Rapid parameter identification and control of an induction machine

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Abstract

Purpose – Traction applications, e.g. the IMs are mainly operated by field-oriented control (FOC). This control technique requires an accurate knowledge of the machine's parameters, such as the main inductance, the leakage inductances and the stator and rotor resistance. The accuracy of the parameters influences the precision of the calculated rotor flux and the rotor flux angle and the decoupling of the machine's equations into the direct and quadrature coordinate system (dq-components). Furthermore, the parameters are used to configure the controllers of the FOC system and therefore influence the dynamic behavior and stability of the control.

Design/methodology/approach – In this paper, three different methods to calculate the machine's parameters, in an automated and rapid procedure with minimal measuring expenditure, are analyzed and compared. Moreover, a method to configure a control that reduces the overall Ohmic losses of the machine in every torque speed operation point is presented. The machine control is configured only with the identified machine parameter.

Findings – Simulations and test bench measurements show that the evolutionary strategy is able to identify the electrical parameters of the machine in less time and with low error. Moreover, the controller is able to control the torque of the machine with a deviation of less than 2 per cent.

Originality/value – The most significant contribution of the research is the potential to identify the machine parameter of an induction motor and to configure an accurate control with these parameters.

Keywords Particle swarm optimization, Induction machine, Parameter estimation, Equivalent circuits, Evolution strategies, Field-oriented control

Paper type Research paper

1. Introduction

The need for validation measurements of electrical machines on a machine test bench rises. For the control of an IM, it is necessary to know the parameters, such as the main inductance L_M, the leakage inductances of the stator and rotor $L_{1,\sigma}$ and $L'_{2,\sigma}$ and the rotor and stator resistance R_1 and R'_2 of the electrical machine to configure the controllers correctly (Zhang *et al.*, 2014). Therefore, a rapid characterization and control of electrical machines is necessary.

An approach for such a rapid characterization and control of an IM for traction applications is described and assessed in this paper. This approach is separated into two parts: first, the identification of the machine's parameters and the control of the machine using the identified parameters is discussed, and second, the structure of the introduced rapid characterization and control approach for an IM is described (Nell *et al.*, 2017).

The identification procedure uses the measured stator current, stator voltage and speed information during a low-voltage and no-load start-up with a constant stator voltage and constant synchronous frequency to calculate the parameters of the fundamental equivalent circuit diagram of the machine. The machine's stator voltage, stator current, speed and

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torque are measured with a dSPACE controller board ds1103 (Figure 1) and the Yokogawa power analyzer WT1800. Using MATLAB, the k measured values are used to numerically calculate the equivalent circuit diagram parameters. For this purpose, three methods are introduced, discussed and analyzed: first, a particle swarm optimization (PSO) method (Huynh and Dunnigan, 2010; Karimi *et al.*, 2007; Kennedy and Eberhart, 1995); second, an R-X method (Lin *et al.*, 2012), which relies on the measured overall machine reactance and resistance; and third, an evolutionary strategy (Rechenberg, 1984; Schwefel, 1995).

2. Particle swarm optimization

The particle swarm optimization is a computational method analogous to biological swarm behavior (Kennedy and Eberhart, 1995). A swarm of, in this case, m different parameter sets $\hat{\Theta}m$ is moved through a search area to get the best solution. The direction of movement relies on the quality of the individual set and the overall best set. The quality is determined by the mean square error of the measured and recalculated stator currents $i_{1,\,dq}$ and $\hat{\mathbf{i}}_{1,\,dq}$ in dq-components [equation (1)]. The fitness is calculated with N measurement points. In this paper, in contrast to Sakthivel and Subramanian (2012), the PSO is used without any knowledge of the machine's manufacturer data.

