Energy Conversion and Management 51 (2010) 600–605

Contents lists available at ScienceDirect

Energy Conversion and Management

journal homepage: www.elsevier.com/locate/enconman

On state estimation in electric drives

A.E. Leon *, J.A. Solsona

Instituto de Investigaciones en Ingeniería Eléctrica (IIIE) "Alfredo Desages" (UNS-CONICET), Departamento de Ingeniería Eléctrica y de Computadoras, Universidad Nacional del Sur (UNS), 1253 Alem Avenue, P.O. 8000, Bahía Blanca, Argentina

ARTICLE INFO

Article history:
Received 9 April 2009
Accepted 7 November 2009
Available online 2 December 2009

Keywords:
State estimation
Electric drives
Robustness
Sensorless control
Observers
Dirty derivative

ABSTRACT

This paper deals with state estimation in electric drives. On one hand a nonlinear observer is designed, whereas on the other hand the speed state is estimated by using the dirty derivative from the position measured. The dirty derivative is an approximate version of the perfect derivative which introduces an estimation error few times analyzed in drive applications. For this reason, our proposal in this work consists in illustrating several aspects on the performance of the dirty derivator in presence of both model uncertainties and noisy measurements. To this end, a case study is introduced. The case study considers rotor speed estimation in a permanent magnet stepper motor, by assuming that rotor position and electrical variables are measured. In addition, this paper presents comments about the connection between dirty derivators and observers, and advantages and disadvantages of both techniques are also remarked.
© 2009 Elsevier Ltd. All rights reserved.

1. Introduction

In the modern industry, motion control is a topic of vital importance and a lot of mechanisms applied in speed and position control use electric drives [1–3]. There exist different kinds of electric drives. The production is in continuous evolution due to the change rate of the technology allows to build motors and converters increasing the reliability and decreasing the cost [4,5]. However, in many applications it is necessary to use sophisticated control strategies to obtain high performance drives. Generally, these strategies are based on the machine dynamic model by using state-space representation [6–8]. In the last 10 years, different new strategies have been used to design nonlinear control laws. Among others, the feedback linearization [9,10], inter-connection and damping assignment [11], adaptive control [12] and back-stepping [13] can be mentioned. These strategies allow to obtain high performance drives. Nevertheless, regarding from the implementation point of view a drawback appears. In order to implement the control strategies all state measurements are needed. To overcome this drawback a lot of proposals can be found in the literature. The more common approach consists in using nonlinear laws including estimators in the closed control loop. In this way, some sensors are avoided resulting in a more practical and cheaper controller [14–18].

In electrical drive applications are frequently found speed estimates obtained from position measurements, acceleration estimators based on speed sensors, and mechanical-sensorless schemes to avoid mechanical sensors.

A lot of these estimators include a prediction term based on the model and a correction term that weighed in some way, provides the information contained in the model and the measurements. The majority of estimation algorithms can be included in some of the following categories:

- *Open loop estimators*: they use a model to predict the variable value [19].
- *High gain observers*: they consider a model for the signal prediction and a correction term that is a smooth function of the measured and the estimated variables [20].
- *Sliding mode observers*: they use a prediction based on the model and a hard nonlinear function of the measurements and/or the estimated variables as a correction term [21].
- *Estimators differentiating the measurement*: they employ a high pass filter (named dirty derivator in this work) [22].
- *Stochastic observers*: they are similar to the high gain observers, but inside a stochastic context. The most widely diffused stochastic observers are the Kalman filter and its non linear version, the Extended Kalman filter [23].

There exist a great number of papers introducing algorithms that can be framed in some of the mentioned categories (see, for instance [24], to find a revision for permanent magnet *AC* motors based drives). In other researches, Hakan Akpolat et al. [25] use a derivator to estimate the speed from the position measurement, and Vainio [26] propose a derivator to estimate the acceleration from the speed measurement. In [22], speed is estimated

* Corresponding author. Tel.: +54 291 459 5101x3338; fax: +54 291 459 5154.
E-mail addresses: aleon@ymail.com (A.E. Leon), jsolsona@uns.edu.ar (J.A. Solsona).

0196-8904/$ - see front matter © 2009 Elsevier Ltd. All rights reserved.
doi:10.1016/j.enconman.2009.11.007

differentiating the position measurement. Harnefors and Nee [27] introduce a position and speed observer-based estimator for *AC* motors, using electric variable measurements. In [28] mechanical variables are estimated from electrical ones in a brushless *DC* motor. In [29] a nonlinear reduced-order observer is used to estimate mechanical variables in a permanent magnet synchronous motor.

