A fast online full parameter estimation of a PMSM with sinusoidal signal injection

Qian Liu and Kay Hameyer
Institute of Electrical Machines, RWTH Aachen University, Germany
Email: Qian.Liu@iem.rwth-aachen.de

***Abstract*—In this paper, a fast online parameter estimation scheme with sinusoidal d-axis current injection is introduced. Compared to the existing parameter estimation strategies, the proposed estimation scheme has relative faster convergence time and is feasible in the transient operation. This estimation scheme is realized by the recursive least square algorithm based on different operating points of the Permanent Magnet Synchronous Machine (PMSM). With the proposed estimation scheme, the four parameters of the PMSM can be simultaneously estimated online. The derivatives of the d- and q-axis currents are considered in the proposed estimation scheme so that it is feasible in both steady state and transient state operation. The sampling principle is discussed to avoid the rank deficient problem for the estimation. An averaged sliding window is introduced for the estimation to minimize the estimation error from the A/D conversion and to reduce the influence of the measurement noise. The proposed estimation scheme is validated by the experimental results and compared with the parameter estimation with square wave current injection.**

I. Introduction

Nowadays, the PMSM is widely used as generators, traction machines and servo motors in the industry applications such as wind turbines and electrical vehicles due to its high power density and efficiency. The parameters of the PMSM vary due to different load and environmental conditions, which can deteriorate the performance of the controller and even leads to instability of the drive system. In order to achieve the high performance control of the PMSM, especially for the full utilization of the PMSM considering voltage and current limitations, the multi-parameters of the PMSM should be accurately estimated. On the other hand, to improve the efficiency of the PMSM such as the maximum torque per ampere (MTPA) and maximum torque per voltage (MTPV) operations, the accurate multi-parameters of the PMSM are also required.

Two strategies are proposed for the parameter estimation of the PMSM: offline and online estimation. Due to the development of the numerical simulation software for the electrical machines, one of the offline parameter estimation scheme is based on the finite element analysis (FEA) [1] of the PMSM simulation. The estimation with FEA can be accurate on the inductances with saturation effects. However, it is difficult to estimate the flux linkage and resistance of the PMSM with different environmental considerations such as the temperature. The other offline estimation scheme is based on the offline measurement data of the PMSM by using the locked rotor test with DC voltage step response [2], [3] or the AC sinusoidal voltage test [4], [5]. With this offline estimation scheme, massive measurements have to be executed in the entire operating range of the PMSM to obtain the parameter look-up table.

In order to reduce the efforts of the parameter estimation and to increase the adaptivity of the PMSM drive system, the online parameter estimation is introduced with the modern control theories such as the adaptive system [6], [7], recursive least square (RLS) [8]–[10], extended Kalman filter (EKF) [11], [12], Adaline neural network (NN) [13] and other estimators [14]. The estimability of the PMSM machine parameters is shown in [15] that at most two parameters of the PMSM can be estimated simultaneously without extra signal injection. In this case, only part of the machine parameters can be identified online while the other ones are considerd to be known, which are proposed in most of the aforementioned literatures. The precise of the estimated parameters depend on the certainty of the known ones. In [16], a full parameter estimation scheme using RLS is proposed. However, the observability of the estimator only holds during the transient state. In order to realize the accurate estimation of all parameters for the PMSM, the square wave current injection is introduced to overcome the rank-deficient problem using two different operating points [13]. However, it is only feasible during the steady state operation of the PMSM. A combined slow and fast RLS algorithm for the online estimation of all parameters of the PMSM is introduced in [9], which can be operated at transient state operation. However, with the slow and fast RLS algorithm, the incorrect convergence of the estimated parameters is shown in the simulation and experimental results.

In this paper, a sinusoidal d-axis current injection is combined with the RLS algorithm to estimate all parameters of the PMSM online. The sinusoidal current injection and a proper sampling rate for the estimation can prevent the RLS algorithm from the ill convergence problem. The current derivatives of d- and q-axis are considered within the RLS algorithm so that the proposed estimation scheme is feasible in both steady state and transient state operation. An averaged sliding window is introduced to reduce the error caused by the discretation of the current derivatives from a continuous system. In the end, the performance of the proposed estimation scheme is validated by the experimental results.

