Motor parameters estimation from industrial electrical measurements

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***Abstract*—Voltage and current sensors integrated in modern electrical equipment can enable extraction of advanced information on the network and the connected devices. While traditional methods for protection and network managements rely upon processing of these signals at low speed, high-frequency processing of the raw current and voltage signals can unveil information about the type of electrical load in the networks. In particular, the common case of three-phase induction machines is considered in this paper. Motor parameters are instrumental information for control, monitoring and diagnostic. A classical approach is to measure motor parameters using off-line dedicated measurements. In this paper, we propose a method for motor parameters estimation from electrical measurements during motor start-up. Given samples of current and voltage signals during motor start-up, the model parameters are identified using classical non-linear system identification tools. While the classical theory is developed using current sensors, in this paper the method is extended to a common type of industrial current sensors, i.e., Rogowski coil sensors, and signal processing methods are presented to overcome the non-ideality caused by this type of sensors. Numerical tests performed on real data show that effective motor parameters identification can be achieved from the raw current and voltage measurements.**

I. Introduction

Electrical grids have recently undergone great advancement in terms of monitoring and protection. One of the areas that have seen major improvements is the availability of electrical sensors. Modern electrical devices of electrical systems are often equipped with voltage and current sensors. Their primary purpose is to measure macro-parameters such as the root-mean-square (RMS) values of the voltage and current, as well as the active and reactive power. These data are usually calculated at relatively low frequency, e.g., every second, and transmitted to supervisory systems. On the other hand, modern electrical devices are equipped with advanced sensors and data acquisition systems that are able to sample the electrical signals at a faster sampling rate (e.g., 1-10 kHz). Also, the digital architecture of modern electrical devices allows them to communicate and/or process these data at high speed. Therefore, the availability of fast electrical data along with the capability of communication/processing offers the possibility to extract advanced information on the electrical system.

Induction machines are the workhorse in industry and contribute to almost half of the total electrical energy consumed [1]. Monitoring and control of the induction machines require electrical parameters of the motor. Nowadays, this information is obtained with the use of off-line dedicated electrical instruments and ad-hoc tests; performing these measurements can be a complex and time consuming task. Furthermore, motor parameters might change with the aging of the equipment and are affected by several uncertain aspects, like ambient conditions and electrical connection. Therefore, repeated measurements might be required. To overcome these challenges, this paper presents signal processing techniques to estimate motor parameters from the three-phase voltage and current measurements acquired directly on the motor after installation, during normal start-up.

In this paper, we focus our attention on three-phases induction machines, but the method can be extended to synchronous and direct current (DC) machines [2]. The goal of this paper is to present the signal processing methods to achieve motor parameters identification with the minimum user intervention. That is, solely upon the electrical signals and a few nameplate data, one has to be able to estimate motor parameters in an industrial plant. To achieve this goal, a model-based approach is adopted. Each motor in the industrial plant is modeled with a classical electrical machine model.

The identification procedure can be performed during the first motor start-up, and can be periodically repeated at each motor start-up to assess parameter variations. The current and voltage transients of each motor start-up are stored, and the motor model parameters are identified via classical non-linear least-squares (NLS) identification methods. This problem was already considered in [3] with the focus on the identification of motor parameters from electrical measurements taken using lab equipment. The contribution of this paper is the extension of the formalism in [3] to accommodate typical industrial current measurements. In fact, while the classical motor model theory is developed based on the current and voltage signals, widespread industrial current sensors cannot directly sense high currents. A typical example is the Rogowski coil sensor, whose output is proportional to the current *derivative* instead of the current [4]. Rogowski coils have been successfully adopted for several classical applications involving RMS calculation around the main electrical frequency, but utilization of Rogowski coil data for transient applications is highly unexplored. While the output signal of the Rogowski coil can be integrated to estimate the current, the alternative approach of modelling directly the current derivative is also considered in this paper.

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The remainder of the paper is organized as follows: The signal model and problem statement are described in Sec. II. Non-linear parameter identification is presented in Sec. III and extended in Sec. IV for Rogowski coil data. Numerical tests performed on real data acquired with both high-quality sensors and industrial sensors are presented in Sec. V. Finally, concluding remarks are discussed in Sec. VI.

