Chapter 3

Real-Time Estimation of the Induction Machine Parameters

3.1. Introduction

The identification of processes is a huge field grouping very different approaches. This diversity is linked, on the one hand, on the model diversity: parametric knowledge models (transfer functions, state models) or behavior model (neuron networks, vague logic, transfer functions, state models, etc.), non-parametric models (unit responses, frequency responses, etc.), deterministic or stochastic models, and on the other hand, at the various operating contexts: online or offline, in open or closed-loop, with or without the control of input signals, etc. The objective of this chapter is to report on the major approaches adapted for the real-time parametric identification of dynamic processes, and especially, induction motors.

But, before considering the solutions, we must present the outline of the problem. The implementation of real-time identification techniques is a complex problem because of the large number of issues that need to be addressed simultaneously and coherently. First, there are problems linked to the definition of the model structure (characterization phase) requiring good expertise of the process, notably in the case of a knowledge model:

– is the model appropriate in relation to the process and the identification technique?

– would a simpler model not be as satisfactory?

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– are the inevitable simplifying hypotheses that it presumes realistic and relevant for the application involved?

– can the model be uniquely identified?

We must also consider all that involves the data (its acquisition, information content, and formatting):

– is the data processed relevant: does it contain the information necessary to the estimation of all parameters?

– when we do not control the process input signals, how can we detect that the data does not satisfy the identification?

– are the measurements sufficiently accurate: is the instrumentation retained adapted in quantity and quality?

– must we introduce analog or digital pretreatments to improve the signal quality (isolating a specific part of the spectrum of measurements or compensate an instrumental error)?

Finally, there are also implementation problems. This implementation is digital with few exceptions:

– is the optimization algorithm well adapted to real-time: does it not risk diverging; is its calculation cost reasonable; does it suffers initialization or restart problems?

– how do we efficiently adjust the parameters of the identification algorithm?

– does the discretization of the model and the data sampling cause specific problems (stability of the model, aliasing, etc.)?

This all means that the implementation of real-time identification techniques is often trickier than the implementation of its natural complementary controls. We should keep in mind two major points. The first one involves the consistency of the trio made up of the model, data, and algorithm of identification. In this chapter, we will often come back to this point, notably through applications. The second point involves the expertise of identification algorithms. What ensures the success and efficiency of basic approaches, such as least squares, is their implementation simplicity and the low level of knowledge required. For most applications, it is not the ideal method, but it is certainly preferable to a more powerful, but not mastered, method.

Before addressing the presentation of real-time identification methods, we will recall the major objectives of the real-time parametric identification. We will then discuss the fundamental problems that it raises in general and, in particular, with regard to electrical machines.

3.2. Objectives of parameter estimation

The increasing power of calculators used for the control of systems enables the integration of complementary functions such as the adaptation of this control in real-time or the online diagnosis of the system. These two functions can be achieved with the help of real-time estimation of system parameters.

3.2.1. *On control*

The most frequent application of real-time parametric identification today is the implementation of adaptive controls. There are multiple variations of the adaptive control, from the automatic parameter adjustment of a simple PID controller (the most widely used solution in industrial applications) to predictive control, with the methods of pole placement or stochastic approaches. Scientific literature in this field is extremely abundant. The interested reader can consult [AST 93, GOO 84, LAN 86, MOS 93]. These approaches mainly use behavior models, explicitly or implicitly. These models are mainly adapted to the algorithm of identification associated with them, and are generally only representative of the real system's behavior close to an operation point.

The approaches based on a knowledge model are not as common. In general, they require a specific methodology, adapted to the characteristics of the model, and notably to its non-linearities or its internal couplings when the system is multivariate. The advantage (or the disadvantage, depending on the scientific culture of the user) of an approach by a knowledge model is that it is based on the use of prior information. In this way, in the case of electrical machines, we can easily define reasonable variation ranges of its electrical parameters. We also evaluate the influence of the temperature on resistances and the influence of the magnetic saturation on inductances.

Take the case of an induction machine driven by vector control. The estimation of its electrical and mechanical parameters will make the adjustment of loops constituting this control possible:

– if current loops are present, the gain of their controller is directly dependent on the global leakage inductance brought back to the stator because it determines the impedance module of the machine with frequencies close to the critical point;

– rotor parameters (inductance and resistance) are necessary for the accurate adjustment of the vector control because the rotor time constant conditions the direction of the reference;

– the knowledge of the stator resistance makes it possible to extend the sensorless mechanical controls toward low speeds; and

– mechanical parameters (and mainly the global inertia driven by the machine) are necessary to adjust the speed loop controller.

In this field, scientific literature is abundant, because the imagination of researchers was very productive and several approaches were explored, notably to achieve adaptive vector controls [LOR 98]. Among the traditional approaches, we can cite least squares [ELT 90, GAR 94, STE 94, TOU 94, VEL 89], the adaptive reference model [HAB 93, JEM 94, SNG 95, SUM 93, TUN 94], the extended Kalman filter [ATK 89, ATK 91, CAV 89, IWA 89, KAT 91, LIN 96, ORL 96, PET 95, SAT 87, WES 92, ZAI 92], and the extended Luenberger observer [DU 93, DU 95, ORL 89, RIB 95]. We also find more original or specific approaches: methods based on the vector control decoupling [BAU 96, LEO 85], on real-time FFT [ACA 91], on a gradient method [HOL 91], on the analysis of active and reactive power [IRI 86], or set-membership approach [DUR 99]. These studies often consider the estimation of a single parameter, but sometimes it is the identification of the complete electrical model, or a combination of electrical and mechanical parameters.

Modern industrial variable speed drives, which can equally operate synchronous or induction machines (with sensor or sensorless), more often integrate self-adjustment (with prior identification, off-line) and real-time adaptation functions. The latter makes it possible to take into account the parametric variations and notably thermal variations of resistances or the evolution of mechanical load. Nevertheless, it is sometimes more a question of commercial argument than a real necessity. In fact, reality shows that, in most applications, it is not necessary to have rigorous adjustment of the parameters of vector control for it to work properly, especially if it is part of a speed loop providing the user with the control he expects and hiding load-control imperfections. In high-power applications, the main advantage of accurately adjusted vector control is the guarantee of maximum performance: an inaccurately adjusted control leads to flux variations and non-optimal operation, which can lead to increased saturation and thus additional losses [KRI 87, NOR 85].

As we can see, control adjustment relies on certain parameters of the model. Nevertheless, it may also be necessary to estimate other parameters, because their influence may disturb the estimation of the desired parameters. In this way, even if we are only interested in thermal resistance variations of an electrical machine, it is vital to understand the value of inductances that will have a determining effect at high speed [LOR 93, PEN 93, RIB 97].

Even though the PID controller has a predominant place in the control of industrial processes and notably in the field of electrical engineering, more powerful and more sophisticated controls seem to be developing. In order to minimize the number of sensors, these controls, often based on the knowledge of the state of the system, rely on observers. Since these observers also rely on a system model, it is important to either guarantee their robustness in terms of uncertainties or parametric variations or to make the model evolve in real-time. Some structures, such as the extended Kalman filter or the extended Luenberger observer, are adaptive observers simultaneously integrating the functions of parametric identification and state reconstruction.

3.2.2. *Diagnosis*

Real-time parameter identification and estimation also play an important role in online diagnosis methods [SIM 03].

This type of diagnosis can be based on two categories of approach. The first is based on the estimation and analysis of the evolution of a parameter characteristic of the state of the system. A default is detected when this parameter reaches a critical threshold. Depending on applications, we either use a "healthy" system model (before the default) in which the parameter represents the evolution of its state, or a specific model dedicated to the detection of a particular default. In this way, the stator resistance estimation of a three-phase machine makes it possible to evaluate its temperature and to intervene in case of overheating. The approaches of the second category are based on analysis of the error (the residuals) between real system outputs and the outputs of a model or observer. The main problem is then to generate residuals that are characteristic of a specific default and not affected by sensor or modeling errors. For this technique to be robust in terms of the system evolution or normal variations, we can consider achieving a generator of adaptive residuals relying on a parametric identification of the model.

In terms of electrical machines, an online diagnosis has an advantage in two types of situations: it is a high-power and costly machine, always in operation, which excludes any off-line diagnosis, or a low-power machine without strong intrinsic value, but fulfilling a critical function. Real-time observation also enables the implementation of predictive maintenance guaranteeing optimal availability of the system and a reduction of maintenance costs by the reduction of parts inventory and the programming of interventions at the appropriate moment.

Although robust, electrical machines can present mechanical or electrical failures, maybe caused by manufacturing default, harsh operating conditions, or simply natural aging. Reliability studies [ALL 86, BON 92, SIN 03] show that the

main causes of failures are mechanical and mostly involve bearings (approximately 50% of failures). Diagnosis techniques based on frequency approaches showed their efficiency in detecting this type of failure where the main characteristic is to be synchronized with the rotor movement. In this context, two categories of approaches can be considered. The first, which is used in manufacturing to monitor high-power machines, is based on the synchronous analysis of a vibratory measure obtained with the help of accelerometers. The second is based on the spectrum analysis of the power currents avoiding the use of additional sensors.

The diagnosis methods based on parametric models are more pertinent with electrical default especially stator ones, that constitute the second cause of machine failures. Scientific literature is also very rich in this field [BEN 99]. These studies can be classified according to the desired failure and the approach used for detection, or less frequently, localization [SIN 03]. They often use the identification of a parametric model to detect the abnormal variation of a parameter characteristic of the state of the machine. Most of these studies aim to notifying that an incident has occurred. Nevertheless, others consider a predictive approach of maintenance through thermal monitoring of the machine. In order to avoid using a temperature probe, notably at machine rotor, several studies consider this monitoring through the online estimation of winding resistance [BEG 99, FOU 05, LEE 03].

