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Simultaneous rotor and stator resistance estimation of squirrel cage induction machine with a single extended kalman filter

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Abstract

Accurate knowledge of rotor and stator resistance variations in a squirrel-cage induction motor (SCIM) is crucial for the performance of sensorless control of SCIM over a wide range of speeds. This study seeks to address this issue with a single Extended Kalman Filter (EKF) based solution, which is also known to have accuracy limitations when a high number of parameters/states are estimated with a limited number of inputs. To this aim, different from the author's previous approach in operating several EKFs in an alternating manner (the so-called braided EKF), an 8^{th}-order EKF is implemented in this study to test its performance for the simultaneous estimation of rotor and stator resistances with a single algorithm. Beyond the resistances, the EKF observer also estimates the load torque, rotor and stator fluxes and speed in the wide speed range ($-n_{max} < 0 < n_{max}$). The results indicate success with the accurate estimation of only one resistance at a time, and an acceptable performance in speed estimation only after considerable tuning of the covariance matrix coefficients, hence the superiority of the braided EKF approach to the 8^{th}-order EKF in sensorless control of SCIMs with the available current and voltage inputs.

Key Words: *Extended Kalman filter (EKF), induction machine, sensorless control, rotor and stator resistance estimation*

1. Introduction

Sensorless high performance control of squirrel cage induction machine (SCIM) over a wide range of speeds depends on the knowledge of electrical and mechanical uncertainties at high accuracy [1]. Different solutions are proposed in the observer design of fifth order, nonlinear and time varying SCIM dynamic model. In addition to the estimation of rotor resistance R_r', which is affected by frequency and temperature variations, estimation of stator resistance R_s which is also affected by temperature variations are required in order to reach a correct speed and flux values at high accuracy.

There are many studies that have investigated the design of an SCIM observer. By the help of the adaptive model approach, the speed is estimated with adaptation a rule produced for different rotor and stator models of SCIM [2]. However, this method is, in practice, difficult to apply due to the integration operation in the calculations. Luenberger observer [3], which is a deterministic estimation approach, is widely used for the estimation of rotor fluxes and speed of SCIM. However, this deterministic approach is not sufficient for the high performance sensorless control due to the nonlinear, stochastic, parameter varying behavior of SCIM. Sliding Mode Control is also widely used for the sensorless control of SCIMs [4, 5].

Extended Kalman Filter (EKF) based observers are also widely used in order to estimate electrical and mechanical uncertainties of SCIM [6–12]. In [10], the speed, which is estimated directly as a parameter, is also used in a direct vector control algorithm. In [9], in addition to flux and speed estimation (with the use of equation of motion), the load torque and rotor resistance is simultaneously estimated in a single EKF algorithm. It is also a well-known fact that, for an accurate estimation performance in the sensorless control of induction motors over the whole speed range, an accurate knowledge of R_s and R_r' is crucial. Yet, this is a well-known challenge among induction motor sensorless control researchers, as also mentioned in [12], where the simultaneous estimation of these two motor parameters is said to cause instability. To address this issue, the Braided EKF algorithm [6, 7, 12] is proposed in order to estimate rotor and stator resistances simultaneously with the use of two 7^{th}-order EKF algorithms executed in an alternating manner; the study in [12] also demonstrates the good performance of this method in persistent operation at zero speed.

This study also aims to provide an EKF based solution to the simultaneous estimation of rotor and stator resistances to address the challenge mentioned in [12], but with a single EKF algorithm, different from the braided approach in [7] and [12]. However, the results indicate success with the accurate estimation of only one resistance at a time, and an acceptable performance in speed estimation only after considerable tuning of the covariance matrix coefficients, hence the superiority of the braided EKF approach in sensorless control of SCIMs with the available current and voltage inputs.

2. Extended SCIM model for 8^{th}-order EKF algorithm

In this section, the fifth order, nonlinear dynamic model of the SCIM [13] is extended for the derivation of the 8^{th}-order EKF model as follows [6, 10]:

$$\dot{\mathbf{x}}(t) = A(\mathbf{x}(t))\,\mathbf{x}(t) + \mathbf{B}\,\mathbf{u}(t) + \mathbf{w}(t) \tag{1}$$

