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Abstract:

Accurate and efficient control of electric motors is dependent on knowledge of motor parameters such as the resistance and the inductance of the winding. However, these parameters are often unavailable to the control designer because they are dependent on the motor design and may change due to environmental effects such as temperature. An accurate real-time method to determine the values of these unknown parameters can improve motor performance over the entire operating range. In this work, a parameter estimation technique based on a bank of Kalman filters is used to adaptively estimate the motor winding resistance. Simulation results for a 3.5 horsepower interior permanent magnet (IPM) synchronous motor operating at rated torque demonstrate that this technique may be used for real-time estimation of motor parameters.

SECTION I. Introduction

Most high-performance motor control techniques, such as field-oriented control (FOC), require that motor parameters such as stator resistance be known for best results. However, these parameters are often only approximately known and often drift due to operating conditions such as temperature [1]. This parameter uncertainty can lead to detuning of the control, particularly during certain motor operating points such as low speed, high torque.

Although parameter knowledge is important for high performance motor control, estimation of parameters such as stator resistance using model-based techniques has had mixed results [1]. Many investigations have attempted to estimate motor parameters during operation with varying degrees of success. Among these investigations, the extended Kalman filter (EKF) was used in [2] to estimate the rotor time constant of an induction motor. Estimating individual motor parameters was not addressed in this work. The braided extended Kalman filter in [3], [4] simultaneously identified stator resistance and rotor resistance of an induction motor using two EKFs that differed only in the last state estimated: the first included the stator resistance in the estimator and the second included the rotor resistance in the estimator.

Model reference adaptive system (MRAS) techniques [5], [6] have also been used to estimate various induction motor parameters with some success. In [7], the stator resistance and rotor resistance of an induction motor are estimated for use in monitoring the temperature of the motor. The rotor resistance and the rotor flux linkages are found from the MRAS, and stator resistance is calculated from the flux linkages. Since temperature monitoring was the primary interest, this work focused on operating conditions at higher speeds and did not address the challenging case of low speed, high torque operation. In [8] induction motor parameter estimation at lower speeds is considered. The model in the MRAS is based on a model for the flux linkages. Induction motor parameter estimation over the entire speed range is also considered in [9]. Reactive power is used as the model in the MRAS to reduce sensitivity to operating speed. Although induction motor parameter estimation has been investigated in these studies, the existing literature on parameter estimation for permanent magnet motors is significantly less.

In this work, the problem of parameter estimation for permanent magnet motors is considered. The adaptive estimation technique used in this work is based on a bank of Kalman filters to identify motor parameters when given the motor terminal voltages and phase currents. The stator resistance of an interior permanent magnet (IPM) synchronous motor is estimated, although the technique is easily adapted to estimating motor inductance as well. The primary advantage of this technique is that although system parameters are estimated in addition to the states, the estimator remains linear for a linear system unlike parameter estimation using an extended Kalman filter.

This paper consists of five sections including this introduction. In Section II, the model for the permanent magnet motor is presented. The adaptive estimation technique is described in Section III. The 3.5 hp motor is described and simulated in Section IV. The motor is simulated at rated torque and three different speeds: rated speed, half rated speed, and quarter rated speed. In addition, the performance of the estimator is investigated for different stator resistances. The results are summarized in Section V.

SECTION II. The Permanent Magnet Synchronous Motor Model

Although any state space model that sufficiently models the desired motor characteristics may be used, the $dq0$ model [10] is used in this work. The continuous time $dq0$ model of the IPM motor is given in (1) as

$$\begin{bmatrix} \dot{i}_d \\ \dot{i}_q \\ \dot{i}_0 \end{bmatrix} = \begin{bmatrix} -\frac{r_s}{L_{dd}} & \frac{\omega_e L_{qq}}{L_{dd}} & 0 \\ -\frac{\omega_e L_{dd}}{L_{qq}} & -\frac{r_s}{L_{qq}} & 0 \\ 0 & 0 & -\frac{r_s}{L_{00}} \end{bmatrix} \begin{bmatrix} i_d \\ i_q \\ i_0 \end{bmatrix} + \begin{bmatrix} \frac{1}{L_{dd}} & 0 & 0 \\ 0 & \frac{1}{L_{qq}} & 0 \\ 0 & 0 & \frac{1}{L_{00}} \end{bmatrix} \begin{bmatrix} v_d - e_d \\ v_q - e_q \\ v_0 - e_0 \end{bmatrix} \quad (1)$$

Here, r_s is the stator resistance, L_{dd} is the d-axis self inductance, L_{qq} is the q-axis self inductance L_{00} is the 0-axis self inductance, and ω_e is the motor speed in electrical radians per second (e.rad/s).

