Partial-Update Kalman Filter for Permanent Magnet Synchronous Motor Estimates Under Intermittent Data

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Abstract The partial-update Kalman filter (PKF) is an extension of the Schmidt Kalman filter, which can improve the capabilities of the conventional extended Kalman filter for handling model uncertainties and nonlinearities. Herein, we adapt the PKF to estimate the states and parameters of electric machines, particularly in cases with intermittent observations. To account for missing data within the filter, the arrival of new measurements is treated as a Bernoulli process. We show that the estimation error of the proposed filter remains bounded if the system satisfies mild assumptions. Moreover, we show that the prediction error covariance matrix is guaranteed to be bounded if the observation arrival rate has a lower bound. Hardware experiments validate this technique for a surface-mounted permanent magnet synchronous motor.

Index Terms Estimation, Kalman filters, permanent magnet motors, system identification.

I. INTRODUCTION

Accurate and robust estimation of states and parameters of electric machines are needed for drive design and control, system-level studies, or condition monitoring [1]. Online estimation approaches, e.g., Kalman filter, are indispensable as machine parameters can change during its operation [2]. Kalman filter-based estimators are popular due to their simple yet stochastic structure, which incorporates both process and measurement noises. This helps them compensate for the modeling errors given a wide operating range and parameter variations. Popular Kalman filter applications in electric machines include (1) state estimation, e.g., flux or speed [3], [4], (2) parameter estimation [5], [6], and (3) condition monitoring [7], [8]. State estimation usually involves observer design for hard-to-measure signals such as flux linkages or rotor currents. Parameter estimation obtains a set of machine parameters, such as resistances and inductances. Alternatively, estimates of parameters such as rotor resistance (in an induction motor) or the number of short-circuited turns in the stator winding can be used as indicators of faults. While Kalman filters are intended for linear systems, an extended Kalman filter (EKF) can be used for nonlinear systems such as electric machines [9], [10]. Limitations of EKFs include (1) error due to linearizing nonlinear system equations, (2) tedious filter tuning, i.e., finding correct noise covariance matrices, and (3) ensuring a stable operation. In this paper, we address these issues through a partial-update Kalman filter, and validate our findings on a permanent magnet synchronous motor (PMSM).

Nuisance parameters are those (such as static biases) that are not required to be estimated, but whose uncertainties need to be considered to better estimate variables of interest. In such cases, the Schmidt Kalman filter (SKF) accounts for uncertainties in system parameters and provides better estimates compared to the standard Kalman filter [11]. Therein, nuisance parameters are added as a part of the state vector to incorporate model uncertainties. However, these parameters are only considered, and not estimated, i.e., even though they are not estimated directly, the state estimates and covariance are updated based on an estimated parameter covariance [11]. In this way, the parameter uncertainty is propagated through the dynamic system while avoiding issues regarding simultaneous estimation of states and nuisance parameters (such as increased computational cost and possible instabilities) [12]. SKFs can be especially helpful
for parameters with low observability. Such scenarios can also occur in machine applications, e.g., the load torque can often act as a nuisance parameter in an estimation problem. Treatment of nuisance parameters is fairly limited in the context of electric machines.

Partial-update Kalman filter (PKF) is a hybrid approach between SKF and EKF that can improve upon the performances of both by tuning gains [13]. Unlike the SKF, which chooses between a full or non-update of a given state/parameter, in the PKF, a partial update of that given state/parameter is considered. Herein, we adopt the PKF to estimate PMSM states and parameters. Filter equations are obtained by modifying the measurement update stage of the EKF. This can improve the handling of uncertainties and nonlinearities, while maintaining simplicity and low computational costs of EKF [14].

In practice, not all machine states are observable from its terminal measurements. Moreover, measured signals can be noisy, or lost due to faulty sensory devices. This intermittency in observed data can significantly degrade the estimation performance [15], [16]. Stability and convergence of the estimation process for linear, extended, unscented, and Cubature Kalman filters in the presence of intermittent observations have been studied in [17]–[20]. The authors of [21] propose an event-based state estimation/filtering problem for time-varying nonlinear dynamical networks subject to missing measurements. To the best of our knowledge, there are no results reported in the literature on stability and convergence properties of PKF subject to intermittent measurements. Figure 1 provides an overview of the proposed methodology. The contributions of this paper can therefore be summarized as follows:

- We have introduced the concept of intermittent data for PKF, and applied it on PMSM for state and parameter estimation problems.
- We analyzed the error dynamics of the proposed filter.
  The required conditions and assumptions to guarantee the boundedness of the estimation error and the error covariance matrix are also derived. Moreover, an expression of critical arrival rate of measurement data under which the filter is stable and accurate is obtained.
- PKF is verified through simulated and experimental studies for PMSM under varying operating conditions.

This paper is arranged as follows. Section II provides the notations. Section III summarizes machine models, their augmentation, and their discretization. In Section IV, the implementation of EKF and PKF, as well as measurement losses, are studied. In Section V, the feasibility of PKF to perform machine estimates despite measurement loss is investigated by studying the boundedness of estimation errors and covariance matrix. Section VI investigates the theoretical results for a PMSM using both numerical simulation and hardware measurement. Section VII provides summary remarks.

II. NOTATIONS

$\mathbb{R}^n$ represents the set of $n$-dimensional real vectors. Given a matrix $A$, let $A^\top$ and $A^{-1}$ denote, respectively, its transpose and inverse. The $n$-dimensional identity matrix is denoted as $I_n$. $\| \|$ stands for the euclidean norm of vectors and the spectral norm of matrices, and $\| \|_2$ denotes the $L^2$-norm of vectors. $\mathbb{E}[x]$ represents the expectation (expected value) of $x$. $\lambda_{\min}(\cdot)$ and $\lambda_{\max}(\cdot)$, respectively, denote the smallest and the largest eigenvalues of a real matrix.

III. PMSM MODELING FOR ESTIMATION PURPOSES

Here we discuss the dynamic model of a PMSM for use in the estimation algorithm, its augmentation, and discretization.