For the calculation of the currents, the measured stator voltages and the individual parameter set are considered. The PSO has multiple parameters to be set and different methods to proceed (Huynh and Dunnigan, 2010; Karimi *et al.*, 2007; Lin and Xu, 2015; Sakthivel and Subramanian, 2012). In Karimi *et al.*'s study (2007), a standard and in Huynh and Dunnigan's study (2010), an advance or dynamic PSO were introduced:

$$\mathbf{FIT}(\hat{\Theta}m) = \frac{1}{N}\sum_{i=1}^{N}\left(\|i^{m}_{1,q,i} - \hat{\mathbf{I}}^{m}_{1,q,i}\|^2 - \|i^{m}_{1,d,i} - \hat{\mathbf{I}}^{m}_{1,d,i}\|^2\right) \tag{1}$$

Simulations, done in this paper, show that the dynamic method can find the correct electrical parameters of the IM under certain conditions. First, the parameters of the PSO must be set correctly, which is extremely difficult without any knowledge about the machine parameter range. Second, satisfactory results are only reached with good initial electrical parameters of the IM. Without a good approximation of these initial values, the method can get stuck in a local minimum.

The results of the simulations are shown in Figure 2, where $\Delta\hat{R}_2^+$ is the deviation of the rotor resistance in the rotor flux oriented equivalent circuit diagram, $\Delta\hat{L}^+_{1,\sigma}$ the

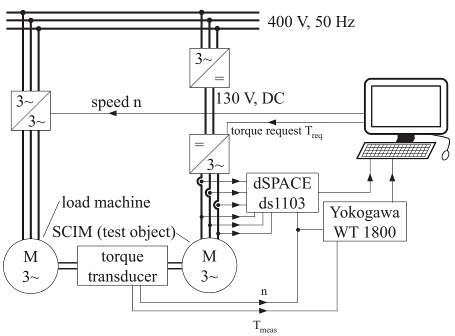


Figure 1.
Test bench setup for the automated parameter identification and control

deviation of the stator leakage inductance and $\Delta\hat{L}_M^+$ the deviation of the main inductance. To validate the method, the deviations of the estimated parameters relative to the given ones are calculated for the rotor flux oriented circuit. The comparison in the rotor or stator flux-oriented circuit is necessary because the identified parameters belong to an equivalent circuit with an arbitrarily transformation factor, which all describe the same physical effect. In the rotor flux-oriented circuit, one parameter is set to zero and the transformation factor is fixed. The simulations are done with a sampling time $t_s = 1\,\mu s$ and a white noise amplitude for the stator voltage, stator current and rotor speed of $N_w = \pm 3$ V/A/rpm. The noise amplitudes are added to the simulated stator voltage, stator current and speed. With accurate initial values, in a range of less than 10 per cent of the supposed machine parameters, the method is able to find the parameters with an error of less than 1 per cent (#PSO1). If the method gets stuck in a local minimum, the error is obviously higher. In simulation #PSO2, the error for the estimated main inductance is up to 14.38 per cent. Simulation #PSO3 in Figure 2 shows the influence of bad initial machine parameters. If the initial machine parameters are not close to the real ones, the PSO method is no longer able to find the right parameters. With initial parameters that are in the range of 0 to 300 per cent of the supposed parameters, the error rises up to over 50 per cent (#PSO3).

Overall, this method turns out to be unpractical for an automated and rapid parameter identification of an IM due to the need of appropriate initial values of the machine parameters and there is a possibility to stick in a local minimum.

3. R-X method

The R-X method is based on the calculated overall machine resistance R and reactance X. With equations (2) and (3) and a minimization technique, the T-equivalent circuit diagram parameters R_1, X_M, R'_2, $X_{1\sigma}$ and $X'_{2\sigma}$, where R_1 is the stator resistance, X_M is the main reactance, R'_2 the rotor resistance, $X_{1\sigma}$ the stator leakage reactance and $X'_{2\sigma}$ the rotor leakage inductance, can be calculated from the measured slip dependent resistance R (s(k)) and reactance $X(s(k))$, where $s(k)$ stands for the slip in the k-th sample point (Lin *et al.*, 2012). The measurement of R (s(k)) and X (s(k)) is similar to the that of the IEEE standard measurements (IEEE Std 112-2004, 1996):

$$R = R_1 + \frac{X_M^2 \frac{R'_2}{s}}{\left(\frac{R'_2}{s}\right)^2 + \left(X_M + X'_{2,\sigma}\right)^2} \tag{2}$$