3.3. Fundamental problems

When we consider the identification of a relatively complex system, the first problem is the choice of the model structure (characterization). We must watch out for habits and not naively use models that were developed for other uses. A control model may not be identifiable. The search for identification, and specifically for diagnosis, models turns out to be a very rich scientific field. Between the “white box” approach (pure knowledge model) and the “black box” approach (behavior model), there is a wide range of models to explore. The best compromise between complexity and accuracy is often achieved with an intermediate approach associating a macroscopic analysis of the major physical phenomena involved in the context concerned and a behavioral representation of secondary phenomena, the main problem being making the correct simplifying hypotheses. We must also keep in mind that the model will have to be discretized for a digital implementation. We will clarify a few aspects of characterization in the first part of this section.

The second fundamental problem is the informational content of data. For an off-line application, the idea is generally to choose the test(s) that will guarantee the estimation of desired parameters with sufficient precision. In the case of an online application, it is quite rare to introduce excitation only dedicated to the identification of the process. In general, we must only use the available signals generated by the

control itself. This creates two problems. On one hand, the closed-loop control introduces a strong correlation between input and output noises resulting in the faulty algorithm of identification. On the other hand, during steady-state mode phases, data can be too sparse to enable identification of the process. It is, therefore, necessary to monitor the identification for it not to diverge. We will see later how to analyze the data in order to detect this risk.

3.3.1. *Identifiability, parameterization, and validation of the model*

3.3.1.1. *Identifiability and parameterization of the model*

In general, the model must be structurally identifiable, i.e., through a suitable choice of input, all the parameters can be uniquely estimated. If that is not the case, there is an unlimited number of possible solutions and the estimated parameters lose their physical sense. Nevertheless, this does not mean that the model obtained is completely unusable. In some applications, it can be suitable as an input-output behavioral model.

There are different techniques to test the structural identifiability of a model [WAL 94]. When we consider a linear state model, a simple methodology consists in showing that the matrix of input-output transfer is uniquely defined by the same number of parameters as the original model. We will apply this approach to the induction motor model. We will see that for the machine, identifiability of the model goes through a re-parameterization, leading to a reduction in the number of parameters, which is beneficial for a real-time implementation.

The choice of parameterization is clearly linked to the nature of the models available, but also depends on how the parameters will be used. For a given model, it is often possible to choose between several parameterizations. Take the example of a circuit R-L. We can choose to estimate R and L, or the time constant L/R and one of the two parameters. In theory, these choices are equivalent, but in practice, the digital aspects can lead to very different precisions. Generally, it is better to choose parameters with similar orders of magnitude in order to limit the digital problems caused by badly conditioned calculations. This can be obtained in relative dimensions, on the basis of reference values correctly chosen.

3.3.1.2. *Validation of the model*

It is impossible to prove that a model is valid. We can only verify that it is adapted to the reproduction of the behavior of the real system in certain conditions. Verifying that the model obtained actually reproduces the test with which it has been identified only shows that the optimization algorithm worked well; it extracted the relevant data from this test. But the model may only be suitable for this specific test.

We must therefore test it in other conditions and with different inputs. In this way, the richer and more varied the tests, the more we will be able to trust the model. In addition, it is very important to analyze modeling errors. For an optimal model, this error must be random and decorrelated from the system state variables [WAL 94].

The identification of a model is the result of a complex process involving several elements liable to fail or be inaccurate. In certain cases, it is possible that these problems are compensated by the model itself, making them invisible. Consider the basic example of the measurement of a resistance with the help of a current probe and a voltage probe. If one of the probes has a gain error, this error will lead to an estimation error. However, this false estimation will perfectly reproduce the measurements.

3.3.1.3. *Identifiability and parameterization of the induction motor model*

Consider the case of the induction machine constituting an excellent example of an application. A simple representation of the machine is obtained under the following conditions:

- the three-phase winding is symmetrical and its neutral is insulated;
- the distribution of the electromotive force in the air gap is sinusoidal;
- the machine is not saturated; and
- the skin effect, iron losses, and slot effects are insignificant.

The equations of the induction motor, expressed in complex form, in a reference frame turning at arbitrary angular frequency ω_x, are then written as:

$$\begin{aligned} U_s &= R_s I_s + j\omega_x \Phi_s + \frac{d\Phi_s}{dt} \\ 0 &= R_r I_r + j(\omega_x - \omega_m)\Phi_r + \frac{d\Phi_r}{dt} \\ \Phi_s &= L_s I_s + L_m I_r \\ \Phi_r &= L_r I_r + L_m I_s \\ C_{em} &= 1.5 p L_m \operatorname{Im}\left(I_s \operatorname{conj}(I_r)\right) \end{aligned} \qquad [3.1]$$

Variables U_s, I_s, I_r, Φ_s, Φ_r, ω_m and C_{em} represent the stator voltage, stator and rotor currents, stator and rotor fluxes, mechanical speed (multiplied by the number of pole pairs), and the electromagnetic torque, respectively. Parameters R_s, R_r, L_s, L_r and L_m indicate stator and rotor resistances, stator, rotor, and magnetizing cyclic inductances. The three-phase to two-phase transformation retained preserves the amplitude of signals, explaining the 1.5 factor involved in the torque expression.

In order to be able to identify the machine, it must be uniquely defined by a set of parameters. Traditionally, the induction machine is characterized by the previous parameters that show two leakage inductances: $L_{fs} = L_s - L_m$ and $L_{fr} = L_r - L_m$. This model is characterized by five parameters and cannot be identified only from electrical signals at the stator. This is verified from the complex dynamic impedance of the machine:

$$Z_s(s) = \frac{U_s}{I_s} = R_s + L_s(s + j\omega_x) - \frac{L_m^2}{L_r}\frac{(j\omega_x + s)\left(j(\omega_x - \omega_m) + s\right)}{\frac{R_r}{L_r} + j(\omega_x - \omega_m) + s} \qquad [3.2]$$

This expression shows that the induction motor is uniquely defined only by four parameters: R_s, L_s, the rotor time constant $T_r = L_r/R_r$ (or its inverse) and L_m^2/L_r (or equivalently with the Blondel dispersion factor $\sigma = 1 - L_m^2/L_r L_s$). There are unlimited number of solutions $\{R_s, L_s, L_m, R_r, L_r\}$ to define the same machine. This offers a degree of freedom that we can use depending on how we use the model. The arbitrary grouping of stator leakages ($L_{fr} = 0$ and $L_r = L_m$) simplifies the model used for the identification of parameters, without modifying the impedance, or the machine torque, because this torque does not depend on the distribution of the leakage inductances.

In order to improve the model precision, we can consider iron losses (by Foucault current and by hysteresis) and magnetic saturation in the case of variable flux operation. The number of electrical parameters to be estimated will then slightly increases. In the equivalent single-phase diagram, we can introduce, in parallel with the magnetization inductance, a resistance, R_f, representing iron losses. In theory, the presence of this resistance makes stator and rotor leakage inductances identifiable, leading to the estimation of six parameters. In reality, [LAR 05] showed that this problem is badly conditioned and leakages cannot easily be separated. Magnetic saturation can be modeled by introducing a function $L_m(\Phi_r)$ and [LAR 05] established that a simple expression like $L_m(\Phi_r) = L_{m0}(1 + A\Phi_r^n)^{-1}$, where n is an integer, is well adapted.

3.3.2. *Choice of the sampling period and digital problems*

3.3.2.1. *General case*

Knowledge models and gray box type models are continuous time models. It is therefore necessary to discretize them in the context of a digital implementation. Conversely, a behavior model can directly be defined in discrete time.

There are different techniques to discretize a continuous model. Some are approximate (Euler method, W transform, etc.) and others are exact, as long as we know in advance the evolution of input signals during the discretization period. In the case of a control model, there is no problem since, by principle, input signals are hold (constant) over a control period. For the identification, that is not necessarily true, it is sometimes preferable to consider different periods of discretization for control and identification. This can be necessary to enable the execution of a real-time complex identification algorithm. In this case, the usual discretization approach cannot be used. We will see how to solve this problem simply by interpolation or over-sampling in the induction machine application.

When the problem created by the input dynamic is resolved, we still need to reproduce the internal dynamic (poles and zeros) of the continuous model. We could assume, as in control, that the best performances will be obtained with a short sampling period. In reality, even though this would actually make discretization of the model easier, on the one hand, by authorizing, for example, the use of an approximation by a first order development of the matrix exponential (Euler method), we would, on the other hand, risk desensitizing the parameters for estimation. In fact, the smaller the discretization step, the smaller will be the volume of information to be used in a step, thus amplifying the uncertainty and variation of estimations, as well as the digital problems and risks of divergence (through loss of identifiability).

In addition, as with the control, in the case of a real-time estimation also, step reduction implies the increase of the calculation power, which can be very critical if we use a complex algorithm. The choice of the sampling period is therefore complex. When possible, the best case would be to be able to choose a period adapted to the dynamic of the parameters to be estimated, in order to correctly follow their variations.

3.3.2.2. *Discretization of the IM dynamic model*

We will now consider two opposite approaches of state model discretization of the induction motor. The first one uses a traditional methodology, resulting in a full order model requiring a short period of discretization. The second one is based on the reversal of input and output, and it provides a reduced order model authorizing large sampling periods that will reveal themselves to be better adapted to the estimation of the machine parameters.

