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Rotor Temperature Modeling of an Induction Motor using Subspace Identification ⋆

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Abstract: Knowledge of the rotor temperature is important for an efficient and secure operation of induction motors, especially in electric vehicles. However, in vehicle applications, measuring the rotor temperature is not possible, making a model-based estimation necessary. In this paper, the modeling of the rotor temperature is presented based on subspace identification, a black-box system identification method. The performed steps to achieve a high quality model are described in detail, including a systematic selection of inputs from the large amount of available signals. The resulting model is applied as an open-loop observer and evaluated using measurements of a specially equipped induction motor on a test bench, where the rotor temperature was measurable. Finally, some remarks are given regarding the on-board implementation of the identified model into a vehicle control unit for open-loop observation of the rotor temperature.

Keywords: Induction motors, Dynamic modeling, System identification, Observers, Open-loops, Subspace methods

1. INTRODUCTION

The efficiency and reliability of electric drives plays an important role in many technical systems. This holds especially for electric vehicles, where limited energy in the batteries requires high efficiencies to achieve competitive driving ranges compared to conventional combustion engine vehicles. Therefore, due to their high efficiency, permanent magnet synchronous motors are widely used for this application. However, induction motors are an interesting alternative due to their comparatively low price and good robustness. Thermal overload of induction motors is a main reason for failures (see e.g. Briz et al. (2008) and the references therein). For vehicle applications, to reach the required efficiencies as well as power and energy densities, these motors are operated as closely as possible to their designed operation limits, making failures due to thermal overload even more likely. Additionally, to increase the efficiency of induction motors, sophisticated control algorithms have been developed over the last years. They require the rotor temperature to be known, as an increasing rotor temperature results in a higher coil resistance and thus in higher losses. While the temperature of the stator can be measured easily, the temperature of the rotating part of the motor is not measurable on-board a vehicle. Instead, an estimator for this temperature is required, which accurately computes the temperature signal and is computationally simple enough for a real-time application in an electronic control unit (ECU) of the vehicle.

In literature, there exist various methods to estimate the rotor temperature during operation of the motor. Many approaches, like Kral et al. (2004) and Kral et al. (2012), are based on simplified thermal models. Others estimate the rotor resistance, e.g. Beguenane and Benbouzid (1999). A relatively new approach is to inject an additional electric signal with specific properties into the terminals of the motor and then determine the motor state from the response on these signals. This approach is presented e.g. in Briz et al. (2008). Common to all these approaches is the difficulty to determine the necessary parameters of the underlying models, especially if there is no knowledge available on the internal construction of the motor.

In contrast, an open-loop observer approach based on a black-box model is used in this paper. The model is retrieved from measurement data of the input and output signals, i.e. by system identification (black-box modeling, see e.g. Ljung (1999)). This approach does not rely on any information about the internal processes or constructional parameters of the motor (except general assumptions like LTI), but requires the rotor temperature to be measurable at least on a test bench to generate the identification data set. However, in laboratory environments, such rotor temperature measurements are possible even for machines of which the constructional parameters are unknown. In addition, black-box models are typically relatively simple due to the implicit order reduction, but still accurate, which is beneficial for the on-board application in a vehicle control unit.

Subspace-based state-space system identification (4SID), which is often called subspace identification (SID) in short,

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is a class of system identification methods developed in the last few decades. Most of the SID methods identify the system order and system parameters of a discrete time state-space model in a non-iterative procedure. A detailed comparison of the most commonly used methods can be found e.g. in Buchholz (2010). In this work, the "Predictor-Based Subspace-Identification" (PBSID, see Chiuso and Picci (2005); Chiuso (2007a)) in its optimized version (also called PBSIDopt in some publications) is applied on the problem of identifying the rotor temperature model of the induction motor.

This paper is organized as follows: Section 2 introduces the basic mathematical notation and shortly revisits the applied PBSID method for linear, time-invariant (LTI) systems. The main contribution of this paper is given in Section 3, where the derivation of the black-box model for the open-loop rotor temperature observer is described in detail. It starts with a description of the measurements and optimal identification setup to yield an accurate model. Then, the identification results are presented and validated within the open-loop observer application. Finally, remarks on the model initialization as well as on computational aspects for on-board applications are given. The paper closes with some conclusions in Section 4.