	$\#PSO_1$	$\#PSO_2$	$\#PSO_3$
$\Delta\hat{R}_2^+$ in %	–0.89	4.29	13.37
$\Delta\hat{L}_{1,\sigma}^+$ in %	–0.10	1.10	61.56
$\Delta\hat{L}_M^+$ in %	0.28	–14.38	–4.27

$\#PSO_1$: $t_s = 1\,\mu s$, $N_W = \pm 3$ V/A/rpm, Run 1, $\Theta_{init} \in (0.9 * \Theta, 1.1 * \Theta)$
$\#PSO_2$: $t_s = 1\,\mu s$, $N_W = \pm 3$ V/A/rpm, Run 2, $\Theta_{init} \in (0.9 * \Theta, 1.1 * \Theta)$
$\#PSO_3$: $t_s = 1\,\mu s$, $N_W = \pm 3$ V/A/rpm, Run 1, $\Theta_{init} \in (0.0 * \Theta, 3.0 * \Theta)$

Figure 2.
Deviation of given and identified machine parameters in the rotor flux-oriented equivalent circuit diagram under different noise and sampling times (PSO)

$$X \approx X'_{2,\sigma} + X_M - \frac{s^2 X_M^2 \left(X_M + X'_{2,\sigma}\right)}{R'^2_2 + s^2 \left(X_M + X'_{2,\sigma}\right)^2} \tag{3}$$

The used minimization techniques considered are a gradient method and an evolutionary strategy. For the gradient method, an objective function J_R (4) is determined from the measured resistance $R(s(k))$ and the unknown machine parameters of the T-equivalent circuit X_M, R'_2, $X_{1\sigma}$ and $X'_{2\sigma}$:

$$J_R = \sum_{k=0}^{N-1} \left[Q(s(k))\left(1 + (s(k))^2 K_1\right) - s(k)K_2\right]^2 \tag{4}$$

$$\text{with} \quad Q(s(k)) = R(s(k)) - R_1; \quad K_1 = \frac{\left(X_M + X'_{2,\sigma}\right)^2}{R'^2_2}; \quad K_2 = \frac{X_M^2}{R'_2}$$

Here, $Q(s(k))$ is the slip-dependend resistance substracted by the stator resistance, K_1 and K_2 are the auxiliary variables and N is the number of measurement points. The gradient method applied to this objective function leads to [equation (5)] for the parameters K_1 and K_2, which implied an inversion of the matrix A:

$$\begin{bmatrix} K_1 \\ K_2 \end{bmatrix} = \begin{bmatrix} \sum_{k=0}^{N-1} (s(k))^4 (Q(s(k)))^2 & -\sum_{k=0}^{N-1} (s(k))^3 Q(s(k)) \\ -\sum_{k=0}^{N-1} (s(k))^3 Q(s(k)) & \sum_{k=0}^{N-1} (s(k))^2 \end{bmatrix}^{-1} \times \begin{bmatrix} \sum_{k=0}^{N-1} (s(k))^2 (Q(s(k)))^2 \\ \sum_{k=0}^{N-1} s(k) \quad Q(s(k)) \end{bmatrix} = A^{-1} \times B \tag{5}$$

The matrix A of equation (5) can be ill-conditioned, which leads to high errors in the parameter identification process. Especially for a high number of measurement point, the matrix A can be ill-conditioned. Again, the rotor flux-oriented machine parameters are taken into account for the validation of the method. The simulation result $\#RX_4$ in Figure 3 shows errors up to 600 per cent. Even with less values and therefore a better-conditioned matrix, the error is high, due to few measurement values ($\#RX_5$). The minimization of the objective function J_R with the evolutionary strategy produces satisfactory results under some conditions. First, the synchronous frequency must be constant. Second, because the method is not highly robust to noise, the measured values must have a low noise or be filtered. With moving average filtered measurement values, with a window length of 15 μs, a little noise amplitude of $N_w = \pm 3$ V/A/rpm and a low sampling time of $t_s = 1\mu s$, the error of the estimated parameters is less than 10 per cent, as shown in the simulation $\#RX_1$. Without a moving average filter or with a larger sampling time, the accuracy of the estimated parameters decreases clearly (#RX_2, #RX_3). Therefore, the R-X method can only be used under the mentioned.