3.3.2.2.1. Fourth-order state model

If we only consider a leakage inductance on the stator side and we choose the components of the stator current and rotor flux as state variables, from [3.1], we deduct the following complex state equations:

$$\begin{cases} \dfrac{\mathrm{d}I_\mathrm{s}}{\mathrm{d}t} = \left(-\dfrac{R_\mathrm{s}+R_\mathrm{r}}{L_\mathrm{fs}} - j\omega_x \right) I_\mathrm{s} + \dfrac{1}{L_\mathrm{fs}} \left(\dfrac{R_\mathrm{r}}{L_\mathrm{r}} - j\omega_\mathrm{m} \right) \mathrm{F}_\mathrm{r} + \dfrac{1}{L_\mathrm{fs}} U_\mathrm{s} \\ \dfrac{\mathrm{dF}_\mathrm{r}}{\mathrm{d}t} = \left(-\dfrac{R_\mathrm{r}}{L_\mathrm{r}} - j\left(\omega_x - \omega_\mathrm{m}\right) \right) \mathrm{F}_\mathrm{r} + R_\mathrm{r} I_\mathrm{s} \end{cases} \quad [3.3]$$

By separating the real part (axis α) and imaginary part (axis β) from equations and by supposing that the speed slowly varies, we obtain the following usual state model:

$$\begin{cases} \dot{X}_4 = A_4 X_4 + B_4 U_4 \\ Y_4 = C_4 X_4 \end{cases} \quad [3.4]$$

with $X_4 = [I_{s\alpha}\ I_{s\beta}\ \Phi_{r\alpha}\ \Phi_{r\beta}]^T$, $U_4 = [U_{s\alpha}\ U_{s\beta}]^T$, and $Y_4 = [I_{s\alpha}\ I_{s\beta}]^T$ and:

$$A_4 = \begin{bmatrix} -\dfrac{R_\mathrm{s}+R_\mathrm{r}}{L_\mathrm{fs}} & \omega_x & \dfrac{R_\mathrm{r}}{L_\mathrm{fs}L_\mathrm{r}} & \dfrac{\omega_\mathrm{m}}{L_\mathrm{fs}} \\ -\omega_x & -\dfrac{R_\mathrm{s}+R_\mathrm{r}}{L_\mathrm{fs}} & -\dfrac{\omega_\mathrm{m}}{L_\mathrm{fs}} & \dfrac{R_\mathrm{r}}{L_\mathrm{fs}L_\mathrm{r}} \\ R_\mathrm{r} & 0 & -\dfrac{R_\mathrm{r}}{L_\mathrm{r}} & \omega_x - \omega_\mathrm{m} \\ 0 & R_\mathrm{r} & \omega_\mathrm{m} - \omega_x & -\dfrac{R_\mathrm{r}}{L_\mathrm{r}} \end{bmatrix} \quad B_4 = \frac{1}{L_\mathrm{fs}} \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$$C_4 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

This model is perfectly well adapted to the simulation of the machine, but it has several drawbacks for its real-time identification. Its first problem is being of the full order, leading to a significant calculation volume if we want a simultaneous estimation of the state and the four electrical parameters of the model. The major disadvantage is that it requires a very short discretization step, often lower than a millisecond. This is imposed by the pole associated with leakage inductance L_fs and by the high dynamic of inputs (stator voltage). Finally, the exact discretization of this model is intensive. We generally use first order approximations (Euler) or, less frequently, second order of the development of the matrix exponential. Even though it is more intensive to manage, notably for the calculation of the tangent linearized model that the Kalman filter and the extended Luenberger observer require, second order offers a better compromise between precision and discretization step. We will then use:

$$\begin{aligned} A_{\mathrm{d}4} &= e^{A_4 T_e} \approx I + A_4 T_e + \tfrac{1}{2} A_4^2 T_e^2 \\ B_{\mathrm{d}4} &= A_4^{-1}\left(A_4 - I\right) B_4 \approx T_e \left(A_4 + \tfrac{1}{2} A_4 T_e\right) B_4 \end{aligned} \quad [3.5]$$

When the sampling period of control and identification data are equal, we can consider that the input is hold (U(t) = U_k), otherwise, it is preferable to use an interpolated input over two steps ($U_{4,k'} = (U_{4,k} + U_{4,k+1})/2$). Or:

$$\begin{cases} X_{4,k+1} = A_{\mathrm{d}4} X_{4,k} + B_{\mathrm{d}4} U_{4,k'} \\ Y_{4,k} = C_4 X_{4,k} \end{cases} \quad [3.6]$$

3.3.2.2.2. Reverse second order model

If we switch input and output, quick dynamic poles disappear and we have the following second order model:

$$\begin{cases} \dot{X}_2 = A_2 X_2 + B_2 U_2 \\ Y_2 = C_2 X_2 + D_2 U_2 + E_2 \dot{U}_2 \end{cases} \quad [3.7]$$

with $X_2 = \begin{bmatrix} \Phi_{\mathrm{r}\alpha} & \Phi_{\mathrm{r}\beta} \end{bmatrix}^T$ and:

$$A_2 = \begin{bmatrix} -R_{\mathrm{r}}/L_{\mathrm{r}} & \omega_x - \omega_{\mathrm{m}} \\ \omega_{\mathrm{m}} - \omega_x & -R_{\mathrm{r}}/L_{\mathrm{r}} \end{bmatrix}, B_2 = \begin{bmatrix} R_{\mathrm{r}} & 0 \\ 0 & R_{\mathrm{r}} \end{bmatrix}, C_2 = \begin{bmatrix} -R_{\mathrm{r}}/L_{\mathrm{r}} & -\omega_{\mathrm{m}} \\ \omega_{\mathrm{m}} & -R_{\mathrm{r}}/L_{\mathrm{r}} \end{bmatrix}$$
$$D_2 = \begin{bmatrix} R_{\mathrm{s}} + R_{\mathrm{r}} & -\omega_x L_{\mathrm{fs}} \\ \omega_x L_{\mathrm{fs}} & R_{\mathrm{s}} + R_{\mathrm{r}} \end{bmatrix}, E_2 = \begin{bmatrix} L_{\mathrm{fs}} & 0 \\ 0 & L_{\mathrm{fs}} \end{bmatrix}$$

This model is not a true state model because it involves the input derivative in the output equation, but that is not a problem for identification algorithms. In addition, it is the derivative of currents that are usually correctly measured. In practice, this derivative will be obtained with a state variable filter (producing a filtered derivative). The inverse model enables a significant reduction in calculation power necessary for a real-time implementation because of its reduced order, but it also authorizes very long discretization steps while remaining precise, because of the low dynamic of inputs and poles. Finally, it is very easy to discretize it exactly, especially if we choose to work in the rotor reference frame ($\omega_x = \omega_{\mathrm{m}}$):

$$\begin{aligned} A_{\mathrm{d}2} &= \mathrm{e}^{A_2 T_{\mathrm{e}}} = \mathrm{e}^{-(R_{\mathrm{r}}/L_{\mathrm{r}})T_{\mathrm{e}}} I \\ B_{\mathrm{d}2} &= A_2^{-1}\left(A_2 - I\right) B_2 = L_{\mathrm{r}}\left(1 - \mathrm{e}^{-(R_{\mathrm{r}}/L_{\mathrm{r}})T_{\mathrm{e}}}\right) I \end{aligned} \quad [3.8]$$

In reality, writing an exact discrete model is only possible if we know the evolution of input signals in the period of discretization T_e. We cannot presume that the inputs are hold because we want to use a much longer discretization step than the control step. If we want greater precision, we can oversample the input and use a higher polynomial approximation [LOR 00], but in practice, a linear interpolation ($U_{2,k'} = (U_{2,k} + U_{2,k+1})/2$) is sufficient, which results in:

$$\begin{aligned} X_{2,k+1} &= A_{d2} X_{2,k} + B_{d2} U_{2,k'} \\ Y_{2,k} &= C_2 X_{2,k} + D_2 U_{2,k} + E_2 \dot{U}_{2,k} \end{aligned} \quad [3.9]$$

In the section dedicated to the extended Kalman filter, we will see that this model authorizes discretization steps of several dozen milliseconds, while requiring much smaller calculation volume than the full order model.

3.3.3. *Monitoring and information analysis*

Any real-time process control or management must be monitored in order to guarantee reliable operation without any risks, whether for the process instruments or its environment. Even a simple industrial PID controller is monitored: it necessarily integrates anti-windup devices, and transition procedures smoothly from the manual to the automatic mode. This monitoring is even more vital in the case of adaptive control where the increased complexity adds new risks of malfunction. The idea mainly is to monitor the online identification procedure. Unfortunately, even though the adaptive control was the subject of several studies and abundant scientific literature, the problem caused by its real-time monitoring was not addressed in detail [HAG 00]. In manufacturing, adaptive control has a bad reputation. It is considered unreliable and the companies proposing this type of function closely guard their know-how. In scientific and manufacturing terms, adaptive control monitoring and, more specifically, parametric identification is therefore a field that still has to be explored. The first part of this section clarifies the major facets of the problems linked to this monitoring. The second one succinctly introduces informational analysis, which is an efficient tool in resolving some of these problems.

3.3.3.1. *Monitoring problem*

When an appropriate model is chosen and an optimization algorithm is correctly set, the result of the estimation is not guaranteed; the information that we are extracting from data has to be present, and it must not be corrupted by noise that does not respect the working hypotheses like, for instance, being correlated with the estimated quantities. This point is often tricky, especially because we are attempting

to achieve a versatile system that can operate with very different processes. But, even if we aim for a specific application, such as the identification of a particular type of electrical machine, guaranteeing the efficiency of the estimator in any circumstance is not obvious.

In practice, it is usually not possible to make an algorithm of identification work continuously. This would mean that the data permanently contains enough information to ensure the convergence of the algorithm, or at least avoid its divergence. We could then imagine injecting extra-signals to sensitize desired parameters. Unfortunately, in order for these signals to be efficient, their level must be sufficient, often with unfortunate consequences that the user is not ready to accept: disruption of normal operation, additional losses, etc. Permanently injecting extra-signals is usually excluded. In certain applications, it is possible to do it temporarily, or periodically, or during specific sequences. In this case, the monitoring system knows when it must restart and stop the identification algorithm. Conversely, if we only use the natural process signals, the major problem is detecting the presence or absence of necessary information. For this, two types of approaches can be considered:

– expert system type approaches using a series of rules based on the process' point of operation. In this way, in the case of induction motor adaptive control, it would be careless to attempt to estimate its rotor resistance when the torque set point is zero. Hägglung [HAG 00] proposes a generic approach to transient state detection, based on the monitoring of output signals filtered by a high-pass filter;

– digital approaches based on an informational data analysis. The idea is to detect that a matrix characteristic of the operation of the optimization algorithm becomes singular. In the second part of this section, we will introduce this type of analysis.

