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Online Parameter Estimation of PMSM in EV Powertrain Including Thermal Measurements

Arnout Zwartbol[†], Jianning Dong[*], Pavol Bauer[*] and Henk Polinder[†]
[*] Faculty of Electrical Engineering, Mathematics and Computer Science
[†] Faculty of Mechanical, Martitime and Materials Engineering
Delft University of Technology, Delft, The Netherlands
J.Dong-4@tudelft.nl

***Abstract*—This paper proposes an online motor-parameter-estimator for a permanent magnet synchronous motor (PMSM) in an electric vehicle (EV) powertrain. The proposed method uses a recursive least squares filter approach in combination with the discrete time dynamic voltage equations. Stator resistance estimation is decoupled from the estimator using thermal measurements. Compared to conventional approach, the proposed method is more reliable and less noisy since it does not rely on the low contribution of stator resistance in the voltage equation. Both simulations and experiments are carried out to validate the proposed method. A sensitivity analysis shows the approach is robust against rotor position error.**

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 electric vehicle (EV) application the motor is torque controlled. 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) or maximum torque per flux (MTPF) point. The conventional approach is to store the motor parameters in look-up table (LUTs) 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 permanent magnet synchronous motor (PMSM) are the stator resistance R_s, d-axis inductance L_d, q-axis inductance L_q, PM 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 has to wait for the transients to die out. Therefore most recent research uses the discrete time 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 error. Lastly the estimators were experimentally verified on a real motor.

II. Methodology

A. PMSM model

The estimator was implemented in the rotor dq reference frame with the discrete dynamic voltage equations. In this way the estimator is valid in both steady state and transient

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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 d-axis and q-axis voltages, i_d and i_q d-axis and q-axis currents, T_s the sampling-time and ω_e the 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]. The perturbation current i_{dper} on the d-axis is:

$$i_d = i_{dset} + i_{dper} \tag{3}$$

$$i_{dper} = A \sin(2\pi f) \tag{4}$$

where A and f are amplitude and frequency of the perturbation current.

To keep the torque unchanged, perturbation i_{qper} is applied on the q-axis accordingly:

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

where i_{dset} and i_{qset} are the set points of dq currents.

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 estimation is based on the estimated motor parameters and current feedback from measurements:

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

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

III. Simulation

The motor parameter estimation methods are simulated with a PMSM model in the dq reference frame. Motor parameters in the model are set from the LUTs, and used as reference to validate the estimators. Measurement noise was simulated by contaminating the measurement with white noise.

Two simulation scenarios are considered to evaluate the performance of the two methods under both large torque variations and in wide speed range. In both scenarios, the perturbation current applied on the d-axis is $20\,\mathrm{A}$, $50\,\mathrm{Hz}$.

A. Scenario 1, Low Speed Torque Ramp

In scenario 1, the motor is running at a constant low speed of $120\,\mathrm{r/min}$. At $t = 0.5\,\mathrm{s}$, a load torque ramp of $5\,\mathrm{kNm/s}$ is applied for 2 seconds.

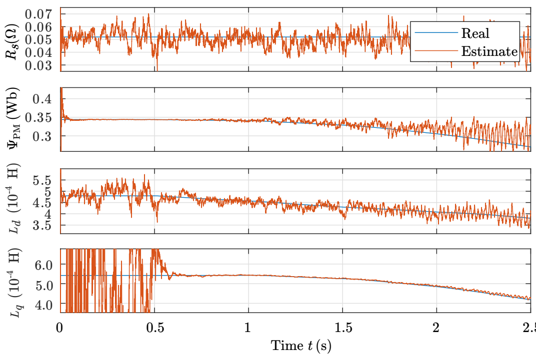

Fig. 1. Parameter identification results of 4PE method in Scenario 1.