4. Evolutionary strategy

The evolutionary strategy is a metaheuristic optimization algorithm based on the theory of evolution and related mechanisms, such as mutation, selection and inheritance. The use of the theory of evolution to solve technical problems was described by Rechenberg and Schwefel (Rechenberg, 1984; Schwefel, 1995) in the 1980s. In this method, the mean squared error J(1) is used as a quality characteristic or fitness function. In a (μ, λ) strategy, where μ stands for the number of parents and λ for the number of progenies, the λ descendant parameter sets are compared due to their fitness (1). The best μ of these sets will be selected, will survive the current generation and will pass into the next generation. The new parent parameter sets will undergo stochastic mutation and reproduction processes to generate new progenies (Rechenberg, 1984; Schwefel, 1995). This procedure is convergent and will soon reach the minimal fitness J, as shown in Figure 4. The procedure is shown in Figure 5.

The simulations of the evolutionary strategy are done with different sampling times t_s and different white noise amplitudes N_w. As for the first two methods, the validation is done by analyzing the deviation of the estimated parameters relative to the given ones, both for the rotor flux-oriented circuit.

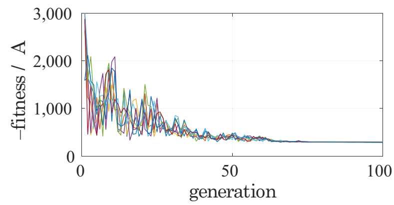
For sampling times of $t_s = 1\ \mu$s and $t_s = 6.25$ ms, the simulation results show a good accuracy of the estimated parameters, also for high noise amplitudes up to $N_w = \pm 10$ V/A/rpm. In Simulations #1, #2, #4, #5, #7 and #8, listed in Figure 6, the error is less than 2 per cent. A long sampling time of $t_s = 56$ ms leads to higher errors, which is shown in the results of Simulation #3, #6 and #9. With higher noise, the error increases. Compared to the errors of the PSO and the R-X method, which occur at short sampling times and low noise amplitudes, the error is with less than 12 per cent still in a good range. Moreover, the simulations show that the process of the evolutionary (μ, λ) strategy does not stick in local

Figure 3.
Deviation of given and identified machine parameters in the rotor flux-oriented equivalent circuit diagram under different noise and sampling times (RX-Method)

	#RX_1	#RX_2	#RX_3	#RX_4	#RX_5
$\Delta\hat{R}_2^+$ in %	–4.48	16.00	–13.53	605	779
$\Delta\hat{L}_{1,\sigma}^+$ in %	–8.26	–411	–99	–500	–273
$\Delta\hat{L}_M^+$ in %	–0.55	30	4.05	–60	404

#RX_1 t_s =	1 μs,	$N_w = \pm 3$ V/A/rpm,	evolutionary strategy,	Moving average
#RX_2 t_s =	1 μs,	$N_w = \pm 3$ V/A/rpm,	evolutionary strategy,	no Moving average
#RX_3 t_s =	1 μs,	$N_w = \pm 3$ V/A/rpm,	evolutionary strategy,	Moving average
#RX_4 t_s =	6.25 μs,	$N_w = \pm 3$ V/A/rpm,	gradient method,	Moving average
#RX_5 t_s =	1 μs,	$N_w = \pm 3$ V/A/rpm,	gradient method,	Moving average

Figure 4.
Mean squared error (fitness) of an evolutionary strategy for the parameter identification (simulation)