The first category of approach depends on the process involved, whereas the second one is more linked to the algorithm of identification. For more security, we may consider the combination of both approaches whenever possible. In fact, regardless of the approach chosen, the decision will be all the more tricky, as the measuring noises are significant.

Monitoring must also manage the initialization of the identification, as well as the transitions during its reactivation. Depending on the type of user targeted, the initialization can be manual (experienced operator) or automatic (novice operator). An automatic initialization will only require from the operator the information that is easily accessible (e.g. the rating plate of the machine) or that is qualitative. Sometimes, a sequence of tests is done beforehand, without apparent operation of the process. One of the major points in the initialization phase is the choice of data sampling period, as well as the definition of low-pass filters for optimizing their

signal-noise ratio. Finally, since the algorithms used in real-time are necessarily recursive, it is important to manage their startup well. The idea is obviously to guarantee smooth transitions, as well as preserving prior information, which is still relevant, as best as possible. In this way, when we want to estimate several parameters simultaneously and one of them is no longer accessible, the best would be to be able to continue to estimate the others.

3.3.3.2. *Information analysis and global identification*

The goal of global identification proposed by Richalet is not to find an optimal model, but all suitable models in relation to characterization errors and instrumental errors [RIC 91]. This approach has several advantages. We can notably evaluate uncertainties on estimated parameters and see if parametric errors are coupled. We can then detect identifiability losses resulting in parametric compensation.

3.3.3.2.1. Distance of structure and distance of state

Each model is represented by a point M with coordinates forming the vector of parameters $\Theta = [\theta_1, \theta_{2\ldots}, \theta_p]^T$. If we assume that the structure chosen perfectly represents the process, there is a vector $\Theta_o = [\theta_{o1}, \theta_{o2, \ldots} \theta_{op}]^T$ corresponding exactly to the process.

In ideal identification conditions, the optimum point is in O; the model then behaves exactly as the real system for all input (for identical initial states). In practice, because of characterization errors and measuring noises, this will not be the case. We define a structure distance from the gap between the parameters of the model and the parameters of the object to identify. In general, the distance used is the Euclidian standard in parametric space, which is:

$$D(\mathrm{O},\mathrm{M}) = \left\| \Theta - \Theta_o \right\|^2 \qquad [3.10]$$

But, we can also use a more general quadratic form, such as $D(\mathrm{O},\mathrm{M}) = (\Theta - \Theta_o)^T P (\Theta - \Theta_o)$, in order to introduce a weighing factor for each parameter.

The objective of any identification algorithm is to cancel distance D(O, M). Since point O is by definition unknown, the cancellation is not possible and the algorithm attempts to minimize another distance, called distance of state, characterizing the gap between model and object outputs:

$$D(\Theta) = \int_T \left(Y(t,\Theta) - Y_o(t) \right)^T \left(Y(t,\Theta) - Y_o(t) \right) \mathrm{d}t \qquad [3.11]$$

where $Y(t,\Theta)$ and $Y_o(t)$ are model outputs (depending on parameters θ_i) and object outputs, respectively. The horizon of observation is represented by T, the time of the observation.

For a sampled test containing N samples, the distance of state is defined as follows:

$$D(\Theta) = \sum_{k=1}^{N} \left(Y(k,\Theta) - Y_o(k)\right)^T \left(Y(k,\Theta) - Y_o(k)\right) \quad [3.12]$$

An isodistance (Iso-D) is the surface of the parametric space in which the distance of state has a set constant value. According to [RIC 91], the real goal of the identification must be the search for the minimum D^* level of the distance we can reach instead of the search for the minimum of D. This minimum level considers noise and characterization errors. When characterization and estimation of parameters are perfect, model outputs and the process output are only different because of the measuring noise W:

$$Y(\Theta_o) = Y_o + W \quad [3.13]$$

The minimum distance of state that can be reached is then valued at:

$$D^* = D(\Theta_o) = \int_T W^T W \, dt \quad [3.14]$$

Distance D^* represents the noise energy in the horizon of identification. The role of the estimator is to adjust estimation $\hat{\Theta}$ to minimize $D(\hat{\Theta})$. Nevertheless, $D(\hat{\Theta})$ must not be lower than D^*, otherwise, that means that the estimator is attempting to also explain the error of the model. In addition, uncertainties linked to noise result in distorting the iso-D surface. The progression of iterative algorithms can then be false. Depending on the position of the initial point, these algorithms will converge to different local minima of the parametric space. The structure of iso-Ds in the parametric space reports the sensitivity of the parameters for the test protocol. A parameter is sensitized by a test depending on the size of the uncertainty interval (corresponding to minimal D^* iso-D). The tighter the iso-Ds in the direction of a parameter, the more that parameter is sensitized. The form of iso-Ds can provide us with a criterion to detect loss of identifiability.

3.3.3.2.2. Connection between distance of structure and distance of state

Sensitizing a parameter means giving it an important role during the test. A small variation of this parameter leads to a slight effect in the output signal. The influence

of parameters can be evaluated with the help of sensitivity functions connecting the variations of parameters to variations of model output signals. The sensitivity function of output y_i, at step k, in relation to parameter θ_j is defined by:

$$\sigma_{ij}(k) = \frac{\partial y_i(k,\Theta)}{\partial \theta_j} \qquad [3.15]$$

When the model parameters have very different orders of magnitude, it becomes more interesting to know the functions of sensitivity in relation to relative parameter variations: $\sigma_{r,ij}(k) = \theta_j \sigma_{ij}(k)$.

First, we will consider the parameters of a linear model such a least square model. We note the matrix made up of input signals (explanatory variable) as X and the output vector (explained variable) as Y. We have:

$$Y(k) = X^T(k)\Theta \Leftrightarrow \begin{bmatrix} \vdots \\ y_i(k) \\ \vdots \end{bmatrix} = \begin{bmatrix} \ddots & \vdots & \iddots \\ \cdots & x_{ij}(k) & \cdots \\ \iddots & \vdots & \ddots \end{bmatrix} \begin{bmatrix} \vdots \\ \theta_j \\ \vdots \end{bmatrix} \qquad [3.16]$$

The function of sensitivity σ_{ij} of output i in relation to parameter j is then written as:

$$\sigma_{ij}(k) = \frac{\partial y_i(k,\Theta)}{\partial \theta_j} = x_{ij}(k) \qquad [3.17]$$

The functions of sensitivity are simply equal to components x_{ij} of explanatory variable X. Distance of state, from [3.12], is written as:

$$\begin{aligned} D(\Theta) &= \sum_{k=1}^{N} \left(X(k)^T\Theta - X(k)^T\Theta_o \right)^T \left(X(k)^T\Theta - X(k)^T\Theta_o \right) \\ &= \sum_{k=1}^{N} \left(\Theta - \Theta_o\right)^T X(k)X(k)^T \left(\Theta - \Theta_o\right) = \tilde{\Theta}^T \left(\sum_{k=1}^{N} X(k)X(k)^T \right) \tilde{\Theta} \end{aligned} \qquad [3.18]$$

with $\tilde{\Theta} = \Theta - \Theta_o$. We can also write the distance of state with relative functions of sensitivity:

$$D(\Theta) = \tilde{\Theta}_r^T \left(\sum_{k=1}^{N} X_r(k)X_r(k)^T \right) \tilde{\Theta}_r \qquad [3.19]$$

with $\tilde{\theta}_{rj} = (\theta_j - \theta_{oj})/\theta_{oj}$ as the components of relative errors and $x_{r,ij} = \theta_j x_{ij}$ as those of relative explanatory variable X_r. For a linear model in relation to parameters, there is therefore equivalence between distance of state and distance of structure.

We will now consider the case of a non-linear model. Suppose that the distance of state accepts a Taylor development surrounding point O:

$$D(\Theta_o + \tilde{\Theta}) = D(\Theta_o) + G(\Theta_o)\tilde{\Theta} + \tfrac{1}{2}\tilde{\Theta}^T H(\Theta_o)\tilde{\Theta} + ... \quad [3.20]$$

where $G(\Theta_o)$ and $H(\Theta_o)$ are the gradient and Hessian of distance of state at point Θ_o, respectively. Vector $\tilde{\Theta}$ represents the gap between current point M and point O. By definition, Θ_o is the vector of the surface minimum coordinates. Distance and gradient are therefore zero in this point: $D(\Theta_o) = 0$ and $G(\Theta_o) = 0$. Or:

$$D(\Theta_o + \tilde{\Theta}) \approx \tfrac{1}{2}\tilde{\Theta}^T H(\Theta_o)\tilde{\Theta} \quad [3.21]$$

The Hessian represents the second derivative of the distance in relation to parameters. After a few calculations [RIC 91], we show that it is expressed with help from sensitivity functions:

$$H(\Theta_o) = \left.\frac{\partial^2(\Theta)}{\partial^2\Theta}\right|_{Q=Q_o} = 2\sum_{i=1}^{n_s}\sum_{k=1}^{N}\begin{bmatrix}\sigma_{i1}(k)\\ \vdots \\ \sigma_{ip}(k)\end{bmatrix}\left[\sigma_{i1}(k)\cdots\sigma_{ip}(k)\right] \quad [3.22]$$

where n_S designates the number of outputs and p the number of estimated parameters. In the linear case, we find the result [3.20] because the sensitivity functions are equal to the components of explanatory variable X. The Hessian is therefore the sum of the sensitivity contributions of each output in relation to each parameter. In conclusion, for a non-linear model, the distance of state surrounding point O is also a parametric distance.