$$\mathbf{z}(t) = \mathbf{H}\,\mathbf{x}(t) + \mathbf{v}(t) \tag{2}$$

$$\frac{d}{dt}\underbrace{\begin{pmatrix} i_{s\alpha}(t) \\ i_{s\beta}(t) \\ \psi_{r\alpha}(t) \\ \psi_{r\beta}(t) \\ \omega_m(t) \\ T_L(t) \\ R_r(t) \\ R_s(t) \end{pmatrix}}_{\dot{\mathbf{x}}(\mathbf{t})} = \underbrace{\begin{pmatrix} -\frac{L_m^2 R_r(t)}{L_\sigma L_r^2} - \frac{R_s(t)}{L_\sigma} & 0 & \frac{L_m R_r(t)}{L_\sigma L_r^2} & \frac{L_m}{L_\sigma L_r^2}\omega_m(t) & 0 & 0 & 0 & 0 \\ 0 & -\frac{L_m^2 R_r(t)}{L_\sigma L_r^2} - \frac{R_s(t)}{L_\sigma} & -\frac{L_m}{L_\sigma L_r^2}\omega_m(t) & \frac{L_m R_r(t)}{L_\sigma L_r^2} & 0 & 0 & 0 & 0 \\ \frac{L_m R_r(t)}{L_r} & 0 & -\frac{R_r(t)}{L_r} & -p\omega_m(t) & 0 & 0 & 0 & 0 \\ 0 & \frac{L_m R_r(t)}{L_r} & p\omega_m(t) & -\frac{R_r(t)}{L_r} & 0 & 0 & 0 & 0 \\ -\frac{3}{2}\frac{p}{J_L}\frac{L_m}{L_r}\psi_{r\beta}(t) & \frac{3}{2}\frac{p}{J_L}\frac{L_m}{L_r}\psi_{r\alpha}(t) & 0 & 0 & 0 & -\frac{1}{J_L} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}}_{A(x(t))} \underbrace{\begin{pmatrix} i_{s\alpha}(t) \\ i_{s\beta}(t) \\ \psi_{r\alpha}(t) \\ \psi_{r\beta}(t) \\ \omega_m(t) \\ T_L(t) \\ R_r(t) \\ R_s(t) \end{pmatrix}}_{\mathbf{x}(\mathbf{t})} + \underbrace{\begin{pmatrix} \frac{1}{L_\sigma} & 0 \\ 0 & \frac{1}{L_\sigma} \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{pmatrix}}_{\mathbf{B}} \underbrace{\begin{pmatrix} V_{s\alpha} \\ V_{s\beta} \end{pmatrix}}_{\mathbf{u}(\mathbf{t})} + \mathbf{w}(t) \tag{3}$$

$$z(t) = \underbrace{\begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}}_{\mathbf{H}} \underbrace{\begin{pmatrix} i_{s\alpha}(t) \\ i_{s\beta}(t) \\ \psi_{r\alpha}(t) \\ \psi_{r\beta}(t) \\ \omega_m(t) \\ T_L(t) \\ R_r(t) \\ R_s(t) \end{pmatrix}}_{\mathbf{x}(\mathbf{t})} + \mathbf{v}(t)\,. \tag{4}$$

Here, $\boldsymbol{w}$(t) and $\mathbf{v}$(t) are Gaussian system and measurement noises, respectively [14], [15]. $\mathbf{H}$ represents the measurement matrix. $V_{s\alpha}$ and $V_{s\beta}$ represent the input voltages applied to the SCIM model. Finally, $i_{s\alpha}$ and $i_{s\beta}$ represent the currents of the SCIM model. Currents of this dynamic model can be defined as the output of the system.

3. Development of EKF algorithm

The filter now bearing his name was developed in 1960 by Rudolf Kalman [15] and has and is used in many different applications. Extended Kalman Filters (EKF) are used for nonlinear models like SCIM model [9]. EKF based observer is very suitable for SCIM model due to electrical and mechanical uncertainties of the machine. In addition, voltage source inverters used for applying different speeds by altering the frequency is a source of voltage and current harmonics. Therefore, the stochastic approach EKF based observer gives convenient results for estimating the uncertainties of such high order, time varying nonlinear model [7]. EKF algorithm consists of two sections: time update and measurement update equations.

EKF algorithm proposed in [6] is illustrated in Figure 1 [6–8]. The following equation is used as a system matrix:

$$\underbrace{\begin{pmatrix} i_{s\alpha}(k+1) \\ i_{s\beta}(k+1) \\ \psi_{r\alpha}(k+1) \\ \psi_{r\beta}(k+1) \\ \omega_m(k+1) \\ T_L(k+1) \\ R_r(k+1) \\ R_s(k+1) \end{pmatrix}}_{x_{k+1}} = \underbrace{\begin{pmatrix} 1-\frac{L_m^2 T_s}{L_\sigma L_r^2}R_r(k)-\frac{T_s}{L_\sigma}R_s(k) & 0 & \frac{L_m T_s}{L_\sigma L_r^2}R_r(k) & \frac{L_m T_s}{L_\sigma L_r^2}\omega_m(k) & 0 & 0 & 0 & 0 \\ 0 & 1-\frac{L_m^2 T_s}{L_\sigma L_r^2}R_r(k)-\frac{T_s}{L_\sigma}R_s(k) & -\frac{L_m T_s}{L_\sigma L_r^2}\omega_m(k) & \frac{L_m T_s}{L_\sigma L_r^2}R_r(k) & 0 & 0 & 0 & 0 \\ \frac{L_m T_s}{L_r}R_r(k) & 0 & 1-\frac{T_s R_r(k)}{L_r} & -pT_s\omega_m(k) & 0 & 0 & 0 & 0 \\ 0 & \frac{L_m T_s}{L_r}R_r(k) & pT_s\omega_m(k) & 1-\frac{T_s R_r(k)}{L_r} & 0 & 0 & 0 & 0 \\ -\frac{3}{2}\frac{p}{J_L}\frac{L_m T_s}{L_r}\psi_{r\beta}(k) & \frac{3}{2}\frac{p}{J_L}\frac{L_m T_s}{L_r}\psi_{r\alpha}(k) & 0 & 0 & 1 & -\frac{T_s}{J_L} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}}_{\phi(k)} \underbrace{\begin{pmatrix} i_{s\alpha}(k) \\ i_{s\beta}(k) \\ \psi_{r\alpha}(k) \\ \psi_{r\beta}(k) \\ \omega_m(k) \\ T_L(k) \\ R_r(k) \\ R_s(k) \end{pmatrix}}_{x_k} + \underbrace{\begin{pmatrix} \frac{T_s}{L_\sigma} & 0 \\ 0 & \frac{T_s}{L_\sigma} \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{pmatrix}}_{B} \underbrace{\begin{pmatrix} V_{s\alpha}(k) \\ V_{s\beta}(k) \end{pmatrix}}_{u(k)} + w(k). \tag{5}$$

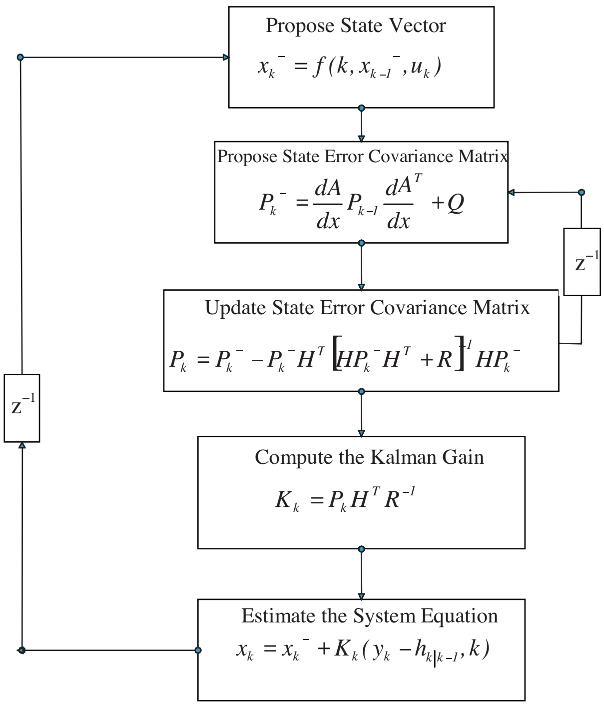

Figure 1. Block diagram showing the EKF algorithm.

The EKF algorithm steps are as follows:

(0) *Propose initial conditions.*

(1) *Propose state vector:* $$\hat{x}_k^- = f(k, \hat{x}_{k-1}^-, u_k) \tag{6}$$

(2) Propose state error covariance matrix: $$P_k^- = \frac{dA}{dx} P_{k-1} \frac{dA}{dx}^T + Q \tag{7}$$

(3) Update state error covariance matrix: $$P_k = P_k^- - P_k^- H^T \left[H P_k^- H^T + R \right]^{-1} H P_k^- \tag{8}$$

(4) *Compute Kalman gain:* $$K_k = P_k H^T R^{-1} \tag{9}$$

(5) *Estimate system estimation:* $$\hat{x}_k = \hat{x}_k^- + K_k(y_k - h_{k|k-1}, k) \tag{10}$$

Here, matrices **Q** and **R** are the covariance matrices of system and measurement noise matrices w_k and v_k, respectively [8]. These values change every step of this algorithm. However, these matrices are considered as constant in this study, which are very effective in the optimality of the system.