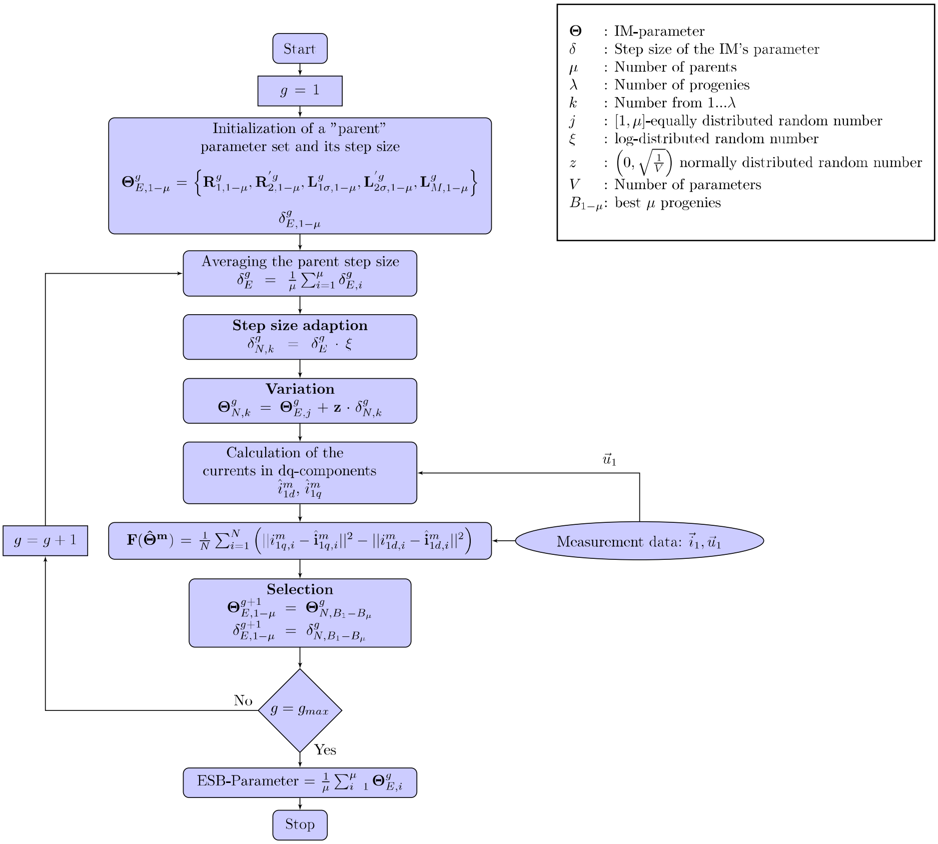


Figure 5.
Evolutionary strategy

Figure 6.
Deviation of given and identified machine parameters in the rotor flux-oriented equivalent circuit diagram under different noise and sampling times (evolutionary strategy)

	#1	#2	#3	#4	#5	#6	#7	#8	#9
$\Delta\hat{R}_2^+$ in %	–0.24	0.02	3.13	0.13	0.47	3.59	1.23	1.78	4.83
$\Delta\hat{L}_{1,\sigma}^+$ in %	0.5	0.18	–0.44	0.72	0.27	–0.71	1.39	0.66	–1.07
$\Delta\hat{L}_M^+$ in %	–0.28	–0.16	–12.5	–0.03	0.12	–11.86	0.71	0.91	–10.34

#1: t_s = 1 µs, $N_w = \pm$ 3 V/A/rpm; #2: t_s = 6.25 ms, $N_w = \pm$ 3 V/A/rpm
#3: t_s = 56 ms, $N_w = \pm$ 3 V/A/rpm; #4: t_s = 1 µs, $N_w = \pm$ 6 V/A/rpm
#5: t_s = 6.25 ms, $N_w = \pm$ 6 V/A/rpm; #6: t_s = 56 ms, $N_w = \pm$ 10 V/A/rpm
#7: t_s = 1 µs, $N_w = \pm$ 10 V/A/rpm; #8: t_s = 6.25 ms, $N_w = \pm$ 10 V/A/rpm
#9: t_s = 56 ms, $N_w = \pm$ 10 V/A/rpm

minima. In addition, the simulated and with the estimated parameters calculated current also agree closely (Nell *et al.*, 2017).

The evolutionary strategy turned out to be a practical, fast and accurate method to identify the parameters of an IM. It is very accurate if the noise amplitude is low and the sampling time is not to large. It shows fast convergence, even for high disturbance and few measurement values.

