Totally Adaptive Observer for Speed Sensorless Induction Motor Drives: Simply a Cost of Extra Energy Consumption

Jiahao Chen, Jin Huang, Ming Ye
College of Electrical Engineering, Zhejiang University, Hangzhou, China, horychen@qq.com

***Abstract*—This paper addresses the method for online total parameters adaptation in speed sensorless induction motor drives. It is assumed that all the equivalent circuit parameters are poorly known. Based on the parameter sensitivity analysis, a high frequency low amplitude AC signal is superimposed onto magnetizing current so the norm of the regressive matrix of voltage model is boosted, which rejects the disturbance of the unknown flux error. Effective simulation results are included.**

***Index Terms*—opic—Parameter estimation, induction motor drives, speed sensorless, sensitivity analysis.opic—Parameter estimation, induction motor drives, speed sensorless, sensitivity analysis.T**

NOMENCLATURE

We use notations $r_s, L_s, L_m, L_r, r_r, u_s, \psi_r, i_s, i_r$ for T-circuit model, where ψ denotes flux linkage, u voltage, i current, r resistance, L inductance, and subscripts '$_s$', '$_r$' and '$_m$' designate stator, rotor, and magnetizing, respectively. And we adopt notations $r_s, L_\sigma, L_\mu, r_{req}, u_s, \psi_\mu, i_s, i_{req}, i_\mu \triangleq i_s + i_{req}$ for inverse Γ-circuit model, where $\psi_\mu \triangleq \frac{L_m}{L_r}\psi_r = L_\mu i_\mu$, $i_{req} \triangleq \frac{L_r}{L_m} i_r$, $r_{req} \triangleq \frac{L_m^2}{L_r^2} r_r$, $L_\mu \triangleq \frac{L_m^2}{L_r}$, $L_\sigma \triangleq L_s - L_\mu$, and the reciprocal of the rotor time constant is denoted by $\alpha = \frac{r_r}{L_r}$. Finally, we use ˆ and ˜ to denote estimated value and error, respectively (e.g., $\tilde{\theta} = \theta - \hat{\theta}$). $I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$, $J = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$.

I. REVIEW ON MULTIPLE PARAMETERS IDENTIFICATION IN AC DRIVES

The adaptive output regulation problem of a speed sensorless AC motor has been a formidable problem because the outputs (e.g., flux modulus and speed) are not measured. As a result, it differs from the classic adaptive control problem where the convergence of parameter adaptation is not necessary. In other words, any uncertainty in parameters affects the controlled accuracy of outputs to some extent. łKubota1994TDDAeRasmussen2001ChenHuang—LKY Form Matrosovrs

In most cases, full parameters identification can be achieved in drives with speed sensors [1], [2], but the full parameters identification is dismissed in the speed sensorless implementation [3]. Thus, the research on online identification of both resistances and inductances (in speed/position sensorless drives) is not many in literature.

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A. Induction Motor

For induction motor (IM), a back-stepping designed observer that is adaptive to r_s, r_{req}, L_μ and ω, has been proposed by Rasmussen et al. [4][1], and to fulfill the persistent excitation condition, a square wave is superimposed onto magnetizing current. But, it is locally stable, and requires the knowledge of L_σ. On the other hand, a speed estimator that is immune to uncertainty in L_σ, is given in [6], and it is extended to further include r_s and r_{req} identification. But, it in turn needs the knowledge of L_μ (as well as that of rotor inertia). Finally a research on total parameter identification is given by Minami et al. [**?**], [7], where they devise three interconnected regression models for ω, r_s, and other electrical parameters, respectively. In their implementation, parameters converge only if $\hat{r}_s$ has to be set to a fixed value. The method can be interpreted as the subset selection [8], [9], and has been also applied to synchronous generator [10].

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B. Permanent Magnet Synchronous Motor

For surface-mounted permanent magnet synchronous motor (PMSM), an adaptive interconnected observer is proposed [11], where an interconnected rearrangement of the motor model has resulted in two bilinear sub-systems. The results are: i) asymptotical convergence of estimation of stator resistance, stator inductance, load torque, rotor speed, and rotor position; ii) all the estimation errors are *practically stable* if exposed to uncertainty in rotor flux magnitude and other mechanical parameters. But, the *regularly* persistent excitation (PE) conditions of the inputs (to each sub-system) are not examined therein, so that the existences of the upper bounds of time-varying gain matrices (denoted by S_1, S_2 and S_η in [11]) are not assured. Actually, since the regular PE condition is represented by the state transition matrix (defined by $\frac{d}{dt}\Phi_u(\tau,t) = A(u(\tau))\Phi_u(\tau,t)$, $\Phi_u(t,t) = I$, where u denotes input), it is difficult to be checked, as stated in Zhang [12].

