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State and Parameter Estimation for Field-oriented Control of Induction Machine Based on Unscented Kalman Filter

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***Abstract*—Modern electric machines are required to have the best possible dynamic performances. In induction machines this is achieved by control strategies that are applied with respect to the flux in the air gap and therefore they require precise information on flux position. This paper proposes an observer with autotuning capability that uses the unscented Kalman filter algorithm for providing on-line estimation of states and parameters of the fundamental wave model of the machine. The algorithm uses power converter reference values of stator voltages, measured stator currents and rotor speed as inputs. Such observer provides accurate estimates of flux position and fundamental stator currents required for e.g. field-oriented control, taking into account machine parameters variability. Design procedure of the observer is presented and both simulation and experimental results are provided.**

***Index Terms*—Induction Machine, Parameter and State Estimation, Dual Unscented Kalman Filter, Flux Position Estimation.**

I. Introduction

Increasing demands for dynamic performances of electrical drives led to the fact that field-oriented control (FOC) or direct torque control (DTC) have been adopted as standard control strategies in widely-spread industrial applications for last 15 years [1]. Both approaches and their derivatives are based on a precisely determined machine flux position in order to fully exploit their capabilities.

Fundamental wave approach is a generally accepted method for obtaining the flux position. It assumes ideal and sinusoidal flux distribution in the machine air gap. However, sinusoidal flux approximation neglects saliencies, saturation and other nonlinearities due to machine physics and geometry. This results in an inability of the control system to precisely determine the flux position, which ultimately leads to undesired torque ripple and degradation of the system performance. Another feature that aggravates the determination of flux position is variability of machine parameters due to e.g. temperature-dependent machine characteristic.

There are several proposed improvements of the fundamental wave approach to alleviate these problems: a simple parameter adaptation based on the machine data sheet [1], indirect flux detection by online reactance measurement (INFORM) [2], high-frequency signal injection for the detection of anisotropic properties of the machine [3] etc.

In this paper we propose to use a dual unscented Kalman filter for both state and parameter estimation of the fundamental wave induction machine model. It is conceived as an add-on to the existing control system that:

- filters the phase currents measurements and extracts fundamental current components needed for FOC or DTC without the introduction of additional delays,
- estimates delay-free non-measured states of the fundamental wave model, such as the flux position,
- adapts the control system to variations of parameters of the fundamental wave model.

Unscented Kalman Filter (UKF) was first proposed by Julier et al [4], and further developed by Wan and van der Merwe [5]. It is an alternative, derivative-free approach in estimation theory that in the case of nonlinear systems shows better results than linearization-based Kalman filter algorithms.

This paper is organized as follows. The fundamental wave model of a squirrel-cage induction machine is described in Section II together with the theoretical basis for FOC strategy. Section III presents the UKF algorithm. In section IV a design procedure of UKF for both state and parameter estimation is described. Section V provides MATLAB/Simulink simulation results obtained with the proposed algorithm applied on an ideal model of the machine. Off-line estimation procedure is validated on the acquired real machine measurements and results are presented in Section VI. Conclusions are drawn in Section VII.

II. Mathematical model of an AC machine

There are several approaches in modelling an AC induction machine [6]. One of the most common is the representation of machine stator and rotor phases in the two-phase common rotating (d, q) coordinate system, which is suitable for field-oriented control application. A rotor-based field-oriented control (RFOC) implies that the common rotating (d, q) frame is aligned with rotor flux linkage:

$$\bar{\psi_r} = \psi_{rd} + j0, \tag{1}$$

and the complex value of $\bar{\psi_r}$ becomes a scalar ψ_{rd}.

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Nonlinear mathematical model of an AC squirrel-cage induction machine based on classical dynamic equations that assume sinusoidal flux density distribution is [6]:

$$\frac{\mathrm{d}i_{sd}}{\mathrm{d}t} = \theta_1 \left(u_{sd} + \Delta u_{sd} - \theta_2 i_{sd}\right), \tag{2}$$

$$\frac{\mathrm{d}i_{sq}}{\mathrm{d}t} = \theta_1 \left(u_{sq} + \Delta u_{sq} - \theta_3 i_{sq}\right), \tag{3}$$

$$\frac{\mathrm{d}i_{mr}}{\mathrm{d}t} = \theta_4 \left(i_{sd} - i_{mr}\right), \tag{4}$$