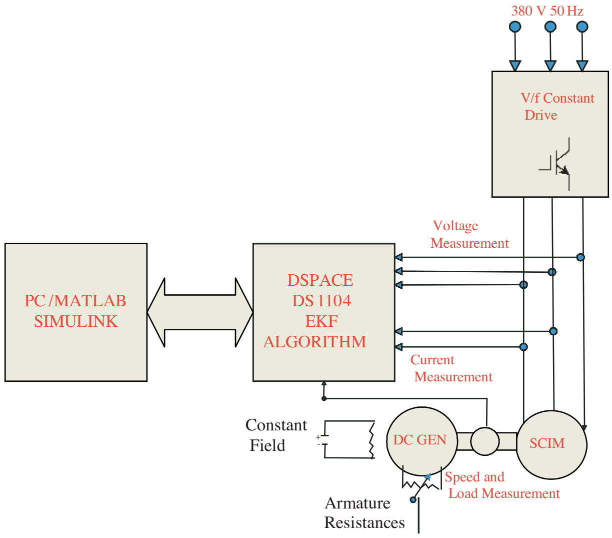

Figure 2. Diagram showing the experimental test bed on which to drive the algorithm.

4. Simulation results

4.1. Estimation with the seventh order EKF based observer

First, seventh order EKF algorithm [7] is generated in Matlab/Simulink with 100 μs sampling time. Stator and rotor resistances R_s and R_r are changed in the motor model at different points in the simulation, and the EKF algorithm is expected to follow variations. Motor parameters used in the simulations and values used in the experiments are shown in Table 1.

Table 1. SCIM parameters used in the experiments.

$R_s(\Omega)$	$R_r(\Omega)$	L_m(H)	L_r(H)	L_s(H)	n(rpm)
2,283	2,133	0.22	0.23	0.23	1430
V(volt)	J(kg. m^2)	p	P(kW)	B (Nm/rad/s)	
380	0.05	2	3	0.001	

Table 2. DC generator parameters used in the experiments.

$R_a(\Omega)$	L_a(mH)	I_a(A)	V(volt)	$T_L(N_m)$	n(rpm)
1	10	17	110	24	1500
J(kg. m^2)	P(kW)		B (Nm/rad/s)		
0.0825	3		0.002		

5 Nm constant torque is applied to the motor. The motor is directly started by applying 50 Hz, 380 V utility voltage. Simulation results are shown in Figure 3.

During the time of simulations, resistance values of SCIM model are changed from their nominal values at certain times. Models EKF_R and EKF_S successfully followed the increased value of parameters as well as speed and torque. 5 Nm constant torque is applied in both simulations. Torque value converged to more than 5 Nm due to viscous friction constant B in the SCIM model. It means that algorithm also successfully estimates the viscous friction constant. Details for the estimation of friction constant can be seen in [8]. As a result, same results from the previous studies are obtained in the algorithms EKF_R and EKF_S.