5. Parameter identification on the test bench

The evolutionary strategy was used to estimate the parameters of an unknown 40 kW IM on the machine test bench. The only necessary and known information about the machine are the number of pole pairs and the nominal machine voltage U_N and stator frequency f_N. The nominal machine voltage and stator frequency are necessary to operate the machine at non-saturation conditions and to identify the parameters without saturation effects. The stator current, stator voltage and speed measurement were done with the dSPACE controller board ds1103 and a sampling time of t_s = 1 ms. The stator resistance was measured offline and is considered as a constant. In contrast to Orlowska-Kowalska and Lis (2009), the identification process was done during a no-load and low-voltage start-up, so that no further adjustments to operate at standstill are necessary and a constant voltage and frequency can be used to operate the IM for the identification procedure. The results of the parameter estimation for the stator resistance R_1, the rotor resistance R^2, the stator leakage inductance $L^+_{1,\sigma}$ and the main reactance L^+_M in the rotor flux-oriented equivalent circuit diagram are shown in Figure 7. The parameters are in a tolerance band of (−2.5 per cent; 4.5 per cent). The test validates the evolutionary strategy to be a good method for the parameter identification.

6. Controller design

The control of the IM used here is a modified torque control illustrated in Figure 8. It consists of a flux controller, a d- and q-current controller, which output parameters are named with the index R, a decoupling network, which output parameters are named with the index E, and a flux model. The deviation of the actual parameter value and its reference value is described by the letter e. Instead of a torque controller, a calculation of the reference torque T_{ref} is used. The reference values of the torque and rotor flux are given by a control strategy. This control strategy is based on the equivalent circuit of the machine using the estimated parameters. In an I_1-f_2-Plane, every operation point of the machine can be calculated (Von Pfingsten *et al.*, 2017). The rotor flux $\Psi_2^{'}$ and the Ohmic losses of the machine can also be calculated with the equivalent circuit diagram

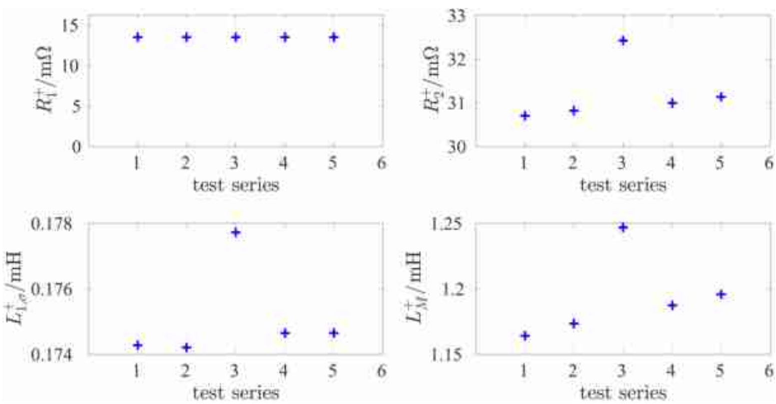


Figure 7.
Test results of the parameter identification performed on the 40-kW IM on the test bench