$$\frac{\mathrm{d}\rho}{\mathrm{d}t} = p\omega_g + \theta_4 \frac{i_{sq}}{i_{mr}}, \tag{5}$$

where $i_{sd,q}$ and $u_{sd,q}$ are stator currents and voltages in (d, q) frame, i_{mr} is magnetizing current, ρ is the flux electrical angle, p is the number of machine pole pairs, ω_g is rotor mechanical speed and $\Delta u_{sd,q}$ are given with:

$$\Delta u_{sd} = (\theta_2 - \theta_3)\, i_{mr} + \frac{1}{\theta_1}\omega_e i_{sq}, \tag{6}$$

$$\Delta u_{sq} = -\frac{\theta_2 - \theta_3}{\theta_4}\omega_e i_{mr} - \frac{1}{\theta_1}\omega_e i_{sd}. \tag{7}$$

Model parameters are: $\theta_1 = \frac{1}{\sigma L_s}$, $\theta_2 = R_s + \frac{L_m^2}{L_r^2} R_r$, $\theta_3 = R_s$, $\theta_4 = \frac{1}{T_r}$ and $\sigma = (1 - \frac{L_m^2}{L_s L_r})$. Equivalent circuit parameters L_s, L_r, L_m, R_s, R_r are stator, rotor and mutual inductance, stator and rotor resistance, respectively. Variable ω_e is the speed of magnetizing flux rotation and corresponds to the frequency of supplied voltage.

For reliable estimation of i_{sd} and i_{sq} currents, the dependency on flux angle ρ has to be included in relations (2) and (3). It can be done by introducing line voltages in (a, b, c) coordinate system and by applying Park's and Clark's transform [6], which results in:

$$\begin{aligned} u_{sd} &= \tfrac{2}{3}\cos\rho\, u_{ab} + \left(\tfrac{1}{3}\cos\rho + \tfrac{\sqrt{3}}{3}\sin\rho\right) u_{bc}, \\ u_{sq} &= -\tfrac{2}{3}\sin\rho\, u_{ab} + \left(-\tfrac{1}{3}\sin\rho + \tfrac{\sqrt{3}}{3}\cos\rho\right) u_{bc}. \end{aligned} \tag{8}$$

Equations (2)-(8) represent a complete nonlinear mathematical model of the squirrel-cage induction machine for RFOC. Using parameters in form $\theta_{1,..,4}$ has proven to be more favorable for parameter estimation since real equivalent-circuit parameters are strongly masked in mutual products. In addition, small variations of real parameters cause very large changes of $\theta_{1,..,4}$, i.e. 1% change of inductances and resistances causes about 10% change of θ and results in a poor estimation quality (even divergence).

Described model can be generally represented as:

$$\dot{x} = F(x, u), \tag{9}$$

where $x = [i_{sd}\ i_{sq}\ i_{mr}\ \rho]$ is the state vector, $u = [u_{ab}\ u_{bc}\ \omega_g]$ is the input vector and $F(\cdot)$ is a vector function. If the flux position used in calculations deviates from the real flux position, (d, q) coordinate system becomes unaligned and relation (1) is no longer valid, which introduces error and model discrepancy. The DTC algorithm is somewhat more resilient to this issue but nevertheless, an accurate flux angle is of great importance for the machine performance.

Stator currents are usually measured in electrical machines and measurement vector is therefore chosen as $y = [i_a\ \ i_b]^\mathsf{T}$ ($i_a + i_b + i_c = 0$ is assumed), generally represented as:

$$y = H(x). \tag{10}$$

The measurement vector is related with d, q coordinate system through:

$$\begin{aligned} i_a &= i_{sd}\cos\rho - i_{sq}\sin\rho, \\ i_b &= i_{sd}\left(-\tfrac{1}{2}\cos\rho + \tfrac{\sqrt{3}}{2}\sin\rho\right) + i_{sq}\left(\tfrac{1}{2}\sin\rho + \tfrac{\sqrt{3}}{2}\cos\rho\right). \end{aligned} \tag{11}$$

Kalman filter algorithm requires a stochastic mathematical model and therefore (9) and (10) are augmented to include process and measurement noise v and n, respectively:

$$\dot{x} = F(x, u, v), \tag{12}$$

$$y = H(x, n). \tag{13}$$

In this application $v \in \mathbb{R}^4$ is selected whereas each component of v is added to the corresponding dynamical equation (2)-(5). Measurement noise $n \in \mathbb{R}^2$ is selected whereas each component of n is added to the corresponding equation in (11).