In this work, the current and voltage vectors are represented in a shorthand form such that the subscript of the vector indicates the components of that vector. For example, the current vector $[i_x i_y i_z]^T$ is represented as i_{xyz}. The state vector i_{dq0} is the phase current of the motor in the $dq0$ reference frame, v_{dq0} is the voltage applied to the motor in the $dq0$ reference frame, and e_{dq0} is the motor back electromotive force (emf) in the $dq0$ reference frame. The abc phase currents are measured and can be related back to the states (the $dq0$ currents) using the transformation

$$\begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} = \begin{bmatrix} \cos(\sigma) & -\sin(\sigma) & 1 \\ \cos(\sigma - \frac{2\pi}{3}) & -\sin(\sigma - \frac{2\pi}{3}) & 1 \\ \cos(\sigma - \frac{4\pi}{3}) & -\sin(\sigma - \frac{4\pi}{3}) & 1 \end{bmatrix} \begin{bmatrix} i_d \\ i_q \\ i_0 \end{bmatrix} \quad (2)$$

Here, σ is the electrical position of the rotor in radians. When the rotor speed is constant, this can be expressed as $\sigma = \omega t$. The $dq0$ voltages can be found from the abc phase voltages by inverting the transformation matrix in (2).

The system of (1) and (2) can be written in standard state space form as

$$\begin{aligned} \dot{x} &= A_c x + B_c u \\ y &= C_c x \end{aligned} \quad (3)$$

Here, the state vector x is the vector of $dq0$ currents i_{dq0}, the control vector u is the difference between the vector of $dq0$ terminal voltages v_{dq0} and the vector of the $dq0$ back emf e_{dq0}, and the measurement vector y is the vector of measured abc phase currents i_{abc}. The system matrix A_c, the control matrix B_c, and the measurement matrix C_c can be inferred from (1) and (2).

Since this technique is likely to be implemented on a microcontroller, the motor model is discretized using the trapezoidal method, which yields

$$\begin{aligned} x_{k+1} &= A_k x_k + B_k u_k \\ y_k &= C_k x_k \end{aligned} \quad (4)$$

where

$$\begin{aligned} A_k &= (I_3 - 0.5TA_c)^{-1}(I_3 + 0.5TA_c) \\ B_k &= 0.5T(I_3 - 0.5TA_c)^{-1}B_c \end{aligned} \quad (5)(6)$$

Here, T is the sampling period in seconds, and I_3 is the 3×3 identity matrix.

SECTION III. Adaptive Estimation via Bank of Kalman Filters

In this technique, the parameters of a system, in this case an IPM motor, can be adaptively estimated using knowledge of the states from the measurements of the abc phase currents and the control through the terminal voltage of the motor in the $dq0$ reference frame as well as some assumptions about the nature of the unknown parameters. It is assumed that the unknown parameter is constant or slowly varying and lies within a range with known upper and lower bounds. This range is then quantized into N possible values, and one Kalman filter is designed for each possible parameter value, or hypothesis. The set of hypothesis parameter values is represented as $R = \{R_1, R_2, \ldots, R_i, \ldots, R_N\}$. The conditional probability of each Kalman filter in this bank based on the current measurements is calculated, and the filter with a conditional probability that approaches 1 is the closest to the actual parameter value. This filter structure is demonstrated in Fig. 1 [11] for an unknown stator resistance.

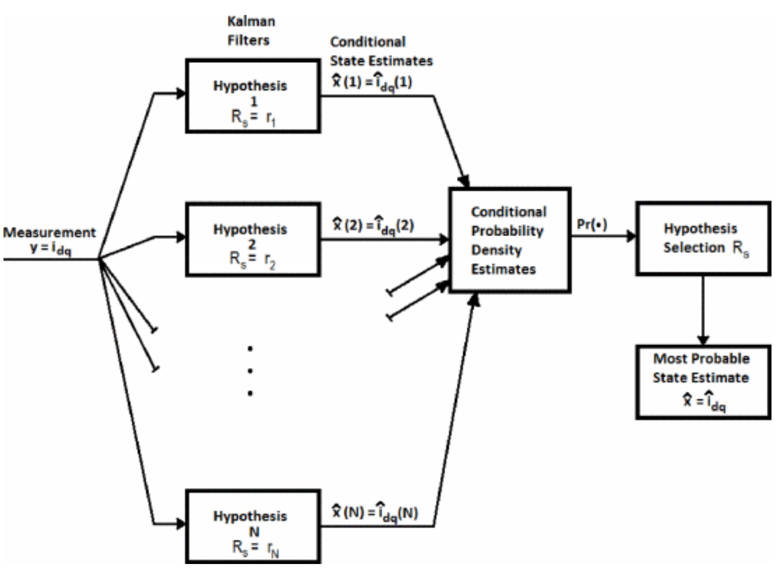

Fig. 1. Block diagram of adaptive estimation technique based on banks of kalman filters [11].