Notation. Column vectors are denoted with bold face, while matrices are denoted with capital bold face. The symbol $(\cdot)^T$ denotes transposition, while $\mathrm{tr}(\cdot)$ denotes the trace of a matrix. The operator $\dot{x}(t)$ represents time derivative if applied to a univariate signal, and the component-wise derivative if applied to a multivariate signal. $\mathbf{I}_N$ represents the identity matrix of size $N \times N$.

II. Signal model and problem statement

A. Continuous-time motor model

The dynamic model of a three-phase asynchronous motor will be presented starting from its phase relations, using the classic model presented in [1, Ch. 4]. We assume linearity of the inductances and a total lack of losses in the iron. The three identical stator windings, symmetrically placed, create three magnetic axes with a $2\pi/3$ displacements. Similarly, the rotor windings create three magnetic axes. Let us denote with $\theta_r = \theta_r(t)$ the angle between the a- stator axis and a- rotor axis. The induction machine can then be described by following equations [1, p. 142]:

$$\mathbf{v}_{abc,s}(t) = r_s \mathbf{I}_3 \mathbf{i}_{abc,s}(t) + \dot{\boldsymbol{\lambda}}_{abc,s}(t) \qquad (1)$$

$$\mathbf{v}_{abc,r}(t) = r_r \mathbf{I}_3 \mathbf{i}_{abc,r}(t) + \dot{\boldsymbol{\lambda}}_{abc,r}(t) \qquad (2)$$

where $\mathbf{v}_{abc,s}(t) := [v_{as}(t), v_{bs}(t), v_{cs}(t)]^T$ is the three-phase stator voltage, $\mathbf{i}_{abc,s}(t) := [i_{as}(t), i_{bs}(t), i_{cs}(t)]^T$ is the three-phase stator current, $\mathbf{v}_{abc,r}(t) := [v_{ar}(t), v_{br}(t), v_{cr}(t)]^T$ is the three-phase rotor voltage, $\mathbf{i}_{abc,r}(t) := [i_{ar}(t), i_{br}(t), i_{cr}(t)]^T$ is the three-phase rotor current, $\boldsymbol{\lambda}_{abc,s}(t) = [\lambda_{as}(t), \lambda_{bs}(t), \lambda_{cs}(t)]^T$ is the three-phase stator fluxes, and $\boldsymbol{\lambda}_{abc,r}(t) = [\lambda_{ar}(t), \lambda_{br}(t), \lambda_{cr}(t)]^T$ is the three-phase rotor fluxes. r_s and r_r represent the constant stator and rotor resistance, respectively. The flux linkage can be written as [1, p. 143]

$$[\boldsymbol{\lambda}_{abc,s}(t)^T, \boldsymbol{\lambda}_{abc,r}(t)^T]^T = \begin{bmatrix} \mathbf{L_1} & \mathbf{L_2} \\ \mathbf{L_2}^T & \mathbf{L_3} \end{bmatrix} [\mathbf{i}_{abc,s}(t)^T, \mathbf{i}_{abc,r}(t)^T]^T \qquad (3)$$

where: $\mathbf{L_1} := \begin{bmatrix} L_{ss}+L_{ms} & -\frac{1}{2}L_{ms} & -\frac{1}{2}L_{ms} \\ -\frac{1}{2}L_{ms} & L_{ss}+L_{ms} & -\frac{1}{2}L_{ms} \\ -\frac{1}{2}L_{ms} & -\frac{1}{2}L_{ms} & L_{ss}+L_{ms} \end{bmatrix}$, $\mathbf{L_2} :=$
$\begin{bmatrix} L_{sr}cos(\theta_r) & L_{sr}cos(\theta_r + \frac{2\pi}{3}) & L_{sr}cos(\theta_r - \frac{2\pi}{3}) \\ L_{sr}cos(\theta_r - \frac{2\pi}{3}) & L_{sr}cos(\theta_r) & L_{sr}cos(\theta_r + \frac{2\pi}{3}) \\ L_{sr}cos(\theta_r + \frac{2\pi}{3}) & L_{sr}cos(\theta_r - \frac{2\pi}{3}) & L_{sr}cos(\theta_r) \end{bmatrix}$,
and $\mathbf{L_3} := \begin{bmatrix} L_{rr}+L_{mr} & -\frac{1}{2}L_{mr} & -\frac{1}{2}L_{mr} \\ -\frac{1}{2}L_{mr} & L_{rr}+L_{mr} & -\frac{1}{2}L_{mr} \\ -\frac{1}{2}L_{mr} & -\frac{1}{2}L_{mr} & L_{rr}+L_{mr} \end{bmatrix}$.