3.3.3.2.3. Hessian conditioning and parametric uncertainty

Traditional estimators, such as least squares search for a minimum, that is, a set of parameters, minimizing the distance of state for a specific criterion. In practice since the measurements are noisy, in the assumption that these noises are independent from sensitivity functions, the solution to find is actually the minimum obtained. On the other hand, if there is correlation between these quantities, the minimum does not represent the set of solution parameters. In fact, this comes down to using noise as information on the model, thus producing a bias [RIC 91]. In these

conditions, the best identification does not correspond to the minimum distance. Global identification does not look for a unique value of parameters, but a volume defined by the isodistance containing all "acceptable" values and notably the desired value. If we consider that the energy of noise is low enough for the minimal D^* isodistance to authorize the second-order approximation of equation [3.21], we have:

$$\tilde{Q}^T \frac{H(\Theta_o)}{2D^*}\tilde{\Theta} = 1 \qquad [3.23]$$

Since matrix H is symmetrical and semi-defined positive by design, its eigenvalues λ_k are positive or zero. Expression [3.23] defines a hyperellipsoid with axes half-lengths valued at $\sqrt{2D^*/\lambda_k}$. In the case of estimation with a dimension that is greater than two, we can visualize this hypervolume by plane projections resulting in ellipses (Figure 3.1). We can also determine the maximum uncertainty in each parameter for a set distance. We show that uncertainty in parameter θ_i is given by:

$$\tilde{\theta}_{i,\max} = \sqrt{2 f_{i,i} D^*} \qquad [3.24]$$

where $f_{i,i}$ is diagonal element i, of the inverse of Hessian H.

When one of the inherent values is zero, the ellipsoid degenerates into a tube. Errors in parameters are then infinite. This also happens when the Hessian is singular. This means that the model cannot be identified: we cannot estimate each parameter, but only a function linking them (and corresponding to the direction of the eigenvector associated with the null eigenvalue). Except in specific cases, it is preferable that the errors be evenly distributed throughout all parameters: the ideal hyperellipsoid is thus a hypersphere.

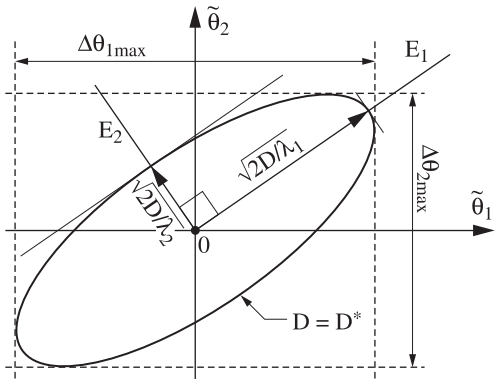

Figure 3.1. *Projection of plane (θ_1, θ_2) of an iso-D*

3.4. Least square methods

The least square method was imagined by Gauss in 1795 to reduce his calculation errors on the position of the planets. This affiliation could have predestined it to applications involving electrical machines, all the more so as it offers great ease of implementation including low calculation cost and adjustment simplicity.

As long as we have a linear model in relation to parameters, the recursive variations of least square methods enable a real-time tracking of variable parameters. In fact, compared to other approaches, the least square method and its derivatives were not widely applied to the parametric identification of electrical machines.

In the second part of this section, we will see the problems with the identification of the induction motor.

3.4.1. *Principle of least squares and instrumental variables*

The least square method assumes that the identified system can be represented by a linear model:

$$Y_k = X_k^T \Theta + V_k \qquad [3.25]$$

where Y, X, Θ, and V designate the output vector, the regressor, the vector of p parameters to estimate and an additive noise vector, respectively. V is an additive noise vector. In order for the estimation given by least squares not to be biased, these noises must have zero mean and they must not be correlated with the regressor components. Index k represents the sampling time: $t_k = kT_e$.

3.4.1.1. *Least squares and recursive least squares*

For a horizon of N samples, the least squares estimation is provided by Mendel [MEN 95]:

$$\hat{\Theta}_N = \left(\sum_{k=1}^{N} X_k X_k^T \right)^{-1} \sum_{k=1}^{N} X_k Y_k \qquad [3.26]$$

This estimation minimizes the norm of the error of prediction $\varepsilon_k = Y_k - X_k^T \hat{\Theta}_k$. We can also consider minimizing a weighted error, according to temporal k index (e.g. to favor more recent data), or according to the output (favoring the most precise measurements). Information matrix $R_N = \sum_{k=1}^{N} X_k X_k^T$ plays a very important role in

this calculation. For it to be full order and therefore invertible, data must be sufficiently rich.

There are several variations of the recursive least square algorithm. In theory, they all provide estimations that are identical to those obtained by expression [3.26]. In practice, depending on the characteristics of the model, some variations offer better numerical precision. When the dimension of the output vector is lower than the parameter vector, the following "covariance" form is preferable because it leads to the reversal of a reduced dimension matrix [MEN 95]:

$$\begin{aligned} \hat{\Theta}_k &= \hat{\Theta}_{k-1} + K_k \left(Y_k - X_k^T \hat{\Theta}_{k-1} \right) \\ K_k &= P_{k-1} X_k \left(\lambda I + X_k^T P_{k-1} X_k \right)^{-1} \\ P_k &= \left(I - K_k X_k^T \right) \lambda^{-1} P_{k-1} \end{aligned} \qquad [3.27]$$

This algorithm reveals the forgetting factor $\lambda \leq 1$, which is generally set empirically [WAL 94]. The estimation of the parameters is updated according to the error of prediction $\varepsilon_k = Y_k - X_k^T \hat{\Theta}_{k-1}$ and gain K_k, sometimes called Kalman gain because of its similarity with that of the Kalman filter (see section 3.5). This variation is called covariance form, because P_k is equivalent to a variance-covariance matrix.

3.4.1.2. *Instrumental variables*

If some components of noise V and regressor X are correlated, the estimation of least squares is biased. This bias is valued at:

$$\tilde{\Theta}_N = \hat{\Theta}_N - \Theta_o = \left(\sum_{k=1}^{N} X_k X_k^T \right)^{-1} \sum_{k=1}^{N} X_k V_k \qquad [3.28]$$

When the bias is a problem (it is not always the case), we can try to eliminate it using the instrumental variable method. This method consists of replacing the components of regressor X by signals highly correlated with its components, but decorrelated from noise V. If we note as Z the vector of instrumental variables thus obtained, the estimation is written as:

$$\hat{\Theta}_N = \left(\sum_{k=1}^{N} Z_k X_k^T \right)^{-1} \sum_{k=1}^{N} Z_k Y_k \qquad [3.29]$$

This expression corresponds to the following recursive form, by introducing the forgetting factor λ:

$$\begin{aligned} \hat{\Theta}_k &= \hat{\Theta}_{k-1} + K_k \left(Y_k - X_k^T \hat{\Theta}_{k-1} \right) \\ K_k &= P_{k-1} Z_k \left(\lambda I + X_k^T P_{k-1} Z_k \right)^{-1} \\ P_k &= \left(I - K_k X_k^T \right) \lambda^{-1} P_{k-1} \end{aligned} \qquad [3.30]$$

The problem with this method is in the definition of instrumental variables, which must be decorrelated from the noise while remaining correlated enough with the components of the regressor so that the new information matrix $R_N = \sum_{k=1}^{N} Z_k X_k^T$ is invertible and, if possible, well conditioned [LAN 93]. Several instrumental variable generation techniques were proposed. When the noises are high frequency compared to the dynamic of the identified system, we can replace the components of the regressor by their delayed value in order to decorrelate them from the noise. Another technique consists in generating instrumental variables from filtered input signals; the ideal filter would be the desired model. We then proceed iteratively by using a model deduced from the estimation obtained in the previous step as a filter. This model is initialized by traditional least squares. When we work off-line with a short data length or online with a low forgetting factor, we must be careful with the choice of instrumental variables in order to guarantee information matrix invertibility. The main advantage with instrumental variables is that there is no requirement for a specific hypothesis for the process generating noise V, contrary to other methods, such as generalized or extended least squares [WAL 94].

3.4.1.3. *Monitoring and parametric uncertainty*

We come back to the information analysis presented in section 3.3.3.2. We have seen that for a linear model in relation to parameters, distances of state and structure are equivalent (equation [3.19]), that sensitivity functions are given by the regressor components (equation [3.17]), and that the Hessian of the distance of state is in fact the information matrix (with a factor two): $D(\Theta) = \tilde{\Theta}^T R_N \tilde{\Theta}$. The condition number of information matrix R_N therefore plays a very important role in the operation and precision of the estimator.

Despite its simplicity, the least squares algorithm requires a few precautions, especially for an online application [WAL 94]. Because of the forgetting factor, matrix P_k may explode if $X = 0$, because we then obtain $P_k = P_{k-1}/\lambda$. If $\lambda < 1$, gain K_k no longer leans toward zero and, because of the unavoidable characterization errors, estimations no longer converge. It is therefore preferable to lock the estimations when the prediction error is low. To keep matrix P_k from becoming

singular for numeric reasons, we can increase its diagonal terms by adding small term α, or use a U-D factoring algorithm, because P_k is symmetrical. In some cases, and notably when parameters vary by step, it is better to eliminate the forgetting factor (by using $\lambda = 1$) and to monitor prediction error ε_k. When it takes an improbable value, we simply have to increase matrix P_k which was leaning toward zero (as well as gain K_k) to reactivate the adaptation of the parameters [WAL 94].