For interior PMSM, provided that rotor speed and rotor position are estimated from extended electromagnetic force (EEMF) model, a stand-alone RLS (recursive least-square) based parameter identification of stator resistance and both

[1]A journal version of this back-stepping design by different authors can be found in [5].

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d-axis and q-axis inductances, is achieved by injecting pseudo random binary sequence onto both γ-axis and δ-axis current commands [13]. It should be noted that the parameter vector in the linear regression model is function of rotor speed and rotor position error, so the parameter identification is only valid in steady state, and may be vulnerable to sudden load change. Besides, RLS does not account for noise and modelling error (e.g., rotor flux harmonics) in data matrix.

Finally, it is reported that simultaneous identification of stator resistance and rotor flux magnitude is not possible in normal operation of sensorless PMSM drives [14].

II. The Practical Flux Observer for IM

We construct the following practical flux observer in stator α-β frame (p means time derivative) [15]

$$\begin{cases} p\hat{\psi}_\mu^{VM} = u_s^* - \hat{r}_s i_s - D\hat{L}_\sigma p i_s + v^{VM} \\ p\hat{\psi}_\mu^{CM} = -\hat{\alpha}\left(\hat{\psi}_\mu^{CM} - \hat{L}_\mu i_s\right) + \hat{\omega} J \hat{\psi}_\mu^{CM} \end{cases} \quad (1)$$

where $DL_\sigma = |i_s| \frac{d}{d|i_s|} L_\sigma(|i_s|) + L_\sigma(|i_s|)$ is the dynamic total leakage inductance, $\hat{\alpha} = \hat{r}_{req} \big/ \hat{L}_\mu$ and ω the electrical angular speed; To simulate the critical instability of the voltage model, we introduce the bias and drift vector b in the command voltage $u_s^* = u_s + b$ [16], and the corrective term follows as $v^{VM} = -\hat{b} - k^{VM}\varepsilon,\ k^{VM} \in R_+$; Superscripts '^{VM}' and '^{CM}' stand for voltage model and current model, respectively. Equation (1) describes two open-loop flux estimators that imitate each other through corrective term v^{VM} and parameter adaptation laws $\dot{\hat{\theta}} = \Gamma^{-1}\left[\ \Phi^{VM^T} \quad \Phi^{CM^T}\ \right]\varepsilon$. (New symbols are defined below.)

Now, let define the flux mismatch ε and flux error e, and it yields the error dynamics (2)

$$\begin{cases} \varepsilon \triangleq \hat{\psi}_\mu^{VM} - \hat{\psi}_\mu^{CM} \\ e \triangleq \psi_\mu - \hat{\psi}_\mu^{CM} \end{cases} \Rightarrow p\begin{bmatrix} \varepsilon \\ e \end{bmatrix} = \begin{bmatrix} -k^{VM}I & -\alpha I + \omega J \\ 0_{2\times 2} & -\alpha I + \omega J \end{bmatrix}\begin{bmatrix} \varepsilon \\ e \end{bmatrix} + \begin{bmatrix} \Phi^{VM} & \Phi^{CM} \\ 0_{2\times 4} & \Phi^{CM} \end{bmatrix}\tilde{\theta} \quad (2)$$

where $\tilde{\theta}$ is the error vector of parameters, Φ^{VM} and Φ^{CM} the blocks of the regressive matrix, and Γ^{-1} the diagonal gain matrix

$$\tilde{\theta} = \left[\ \tilde{\theta}^{VM^T} \quad \tilde{\theta}^{CM^T}\ \right]^T, \tilde{\theta}^{VM} = \left[\ \tilde{b}_\alpha \quad \tilde{b}_\beta \quad \tilde{r}_s \quad D\tilde{L}_\sigma\ \right]^T, \tilde{\theta}^{CM} = \left[\ \tilde{r}_{req} \quad \tilde{L}_\mu \quad \tilde{\omega}\ \right]^T$$

$$\Phi^{VM} = \begin{bmatrix} 1 & 0 & i_{\alpha s} & p i_{\alpha s} \\ 0 & 1 & i_{\beta s} & p i_{\beta s} \end{bmatrix}, \Phi^{CM} = \begin{bmatrix} i_{\alpha s} - L_\mu^{-1}\hat{\psi}_{\alpha\mu}^{CM} & \hat{\alpha}L_\mu^{-1}\hat{\psi}_{\alpha\mu}^{CM} & -\hat{\psi}_{\beta\mu}^{CM} \\ i_{\beta s} - L_\mu^{-1}\hat{\psi}_{\beta\mu}^{CM} & \hat{\alpha}L_\mu^{-1}\hat{\psi}_{\beta\mu}^{CM} & \hat{\psi}_{\alpha\mu}^{CM} \end{bmatrix}$$

