2 \times R_{sn}$. (a) Variation of $n_m$ and $\hat{n}_m$. (b) Variation of $i_{\text{load}}$ and $\hat{i}_L$. (c) Variation of $e_{n_m}$. (d) Variation of $e_{\text{LL}}$. (e) Variation of $\hat{R}_r'$. Low speeds. Therefore, proper and continuous updates of $R_s$ are essential for the EKF $- R_r'$ algorithm throughout the whole speed range for accurate estimations of flux, load torque, and velocity.

B. Scenario II—Load-Torque and Rotor-Resistance Variations for EKF $- R_s$, (Fig. 5)

In this section, the EKF $- R_s$ algorithm will be tested for load-torque and rotor-resistance variations. To this aim, while the IM is running at 849.5 rev/m under no-load and the switched array resistance of 7.8 Ω is connected to the armature, the field supply of the dc generator is switched on at $t = 2$ s; thus, the IM is loaded with 20.9 N · m at 815.5 rev/m. The variation of the load torque inherently varies $R_r'$, and since the extended model of EKF $- R_s$ assumes $R_r'$ to be constant, a considerable amount of error occurs in the estimated load torque and, consequently, in the estimated velocity and flux. However, $i_{\alpha}$ and $i_{\beta}$ errors remain within a very small band of ±0.4 mA, as shown in Fig. 5(f). The resulting performance of this scenario is presented in Fig. 5(a)–(h).

To demonstrate the importance of proper $\hat{R}_r'$ updates for the performance of the EKF $- R_s$ algorithm, starting at $t = 13.3$ s, the algorithm is updated with the accurate $\hat{R}_r'$ values obtained from EKF $- R_r'$ in Scenario I. The velocity- and torque-estimation errors, which were at a significant level prior to $\hat{R}_r'$ updates at 13.3 s, start converging toward zero. Thus, this scenario indicates the importance of accurate $\hat{R}_r'$ values for the performance of the EKF $- R_s$ algorithm and also emphasizes the need for simultaneous $R_s$ and $R_r'$ updates.
Fig. 8. Experimental results for braided EKF for low-speed operation. (a) Variation of $n_m$ and $\hat{n}_m$. (b) Variation of $i_{ind}$ and $\hat{i}_L$. (c) Variation of $\hat{R}_r'$. (d) Variation of $R_e$. (e) Variation of the estimated position of the flux with reference to the stator stationary axis. (f) Variation of $e_{n,m}$. (g) Variation of $e_{IL}$.

C. Scenario III—Load-Torque and Rotor-Resistance Variations Under Braided EKF, (Fig. 6)

In this section, the performance of the braided EKF algorithm will be evaluated under rotor-resistance variations. To this aim, while the IM is running at 849.5 rev/m under no-load and the switched array resistance of 7.8 $\Omega$ is connected to the armature, the field supply of the dc generator is switched on at $t = 7.2$ s; thus, the IM is loaded with 20.74 N·m at 819.7 rev/m, which also causes an increase in $\hat{R}_r'$. At $t = 19$ s, the scenario is switched to its initial status by switching off the
dc-generator field supply. The resulting performance is given in Fig. 6(a)–(h).

Inspecting the results, it can be seen that the braided EKF has, in fact, achieved a significantly improved performance over individual EKFs, with the simultaneous estimation of $R_s$ and $R'_f$ throughout the operation. Hence, in spite of $R'_f$ variations between $t = 7$ and 19 s, the estimation errors are significantly lower (and almost zero) in comparison to the errors obtained with EKF $- R_s$ only, which performs $R_s$ estimation only while $R'_f$ variations are taking place.

D. Scenario IV—Stator-Resistance Variations Under Braided EKF, (Fig. 7)

In this section, the performance of the braided EKF will be evaluated under $R_s$ variations. To this aim, the scenario is started with an incorrect initialization of $R_s(0^+) = 2 \times R_{sn}$, while only EKF $- R'_f$ is running for a while and at $t = 7.27$ s, the braided algorithm starts. The resulting performance of this scenario is given in Fig. 7(a)–(e).

Inspecting the results, the following can be noted: The estimation error obtained in the initial period when only the EKF $- R'_f$ is running is on, under a variation in $R_s$, is significantly reduced as soon as the braided EKF algorithm is switched on. As shown in Fig. 7, all errors quickly approach zero as soon as the braided EKF is switched on, in spite of the variation in $R_s$.

E. Scenario V—Low-Speed Operation Under Braided EKF, (Fig. 8)

Finally, the performance of the braided EKF algorithm is tested in low-speed operation; to this purpose, while the IM is running at 821.7 rev/m under a load torque of 19.17 N·m, the velocity and load torque are decreased to 54.5 rev/m and 2.85 N·m, respectively, with a linear variation given to the velocity reference on the ac drive. At $t = 22$ s, the scenario is switched back to the initial status. The resulting performance is given in Fig. 8(a)–(g).

Inspecting the estimation errors of the velocity and load torque in Fig. 8(f) and (g), respectively, it can be noted that the braided EKF outperforms the individual EKF $- R_s$ and EKF $- R'_f$ algorithms. Hence, the benefits of the braided EKF algorithm over individual EKF algorithms are evident in the whole velocity range, particularly under unmatched $R_s$ and $R'_f$ variations; therefore, $R'_f$ variations while EKF $- R_s$ is running or $R_s$ variations when the estimator is EKF $- R'_f$. The switching action provided by the braided algorithm at every time step ensures better prediction and correction against all uncertainties and parameter variations.

V. CONCLUSION

The proper estimation of temperature- and frequency-based uncertainties of $R_s$ and $R'_f$ is known to be essential for the accuracy of flux and velocity estimation in IM sensorless control; however, the simultaneous estimation of $R_s$ and $R'_f$ has frequently been reported as a challenge in previous literature on sensorless IM control.

There have been only a few studies achieving the simultaneous estimation of $R_s$ and $R'_f$ in sensorless control, either by the use of open-loop estimators or by developing different estimation techniques for different states and parameters in the IM model or by signal injection, which requires additional and customized measures to be taken. In this paper, a more flexible approach is proposed to the solution of the problem that does not require signal injection or algorithm changes and is based on the consecutive use of two EKF algorithms of the same nature and configuration for the simultaneous estimation of $R_s$ and $R'_f$ in addition to the load torque, flux, and velocity.

The solution offered by the braided approach exploits the fast convergence rate of EKFs as well as the persistent excitation properties introduced by the model (or system) noise and measurement noise inherent to EKF, increasing estimation accuracy in transient state as well as in steady state, without the need for external signal injection. However, the computational complexity and deteriorated performance of EKFs with the increased number of estimated states is also a well-known fact. To overcome this problem in this paper, the two EKF algorithms estimating $R_s$ and $R'_f$ are utilized in a braided manner, thus achieving the accurate estimation of a high number of parameters and states than would have been possible with a single EKF algorithm.

Experimental results taken under challenging scenarios demonstrate the performance achieved by the proposed algorithm in a wide speed range with significantly increased accuracy in the estimation of flux and velocity, in comparison to single EKF algorithms which estimate $R_s$ or $R'_f$ only or other approaches taken in previous studies. The results also motivate the utilization of the proposed estimation technique in combination with a variety of control methods for IMs or other electrical machines that require the accurate knowledge of a large number of parameters.

REFERENCES


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