Online-parameter-estimation of a PMSM in an EV-powertrain: including thermal measurements

Arnout Zwartbol and Jianning Dong

***Abstract*—This paper proposes an online motor-parameter-estimator for a PMSM in an EV-powertrain. The proposed method differs from the conventional approach by using thermal measurements to decouple the resistance estimation from the rest of the estimation. Conventional approaches use the voltage and current measurements to estimate all parameters at once. However the resistance estimation was often found to be unreliable and noisy due to the low-contribution in the voltage-equations. A recursive least-squares filter approach in combination with the discrete-time dynamic voltage-equations was adopted. In this way the estimator was valid in both transient and steady-state operation while providing a robust estimation over the entire operating range. The proposed estimator was validated both using simulations and experimentally. A sensitivity analysis showed the proposed estimation approach is more robust against rotor-position error leading to smaller errors in the estimation. In the experimental validation the proposed estimator showed reliable estimation over the entire operating-range of the PMSM whereas for the conventional method the unreliable resistance, caused estimation error on the other parameters. The proposed method can be adopted for online maximum-torque-per-ampere control and adaptive-torque-control in an EV-powertrain.**

***Index Terms*—Parameter estimation, RLS, Recursive least-squares, EV-powertrain, PMSM, Thermal estimation**

I. Introduction

THE application of electric motors in a powertrain present interesting challenges for motor control. This is especially the case for modern high performance motors which are continuing to get smaller and lighter and as a consequence often operate at their limits. This is especially an issue in the case of traction-motors where loads can change very quickly (i.e. for an overtake). This comes at the cost of non-linear parameter variations during operation [1]. The parameter variations are both of a thermal and electrical origin. The temperature in an electric motor can change relatively quickly due to the significant power-density's and low thermal-masses of modern motors. In an EV application the motor is torque-controlled using the torque-equation (15). Knowledge of the motor-parameters over the entire operating range is necessary to accurately control torque and operate the motor in the maximum torque per ampere(MTPA) point. The conventional approach is to store the motor-parameters in a look-up table for the current conditions. However these do not capture thermal-parameter variation and require in-depth knowledge of the motor. An alternative method is online-parameter-estimation of electrical machines using available current and voltage measurements. The 4 parameters of the PMSM are the stator-resistance R_s, d-inductance L_d, q-inductance L_q, flux-linkage Ψ_{PM}. Most research of motor-parameter estimation until now has focused on the identification of parameters in constant speed/load-scenarios i.e. a steady-state scenario, the estimation was therefore often implemented using the simplified steady-state voltage equations. [2]–[4]. Because the voltage-equations consist of 2 equations in steady-state at most 2 of the 4 parameters can be estimated, this is called rank-deficiency. However by introducing current perturbation, all 4 parameters can be estimated over time. The problem of the steady-state equations is that the equations are not valid during the transients and the estimator needs to wait for the transients to die out. Therefore most recent research uses the discrete-dynamic equations [5]–[7] to deal with the derivative terms and are valid during transients which allows estimation in all conditions. However there has been little investigation into the application of a parameter estimator to track the parameter variation over a wide-operating range as encountered for an EV application. The difficulty encountered in most previous research when trying to estimate all parameters, is that achieving correct R_s estimation using the voltage-equations was particularly difficult [6]–[8]. The estimation of R_s is difficult due to the small contribution in the voltage equation and strong coupling with Ψ_{PM} at low speeds [5]. As a result R_s was often fixed to the nominal value to reduce the noise and error on other parameters [6], [7]. However this does not allow to track the parameter variation of R_s. This is especially important in an EV-application where temperature conditions can widely vary. An error on the R_s can lead to significant parameter error in low-speed high-torque operation. Therefore thermal estimation of R_s is proposed to decouple it from the rest of the estimation. In this way the stability of the estimation is improved and can be applied over a wide-operating range. Thermal estimation of R_s was previously successfully applied by Balamurali et al [4] but in this case the steady-state equations were used and an experimental verification over a wide operating range was lacking. This paper starts by explaining the methodology behind the parameter estimation, the used discretized motor equations, perturbation strategy, RLS algorithm and parameter mappings. The parameter approaches were subsequently validated using simulations and additionally a sensitivity analysis was performed to simulate the case of rotor-position angle-error. Lastly the estimators were experimentally verified on a real motor.