III. Unscented Kalman filter algorithm

The UKF represents a novel approach for estimations in nonlinear systems and provides better results than extended Kalman filter (EKF) in terms of mean estimate and estimate covariance [4]. The core idea of UKF lies in unscented transformation, the way of propagating Gaussian random variables (GRV) through a nonlinear mapping. The unscented transformation is performed using so-called sigma points, a minimal set of carefully chosen sample points that enables better capturing of mean and covariance of mapped GRVs than simple point-linearization of the mapping: posterior mean and covariance are accurate to the second order of the Taylor series expansion for any nonlinearity as proven in [5].

An attractive feature of UKF is that partial derivatives and Jacobian matrix (like in EKF) are not needed and continuous-time nonlinear dynamics equations are directly used in the filter, without discretization or linearization. Computational effort of UKF with carefully implemented algorithm can be similar to that of the EKF. More information can be found in [4] and [5] while different applications of UKF are presented in [7]-[10]. The UKF algorithm is given in the sequel.

A. Initialization and time update

In order to compute a proper set of sigma points, the estimated state vector $\hat{x}_k$ in a discrete time-instant k is augmented to include means of process and measurement noise $\bar{v}$ and $\bar{n}$:

$$\hat{x}_k^a = \mathbb{E}(x_k^a) = \left[\hat{x}_k^T\ \ \bar{v}\ \ \bar{n}\right]^T, \tag{14}$$

where $\mathbb{E}(\cdot)$ denotes the expectation of a random variable. State covariance matrix $\mathbf{P}_k$ is also augmented accordingly:

$$\mathbf{P}_k^a = \mathbb{E}\left((x_k^a - \hat{x}_k^a)^T (x_k^a - \hat{x}_k^a)\right) = \begin{bmatrix} \mathbf{P}_k & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{R}^v & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{R}^n \end{bmatrix}, \tag{15}$$

where $\mathbf{R}^v$ and $\mathbf{R}^n$ are process and measurement noise covariance matrices, respectively. Time update algorithm starts with the unscented transformation and by forming the sigma points matrix $\mathcal{X}_k^a$:

$$\mathcal{X}_k^a = \left[\hat{x}_k^a \quad \hat{x}_k^a + \gamma\sqrt{\mathbf{P}_k^a} \quad \hat{x}_k^a - \gamma\sqrt{\mathbf{P}_k^a}\right]. \tag{16}$$

Variable $\sqrt{\mathbf{P}_k^a}$ is the lower-triangular Cholesky factorization of matrix $\mathbf{P}_k^a$ and $\gamma = \sqrt{L+\lambda}$ is a scaling factor. Parameter L is the dimension of augmented state x_k^a and parameter λ determines the spread of sigma points around the current estimate, calculated as:

$$\lambda = \alpha^2 (L + \kappa) - L. \tag{17}$$

Parameter α is usually set to a small positive value e.g. $10^{-4} \leq \alpha \leq 1$ and κ is usually set to 1. There are $2L+1$ sigma points used for the transformation, which correspond to the columns in $\mathcal{X}_k^a = \left[(\mathcal{X}_k^x)^T \ (\mathcal{X}_k^v)^T \ (\mathcal{X}_k^n)^T\right]^T$.

Time-update equations used to calculate prediction of state $\hat{x}_{k+1}^-$ and state covariance $\mathbf{P}_{k+1}^-$ as well as prediction of output $\hat{y}_{k+1}^-$ are:

$$\begin{aligned}
\mathcal{X}_{i,k+1|k}^x &= F\left(\mathcal{X}_{i,k}^x, u_k, \mathcal{X}_{i,k}^v\right), \quad i = 0, ..., 2L, && (18)\\
\hat{x}_{k+1}^- &= \sum_{i=0}^{2L} W_i^{(m)} \mathcal{X}_{i,k+1|k}^x, && (19)\\
\mathbf{P}_{k+1}^- &= \sum_{i=0}^{2L} W_i^{(c)} \left(\mathcal{X}_{i,k+1|k}^x - \hat{x}_{k+1}^-\right) \times \\
&\quad \left(\mathcal{X}_{i,k+1|k}^x - \hat{x}_{k+1}^-\right)^T, && (20)\\
\mathcal{Y}_{i,k+1|k} &= H\left(\mathcal{X}_{i,k+1|k}^x, \mathcal{X}_{i,k}^n\right), \quad i = 0, ..., 2L, && (21)\\
\hat{y}_{k+1}^- &= \sum_{i=0}^{2L} W_i^{(m)} \mathcal{Y}_{i,k+1|k}, && (22)
\end{aligned}$$

