Rotor and Stator Resistance Estimation of Induction Motor Based on Augmented EKF

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***Abstract*—This paper deals with rotor and stator resistance estimation of induction motor (IM) drive based on augmented Extended Kalman Filter (EKF). The proper knowledge of rotor flux magnitude and flux position is a necessary condition for high performance induction motor control (Rotor Flux Field Oriented Control - RFOC etc.). The rotor flux estimator for RFOC is typically based on mathematical model of induction motor in dq coordinates, which are sensitive to rotor resistance value. The rotor and stator resistances are temperature dependent and could increase up to twice the nominal values. This paper deals with rotor flux estimator for induction motor without any temperature sensors. Whereas the EKF based methods commonly used the rotating reference frame based IM models, presented method is based on the stationary reference frame model of the IM. The augmented state space vector of EKF model of IM is used for rotor flux and rotor and stator resistances estimation. The paper consist of simulation as well as experimental results.**

I. Introduction

A fast torque control with constant switching pulse width modulation (PWM) frequency is the main advantage of the rotor flux field oriented control. The basic control structure based on PI controllers with decoupling algorithm between dq axes is well known and established as common control algorithm of industrial drives (fig. 1.-located in the bottom part of the paper). This research has been motivated by the industrial demand for high-dynamics RFOC without harmful temperature dependency of the rotor flux calculation. Various papers have been presented for rotor time constant or rotor resistance adaptation. These methods could be divided into three groups.

The first group of methods are based on the model reference adaptive systems MRAS e.g. [1], [2], [3]. The main idea of these methods is to use the voltage model of the IM, which is not sensitive to rotor resistance value as a reference model. The difference between current model and reference voltage model of IM is used for current model adaptation. These adaptation methods could be slow and sensitive [4]. The stator resistance variation, voltage drops and deadtime effects of power converter etc. could have the strong impact on precision of rotor resistance estimation. On the other hand MRAS methods are computational effective and thus could be implemented in low cost processors.

The second group of methods are nonlinear estimators based for example on neural networks [5], [6], [7], fuzzy systems [8], [9], sliding mode observers [10] etc. These methods are mostly difficult to implement. Furthermore, nonlinear observer based methods have generally high computational requirements. Moreover, the robustness of these methods to stator resistance variation and nolinear phenomena of power converter are oftenly not sutisfied.

The third group of methods is based on EKFs. EKF is linearized version of popular Kalman filter [11]. The Kalman filter is optimal state estimator for linear systems with gaussian disturbances. EKFs methods can estimate the actual values of the rotor flux, stator currents, motor speed, motor parameters etc. and thus could be more universal than previous mentioned methods. The computational requirements of EKFs are mainly influenced by the size of the EKFs state space vector. Whereas the EKF based methods commonly uses the rotating reference frame based IM models [12], presented method is based on the stationary reference frame model of the IM. The EKF model is augmented by rotor and stator resistance estimation. In the paper is described that the stator resistance estimation has large impact on the precision of the rotor resistance estimation.

The advantage of selected stationary reference model of the IM is presented in section II. The stationary reference frame model used for EKF derivation is described in section III. The section IV is focused on the EKF algorithm used for rotor resistance estimation. The section V describes the IM control structure used for simulation and for laboratory prototype of the IM drive. The section VI is dedicated to simulation and experimental results and the last section is conclusion.

II. Induction Motor Model Selection for Rotor Resistance Estimation

The mathematical models of IM could be generally divided into two types. The first one is stationary reference frame ($\alpha\beta$) model and the second one is model in the rotating reference frame (dq). The model in dq reference frame could be affected by non-correct dq angle causes difference between real and estimated position of flux. The Kalman filter based approaches for rotor resistance estimation used the error between predicted currents of model and measured currents to adapt states or estimated parameters of model. The dq currents are gained from the measured currents by Park

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transform based on the knowledge of the rotor flux position and thus they are dependent on correct transform. The rotor resistance mismatch between real IM and its model causes differences in real and estimated position and amplitude of the rotor flux. Furthermore the Kalman filters work best with the Gausian (normal) types of the noise distribution and park transform changes the probabilistic distribution of the noise in dq currents. Mainly for these reasons it is better to use stationary reference frame models for rotor resistance estimation.