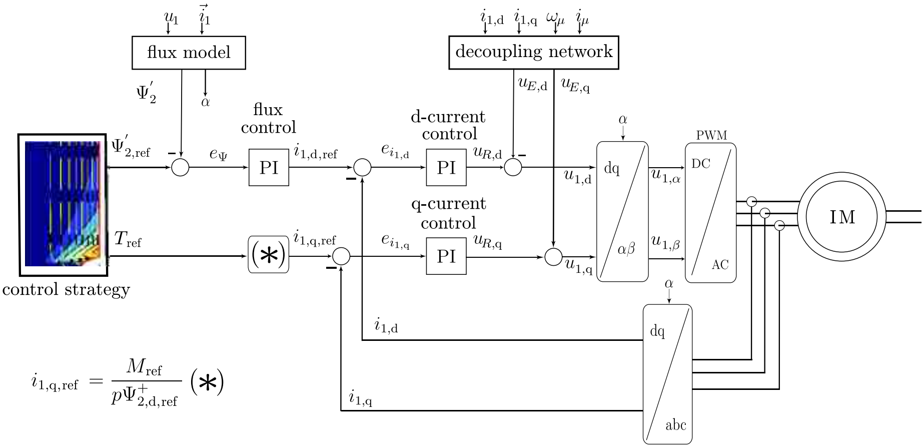


Figure 8.
Used control circuit of the IM

and can be illustrated in the I_1-f_2-Plane (Von Pfingsten *et al.*, 2017). The control strategy calculates the reference rotor flux $\Psi'_{2,\mathrm{ref}}$ for a given reference torque T_{ref} for the minimal Ohmic losses. Besides the control strategy, the estimated parameters are used to configure the flux model and the decoupling network. In this paper, a U_1/I_1-model is used, due to its property of using only the rotor flux-oriented machine parameters and its insensitivity of the rotor temperature change (Zhang *et al.*, 2014). With the identified machine parameters, the machine can be controlled in the unsaturated regions. To operate the machine in saturation, the saturation dependency of the inductance L_1 has to be considered. L_1 is identified previously and deposited in a look-up table. The configuration of the flux and current controller is based on the stator voltage equation of the IM [equation (6)], where $i_{1,\,d}$ and $i_{1,\,q}$ are the stator currents in dq-components, $u_{1,\,d}$ and $u_{1,\,q}$ are the stator voltages in dq-components, σ is the total leakage factor, τ_1 and τ_2 are the stator and rotor time constant, respectively, $\Psi'_{2,d}$ is the d-component of the rotor flux, L_1 is the stator inductance, L_2 is the rotor inductance, ω_2 is the slip frequency and ω_μ is the rotor flux frequency:

$$\underbrace{\frac{di_{1,d}}{dt} + \left(\frac{1}{\sigma\tau_1} + \frac{1-\sigma}{\sigma\tau_2}\right)\cdot i_{1,d}}_{} = \frac{1}{\sigma L_1}\cdot u_{1,d} + \frac{1-\sigma}{\sigma L_M \tau_2}\cdot \Psi'_{2,d} + \omega_\mu \cdot i_{1,q}$$
$$\overbrace{\frac{di_{1,q}}{dt} + \left(\frac{1}{\sigma\tau_1} + \frac{1-\sigma}{\sigma\tau_2}\right)\cdot i_{1,q}}^{PT_1-characteristic} = \frac{1}{\sigma L_1}\cdot u_{1,q} + \omega_2\frac{1-\sigma}{\sigma L_M}\cdot \Psi'_{2,d} - \omega_\mu \cdot i_{1,d} \quad (6)$$

From the stator voltage equations, the transfer functions for the stator current $G_{\mathrm{S},i_1}(s)$ and rotor flux $G_{\mathrm{S},\,\Psi^{+}_{2,d}}(s)$ are derived in equations (7) and (9). With these transfer functions, the amplitude optimum, the symmetrical optimum and the estimated machine parameters, the transfer functions of the PI current and flux controller can be calculated. For the inner current control loop, the optimum amount is taken into account. Therefore, the current controller transfer function $G_{\mathrm{R},i_1}(s)$ can be expressed by equation (8). For the outer flux control loop, the symmetrical optimum is taken into account, which leads to the flux controller transfer function $G_{\mathrm{R},\,\Psi^{+}_{2,d}}(s)$ in (10):

$$G_{S,i_1}(s) = \frac{V_{S,i_1}}{1 + s\tau_{S,i_1}} \tag{7}$$

$$G_{R,i_1}(s) = V_{R,i_1} \cdot \frac{1}{s} \tag{8}$$

$$G_{S,\Psi_{2,d}^+}(s) = \frac{L_M^+}{1 + \tau_2 s} \cdot \frac{1}{1 + \tau_{sub} s} \tag{9}$$

$$G_{R,\Psi_{2,d}^+}(s) = V_{R,\Psi_{2,d}^+} \cdot \frac{1 + s\tau_{n,\Psi_{2,d}^+}}{s\tau_{n,\Psi_{2,d}^+}} \tag{10}$$