2. PBSID FOR LTI SYSTEMS

The general flow chart of common SID methods is given in Fig 1. Their goal is a non-iterative determination of the system order n and parameters of a discrete time state-space model

$$\boldsymbol{x}(k+1) = \boldsymbol{\Phi}\boldsymbol{x}(k) + \boldsymbol{H}\boldsymbol{u}(k)\,, \tag{1a}$$

$$\boldsymbol{y}(k) = \boldsymbol{C}\boldsymbol{x}(k) + \boldsymbol{D}\boldsymbol{u}(k) \tag{1b}$$

based on measurements of the system inputs $\boldsymbol{u} \in \mathbb{R}^{n_u}$ and outputs $\boldsymbol{y} \in \mathbb{R}^{n_y}$ of the system. The state vector is thereby denoted by $\boldsymbol{x} \in \mathbb{R}^{n}$. In this paper, the optional direct feedthrough term $\boldsymbol{D}\boldsymbol{u}(k)$ in the output equation (1b) is not used. The sampling time of the model $T_s \in \mathbb{R}^+$ equals the fixed sampling time of the measurements.

The PBSID method is one of the youngest subspace algorithms first introduced by Chiuso and Picci (2005); Chiuso (2007a,b). In the following, the basic idea and procedure of the PBSID method are summarized in a descriptive form. A detailed mathematical description can be found in the original literature (Chiuso (2007a,b)) as well as e.g. in van Wingerden (2008); Buchholz (2010); Buchholz and Werner (2012).

In the first step (data conditioning), the measured data is arranged in matrices with block-hankel structure. The data is thereby divided into a past horizon with length p and a future horizon with length f with $n \le f \le p$. These matrices are used in the second step (data preprocessing) to estimate a high order autoregressive with exogenous inputs (ARX) model (HOARX). The parameters of this ARX model coincide with the elements of the so called *oblique predictor* $\boldsymbol{\mathcal{O}}_{p,f}$, which hence can be constructed from these estimates. The oblique predictor represents the autoregressive part of the system for the whole data set and can moreover be denoted as a matrix product of some extended observability matrix and a state sequence, which are both unknown. In the noise-free case, the rank of $\boldsymbol{\mathcal{O}}_{p,f}$ equals the system order n (see e.g. Buchholz (2010)). In this case, the state sequence can be computed directly from the oblique predictor using the singular value decomposition (SVD) and based on this state sequence, a least squares (LS) estimate of the parameters of the state-space model (1) can be retrieved (step 4, parameter estimation).

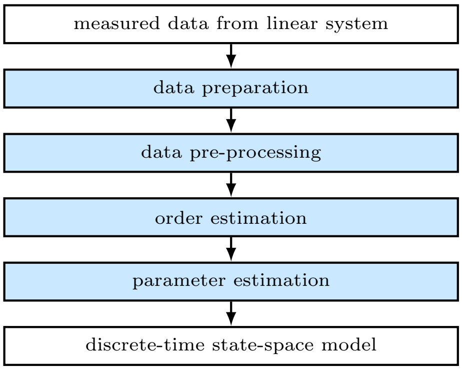

Fig. 1. Common flow chart of 4SID methods (following Buchholz (2010))

In practical cases, the oblique predictor has full rank due to noise in the measurement data. However, the system order can be estimated to be equal to the relevant singular values of the oblique predictor (step 3, order estimation). Due to the reconstruction property of the SVD, the state sequence can be calculated by using only the n largest singular values with the corresponding singular vectors. Then, again the state-space parameters of the model (1) can be computed using LS estimator. The resulting model is not unique and only one mathematical representation of the input output behavior. Without additional knowledge, which usually is not available for the black-box identification setup, the identified parameters and state variables cannot be interpreted physically.

For this work, a PBSID implementation in Matlab based on the toolbox Houtzager et al. (2012) was used with a fixed value of $p = f = 10$ for the past and future horizon, which has shown to be a good choice in a preliminary assessment. Available extensions of the PBSID algorithm, e.g. for linear parameter-varying (LPV) systems as introduced in van Wingerden (2008); Buchholz and Werner (2012), were not required due to the linear behavior of the rotor temperature, as can be seen in the next section.

3. ROTOR TEMPERATURE MODEL IDENTIFICATION

The induction motor under investigation is a prototype motor from an industrial project partner for applications in full-electric vehicles. It is a liquid cooled motor with squirrel cage and a peak power of approximately 144 kW. To generate data for identification and validation, the prototype motor is equipped with a telemetry system in the rotor and was operated on a test bench of the project partner.

3.1 Measurement Data

With the telemetry system, it is possible to measure the temperature on dedicated spots within the rotor while the