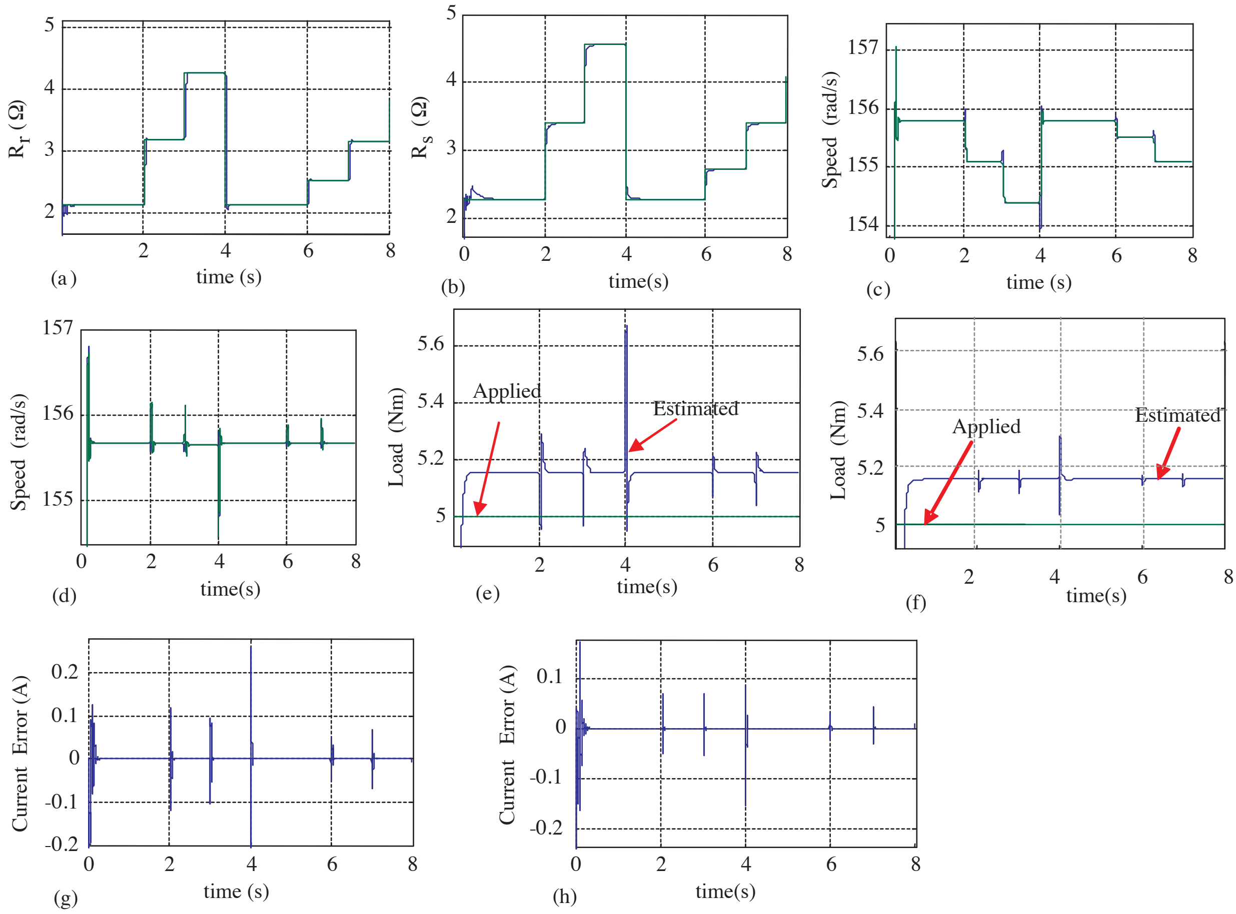

Figure 3. Simulation Results for 7^{th} order EKF. (a) $\underline{R}_r$ variation with EKF_R. (b) R_s variation with EKF_S. (c) Speed variation with EKF_R. (d) Speed variation with EKF_S. (e) Load Variation with EKF_R. (f) Load Variation with EKF_S. (g) Current Error with EKF_R. (h) Current Error with EKF_S.

4.2. Estimation with the eighth order EKF based observer

Simultaneous estimation of rotor and stator resistances have been estimated using the extended eighth order EKF algorithm. Toward this end, discretized equation (5) was used as a system model. In order to test the algorithm in the worst case, the value of R_r' is increased, and the same time the value of R_s is decreased. Simulation results are shown in Figure 4 and matlab/simulink diagram can be seen in Figure 7.

