STATE ESTIMATION AND OBSERVABILITY ANALYSIS OF AC DRIVES

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Abstract: This paper deals with state estimation methods for alternating current electric drives, mainly in sensorless scenario. Both induction machines and synchronous drives are discussed. The main contribution to the state of the art is probably solving of several observability conditions, on which the estimation is only possible.

Keywords: AC drives, AC induction machine, Permanent magnet synchronous motor, observability analysis, Kalman filtering, EM algorithm

1 INTRODUCTION

Alternating current electrical drives found their way to everyday life applications due to their high reliability, durability and ease of maintenance. Sometimes speed and position measurement can be overly expensive. In this case, sensorless methods can be applied. Typical sensorless application consists of a PWM inverter as a voltage source and a current measurement device (Hall-effect sensor). No position or speed sensor is mounted. Mechanical quantities required for high-performance control are only estimated, typically based on some numerical computations. In this article, we focused on several sensorless algorithms. Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF) and Particle Filter (PF) as well as Moving Horizon Estimator (MHE) were used.

But for any kind of estimation, observability of the physical quantity is necessary. That's the reason why observability for several cases has been investigated. Sufficient conditions for observability of speed, position, load torque and moment of inertia are stated in the next section.

2 OBSERVABILITY ANALYSIS

We proceeded from the aprroaches in [2], where conditions for asynchronous motor observability in sensorless scenario are found. In the aprroach the observability matrix is calculated and its determinant is obtained. As the matrix must have a full rank for the system to be observable, the determinant cannot equal zero. More details are not discussed here due to the lack of space. We note that the criterion used gives only sufficient, not necessary conditions.

2.1 IPMSM MOTOR

Let's start with an interior permanent magnet sychronous motor (IPMSM). For observability analysis, we need to carry out our computations in a stator reference frame. For the mostly used case, we try to estimate the position and the speed only from currents. The state variables are i_a, i_b, ω, θ, meaning stator current components in carthesian coordinates, electrical angular speed and angular position, respectively. Observability determinant consists of about 40 complicated terms. However, we found an easy way to simplify this: the use of Park's transform (rotation) as well as grouping terms, which allows for plugging in equations of state variable derivatives. The final equation has a form of

$$0 \neq -\left(\frac{\mathrm{d}i_q}{\mathrm{d}t}(i_d + \frac{K_e}{L_d - L_q}) - i_q\frac{\mathrm{d}i_d}{\mathrm{d}t}\right) + \omega\left(\left(i_d + \frac{K_e}{L_d - L_q}\right)^2 + i_q^2\right), \tag{1}$$

where K_e is a rotor permanent magnet flux and i_d, i_q are components of stator current in a rotor reference frame. Let's start with an assumption that the rotor is fixed, so the speed is zero (on this condition, SPMSM is unobservable). We can consider the equation 1 as a form of ordinary differential equation, and integrate it in time to obtain the following condition (C_5 is an arbitrary constant):

$$\left|i_d(t) + \frac{K_e}{L_d - L_q}\right| |C_5| \neq |i_q(t)|. \tag{2}$$

So one of the current components must not be linearly dependent on the the second one. In normal operation modes, the condition is almost always true, since there exists a rotating magnetic field. So we have proven observability of the IPMSM motor when the rotor is fixed and the field is rotating.

The case of non-zero speed can be treated similarly. Againg we have a form of ordinary differential equation, resulting in

$$\theta + \theta_0 \quad \neq \quad -\arctan\frac{\left(i_d + \frac{K_e}{L_d - L_q}\right)}{i_q}. \tag{3}$$

The interpretation is as follows: left and right sides of the equation are equal only when the currents are rotating in an opposite direction than the rotor. That is only one time instant, as this require the rotor to rotate in an anti-synchronous manner, which is physically impossible. The observability is proven.

