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Observability measurement and control strategy for induction machine sensorless drive in traction applications

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Abstract: Electrical traction using induction machine sensorless control requires high observer performance for all speed ranges, even for low speed or regenerative braking conditions which appear frequently during long time. It is well known that the speed of induction motors is unobservable at very low stator frequencies. This paper uses an observability index to continuously analyze speed observability for sensorless control of induction machines. The correlation between observability-index and observer performance is illustrated in a Hardware in the Loop (HIL) experimental test-bench combining the well-known vector control with an extended Kalman filter. Thanks to the observability-index information, an optimal strategy is proposed to design controllers to guide the system away from undesirable behavior and avoid the weak observability-index region by taking into account all working constraints. A simplified case is presented to improve the speed observer performance, which was tested in the same conditions with the same HIL test-bench to experimentally validate the proposed sensorless control for traction applications.

Keywords: Railway electric traction, induction machine sensorless drive, observability analysis, electric automotive control, application of power electronics.

1. INTRODUCTION

To reduce the number of physical sensors, and the direct and maintenance costs they induce, industrial solutions have been based on state observers for years. For an induction machine drive, the speed sensor is the most critical because of its cost and its high failure rate compared to current and voltage sensors. In the case of a traction application, the high failure rate of the speed sensor is mainly caused by the harsh environment (vibration, impacts, temperature...). However, in this application, it is compulsory to have a precise sensorless drive on the entire speed and torque range. The problem of the speed sensorless induction machine drive has been first addressed in the 1980s (Tamai et al. (1985)). Such a drive nevertheless suffers from one major drawback for an industrial application: it cannot in the same time be adapted to any kind of induction machine and regulate the torque precisely on the whole speed range (Kim and Sul (2011)). This is due, on one hand, to speed unobservability when the fundamental modeling is used with the aim of an application to a wide kind of induction machines, and on the other hand, to the dependency to the machine geometry of high frequency injection methods used to get additional speed information at very low stator frequency. The critical points are known to be around zero stator frequency (Canudas De Wit et al. (2000)), and the difficulty will be all the higher as it remains in this area for a long time. For a railway traction application, this corresponds to an electrical braking up to zero speed or to a rollback start, when the speed takes negative values while the torque takes positive ones, the equivalent of a hill start in an automotive application. While (Ghanes et al. (2006)) proposes a way to ensure the stability of speed observation during these phases that can be adapted easily to any kind of induction machine, it does not permit to ensure the precision and the dynamic of this observation for a long rollback start. In a railway application, rollback starts can take as long as tenths of seconds.

In this paper, a deep analysis of the observability is undertaken and used to design a control approach taking into account continuous observability measurements. The weak observability avoidance strategy proposed in this work can be easily implemented for different industrial uses of induction machines speed sensorless drive such as in traction application.

The paper is organized as follows: after some preliminaries, an observability analysis and its continuous measurement for nonlinear systems are presented in section 2, the application to the case of an induction machine is studied in section 3. Section 4 uses this continuous observability

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measurement to analyze more precisely the speed observability evolution. Section 5 proposes a general approach to take into account observability in a control. A weak observability-index avoidance strategy tested in railway traction case shows that it is possible to use a speed sensorless drive to control the torque precisely on the whole speed range, including during a rollback start.

2. PRELIMINARIES

The study of system observability and controllability can be traced back to the development of state space representations by Kalman (Kalman (1960)). Although these concepts have been widely used for the study of linear systems, their applicability to the analysis of nonlinear systems was limited. In the 1970s, major works by Hermann and Krener (Hermann and Krener (1977)) and Sussmann (Sussmann (1976)), presented alternative means to study the observability of nonlinear systems. These approaches relied on Lie algebra and geometric control theory.

2.1 Observability analysis : Lie derivative

In a nonlinear system, the traditional approach of identifying the observability through the use of an observability gramian fails. However, the observability of nonlinear systems may be evaluated by the analysis of the rank condition of the observability matrix using Lie derivatives (Hermann and Krener (1977)).