A Zwartbol is with the Department of Mechanical Engineering, Delft University of Technology, Delft
J. Dong is with the Department of Electrical Engineering, Delft University of Technology

II. Methodology

A. PMSM motor-model

The estimator was implemented in the rotor-reference frame (dq-frame) with the discrete dynamic voltage-equations. In this way the estimator is valid in both steady-state and transient operation. This property is very important in the case of an online-estimator in an EV-powertrain which should be able to estimate the motor-parameters under all conditions. The motor equations in this frame are as follows:

$$\begin{bmatrix} u_d(k-1) \\ u_q(k-1) \end{bmatrix} = \begin{bmatrix} R_s & -\omega_e L_q \\ \omega_e L_d & R_s \end{bmatrix} \begin{bmatrix} i_d(k-1) \\ i_q(k-1) \end{bmatrix} + \begin{bmatrix} L_d & 0 \\ 0 & L_q \end{bmatrix} \frac{1}{T_s} (\begin{bmatrix} i_d(k) \\ i_q(k) \end{bmatrix} - \begin{bmatrix} i_d(k-1) \\ i_q(k-1) \end{bmatrix}) + \omega_e \Psi_{PM} \begin{bmatrix} 0 \\ 1 \end{bmatrix} \tag{1}$$

where u_d and u_q are the voltages, i_d and i_q the currents, R_s stator-resistance ,L_d d-axis inductance, L_q q-axis inductance, Ψ_{PM} flux-linkage, T_s sampling-time and ω_e electrical frequency.

The current derivatives are approximated using the forward-Euler method:

$$\frac{di_d}{dt} = \frac{i_d(k) - i_d(k-1)}{T_s} \tag{2}$$

B. Perturbation

To solve the problem of rank-deficiency and estimate all parameters. A persistent excitation was added to the i_d, i_q reference currents. The perturbation currents are added to the reference currents that satisfy the MTPA/MTPF condition. The implementation of the current-injection does not have a detrimental impact on drive comfort because it is torque-ripple free, a similar approach was used by Kubo et al. [6].

$$i_{dper} = A \sin(2\pi f) \tag{3}$$

$$i_d = i_{dset} + i_{dper} \tag{4}$$

$$i_q = (i_{qset} + i_{qper}) = \frac{(\Psi_{PM} + i_{dset}(L_d - L_q)) i_{qset}}{\Psi_{PM} + (i_{dset} + i_{dper})(L_d - L_q)} \tag{5}$$

C. RLS Algorithm

To perform the estimation the recursive linear-least squares method was implemented. The data-structure for the estimation is as follows:

$$y = F\theta + \epsilon \tag{6}$$

where y is the output matrix, F the linear regressor matrix, θ the estimated parameter matrix and ϵ the measurement noise which is assumed zero-mean white-noise. The best estimate is found by minimizing the square-error of measurement and estimation.

$$\min_{\theta} \quad \epsilon^T \epsilon = (y - F\theta)^T (y - F\theta) \tag{7}$$

The optimal RLS estimator implementation is given by Algorithm 1, which is the optimal estimator where the estimates are the unbiased and minimum-variance estimates for the given measurement conditions. The forgetting factor is implemented to give more weight to recent measurements, in this way the parameter variation can be tracked.

Algorithm 1 RLS algorithm with forgetting factor λ

for $k = 1$:end **do**
  read(y_k, F_k)
  $K_k = P_k F_k^T (F_k P_k F_k^T + I)^{-1}$
  $\hat{\theta}_{k+1} = \hat{\theta}_k + K_k (y_k - F_k \hat{\theta}_k)$
  $P_{k+1} = \lambda^{-1} (I - K_k F_k) P_k$
end for

1) Conventional: 4 parameter estimator (4PE) approach: To implement the RLS algorithm to the motor-parameter estimation problem, the following mapping of the motor-parameters to the voltage-output was used:

$$y = \begin{bmatrix} u_d(k) \\ u_q(k) \end{bmatrix} \tag{8}$$

$$F = \begin{bmatrix} i_d(k) & \frac{i_d(k+1) - i_d(k)}{T_s} & -\omega_e(k) \cdot i_q(k) & 0 \\ i_q(k) & \omega_e(k) \cdot i_d(k) & \frac{i_q(k+1) - i_q(k)}{T_s} & \omega_e(k) \end{bmatrix} \tag{9}$$

$$\theta = \begin{bmatrix} R_s \\ L_d \\ L_q \\ \Psi_{PM} \end{bmatrix} \tag{10}$$

2) Proposed: 3 parameter estimator approach (3PE): In the proposed approach the stator-resistance R_s is instead estimated using the thermal measurements of the stator-winding. In this way the estimation is decoupled from the rest of the estimation using the voltage and current measurements. The temperature is measured per phase by 3 Pt100 temperature sensors that are integrated in the slots. The temperature dependent value of $R_s(T)$ is calculated using formula (11).

$$R_s(T) = R_{s0} \cdot (1 + \alpha(T - T_{ref}) \tag{11}$$

where R_{s0} is the nominal resistance value, T_{ref} the nominal temperature and α the temperature coefficient of resistance. The voltage measurements used by the reduced RLS estimator are corrected by subtracting the estimated voltage-drop over the resistance. This has as a side-benefit a reduced computational effort.