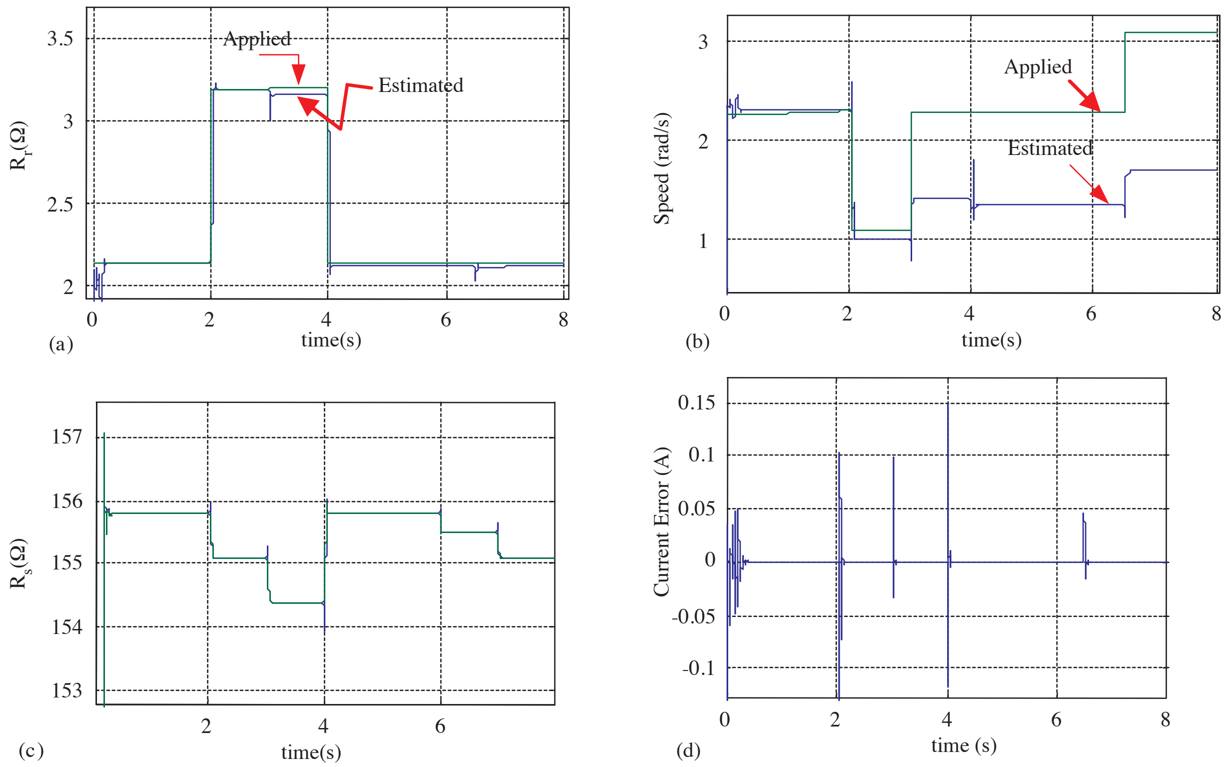

Figure 4. Simulation Results with 8^{th} Order EKF. Graphs show variation in time of (a) R_r, (b) R_s, (c) Speed, and (d) current error.

It is obvious from the simulation results that 8^{th} order EKF results are not as successful as 7^{th} order EKF results. If one of the resistance values, only, change during the simulation, impressive results are obtained. But, if the resistance values are simultaneously changed to check the power of algorithm, one of the parameters converges to wrong value, as obviously seen in Figures 4(a) and 4(b).

5. Experimental results

Experimental test-bed representation is given in Figure 2. EKF algorithms and all analog signals are handled on a Power PC-based DS1104 controller board. A torque sensor with 0–50 Nm measuring range and an incremental encoder with 1024 pieces per revolution are used in order to verify the estimated load torque and speed values. Voltage and current data are sent to the DSP by the help of LEM current sensors. EKF algorithms are loaded and examined in the system with the help of Control Desk software by dSPACE, and Matlab /Simulink. All simulations and experiments are sampled in 100 μs increments.

In the experiments, SCIM is operated with the open loop V/f constant frequency converter. Speed reversals can be realized in the desired time by the help of acceleration times defined in the drive. A DC generator, of which detailed parameters are given in Table 2, is used in order to load the motor by turning on and off the resistances connected to the armature circuit.

First, the 7^{th} order EKF algorithm is implemented estimating R_r' only as rotor resistance. Variations in the rotor resistance are examined with speed reversals. Additionally, the SCIM is loaded by the help of DC generator and variations in the rotor resistances and load torques are examined. Variation in the rotor resistance covers the previous studies as can be seen in Figures 5(a) and 5(b). Satisfactory results are also obtained in the estimation of load torque which can also be seen in the Figures 5(c)–(e). The results of the 7^{th} order EKF overlap with the previous study in [8].