Since one Kalman filter is designed for each hypothesized parameter value, there is a trade-off between computation complexity of the Kalman filter bank and the resolution of the parameter estimate. As the number of Kalman filters in the bank increases, the computation complexity also increases. However, as the number of Kalman filters in the bank decreases, the resolution of the parameter estimate decreases. In many cases, due to the limits of microcontrollers used in motor applications, the computation complexity will be the limiting factor. Hence, as many Kalman filters as is computationally practical should be used. If the resolution is not satisfactory, the bank can be reinitialized after it converges using the initial parameter estimate to determine the new, smaller range of possible parameter values.

The conditional probability of each Kalman filter can be found using Bayes' Rule, where $p(\,)$ represents a probability density function:

$$p(R_i|Y_k) = \frac{p(Y_k,R_i)}{\sum_{m=1}^{N} p(Y_k|R_m)p(R_m)} \quad (7)$$

Expanded and simplified, the posterior probability $p(R_i|Y_k)$ can be written as

$$p(R_i|Y_k) = \frac{p(y_k|Y_{k-1},R_i)p(R_i|Y_{k-1})}{\sum_{m=1}^{N} p(y_k|Y_{k-1},R_m)p(R_m|Y_{k-1})} \quad (8)$$

Here, y_k represents the measurement at time k, Y_{k-1} represents the set of all measurements up to and including time $k-1$, and R_i represents the possible value of the unknown parameter to which an instance of the Kalman filter is tuned. Equation (8) can be solved recursively where $p(R_i|Y_{k-1})$ is the previous value of the posterior probability. Convergence occurs when the posterior probability of the filter corresponding to the hypothesis closest to the correct parameter value approaches 1, while the posterior probability of all other filters approaches 0. The proof of convergence is described in detail in [12].

Equation (8) can converge independent of the form of the probability densities. However, all system and measurement noises are assumed to be Gaussian in this work, which produces Gaussian conditional probabilities. Since the probability density function is known for Gaussian distributions, the portion of (8) that cannot be found as part of the recursion can be calculated as

$$p(y_k|Y_{k-1},R_i) = (2\pi)^{-3/2}\left|\Omega_{k|R_i}^{-1}\right|^{1/2} \cdot \exp\left(-\frac{1}{2}\tilde{y}_{k|R_i}^{T}\Omega_{k|R_i}^{-1}\tilde{y}_{k|R_i}\right) \quad (9)$$

where the innovations sequence associated with the Kalman filter tuned to R_i is

$$\tilde{y}_{k|R_i} = y_k - \hat{y}_{k|k-1,R_i} \quad (10)$$

and the design covariance for the Kalman filter tuned to R_i is

$$\Omega_{k|R_i} = C_k P_{k|R_i} C_k^T + GWG^T \quad (11)$$

Then, (10) and (11) are substituted into (9), which is substituted into (8). The Kalman filter equations are provided in the Appendix.

Although producing a state estimate is not required to identify the value of the unknown parameter, a state estimate that includes the parameter uncertainty can be obtained easily. This estimate uses the result from each Kalman filter in the bank and weights the result using the corresponding posterior probability. The weighted state estimate can be written as

$$\hat{x}_{k|k-1} = \sum_{i=1}^{N} \hat{x}_{k|k-1,R_i} p(R_i|Y_k) \quad (12)$$

where $\hat{x}_{k|k-1,R_i}$ is the state estimate produced by the Kalman filter tuned to R_i.

SECTION IV. Simulation Results

A. The Case Study 3.5 hp Motor

The ratings of the IPM motor used in simulation are given in Table I. All motor parameters, including the self and mutual inductances, the phase resistance, and the first thirteen harmonics of the open circuit back emf, were previously calculated using Finite Element Analysis. The back emf of the motor contains significant odd harmonics, which produces a trapezoidal back emf as shown in Fig. 2 rather than a sinusoidal back emf. Since the voltage applied to the motor terminals is sinusoidal and the back emf is trapezoidal, the phase currents will also contain several higher order harmonics. The motor is operated at rated torque for three different speeds: rated speed, half speed, and quarter speed. It is assumed that all of the phase voltages and currents are available. In each simulation, 20 samples will be taken per fundamental cycle. Thus, as the motor speed decreases, the sampling period becomes larger. The relatively large number of samples taken per fundamental cycle is used to account for the higher harmonics in the back emf and the phase current.

Table I Ratings of the IPM machine under investigation.