Remark: It can be shown that identifying the bias and drift vector b (along with other parameters) is not a burden at all, even in the case where sinusoid is superimposed onto magnetizing current command i_{Ms}^* to distinguish r_{req} from ω, because the frequency of the sinusoid should be different from synchronous frequency of the field [17], [18].

Remark: The influence of $\tilde{L}_\mu$ depends on certain machines. Specifically, for machines with large rotor time constant, uncertainty in $\hat{L}_\mu$ won't cause large errors on other estimated parameters such as $\hat{r}_s$ and $\hat{\omega}$.

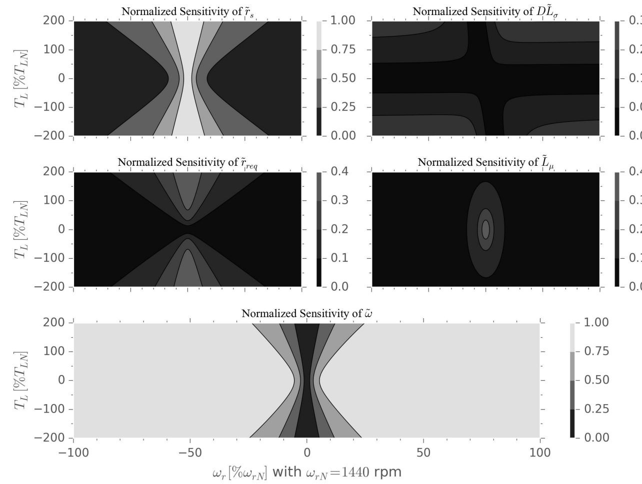

Fig. 1. Normalised sensitivity of parameter error over the working condition plane T_L-ω, i.e., the contour of magnitude of each column of Φ_N.

A. Parameter Sensitivity Analysis with respect to Working Conditions

During the sensitivity analysis, along with $\tilde{b}$, the second order error terms are also neglected [19], so it reaches at

$$\Phi_N\tilde{\theta}_N \approx \begin{bmatrix} r_s i_{\alpha s} & DL_\sigma p i_{\alpha s} & -r_{req} i_{\alpha,req} & r_{req} i_{\alpha\mu} & -\omega\psi_{\beta\mu} \\ r_s i_\beta & DL_\sigma p i_{\beta s} & -r_{req} i_{\beta,req} & r_{req} i_{\beta\mu} & \omega\psi_{\alpha\mu} \end{bmatrix}\begin{bmatrix} \tilde{r} \\ D\tilde{L} \\ \tilde{r}_{re} \\ \tilde{L} \\ \end{bmatrix}$$

And for each normalised parameter error, the magnitude of the corresponding column of Φ_N is plotted over different working conditions (i.e., load T_L and speed ω), as shown in Fig. 1, in which the flux modulus is kept constant. All the numerical values are the same with those of [15], i.e., $r_s = 3.04\,\Omega$, $r_r = 1.69\,\Omega$, $L_s = L_r = 0.4826$ H, $L_m = 0.47$ H, and $T_{LN} = 26.5$ Nm.

Remark: At low speed, where $\tilde{\omega}$ sensitivity becomes comparable with that of $\tilde{L}_\mu$ and $\tilde{r}_{req}$, it is desired to identify L_μ and r_{req} along with r_s, so that speed estimation accuracy is improved. Note that to ensure the PE condition, usually sinusoids are superimposed onto the magnetizing current command i_{Ms}^*. On the contrary, according to the sensitivity analysis, at high speed, only DL_σ needs to be updated (if the load is sufficiently heavy). As a result, the requirement of flux modulus varying is relaxed. This is reasonable, because above the rated speed where stator voltage command u_s^* approaches voltage limitations of the inverter, flux modulus variation will impair motor torque capability.