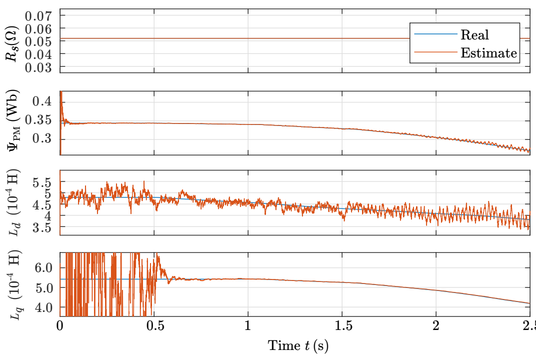

Fig. 2. Parameter identification results of 3PE method in Scenario 1.

The simulation results of the 4PE method and the 3PE method are shown in Figure 1 and 2 respectively. Both methods are able to track the parameter variation. However the proposed 3PE shows much less noise in Ψ_{PM} estimation. The 4PE method shows severe noise when the torque is high. This is as expected and is caused by the strong coupling between R_s and Ψ_{PM} at low speed.

B. Scenarios 2, Varying Speed

In scenario 2, the motor is first accelerated from standstill to the corner speed with a constant torque $7000\,\mathrm{Nm}$ from $t = 0\,\mathrm{s}$ to $4.5\,\mathrm{s}$. Then the motor is accelerated further to $500\,\mathrm{r/min}$ with flux weakening.

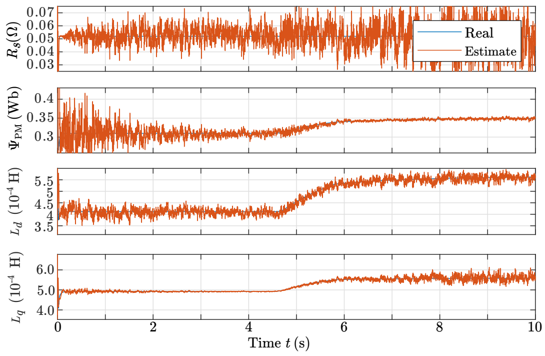

Fig. 3. Parameter identification results of 4PE method in Scenario 2.

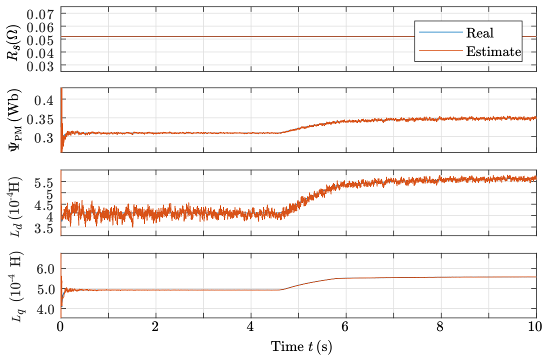

Fig. 4. Parameter identification results of 3PE method in Scenario 2.

The estimation results obtained from the two method in scenario 2 are shown in Figure 3 and 4 respectively. Apparently the 3PE method has less noise in a wide speed range. The 4PE method shows large noise in R_s at high speed and in Ψ_{PM} at low speed.

C. Sensitivity Study

The simulation in the two scenarios shows the proposed 3PE method is able to deal with white noises in measurements. However, in many cases, the measurement are often biased by a constant offset. For PMSM, the rotor position is one of the most important variables for both control and parameter estimation because an error in it affects the transformation of all other electrical variables. Therefore, the sensitivity on the rotor angle error is first investigated.

The motor is simulated at $273\,\mathrm{r/min}$ with a load of $3000\,\mathrm{Nm}$. The rotor position error θ_{err} is introduced to the model incrementally. Parameters estimated from the two methods with various θ_{err} are normalized to corresponding real values. The results are compared in Table I. As θ_{err} increases, the large the overestimation in L_q in both methods, which is caused by the cross coupling between dq-axis and leakage of permanent magnet flux to the q-axis when there is error in the rotor position. Since the 4PE method estimates R_s directly from the voltage equation, the estimation of R_s is highly deteriorated by θ_{err}, which also causes larger error in Ψ_{PM} estimation because their coupling in the voltage equation. The 3PE method, on the contrary, is able to limit the error in Ψ_{PM} within 2% because estimation of R_s is decoupled from the voltage equations. The accuracy of estimation in R_s and Ψ_{PM}, as we can see later, is essential for accurate torque estimation.