$$y = \begin{bmatrix} u_d(k) - R_s i_d \\ u_q(k) - R_s i_q \end{bmatrix} \tag{12}$$

$$F = \begin{bmatrix} \frac{i_d(k+1) - i_d(k)}{T_s} & -\omega_e(k) \cdot i_q(k) & 0 \\ \omega_e(k) \cdot i_d(k) & \frac{i_q(k+1) - i_q(k)}{T_s} & \omega_e(k) \end{bmatrix} \tag{13}$$

$$\theta = \begin{bmatrix} L_d \\ L_q \\ \Psi_{PM} \end{bmatrix} \tag{14}$$

The torque-estimate is calculated based on the estimated motor-parameters and current feedback-measurements:

$$T_{est} = \frac{3}{2} p_p (i_q (\Psi_{PM} + (L_d - L_q) i_d)) \tag{15}$$

P_p is the number of pole-pairs of the machine.

III. Simulation

The motor-parameter estimation was simulated on a PMSM motor-model in the DQ-frame. Where the motor-parameters from the look-up table are used as reference to validate the estimators. Measurement noise was simulated by contaminating the measurement with white-noise.

The 4PE and 3PE were verified by simulating 2 typical operating modes: a torque-ramp in the MTPA-region and a constant torque with increasing speed entering into field-weakening operation where constant-power is maintained.

TABLE I
Scenario 1

Parameters	Values
λ	[0.99 0.99 0.99 0.99]
Perturbation	20A 50 Hz
Speed	120 RPM / 22 km/h
Torque	5kNm ramp for 2 sec(@0.5s)

1) Constant-speed: MTPA operation: The 3PE shown in figure 1 and the 4PE shown in figure 2 are both able to track the parameter variation. However the proposed 3PE shows much less noise on the Ψ_{PM} estimation compared to the conventional 4PE approach where noise is very severe at high torques and low-speeds. This is expected and is due to the strong coupling of R_s and Ψ_{PM} at these lower speeds.

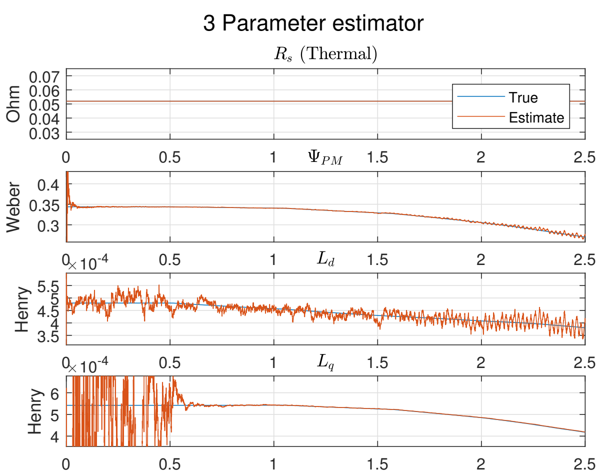

Fig. 1. 3PE MTPA constant-speed

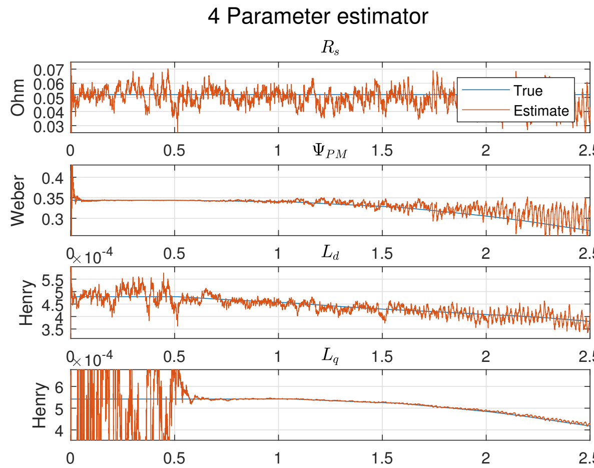

Fig. 2. 4PE MTPA constant-speed

2) Variable-speed: MTPA and Field Weakening: In a variable speed scenario it can be seen that the proposed 3PE shown in figure 3 shows good performance over a wide speed-range. Whereas the 4PE shown in figure 4 has noisy estimation of Ψ_{PM} at low-speed. Furthermore it can be seen that estimation of R_s becomes more noisy at high-speeds.