In spite of either of the above techniques can be used, the estimator performances vary in the presence of uncertainty. For this reason, there exist some aspects to be kept in mind for choosing the estimator when both model uncertainties and noisy measurements are present.

In practice, it is common to find dirty derivators and observers. These estimators are treated in different ways and their connection, to the best knowledge of the authors, cannot be found in the literature. However, both estimators can be connected. By understanding this connection, it is possible to choose the more appropriate estimator depending on the application case. To this end, a case study is introduced. The case study considers rotor speed estimation in a Permanent Magnet (PM) stepper motor, by assuming rotor position and electrical variables are measured.

This work is organized as follows: In Section 2 the PM stepper motor model is presented and the speed estimation case is described. The performance analysis under model uncertainties and noisy measurements is introduced in Section 3. Finally, in Section 4 conclusions are drawn.

2. Speed estimation

The problem of estimating the mechanical variables (position, speed and/or acceleration) by using measurements from mechanical and/or electrical variables (voltages and currents) is often found in motion control based on electrical drives. To this end, different kinds of estimators have been introduced. In general, estimators are constructed to guarantee the estimation error tends to zero with a predetermined convergence rate. A well-known estimation technique uses an observer consisting of a prediction and a correction term.

In position control applications, speed is usually estimated to obtain high performance controllers. Among others are frequently found dirty derivators and observers. In a given case, the designer could inquire which is the more appropriate option to achieve good performance. The key for selecting between a dirty derivator and an observer is to understand the connection between them.

In this paper, in order to establish the connection between dirty derivators and observers, a case study is developed. For this purpose, subsections below present a nonlinear observer with linear error dynamics and a dirty derivator to estimate speed in a PM stepper motor.

2.1. PM stepper motor model

The PM stepper motor model is described in stationary two-axes reference frame by the following equations (see [30]):

$$\dot{\theta} = \omega, \tag{1}$$

$$\dot{\omega} = \frac{T_e}{J} - \frac{B}{J}\omega - \frac{K_D}{J}\sin(4N_r\theta), \tag{2}$$

$$\dot{i}_\alpha = -\frac{R}{L}i_\alpha + \frac{K_m}{L}\omega\sin(N_r\theta) + \frac{v_\alpha}{L}, \tag{3}$$

$$\dot{i}_\beta = -\frac{R}{L}i_\beta - \frac{K_m}{L}\omega\cos(N_r\theta) + \frac{v_\beta}{L}, \tag{4}$$

with,

$$T_e = K_m\left(i_\beta\cos(N_r\theta) - i_\alpha\sin(N_r\theta)\right), \tag{5}$$

where i_α, i_β and v_α, v_β are currents and voltages in phases α and β, respectively. L and R are the self-inductance and resistance of each phase winding, K_m is the motor torque constant, N_r is the number of rotor teeth, J is the rotor inertia, B is the viscous friction constant, ω is the rotor speed, θ is the motor position, and the term $K_D\sin(4N_r\theta)$ is the detent torque.

2.2. Observer-based estimation with lineal error dynamics

In order to construct a rotor speed estimator for the PM stepper motor, it is possible to design an asymptotic reduced-order observer with linear dynamics error. The key to obtain exponential convergence to zero of the estimation error resides in an appropriate election of the observer prediction term. For instance, the prediction term can be based on the model given by (1)–(4). Recalling equation describing the mechanical dynamics, yield,

$$\dot{\omega} = \frac{T_e}{J} - \frac{B}{J}\omega - \frac{K_D}{J}\sin(4N_r\theta). \tag{6}$$

From (6) a Luenberger-like observer is proposed,

$$\dot{\hat{\omega}} = \underbrace{\frac{T_e}{J} - \frac{B}{J}\hat{\omega} - \frac{K_D}{J}\sin(4N_r\theta)}_{\text{prediction term}} + \underbrace{K(\dot{\theta} - \dot{\hat{\theta}})}_{\text{correction term}}, \tag{7}$$

where "$\wedge$" stands for estimated value, and K is the correction term gain. Note that in order to obtain the speed estimate, the derivative of θ is needed. In this case, the high-frequency noise could be amplified. To overcome this drawback a variable change on Eq. (7) is introduced. Firstly, it is defined a new intermediate variable, ξ,

$$\xi \triangleq \hat{\omega} - K\theta, \tag{8}$$

which will allow us to obtain the speed estimation without having to derivate the position measurement. Differentiating (8) it is obtained,

$$\begin{aligned}\dot{\xi} &= \dot{\hat{\omega}} - K\dot{\theta}, \\ &= \frac{T_e}{J} - \frac{B}{J}\hat{\omega} - \frac{K_D}{J}\sin(4N_r\theta) - K\hat{\omega}.\end{aligned} \tag{9}$$

Finally, replacing (8) in (9) the speed estimator description is obtained,

$$\dot{\xi} = -\left(\frac{B}{J} + K\right)\xi - \left(\frac{BK}{J} + K^2\right)\theta + \frac{T_e}{J} - \frac{K_D}{J}\sin(4N_r\theta), \tag{10}$$

$$\hat{\omega} = \xi + K\theta. \tag{11}$$

It should be noticed that the speed model plays an important role in the observer performance, since the convergence to zero of the error is only obtained if model represents exactly to the motor. When the parameters in the speed model are not perfectly known, the observer's robustness must be analyzed.