The torque equilibrium equation completes the model as follows:

$$\dot{\omega_r}(t) = \frac{N_p}{2} \frac{T_e(t) - T_\ell(t)}{J_r}, \text{ where } \omega_r(t) := \dot{\theta}(t). \qquad (4)$$

$T_e(t)$ is the produced torque and $T_\ell(t)$ represents the torque load which can be modeled with a linear coefficient of friction a, i.e., $T_\ell(t) = a\omega(t)$ [3].

Assuming that the motor is balanced, it holds that $i_{as}(t) + i_{bs}(t) + i_{cs}(t) = 0$ and $i_{ar}(t) + i_{br}(t) + i_{cr}(t) = 0$, and the same conditions are enforced to voltage and fluxes. In this case, the motor model equations can be simplified. Let us define a constant matrix

$$\mathbf{C} := \frac{2}{3} \begin{bmatrix} 1 & -0.5 & -0.5 \\ 0 & -\sqrt{3}/2 & \sqrt{3}/2 \\ 0.5 & 0.5 & 0.5 \end{bmatrix}.$$

Given a vector $\mathbf{s}_{abc} := [s_a, s_b, s_c]^T \in \mathbb{R}^3$, the following transformation $\mathbf{s}_{qd0} = \mathbf{C}\mathbf{s}_{abc}$ can be applied, with $\mathbf{s}_{qd0} := [s_q, s_d, s_0]^T \in \mathbb{R}^3$. If the vector $\mathbf{s}_{abc}$ represents either the current or the voltage signal of a balanced three-phase induction machine, then $s_0 = 0$, and the original vector can be represented by only the qd-components, i.e., $\mathbf{s}_{qd} := [s_q, s_d]^T \in \mathbb{R}^2$. The aforementioned transform is known in literature as *Clarke transform* and it simplifies the dynamical analysis of a balanced three-phase induction machine [1]. Applying the Clarke transform to the stator voltage and current signals (which can be measured), yields $\mathbf{u}(t) := [v_{qs}(t), v_{ds}(t)]^T$ and $\mathbf{y}(t) := [i_{qs}(t), i_{ds}(t)]^T$.

Let us denote with $\psi_{qs}(t) = \omega_e \lambda_{qs}(t)$, $\psi_{ds}(t) = \omega_e \lambda_{ds}(t)$, $\psi_{qr}(t) = \omega_e \lambda_{qr}(t)$, and $\psi_{dr}(t) = \omega_e \lambda_{dr}(t)$ the fluxes per unit of time, and ω_e the nominal electrical frequency.

Let $\mathbf{x}(t) \in \mathbb{R}^5$ denote a (time-varying) state variable defined as $\mathbf{x}(t) := [\psi_{qs}(t), \psi_{ds}(t), \psi_{qr}(t), \psi_{dr}(t), \omega_r(t)]^T$. Finally, let $\mathbf{p}$ denote the (constant) vector of unknown model parameters, where $\mathbf{p} \in \mathbb{R}^7$, is defined as $\mathbf{p} = [R_s, R_r, X_{\ell s}, X_{\ell r}, X_m, J_r, a]^T$, where $X_{\ell s}$, $X_{\ell r}$, and X_m are the reactances calculated at the nominal frequency ω_e.

Given the aforementioned definition, the balanced three-phase induction machine model can be compactly written as follows:

$$\dot{\mathbf{x}}(t) = f(\mathbf{x}(t), \mathbf{u}(t), \mathbf{p}), \qquad (5)$$

$$\mathbf{y}(t) = g(\mathbf{x}(t), \mathbf{p}), \qquad (6)$$

where f and g are nonlinear functions which can be represented in a matrix form as

$$\dot{\mathbf{x}}(t) = \mathbf{A}(t)\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{c}(t) \qquad (7)$$

where $\mathbf{A}(t)$, $\mathbf{B}$, and $\mathbf{c}(t)$ are defined in eq. (8) and

$$\mathbf{y}(t) = \frac{1}{X_{\ell s}} \begin{bmatrix} 1 - \frac{X_{mq}}{X_{\ell s}} & 0 & -\frac{X_{mq}}{X_{\ell r}} & 0 & 0 \\ 0 & 1 - \frac{X_{md}}{X_{\ell s}} & 0 & -\frac{X_{md}}{X_{\ell r}} & 0 \end{bmatrix} \mathbf{x}(t).$$

It is worth point out that the system is non-linear since $\mathbf{A}(t)$ and $\mathbf{c}(t)$ depend on $\mathbf{x}(t)$.