2.2 Estimate of a load torque and moment of inertia

We have tried to obtain a sensorless estimate of two more parameters of the motor: load and moment of inertia. At first, we investigated the observability conditions and we found (using similar approach as above) the same conditions for both synchronous and asynchronous motors. The first one for the synchronous drive being

$$-L_d L_q\left(\frac{\mathrm{d}i_q}{\mathrm{d}t}(K_e + (L_d - L_q)i_d) + (Ld - Lq)i_q\frac{\mathrm{d}i_d}{\mathrm{d}t}\right) \neq 0 \tag{4}$$

and for the asynchronous one

$$(L_m^2 - L_r L_s)\left(\Psi r_\beta\frac{\mathrm{d}i_\alpha}{\mathrm{d}t} + i_\alpha\frac{\mathrm{d}\Psi r_\beta}{\mathrm{d}t} - i_\beta\frac{\mathrm{d}\Psi r_\beta}{\mathrm{d}t} - \Psi r_\alpha\frac{\mathrm{d}i_\beta}{\mathrm{d}t}\right). \tag{5}$$

Here $\Psi r_\alpha, \Psi r_\beta$ are magnetic flux components. Both equations have the same meaning – time derivative of electrical (generated) torque. So the motor must generate a changing torque to distinguish between the load torque and the moment of intertia. This is not only sufficient condition, but also necessary (otherwise we would have one equation with two unknowns).

3 ESTIMATORS AND CONTROL

From the tests done, EKF and UKF reached similar performance in terms of mean square error, PF did not work better. Interesting properties has MHE, being very insensitive to Euler integration errors (satisfactory results up to sampling period 2ms).

The control setting was classical vector control for both drive types. The inner loop regulates current components, the outer one speed and the field (for asynchronous motor). In a normal start-up, the

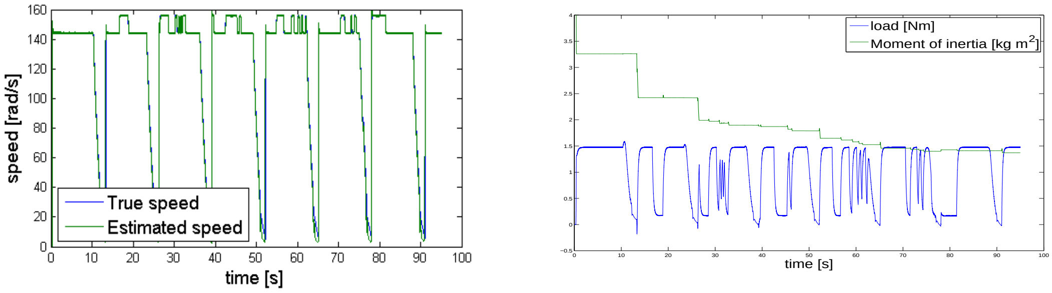

Figure 1: True and estimated quantities - speed (a), and load torque and moment of inertia (true moment of inertia about 0,0016, displayed 1000× higher value to scale to the load) (b)

speed controller saturates and requires constant currents. This in turn causes constant torque, and the motor looses observability, when we estimate also the moment of inertia and load torque. That's why the test has been conducted only on a free running motor.

A well-known problem in the implementation of a Kalman-filter based estimator is tuning. We need to set the covariance matrix for a process noise and for a measurement noise. Commonly this is done manually and the matrices become hand-engineered parameters. However, this can be quite easily overcome utilizing an EM (Expectation Maximization) algorithm. In our case, it iteratively changes two steps: it obtains the best state estimate by Extended Kalman Smoother (RTS Smoother), and based on that it recalculates the covariance matrices [1].

4 EXPERIMENTAL VERIFICATION

The experiments were carried out on an asynchronous drive in an uncontrolled setting. We sampled measured data (voltages and currents) with an osciloscope with changing load and speed. The rest was done offline on a PC. The first step was to identify the drive parameters by simplex method (sum of square errors as a cost function). After that the data was passed to the aforementioned EM algorithm to obtain covariance matrices. Finally, other measured sequence was processed by the Extended Kalman filter to test the observability of speed, load torque and moment of inertia. The result is on the figure 3.

5 CONCLUSION

To our best knowledge, this work was the first thorough treatment of the observability issues connected to the IPMSM drive. Also the observability analysis of moment of inertia and load torque has never been published in literature. As a spin-off, estimation and control algorithms have been implemented in Matlab. The EM algorithm was proven to help to find suitable parameters for the Kalman filter. And all was tested on the real data to support derived conditions.

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