II. Model of the PMSM and parameter identifiability

The model of the PMSM is usually presented in the dq reference coordinate system after the Park Transformation. The typical base frequency continuous model of a PMSM in the synchronous rotational dq coordinates is shown by

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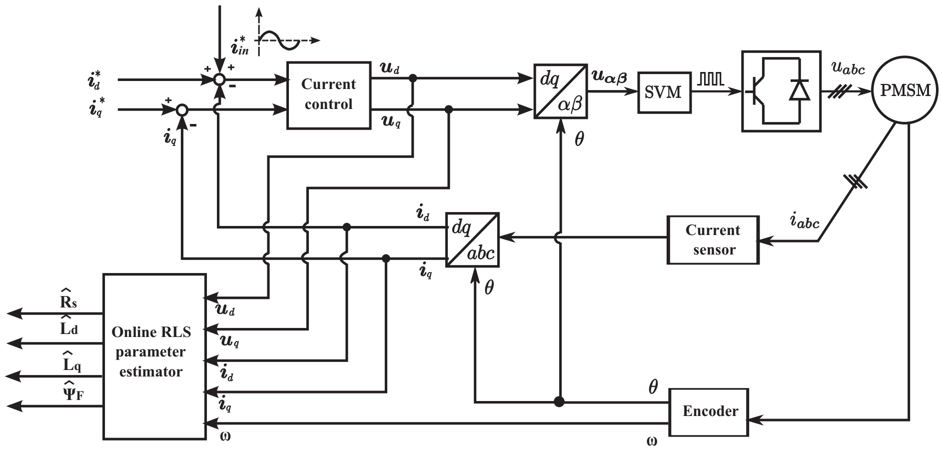

Fig. 1. Block diagram for the proposed parameter estimation.

the following equations after the amplitude invariant Park Transformation:

$$\frac{di_d}{dt} = -\frac{R}{L_d}i_d + \frac{\omega L_q i_q}{L_d} + \frac{u_d}{L_d}, \tag{1}$$

$$\frac{di_q}{dt} = -\frac{R}{L_q}i_q - \frac{\omega L_d i_d}{L_q} - \frac{\omega \Psi_F}{L_q} + \frac{u_q}{L_q}, \tag{2}$$

where R, L_d, L_q and Ψ_F are the stator resistance, inductance on d,q-axis and the magnetic flux of the PMSM respectively.

The identifiability of the PMSM parameters can be evaluated by using the observability of the following extended model of the PMSM [15]:

$$\begin{cases} \frac{di_d}{dt} & = -\frac{R}{L_d}i_d + \frac{\omega L_q i_q}{L_d} + \frac{u_d}{L_d}, \\ \frac{di_q}{dt} & = -\frac{R}{L_q}i_q - \frac{\omega L_d i_d}{L_d} - \frac{\omega \Psi_F}{L_q} + \frac{u_q}{L_q}, \\ \frac{dR}{dt} & \cong 0, \\ \frac{dL_d}{dt} & \cong 0, \\ \frac{dL_q}{dt} & \cong 0, \\ \frac{d\Psi_F}{dt} & \cong 0 \end{cases} \tag{3}$$

The local observability of the nonlinear system (3) can be studied with the help of the rank of its Jacorbian Maxtrix of the following matrix $\boldsymbol{O}$, which is shown below:

$$\boldsymbol{O} = \begin{bmatrix} i_d & i_q & \frac{di_d}{dt} & \frac{di_q}{dt} & \cdots & \frac{d^5 i_d}{dt^5} & \frac{d^5 i_q}{dt^5} \end{bmatrix}^T \tag{4}$$

where the subscript T denotes the transpose of the matrix. Using the symbolic calculation toolbox in Matlab, it is easy to obtain the Jacorbian Matrix $\boldsymbol{J}$ of the matrix $\boldsymbol{O}$ as well as the rank of $\boldsymbol{J}$.