Finally, matrix P_k can provide precious indications on the precision of estimations. When the components of V noise vector are Gaussian, decorrelated between each other and all with variance σ^2, the matrix of variance-covariance of the estimation error $\tilde{\Theta} = \hat{\Theta} - \Theta_o$ equals [MEN 95]:

$$E\left\{\tilde{\Theta}\tilde{\Theta}^T\right\} = \sigma^2 P_k \qquad [3.31]$$

As long as we know the standard deviation σ of measuring noises, we can determine that of estimations. The equiprobability hyperellipsoid containing 95% of possible developments (corresponding to three standard deviations) is defined by:

$$\tilde{\Theta}^T P_k^{-1} \tilde{\Theta} = (3\sigma)^2 \qquad [3.32]$$

Eigenvalue monitoring, or more simply put, diagonal terms of matrix P_k makes it possible to detect the risks of divergence of the estimator.

3.4.2. *Application to the induction motor*

Because of the complexity of methods such as the Kalman filter or the extended Luenberger observer, it is tempting to want to use an algorithm that is simpler to implement and adjust. For a relatively simple industrial application, least squares seems to be an interesting alternative. And yet, we do not find many studies applying least squares to the identification of electrical machines and most often, these studies involve the estimation of a single parameter. In the case of the induction motor, the idea is generally to achieve an adaptive vector control by estimating the rotor time constant or resistance. To our knowledge, the first article to propose an online estimation of all (or almost all) electrical parameters of the machine is by [STE 94]. On the basis of this article, G. Dehay started his research for his thesis [DEH 96] and the major results are discussed in this section. This thesis clearly establishes that the least squares method is not adapted to the identification of the complete electrical model of the induction motor because this model is not suitable to a format that is compatible with least squares. This goes back to the comments in section 3.3 on the importance of the coherence of the data, the estimation algorithm and the model.

3.4.2.1. *Linear model in relation to parameters*

The idea is to obtain, from electrical equations of the induction motor, a linear model in relation to parameters, while eliminating the unmeasurable internal quantities that the fluxes are. If we want to simultaneously estimate the four electrical parameters of the machine, it is not possible to write an ideal model. We will use the approximate solution, which seems to be the best and was proposed by [STE 94]. After a few basic manipulations of equations [3.3], we arrive at the following model presented in complex notations to simplify writing:

$$y = X^T \Theta \qquad [3.33]$$

with

$$y = \frac{\mathrm{d}^2 i_\mathrm{s}}{\mathrm{d}t^2} - j\omega_\mathrm{m} \frac{\mathrm{d}i_\mathrm{s}}{\mathrm{d}t} + j \frac{\mathrm{d}\omega_\mathrm{m}}{\mathrm{d}t} \frac{\psi_\mathrm{r}}{L_\mathrm{f}}$$

$$\Theta^T = \left[-\left(\frac{R_\mathrm{s} + R_\mathrm{r}}{L_\mathrm{f}} + \frac{R_\mathrm{r}}{L_\mathrm{r}} \right) - \frac{R_\mathrm{s} R_\mathrm{r}}{L_\mathrm{f} L_\mathrm{r}} \frac{R_s}{L_\mathrm{f}} \frac{1}{L_\mathrm{f}} \frac{R_\mathrm{r}}{L_\mathrm{f} L_\mathrm{r}} \right]$$

$$X^T = \left[\frac{\mathrm{d}i_\mathrm{s}}{\mathrm{d}t} \; i_\mathrm{s} \; j\omega_\mathrm{m} i_\mathrm{s} \; \frac{\mathrm{d}u_\mathrm{s}}{\mathrm{d}t} - j\omega_\mathrm{m} u_\mathrm{s} \; u_\mathrm{s} \right]$$

This model raises several major criticisms. This first one is that, despite all our efforts, the flux is still present in the model: it appears in the *Y* output, multiplied by the angular acceleration. Unless we have a measure of the flux, we will only be able to use this model at a quasi-constant speed (otherwise the term linked to the flux is generally significant [DEH 96]). The second criticism involves the five-dimension parameter vector, while we are searching for four electrical parameters. In addition, the relation between the least squares parameters is non-linear: $\theta_2 = \theta_3 \theta_4 / \theta_5$. [STE 94] proposes the estimation of the stator resistance independently and the replacement of stator u_S voltage by $v_\mathrm{s} = u_\mathrm{s} - R_\mathrm{s} i_\mathrm{s}$. We then obtain a new parameterization and a new regressor *X*, since the output is unchanged:

$$\Theta^T = \left[-\left(\frac{R_\mathrm{r}}{L_\mathrm{f}} + \frac{R_\mathrm{r}}{L_\mathrm{r}} \right) \frac{1}{L_\mathrm{f}} \frac{R_\mathrm{r}}{L_\mathrm{f} L_\mathrm{r}} \right] \text{ and } X^T = \left[\frac{\mathrm{d}i_\mathrm{s}}{\mathrm{d}t} \; \frac{\mathrm{d}v_\mathrm{s}}{\mathrm{d}t} - j\omega_\mathrm{m} v_\mathrm{s} \; v_\mathrm{s} \right] \qquad [3.34]$$

There remains a last problem linked on one hand to the presence of derivatives of electrical signals in *y* and *X*, and on the other hand, to the expression of the second component of *X*: $x_2 = \dot{v}_\mathrm{s} - j\omega_\mathrm{m} v_\mathrm{s}$. In fact, at average or high speed, each of the terms of this difference is great, but since they are close, their difference is small. In practice, a small error on one of the two terms is sufficient for the model to be significantly disturbed (for more detail, see [DEH 96]).

3.4.2.2. *Implementation of least squares*

In order to apply the least squares algorithm to the previous model, we simply have to rewrite the latter by separating the real from the imaginary parts. In fact, the problem resides in the numerous precautions to be taken while trying to obtain a correct result from experimental data. First, as indicated previously, we must limit the acceleration of the machine during the test. Then, we must use a very careful instrumentation to collect the stator voltage and currents (we must not use voltage references). As Figure 3.2 shows, we used four Hall effect sensors (to measure two line currents and two interphase voltages) followed by anti-aliasing filters (fifth order Bessel filter). Finally, to obtain a precise calculation of voltage and current derivatives, the measures were oversampled at 5 kHz. Data is then filtered by forth order filter with a cut-off frequency of 100 Hz. Finally, the derivative is obtained by a polynomial method over five points and resampled at 1 kHz before being injected in the least squares algorithm. All these operations are vital in limiting the large amplitude transient errors to which least squares are very sensitive.

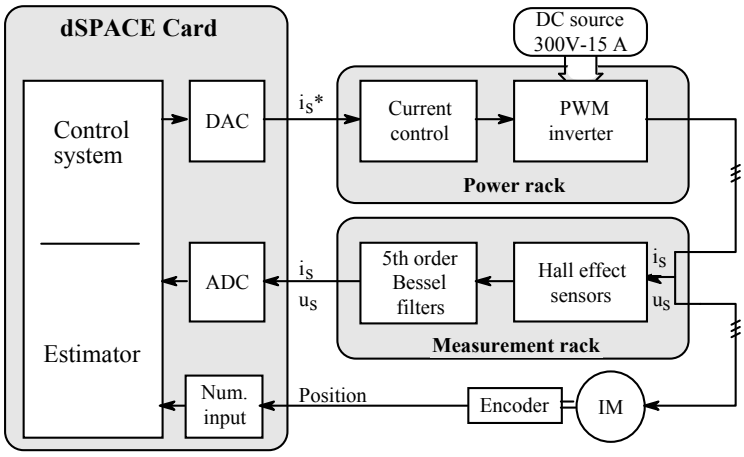

Figure 3.2. *Benchmark structure*

3.4.2.3. *Experimental results*

The following results [DEH 96] were obtained with a 750 W squirrel-cage induction motor whose characteristics are presented in Table 3.3 (see section 3.8). This machine is controlled by a vector law implemented in a DS1102 card and powered by a PWM inverter with a modulation frequency of 18 kHz. Figure 3.3 presents the test used. The problem is finding the right compromise between a test that is sufficiently rich so that its information content can offer a good sensitization of all estimated parameters, without the machine acceleration being too great.

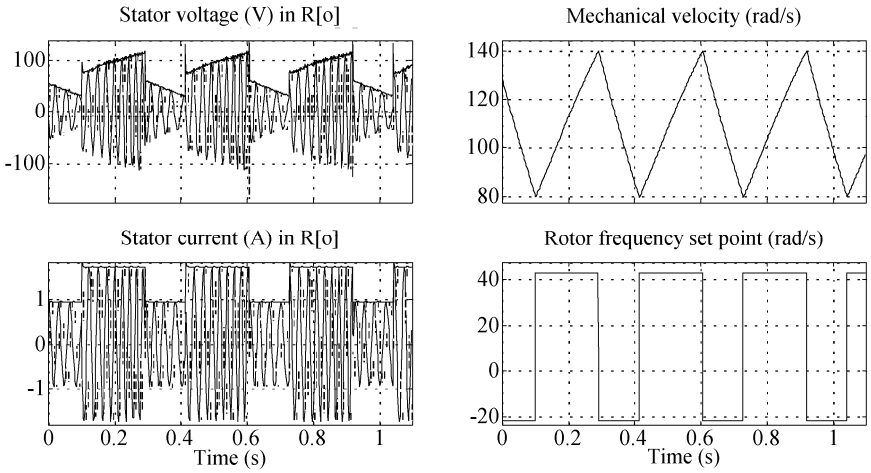

Figure 3.3. *Raw measures: two-phase voltage and current (in the fixed reference), mechanical speed, and rotor angular frequency*

On the left, Figure 3.4 presents the estimations delivered by the least squares and on the right, the corresponding rotor parameters (L_r, R_r, and T_r). We can note that, for $t < 0.1$ s, the estimations are very far from their final value. In fact, during this first phase, the machine is almost in electric steady-state making the estimation of three electrical parameters not possible: we then only have two independent pieces of information and as Figure 3.5 shows, normalized information matrix P_n is almost of rank two. At $t = 0.1$ s, there is a change in torque set point modifying the rotor frequency and the amplitude of currents simultaneously. The result is additional information improving the informational richness of the data considerably; the condition number of P_n goes from 10^5 to 10^2 with the help of the evolution of one of the three eigenvalues (Figure 3.5). There is then a quick convergence of parameters. The dash-dot lines represent the final result of identification by an extended Kalman filter from the same test. We can observe that, even though for the least square parameters, both identifications are very close; it is not the same for electrical parameters which are the real objective of this identification. This comes from the fact that the conversion of LS parameters into electric parameters is not well conditioned.