2.3. Dirty derivator-based estimation

As mentioned, in many cases measurements are differentiated to obtain estimates to be used in control strategies. However, it must be kept in mind that derivative is an anticausal operator computable only in a theoretical way. In practice to obtain a causal estimate, the derivative operator is often approximated by a high pass filter (dirty derivator). The dirty derivator transfer function is given by,

$$D(s) = \frac{\widehat{\Omega}(s)}{\Theta(s)} = \frac{s}{(\tau s + 1)} = \frac{K}{\left(1 + \frac{K}{s}\right)}, \tag{12}$$

where $K = 1/\tau$ is a positive constant. In this case, the measurement and the estimate are related as follows:

$$\hat{\omega}(s) = \dot{\hat{\theta}}(s) = \frac{K}{(1+\frac{K}{s})}\theta(s). \tag{13}$$

By assuming that Laplace Transforms exist, Eq. (13) can be written in the time domain in the following way:

$$\left(1+\frac{K}{s}\right)\hat{\omega}(s) = K\theta(s),$$
$$\hat{\omega}(s) + K\hat{\theta}(s) = K\theta(s),$$
$$\mathscr{L}^{-1}\{\hat{\omega}(s) + K\hat{\theta}(s)\} = \mathscr{L}^{-1}\{K\theta(s)\},$$
$$\hat{\omega}(t) = K\Big(\theta(t) - \hat{\theta}(t)\Big), \tag{14}$$

then,

$$\hat{\omega} = \dot{\hat{\theta}} = 0 + K(\theta - \hat{\theta}). \tag{15}$$

Differentiating (15) the estimator can be expressed as follows:

$$\dot{\hat{\omega}} = \underbrace{0}_{\text{prediction term}} + \underbrace{K(\dot{\theta} - \dot{\hat{\theta}})}_{\text{correction term}}. \tag{16}$$

In this point it is possible to see the connection between the two ways of estimation presented above. The estimate obtained with a dirty derivator is equivalent to the estimate obtained with an observer with constant gain in the correction term and speed prediction term equal to zero (compare (7) and (16)). In many cases, the value of the speed can be different from zero, so that a big estimation error can be introduced for selecting the prediction term in a wrong way. In the next section, this phenomenon is analyzed.

3. Analysis in presence of uncertainty

Following, an analysis by assuming uncertainties in the estimator prediction terms and noisy measurements is introduced.

3.1. Estimation error analysis

Let us denote the actual speed value by η (i.e. $\dot{\theta} = \eta$) and the position estimation error by $\varepsilon_\theta = \theta - \hat{\theta}$. Then, from (14) the position estimation error dynamics results,

$$\dot{\varepsilon}_\theta = \eta - K\varepsilon_\theta, \tag{17}$$

then, solving the previous differential equation,

$$\varepsilon_\theta(t) = \varepsilon_\theta(0)e^{-Kt} + \int_0^t e^{-K(t-\tau)}\eta(\tau)d\tau, \tag{18}$$

where it is assumed that the integral exists. Therefore by using (15),

$$\dot{\hat{\theta}} = K\left(\varepsilon_\theta(0)e^{-Kt} + \int_0^t e^{-K(t-\tau)}\eta(\tau)d\tau\right), \tag{19}$$

and the speed estimation error is,

$$\varepsilon_\omega = \eta - \hat{\omega} = \eta - \dot{\hat{\theta}}, \tag{20}$$

then by replacing Eq. (19) in (20) yield,

$$\varepsilon_\omega(t) = \eta(t) - K\left(\varepsilon_\theta(0)e^{-Kt} + \int_0^t e^{-K(t-\tau)}\eta(\tau)d\tau\right). \tag{21}$$

The speed estimation error depends on the rotor speed and its convergence to zero is strong dependent on the speed value. Except for particular speed values, the estimation error does not converge to zero. This is due to that zero was chosen as value for the prediction term. It is very important to note that the error appearing between the actual speed and the estimated speed depends on the estimator prediction value (zero when the dirty derivator is used).