TABLE I
ESTIMATED RESULTS WITH DIFFERENT ROTOR POSITION ERRORS (NORMALIZED TO REAL VALUES)

θ_{err}	Parameters	3PE results	4PE results
2.5°	R_s	-	1.0949
	L_d	0.999	0.999
	L_q	1.075	1.075
	Ψ_{PM}	0.996	0.989
5.0°	R_s	-	1.252
	L_d	0.999	0.999
	L_q	1.151	1.148
	Ψ_{PM}	0.991	0.972
7.5°	R_s	-	1.4843
	L_d	0.999	0.999
	L_q	1.227	1.2188
	Ψ_{PM}	0.984	0.947

IV. EXPERIMENTAL VALIDATION

The estimator was implemented in a motor drive for EV powertrain to evaluate the estimators experimentally. The schematic overview of the control implementation is shown in Figure 5. An in wheel motor (IWM) for a city-bus application is used for experiments. Main parameters of the motor are shown in Table IV. HBM eDrive testing system is used as the data acquisition setup to log the measured torque from the torque transducer and log the parameter estimated.

A. Discussion on Voltage Measurement

The parameter estimation is highly affected by imperfections in measurements. 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 voltage and current are measured as phase values. To correctly reconstruct the voltage and current measurements from the 3-phase domain to the dq-domain using the Clarke and Park transforms. The voltage, current and rotor position measurements should be precisely in phase. Therefore, the filtering delays and attenuation have to be compensated 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 effects on active power.

In practice, there are different ways to obtain the 3 phase voltage measurements. They can either be reconstructed from the measured DC-link voltage and duty-cycles or measured at the terminals. The reconstruction is however always an approximation because of the nonidealities in the inverter. Nonidealities include 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 some nonidealities can be inherently taken into account. However, due to the fast-switching nature of the pulse width modulated (PWM) voltage, the voltage measurement needs hardware low-pass filtering to prevent aliasing when the measurement is sampled at a limited sampling frequency. The consequence of this filtering is phase delay and attenuation of the measured voltage.

In the experiment, the voltage and current measurements are sampled using zero-order hold (ZOH) at a sampling period of $T_s = 10^{-4}$ s, filtered with a 2-point moving average FIR filter and a 1st order low-pass filter. The transfer functions of the three stages and their phase delays are shown in Table II.

TABLE II
TRANSFER FUNCTIONS AND PHASE DELAYS OF FILTERS

Name	Transfer Function	Phase Delay
ZOH	$H_{ZOH}(s)=\frac{1-e^{-sT_s}}{sT_s}$	$\frac{\omega_e T_s}{2}$
FIR filter	$H_{FIR}(s)=\frac{1}{2}(1+e^{-sT_s})$	$\frac{\omega_e T_s}{2}$
Current low pass filter	$H_{If}(s)=\frac{1}{s+\omega_{If}}$	$\approx \frac{\omega_e}{\omega_{If}}$
Voltage low pass filter	$H_{Uf}(s)=\frac{1}{s+\omega_{Uf}}$	$\approx \frac{\omega_e}{\omega_{Uf}}$

The compensation is implemented by matching the 1st order low-pass filter poles in measurements with a zero-pole filter shown in (16), where the filtering pole of the voltage measurement is replaced by the current measurement pole using pole-zero cancellation.

$$H_{Ucom}(z) = (\frac{1-e^{-T_s\omega_{If}}}{1-e^{-T_s\omega_{Uf}}})(\frac{z-e^{-T_s\omega_{Uf}}}{z-e^{-T_s\omega_{If}}}) \tag{16}$$

The measured position angle should also be compensated both the filtering delays and the rotating angular frequency:

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

Both the voltage reconstruction (U_{rc}) and the phase terminal measurement (U_{pm}) methods are implemented in the experiment. The estimated parameters using both methods and the 4PE estimator are compared to the LUT values in Table III. The comparison is done at $2000\,\mathrm{Nm}$ and $120\,\mathrm{r/min}$.