Considering the nonlinear system Σ

$$\Sigma : \begin{cases} \dot{x} = f(x,u) \\ y = h(x), \end{cases} \tag{1}$$

where the state x is in $\mathbb{R}^n$; $u \in \mathbb{R}^m$ is the control signal; $y \in \mathbb{R}^p$ is the output vector and f and h are nonlinear function of suitable dimensions. The observability matrix of the system $\mathcal{O}_\Sigma$ is given by

$$\mathcal{O}_\Sigma = \frac{\partial L}{\partial x}, \tag{2}$$

where L is the observation space of the system :

$$L = \begin{bmatrix} \mathcal{L}_f^0 h \\ \mathcal{L}_f^1 h \\ \vdots \\ \mathcal{L}_f^p h \end{bmatrix} \text{ and } \begin{cases} \mathcal{L}_f^0 h = h \\ \mathcal{L}_f h = \frac{\partial h}{\partial x} f \\ \forall k \in \mathbb{N}^*, \mathcal{L}_f^k = \mathcal{L}_f(\mathcal{L}_f^{k-1} h) \end{cases} \tag{3}$$

Theorem 1. (Hermann and Krener (1977)) : If system (1) satisfies the observability rank condition at x_0, it is locally weakly observable at x_0.

The observability rank condition is necessary and sufficient as soon as the system is weakly controllable (Hermann and Krener (1977), Theorem 3.12), which covers most cases. In almost all cases, it is thus correct to identify as unobservable points those for which the rank condition is not respected. Indeed, the notion of a measurement of observability has additional significance for nonlinear systems, where certain sections of the system trajectory may correspond to unobservable regions for a given output equation. One of the methods for evaluating the observability (continuously) of a nonlinear system is based on the use of Lie derivatives evaluated at various locations along the system trajectory.

The first element to notice is that this concept can only provide qualitative results (binary information) on the observation system. Obviously, quantitative measurement of observability i.e. an information of how far a system is from becoming unobservable, is a key issue in practical applications on state estimation theory.

2.2 Observability measurement : observability index

The problem of a continuous measurement of observability has been treated for linear systems using both the observability matrix and the observability gramian (Müller and Weber (1972)). Among the proposed measurements, such as the observability of the least observable state (minimum eigenvalue of the observability matrix or gramian), or a mean observability of the system (determinant and trace of the observability matrix or gramian), each one can give a different part of the information. No one can be seen as the best observability continuous measurement. Its interest is nevertheless limited in real application since, for a linear system, the observer tuning is done only once and does not depend on the working point of the system.

For nonlinear systems, the information of a continuous measurement of observability offers more perspective for observer or control tuning. However a similar definition is more complicated to get and to prove. The definitions found in the literature mainly use the observability matrix (Böhm et al. (2008)) or the empirical observability gramian (Krener and Ide (2009), Singh and Hahn (2006)). The empirical observability gramian, described in (Lall et al. (2002)), provides a numeric value of the observability. Its result is relevant for a given point or trajectory. On the other hand, the observability matrix provides an analytic value that remains relevant for all points or trajectories. Thus, we chose to use the observability matrix to define the observability continuous measurement.

Once the matrix used to support the definition has been chosen, the quantitative measurement of observability remains to be defined. The same way than for linear systems, three criteria can be used : the minimum eigenvalue, the trace or the determinant. The similar need to reduce the information contained in a matrix to a scalar number exists for identification problems using the sensibility matrix (Qian et al. (2014)). We can thus refer to these works to select the most interesting criteria (Franceschini and Macchietto (2008)). The use of the determinant of the matrix is presented as the most significant since it considers the confidence in the observation of the global system, considering the errors committed on each state weighted by the sensibility of the observation to this given state. This criterion is also invariant with re-scaling transformations and it is the most used.

Definition 1. (Observability index) the continuous measurement of the observability of the system Σ, η_Σ, is :

$$\eta_\Sigma = \det(\mathcal{O}_\Sigma^T \mathcal{O}_\Sigma), \tag{4}$$

where $\mathcal{O}_\Sigma$ is the observability matrix given by (2).

The larger this value is, the farther the system will be from unobservable region.

Remark 1. The important point is that the determinant of the observability matrix (2) tends to zero when approaching unobservable regions i.e. the correction term