where i is the index of columns in matrix $\mathcal{X}_k^a$ (and also in $\mathcal{X}_k^x$, $\mathcal{X}_k^v$, $\mathcal{X}_k^n$) starting from value zero. Weights for mean and covariance calculations are given by:

$$\begin{aligned}
W_0^{(m)} &= \tfrac{\lambda}{(L+\lambda)}, \\
W_0^{(c)} &= \tfrac{\lambda}{(L+\lambda)} + \left(1 - \alpha^2 + \beta\right), && (23)\\
W_i^{(m)} &= W_i^{(c)} = \tfrac{\lambda}{2(L+\lambda)}, \quad i = 1, ..., 2L.
\end{aligned}$$

For Gaussian distributions, $\beta = 2$ is optimal.

B. Measurement update

Measurement update algorithm is performed in the similar way as in classical Kalman filter but requires also output covariance matrix $\mathbf{P}_{\tilde{y}_{k+1}\tilde{y}_{k+1}}$ and cross-covariance matrix $\mathbf{P}_{\tilde{x}_{k+1}\tilde{y}_{k+1}}$:

$$\begin{aligned}
\mathbf{P}_{\tilde{y}_{k+1}\tilde{y}_{k+1}} &= \sum_{i=0}^{2L} W_i^{(c)} \left(\mathcal{Y}_{i,k+1|k} - \hat{y}_{k+1}^-\right) \times \\
&\quad \left(\mathcal{Y}_{i,k+1|k} - \hat{y}_{k+1}^-\right)^T, && (24)
\end{aligned}$$

$$\begin{aligned}
\mathbf{P}_{\tilde{x}_{k+1}\tilde{y}_{k+1}} &= \sum_{i=0}^{2L} W_i^{(c)} \left(\mathcal{X}_{i,k+1|k}^x - \hat{x}_{k+1}^-\right) \times \\
&\quad \left(\mathcal{Y}_{i,k+1|k} - \hat{y}_{k+1}^-\right)^T, && (25)
\end{aligned}$$

followed by the correction of predicted states and covariance:

$$\begin{aligned}
\mathbf{K}_{k+1} &= \mathbf{P}_{\tilde{x}_{k+1}\tilde{y}_{k+1}} \mathbf{P}_{\tilde{y}_{k+1}\tilde{y}_{k+1}}^{-1}, && (26)\\
\hat{x}_{k+1} &= \hat{x}_{k+1}^- + \mathbf{K}_{k+1}\left(y_{k+1} - \hat{y}_{k+1}^-\right), && (27)\\
\mathbf{P}_{k+1} &= \mathbf{P}_{k+1}^- - \mathbf{K}_{k+1}\mathbf{P}_{\tilde{y}_{k+1}\tilde{y}_{k+1}}\mathbf{K}_{k+1}^T. && (28)
\end{aligned}$$

where $\mathbf{K}_k$ is Kalman gain matrix.

At the time-instant k measurement update is executed first. It results in current estimates which may be used for the control algorithm, i.e. to obtain the current input u_k. These two parts are time-critical in the on-line implementation. They are followed by time-update algorithm part which should be finished by the next sampling instant $(k+1)$ when new measurements arrive.

IV. Observer design

A. State and parameter estimation

Previous sections described mathematical model of the induction machine and theoretical basis for UKF. This section is focused on ways of implementing the estimation algorithm. There are two ways of implementing both state and parameter estimation. First is by including parameters in the state vector and forming a new augmented state vector $x_p = [i_{sd}\ i_{sq}\ i_{mr}\ \rho\ \theta_1\ \theta_2\ \theta_3\ \theta_4]^T$ and use it in the estimation procedure. This approach is called joint Kalman filter. Another approach is a dual Kalman filter, which uses separate filters for states and parameters. This way two state vectors are formed $x = [i_{sd}\ i_{sq}\ i_{mr}\ \rho]^T$, and $\theta = [\theta_1\ \theta_2\ \theta_3\ \theta_4]^T$ and two estimation algorithms are executed sequentially at each sampling instant. Both state and parameter Kalman filters share the same measurement noise description ($\mathbf{R}_x^n = \mathbf{R}_\theta^n$) whereas the process noise in both is four-dimensional (matrices $\mathbf{R}_x^v$, $\mathbf{R}_\theta^v$). The dual Kalman filter is often referred to as a 'braided' Kalman filter in the electrical drives community.