III. Parameter Sensitivity Shaping

Once we choose to adopt the flux observer given in (1), we decide to bear with the theoretical disturbance of the unknown flux error e. In this case, the PE condition is not anymore a sufficient condition for parameter convergence, but for merely

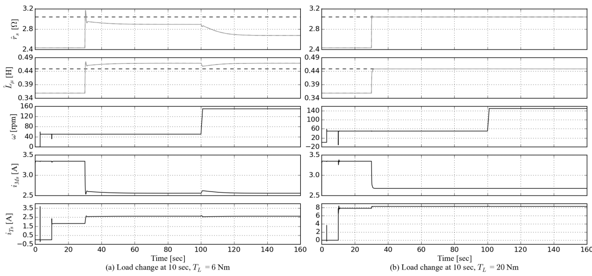

Fig. 2. Simulated simultaneous identification of r_s and L_μ when sensed speed is used for control. The control strategy is the indirect field orientated control. Speed command is firstly $\omega^* = 50$ rpm and then goes up to $\omega^* = 150$ rpm. (a) biased estimation at light load. (b) consistent estimation at heavy load.

bounded parameter estimation (indeed, the parameter error can become quite large) [20].

Intuitively, disturbance reduction is desired, or equivalently, the gain of the 'disturbance channel' should be lowered, e.g., via a observer pole assignment by Tomita et al. [21]. However, the observer pole assignment affects not only flux error e, but also parameter estimation, so it is not considered. Rather, our objective is then changed to raise the 'signal-to-noise ratio'. That is, we can boost the norm of VM's regressive matrix Φ^{VM}, by injecting relatively high frequency AC signal onto magnetizing current (the so-called parameter sensitivity shaping). This assures the convergence of θ^{VM} even when exposed to e at low speed, where the sensitivity of $\tilde{L}_\mu$ becomes remarkable. *After $\tilde{\theta}^{VM}$ tends to zero, the asymptotical stability of the whole error dynamics* (2) *is guaranteed by the PE condition as well as the multi-variable LKY lemma (see Appendix of [15]).*

A. Identifying only r_s and L_μ for Illustrating the Effect of Disturbance e

We simulate the simultaneous identification of r_s and L_μ, when speed is sensed (see Fig. 2). The PE condition in this case is always satisfied, as long as the load torque is nonzero. Note that the sensitivity of $\tilde{L}_\mu$ is higher at lighter load, and it leads to larger disturbance e. Consequently, large e causes errors on $\hat{r}_s$ and $\hat{L}_\mu$, even when the PE condition ($T_L \neq 0$) is satisfied.

B. Low Speed Operation with Total Parameters Adaptation

Simulation results of the adaptive flux observer (1) are given in Fig. 3. Observe that, thanks to the high frequency low amplitude flux variation, the speed distortion is found very limited.

IV. Conclusion

We have presented a totally adaptive observer that is adaptive to r_s, L_σ, r_{req}, L_μ, and ω, which works even during speed transient. The only requirement to achieve this is the well-selected pulsating of the magnetizing current, though this will cause extra energy consumption (such as copper loss and iron loss). This statement is supported by the parameter sensitivity

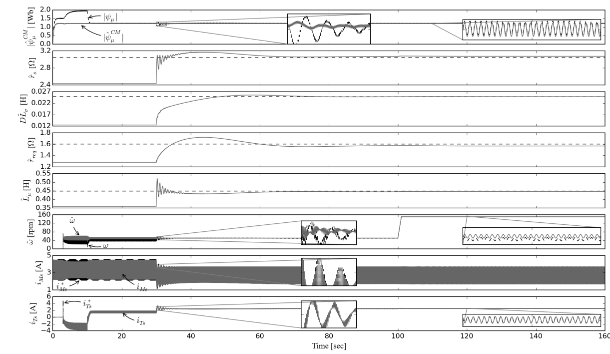

Fig. 3. Simulated total parameters adaptation in speed sensorless IM drive. Flux modulus command is $|\psi_\mu^*| = 1.2 + 0.01\sin(50\pi t)$ Wb. i_{Ms} is the magnetizing current, while i_{Ts} is the torque current. Except speed, adaptation begins at $t = 30$ sec. $k^{VM} = 100$, and $\Gamma^{-1} = \mathrm{diag}(0, 0, 25, 0.1, 25, 15, 6e5)$.

analysis. The study is still primitive, where we have to assume there is no skin effect, and L_σ is constant so that $L_\sigma = DL_\sigma$.

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