III. Stationary Reference Frame Model of IM

For EKF estimator derivation were used equations (1 - 5) of the IM in stationary reference frame. The model is by following equations and parameters:

$$\frac{di_{S\alpha}}{dt} = -\left(aR_{S(t)} + bR_{R(t)}\right) i_{s\alpha(t)} + cR_{R(t)}\Psi_{R\alpha(t)} + e\omega_{(t)}\Psi_{R\beta(t)} + fu_{S\alpha(t)} \quad (1)$$

$$\frac{di_{S\beta}}{dt} = -\left(aR_{S(t)} + bR_{R(t)}\right) i_{s\beta(t)} + cR_{R(t)}\Psi_{R\beta(t)} - e\omega_{(t)}\Psi_{R\alpha(t)} + fu_{S\alpha(t)} \quad (2)$$

$$\frac{d\Psi_{R\alpha}}{dt} = gR_{R(t)}i_{s\alpha(t)} + hR_{R(t)}\Psi_{R\alpha(t)} - k\omega_{(t)}\Psi_{R\beta(t)} \quad (3)$$

$$\frac{d\Psi_{R\beta}}{dt} = gR_{R(t)}i_{s\beta(t)} + hR_{R(t)}\Psi_{R\beta(t)} + k\omega_{(t)}\Psi_{R\alpha(t)} \quad (4)$$

$$\frac{d\omega}{dt} = l\Psi_{R\alpha(t)}i_{s\beta(t)} - l\Psi_{R\beta(t)}i_{s\alpha(t)} - nM_{Z(t)} - o\omega_{(t)} \quad (5)$$

With parameters:

$a = \frac{1}{\sigma L_S}$, $b = \frac{1-\sigma}{\sigma L_R}$, $c = \frac{1-\sigma}{\sigma L_R L_M}$, $e = \frac{1-\sigma}{\sigma L_M}p_p$, $f = \frac{1}{\sigma L_S}$, $g = \frac{L_M}{L_R}$, $h = \frac{1}{L_R}$, $k = p_p$,$l = \frac{3}{2}\frac{p_p}{J}\frac{L_M}{L_R}$, $n = \frac{1}{J}$, $o = \frac{B}{J}$

This parametrization was used to reduce the computational requirements of model calculation with extracted state variables and time-variant (temperature dependent) rotor and stator resistances. The EKF model of the drive doesnt contain the last (5) motion equation, because its not required for rotor resistance estimation with speed measurement.

IV. Extended Kalman Filter for Rotor Resistance Estimation

The presented EKF model has rotor and stator resistance adaptation and estimated rotor resistance can follow resistance drift caused by temperature. The model is described by matrices in Table II (located in the bottom part of the paper). The main advantage is the low sensitivity of the rotor flux estimation to rotor and stator resistances as well as inverters dead-times effects and voltage drops. The main drawback is larger computational requirement. The EKF is the nonlinear version of the popular Kalman filter. The nonlinear model is linearized by using Jacobian matrix (Table III) and algorithm contains two basic steps: prediction and update (correction).

Prediction step

$$\hat{x}_{(k+1|k)} = A_{D(\omega,R_R,R_S)}x_{(k)} + B_D u_{(k)} \quad (6)$$

$$P_{(k+1|k)} = JP_{(k)}J^T + Q \quad (7)$$

Update step

$$K_{(k)} = \left(P_{(k+1|k)}C_D^T\right) / \left(C_D P_{(k+1|k)}C_D^T + R\right) \quad (8)$$

$$P_{(k+1)} = P_{(k+1|k)} - K_{(k)}C_D P_{(k+1|k)} \quad (9)$$

$$x_{(k+1)} = \hat{x}_{(k+1|k)} + K_{(k)}\left(y_{(k)} - C_D\hat{x}_{(k+1|k)}\right) \quad (10)$$