A. PERMANENT-MAGNET SYNCHRONOUS MOTOR MODEL

The PMSM model in $q/d$-reference frame is [22]

$$L_d \frac{di_d}{dt} = v_{ds} - R_di_d + P_p\omega_m L_q i_q, \quad (1a)$$

$$L_q \frac{di_q}{dt} = v_{qs} - R_q i_q - P_p\omega_m L_d i_d - P_p\omega_m \lambda_m, \quad (1b)$$

$$J_m \frac{d\omega_m}{dt} = T_e - d_m\omega_m - T_L, \quad (1c)$$

$$\frac{dT_e}{dt} = \omega_m, \quad (1d)$$

$$T_e = \frac{3P_p}{2} (\lambda_m i_q + (L_d - L_q) i_q i_d). \quad (1e)$$

$i_d$, $i_q$, $v_d$, $v_q$, and $v_d$ are the respective currents and voltages terms in the $q/d$-reference frame. $R_i$ is the stator resistance, $L_d$ and $L_q$ are the $q/d$-axes inductances, $\lambda_m$ is the flux of the permanent magnet, and $P_p$ is the pole-pairs. The mechanical subsystem states are the rotor speed $\omega_m$ and rotor position $\theta_m$. Lastly, $J_m$, $d_m$, $T_e$, and $T_L$ are the inertia, friction coefficient, electromagnetic torque, and load torque, respectively.

The PMSM model in stationary axes ($\alpha/\beta$-reference frame) is favorable in speed sensorless applications, as the
stator currents and voltages measurements (in abc-reference) are easily transformed to stationary axes representation. In such a case, the PMSM states are \([i_{\text{st}}, i_{\beta}, \omega_m, \theta_m]^{\top}\), with
\[
\begin{bmatrix}
    f_d \\
    f_q
\end{bmatrix} =
\begin{bmatrix}
    \cos(P_{\theta_m}) & \sin(P_{\theta_m}) \\
    -\sin(P_{\theta_m}) & \cos(P_{\theta_m})
\end{bmatrix}
\begin{bmatrix}
    f_d \\
    f_q
\end{bmatrix}.
\] (2)

For example, \(q/d\) and \(\alpha/\beta\) denote machine variables (e.g., currents and voltages) in \(q/d\)- and \(\alpha/\beta\)-reference frames, respectively. For example, \(i_{\text{st}}\) and \(i_{\beta}\) indicate the stator currents in the \(\alpha/\beta\)-reference frame. As per (2), the PMSM model in \(\alpha/\beta\)-reference frame becomes
\[
\begin{align*}
    L_s \frac{di_{\text{st}}}{dt} &= v_{\text{st}} - R_s i_{\text{st}} + \lambda_m P_{\theta_m} \omega_m \sin(P_{\theta_m}), \\
    L_s \frac{di_{\beta}}{dt} &= -R_s i_{\beta} - \lambda_m P_{\theta_m} \omega_m \cos(P_{\theta_m}), \\
    J_m \frac{d\omega_m}{dt} &= T_e - d_m \omega_m - T_L, \\
    \frac{d\theta_m}{dt} &= \omega_m, \\
    T_e &= \frac{3P_m \lambda_m}{2} (i_{\beta} \cos(P_{\theta_m}) - i_{\alpha} \sin(P_{\theta_m})).
\end{align*}
\] (3)

In this paper, we consider a surface-mounted PMSM where \(L_s = L_\beta = L_d\). The state equations for rotor speed \(\omega_m\) and position \(\theta_m\) take the same form as (1c) and (1d), respectively. To facilitate parameter estimation via Kalman filters, machine models are usually augmented with additional state equations representing the parameters of interest [5]. Let \(p\) denote the set of parameters that need to be estimated. Assuming time-invariant or slowly-varying parameter values, their dynamics can be written as \(\frac{dp}{dt} \approx 0\). Hence, the overall system considered for estimation becomes
\[
\frac{d}{dt} \begin{bmatrix}
    x(t) \\
    p
\end{bmatrix} = \begin{bmatrix}
    F(x(t), u(t)) \\
    0
\end{bmatrix}.
\] (4)

For consistency, we have slightly abused notations by using \(F(x(t), u(t))\) instead of the more accurate \(F(x(t), p, u(t))\).

\section*{B. MODEL AUGMENTATION FOR PARAMETER ESTIMATION}

Machine dynamics in (1) can be compactly written as \(\frac{dx(t)}{dt} = F(x(t), u(t))\), where \(x(t)\) and \(u(t)\) are system states and inputs, respectively. To facilitate parameter estimation via Kalman filters, machine models are usually augmented with additional state equations representing the parameters of interest [5]. Let \(p\) denote the set of parameters that need to be estimated. Assuming time-invariant or slowly-varying parameter values, their dynamics can be written as \(\frac{dp}{dt} \approx 0\). Hence, the overall system considered for estimation becomes
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For consistency, we have slightly abused notations by using \(F(x(t), u(t))\) instead of the more accurate \(F(x(t), p, u(t))\).

\section*{C. DISCRETIZATION OF THE AUGMENTED MODEL}

The augmented system (4) needs to be discretized to obtain a formulation suited for the Kalman filter. Herein, the forward Euler method is used for its simplicity. In this paper, the Kalman filter equations are written for the following general discrete-time system
\[
\begin{align*}
    x_{k+1} &= f(x_k, u_k, w_k), \\
    y_k &= h(x_k, v_k).
\end{align*}
\] (5)

Interested readers can refer to [23] for details on formulating (4) into (5) after discretization for a machine model. \(u_k \in \mathbb{R}^p\), and \(y_k \in \mathbb{R}^m\) are the state, input, and output vectors, respectively, at time instance \(k\). For the PMSM model in (1), it is straightforward to see that \(x_k \triangleq [i_{qs}, i_{ds}, \omega_m, \theta_m]^T\) and \(u_k \triangleq [i_{qs}, v_{ds}]^T\). In this paper, the output \(y_k\) usually comprises of measurable states such as stator currents \((y_k \triangleq [i_{qs}, i_{ds}]^T)\). When rotor speed measurements are also available, \(y_k \triangleq [i_{qs}, i_{ds}, \omega_m]^T\). Continuously-differentiable functions \(f\) and \(h\) represent the system and output models, respectively. \(w_k \sim \mathcal{N}(0, Q_k)\) and \(v_k \sim \mathcal{N}(0, R_k)\) denote process and measurement noise, which are assumed uncorrelated. Noise is inherently present in actual physical systems, hence, it is incorporated within the model (5). Process noise \(w_k\) accounts for the modeling inaccuracies as well as external disturbance inputs, while the measurement noise \(v_k\) represents measurement/sensing error in the output signals.