Rated Power	3.5 hp
Rated Speed	3450 r/min
Rated Torque	7.25 N·m
Rated Current	10 A
Rated Line-to-Line Voltage	240 V

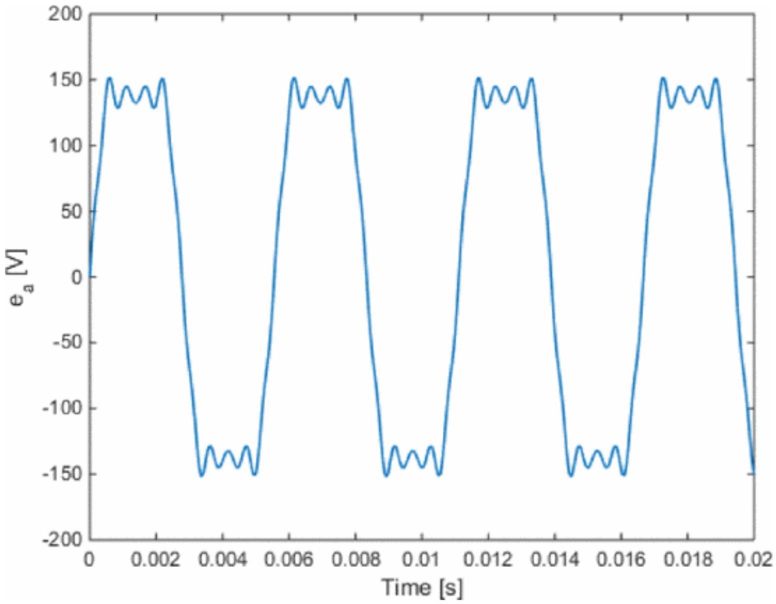

Fig. 2. Phase a open circuit back emf of the motor at rated speed. Since the motor is balanced, the back emf of phase b and phase c are simply phase shifted ±120° from phase a. Note the trapezoidal nature of the waveform.

Additive Gaussian white measurement noise is included in each simulation. It is assumed that the noise present in each current measurement is independent from the noise in each of the other current measurements with zero mean and 0.01 variance. System noise is not modeled in this paper, indicating that the other parameter values and input are known exactly. This restriction will be relaxed in future work. In all of the simulations, the stator winding resistance r_s is assumed to be between 0.2Ω and 0.6Ω Generally, an initial estimate of the motor parameters can be found during the commissioning of the motor drive, and a range of values that encompass the parameter variation during operation can be found from this. The bank consists of five Kalman filters, each one tuned to one of the hypothesized values of r_s within the set $\{0.2, 0.3, 0.4, 0.5, 0.6\}$. The true value of the stator resistance is 0.49Ω, which was calculated previously using finite element analysis. Each of the five posterior probabilities associated with the five Kalman filters is initialized to a probability of 0.2, indicating that the stator resistance has an equal chance of being any of the hypotheses.

B. Results at Rated Speed, Rated Torque

The measured and estimated current of phase a for IPM operation at rated speed and rated torque, as well as the percent error in estimation, is presented in Fig. 3. For all three phases, the percent error is less than 0.2%. Here, it is demonstrated that although the stator winding resistance is unknown and there are significant harmonics in the phase current due to the trapezoidal back emf, the currents can be estimated using the Kalman filter bank.