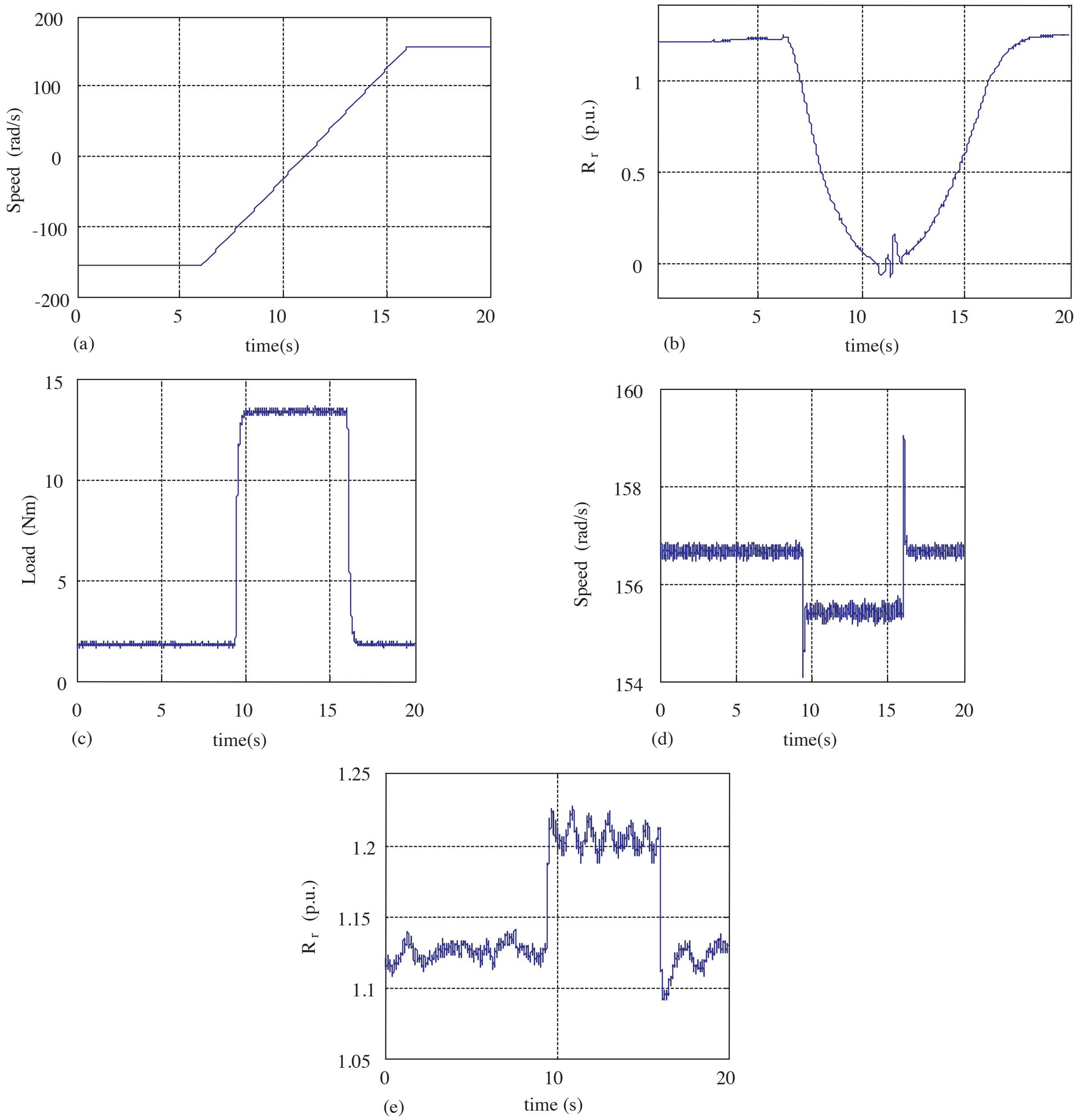

Figure 5. Experimental Results of EKF_R: (a) Speed reversal; (b) Variation of R_r under speed reversal; (c) Loading at full speed; (d) Variation of speed with load; (e) Variation of R_r under loading. All as a function of time.

Next, the 8^{th}-order EKF is implemented on the SCIM system for the simultaneous estimation of the rotor and stator resistances. As can be seen from the results in Figure 6, the 8^{th}-order EKF algorithm successfully estimates rotor resistance just as the 7^{th}-order EKF, but fails to correctly estimate the stator resistance.