\section*{IV. PARTIAL-UPDATE KALMAN FILTER WITH INTERRUPTED OBSERVATIONS}

In this section, we first describe a summary of the EKF framework in the presence of intermittent observations. Then, we establish the filter equations for the PKF without and with intermittent measurements.

\section*{A. EXTENDED KALMAN FILTER}

In a Kalman filter and its nonlinear variant, EKF, the state estimates are obtained in a recursive fashion using two stages, time update and measurement update. In the time-update stage, an estimate of the state \(x_k\) is denoted as \(\hat{x}_{k|k-1}\), which represents the estimate at the \(k\)th time instance based on measurements \([y_1, y_2, \ldots, y_{k-1}]\). In the measurement update stage, the estimate of the state \(x_k\) is denoted as \(\hat{x}_{k|k}\), which represents the estimate based on measurements \([y_1, y_2, \ldots, y_{k-1}, y_k]\). Given that Kalman filter is designed for linear systems, formulations for EKF require linearization of the system model at the operating condition. Since the functions \(f\) at \((\hat{x}_{k|k}, u_k, 0)\) and \(h\) at \((\hat{x}_{k|k-1}, 0)\) are continuously differentiable, they can be written using Taylor expansions as
\[
\begin{align*}
    h(x_k, v_k) &= h(\hat{x}_{k|k-1}, 0) + C_k (x_k - \hat{x}_{k|k-1}) + D_k v_k + \phi(x_k, \hat{x}_{k|k-1}, u_k, w_k), \\
    f(x_k, u_k, w_k) &= f(\hat{x}_{k|k}, u_k, 0) + A_k (x_k - \hat{x}_{k|k}) + G_k w_k + \phi(x_k, \hat{x}_{k|k}, u_k, w_k),
\end{align*}
\] (6)

where
\[
\begin{align*}
    A_k &= \frac{df}{dx}(\hat{x}_{k|k}, u_k, 0), \\
    C_k &= \frac{dh}{dx}(\hat{x}_{k|k-1}, 0), \\
    \phi &= \frac{df}{dx}(\hat{x}_{k|k}, u_k, 0), \\
    \phi &= \frac{df}{dx}(\hat{x}_{k|k-1}, 0), \\
    \phi &= \frac{df}{dx}(\hat{x}_{k|k-1}, 0).
\end{align*}
\] (7)

Terms \(f\) can be formulated from the PMSM models in (1) and (3) whereas \(h\) depends upon available measurements. Thereafter, the EKF time and measurement update equations can be written as [24]

1) \textbf{TIME UPDATE}
\[
\begin{align*}
    \hat{x}_{k+1|k} &= f(\hat{x}_{k|k}, u_k, 0) + A_k (x_k - \hat{x}_{k|k}) + G_k w_k + \phi(x_k, \hat{x}_{k|k}, u_k, w_k), \\
    P_{k+1|k} &= A_k P_{k|k} A_k^T + Q_k.
\end{align*}
\] (8, 9)
2) MEASUREMENT UPDATE

\[ \mathbf{K}_{k+1} = \mathbf{P}_{k+1|k} \mathbf{C}_{k+1}^{-1} \left( \mathbf{C}_{k+1} \mathbf{P}_{k+1|k} \mathbf{C}_{k+1}^{\top} + \mathbf{R}_{k+1} \right)^{-1}, \]
\[ \hat{\mathbf{x}}_{k+1|k+1} = \hat{\mathbf{x}}_{k+1|k} + \mathbf{K}_{k+1} (\mathbf{y}_{k+1} - \mathbf{h}(\hat{\mathbf{x}}_{k+1|k}, 0)), \]
\[ \mathbf{P}_{k+1|k+1} = (I_n - \mathbf{K}_{k+1} \mathbf{C}_{k+1}) \mathbf{P}_{k+1|k}. \]

Matrices \( \mathbf{P}_{k+1|k} = \mathbb{E}[(\mathbf{x}_{k+1} - \hat{\mathbf{x}}_{k+1|k})(\mathbf{x}_{k+1} - \hat{\mathbf{x}}_{k+1|k})^{\top}] \) and \( \mathbf{P}_{k+1|k+1} = \mathbb{E}[(\mathbf{x}_{k+1} - \hat{\mathbf{x}}_{k+1|k+1})(\mathbf{x}_{k+1} - \hat{\mathbf{x}}_{k+1|k+1})^{\top}] \) denote the estimation error covariance matrix for the time update and measurement update, respectively. \( \mathbf{K}_k \) denotes the Kalman gain. \( \mathbf{Q}_k \) and \( \mathbf{R}_k \) are the covariances for the process and measurement noises, as discussed in Section III-C. Results from (11) and (12) are the final estimates from the EKF.

B. EKF WITH INTERMITTENT LOSS IN MEASUREMENTS

Herein, we consider a case in which estimation needs to be performed under lossy measurements or intermittent observations [17]. In such cases, the arrival of the observation at time \( k \) is modeled as a Bernoulli process \( \gamma_k \) with the parameter \( \kappa \), where probability \( \mathbb{P}[\gamma_k = 1] = \kappa \), hence, \( \mathbb{P}[\gamma_k = 0] = 1 - \kappa \). In order to incorporate intermittent observations, the measurement update equations (11)–(12) in EKF are modified as [17]

\[ \hat{\mathbf{x}}_{k+1|k+1} = \hat{\mathbf{x}}_{k+1|k} + \gamma_k \mathbf{K}_{k+1} (\mathbf{y}_{k+1} - \mathbf{h}(\hat{\mathbf{x}}_{k+1|k}, 0)), \]
\[ \mathbf{P}_{k+1|k+1} = (I_n - \gamma_k \mathbf{K}_{k+1} \mathbf{C}_{k+1}) \mathbf{P}_{k+1|k}. \]

It is assumed that the actual value of \( \gamma_{k+1} \) along with the measurement \( y_{k+1} \) are transmitted to the filter [17], [18].