TABLE II
Scenario 2

Parameters	Values
λ	[0.99 0.99 0.99 0.99]
Perturbation	20A 50 Hz
Speed	0-500 RPM / 0-90 km/h
Torque	7000(0-4.5s) Nm

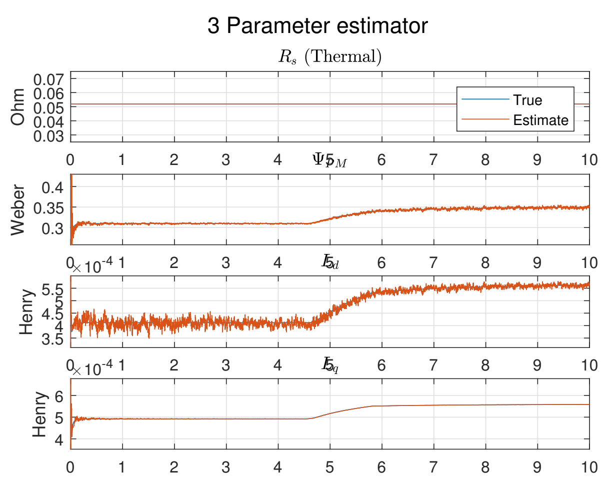

Fig. 3. 3PE Variable-speed MTPA+FW

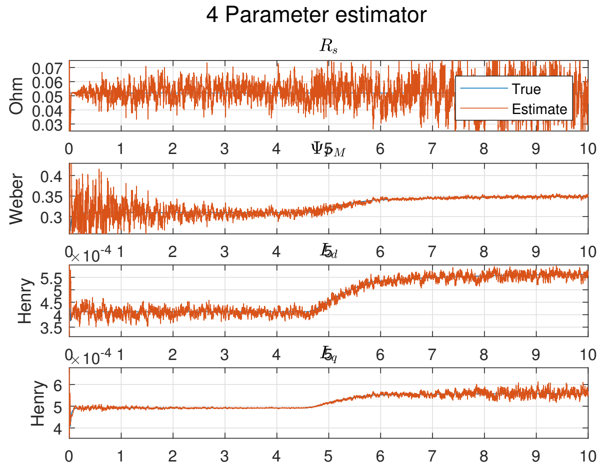

Fig. 4. 4PE Variable-speed MTPA+FW

A. Sensitivity Analysis

Correct parameter estimation depends on the quality of the measurements, the estimator can deal with white noise very well. But an error in the rotor-position angle will influence the estimation. It was therefore also investigated how an uncertainty such as rotor-position angle influences the accuracy of estimated parameters.

1) Rotor position error: Rotor position error was simulated by introducing a bias to the rotor-position used for the Park transform for both the voltage and current measurements. Rotor position-error was simulated in incrementations of 2.5 deg. The results are shown in Table III, IV, V.

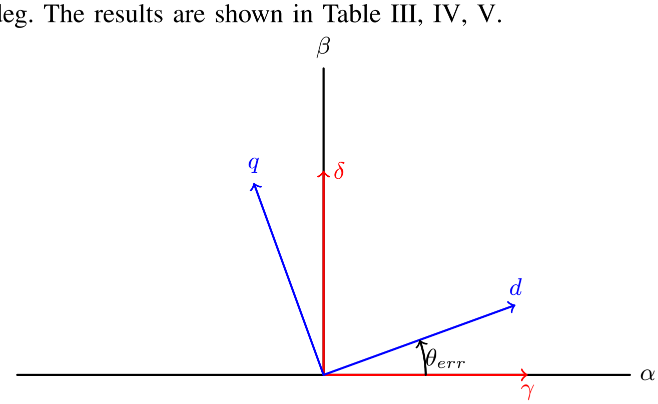

TABLE III
θ_{err} = 2.5 DEG (50 KM/H 3000NM)

	3 Par	4 Par
R_s	-	1.0949
L_d	0.999	0.999
L_q	1.075	1.075
Ψ_{PM}	0.996	0.989

In the case of the 3PE it can be clearly seen that the leakage of the B-EMF is attributed to the L_q as it is now overestimated by more then 15 percent. The error on the Ψ_{PM} it-self is within 1 percent which is very acceptable. The 4PE shows overestimation of both R_s and L_q while more significantly underestimating the Ψ_{PM} compared to the proposed 3PE. Just like the 3PE the leaking B-EMF is the culprit, however the error is now attributed mostly to the resistance. Overall the 3PE with thermally estimated R_s shows more robustness in case of position-error compared to the 4PE due to the decoupling, the subsequent error on the important Ψ_{PM} parameter is reduced although there is still significant overestimation of L_q.