A general conclusion can be obtained after the calculation of the rank of the Jacorbian matrix $\boldsymbol{J}$ with dimension 12×6. For any curernt profile in steady state or transient states, $rank(\boldsymbol{J}) = 4$ always holds after the symbolic calculation results. Therefore, at most two parameters of the PMSM can be identified except the estimatable currents i_d and i_q when using the continuous model of the PMSM. With this conclusion, it implies that even with current injection to keep the machine in transient state, the identifiability of the four parameters R, L_d, L_q and Ψ_F is weak, if a very small sampling time is utilized for the parameter estimator.

III. RLS ALGORITHM

The RLS algorithm is utilized in this paper to implement the estimation of the full parameters of the PMSM. The RLS algorithm with a forgetting factor compromises the convergence rate of the estimated parameters and the filtering effect on the measurement noise. The RLS algorithm is described by the following equations:

$$\begin{aligned} \hat{\boldsymbol{\theta}}(n) &= \hat{\boldsymbol{\theta}}(n-1) + \boldsymbol{K}(n)(\boldsymbol{y}(n) - \boldsymbol{\varphi^T}(n)\hat{\theta}(n-1)) \\ \boldsymbol{K}(n) &= \boldsymbol{P}(n-1)\boldsymbol{\varphi}(n)(\lambda\boldsymbol{I} + \boldsymbol{\varphi^T}(n)\boldsymbol{P}(n-1)\boldsymbol{\varphi}(n))^{-1} \\ \boldsymbol{P}(n) &= \frac{1}{\lambda}(\boldsymbol{I} - \boldsymbol{K}(n)\boldsymbol{\varphi^T}(n))\boldsymbol{P}(n-1), \end{aligned}$$

where $\boldsymbol{y} = \boldsymbol{\varphi^T\theta}$ is the system description for the parameter estimation. $\boldsymbol{y}$ and $\boldsymbol{\varphi}$ are the outputs and states; $\boldsymbol{\theta}$ and $\hat{\boldsymbol{\theta}}$ are the real and estimated parameter vectors respectively. λ is a positive forgetting factor, which is chosen less than 1. A small forgetting factor results in fast convergence rate of the parameter estimation but large noise level in estimated values. Therefore, a proper forgetting factor should be chosen to achieve a trade-off between the convergence rate and the noise level.

IV. PROPOSED ESTIMATION SCHEME OF THE MACHINE PARAMETERS

In order to achieve a fast estimation for the four parameters of the PMSM, an estimation scheme using RLS is proposed with sinusoidal current injection in the d-axis. The block diagram for the PMSM with online paramter estimation is shown in fig. 1.

A. injected current signal

Due to the high frequency current injection in the d-axis, the current $i_d(t)$ contains a DC component and a high frequency AC componnet, which can be described by the following equation:

$$i_d(t) = i_D(t) + A\sin(2\pi f_{in} t), \tag{5}$$

where $i_D(t)$ is the DC component without current injection. A and f_{in} are the amplitude and frequency of the injected

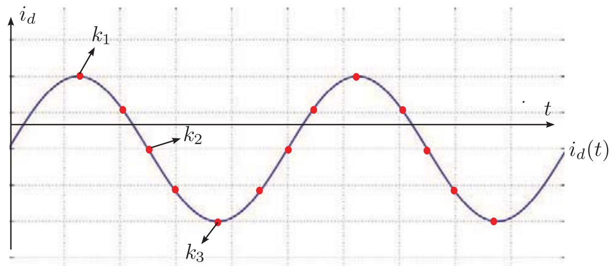

Fig. 2. Sampling of the current i_d.

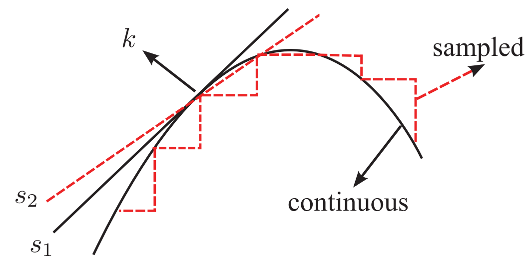

Fig. 3. Error between the discrete and continuous derivatives.