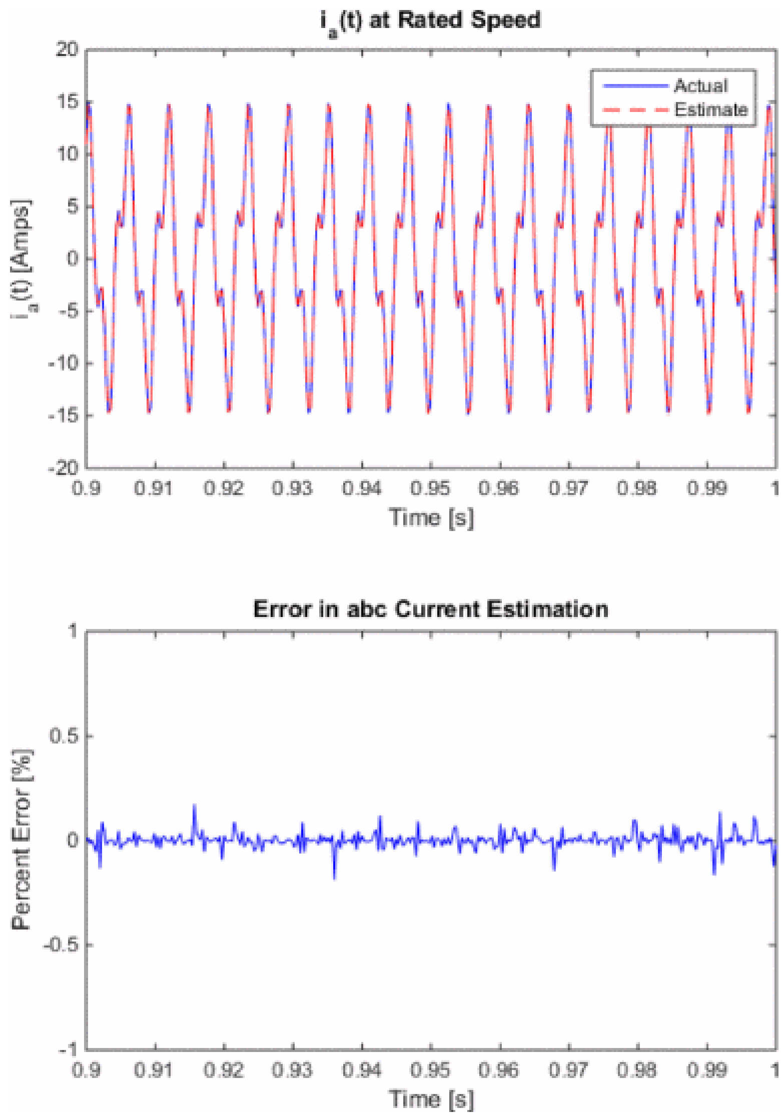

Fig. 3. Simulated phase a current of the IPM motor operating at rated speed, rated torque.

In Fig. 4, the probability of each of the five stator winding resistance hypotheses is shown as a function of time. One of the probability curves which corresponds to the value closest to the actual stator resistance approaches 1, while the other four probability curves corresponding to values farther from the correct value approach zero. The probabilities also converge to their final value in under one second of operation. From this plot, the stator resistance estimate for the motor is 0.5Ω. As stated previously, the actual value of the stator resistance is 0.49Ω, and of the options the bank had, 0.5 is the closest, indicating the estimator converged as expected.

C. Results at Half Rated Speed, Rated Torque

The measured and estimated current of phase a for IPM operation at half rated speed and rated torque, as well as the percent error in estimation, is shown in Fig. 5. Note that compared to Fig. 3, the fundamental frequency of the phase current decreases. For all three phases, the percent error is less than 0.25%. Again the currents can be estimated accurately using the Kalman filter bank despite the significant current and back emf harmonics, the decreased motor speed, and the unknown stator winding resistance.

In Fig. 6, the probability of each of the five stator winding resistance hypotheses is presented over time. Again, the probability curve associated with the correct hypothesis approaches 1 while the other probability curves approach zero. As expected, the stator winding resistance is estimated as 0.5Ω. In this simulation, the parameter estimation converges in approximately 0.6 seconds, which is faster than the estimation at rated speed.

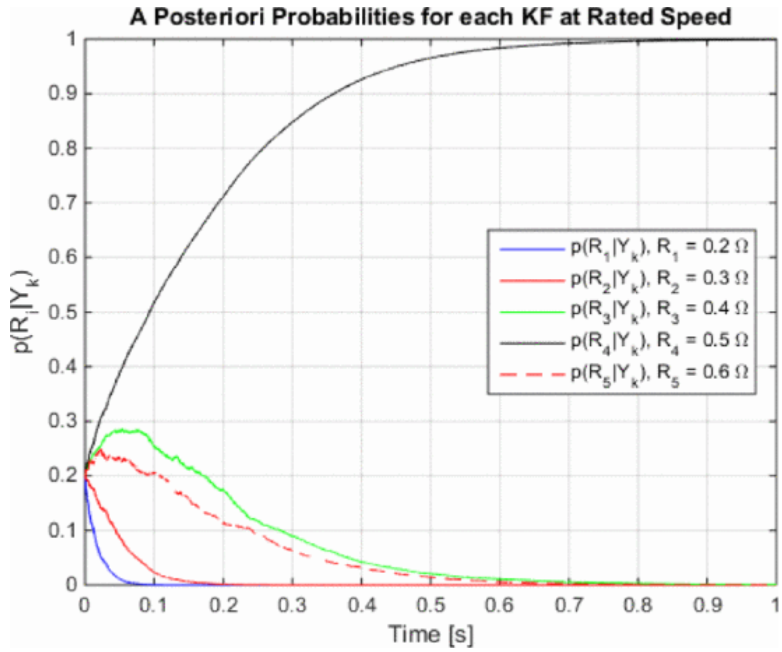

Fig. 4. Posterior probabilities of the stator resistance hypotheses used in the bank of kalman filters. The motor is operating at rated speed, rated torque. Here, the bank estimates the stator resistance as 0.5 Ω. The actual resistance is 0.49 Ω.