C. PARTIAL-UPDATE KALMAN FILTER

The PKF finds the estimates for states and the estimation error covariance matrix as a convex combination of results from the time update and the measurement update of the EKF. For every time instance \( k \), the element-wise representation for the PKF is [13], [14]

\[ \hat{\mathbf{x}}_{k+1|k}^{\text{PKF}} = \rho_i \hat{\mathbf{x}}_{k+1|k}^i + (1 - \rho_i) \hat{\mathbf{x}}_{k+1|k+1}^i, \]
\[ \mathbf{P}_{k+1|k}^{\text{PKF}} = \rho_i \mathbf{P}_{k+1|k}^i + (1 - \rho_i) \mathbf{P}_{k+1|k+1}^i. \]

\( \hat{\mathbf{x}}_{k+1|k}^{\text{PKF}} \) is the state estimate via PKF, where superscript \( i \) denotes the \( i \)th element of the state vector. \( \mathbf{P}_{k+1|k}^{\text{PKF}} \) is the estimation error covariance matrix with superscript \( i \) representing the matrix element in the \( i \)th row and \( j \)th column. The partial-update state equation (15) is a convex combination of the prior state vector (8) and the updated (posterior) state vector in (13). A similar idea is followed for the partial-update covariance equation (16) as well. \( \rho_i = 1 - \beta_i \), where \( \beta_i \in [0, 1] \) is the weight percentage of the measurement update used. For \( \beta_i = 0 \) and \( \beta_i = 1 \), the PKF reduces to the Schmidt (with no measurement update for \( i \)th element) and the EKF (with full measurement update), respectively.

D. PKF WITH INTERMITTENT MEASUREMENT

We extend the PKF in [13] and [14] to incorporate losses within measurement signals. Using the formulation for the EKF with measurement loss, (13) and (14), the PKF for measurement loss can be written as

1) TIME UPDATE

\[ \hat{\mathbf{x}}_{k+1|k} = f(\hat{\mathbf{x}}_{k|k}, \mathbf{u}_k, 0), \]
\[ \mathbf{P}_{k+1|k} = \mathbf{A}_k \mathbf{P}_{k|k} \mathbf{A}_k^{\top} + \mathbf{Q}_k. \]

2) MEASUREMENT UPDATE

\[ \hat{\mathbf{x}}_{k+1|k+1} = \hat{\mathbf{x}}_{k+1|k} + \gamma_{k+1} \mathbf{K}_{k+1} (\mathbf{y}_{k+1} - \mathbf{h}(\hat{\mathbf{x}}_{k+1|k}, 0)), \]
\[ \mathbf{P}_{k+1|k+1} = \mathbf{P}_{k+1|k} - \gamma_{k+1} \mathbf{K}_{k+1} \mathbf{C}_{k+1} \mathbf{P}_{k+1|k} + \gamma_{k+1} \mathbf{K}_{k+1} \mathbf{C}_{k+1} \mathbf{P}_{k+1|k}. \]

Note that the PKF formulations has a three-stage form compared to the EKF, which involves only two stages. Equations (15) and (16) can be reorganized to give the PKF a two-stage form. Vectorizing (15) while using (11) results in

\[ \hat{\mathbf{x}}_{k}^{\text{PKF}} = \Gamma \hat{\mathbf{x}}_{k+1|k} + (I_n - \Gamma) \hat{\mathbf{x}}_{k+1|k+1}, \]
\[ = \Gamma \hat{\mathbf{x}}_{k+1|k} + (I_n - \Gamma) \mathbf{K}_{k+1} (\mathbf{y}_{k+1} - \mathbf{h}(\hat{\mathbf{x}}_{k+1|k}, 0)), \]
\[ = \hat{\mathbf{x}}_{k+1|k} + \mathbf{K}_{k+1} (\mathbf{y}_{k+1} - \mathbf{h}(\hat{\mathbf{x}}_{k+1|k}, 0)), \]

where \( \mathbf{K}_k = (I_n - \Gamma) \mathbf{K}_k \) and \( \Gamma = \text{diag} \{ \rho_1, \rho_2, \ldots, \rho_n \} \). Similarly, (16) can be vectorized as (see Section III in [14])

\[ \mathbf{P}_{k+1}^{\text{PKF}} = (I_n - \mathbf{K}_{k+1} \mathbf{C}_{k+1}) \mathbf{P}_{k+1|k} + \Gamma \mathbf{K}_{k+1} \mathbf{C}_{k+1} \mathbf{P}_{k+1|k}. \]

Note that (17) and (18) resemble the measurement update form of the EKF in (11) and (12), respectively, and are functions of time update terms. In the following sections, we will replace the subscript ‘pkf’ with \( k + 1 \) in (17) and (18) to have a formulation similar to EKF.
Figure 2 shows the block diagram for the PKF. Given $\bar{K}_k = (I_n - \Gamma)K_k$, the PKF can be obtained by adding a block (shaded green in Figure 2) within the conventional EKF. Note that the formulations presented in this section can be extended to other types of machines.

V. BOUNDS ON THE ESTIMATION ERROR AND THE ERROR COVARIANCE MATRIX

In this section, we investigate the feasibility of the PKF (19)–(22) for estimation despite measurement loss. First, we present the estimation error dynamics followed by a detailed boundedness study.