sinusoidal singal. The current closed loop of the PMSM is often designed as a low pass filter with the transfer function:

$$i_d = \frac{1}{1+\tau s}, \tag{6}$$

where τ is the frequency band of the current closed loop of the PMSM. To realized the desired amplitude and phase angle for the real injected current, the reference value of the injected signal i_{in}^* is obtained by the following equation:

$$i_{in}^*(t) = A\sin(2\pi f_{in}t) + 2\pi f_{in}A\sin(2\pi f_{in}t). \tag{7}$$

B. Principle of the estimation

In the last section, it is shown that a very large sampling frequency results in weak observability for the four parameters estimation of the PMSM. In order to avoid the ill convergence of the estimator, a sampling principle considering the sinusoidal injected signal is proposed. An example sampling of the d-axis current is shown in fig. 2, where k_1, k_2 and k_3 denote the sampling instants for the estimator. With the sinusoidal current injection, the d-axis current consists of DC and AC components. The time instants k_1 and k_3 are at the peak of the AC component, while k_2 is at the zero of the AC component. Consider the model of the PMSM at the sampling instants k_1 and k_2:

$$\begin{bmatrix} u_d(k_1) \\ u_d(k_2) \\ u_q(k_1) \\ u_q(k_2) \end{bmatrix} = \begin{bmatrix} i_d(k_1) & \frac{di_d(k_1)}{dt} & -\omega i_q(k_1) & 0 \\ i_d(k_2) & \frac{di_d(k_2)}{dt} & -\omega i_q(k_2) & 0 \\ i_q(k_1) & \omega i_d(k_1) & \frac{di_q(k_1)}{dt} & \omega \\ i_q(k_2) & \omega i_d(k_2) & \frac{di_q(k_2)}{dt} & \omega \end{bmatrix} \begin{bmatrix} R \\ L_d \\ L_q \\ \Psi_F \end{bmatrix} \tag{8}$$

In equation (8), the speed of the PMSM is considered to be unchanged during the sample instants k_1 and k_2. Equation (8) holds under the assumption that the time interval between two adjacent points k_1 and k_2 is relatively small so that the parameter variation during the sampling time interval can be neglected. This assumption can be matched by fulfilling two conditions. One is choosing a relative fast sampling rate for the estimator so that the current variation between two adjacent sampling points is small. The other is using small injected signal which results in negligible influence on the parameters.

The observability of the four parameters in equation (8) can be analyzed by the rank of the following matrix:

$$B = \begin{bmatrix} i_d(k_1) & \frac{di_d(k_1)}{dt} & -\omega i_q(k_1) & 0 \\ i_d(k_2) & \frac{di_d(k_2)}{dt} & -\omega i_q(k_2) & 0 \\ i_q(k_1) & \omega i_d(k_1) & \frac{di_q(k_1)}{dt} & \omega \\ i_q(k_2) & \omega i_d(k_2) & \frac{di_q(k_2)}{dt} & \omega \end{bmatrix}.$$

In the system equation (8) and the matrix B, the derivatives of the currents remain. Therefore, the parameter estimation with the system (8) is feasible in the transient state. Due to the complex structure of the matrix B, it is difficult to show the full rank of B for the general operation of the PMSM. However, the identifiability is broken if and only if the determinant of B equals to 0, which is only the special pattern of the PMSM operation. On the other hand, take into account in steady state case (worst case [15]), the derivatives of the DC component current $\frac{di_D(t)}{dt} = 0$ and $\frac{di_q(t)}{dt} = 0$. The matrix B can be simplified as:

$$B' = \begin{bmatrix} i_D + A & 0 & -\omega i_q & 0 \\ i_D & 2\pi f_{in}A & -\omega i_q & 0 \\ i_q & \omega(i_D + A) & 0 & \omega \\ i_q & \omega i_D & 0 & \omega \end{bmatrix}.$$

It is simple to find out that the rank of the matrix B' is 4, if the current i_q and the speed ω are non-zero. Similarly with sampling instants k_2 and k_3, the rank of the matrix A is also 4 in the steady state. Therefore, there is at least one sampling pattern (e.g. k_1, k_2, k_3 and so on) guarantees the parameter identifiability for the sinusoildal current injection. In order to achieve a fast convergence time for the parameter estimation, more sampling points can be chosen within one period of the injected sinusoidal signal such as the red dots between k_1, k_2 and k_3 in fig. 2. The sampling frequency for the parameter estimator can be determined as $f_{esti} = mf_{in}$, where m is the sampling points in each period of the injected sinusoidal signal. The determination of m and f_{in} will be discussed in the following section.