Dual Kalman filter requires less computational effort (two covariance matrices with dimensions 4×4 instead of one with dimensions 8×8) and it proved to be more stable in this particular application. States are estimated with newest available parameter information ($\hat{\theta}_{k-1}$), and parameter estimation is used with the newest available state information ($\hat{x}_{k-1}$) as shown in Fig. 1.

State estimation is performed exactly the same as described in previous section with relations (14)-(28). Process and measurement noise means $\bar{v}$ and $\bar{n}$ are zero values. A Runge-Kutta numerical integration algorithm is applied to (18) for obtaining state values at the next time step.

Parameter estimation is executed in the same manner as estimation of states with following differences:

- relation (18) is simply $\hat{\theta}_{k+1}^- = \hat{\theta}_k$,
- there are no parameters included in (13) so $\hat{x}_k$ is put into (12) along with parameter prediction $\hat{\theta}_{k+1}^-$. This

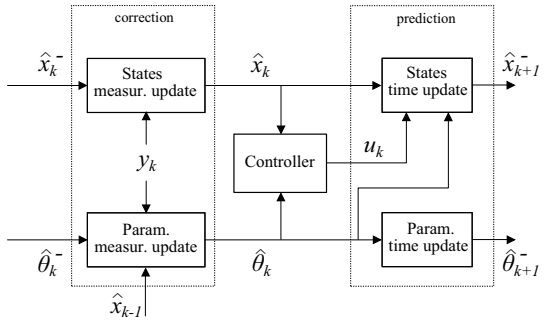

Fig. 1. Dual unscented Kalman filter scheme.

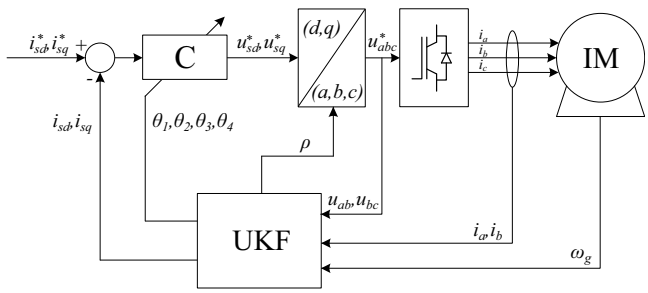

Fig. 2. Field-oriented control loop with dual unscented Kalman filter ('UKF'). Block 'C' represents the controller, block 'IM' is the induction machine. Variables denoted with uppercase star '*' are referent values.

way a parameter-dependent state estimation $\hat{x}^{-}_{k+1}(\theta)$ is obtained, which is then used for output prediction in (21).

Whole control system block scheme is shown in Fig. 2.

B. Observability

The observability of linear systems is often presented as a rank of the observability matrix. It is a measure of how well internal states of a system can be inferred by knowledge of its external outputs [11]. For the case of nonlinear systems, the observability is analyzed by following the linear system approach and by using Lie derivative [11]. The Lie derivative of H from (10) with respect to F from (9) is expressed as:

$$L_F(H) = \nabla H \cdot F = \left[\frac{\partial H}{\partial x_1}, \cdots, \frac{\partial H}{\partial x_n}\right] \cdot \begin{bmatrix} f_1(x) \\ \vdots \\ f_n(x) \end{bmatrix}. \quad (29)$$

Higher order of Lie derivatives are calculated from:

$$L_F^i(H) = \frac{\partial}{\partial x}\left[L_F^{i-1}(H)\right] \cdot F, \qquad i = 1, ..., n-1, \quad (30)$$

and finally, a Lie derivative matrix is formed:

$$\mathbf{L} = \begin{bmatrix} L_F^0(h_1) & \cdots & L_F^0(h_m) \\ \vdots & \ddots & \vdots \\ L_F^{n-1}(h_1) & \cdots & L_F^{n-1}(h_m) \end{bmatrix}, \quad (31)$$

where m is the dimension of H.