Since we have two sets of rotor parameters (one provided by the least squares and the other by a Kalman filter), how do we know which one is best? A pragmatic solution simply consists of testing them in real-life situation. Considering that our online identification is destined to achieve adaptive vector control, we have injected

each set of parameters in a field-oriented control where the performances were observed. Figure 3.6 shows that the parameters provided by the Kalman filter provide better control of the machine torque. The torque was determined from mechanical speed, and the machine has a known load.

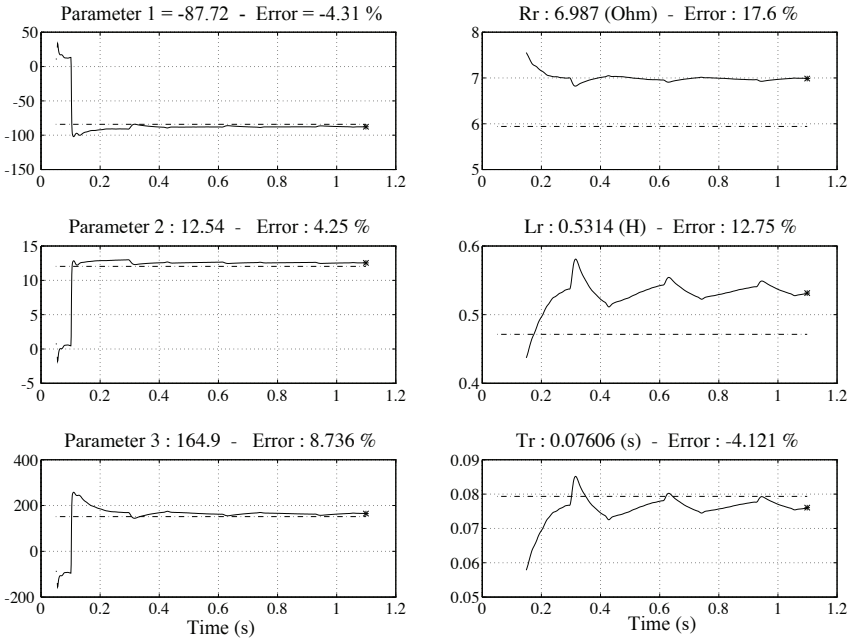

Figure 3.4. *Estimation of LS parameters (dash-dot line: Kalman filter)*

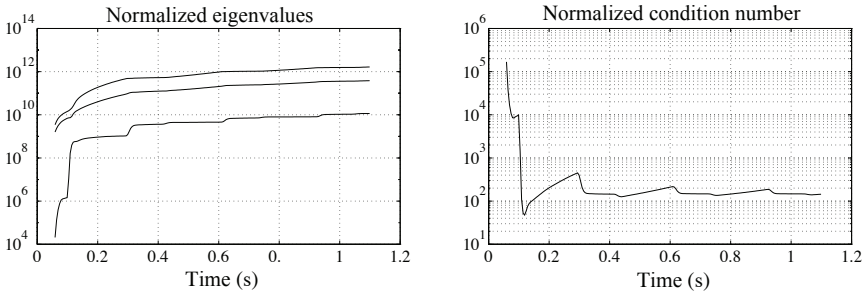

Figure 3.5. *Test conditioning*

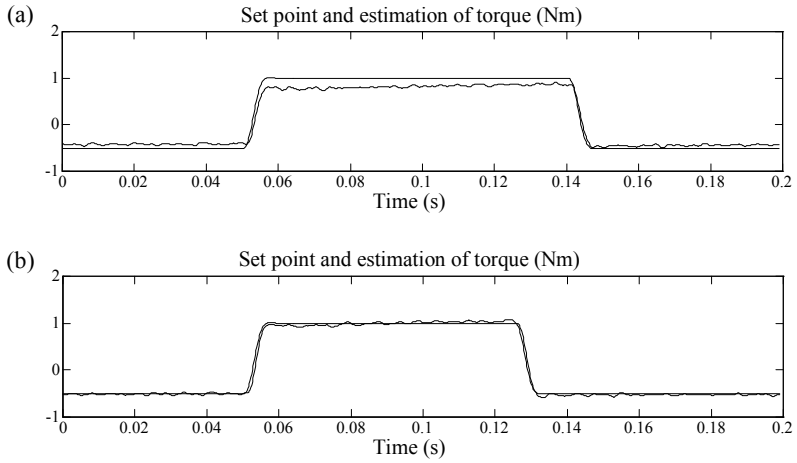

Figure 3.6. *Use of estimated parameters: (a) least squares; (b) Kalman filter*

3.5. Extended Kalman filter

The Kalman filter is a state observer for a linear system represented by a state model disturbed by different sources of noise. Under certain hypotheses that we will clarify later, its estimation is optimal in the sense of minimal variation estimation. Contrary to the other approaches presented in this chapter, the Kalman filter fits in a stochastic context requiring minimal knowledge of noises affecting the model and data. For some, it is an advantage to be able to use complementary and available information and for others, it is a drawback hindering its implementation (see section 3.6.2.3). This clearly shows the importance of the prerequisites in the efficient use of a method of identification.

Several variations of the Kalman filter were proposed, notably to avoid numeric problems linked to the evaluation of ill-conditioned covariance matrices. Nevertheless, the most commonly used form in studies involving electrical machines remains the one initially proposed by Kalman [KAL 60] or possibly the Joseph form [GRE 93], which is less sensitive to numerical errors. In general, the latter preserves the symmetry of covariance matrices better.

The Kalman filter is based on a stochastic state model involving a vector of state noises W and a vector of output noises V. For the filter to be optimal, the noises must be white, centered, Gaussian, and decorrelated from estimated variables. It is preferable that state and output noises also be decorrelated between each other; otherwise, we must use a more complex form of the filter [GRE 93]. When the noises do not have a Gaussian probability density, the Kalman filter is no longer the

optimal filter, but it remains the best linear estimator in the sense of trace minimization of covariance matrix for estimation errors.

In order to estimate the parameters of the model, we must consider them as additional state variables. This state extension generally leads to a non-linear model requiring the use of an extended version of the Kalman filter. The simplest extended form, discussed in more detail in the following section, is based on a model linearization by simple first order approximation. This linearization that must be done at each iteration makes the calculation filter slightly more complex.

Even though this approach is very popular, because it is simple to implement, it sometimes presents divergence problems that are difficult to control. Ljung proposed the modification of the Kalman filter by introducing a corrective term involving the sensitivity of the Kalman gain for estimated parameters [LJU 79]. Recent studies [JUL 97] propose the replacement of the first order approximation (tangent model) by a finite difference based on a Stirling development, for a rigorous evaluation of the covariance matrix of estimations. This new approach was notably applied to the speed estimation of the induction motor [SAH 02].

3.5.1. *Principle*

Consider the following non-linear state model in which vectors Φ and Θ designate the state and parameters to estimate, respectively:

$$\begin{aligned} \Phi_{k+1} &= F_{\Phi}\left(\Phi_k, \Theta_k, U_k\right) + W_{\Phi,k} \\ \Theta_{k+1} &= F_{\Theta}\left(\Phi_k, \Theta_k, U_k\right) + W_{\Theta,k} \\ Y_k &= G_{\Phi\Theta}\left(\Phi_k, \Theta_k, U_k\right) + V_k \end{aligned} \qquad [3.35]$$

As previously indicated, to simultaneously estimate the state and parameters of the previous system, we must write the following extended state model:

$$\begin{cases} X_{k+1} = \begin{bmatrix} \Phi_{k+1} \\ \Theta_{k+1} \end{bmatrix} = \begin{bmatrix} F_{\Phi}\left(\Phi_k, \Theta_k, U_k\right) \\ F_{\Theta}\left(\Phi_k, \Theta_k, U_k\right) \end{bmatrix} + \begin{bmatrix} W_{\Phi,k} \\ W_{\Theta,k} \end{bmatrix} = F\left(X_k, U_k\right) + W_k \\ Y_k = G\left(X_k, U_k\right) + V_k \end{cases} \qquad [3.36]$$

W and V are white, centered, and possible Gaussian noises whose covariance matrices are: $E\left\{W_k W_k^T\right\} = Q_k$ *and* $E\left\{V_k V_k^T\right\} = R_k$. We can note that these covariance matrices may vary over time. To apply the Kalman filter, model [3.36] must be

linearized around the current point. Since the goal of this model is to characterize the incidence of state and output noises, it omits deterministic input U:

$$\begin{aligned} \tilde{X}_{k+1} &= \frac{\partial F}{\partial X_k}\tilde{X}_k + W_k = \tilde{A}_d\tilde{X}_k + W_k \\ \tilde{Y}_k &= \frac{\partial G}{\partial X_k}\tilde{X}_k + V_k = \tilde{C}\tilde{X}_k + V \end{aligned} \qquad [3.37]$$

The previous model involves a general parameter evolution equation. In practice, unless we have a specific evolution equation (e.g. linked to thermal drifts), we assume completely random variations of parameters by writing $\Theta_{k+1} = \Theta_k + W_{Q,k}$. In addition, if function F_Φ corresponds to a linear state model, we have:

$$\begin{cases} \Phi_{k+1} = A_{\mathrm{d}}(\Theta_k)\Phi_k + B_{\mathrm{d}}(\Theta_k)U_k + W_{\Phi,k} \\ Y_k = C(\Theta_k)\Phi_k + D(\Theta_k)U_k + V_k \end{cases} \qquad [3.38]$$