Where P (6x6) is covariance matrix, J (6x6) is the Jacobian matrix, Q (6x6 diagonal) is covariance matrix of the process noise, R (2x2 diagonal) is the covariance matrix of the measurement noise (for $\alpha\beta$ currents in our case) and K (2x6) is the Kalman gain. The vector x (6x1) contains predicted currents, rotor fluxes and rotor and stator resistances (see Table II). Vector y (2x1) contains measured currents in $\alpha\beta$ reference frame. Multiplying by C_D (6x2 identity) matrix is the selection process of matrices elements. Despite the fact, that matrices A_D and J are relatively large (but also quite sparse), the algorithm can be implemented in low cost 150 Mhz floating-point DSP processor like TMS320F28335 with $100\mu s$ sampling time for the whole control loop with 40% of processor utilization.

V. RFOC System Description

The whole control system structure is shown in fig. 1. For amplitude and angle flux computation in the RFOC the I_S, ω current model is the most commonly used algorithm (equations 11 - 14). This model is insensitive to stator resistance and voltage drops of IGBTs. The main drawback is visible in eqs. 6, and 7, which are sensitive to rotor resistance. The error in rotor resistance results to error of flux amplitude (eq. 11.) and flux actual speed (eq. 12.). This model is used for comparison with presented method based on EKF. The second popular algorithm for flux computation based on the stationary reference frame voltage model of IM is rotor resistance insensitive. On the other hand, the voltage model is sensitive to stator resistance, converter voltage drops and furthermore computation of fluxes could leads to dc offset problem.

$$\Psi_{R(k)} = \Psi_{R(k-1)} + \left(L_M i_{sd(k)} - \Psi_{R(k-1)}\right)\frac{R_R}{L_R}dT \quad (11)$$

$$\omega_{R(k)} = \frac{i_{sq(k)} R_R L_M}{\Psi_{R(k)} L_R} \quad (12)$$

$$\omega_{s(k)} = p_p \omega_{(k)} + \omega_{R(k)} \quad (13)$$

$$\upsilon_{\psi(k)} = \upsilon_{\psi(k-1)} + \omega_{s(k)} dT \quad (14)$$

The rotor flux position$\upsilon_{\psi(k)}$ is used for currents transform to dq axes and backward transform of output voltages to stationary reference frame. The actual rotor flux value $\Psi_{R(k)}$ is compared with the reference flux and resulted error affects the flux PI controller output. The output of the flux controller is required d axis stator current, which is also controlled by PI type of controller to its required value. The similarly, speed error is minimized by the PI speed controller and resulted required q axis part of current is controlled by PI controller. All controllers are extended with anti-windup part to prevent drift of integration. Decoupling algorithm is used to decouple d and q axes. Resulted d a q voltages are transformed by inverse Park transform to stationary reference frame and the duty cycles of transistors are calculated by the space vector PWM algorithm.

VI. Simulation and Experimental Results

Presented flux estimators (based on EKF and I_S, ω current model) were simulated for two cases. The first case is simulated for PWM inverter model without consideration of dead-time effects and voltage drops. The results are shown in fig. 2. The rotor fluxes in $\alpha\beta$ reference frame and rotor and stator resistances are estimated with minimal errors. The fig. 3 presents the same scenario with inverter dead-times and voltage drops. There is visible marginal error on the estimated stator resistance. The effects of the semiconductors dynamic resistances and dead-times effects etc. are added to the estimated stator resistance. Thanks to this EKF property the rotor resistance and rotor fluxes are still estimated without any significant errors. The fig. 4 presents reduced EKF model without stator resistance estimation with inverter dead-times effects and voltage drops. In this case the errors in the rotor fluxes and resistance are quite large. In the experimental setup (parameters in Table I.) was for RFOC used I_S, ω current model (eq. 6 - 9) with correct parameters and cooled motor (rotor and stator resistances are near to its nominal values). The EKF worked in the open loop and the current model with correct parameters could be used as a reference. In the experiment the EKF was initialized to mismatched parameter value of the rotor or the stator resistance. Fig. 5 shows the transient of $\alpha\beta$ fluxes to mismatch rotor resistance of EKF. The fig. 6 and 7 shows EKF behavior to rotor resistance initialization mismatch in dq reference frame. The stator resistance initialization error case is shown in fig. 8 and 9 (in dq reference frame). The differences between rotor fluxes are very small for all experiments and estimated rotor resistance equal to the real (nominal) value. Stator resistance is not estimated correctly due to voltage drops of inverter IGBTs and dead-time ($2\mu s$) effects. These influences are added to the EKF stator resistance.