A. ERROR DYNAMICS OF THE PKF

The estimation errors during the time update and measurement update can be defined as $e_k + 1|k = (x_k + 1 - \hat{x}_k + 1|k)$ and $e_k + 1|k + 1 = (x_k + 1 - \hat{x}_k + 1|k + 1)$, respectively. Per the formulations of the PKF in (19) and (21), and Taylor expansions in (6) and (7), the estimation error dynamics can be formulated as

$$e_k|k = (I_n - \gamma_k \bar{K}_k C_k)e_k|k - 1 - \gamma_k \bar{K}_k \dot{X}(x_k, \hat{x}_k|k - 1, v_k),$$

and

$$e_k + 1|k = A_k e_k|k + G_k w_k + \dot{\phi}(x_k, \hat{x}_k|k, u_k, w_k).$$

By combining (23) and (24), it can be obtained that

$$e_k + 1|k = A_k(I_n - \gamma_k \bar{K}_k C_k)e_k|k - 1 + r_k + s_k,$$

where

$$r_k \triangleq \dot{\phi}(x_k, \hat{x}_k|k, u_k, w_k) - \gamma_k A_k \bar{K}_k \dot{X}(x_k, \hat{x}_k|k - 1, v_k),$$

and

$$s_k \triangleq G_k w_k - \gamma_k A_k \bar{K}_k D_k v_k.$$

We now present the conditions to ensure that the estimation error and the prediction error covariance matrix from the PKF remain bounded. We assume that the linearization of (5) satisfies a modified uniform observability condition as in [18]. In addition, we consider the following two assumptions.

Assumption 1: There exist positive scalars $\tilde{a}, \tilde{c}, \tilde{d}, \tilde{g}, \tilde{\Gamma}, \tilde{q}, \tilde{r}, \tilde{g}$, and $\tilde{r}$ such that $\|A_k\| \leq \tilde{a}$, $\|C_k\| \leq \tilde{c}$, $\|\dot{D}_k\| \leq \tilde{d}$, $\|G_k\| \leq \tilde{g}$, $\|\Gamma_k\| \leq \tilde{\Gamma}$ and $g_k \leq \tilde{g} I_n$, $r_k \leq \tilde{r} I_n$, $L_k \leq \tilde{L}_k$, $R_k \leq \tilde{R}_k$. Such assumptions acknowledge that linearized system matrices (such as $A_k$ and $C_k$) obtained from PMSM models have bounded elements and represent a physical system. Bounded noise covariance matrices denote that system noises are limited by some physical properties.

Assumption 2: There exist positive constants $\tilde{p}$ and $\tilde{p}$ where

$$p I_n \leq P_k + 1|k \leq \tilde{p} I_n.$$

Condition (28) is closely related to the uniform observability property of the linearized system. Please refer to [25] and [18] for further discussion.

Note that first we prove the boundedness of error assuming that the error covariance matrix is bounded. Later on, we prove the boundedness of the error covariance matrix and feasible conditions associated with it. Moreover, we assume that the residuals of the Taylor expansion in (6) and (7) are bounded in a neighborhood of the point of expansion. Indeed, for all $\|x_k - \hat{x}_k|k\| \leq \delta$ and $\|x_k - \hat{x}_k|k - 1\| \leq \delta X$, there holds

$$\|\phi(x_k, \hat{x}_k|k, u_k, w_k)\| \leq \epsilon \|x_k - \hat{x}_k|k\|^2,$$

and

$$\|X(x_k, \hat{x}_k|k - 1, v_k)\| \leq \epsilon X \|x_k - \hat{x}_k|k - 1\|^2,$$

where $\delta$, $\delta X$, $\epsilon$, $\epsilon X$ are bounded positive real numbers.

B. BOUNDEDNESS OF THE ESTIMATION ERROR

The main goal of this section is to show that the estimation error is stochastically bounded.

Theorem 1: Consider the nonlinear system (5), and the PKF equations (19)–(22). If assumptions 1 and 2 are satisfied, for a bound $\epsilon$ on the stochastic noise covariance matrices, and a bound $\delta > 0$ on the initial estimation error, i.e., $E[\|e_0\|^2] \leq \delta$, the estimation error $e_k|k - 1$ is exponentially bounded in a mean-square sense.

Proof: We define a Lyapunov function $V_k(e_k|k - 1) = e_k|k - 1 P_k^{-1} e_k|k - 1$. As per (25), this function becomes

$$V_k + 1(e_k|k + 1) = \mu_k + e_k|k - 1 P_k^{-1} A_k(I_n - \gamma K_k C_k) e_k|k - 1 + r_k + s_k,$$

where

$$\mu_k = e_k|k - 1 (I_n - \gamma K_k C_k) A_k(I_n - \gamma K_k C_k) e_k|k - 1 + r_k + s_k.$$

The Lyapunov function in (31) can be rewritten as

$$V_k + 1(e_k|k + 1) = \mu_k + e_k|k - 1 P_k^{-1} A_k(I_n - \gamma K_k C_k) e_k|k - 1 + r_k + s_k.$$

The upper bound of the second expression in (32) can be obtained using Theorem A2 in the Appendix. Moreover, from the results of [25], one can show that $\mu_k$ has a positive upper bound, $\bar{\mu}$. Indeed, from Lemma 3.2 and Lemma 3.3 in [25], one can obtain an upper bound for the last two terms that depends on positive real numbers in Assumption 1. Assumption 2, a positive scalar $\delta$ for which $\|e_k|k - 1\| \leq \delta$, and a positive bound $\epsilon$ on stochastic noise covariance matrices, i.e., $E[\|v_k\|^2] \leq \epsilon^2 I_n, E[\|w_k\|^2] \leq \epsilon^2 I_n$. To establish an upper bound on the first three terms, consider that the matrices in
brackets are bounded by positive real numbers per Assumptions 1 and 2. Consequently, the first three terms are also bounded for \( \|e_{k|k-1}\| < \delta \).

Substituting (50) into \( V_{k+1}(e_{k+1|k}) \), taking the conditional expectation, and following the results of [18], [25], we have
\[
\mathbb{E}[V_{k+1}(e_{k+1|k})e_{k|k-1}] \leq (1 - \alpha)V_k(e_{k|k-1}) + \bar{\mu}.
\]

Equation (34) takes the form similar to a bounded stochastic process in Theorem A1 in the Appendix. We are able to apply Theorem A1 with \( \|e_{1|0}\| \leq \delta \). Hence, the proposed PKF for the measurement loss will be bounded in the mean-square sense.