Defining $\psi_{mq}(t) = X_{mq}\left(\frac{\psi_{qs}(t)}{X_{\ell s}} + \frac{\psi_{qr}(t)}{X_{\ell r}}\right)$, $\psi_{md}(t) = X_{md}\left(\frac{\psi_{ds}(t)}{X_{\ell s}} + \frac{\psi_{dr}(t)}{X_{\ell r}}\right)$, and $X_{mq} = X_{md} = 1/\left(\frac{1}{X_m} + \frac{1}{X_{\ell s}} + \frac{1}{X_{\ell r}}\right)$, the relationships between currents and fluxes are $i_{qs}(t) = \frac{\psi_{qs}(t) - \psi_{mq}(t)}{X_{\ell s}}$, $i_{ds}(t) = \frac{\psi_{ds}(t) - \psi_{md}(t)}{X_{\ell s}}$, $i_{qr}(t) = \frac{\psi_{qr}(t) - \psi_{mq}(t)}{X_{\ell r}}$, and $i_{dr}(t) = \frac{\psi_{dr}(t) - \psi_{md}(t)}{X_{\ell r}}$.

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$$\mathbf{A}(t)=\omega_e\begin{bmatrix} \frac{R_sX_{mq}-R_sX_{ls}}{X_{\ell s}^2} & -\frac{\omega_r}{\omega_e} & \frac{R_sX_{mq}}{X_{\ell s}X_{lr}} & 0 & 0\\ \frac{\omega_r}{\omega_e} & \frac{R_sX_{md}-R_sX_{\ell s}}{X_{\ell s}^2} & 0 & \frac{R_sX_{md}}{X_{\ell s}X_{lr}} & 0\\ \frac{R_rX_{mq}}{X_{\ell s}X_{lr}} & 0 & \frac{R_rX_{mq}-R_rX_{lr}}{X_{lr}^2} & \frac{\omega_r}{\omega_e} & 0\\ 0 & \frac{R_rX_{md}}{X_{\ell s}X_{lr}} & -\frac{\omega_r}{\omega_e} & \frac{R_rX_{md}-R_rX_{lr}}{X_{lr}^2} & 0\\ 0 & 0 & 0 & 0 & 0 \end{bmatrix},\mathbf{B}=\begin{bmatrix}\omega_e & 0\\ 0 & \omega_e\\ 0 & 0\\ 0 & 0\\ 0 & 0\end{bmatrix},\mathbf{c}(t)=\begin{bmatrix}0\\0\\0\\0\\ \frac{N_p(T_e(t)-T_\ell(t))}{2J_r}\end{bmatrix} \quad (8)$$

The produced torque is: $T_e = \frac{3N_p}{4\omega_e}(\psi_{qr}(t)i_{dr}(t) - \psi_{dr}(t)i_{qr}(t))$, where N_p is the number of poles.

Due to the nature of the model, it is not possible to identify $X_{\ell s}$ and $X_{\ell r}$ separately. In the equivalent circuit formulation of the model they are connected in a series and are usually replaced with one single parameter equal [3]. Therefore, we have set $X_{\ell s} = X_{\ell r} = X_\ell$.

B. Problem statement and Discrete-time model

We are now in the position for stating our problem. Given the stator voltage and current signals $\mathbf{u}(t)$ and $\mathbf{y}(t)$, the problem is to estimate the constant motor vector $\mathbf{p}$. Before solving this problem, a discrete-time model of eqs. (5) and (6) is required. In fact, since stator voltage and current measurements can be taken at discrete time, the model in (5) and (6) has to be discretized in order to be adopted for parameter identification purposes.