TABLE IV
θ_{err} = 5 DEG (50 KM/H 3000NM)

	3 Par	4 Par
R_s	-	1.252
L_d	0.999	0.999
L_q	1.151	1.148
Ψ_{PM}	0.991	0.972

TABLE V
θ_{err} = 7.5 DEG (50 KM/H 3000NM)

	3 Par	4 Par
R_s	-	1.4843
L_d	0.999	0.999
L_q	1.227	1.2188
Ψ_{PM}	0.984	0.947

B. Effect of thermal changes

As discussed the decoupled 3PE estimator has a separate estimator based on thermal measurements for the estimation of R_s. This allows the estimator to be used over a broad temperature range, compared to other methods where the estimation of R_s was fixed to the nominal value [6], [7]. This assumption can however lead to large errors on the estimation. This is particularly the case in low-speed high-torque conditions. This shown by means of simulation by fixing R_s to the nominal value and varying the true stator temperature (figure 5). In this way underestimation of the R_s leads to large overestimation of Ψ_{PM} and as a consequence on the torque estimation.

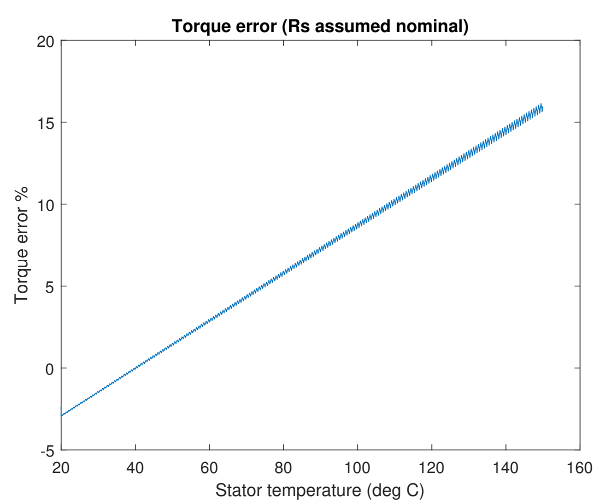

Fig. 5. Error on torque estimation (120RPM 8000Nm)

IV. Experimental validation

The estimator was implemented in the motor-controller hardware to evaluate the estimators experimentally. The schematic overview of the control implementation is shown in figure 7 The In-Wheel-Motor(IWM) for a city-bus application (Table VI) was tested on a test-bench shown in figure 6 on which the motor could be tested up to the rated peak-torque. HBM eDrive Testing was used as the data-acquisition setup to log the measured torque from the torque-transducer and log the parameter estimates. The motor was operated over the whole torque-range by step changing the torque in 1000Nm increments, in this way tracking and convergence of the estimated parameter change due to saturation could be verified.

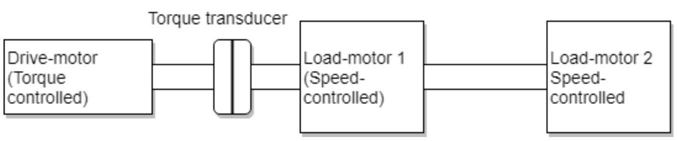

Fig. 6. Test-setup

TABLE VI
IWM-motor specifications

Motor specs	Values
Rated power	125 kW
Poles	50
Rated current	750 A (RMS)
Rated peak-torque	10 kNm
Rated speed	500 RPM
DC-Link	520 V
R_s	50 mΩ
Nominal Ψ_{PM}	0.344 Wb
Nominal L_d	461 nH
Nominal L_q	542 nH

The parameter estimates from the experimental measurements are shown in figure 8 for the 3PE and figure 9 for the 4PE. The look-up table parameters for the same load-case can be seen in figure 10. It can be noticed that the proposed 3PE estimator shows good tracking of the saturation. Compared to the look-up table parameters the estimation of Ψ_{PM} is somewhat underestimated and the estimation of L_q somewhat overestimated. Which could indicate a small rotor-position angle error. The estimation of L_d in saturation seems to be underestimated. The conventional 4PE estimator shows implausible estimation of both R_s and Ψ_{PM} where the overestimation of R_s leads to significant underestimation of Ψ_{PM}. The torque estimate of the 3PE is shown in figure 11 and of the 4PE in figure 12. Initially both estimators perform a really good job in estimating the torque and especially the 4PE torque estimation is really close to the measured torque. The 3PE torque estimation has a small estimation bias which increases with the currents Although there is a bias present the torque estimate does not show sudden divergence like the 4PE which cannot reliably estimate over the operating range.