TABLE I
Nominal Parameters of IM drive

Parameter	Description	Value
P_{rated}	Rated power	4 [kW]
p_p	Number of pole pairs	2
$R_{S\ nominal}$	Nominal stator resistance	1.32 [Ω]
$R_{R\ nominal}$	Nominal rotor resistance	1.51 [Ω]
L_M	Nominal main inductance	0.165 [mH]
L_S	Nominal stator inductance	0.172 [mH]
L_R	Nominal rotor inductance	0.172 [mH]

VII. Conclusions

In this paper, the EKF for stator and rotor resistance estimation for the IM drives was presented. The accurate value of the rotor resistance is required for correct rotor flux estimation. Whereas the EKF based methods commonly used the rotating reference frame based IM models, presented method is based on the stationary reference frame model. The paper results show, that the stator resistance estimation is also necessary condition for high quality rotor flux calculation even the proper stator resistance is known. The impacts of voltage drops of inverter semiconductor devices and dead-times effects on the rotor flux and resistance estimation could be reduced by extending state space vector of EKF model by stator resistance estimation. The paper presents simulation as well as experimentation results. The EKF estimator was implemented in TMS320F28335 DSP processor.

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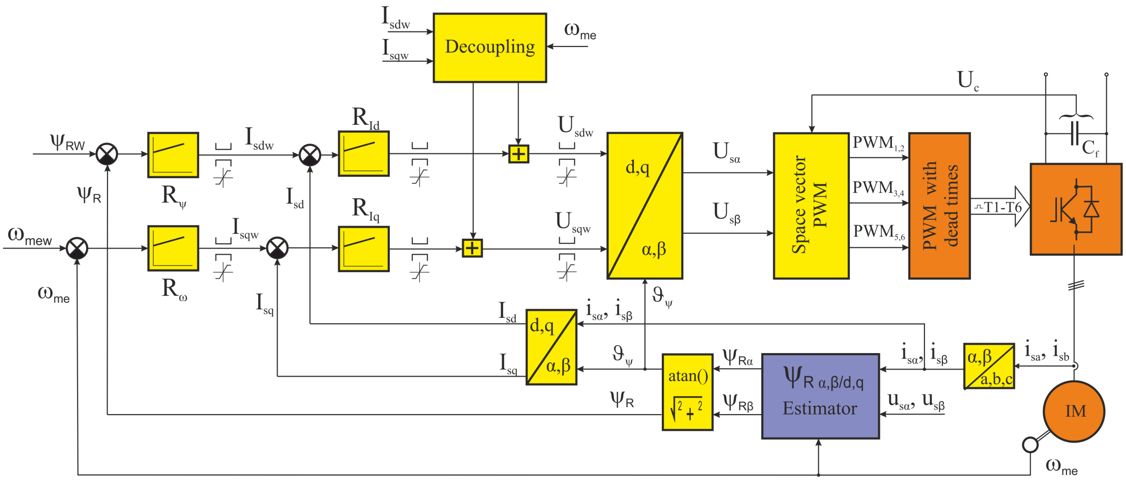

Fig. 1. Rotor flux oriented control with flux estimator based on EKF experimental and simulation setup