C. Averaged sliding window

The current derivatives remain in the system model (8) for the estimation in both steady state and transient operation of the PMSM. In the digital control system, the continuous derivative of the current is approximated by the Forward Euler Discretization:

$$\frac{di_{d,q}}{dt} \approx \frac{i_{d,q}(k) - i_{d,q}(k-1)}{T_s}, \tag{9}$$

where T_s is the sampling time of the digital control system. The discretization results in the error between the continous current derivatives in the PMSM plant and the discrete approximated ones in the digital parameter estimator. An illustration of the deviation between the discrete and continous derivatives is shown in fig. 3, where the solid line s_1 and dashed line s_2 present the continuous and discrete derivatives respectly. According to equation (8), the deviation of the current derivatives can cause the inaccurate estimation of the parameters and even the divergence of the parameter estimator. On the other hand, the noise from the current derivatives is very large, which degrades the performance of the parameter estimator.

In order to reduce the influence of the error caused by the discretization, an averaged sliding window is introduced by taking the integration with half period of the injected sinusoidal signal on both sides of equation (8). The following equation can be obtained:

$$\begin{bmatrix}\widetilde{u_d}(k_1)\\ \widetilde{u_d}(k_2)\\ \widetilde{u_q}(k_1)\\ \widetilde{u_q}(k_2)\end{bmatrix} = \begin{bmatrix}\widetilde{i_d}(k_1) & \widetilde{\frac{di_d}{dt}}(k_1) & -\widetilde{\omega i_q}(k_1) & 0\\ \widetilde{i_d}(k_2) & \widetilde{\frac{di_d}{dt}}(k_2) & -\widetilde{\omega i_q}(k_2) & 0\\ \widetilde{i_q}(k_1) & \widetilde{\omega i_d}(k_1) & \widetilde{\frac{di_q}{dt}}(k_1) & \widetilde{\omega}\\ \widetilde{i_q}(k_2) & \widetilde{\omega i_d}(k_2) & \widetilde{\frac{di_q}{dt}}(k_2) & \widetilde{\omega}\end{bmatrix} \begin{bmatrix}\overline{R}\\ \overline{L}_d\\ \overline{L}_q\\ \overline{\Psi}_F\end{bmatrix}, \tag{10}$$

where the tilde in equation (10) denotes the averaged integral operation with discrete approximation:

$$\widetilde{x}(k) = 2f_{in}\int_{kT_s-\frac{1}{2f_{in}}}^{kT_s} x(t)dt \approx \frac{1}{n}\sum_{i=0}^{n-1} x(k-i)T_s. \tag{11}$$

Here $n = \frac{1}{2f_{in}T_s}$ denotes the number of system sampling points (for the digital controller) in half period of the injected signal. In equation (10), $\overline{R}$, $\overline{L}_d$, $\overline{L}_q$ and $\overline{\Psi}_F$ denote the averaged parameters in half period of the injected signal. It can be noticed that for the steady state operation, there is no difference between the instantaneous parameters and the averaged parameters. For the transient operation, the averaged parameters in half period of the sinusoidal signal are estimated. The integration operation with half peroid of the injected signal can utilize the full symmetry of the sinusoidal signal. Therefore, the error caused by the discretization of the current derivatives can be reduced by the integration. The model (10) can be directly implemented by the RLS algorithm described in section III.

D. Determination of A, f_{in} and m

In order to achieve a reliable estimation of the parameters, the amplitude of injected signal A has to be chosen larger than the measurement noise. However, the large amplitude A results in relatively large torque ripple in the PMSM. On the other hand, a large amplitude A causes relatively large difference in the d-axis inductance L_d of two adjacent sampling points for the estimator, which leads to the inaccuracy of the equation (8) and consequently the inaccuracy of the parameter estimation. Therefore, the amplitude of the injected signal should be chosen as small as possible.