A. Measurement method

To explain the difference between the simulations and the experimental results it must be understood that the estimation is only as good as the accuracy of the measurements, and a bias error of a measurement or delay between the voltage and current measurements will transfer to the estimation results. In the hardware implementation the measurements for the estimator are done in the 3-phase domain. To correctly reconstruct the voltage and current measurements from the 3-phase domain back to the DQ-domain using the Clark and Park transforms. The voltage, current and rotor-position measurements need to be in phase. In order for this to be the case the filtering delays and attenuation have to be compensated for to minimize errors. Particularly the resistance estimation would be sensitive to incorrect synchronization of the voltage and current measurements, due to its small contribution and because it is an active power. In the application of the estimator, there are different ways to obtain the 3 phase-voltage measurements. They can either be reconstructed using the DC-link voltage measurement and duty-cycles or measured at the terminals. The reconstruction is however always an approximation because of the non-idealities present in the inverter. These are for example dead-time, non-linear voltage drops over the switches and turn-on/off delays. Alternatively the voltage can be measured at the phase-terminals, in this way the non-linearities and non-idealities are inherently taken into account. However due to the fast-switching nature of the PWM voltage (a 5-Khz square-wave), the voltage measurement needs hardware low-pass filtering to prevent aliasing when the measurement is sampled at a sampling-frequency of 10 Khz, this filters out the PWM-harmonics and leaves the fundamental voltage. The consequence of this filtering is a phase-delay and an attenuation of the voltage measurement. The voltage and current measurements are sampled using zero-order-hold, filtered with a 2-point moving average FIR filter and a 1st order low-pass filter. The compensation has been achieved by matching the 1st order low-pass filter poles of the voltage and current measurements by the usage of a zero-pole filter shown in equation (16), where the filtering pole of the voltage measurement is replaced by the current measurement pole using pole-zero cancellation.

$$H_{UACfiltinv}(z) = \left(\frac{1 - e^{-T_s \omega_{IACfilt}}}{1 - e^{-T_s \omega_{UACfilt}}}\right)\left(\frac{z - e^{-T_s \omega_{UACfilt}}}{z - e^{-T_s \omega_{IACfilt}}}\right) \tag{16}$$

By correcting the measured position angle according to the filtering delays and electrical-frequency the correct position measurement is used for the Park and Clark transforms this is seen in equation 17.

TABLE VII
Filter properties

Transfer Function	Phase
$H_{FIR}(s) = \frac{1}{2}(1 + e^{-sT_s})$	$Arg(H_{FIR}) = \frac{\omega_e T_s}{2}$
$H_{ZOH}(s) = \frac{1-e^{-sT_s}}{sT_s}$	$Arg(H_{ZOH}) = \frac{\omega_e T_s}{2}$
$H_{IACfilt}(s) = \frac{1}{s+\omega_{filt}}$	$Arg(H_{IACfilt}) \approx \frac{\omega_e}{\omega_{IACfilt}}$