TABLE II
THE DISCRETE STATE SPACE MATRICES OF IM EKF ESTIMATOR (PARAMETRIZATION IN SECTION III)

$$A_D = \begin{bmatrix} 1-\left(aR_{S(t)}+bR_{R(t)}\right)dT & 0 & cR_{R(k)}dT & e\omega_{(k)}dT & 0 & 0 \\ 0 & 1-\left(aR_{S(t)}+bR_{R(t)}\right)dT & -e\omega_{(k)}dT & cR_{R(k)}dT & 0 & 0 \\ gR_{R(k)}dT & 0 & 1-hR_{R(t)}dT & -k\omega_{(k)}dT & 0 & 0 \\ 0 & gR_{R(k)}dT & k\omega_{(k)}dT & 1-hR_{R(t)}dT & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{15}$$

$$B_D^T = \begin{bmatrix} fdT & 0 & 0 & 0 & 0 & 0 \\ 0 & fdT & 0 & 0 & 0 & 0 \end{bmatrix},\ C_D = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{16}$$

$$x_{(k)}^T = [i_{S\alpha(k)}, i_{S\beta(k)}, \Psi_{R\alpha(k)}, \Psi_{R\beta(k)}, R_{R(k)}, R_{S(k)}],\ y_{(k)}^T = [i_{S\alpha(k)}, i_{S\beta(k)}]$$

TABLE III
THE JACOBIAN MATRIX OF IM EKF ESTIMATOR AND Q, R SETTINGS (PARAMETRIZATION IN SECTION III)

$$J = \begin{bmatrix} 1-\left(aR_{S(t)}+bR_{R(t)}\right)dT & 0 & cR_{R(k)}dT & e\omega_{(k)}dT & J_{51} & J_{61} \\ 0 & 1-\left(aR_{S(t)}+bR_{R(t)}\right)dT & -e\omega_{(k)}dT & cR_{R(k)}dT & J_{52} & J_{62} \\ gR_{R(k)}dT & 0 & 1-hR_{R(t)}dT & -k\omega_{(k)}dT & J_{53} & 0 \\ 0 & gR_{R(k)}dT & k\omega_{(k)}dT & 1-hR_{R(t)}dT & J_{54} & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{17}$$

$$J_{51} = c\Psi_{R\alpha(k)}dT - bi_{S\alpha(k)}dT,\ J_{52} = c\Psi_{R\beta(k)}dT - bi_{S\beta(k)}dT,\ J_{53} = gi_{S\alpha(k)}dT - h\Psi_{R\alpha(k)}dT,$$
$$J_{54} = gi_{S\beta(k)}dT - h\Psi_{R\beta(k)}dT,\ J_{61} = ai_{S\alpha(k)}dT,\ J_{62} = ai_{S\beta(k)}dT$$

$$R\epsilon\mathbb{R}^{2x2} = diag([0.005, 0.005]),\ Q\epsilon\mathbb{R}^{6x6} = diag([1\cdot 10^{-8}, 1\cdot 10^{-8}, 1\cdot 10^{-10}, 1\cdot 10^{-10}, 1\cdot 10^{-7}, 1\cdot 10^{-7}])$$

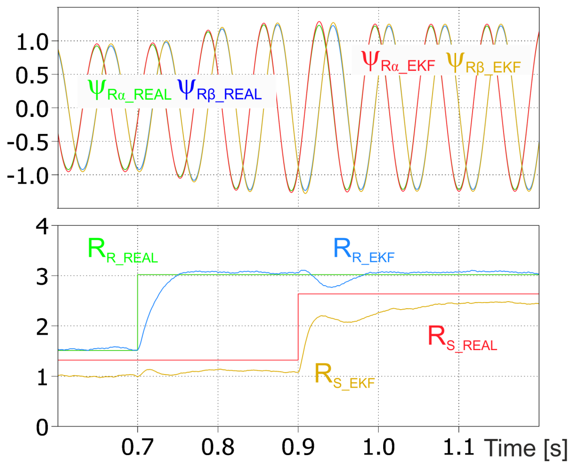

Fig. 2. EKF simulation results for inverter *without* voltage drops and dead-times- R_{R_REAL}, R_{S_REAL}/ R_{R_EKF}, R_{S_EKF} are real/estimated rotor and stator resistances, $\Psi_{R\alpha\_REAL}$, $\Psi_{R\beta\_REAL}$/ $\Psi_{R\alpha\_EKF}$, $\Psi_{R\beta\_EKF}$ are real/estimated rotor fluxes. In 0.7s step change of R_{R_REAL} to $2xR_{R\_NOMINAL}$ and in 0.9s step change of R_{S_REAL} to $2xR_{S\_NOMINAL}$