The proof of the Theorem 1 is based on the boundedness assumption of the estimation error covariance matrix. However, this assumption can be violated when \( y_k = 0 \) for infinitely many \( k \) [18]. Consequently, the behavior of the error covariance matrix will be analyzed, and an upper bound for its expectation in presence of measurement losses will be derived.

### C. BOUNDEDNESS OF THE ERROR COVARIANCE MATRIX

Herein, we show the boundedness of the error covariance matrix.

**Theorem 2:** Suppose that Assumption 1 holds. One can show that there exists a constant \( \bar{p} > 0 \), such that
\[
\mathbb{E}[P_{k+1|k}] \leq \bar{p}I_n,
\]
provided that
- \( C_k^{-1} \) exists and satisfies \( \|C_k^{-1}\| \leq \epsilon^{-1} \), and the measurement data arrival probability satisfies \( \gamma > 1 - \frac{\bar{a}^2 - 2}{1-\alpha} \), or
- the data arrival probability satisfies \( \gamma > \frac{1 - \bar{a}^2}{\lambda^2} \), where \( 0 < \lambda < \lambda_0 \leq 1 \), and \( \lambda_0 \) will be later defined in (44).

**Proof:** To show this, one can consider two scenarios.

**Case 1: The \( C_k \) matrix is invertible.** By combining (10), (20) and (22), the prediction error covariance matrix becomes
\[
P_{k+1|k} = A_k \left( P_{k|k-1} - \gamma_k P_{k|k-1} C_k^T \left( C_k P_{k|k-1} C_k^T + R_k \right)^{-1} C_k P_{k|k-1} - \gamma_k \Gamma P_{k|k-1} \right) + Q_k.
\]

Consider \( \gamma_k \Gamma P_{k|k-1} \left( C_k P_{k|k-1} C_k^T + R_k \right)^{-1} C_k P_{k|k-1} - \gamma_k \Gamma P_{k|k-1} \) in (36). Using the matrix inversion lemma \((A+B)^{-1} = A^{-1} - \gamma_k \Gamma (A^{-1} + \Gamma B)^{-1} \Gamma A^{-1}\), and defining \( A \triangleq C_k P_{k|k-1} C_k^T \) and \( B \triangleq R_k \), we derive
\[
P_{k+1|k} = A_k \left( P_{k|k-1} - \gamma_k P_{k|k-1} C_k^T \left( C_k P_{k|k-1} C_k^T + R_k \right)^{-1} C_k P_{k|k-1} - \gamma_k \Gamma P_{k|k-1} \right) + Q_k.
\]

Using the inequality \((A + B)^{-1} > A^{-1} - A^{-1} \Gamma A^{-1}\), we have [20]
\[
P_{k+1|k} \leq (1 - \gamma_k)A_k P_{k|k-1} A_k^T + \gamma_k \gamma_k A_k C_k^T R_k C_k^{-1} A_k^T + \gamma_k \gamma_k A_k \Gamma P_{k|k-1} \Gamma A_k^T + Q_k.
\]

**Case 2: \( C_k \) matrix is not invertible.** Applying Lemma 2 in [26] to \( \gamma_k \Gamma P_{k|k-1} \left( C_k P_{k|k-1} C_k^T + R_k \right)^{-1} C_k P_{k|k-1} \) in (36) gives
\[
P_{k+1|k} \leq A_k \left( P_{k|k-1} - \gamma_k P_{k|k-1} C_k^T \left( C_k P_{k|k-1} C_k^T + R_k \right)^{-1} C_k P_{k|k-1} - \gamma_k \Gamma P_{k|k-1} \right) + Q_k.
\]

Based on Lemma 2 in [26], \( 0 < \lambda < \lambda_0 \leq 1 \), where
\[
\lambda_0 = \min \{ \lambda_{\min} \left( C_k P_{k|k-1} C_k^T + R_k \right)^{-1} C_k \}.
\]

Such that
\[
\lambda P_{k|k-1} < C_k^T \left( C_k P_{k|k-1} C_k^T + R_k \right)^{-1} C_k.
\]

By combining (43) and (45), we have
\[
P_{k+1|k} \leq A_k \left( P_{k|k-1} - \gamma_k P_{k|k-1} + \gamma_k \Gamma P_{k|k-1} \right) A_k^T + Q_k.
\]

Consequently, similar to the Case 1, it can be concluded that
\[
\mathbb{E}[P_{k+1|k}] < p \sum_{j=0}^{k-1} ((1 - \lambda)^j + (1 - \lambda)^{j+1}) \mathbb{E}[I_n].
\]
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FIGURE 3. Comparison between estimates from (a) EKF and (b) PKF. EKF stability issues can be addressed in PKF through partial update using $\Gamma$.

where $p = \max(\|P_{10}\|, \|\tilde{q}\|)$. Moreover, (47) converges when $\gamma > \frac{1-\tilde{a}^{-2}}{1-\gamma}$ and $\gamma > 1-\tilde{a}^{-2}$. Hence, it is clear that (35) is satisfied. □

Remark 1: The assumption of invertible $C_k$ could be restrictive. However, in most work, e.g., [18]–[20], [27], this is a necessary assumption to find the bound of $P_{k+1|k}$. Compared to [18]–[20], [27], we have shown that even for the case of a singular $C_k$, the $P_{k+1|k}$ matrix is bounded, and a minimum critical value for data loss exists.

Remark 2: For the case of EKF ($\Gamma = 0$), and considering the assumption on the invertible $C_k$ matrix, the critical value $\gamma > 1-\tilde{a}^{-2}$, which corroborates with the results of [18].

VI. VALIDATION AND VERIFICATION

We show that PKF can perform better than the conventional EKF under certain scenarios, and validate the PKF using PMSM hardware. Nominal parameters of PMSM are provided in the Appendix. The machine models and Kalman filters are simulated in Simulink 10.1 (R2020a).