From $\mathbf{L}$, a gradient matrix $\mathbf{dL}$ that consists of all gradients of Lie derivatives with respect to F is derived. If the matrix $\mathbf{dL}$ is a full rank matrix, the system is locally observable and internal states can be inferred by external outputs. For described machine model from Section II F and H are (9) and (10). Matrices $\mathbf{L}$ and $\mathbf{dL}$ are very large and are therefore not given in the paper due to limitation of space, in the sequel we focus more on results.

For the case of machine model with constant parameters: $n = 4$, $m = 2$, $f_1, .., f_4$ are (2)-(5), h_1 and h_2 are (11). Matrix $\mathbf{dL}$ has full rank for every case except when machine speed equals zero, $\mathrm{rank}(\mathbf{dL})|_{\omega_g=0} = 2$. The information that model is unobservable at speeds near zero is a well-known fact about Kalman filter approaches used in i.e. speed estimation and sensorless control of induction machines.

For the case of machine model with variable parameters $n = 8$, $m = 2$. State and measurement functions $f_1, .., f_4$ and h_1, h_2 are the same as in previous case while $f_5, .., f_8$ are zero functions. Following the same procedure, the matrix $\mathbf{dL}$ has also a full rank for every case except when machine speed equals zero, $\mathrm{rank}(\mathbf{dL})|_{\omega_g=0} = 7$. Parameter estimation will also provide better results at speeds that are further from zero.

C. Initialization of Kalman filter algorithms

For both state and parameter estimation there are lots of degrees of freedom (8 estimates are extracted out of 4 non-linear differential equations and 2 measurements) and finding precise parameters of UKF algorithm is of a great importance. In the sequel we give some recommendations how to achieve better performance and results of UKF algorithm.

Covariance matrix elements of the parameter process noise are chosen small enough to ensure slow continuous convergence rate of parameters. Covariance matrix elements of the state process noise are roughly approximated considering the scenario in which parameters have maximum deviations from their original values and then tuned. Measurement noise is chosen as a deviation of ± 10mA in current measurements. By applying the described procedure, following state and parameter process and measurement noise covariance matrices are obtained:

$$\begin{aligned} \mathbf{R}_x^v &= \mathrm{diag}\big([0.044,\ 2\cdot 10^{-3},\ 5\cdot 10^{-7},\ 10^{-7}]\big), \\ \mathbf{R}_\theta^v &= \mathrm{diag}\big([10^{-5},\ 10^{-9},\ 7\cdot 10^{-10},\ 2\cdot 10^{-9}]\big), \\ \mathbf{R}_x^n &= \mathbf{R}_\theta^n = \begin{bmatrix} 4\cdot 10^{-5} & 0 \\ 0 & 4\cdot 10^{-5} \end{bmatrix}. \end{aligned}$$

State estimation starts with turning the device on and initial values of state estimation are chosen as:

$$\hat{x}_0 = \mathbb{E}\left(\hat{x}_0\right) = [0\ 0\ 0\ 0]^T,$$
$$\mathbf{P}_{x0} = \mathbb{E}\left[\left(\hat{x}_0 - \mathbb{E}\left(\hat{x}_0\right)\right)\left(\hat{x}_0 - \mathbb{E}\left(\hat{x}_0\right)\right)^T\right] = 10^{-7}\mathbf{I}_{4\times 4}.$$

Initial values of parameters are chosen as a best guess and parameter estimation covariance matrix $\mathbf{P}_{\theta 0}$ initial values are chosen same as parameter process noise covariance matrix $\mathbf{R}_\theta^v$.

V. Simulation results

Simulation results are obtained using MATLAB/Simulink environment and are performed on the ideal four-pole machine model ($p = 2$). Machine rated values are: stator voltage $U_n = 187$ V, stator current $I_n = 15.18$ A, power and torque $P_n = 5.5$ kW, $T_{gn} = 37.3541$ Nm, frequency $f_n = 50$ Hz. True values of parameters are: $\theta_1 = 96.8335$, $\theta_2 = 1.4277$, $\theta_3 = 0.7182$, $\theta_4 = 4.4444$. Starting parameter values are chosen: $\theta_1 = 106.8335$, $\theta_2 = 1.3277$, $\theta_3 = 0.6182$, $\theta_4 = 3.4444$. Sample time is $T_s = 2 \cdot 10^{-4}$ s. Results are presented and discussed in the sequel.