For instance, it is possible to analyze the performance when the rotor speed is constant,

$$\eta(t) = \Psi. \tag{22}$$

The estimation error can be calculated from (21), such that,

$$\begin{aligned}\varepsilon_\omega(t) &= \Psi - K\left(\varepsilon_\theta(0)e^{-Kt} + \Psi\int_0^t e^{-K(t-\tau)}d\tau\right),\\ &= \Psi - K\left(\varepsilon_\theta(0)e^{-Kt} + \frac{\Psi}{K}(1-e^{-Kt})\right),\\ &= (\Psi - K\varepsilon_\theta(0))e^{-Kt},\end{aligned} \tag{23}$$

therefore in steady state,

$$\lim_{t\to\infty}\varepsilon_\omega(t) = \lim_{t\to\infty}(\Psi - K\varepsilon_\theta(0))e^{-Kt} = 0. \tag{24}$$

In this case the steady state error is equal to zero. However, as it was previously mentioned, it is only a particular case. Note that the actual speed is a constant and the prediction in (16) coincides with the value of the actual speed time-derivative. Nevertheless, in general the asymptotic prediction value must coincide with the actual signal value to attain asymptotic error equal to zero.

For example, we consider now that the actual speed has a ramp behavior, being defined as,

$$\eta(t) = \beta t. \tag{25}$$

Thus, in this case the estimation error is,

$$\begin{aligned}\varepsilon_\omega(t) &= \beta t - K\left(\varepsilon_\theta(0)e^{-Kt} + \beta\int_0^t e^{-K(t-\tau)}\tau d\tau\right),\\ &= \frac{\beta}{K} - \left(K\varepsilon_\theta(0) + \frac{\beta}{K}\right)e^{-Kt},\end{aligned} \tag{26}$$

As consequence the steady state error will be,

$$\lim_{t\to\infty}\varepsilon_\omega(t) = \lim_{t\to\infty}\left(\frac{\beta}{K} - \left(K\varepsilon_\theta(0) + \frac{\beta}{K}\right)e^{-Kt}\right) = \frac{\beta}{K}. \tag{27}$$

This case uncovers two features. One of them, is that when the actual speed is not null, the dirty estimator has steady state error and a prediction term different to zero must be chosen to attain asymptotic exponential convergence. The other feature from the above equation, is that when the estimator gain, K, is increased the steady state error decreases. However, as it is going to be shown in the following lines the K gain should be bounded due to the measurement noise.

Therefore, for a general speed behavior, it is recommended using estimators based on observers having prediction terms based on the speed model. By denoting $\eta_0(t)$ to an arbitrary prediction term, the speed estimation results,

$$\dot{\hat{\theta}} = \eta_0(t) + K(\theta - \hat{\theta}). \tag{28}$$

In this case, the estimation error becomes,

$$\varepsilon_\omega(t) = \eta(t) - K\left(\varepsilon_\theta(0)e^{-Kt} + \int_0^t e^{-K(t-\tau)}\Delta\eta(\tau)d\tau\right), \tag{29}$$

where $\Delta\eta(t) = \eta(t) - \eta_0(t)$ is the prediction error. When $\eta_0(t)$ is a better approximation than zero (the prediction term value for the dirty derivator), the observer (see Eq. (28)) performance is higher than the estimator based on an dirty derivator.

It is important to remark that even under the perfect measurement assumption, the estimator based on a dirty derivator introduces an error (see Eq. (27)) that perhaps it could be diminished when a different value from zero is used for the prediction term of the signal differentiated.

It should stand out that from the point of view of the prediction, one should opt for a η_0 value as similar to η as possible. Given a previous knowledge of the motor, zero is an extreme and only advisable value when the model of the motor is completed unknown.

Previously, it was supposed that the measurement was perfect. However a more realistic case must consider that the measured signal has certain grade of uncertainty (for instance, measurement noise) and it can be modeled adding a signal (we will denote r to this signal). In this case, on the Eq. (28), the estimation dynamics is given by,

$$\begin{aligned}\dot{\hat{\theta}} &= \eta_0 + K((\theta + r) - \hat{\theta}),\\ &= \eta_0 + K(\theta - \hat{\theta}) + Kr,\end{aligned} \tag{30}$$

therefore similarly like it was calculated for the Eq. (29), the estimation error will be,

$$\begin{aligned}\varepsilon_\omega(t) &= \eta(t)\\ &\quad - K\left(\varepsilon_\theta(0)e^{-Kt} + \int_0^t e^{-K(t-\tau)}\Delta\eta(\tau)d\tau + K\int_0^t e^{-K(t-\tau)}r(\tau)d\tau\right).\end{aligned} \tag{31}$$

Eq. (31) shows that when increasing the value of the constant K we achieve a bigger convergence rate to zero of the error. Nevertheless, it must be noted that K multiplies the signal, r representing the uncertainty in the measurement, consequently high values of K amplify uncertainties in the position measurement. As a consequence, the best gain value is a trade-off among the convergence rate, the uncertainty in the prediction term and the uncertainty in the measurement. Since the estimation is a *pondered average* of the prediction and the measurement, it is reasonable to think that the value of the constant K can be increased when the value of the uncertainty or noise in the measurement is low.