A. ADVANTAGES OF PKF

1) STABILITY

We present a simulated case study on the PMSM model, where an observer needs to estimate rotor speed/position and flux linkage using stator current and voltage measurements. Since position information is unavailable, the PMSM model in $\alpha/\beta$-reference frame is used (3). Initial state $[i_{\alpha0}, i_{\beta0}, \omega_m, \theta_m]_{t=0} = [4, 2, 12.5, 0]^{T}$, and respective process noise and measurement noise covariances of $\text{diag}(10^{-4}, 10^{-4}, 10^{-4}, 10^{-4})$ and $\text{diag}(10^{-1}, 10^{-1})$, are considered. The augmented state vector for both filters is $[i_{\alpha0}, i_{\beta0}, \omega_m, \theta_m, \lambda_m]^{T}$ with stator currents $[i_{\alpha0}, i_{\beta0}]^{T}$ as output, and stator voltages $[v_{\alpha0}, v_{\beta0}]^{T}$ as inputs. The voltage and current signals generated from this simulation are sampled at 10 $\mu$s and fed to both EKF and PKF for estimations. The filters are initialized with augmented state $x_0 = [4, 2, 12.5, 0, 0.1]^{T}$, error covariance $P_0 = I_5$, measurement noise covariance $R = \text{diag}(10^{-1}, 10^{-1})$, and the process noise covariance of $Q = \text{diag}(10^{-4}, 10^{-4}, 10^{-4}, 10^{-4}, 10^{-6})$. Note that the matrix $P_0$ is deliberately chosen to take a higher value to replicate a scenario of an ill-tuned filter (smaller values such as $P_0 = 0.001 \times I_5$ denotes higher confidence in initial condition and would prevent EKF divergence). Figure 3 compares the results from both EKF and PKF showing the estimates for speed, position, and flux linkage. The EKF becomes unstable, while the PKF maintains its stability. The PKF can provide convergence since it can control the measurement update with variable $\Gamma$. This additional degree of freedom in the PKF allows to compensate for a bad tuning for the presented scenario. We chose $\Gamma = \text{diag}(0.2, 0.2, 0.2, 0.2, 0.75)$, denoting 80% measurement update for states $[i_{\alpha0}, i_{\beta0}, \omega_m, \theta_m]^{T}$ and only 25% measurement update for the slow-varying parameter $\lambda_m$ [14].

2) NUISANCE PARAMETER

Nuisance parameters are imprecisely known, and their values are not necessarily needed. However, the uncertainties in these parameters need to be accounted for an overall accurate estimation. A straightforward way to handle this would be to include these parameters in the system state (model augmentation) and estimate them along with the states, although, this could lead to a divergence similar to Figure 3a [28]. Another approach is to employ the Schmidt Kalman filter, wherein...
the nuisance parameters are only “considered” during the time update stage of the filter [13]. The PKF can mimic such properties of the SKF through the variable $0$. We present a case to make this point.

Consider a similar scenario where the PMSM model is simulated assuming initial state $[i_{sa}, i_{sb}, \omega_m, \theta_m]^T = [4, 2, 12.5, 0]^T$, with process noise and measurement noise covariances $\text{diag}(10^{-4}, 10^{-4}, 10^{-4}, 10^{-4})$ and $\text{diag}(10^{-1}, 10^{-1})$, respectively. The objective is to only estimate rotor speed and position from stator currents and voltages. However, there is uncertainty in the parameter $\lambda_m$ with its value being around 0.004 (mean) with a standard deviation of 0.001 (assuming Gaussian distribution). In such a scenario, the PKF could be designed that will only “consider” the uncertainty in $\lambda_m$ during the time update stage. The PKF is initialized with an augmented state $x_0 = [4, 2, 12.5, 0, 0.004]^T$, error covariance $P_0 = 0.001 \times I_5$, measurement noise covariance $R = \text{diag}(10^{-1}, 10^{-1})$, and process noise covariance of $Q = \text{diag}(10^{-4}, 10^{-4}, 10^{-4}, 10^{-4}, 10^{-6})$, and $\Gamma = \text{diag}(0.9, 0.9, 0.9, 0.9, 1)$. Note that with this choice of $\Gamma$, the measurement update stage for the parameter $\lambda_m$ is not performed, and the PKF filter mimics an SKF filter known to tackle the uncertainties due to a nuisance parameter.

3) CHOICE OF PARAMETER $\Gamma$

Setting elements of $\Gamma$ as 0 or 1 produces a “bang-bang” like effect and makes the filter mimic EKF and SKF, respectively. As for the partial measurement update, a general rule-of-thumb is that constant or slow-varying states have minimal process noise, hence, can receive limited measurement updates. More observable or high process noise states should receive higher measurement updates. A detailed discussion on tuning $\Gamma$ is provided in [14]. It should also be noted that the estimation performance of the PKF is not sensitive to the choice of $\Gamma$. For example, results from PKF in Figure 4 will be similar to those for $\Gamma = \text{diag}(0.85, 0.85, 0.85, 0.85, 1)$.