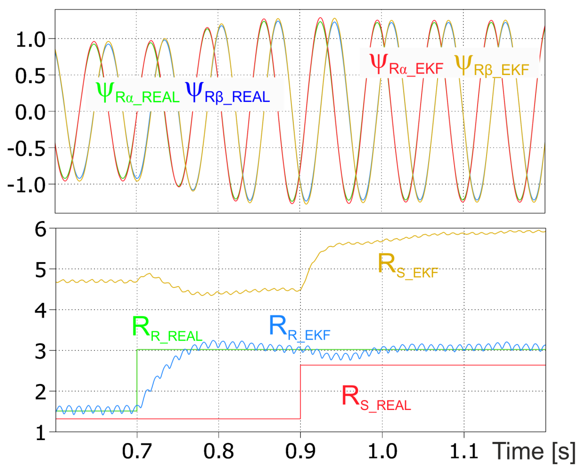

Fig. 3. EKF simulation results for inverter *with* voltage drops and dead-times- R_{R_REAL}, R_{S_REAL}/ R_{R_EKF}, R_{S_EKF} are real/estimated rotor and stator resistances, $\Psi_{R\alpha\_REAL}$, $\Psi_{R\beta\_REAL}$/ $\Psi_{R\alpha\_EKF}$, $\Psi_{R\beta\_EKF}$ are real/estimated rotor fluxes. In 0.7s step change of R_{R_REAL} to $2xR_{R\_NOMINAL}$ and in 0.9s step change of R_{S_REAL} to $2xR_{S\_NOMINAL}$

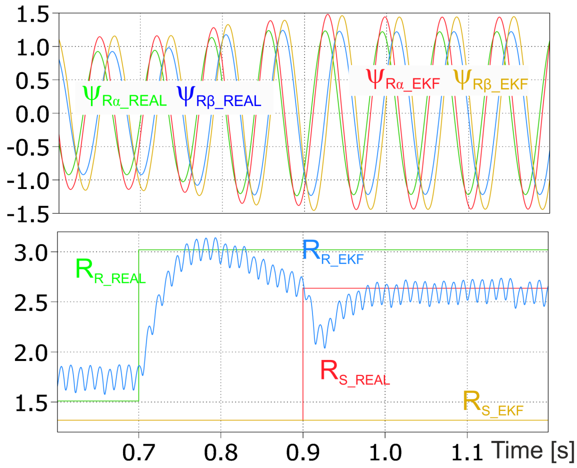

Fig. 4. EKF simulation results for inverter *with* voltage drops and dead-times and without R_{S_EKF} adaptation - R_{R_REAL}, R_{S_REAL}/ R_{R_EKF}, R_{S_EKF} are real/estimated rotor and stator resistances, $\Psi_{R\alpha\_REAL}$, $\Psi_{R\beta\_REAL}$/ $\Psi_{R\alpha\_EKF}$, $\Psi_{R\beta\_EKF}$ are real/estimated rotor fluxes. In 0.7s step change of R_{R_REAL} to $2xR_{R\_NOMINAL}$ and in 0.9s step change of R_{S_REAL} to $2xR_{S\_NOMINAL}$