Figure 3 and 4 show state and parameter estimation of the machine fundamental wave model, for the case of the machine run-up, compared with the states and parameters of the ideal model for the same initial conditions and input sequence. State estimations are pretty accurate even with incorrect parameters. Inaccurate parameters are reflected only through magnetizing current. Most significant result is a very accurate and robust estimate of the flux position obtained using the proposed algorithm. Parameter estimates converge to values that are close to true ones but not exactly the same. This is due to scarce indirect influence of measurement correction on parameter UKF. Moreover, large changes in $\theta_{1,\ldots,4}$ reflect only as small changes in inductances and resistances of the equivalent circuit and still provide pretty accurate state estimation results.

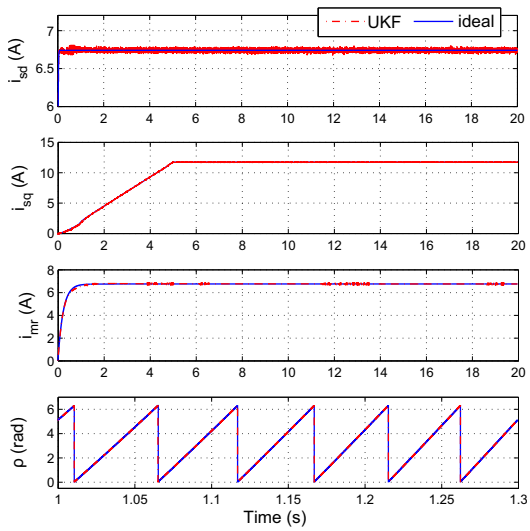

Fig. 3. Comparison of states estimation and ideal model.

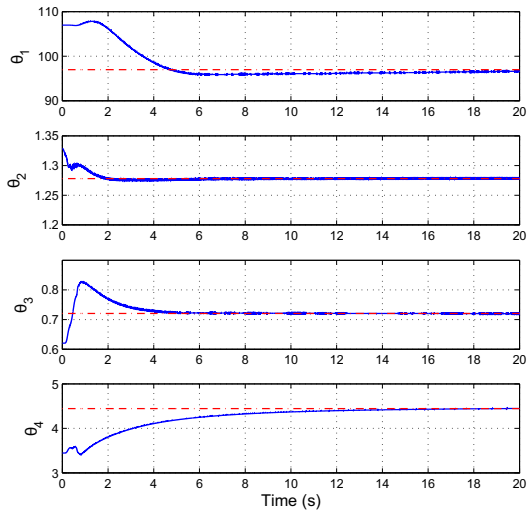

Fig. 4. Simulation results for parameter estimation. True values are denoted with red dash-dot line.

VI. Experimental results

This section provides experimental results for the case of real machine with the same parameters as in the previous section. Results are also compared with the ones obtained with the joint EKF (see [12]). Estimation is performed off-line on acquired measurements and both EKF and UKF have equal initial conditions and are given same voltages and speed as inputs. Experimental measurements are obtained for the case of machine run-up no-load scenario.

A lot of information is sought from only two measurements and the estimator design procedure requires an intense parameter tuning of Kalman filter covariance matrices. It may be observed that all the variations in machine inductances are reflected in parameter θ_1, while θ_2 is additionally influenced by all resistances. Thus, every parameter change in the machine influences θ_1 and θ_2 and a standing assumption is that fixing θ_3 and θ_4 in the dual Kalman filter will still enable the estimator correct operation in terms of providing quality state estimates and model parameters for correct FOC operation. In order to obtain robust and convergent state and parameters estimates, θ_3 and θ_4 are fixed in processing the experimental data.

Figure 5 shows state estimation obtained by EKF and UKF. Flux position estimation is compared to the one used in industrial field-oriented controller for calculating reference phase voltages that are further on passed to the inverter control. Stator currents in (dq) frame denoted as 'real' are obtained from phase stator currents measurements and the flux angle used in industrial field-oriented controller.

Internal states required for FOC are more accurately determined with UKF approach. This is due to more credible mathematical model and more accurate nonlinear mapping used in UKF. Figure 6 evidences that – it shows difference between measurements x and estimates $\hat{x}$ denoted as estimation error $\tilde{x} = \hat{x} - x$. The UKF shows better performance, especially for the case of flux position and quadrature current where the error is twice as small with UKF approach compared to the EKF one.