The derivative of the injected signal is proportional to its frequency f_{in}. A large frequency f_{in} results in large derivative of the injected signal, which decreases the accuracy of the estimation. On the other hand, a small f_{in} decreases the sampling rate of the estimator, which results in slow convergence of the estimated parameters. Therefore, the frequency of the injected signal should be chosen to a proper value for a fast and accurate estimation. The number of sampling points k in one period of the injected signal determines the sampling rate of the estimator. A large k results in large sampling rate, which may cause the weak observability problem described in section II. Therefore, k has to be chosen to a proper value as large as possible.

TABLE I. PARAMETERS OF THE IPMSM

Rated current	i_{max}	2.3A
Rated torque	T_{max}	1.23Nm
Pole pair number	p	4
Stator resistance	R_s	3.3Ω
d-axis inductance	L_d	16mH
q-axis inductance	L_q	20mH
Flux linkage	Ψ_F	0.0886Vs/rad

The parameters A, f_{in} and m can be determined by tunning during the experiments, until the estimated PMSM parameters are identical to the measured values. When compared to the estimation method with square wave current injection in the d-axis [13], the execution and sampling of proposed estimation scheme does not have to wait for the steady state of the PMSM. Therefore, the convergence time of the proposed estimation scheme is faser than the one with square wave current injection if they are with the same algorithm such as RLS. On the other hand, the proposed scheme is feasible in transient state, which is more applicable for the natural operation of the PMSM in the reality.

V. EXPERIMENTAL RESULTS

The proposed estimation scheme is validated by several experiments. The parameters of the test PMSM are shown in table I. The proposed estimation scheme and the current controller are implemented by the dSPACE rapid control prototyping system (DS1103). In order to exclude the uncertainty of the inverter and to shown the performance of the estimator better, a power amplifier is utilized as the voltage source of the PMSM instead of the voltage source inverter. The sampling frequency of the digital controller is set to 8 kHz. The optimum parameters A, f_{in} and m are chosen to 0.1 A, 10 Hz and 40 respectively after the tunning process. Therefore, the sampling frequency of the estimator is 400 Hz. The speed of the IPMSM is controlled at the rotational speed 500 rpm by a load machine. The time constant τ of the current closed loop for the test PMSM is set to 0.01 s.

The estimation with square wave current injection similar to the method described in [13], which is with high accuracy in the steady state, is used as the reference for the comparison with the proposed estimation scheme. Instead of the NN algorithm, the RLS algorthm is utilized for the estimation with square wave current injection so that both estimation schemes have the same algorithm for the comparison. The sampling frequency of the estimator with square wave current injection is tunned to 10 Hz to ensure that i_d and i_q are absolutely settled in steady state.

The current trajectories of the PMSM with square wave and sinusoidal injected signals in steady state are shown in fig. 4. The amplitude of the square wave and sinusoidal injected signals is 0.1 A. The pulse of the square wave is 0.1 s. The experimental results for the parameter estimation with the corresponding current profile are shown in fig. 5. It can be noticed that the proposed estimation scheme has the same steady state values as the one with square wave current injection, which shows the accuracy of the estimated parameters. On the other hand, the convergence time of the proposed estimation scheme is much faster than the one with square wave current injection. The parameters of the propsoed

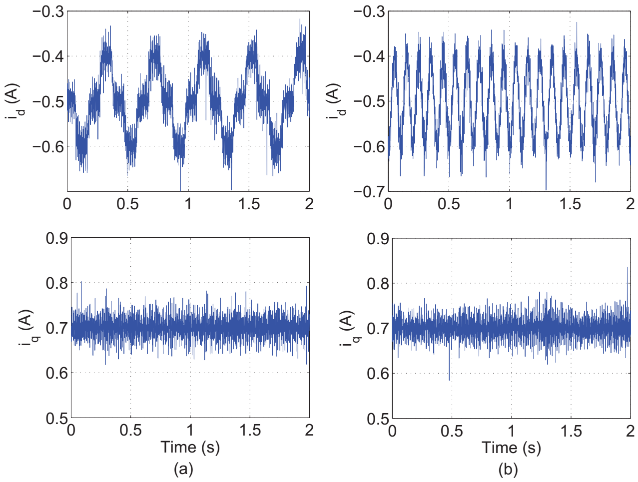

Fig. 4. Current of the PMSM with square and sinusoidal current injection: (a) square current (b) sinusoidal current.