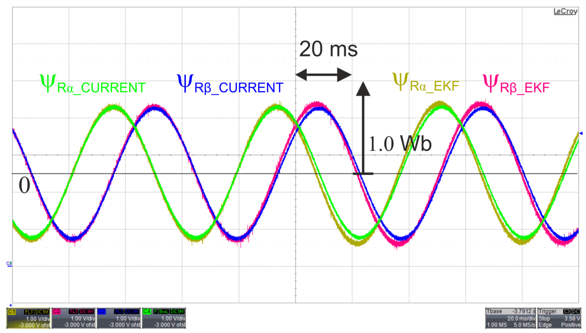

Fig. 5. Experimental setup. Computed $\alpha\beta$ rotor fluxes components of current I_S, ω model with correct resistances and EKF with step change on R_{R_EKF} - transient detail

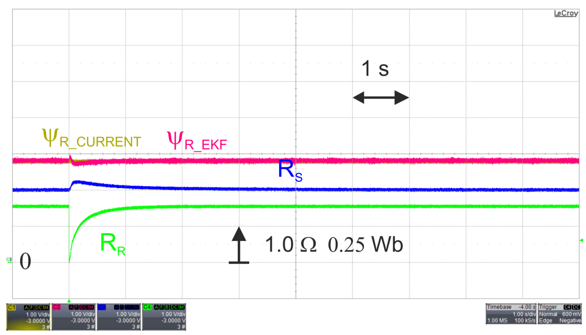

Fig. 6. Measured rotor flux magnitude from current I_S, ω model with correct resistances and EKF with rotor resistance initialization mismatch to 0Ω ($R_{R\ NOMINAL}$=1.51Ω)

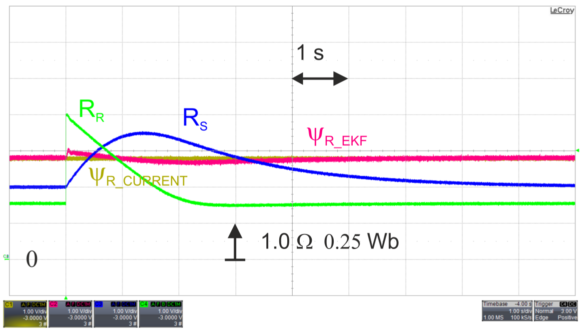

Fig. 7. Measured rotor flux magnitude from current I_S, ω model with correct resistances and EKF with rotor resistance initialization mismatch to 4Ω ($R_{R\ \mathrm{NOMINAL}}$=1.51Ω)

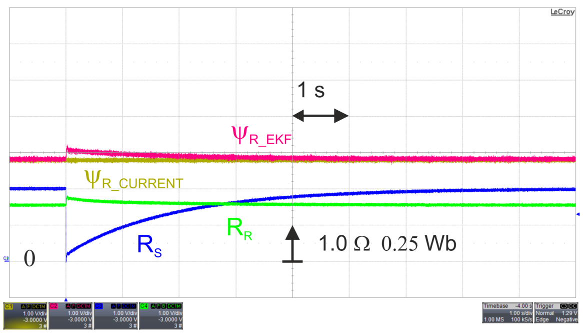

Fig. 8. Measured rotor flux magnitude from current I_S, ω model with correct resistances and EKF with stator resistance initialization mismatch to 0Ω ($R_{S\ \mathrm{NOMINAL}}$=1.32Ω)

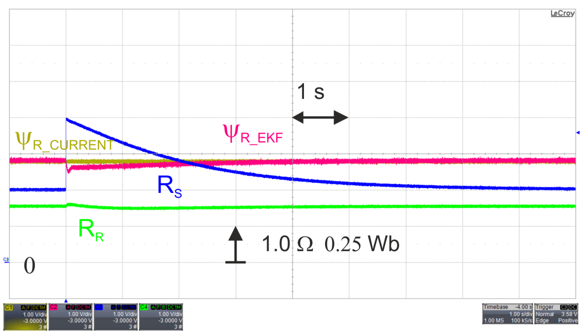

Fig. 9. Measured rotor flux magnitude from current I_S, ω model with correct resistances and EKF with stator resistance initialization mismatch to 4Ω ($R_{S\ \mathrm{NOMINAL}}$=1.32Ω)

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