Table 1
Data and parameters of the devices.

Device	Parameter	Value	Unit
PM Stepper Motor	N_r	50	–
	L	1.1	mH
	R	10	Ω
	K_m	0.113	Nm/A
	K_D	0.0339	Nm
	J	5.7×10^{-6}	kg m^2
	B	1×10^{-3}	Nm s/r
	ω_0	0	r/s
Observer	K_{mo}	$0.9 \times K_m$	Nm/A
	K_{Do}	$0.7 \times K_D$	Nm
	J_o	$1.2 \times J$	kg m^2
	B_o	$1.1 \times B$	Nm s/r
	K (case 1)	104.56	1/s
	K (case 2)	524.56	1/s
	Pole (case 1)	−280	1/s
	Pole (case 2)	−700	1/s
	ω_0	30	r/s
Dirty derivator	K	600	1/s

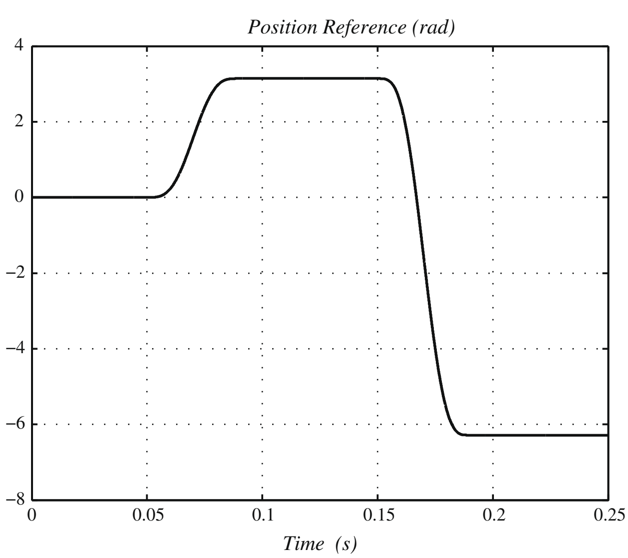

Fig. 1. Position reference.

3.2. Estimator comparison tests

In order to illustrate the performance of the estimators, several tests of a position control in an electrical drive containing a PM stepper motor are presented. Feedback linearization is used as control strategy [30], but in order to satisfy our goal (i.e., to compare estimators) the control law is built by using the actual values.

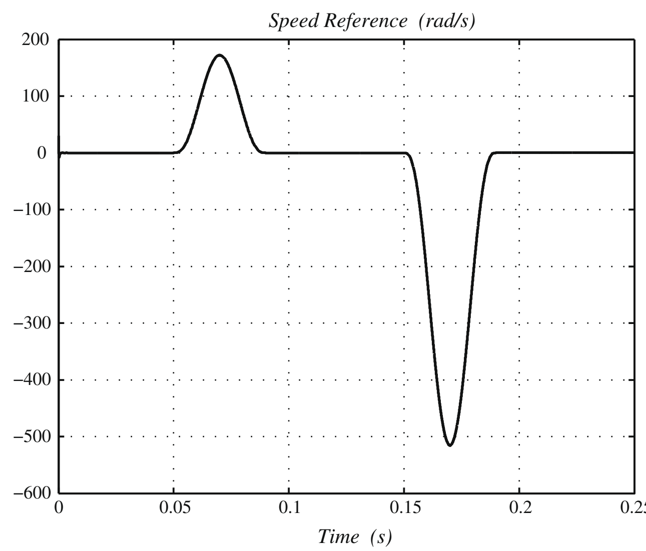

Fig. 2. Speed profile to estimate.