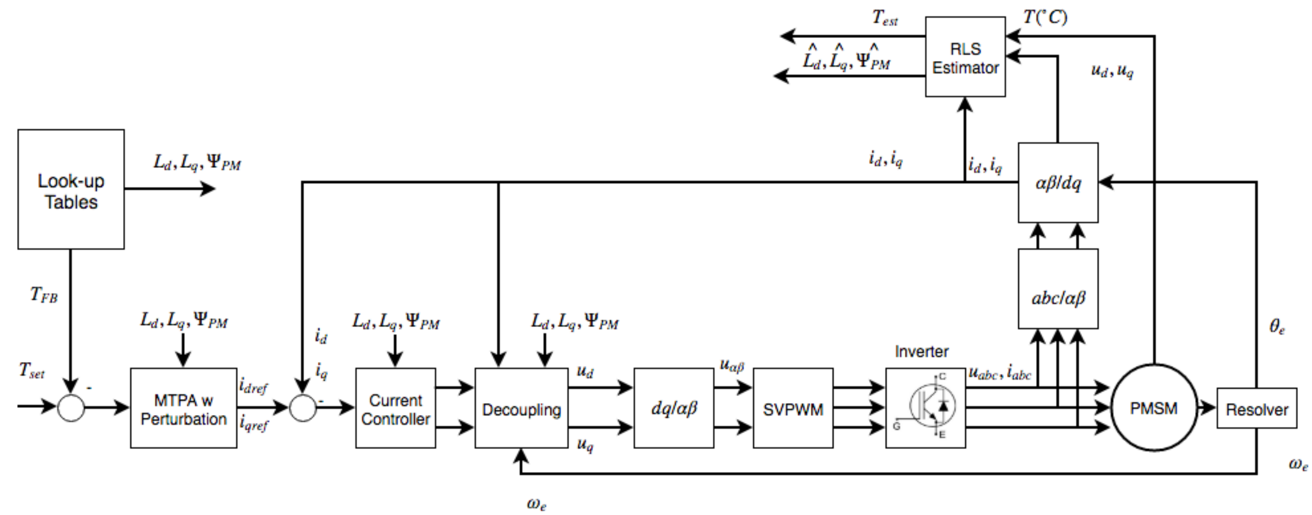

Fig. 7. Block-diagram of the hardware implementation

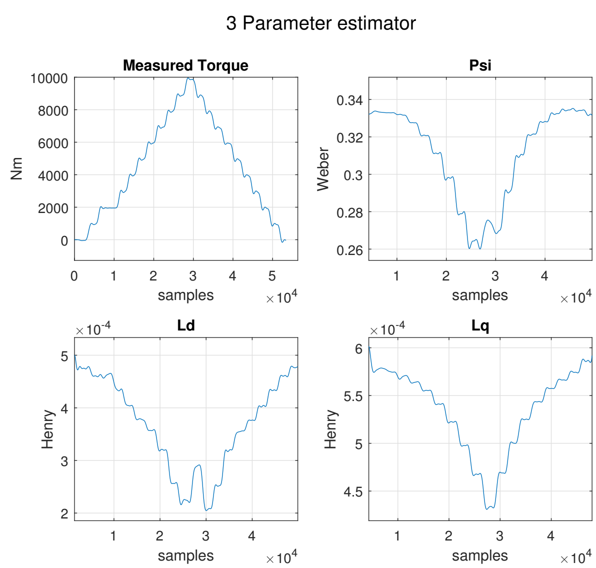

Fig. 8. 3PE experimental estimation

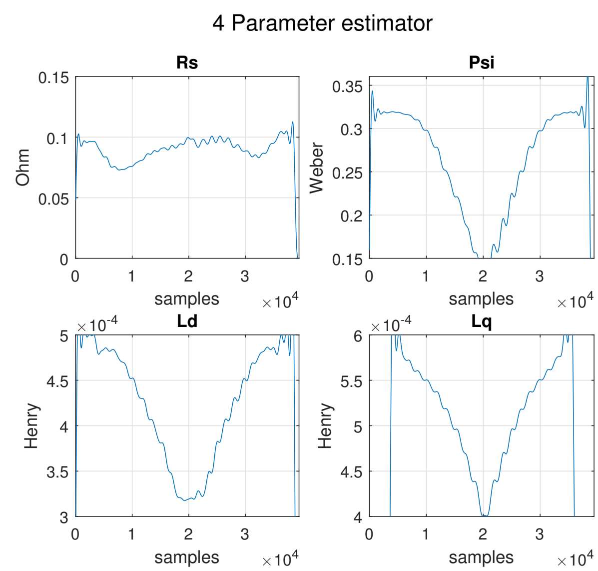

Fig. 9. 4PE experimental estimation

$$\Delta\theta_e = \omega_e(T_s + \frac{1}{\omega_{IAC_filt}}) \tag{17}$$

Neither approach will be perfect, the reconstruction approach(U_{set}) does not account for the inverter non-linearities and the the compensation of the hardware low-pass filter for the voltage-feedback measurement U_{FB} will depend on the pole location which can differ with component variation. Therefore both approaches have been verified experimentally to see which approach gives the most accurate results.

The measuring approaches were compared at 1 operating point at low-torque low-speed. Where inverter non-linearities

TABLE VIII
ESTIMATES 2000NM 120RPM

Parameters	U_{FB}	U_{Set}	Nominal (LUT)
R_s (mOhm)	65	73	50
Ψ_{PM} (Weber)	0.335	0.327	0.344
L_d (nH)	493	461	461
L_q (nH)	539	580	542

have the largest influence. For the comparison the 4PE was used so the effect on R_s estimation could also be verified. It can be seen that particularly estimation of R_s Ψ_{PM} and L_q show closer correspondence to the look-up table when the voltage measurements are used. When the measurement approaches where compared for torque estimation as in figures

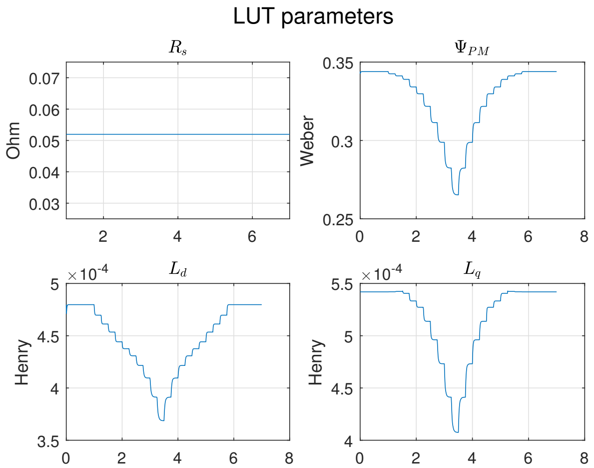

Fig. 10. Look-up-table parameters

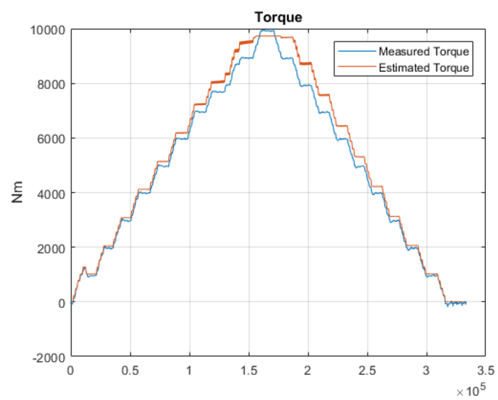

Fig. 11. Torque estimate 3PE (120RPM)