Let us assume that three-phase current and voltage measurements can be taken with sampling period t_s. Let us denote with N the total number of samples. Let us define

$$\mathbf{V}_{abc}:=\begin{bmatrix}v_{as}(t_s)\dots v_{as}(Nt_s)\\ v_{bs}(t_s)\dots v_{bs}(Nt_s)\\ v_{cs}(t_s)\dots v_{cs}(Nt_s)\end{bmatrix},\mathbf{I}_{abc}:=\begin{bmatrix}i_{as}(t_s)\dots i_{as}(Nt_s)\\ i_{bs}(t_s)\dots i_{bs}(Nt_s)\\ i_{cs}(t_s)\dots i_{cs}(Nt_s)\end{bmatrix}.$$

Both voltage and current signals are transformed using Clarke transform as follows:

$$\mathbf{V}_{qd} := \begin{bmatrix}v_{qs}(t_s)\dots v_{qs}(Nt_s)\\ v_{ds}(t_s)\dots v_{ds}(Nt_s)\end{bmatrix} \in R^{2\times N}, \quad \mathbf{V}_{dq} = \mathbf{C}\mathbf{V}_{abc},$$

$$\mathbf{I}_{qd} := \begin{bmatrix}i_{qs}(t_s)\dots i_{qs}(Nt_s)\\ i_{ds}(t_s)\dots i_{ds}(Nt_s)\end{bmatrix} \in R^{2\times N}., \quad \mathbf{I}_{qd} = \mathbf{C}\mathbf{I}_{abc}.$$

In order to simply the notation, let us denote with $s[k]$, the kth sample taken at time kt_s of the generic continuous-time signal $s(t)$, i.e., $s[k] := s(kt_s)$. Applying forward Euler rule to the continuous-time dynamical model in (5) and (6), yields,

$$\hat{\mathbf{x}}[k+1] = \hat{\mathbf{x}}[k] + t_s f(\hat{\mathbf{x}}[k], \mathbf{u}[k], \mathbf{p}) \quad (9)$$

$$\hat{\mathbf{y}}[k] = g(\hat{\mathbf{x}}[k], \mathbf{p}). \quad (10)$$

In most of the scenarios, the motor is starting at standstill, therefore, $\hat{\mathbf{x}}[0] = [0,\ 0,\ 0,\ 0,\ 0]^T$. Clearly, $\mathbf{u}[k]$ represents the kth column of $\mathbf{V}_{qd}$, while, $\hat{\mathbf{y}}[k]$ represents the *predicted* qd-components of the stator current signal at discrete time k from a model with parameter $\mathbf{p}$ and input $\mathbf{u}[k]$.

III. Non-linear parameter identification

Let $\hat{\mathbf{Y}}(\mathbf{p}, \mathbf{V}_{qd}) := [\hat{\mathbf{y}}[1], \dots, \hat{\mathbf{y}}[N]]$ denote the predicted stator current from the discrete-time model in (9)-(10). It is natural to estimate the unknown motor parameter vector $\mathbf{p}$ as the solution of the following least square (LS) problem:

$$\hat{\mathbf{p}} = \ arg \min_{\mathbf{p}\in\mathcal{P}} \mathrm{tr}\left(\left(\mathbf{I}_{qd} - \hat{\mathbf{Y}}(\mathbf{p}, \mathbf{V}_{qd})\right)\left(\mathbf{I}_{qd} - \hat{\mathbf{Y}}(\mathbf{p}, \mathbf{V}_{qd})\right)^T\right), \quad (11)$$

where $\mathcal{P}$ is the set of possible parameters, defined with various constraints on the basis of prior information (e.g., resistances and reactances are positive). The problem in (11) amounts to a non-linear least square (NLS) problem. Despite that on-line sequential optimization algorithms could be envisioned for solving the problem in (11), we have resorted to classical optimization tools that work on data batch. Presenting the solver of the problem in eq. (11) is out of the scope of this paper. Several off-the-shelf softwares can be used for solving (11). The results presented in this paper have been obtained using fmincon function from Matlab [5], but other solvers have achieved comparable performance.

It is known that a careful initialization close to the solution is required to avoid that the algorithm is trapped in a local minimum far form the solution. We have encountered this problem in some of our tests. Nevertheless, we have observed that starting the algorithms with a few initialization points randomly drawn within the feasible set, ends up in estimates of the motor parameters that were always meaningful.