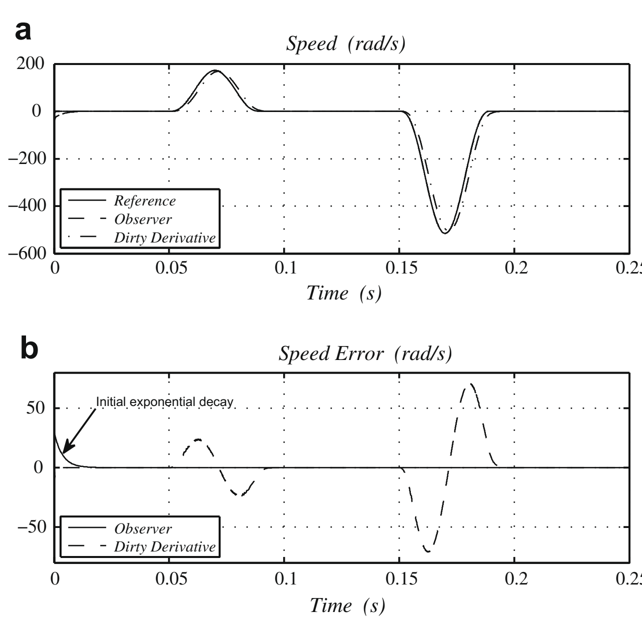

Fig. 3. Speed error without model uncertainty.

Comparisons are carried out taking into account both model uncertainties (see observer rows in Table 1 which show mismatches between actual and observer parameters) and noisy measurement, where we consider a 1.5% of white noise in sensors. The rest of data and parameters used in tests are detailed in Table 1. Position and speed reference trajectories used in the assessment are shown in Figs. 1 and 2.

Firstly, in Fig. 3 the speed estimation errors are illustrated by assuming estimator parameters coincide with the motor ones and state variables are obtained without noise. As it can be seen, after an initial exponential decay (see Fig. 3b), the estimation error converges to zero when the observer with linear error dynamics is used. However, that does not happen in the dirty derivator. When the rotor speed is estimated via a dirty derivator, the estimation error coincides with zero only when actual speed is zero. This agrees with the theoretical derivations from the above section.

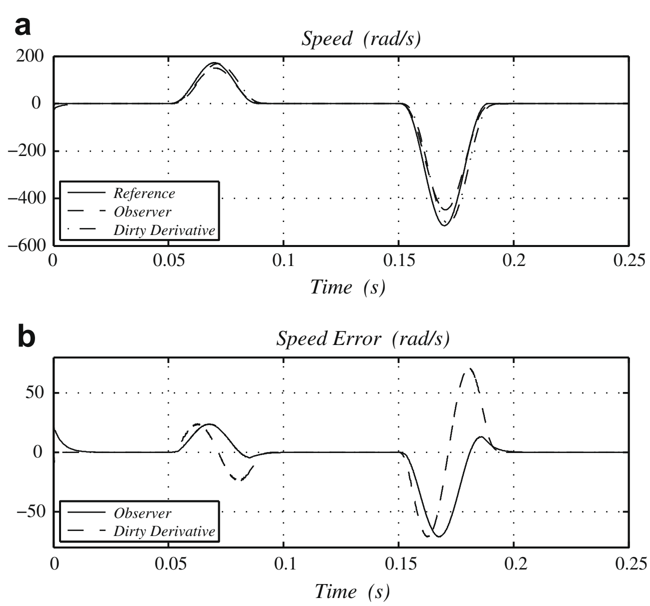

Fig. 4. Speed error with model uncertainty.

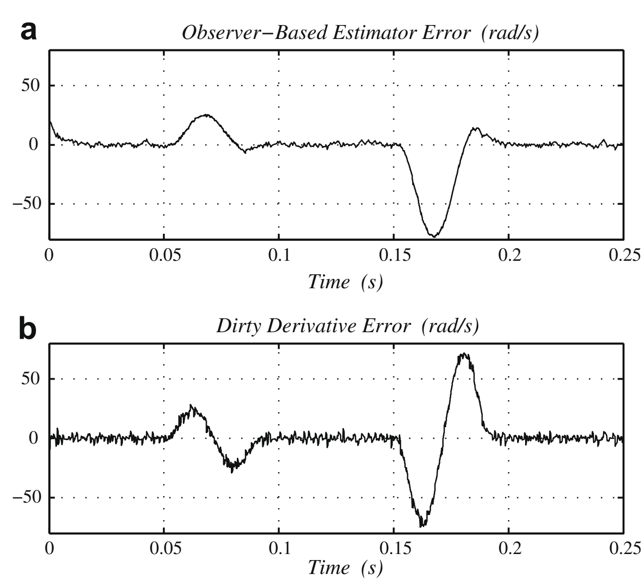

Fig. 5. Speed error with model uncertainty and noisy measurement. Low observer gain, case 1.