$$\text{with} \quad V_{R,\Psi_{2,d}^+} = \frac{\tau_2}{2\tau_{sub} L_M^+}; \quad \tau_{n,\Psi_{2,d}^+} = 4 \cdot \tau_{sub}; \quad \tau_{sub} = 2\tau_{s,i_1}$$

$$V_{s,i_1} = \frac{\tau_{s,i_1}}{\sigma L_1}; \quad V_{R,i_1} = \frac{1}{2\tau_{s,i_1}} V_{s,i_1}; \quad \tau_{s,i_1} = \left(\frac{1}{\sigma\tau_1} + \frac{1-\sigma}{\sigma\tau_2}\right)^{-1}$$

$$\tau_1 = \frac{L_M^*}{R_1^*}; \quad \tau_2 = \frac{L_M^+}{R_2^+}; \quad \text{and } \sigma = \frac{L_{1,\sigma}^+}{L_M^*}$$

All controllers are configured by equation (7)-(10) and the estimated parameters of the rotor flux ($L_{1,\sigma}^+ = \sigma L_1$, L_M^+, R_2^+) and stator flux ($L_{2,\sigma}^*$, $L_M^* = L_1$, R_2^*) oriented equivalent circuit model of the IM.

7. Results of the control

The introduced control of the IM was tested on the test bench with an IM with the number of pole pairs $p = 3$ and unknown machine parameters. The parameters of the machine were identified as described in Section 5. The mean values of the measurement series of each parameter were used to configure the flux model, the decoupling network and the controllers, as described in Section 6. Furthermore, the saturation curve of the inductance L_1 was identified and deposited as a look-up table to consider the saturation. The controller

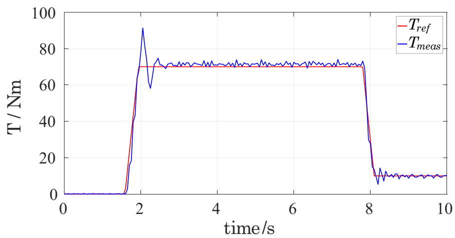


Figure 9.
Step response of the controlled induction machine for a torque step of 70 Nm at 2,500rpm (measurement)

was implemented on a dSPACE controller board ds1103 and the machine driven by an IGBT-inverter of the Semikron Company.

The result of the control is shown in Figure 9. The reference torque T_{ref} is a step from 0 to 70 Nm back to 10 Nm with a fixed rotor speed of 2,500 rpm. The step response T_{meas} shows an overshoot of around 40 per cent and a fast-transient oscillation for the first torque step. The step back to 10 Nm has a lower overshoot. The deviation of the reference and measured and controlled torque is less than 2 per cent.

8. Conclusions

Three rapid approaches to identify the equivalent circuit diagram parameters of an IM are presented in this paper. Their benefits and drawbacks are outlined. The PSO and the RX method turned out to be not accurate enough to identify the machine parameters. The evolutionary strategy proved as a fast and accurate method to do so and was tested on the test bench. Simulations and the test bench measurements show that this method is able to identify the electrical parameters of the rotor flux-oriented equivalent circuit in less time and with low error. With the identified machine parameters, a control strategy for a 40-kW IM, which minimizes the overall Ohmic losses, was implemented and evaluated on the test bench.

The result shows, that the controller, which is configured just with the estimated machine parameters, is able to control the torque of the machine with a deviation of less than 2 per cent. The torque is reached in a short time but with an overshoot of 40 per cent. Further work can focus on damping that overshoot. Moreover, the machine parameter identification process, the configuration of the controller and the control of the machine can be combined in an automatic process.

In this paper, a rapid characterization and Ohmic loss minimal control of an IM was studied in theory and validated by test bench measurements. Because of its rapidity, good results and the fact, that just the stator currents and voltages and the speed of the induction machine are used to identify the machines parameter, which, in turn, are used to configure the control, this approach is a practical application for the identification and control of induction machines.

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