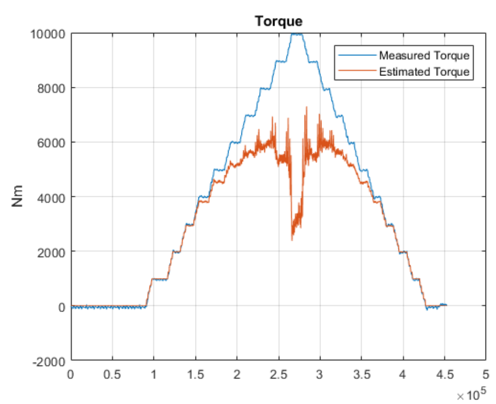

Fig. 12. Torque estimate 4PE (120RPM)

11 and 12 no big differences were found and the same incorrect estimation of R_s and Ψ_{PM} occurred.

V. Conclusion

In this paper it was shown that the proposed estimator can be used to do online tracking of the motor-saturation. The use of thermal-measurements for the estimation of R_s made the estimator less susceptible to noise and more robust. The proposed estimator was validated both using simulations and experimentally. A sensitivity analysis showed the proposed estimation approach is more robust against rotor-position error leading to smaller errors in the estimation. In the experimental validation the proposed estimator showed reliable estimation over the entire operating-range of the PMSM whereas for the conventional method the unreliable resistance, caused estimation error on the other parameters. The estimates were close to the look-up tables but it is expected that in future work the results could be improved further by improving the measurements either by accounting for the inverter non-idealities or application of advanced instantaneous voltage-measurement methods [9] which can sample the PWM-modulated voltage directly without the need for filtering and is therefore less susceptible to error caused by delays.

VI. Acknowledgments

The author wants to thank Patrick Hendriks of e-Traction for the excellent support during my thesis work. Whenever a question came up, Patrick was always very eager to help me out. Thanks! I also want to thank Jianning Dong for his excellent and helpful feedback to help me improve my work.

References

[1] A. Emadi, Ed., *Advanced electric drive vehicles*, ser. Energy, power electronics, and machines. Boca Raton London New York: CRC Press, Taylor & Francis Group, 2015, oCLC: 931656421.

[2] S. J. Underwood and I. Husain, "Online Parameter Estimation and Adaptive Control of Permanent-Magnet Synchronous Machines," *IEEE Transactions on Industrial Electronics*, vol. 57, no. 7, pp. 2435–2443, Jul. 2010.

[3] K. Liu, Q. Zhang, J. Chen, Z. Q. Zhu, and J. Zhang, "Online Multiparameter Estimation of Nonsalient-Pole PM Synchronous Machines With Temperature Variation Tracking," *IEEE Transactions on Industrial Electronics*, vol. 58, no. 5, pp. 1776–1788, May 2011.

[4] A. Balamurali, C. Lai, G. Feng, V. Loukanov, and N. C. Kar, "Online multi-parameter identification of permanent magnet synchronous motors in EV application considering iron losses," in *2016 XXII International Conference on Electrical Machines (ICEM)*, Sep. 2016, pp. 2306–2312.

[5] S. Nalakath, M. Preindl, and A. Emadi, "Online multi-parameter estimation of interior permanent magnet motor drives with finite control set model predictive control," *IET Electric Power Applications*, vol. 11, no. 5, pp. 944–951, 2017.

[6] H. Kubo and Y. Tadano, "Parameter estimation of PMSM driven by PWM inverter based on discrete dynamic model," in *IECON 2016 - 42nd Annual Conference of the IEEE Industrial Electronics Society*, Oct. 2016, pp. 2873–2878.

[7] Q. Liu and K. Hameyer, "High-Performance Adaptive Torque Control for an IPMSM With Real-Time MTPA Operation," *IEEE Transactions on Energy Conversion*, vol. 32, no. 2, pp. 571–581, Jun. 2017.

[8] S. Ichikawa, M. Tomita, S. Doki, and S. Okuma, "Sensorless control of permanent-magnet synchronous motors using online parameter identification based on system identification theory," *IEEE Transactions on Industrial Electronics*, vol. 53, no. 2, pp. 363–372, Apr. 2006.

[9] T. D. Batzel and M. Comanescu, "Instantaneous voltage measurement in pwm voltage source inverters," in *Electrical Machines and Power Electronics, 2007. ACEMP'07. International Aegean Conference on*. IEEE, 2007, pp. 168–173.