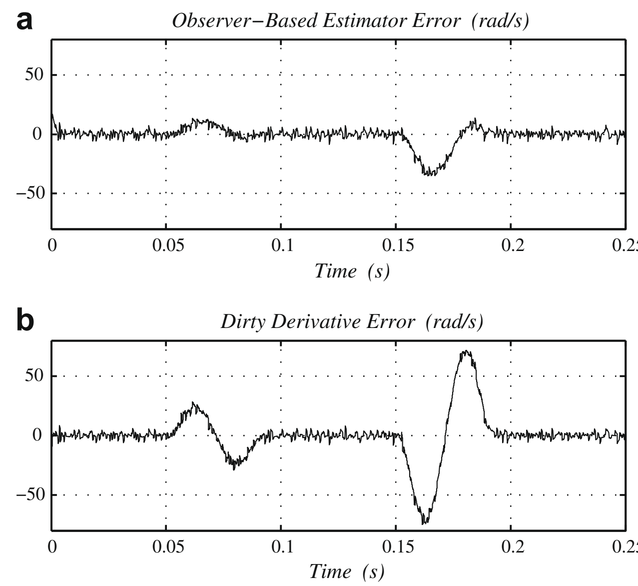

Fig. 6. Speed error with model uncertainty and noisy measurement. High observer gain, case 2.

Note that dirty derivator could perform in a bad way although the parameters are assumed to be known and the measurements are assumed to be perfect.

Then, in Fig. 4 tests taking into account parameter uncertainties are presented. In this case, the observer introduces an error since the prediction term does not copy the model in an exact way.

Finally, both estimators are tested by considering parameter uncertainties and noisy measurements. Two different gain values of the observer correction term have been set. In case 1 (Fig. 5), although both estimation methods present similar error deviation, the dirty derivator is more vulnerable to the noisy measurement than the reduced-order observer which gives a smooth estimation. In case 2 (Fig. 6) a higher gain was selected to the reduced-order observer (see observer gains in Table 1), and it can be seen that estimates are equally noisy, however the observer introduces less error than the dirty derivator.

It is worth to note that in the above tests we considered typical parameter uncertainties. However, if there exists a greater or complete uncertainty of the motor parameters, then the dirty derivator could have a better performance than the observer due to the prediction term will give a bad information during the estimation.

4. Discussion and conclusion

In spite of reduced- and full-order observers could be used, they in most cases, would allow us to improve the estimate regarding uncertainty in the variable measured, but the algorithm to be implemented should integrate a greater number of differential equations. In addition, the full-order observers are, in general, more sensitive to the peaking phenomenon (see [31]) and then it could happen that during the convergence transient, the estimation error grows before arriving to the steady-state value. For this reasons, sometimes a reduced-order observer is preferred.

In the introduced case study, it is clear that the estimator performance strongly depends on both the prediction term uncertainty and the noise in the variable measured. It is frequently found several researches that use either observer whose prediction term is based on a signal model or dirty derivator whose prediction term is equal to zero. For this reason, the connection between both kind of estimators has been introduced in this paper. In addition, it has been demonstrated that robustness is a key issue to be considered in order to choose the estimator (i.e. for choosing the prediction term). In the author opinion, the results introduced in this work should be taken into account to select estimators to be used. Since if a dirty derivator is selected to estimate signals in electric drives, it should be analyzed the replacement of it by a signal-model-based observer due to it could be a better option depending on the uncertainty levels as it was discussed in this paper. Besides, analysis and conclusions developed in this section are not only applicable to electrical drives but also to other similar signal estimation applications.

Acknowledgments

This work was supported by Universidad Nacional del Sur (UNS), Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET) and Agencia Nacional de Promoción Científica y Tecnológica (ANPCyT), Argentina.