TABLE III
ESTIMATED PARAMETERS AT 2000 NM, 120 R/MIN USING TWO VOLTAGE MEASUREMENTS METHODS

Parameters	U_{rec}	U_{pm}	LUT
R_s (mΩ)	73	65	50
Ψ_{PM} (Wb)	0.327	0.335	0.344
L_d (nH)	461	493	461
L_q (nH)	580	539	542

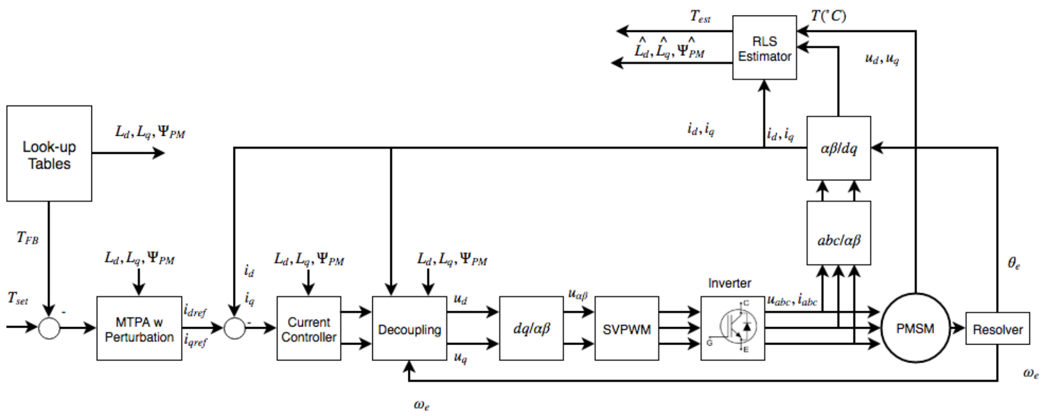

Fig. 5. Block-diagram of the hardware implementation

At the operating of Table III, the inverter non-linearities have significant influence. It can be seen that particularly estimation of R_s Ψ_{PM} and L_q are closer to the LUT values when the phase terminal voltage measurements are used.

B. Results and Comparison

To validate the tracking ability and convergence of the estimators, the motor is operated at stepwise loading over the whole torque range with a step size of $1000\,\mathrm{Nm}$.

TABLE IV
MAIN PARAMETERS OF THE IWM

Parameters	Values
Rated power	125 kW
p	25
Rated current	750 A rms
Peak torque	10 kNm
Rated speed	500 r/min
DC-link voltage	520 V
R_s	50 mΩ
Nominal Ψ_{PM}	0.344 Wb
Nominal L_d	461 nH
Nominal L_q	542 nH

Figure 6 and 7 compare the estimation results of the two methods in the experiments with those obtained from the off-line generated LUTs. It can be noticed that the proposed 3PE estimator shows good tracking of the saturation. Compared to the parameters obtained from LUTs, the Ψ_{PM} from the two methods is generally underestimated and the L_q is over-estimated. It indicates a small rotor position error may exist. The L_d under saturation is 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 estimated torque results from the two methods are compared to the measured values from the torque transducer, as shown in Figure 8 and 9. Both methods are able to estimate torque accurately in the low torque region, especially the 4PE method. The 3PE method shows an estimation bias in the