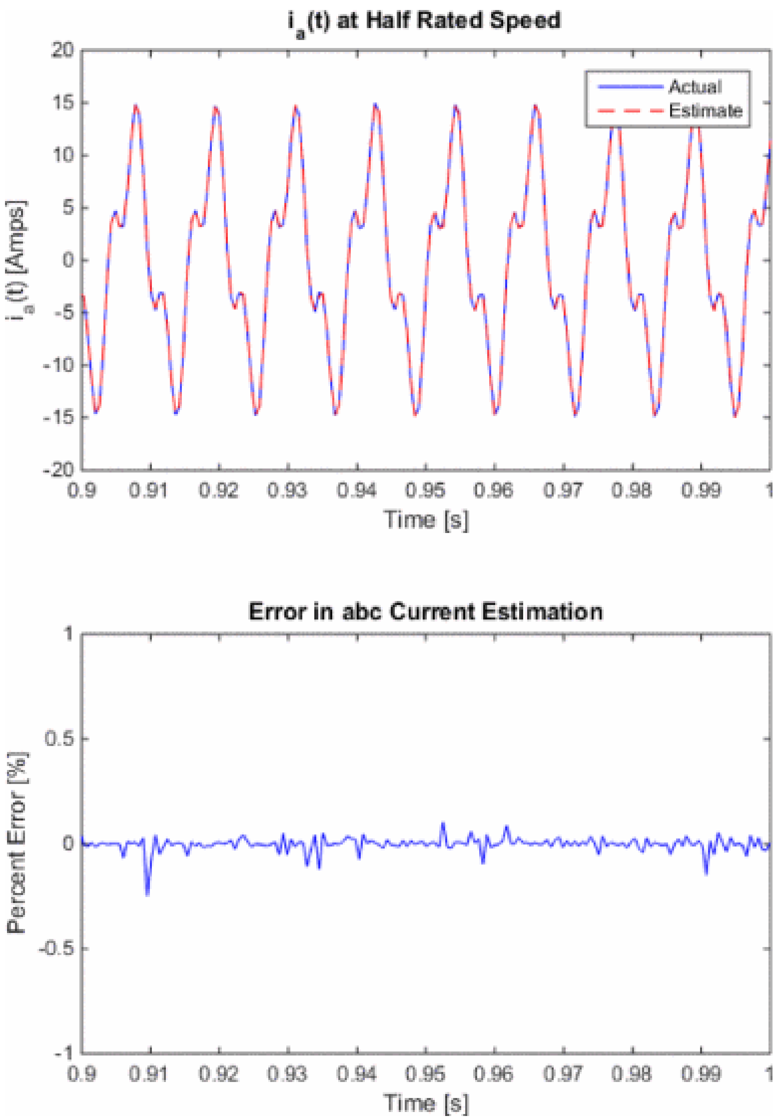

Fig. 5. Simulated phase a current of the IPM motor operating at half rated speed, rated torque.

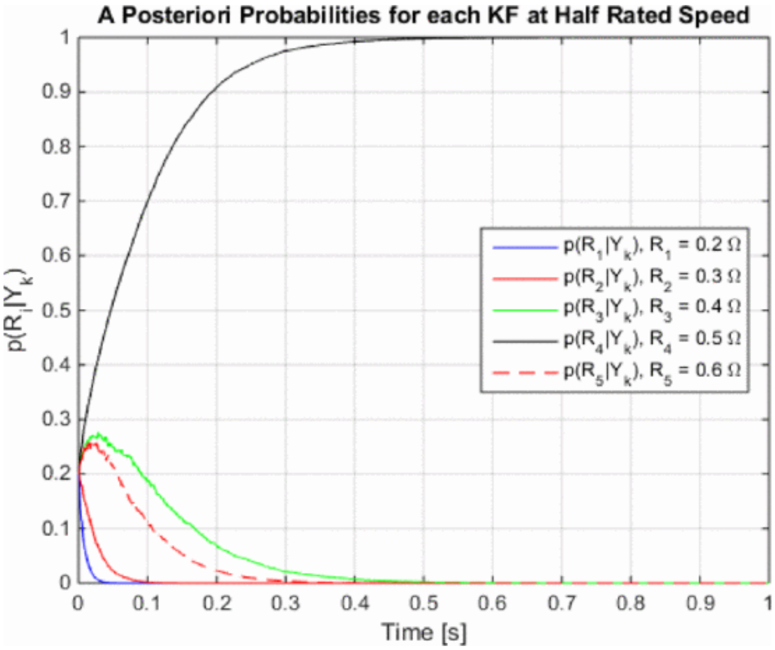

Fig. 6. Posterior probabilities of the stator resistance hypotheses used in the bank of kalman filters. The motor is operating at half rated speed, rated torque. Here, the bank estimates the stator resistance as 0.5 Ω. The actual resistance is 0.49 Ω.

D. Results at Quarter Rated Speed, Rated Torque

The measured and estimated current of phase a for IPM operation at quarter rated speed and rated torque, as well as the percent error in estimation, is presented in Fig. 7. Note that compared to Fig. 3 and Fig. 5, the fundamental frequency of the phase current again decreases. For all three phases, the percent error is less than 0.8%. Although the percent error increases slightly as the speed decreases, the currents can be estimated accurately using the Kalman filter bank despite the significant current and back emf harmonics, the decreased speed, and the unknown stator winding resistance.