References

[1] Guzinski J, Diguet M, Krzeminski Z, Lewicki A, Abu-Rub H. Application of speed and load torque observers in high-speed train drive for diagnostic purposes. IEEE Trans Ind Electron 2009;56(1):248–56.
[2] Boukhezzar B, Siguerdidjane H. Nonlinear control with wind estimation of a DFIG variable speed wind turbine for power capture optimization. Energy Convers Manage 2009;50(4):885–92.
[3] Ustun SV, Demirtas M. Modeling and control of V/f controlled induction motor using genetic-ANFIS algorithm. Energy Convers Manage 2009;50(3):786–91.
[4] Bose BK. Power electronics and motor drives recent progress and perspective. IEEE Trans Ind Electron 2009;56(2):581–8.
[5] Boldea I. Control issues in adjustable speed drives. IEEE Ind Electron Mag 2008;2(3):32–50.
[6] Finch JW, Giaouris D. Controlled AC electrical drives. IEEE Trans Ind Electron 2008;55(2):481–91.
[7] Yazdanpanah R, Soltani J, Arab Markadeh GR. Nonlinear torque and stator flux controller for induction motor drive based on adaptive input–output feedback linearization and sliding mode control. Energy Convers Manage 2008;49(4):541–50.
[8] Vaez-Zadeh S, Jalali E. Combined vector control and direct torque control method for high performance induction motor drives. Energy Convers Manage 2007;48(12):3095–101.
[9] Bodson M, Chiasson J. Differential-geometric methods for control of electric motors. Int J Robust Nonlinear Control 1998;8(11):923–54.
[10] Liutanakul P, Pierfederici S, Meibody-Tabar F. Nonlinear control techniques of a controllable rectifier/inverter-motor drive system with a small dc-link capacitor. Energy Convers Manage 2008;49(12):3541–9.
[11] Ortega R, Lora A, Nicklasson PJ, Sira-Ramrez H. Passivity-based control of Euler–Lagrange systems, mechanical, electrical and electromechanical applications. London: Springer-Verlag; 1998.
[12] Hajatipour M, Farrokhi M. Adaptive intelligent speed control of switched reluctance motors with torque ripple reduction. Energy Convers Manage 2008;49(5):1028–38.
[13] Dawson D, Hu J, Burg T. Nonlinear control of electric machinery. New York (USA): Marcel Dekker; 1998.
[14] Cirrincione M, Pucci M, Cirrincione G, Capolino G-A. Sensorless control of induction motors by reduced order observer with MCA EXIN + based adaptive speed estimation. IEEE Trans Ind Electron 2007;54(1):150–66.
[15] Asaei B, Rostami A. A novel starting method for BLDC motors without the position sensors. Energy Convers Manage 2009;50(2):337–43.
[16] De Angelo C, Bossio G, Solsona J, Garcia GO, Valla MI. Mechanical sensorless speed control of permanent-magnet AC motors driving an unknown load. IEEE Trans Ind Electron 2006;53(2):406–14.
[17] Chuang T-S, Liang J-W. A stator flux oriented current vector control of a sensorless 6/4 SRM for reduction of acoustic noise and vibration. Energy Convers Manage 2008;49(11):3075–9.
[18] Chan TF, Wang W, Borsje P, Wong YK, Ho SL. Sensorless permanent-magnet synchronous motor drive using a reduced-order rotor flux observer. IET Elect Power Appl 2008;2(2):88–98.
[19] Bolognani S, Peretti L, Zigliotto M. Parameter sensitivity analysis of an improved open-loop speed estimate for induction motor drives. IEEE Trans Power Electron 2008;23(4):2127–35.
[20] Ghanes M, De Leon J, Glumineau A. Cascade and high-gain observers comparison for sensorless closed-loop induction motor control. IET Control Theory Appl 2008;2(2):133–50.
[21] Xu Z, Rahman MF. An adaptive sliding stator flux observer for a direct-torque-controlled IPM synchronous motor drive. IEEE Trans Ind Electron 2007;54(5):2398–406.
[22] Behal A, Feemster M, Dawson D, Mangal A. Sensorless rotor velocity tracking control of the permanent magnet stepper motor. IEEE Int Conf Control Appl 2000:150–5.
[23] Szabat K, Orlowska-Kowalska T. Performance improvement of industrial drives with mechanical elasticity using nonlinear adaptive Kalman filter. IEEE Trans Ind Electron 2008;55(3):1075–84.
[24] Johnson JP, Ehsani M, Guzelgunler Y. Review of sensorless methods for brushless DC. In: IAS annual meeting industry applications conference, IAS'99, vol. 1; 1999, pp. 143–50.
[25] Hakan Akpolat Z, Asher GM, Clare JC. Dynamic emulation of mechanical loads using a vector-controlled induction motor-generator set. IEEE Trans Ind Electron 1999;46(2):370–9.
[26] Vainio O. Adaptive derivative estimation for delay-constrained acceleration measurement. IEEE Trans Ind Electron 1999;46(5):933–5.
[27] Harnefors L, Nee H-P. A general algorithm for speed and position estimation of AC motors. IEEE Trans Ind Electron 2000;47(1):77–83.
[28] Tomita M, Senjyu T, Doki S, Okuma S. New sensorless control for brushless DC motors using disturbance observers and adaptive velocity estimations. IEEE Trans Ind Electron 1998;45(2):274–82.
[29] Solsona J, Valla MI, Muravchik C. A nonlinear reduced order observer for permanent magnet synchronous motors. IEEE Trans Ind Electron 1996;43(4):492–7.
[30] Zribi M, Chiasson J. Position control of a PM stepper motor by exact linearization. IEEE Trans Autom Control 1991;36(5):620–5.
[31] Sussmann HJ, Kokotovic PV. The peaking phenomenon and the global stabilization of nonlinear systems. IEEE Trans Autom Control 1991;36(4):424–40.