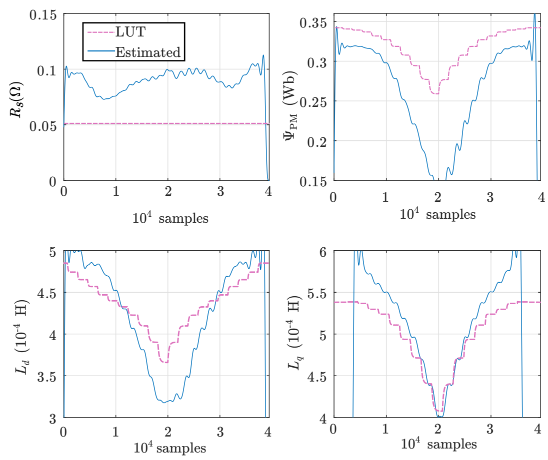

Fig. 6. Experimental parameter estimation obtained from 4PE method.

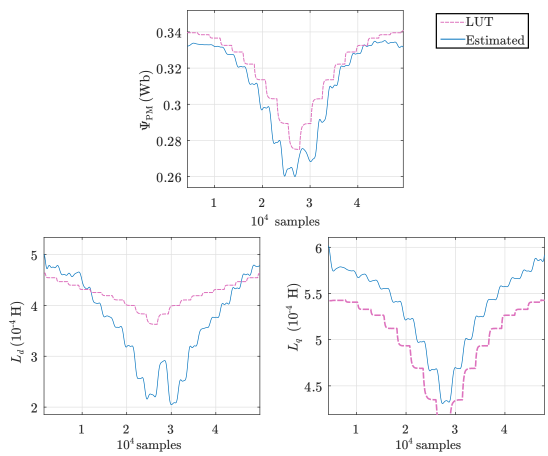

Fig. 7. Experimental parameter estimation obtained from 3PE method.

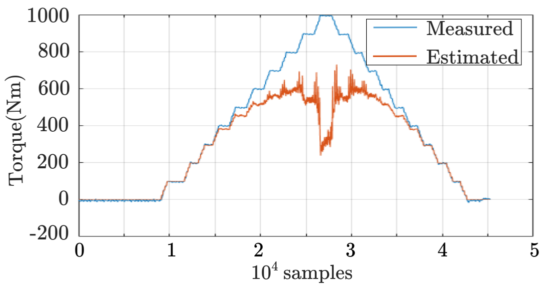

Fig. 8. Experimental torque estimation obtained from 4PE method.

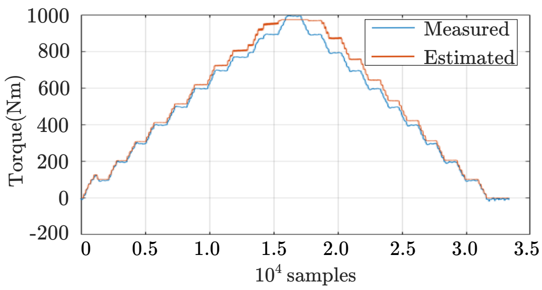

Fig. 9. Experimental torque estimation obtained from 3PE method.

whole torque range which increases with the currents. The 4PE method shows obvious divergence when the torque is high, which makes it unreliable and even unusable.

V. Conclusion

In this paper a online PMSM parameter estimation method which decoupled stator resistance R_s using winding temperature measurement has been proposed. It has shown that the proposed estimator is able to track the motor parameter variations caused by saturation. The use of temperature measurements to estimate R_s makes the estimator less susceptible to noise and more robust. The proposed estimator was validated both using simulations and experiments. A sensitivity analysis showed the proposed estimation approach is more robust against rotor position error. In experiments, the proposed estimator has shown reliable estimation over the entire operating-range of the PMSM whereas for the conventional method the unreliable resistance estimation caused unacceptable estimation error on the other parameters.

In future work the results could be improved further by improving the measurements either by accounting for the inverter non-idealities or applying advanced instantaneous voltage-measurement methods [9] which can sample the PWM voltage directly without the need for filtering and is therefore less susceptible to error caused by delays.

Acknowledgment

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