IV. Signal processing of Rogowski coil data

As mentioned before, many industrial electrical devices are equipped with Rogowski coil sensors, which measure the current derivatives. This is not ideal for our purposes, as the model uses the currents. We propose two possible approaches to cope with the Rogowski coil sensors, which we test with real-world data in Section V:

- Data Integration (DI), where the data are integrated at first, and then used in the cost in eq. (11) with currents predicted from the model in eqs. (9)-(10);
- Model Derivation (MD), where the cost in eq. (11) is modified to accept current derivatives and the predicted current derivatives are calculated from the model in eqs. (9)-(10).

The two methods are further described below.

A. Data integration

Ideal data integration via, e.g., cumulative sum of the current measurements, results in a large drift in the output due to the

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intrinsic bias of the sensor. An effective method is to perform a band pass filtering followed by an ideal integration.

In this paper, we followed the alternative approach to design this integration filter in a data-driven manner. We have performed a short measurement of the real current via a wideband Hall effect sensor that measures directly the current. We have performed this measurement for only one phase. Then, we computed the optimum finite impulse response (FIR) filter that minimizes the LS cost between the direct current measurement and the filtered current derivative. The problem of finding the optimal FIR filter that minimizes the least square cost between the output and the filtered version of the input is often encountered in signal processing and control, and it is referred to as *linear deconvolution* or *input-output linear system identification* [6, Ch. 5], and it amounts to a linear LS problem.

B. Model derivation

An alternative approach to data integration is to calculate the derivative of the model in (6). From the current model in Sec. II-A, the current derivative can be obtained as $\dot{i}_{qs}(t) = \frac{1}{X_{\ell s}}(\dot{\psi}_{qs}(t) - \dot{\psi}_{mq}(t))$, and $\dot{i}_{ds}(t) = \frac{1}{X_{\ell s}}(\dot{\psi}_{ds}(t) - \dot{\psi}_{md}(t))$, where the derivative of the fluxes are readily available from the dynamical equation in (5). If we assume that the data from the Rogowski coil are representative of the current derivatives, and if we arrange the data in a matrix $\dot{\mathbf{I}}_{qd} \in \mathbf{R}^{2\times N}$, estimates of the motor parameters can be obtained solving the following problem:

$$\hat{\mathbf{p}} = arg \min_{\mathbf{p}\in\mathcal{P}} \operatorname{tr}\left(\left(\dot{\mathbf{I}}_{qd} - \hat{\dot{\mathbf{Y}}}(\mathbf{p}, \mathbf{V}_{qd})\right)\left(\dot{\mathbf{I}}_{qd} - \hat{\dot{\mathbf{Y}}}(\mathbf{p}, \mathbf{V}_{qd})\right)^T\right), \tag{12}$$

where $\hat{\dot{\mathbf{Y}}}(\mathbf{p}, \mathbf{V}_{qd})$ are the stator current derivatives generated by the dynamical model with a fixed parameter vector $\mathbf{p}$ and voltage input $\mathbf{V}_{qd}$.

V. Experimental results

Real data were gathered in an rig containing two induction machines connected to two compressors implementing an air flow process. The first motor is a 2-pole 15kW ABB M3AA160MLB2 three-phase induction machine star connected, denoted as *Motor A*. The second motor is a 2-pole 18.5kW ABB M3AA160MLC23GAA three-phase induction machine delta connected, denoted as *Motor B*. Each motor is connected to the electrical grid via contactors to control the switch of the motors (direct on-line start-up).

Two types of data are gathered:

- High-quality current and voltage measurements obtained via a custom made measurement device equipped with wideband Hall effect sensors, LEM LF 205-S and LEM LV 25-P, for current and voltage measurements, respectively. These data are available at 5kHz. Two measurement devices were installed to measure the fed voltage and the absorbed current of each motor;
- Industrial voltage sensors and Rogowski coils to measure the current derivatives. The signals can be sampled at a speed of maximum 9.6kHz even if most of our measurements were taken at 4.8kHz in order to fairly compare the two types of measurements. This device measures the network three phase line-to-line voltage, and the sum of the currents of the two motors.

TABLE I
Motor A. Identified parameters. High-quality current measurements.