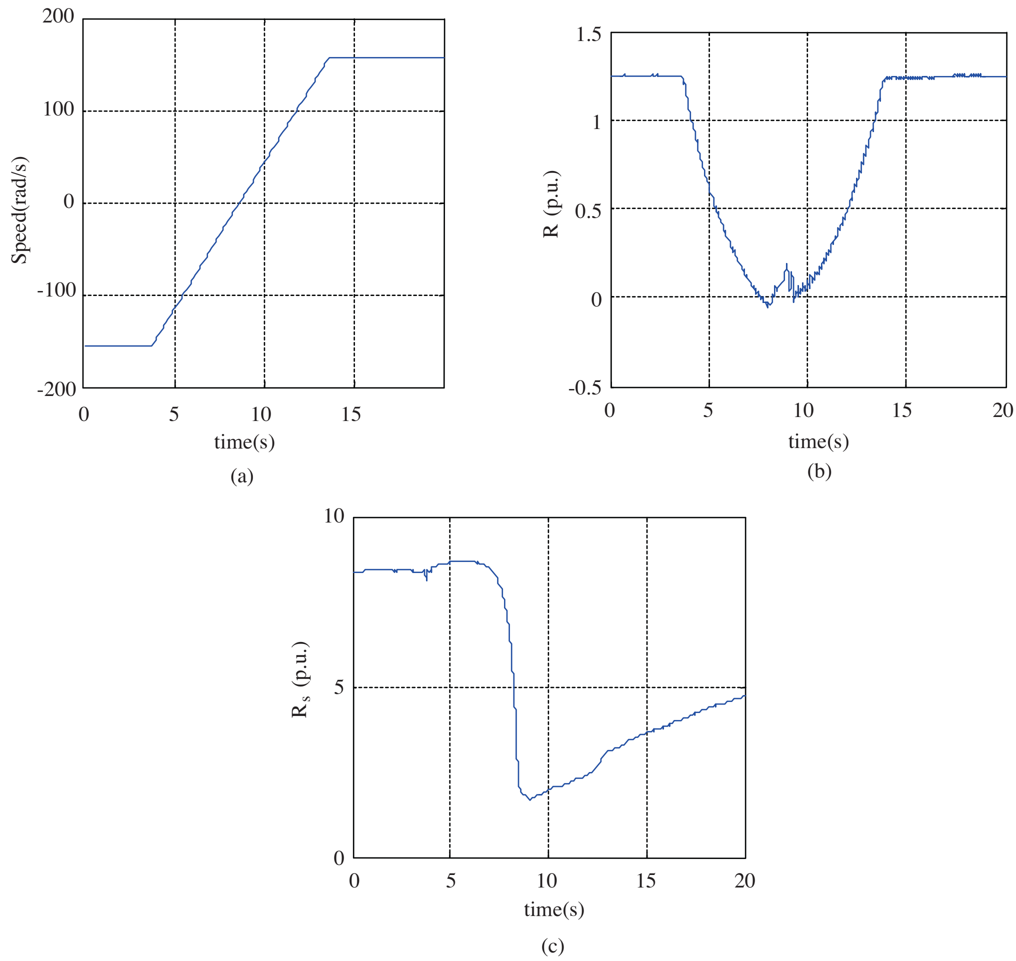

Figure 6. Experimental Results with 8^{th} order EKF: (a) Speed reversal; (b): Variation of R_r with speed reversal; (c) Variation of R_s with speed reversal. All as a function of time.

6. Conclusions

Our study's estimation results for simultaneous rotor and stator resistance with 8^{th}- order EKF simulations are of acceptable performance. However, if the algorithm is constrained by simultaneously changing R_s and R_r, this will cause them to converge different values very similar to their original values. Nonetheless, speed and load estimations were of high accuracy in the simulations. The proper determination of Q and R matrices, which directly affects the optimality, is of a great importance for the duplication of this performance in experimentation. Therefore, new methods which compute Q matrices at every step of the algorithm are needed to reduce error. Hence, currently, the braided EKF algorithm appears to be a better solution for the simultaneous estimation of rotor and stator resistances, which is crucial for wide range operation of SCIM sensorless control, especially at persistent operation around zero speed.

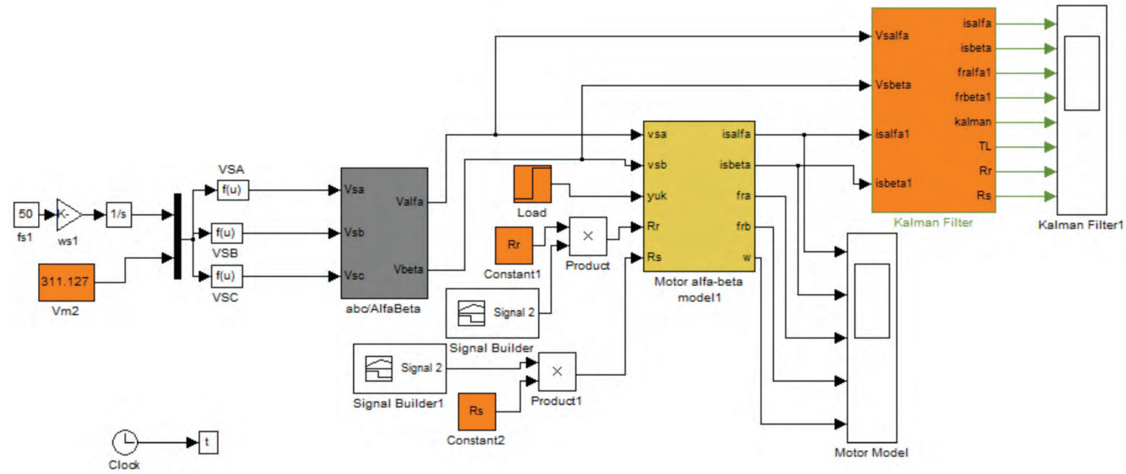

Figure 7. Simulink Diagram of Eighth Order EKF.

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