In Fig. 8, the probability of each of the five stator winding resistance hypotheses is presented over time. Again, the probability curve associated with the correct hypothesis approaches 1, while the remaining probability curves approach zero. As expected, the stator winding resistance is estimated as 0.5Ω. In this simulation, the parameter estimation converges in approximately 0.3 seconds, which is faster than the estimation at both rated speed and half speed.

E. Estimator Performance for Several Stator Resistances

To further demonstrate the viability of this technique, the simulation of this motor at rated operating conditions is repeated for several different stator resistances, including several values that are not represented in the set of hypothesis resistances. The estimator performance as the stator resistance varies from 0.4Ω to 0.5Ω in steps of 0.01Ω is presented in Table II. For each case, the estimator result and the convergence time are found. Here, convergence time is defined as the time it takes for the posterior probability associated with one of the Kalman filters in the bank to reach a value greater than 0.99.

In each case, the estimator converges to the hypothesis resistance that is closest in value to the actual resistance of the motor. Also, as the actual resistance moves farther from the hypothesis resistances the convergence time increases. This increase in convergence time the farther the actual value is from the available hypothesis values may be a useful indicator of any discrepancies between the set of hypotheses and the actual parameter value.

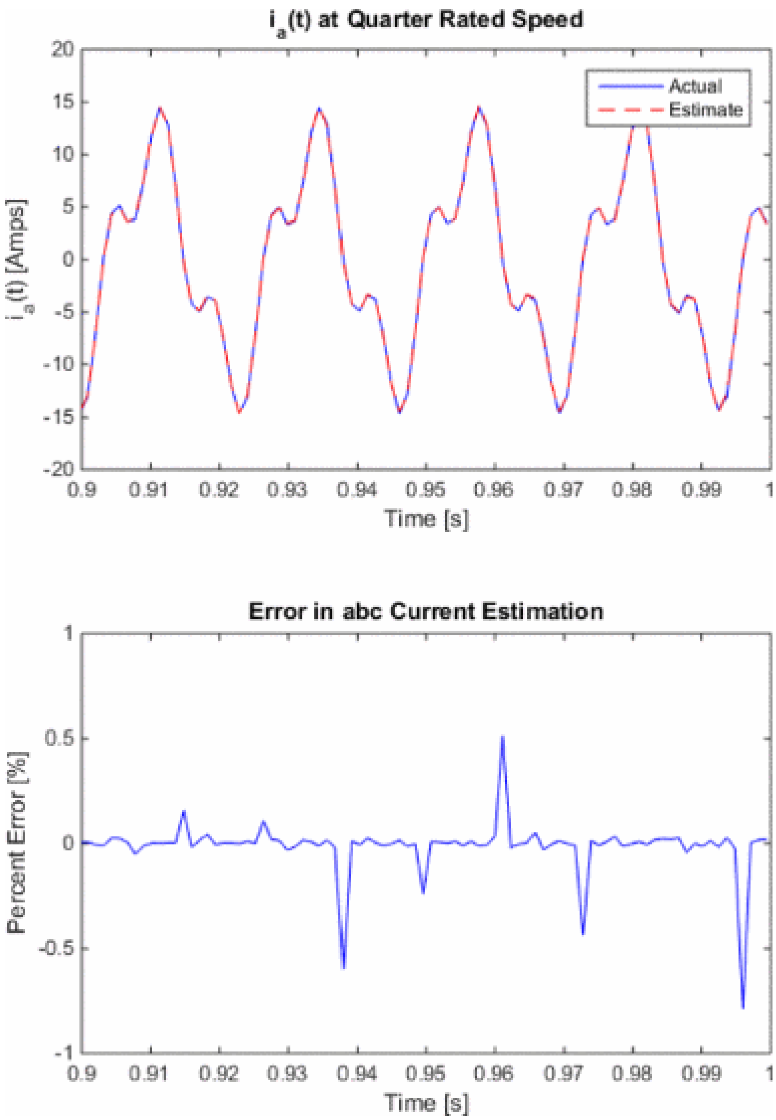

Fig. 7. Simulated phase a current of the IPM motor operating at quarter rated speed, rated torque.