Data	R_s	R_r	X_ℓ	X_m	J_r	a	NMPE
D1MAS1	0.51	0.24	0.61	5.46	0.27	0.047	0.072
D2MAS1	0.51	0.24	0.61	5.44	0.27	0.040	0.073

Two types of measurements are analyzed in this paper:

- Motor A start-ups while Motor B is off;
- Motor B start-ups while Motor A is off.

Also, measurements including both motors start-ups at the same time or with different delays were performed, but this type of data require a different signal processing for background subtraction and they are not treated in this paper.

A. Parameter identification of Motor A

We have first processed the data from Hall current sensors, and we have identified the model parameters via the optimization in (11). To measure the quality of the fitting, we also calculate the normalized mean prediction error, defined as

$$\text{NMPE} = \sqrt{\frac{\operatorname{tr}\left(\left(\mathbf{I}_{qd} - \hat{\mathbf{Y}}(\hat{\mathbf{p}}, \mathbf{V}_{qd})\right)\left(\mathbf{I}_{qd} - \hat{\mathbf{Y}}(\hat{\mathbf{p}}, \mathbf{V}_{qd})\right)^T\right)}{\operatorname{tr}\left(\mathbf{I}_{qd}\mathbf{I}_{qd}^T\right)}}. \tag{13}$$

The identified parameters for two start-ups are listed in Table I. Data D1MAS1 and D2MAS1 are two independent start-ups in same conditions. A transient of 1.6s was adopted for the identification, which consists of 8000 data points. Figure 1 shows the Q component of the measured stator current of D1MAS1 along with the reconstructed Q components of the stator current. It can be appreciated how the reconstructed current after fitting resembles the measured one, except for a few peaks at the inception of the start-up. In all the cases, the NMPE is below 10%.

Next, we want to assess the differences in performance in term of parameters estimates for various data type and identification method which also include processing of Rogowski coil data.

In Tab. II, we considered a Motor A start-up and we perform model identification using the data from Hall effect and Rogowski coil sensors, using both the DI and MD methods. The MD method estimates parameters that are very similar to the Hall effect sensor, while the DI method has identified slightly different parameters. Despite these differences, the three models show a NMPE below 10%. Figure 2 depicts the (scaled) data obtained from a Rogowski coil (i.e., data D3MAS2 considered in Tab. II) vs the current reconstructed via the MD method in (12). It can be seen that the MD method reconstructs effectively the current derivatives.

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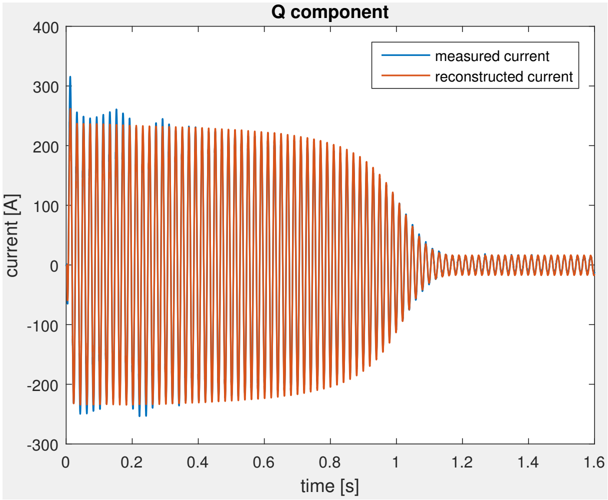

Fig. 1. Q component of the current signal (high-quality measurements via Hall sensor and reconstructed current via (11)).

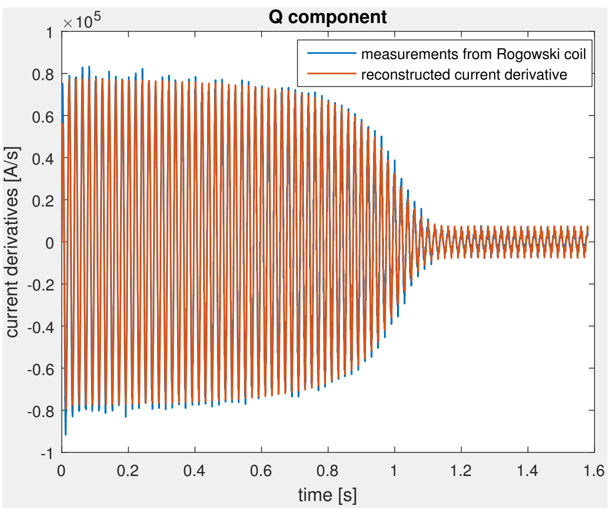

Fig. 2. Q component of the current signal (scaled Rogowski coil measurement and reconstructed current via (12)).