Values θ_3 and θ_4 are fixed on starting values mentioned in Section V, and are thus different from their rated ones. Figure 7 presents the estimation with two-parameter approach that provides accurate estimation of machine variables shown in figures 5 and 6. It may be observed that θ_1 and θ_2 converge to the values that are near the rated ones but do not exactly match them. This is partly due to compensation of model deviation in parameters θ_3 and θ_4, and possibly due to the

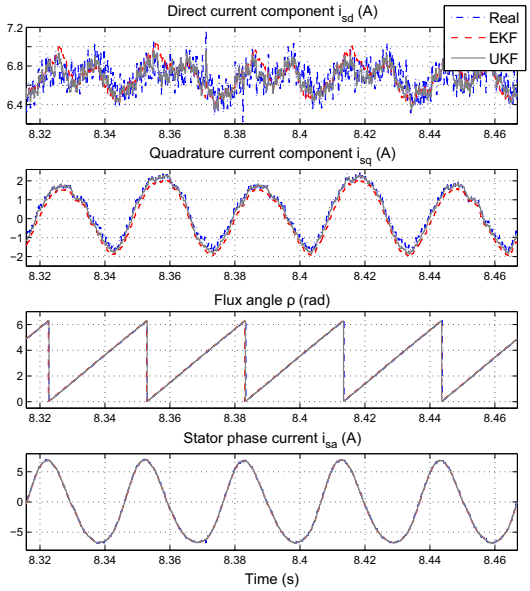

Fig. 5. Comparison of variables estimation with EKF and UKF.

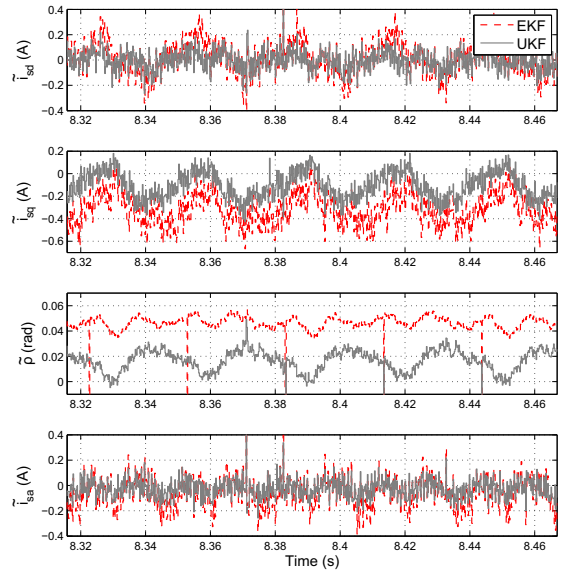

Fig. 6. Estimation errors $\tilde{x} = \hat{x} - x$.

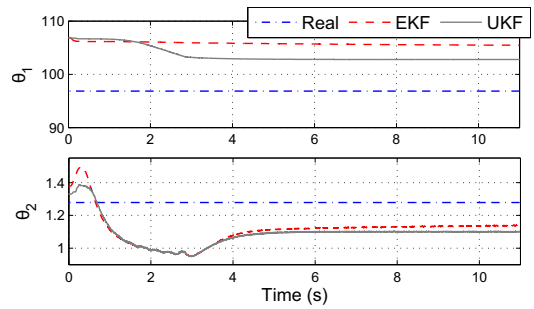

Fig. 7. Parameter estimation with off-line procedure on acquired real system measurements. Red dash-dot line denotes machine rated parameters.

difference between machine actual and rated parameter values. Therefore, it is justified to observe only these two parameters as a trade-off for increasing robustness of the combined state and parameter estimation algorithm.

VII. Conclusions

In this paper we use Kalman filtering for simultaneous estimation of variables and parameters of the induction machine fundamental wave model. Due to hard nonlinearities present in that model we apply unscented Kalman filter in the dual estimation configuration. The estimates are used in field-oriented control and validation of estimation and control performance is done via simulations and experiments. Comparison with conventional extended Kalman filter is also examined. Results show that accurate and robust machine flux position is obtained with the presented algorithm. The described procedure is straightforwardly adaptable to sensorless control techniques or similar problems.

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