B. HARDWARE VALIDATION OF PMSM ESTIMATIONS

A PMSM, with the given specifications and controlled using field-oriented control (FOC) deployed on a Speedgoat real-time target machine [29], is considered in Figure 5. Herein, we run the PKF under two scenarios: 1) sensorless speed estimation (assuming speed measurements are unavailable); 2) Online PMSM parameterization. The machine states, outputs, and inputs for the first case are chosen as $x = [i_{sa}, i_{sb}, \omega_m, \theta_m]^T$, $y = [i_{sa}, i_{sb}]^T$, and $u = [v_{sa}, v_{sb}]^T$, respectively. Note that machine equations are assumed in the $\alpha/\beta$ stationary reference frame (see (3)). Furthermore,
we assume that the mechanical load is unknown (similar to [30]), hence, the machine model is augmented with \( p = T_L \), where \( \frac{dT_L}{dt} \approx 0 \) (\( T_L \) is assumed to be a slowly-varying parameter as discussed in Section III). PMSM measurements are sampled every 100 \( \mu s \). The noise covariance matrices are \( Q = \text{diag}(10^{-2}, 10^{-2}, 10^{-1}, 10^{-1}, 10^{-2}) \) and \( R = \text{diag}(10^{-4}, 10^{-4}) \), with \( \Gamma = \text{diag}(0.2, 0.2, 0.2, 0.2, 0.75) \), \( [i_{\alpha0}, i_{\beta0}, \omega_m, \theta_m, p]_t^T = [0, 0, 0, 0, 0] \), and \( P_0 = I_5 \). Figure 6 shows the estimation results obtained using EKF and PKF considering ideal lossless conditions. From Figure 6, it is clear that both filters provide accurate speed estimations despite multiple changes in speed along with other machine states. Figure 7 shows the estimated results from the PKF operating under measurements with 20% loss in data. This loss is modeled using the Bernoulli Binary Generator block in Simulink. The rotor speed is step-changed at 1.6 s, 2.7 s, and 4.3 s, approximately, by providing new reference speed values from the FOC controller. Figure 8 shows the robustness of PKF under different degrees of data loss. Herein, the sensorless speed estimation is performed for 100 \( \mu s \) sampling time using lossless and lossy signals (from 10% to 50% loss). The PKF estimates still follow the desired values in a satisfactory fashion. Another
important aspect to observe is the sampling time for measurements. Figures 9 and 10 show the speed estimates when the sampling time is increased to 200 μs and 300 μs, respectively. Note that for the lossless cases, the PKF continues to perform satisfactory estimations. As the sampling time is increased, the filter performance degrades with the increase in loss. However, results from the filter are still tracking the desired values with errors within 5% at majority of time instances.

Since machines’ operating conditions can vary, we consider a case similar to [31] for an online estimation of machine state and permanent magnet flux linkage. In this case, the PMSM model is considered in the q/d-reference frame (see (1)). The augmented state can be formed as \( \mathbf{x} = \begin{bmatrix} i_{ds}, i_{qs}, \omega_m, \theta_m, \lambda_m \end{bmatrix}^T \), output as \( \mathbf{y} = \begin{bmatrix} i_{ds}, i_{qs}, \omega_m \end{bmatrix}^T \), and input as \( \mathbf{u} = \begin{bmatrix} v_{ds}, v_{qs} \end{bmatrix}^T \). The covariance matrices are chosen as \( \mathbf{Q} = \text{diag}(0.5, 0.1, 0.1, 1, 10^{-4}) \) and \( \mathbf{R} = \text{diag}(10^{-2}, 10^{-2}, 0.1, 0.1) \), with \( \mathbf{Γ} = \text{diag}(0, 0, 0, 0, 0.8) \). [32]

A. SUPPLEMENTARY THEOREMS

**Theorem A 1**: If a stochastic process \( V_k(\xi_k) \) satisfies the following conditions:

\[
\mathbb{E}[|V_k(\xi_k)|^2] \leq V_k(\xi_k) \leq \bar{v}|\xi_k|^2,
\]

\[
\mathbb{E}[V_k(\xi_k)|\xi_{k-1}] - V_{k-1}(\xi_{k-1}) \leq \mu - \alpha V_{k-1}(\xi_{k-1}),
\]

where scalars \( \gamma, \bar{v}, \mu > 0 \) and \( 0 < \alpha \leq 1 \), then the stochastic process is exponentially bounded in a mean-square sense, i.e. \( \mathbb{E}[|\xi_k|^2] \leq \frac{\gamma}{\alpha} \mathbb{E}[|\xi_0|^2](1 - \alpha^k) + \frac{\gamma}{\alpha} \sum_{i=1}^k (1 - \alpha)^i \).

**Proof**: Please see [20], [25].

**Theorem A 2**: Consider the proposed PKF (19)–(22). If assumptions 1 and 2 are satisfied, there exists a real scalar \( 0 < \alpha < 1 \) such that

\[
\begin{align*}
(I_n - \gamma \mathbf{K_k C_k})^\top A_k^{-1} P_{k+1|k} A_k (I_n - \gamma \mathbf{K_k C_k}) & \\
& \leq (1 - \alpha) P_{k+1|k-1}.
\end{align*}
\]

**Proof**: From (20), we have [18]

\[
P_{k+1|k} = \mathbf{A}_k P_{k|k} A_k^\top + \mathbf{Q}_k > \left( 1 + \frac{q}{2\alpha^2 + \beta} \right) A_k P_{k|k} A_k^\top.
\]

Multiplying \( \mathbf{C}_k + \mathbf{I}_p + \mathbf{I}_m \mathbf{C}_k^\top + \mathbf{R}_k \mathbf{C}_k^\top \) from the right on both sides of (10), we can show

\[
\mathbf{K}_k \mathbf{C}_k P_{k|k-1} = \mathbf{K}_k \left[ \mathbf{C}_k P_{k|k-1} \mathbf{C}_k^\top + \mathbf{R}_k \right] \mathbf{K}_k^\top.
\]

By adding \( \gamma_k \mathbf{K}_k \left[ \mathbf{C}_k P_{k|k-1} \mathbf{C}_k^\top + \mathbf{R}_k \right] K_k^\top \) to the right side of (22), and since \( \gamma_k = \gamma_k^2 \),

\[
aP_{k|k} = (I_n - \gamma_k \mathbf{K_k C_k}) P_{k|k-1} (I_n - \gamma_k \mathbf{K_k C_k})^\top + \gamma_k \mathbf{K_k R_k K_k}^\top + \gamma_k \mathbf{Γ K_k C_k P_{k|k-1} Γ}. \]

By combining (51), (52), and (53), we have

\[
P_{k+1|k} > \left( 1 + \frac{q}{2\alpha^2 + \beta} \right) A_k^\top (I_n - \gamma_k \mathbf{K_k C_k}) \times (I_n - \gamma_k \mathbf{K_k C_k})^\top + \gamma_k \mathbf{K_k R_k K_k}^\top A_k^\top. \]

The rest of the proof is similar to Lemma 6.3 in [18], and is omitted here for brevity.

B. MACHINE PARAMETERS

Nominal parameters of the permanent magnet synchronous machine (32): 24 V, 60 Hz, \( P_p = 4, R_o = 0.8557 \), \( L_d = 0.0012 \), \( L_q = 0.0012 \), \( \lambda_{sat} = 0.005 \) Wb.turn, \( J_m = 3.878 \times 10^{-6} \) kg.m².

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