B. Parameter identification of Motor B

We have also tested the identification method on the Motor B with the goal of assessing the repeatability of the identification routine. As we have seen from Table II that the identified parameters change slightly for different identification methods, we aim at assessing whether the identification is stable, i.e., if the parameters change within different realizations using the same method. For this purpose, we only considered the data integration method for the Rogowski coil data. Three independent start-ups of Motor B where considered. D1MBS1, D2MBS1, and D3MBS1 denotes the data obtained with the high-quality Hall effect current sensor and the respective parameters are obtained solving (11), while D1MBS2, D2MBS2, and D3MBS2 are the data obtained from the Rogowski coil current sensor pre-processed via data-driven integration and successively fed to (11) to perform parameter estimation. The parameter estimates are depicted in Table III. It can be observed that there are some changes in the parameters obtained using the integrated Rogowski coil data vs. using the high-quality current measurements. However, there are minimal changes in the parameters identified from different experimental realizations using the same methods. This means that if we consider Rogowski coil data only and fix the identification method, say DI, we can expect that the results from different realizations are repeatable.

TABLE II
MOTOR A. IDENTIFIED PARAMETERS. HIGH-QUALITY CURRENT MEASUREMENTS VS ROGOWSKI COIL MEASUREMENTS.

Data	R_s	R_r	X_ℓ	X_m	J_r	a	NMPE
D3MAS1	0.50	0.24	0.61	5.40	0.27	0.039	0.070
D3MAS2(DI)	0.78	0.23	0.47	5.46	0.26	0.050	0.061
D3MAS2(MD)	0.53	0.24	0.60	5.20	0.26	0.039	0.081

TABLE III
MOTOR B. IDENTIFIED PARAMETERS FOR VARIOUS INDEPENDENT MEASUREMENTS. HIGH-QUALITY CURRENT MEASUREMENTS VS ROGOWSKI COIL DATA.

Data	R_s	R_r	X_ℓ	X_m	J_r	a	NMPE
D1MBS1	1.21	0.60	1.44	14.09	0.29	0.036	0.085
D2MBS1	1.21	0.60	1.44	14.20	0.29	0.036	0.085
D3MBS1	1.21	0.60	1.44	14.25	0.29	0.036	0.087
D1MBS2	1.89	0.57	1.12	14.03	0.28	0.048	0.065
D2MBS2	1.90	0.57	1.12	14.11	0.28	0.048	0.065
D3MBS2	1.89	0.57	1.12	14.14	0.28	0.048	0.064

VI. CONCLUSIONS

In this paper the problem of motor identification from electrical measurements during the start-up of the motor was treated. Only induction machines were considered in this paper, but the method can be extended for other motor types. The induction machines were modeled with a classical dynamical model. To perform the identification, real data from high-quality current sensors and from Rogowski coils were processed. In order to cope with the non-ideality of Rogowski coil data, data integration and model derivation strategies were proposed. We have observed that, the parameters identified from the Rogowski coil differ from those identified from the high-quality current measurements. Nevertheless, the fitting error is comparable and the results are repeatable, which shows that with Rogowski coil data effective motor parameter identification can be achieved.

REFERENCES

[1] P. C. Krause, et al., *Analysis of electric machinery and drive systems,* John Wiley & Sons, 2013.
[2] C. M. Ong, *Dynamic Simulation of Electric Machinery: using Matlab/Simulink*, Prentice Hall, New Jersey, 1998.
[3] S. R. Shaw and S. B. Leeb, "Identification of induction motor parameters from transient stator current measurements," *IEEE Trans. on Ind. El.*, no. 46, Vol. 139, 1999.
[4] J. D. Ramboz, "Machinable Rogowski coil, design, and calibration," *IEEE Trans. on Instr. and Meas.*, no. 45, Vol. 2, 1996.
[5] URL: https://ch.mathworks.com/help/optim/ug/fmincon.html
[6] L. Ljung, *System identification,* John Wiley & Sons, Inc., 1999.