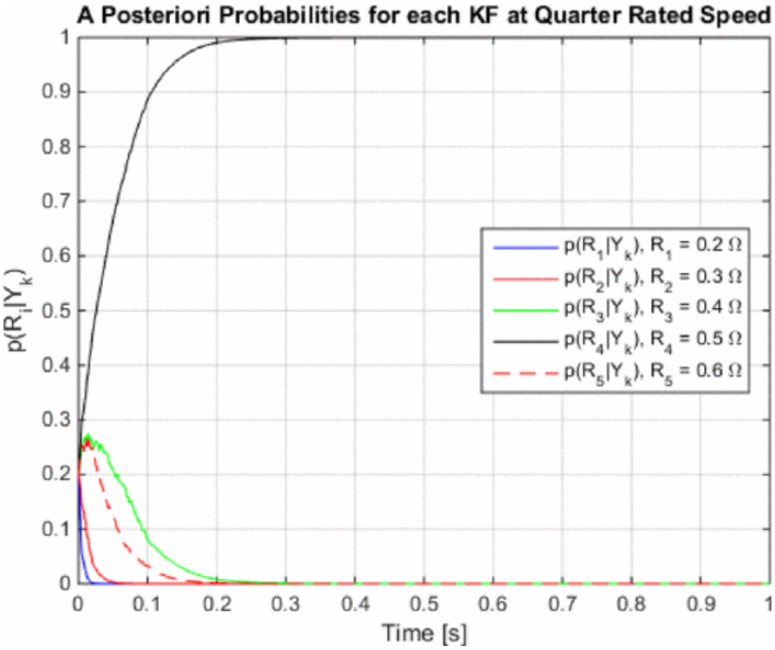

Fig. 8. Posterior probabilities of the stator resistance hypotheses used in the bank of kalman filters. The motor is operating at quarter rated speed, rated torque. Here, the bank estimates the stator resistance as 0.5 Ω. The actual resistance is 0.49 Ω.

SECTION V. Conclusions

In this work, the stator winding resistance of an IPM motor is adaptively estimated using a bank of Kalman filters. The steady state $dq0$ model of the IPM motor is used in this work, but any common motor model that includes the motor parameter of interest can be used with this technique. Simulation results for a case study motor operating at rated torque and three different speed conditions (rated speed, half speed, and quarter speed) are presented. It is shown that the phase currents can be estimated accurately while estimating the motor parameter of interest. The estimation of the stator resistance also converges relatively quickly, although convergence time is affected by discrepancies between the hypotheses and the actual parameter value. Generally convergence occurs more quickly as the operating speed decreases for the operating points considered.

Table II Estimator results and convergence time for several winding resistances.

Actual Resistance (Ω)	Estimator Result (Ω)	Convergence Time (s)
0.4	0.4	0.6643
0.41	0.4	0.7980
0.42	0.4	1.128
0.43	0.4	1.925
0.44	0.4	5.328
0.45	0.5	6.545
0.46	0.5	2.105
0.47	0.5	1.134
0.48	0.5	0.8165
0.49	0.5	0.6690
0.5	0.5	0.6583

Future work will include a comparison between this technique and motor parameter estimation using the extended Kalman filter. The robustness of this technique will also be investigated by modeling small amounts of uncertainty in the known motor parameters. The Kalman filter bank will be modified so that a slowly varying stator resistance can be estimated, which will increase its usefulness in various applications. In addition, the relationship between the convergence time and any discrepancy between the hypotheses and the actual parameter value will be investigated in greater detail. The technique and motor model will also be adjusted so that only knowledge of the fundamental of the back emf is needed rather than complete knowledge of its harmonics.

Consider a linear time varying stochastic system of the form

$$\begin{aligned} x_{k+1} &= A_k x_k + B_k u_k + F_k v_k \\ y_k &= C_k x_k + D_k u_k + G_k w_k \end{aligned} \quad (13)$$

where x_k is the $n \times 1$ state vector, u_k is the $m \times 1$ input vector, and y_k is the $p \times 1$ measurement vector. The $n \times 1$ system noise vector v_k, the $p \times 1$ measurement noise vector w_k, and the initial state value x_0 are independent white random variables with arbitrary densities:

$$\begin{bmatrix} x_0 \\ v_k \\ w_k \end{bmatrix} \sim \left(\begin{bmatrix} \overline{x}_0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} X_0 & 0 & 0 \\ 0 & V_k & 0 \\ 0 & 0 & W_k \end{bmatrix} \right) \quad (14)$$

The Kalman filter for (13) can be expressed as in (15) below. Note that in this formulation the predict and update steps are combined. In this work, N of these equations are used in parallel, one for each value in the parameter set of interest.

$$\hat{x}_{k+1} = A_k \hat{x}_k + B_k u_k + K_k \tilde{y}_k \quad (15)$$

The innovations term $\tilde{y}_k$ is the difference between the measurement and the estimate of the measurement based on the state estimate.

$$\tilde{y}_k = y_k - \hat{y}_k = y_k - C_k \hat{x}_k - D_k u_k \quad (16)$$

The Kalman gain K_k is defined as

$$K_k = A_k P_k C_k^T (C_k P_k C_k^T + G_k W_k G_k^T)^{-1} \quad (17)$$

The covariance of the state estimate P_k can be found from the Riccati equation

$$\begin{aligned} P_{k+1} &= A_k P_k A_k^T + F_k V_k F_k^T \\ &\quad - A_k P_k C_k^T (C_k P_k C_k^T + G_k W_k G_k^T)^{-1} C_k P_k A_k^T \end{aligned} \quad (18)$$

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Keywords

Kalman filters, Induction motors, Permanent magnet motors, Synchronous motors, Resistance, Stator windings