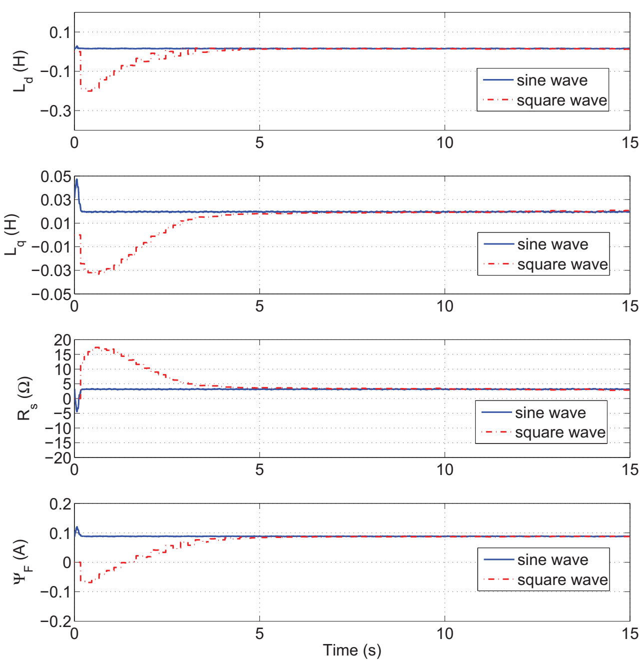

Fig. 5. Estimated parameters of the PMSM in steady state.

estimated scheme is stablized within 0.25 s since it can be executed with relatively high sampling rate during the transient states. Comparatively, the estimation with square wave can only executed in the steady state of the PMSM. Therefore, it has to wait until the PMSM is settled in steadty state, which results in low sampling rate and consequently slow convergence time.

The estimated inductances for the estimation with square wave and sinusoidal current injection depending on different current levels are shown in fig. 6. It can be noticed that the estimated parameters are approximately identical for both estimation schemes. Small difference is shown in the d-axis inductance L_d. However, it is resulted from the measurement

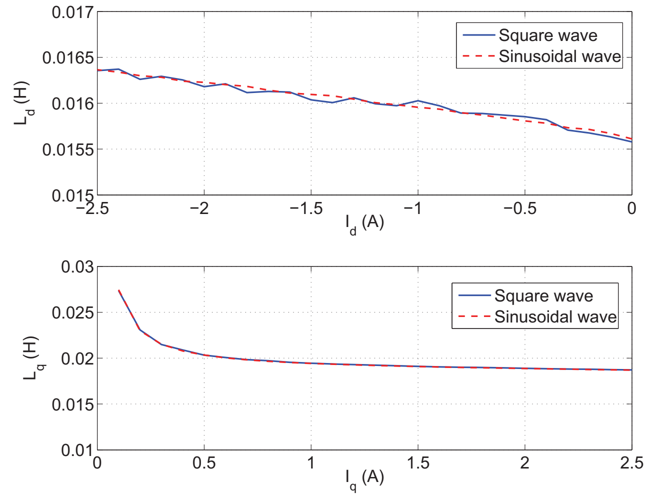

Fig. 6. Estimated parameters depending on the current levels.

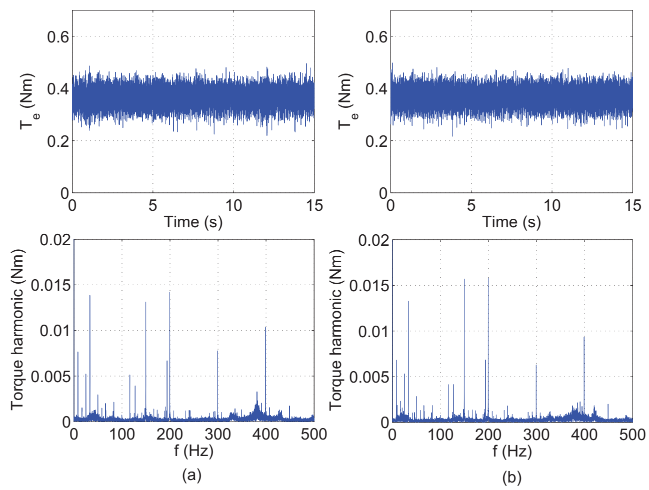

Fig. 7. Torque of the PMSM with and without sinusoidal current injection: (a) without current injection (b) with sinusoidal current injection 0.1 A and 10 Hz.

noise and the difference can be ignored. Therefore, the experimental results show the accuracy of the proposed estimation scheme for the steady state operation. The steady state torque and its high order harmonics of the PMSM with and without sinusoidal current injection are shown fig. 7. For the torque with sinusoidal current injection for the proposed estimation scheme, the current profile is the same with the one in fig. 4 (b). It can be noticed that there is almost no difference between the torques of the PMSM with and without sinusoidal current injection. Therefore, the proposed estimation scheme brings negligible torque ripples to the PMSM.

In order to show the feasiblility of the proposed estimation scheme in the transient state, a relatively large variation of the q-axis current i_q is imposed on the PMSM. The experimental results are shown in fig. 8. The d-axis current with sinusoidal current injection for this experiment is the same as the one in fig. 4 (b). Meanwhile, i_q varies from 0.2 A to 0.7 A periodically. The solid blue curves are the estimated

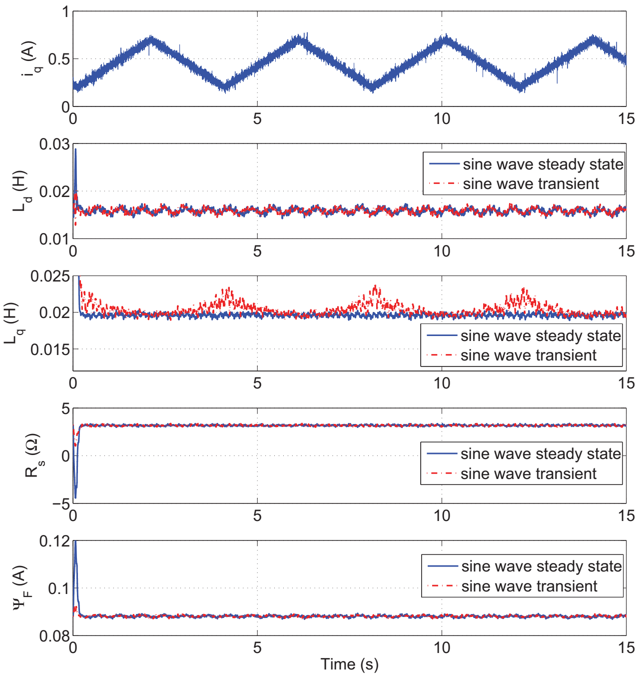

Fig. 8. Estimated parameters of the PMSM in transient state state.

parameters with proposed estimation scheme in steady state with $i_q = 0.7\mathrm{A}$, which has been shown in fig. 5. The dashed red curves show the estimated parameters during the transient state with i_q variation. Since the variation of i_q has limited influence on R, L_d and Ψ_F, the estimated values of R, L_d and Ψ_F converge to the values at steady state. On the other hand, the estimated L_q tracks the variation of i_q. From fig. 6, it is shown that $L_q = 23\mathrm{mH}$ at $i_q = 0.2\mathrm{A}$. Therefore, it can be noticed that the estimated L_q tracks the saturation effect due to the variation of i_q accurately during the transient state operation. Due to the averaged slding window, the estimated L_q lags the variation of i_q slightly.

VI. Conclusion

In this paper, a fast online estimation of the four parameters of the PMSM is proposed. A sinusoidal current injection in d-axis with a proper sampling principle for the estimator can prevent the ill convergence problem for the parameter estimation. The derivatives of the current are considered in such a way that the proposed estimation scheme is feasible in both steady state and transient state operation. To avoid the error convergence of the estimated parameters due to the deviation of discrete derivatives, an averaged sliding window with the length of half period of the sine wave is applied. The experimental results show the excellent performance of the proposed estimation scheme in both steady state and transient state operation. In the steady state operation, the estimated parameters converge to the same values when compared to the square wave current injection method. It is unnecessary for the proposed estimation scheme to wait until the current is settled in steady state. Therefore, when compared to the estimation scheme with square wave current injection, the proposed scheme can achieve fast and relatively accurate convergence for the online estimation of the four parameters of the PMSM in transient operation.

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