In this case, the calculation of the tangent linearized model is written:

$$\begin{aligned} \tilde{A}_{\mathrm{d}} &= \begin{bmatrix} \frac{\partial F_\Phi}{\partial \Phi_k} & \frac{\partial F_\Phi}{\partial \Theta_k} \\ \frac{\partial F_\Theta}{\partial \Phi_k} & \frac{\partial F_\Theta}{\partial \Theta_k} \end{bmatrix} = \begin{bmatrix} A_{\mathrm{d}}(\Theta_k) & \frac{\partial A_d(\Theta_k)}{\partial \Theta_k}\Phi_k + \frac{\partial B_{\mathrm{d}}(\Theta_k)}{\partial \Theta_k}U_k \\ 0 & I \end{bmatrix} \\ \tilde{C} &= \begin{bmatrix} \frac{\partial G}{\partial \Phi_k} & \frac{\partial G}{\partial \Theta_k} \end{bmatrix} = \begin{bmatrix} C(\Theta_k) & \frac{\partial C(\Theta_k)}{\partial \Theta_k}\Phi_k + \frac{\partial D(\Theta_k)}{\partial \Theta_k}U_k \end{bmatrix} \end{aligned} \qquad [3.39]$$

The algorithm of the extended Kalman filter is made up of a prediction step (subscripted variables $k+1|k$) and a correction step (subscripted variables $k+1|k+1$). The prediction step is based on the non-linear state equation and its linearization for the calculation of the variance-covariance matrix of the prediction error:

$$\begin{cases} X_{k+1|k} = F\left(X_{k|k}, U_k\right) \\ P_{k+1|k} = \tilde{A}_{\mathrm{d}}\left(X_{k|k}, U_k\right)P_{k|k}\,\tilde{A}_D\left(X_{k|k}, U_k\right)^T + Q_k \\ Y_{k+1|k} = G\left(X_{k+1|k}, U_{k+1}\right) \end{cases} \qquad [3.40]$$

The correction step is based on the output prediction error and on the Kalman K gain deducted from the linearization of the output equation:

$$K_{k+1} = P_{k+1|k}\,\tilde{C}\left(X_{k+1|k}, U_{k+1}\right)\left(\tilde{C}\left(X_{k+1|k}, U_{k+1}\right)P_{k+1|k}\tilde{C}\left(X_{k+1|k}, U_{k+1}\right)^T + R_{k+1}\right)$$

$$X_{k+1|k+1} = X_{k+1|k} + K_{k+1}\left(Y_{k+1} - Y_{k+1|k}\right) \qquad [3.41]$$

$$P_{k+1|k+1} = P_{k+1|k} - K_{k+1}\Sigma_{k+1}K_{k+1}^T$$

In theory, gain K achieves the optimal weighing between prediction $X_{k+1|k}$ based on the state equation and the correction linked to the output error. The trace of matrix $P_{k+1|k+1}$ is then minimal.

3.5.2. *Tuning of Q and R matrices*

Even though it is a vital point in the implementation of a Kalman filter, the tuning of matrices of state and observation noise covariance is rarely presented. This is undoubtedly linked to the robustness of the filter, and several authors admit to use a trial and error approach, to arrive at a satisfying empirical adjustment. In fact, the tuning of the Kalman filter can be considered based on two completely opposite approaches. The first one consists in adopting a deterministic point of view and using covariance Q and R matrices as simple adjustment parameters. Some studies propose finding an adjustment from the optimization of a deterministic criterion [HIL 00, LAR 93]. Conversely, the second approach uses the stochastic point of view at the origin of the Kalman filter. It is obviously much trickier to implement, because it requires a fine analysis of modeling and measuring errors. In addition, strictly speaking, it presumes that these errors must be represented by white, centered additive noises decorrelated from estimated states. It is obvious that these hypotheses are rarely verified. Nevertheless, when we can obtain an appropriate characterization of these errors, leading to a correct filter adjustment, this filter then provides an optimal estimation as well as an evaluation of the variation of this estimation. This information is vital because an estimation only has value if we know how precise it is. In addition, the analysis of experimental noises and modeling errors highlights the relative importance of the different sources of error and optimize the definition of the model and instrumentation. Even if at first it appears very difficult, the stochastic approach is sufficiently promising to be attempted.

In practice, if we accept that the correlation between state noises W_Φ and W_Θ is zero, we have three variance-covariance matrices to define: Q_Φ, Q_Θ, R. Except in specific cases, these matrices are chosen diagonally, making it possible to only specify the noise variances.

Adjusting matrix Q_Φ is the trickiest because noise W represents the influence of multiple sources or modeling errors during a sampling period. [LOR 00] presents an approach based on the simulation of the main error terms. In order to account for their non-whiteness, we can use the notion of upper-bound model [LAR 81], maximizing the spectral density of noise.

Matrix Q_Θ makes it possible to characterize the variations of estimated parameters. Diagonal terms set their dynamics; a large variance authorizes the tracking of quick variations of a parameter. On the other hand, this estimation will get a large variance. Conversely, a low variance will filter parametric variations. The non-diagonal terms explain couplings. We can then inform the Kalman filter of the coupling of some parameters (thermal or magnetic couplings). Nevertheless, the connection between Q_Θ and the dynamic of parameters is complex, because it also depends on the informational content of data. In general, we proceed empirically by consecutive tests. It is better to work in relative dimensions, so that we can go beyond the disparity of orders of magnitude of the different parameters.

In principle, adjusting matrix R can be addressed as matrix Q_Φ. In general, the output equation is much more simple, facilitating the determination of R.

To be complete, we will also consider initialization $P(0)$ of the covariance matrix of estimation errors. In the case of a non-extended Kalman filter, matrix $P(0)$ mainly determines the initial dynamic of the filter, which is not really important for an online application. On the other hand, a bad $P(0)$ adjustment can compromise the stability of an extended Kalman filter. We will come back to this point in the application of the induction motor.

3.5.3. *Application to the induction motor*

Several research studies proposed the extended Kalman filter for the estimation of fluxes and parameters of the induction machine. The first studies [ATK 89, ATK 91, CAV 89, ZAI 87] focused on indirect vector control and were often limited to the estimation of a single parameter: rotor time constant or rotor resistance. Subsequently, most of the studies proposed a simultaneous estimation of several machine parameters; Iwasaki and Kataoka [IWA 89] were the first to our knowledge to propose the identification of the complete electrical model of the machine (the four estimated parameters were $1/T_r$, $1/L_{fs}$, L_m and R_s). It has been shown that it was illusory to only identify a part of the model [LOR 93]. Nevertheless, the complete identification of the electric machine model is rather difficult notably with a full order model because we then have an extended model of order eight.

3.5.3.1. *Complete order direct model of the induction motor*

In section 3.3.2.2.1, we have seen that the full order state model is expressed in a complex way according to the electrical parameters that we want to estimate. This is even truer when the discrete model is obtained by an second order development of the matrix exponential, making it possible to use a discretization step of approximately 1 ms. In this case, instead of searching for an analytical expression of the tangent linearized model [3.39], it is more efficient to calculate it by finite differences. In addition to the nominal evaluation of the model (necessary for the prediction phase), we will have to make an additional evaluation for each estimated parameter:

$$\tilde{A}_{\mathrm{d4}} = \frac{\partial F_4}{\partial X_k} = \begin{bmatrix} A_{\mathrm{d4}}\left(\Theta_k\right) & J_{\mathrm{F4}} \\ 0 & I \end{bmatrix}, \quad \tilde{C}_4 = \frac{\partial G_4}{\partial X_k} = \begin{bmatrix} C_4 & 0 \end{bmatrix} \qquad [3.42]$$

with:

$$\begin{aligned} J_{\Phi 4,k} &= \frac{\partial A_{\mathrm{d4}}\left(\Theta_k\right)}{\partial \Theta_k}\Phi_k + \frac{\partial B_{\mathrm{d4}}\left(\Theta_k\right)}{\partial \Theta_k}U_{k'} \\ &\approx \left[\ldots \frac{A_{\mathrm{d4}}\left(\theta_{1,k},\ldots,\theta_{i,k}+\delta\theta_i,\ldots\right) - A_{\mathrm{d4}}\left(\theta_{1,k},\ldots,\theta_{i,k},\ldots\right)}{\delta\theta_i}\Phi_k \ldots \right] \\ &+ \left[\ldots \frac{B_{\mathrm{d4}}\left(\theta_{1,k},\ldots,\theta_{i,k}+\delta\theta_i,\ldots\right) - B_{\mathrm{d4}}\left(\theta_{1,k},\ldots,\theta_{i,k},\ldots\right)}{\delta\theta_i}U_{k'} \ldots \right] \end{aligned} \qquad [3.43]$$

3.5.3.2. *Reduced order model of the induction motor*

Conversely, from the full order model, the reduced order discrete model of the machine is expressed simply according to its electrical parameters, notably if it is written in the mechanical reference. By noting $N_{\mathrm{r}} = 1/L_{\mathrm{r}}$, we obtain:

$$\begin{aligned} X_{2,k+1} &= A_{\mathrm{d2}}X_{2,k} + B_{\mathrm{d2}}U_{2,k'} \\ Y_{2,k} &= C_2X_{2,k} + D_2U_{2,k} + E_2\dot{U}_{2,k} \end{aligned} \qquad [3.44]$$

with $\mathrm{X}_2 = \begin{bmatrix} \Phi_{\mathrm{r}\alpha} & \Phi_{\mathrm{r}\beta} \end{bmatrix}^{\mathrm{T}}$, $X_2 = \begin{bmatrix} \Phi_{\mathrm{r}\alpha} & \Phi_{\mathrm{r}\beta} \end{bmatrix}^{T}$, $U_2 = \begin{bmatrix} I_{\mathrm{s}\alpha} & I_{\mathrm{s}\beta} \end{bmatrix}^{T}$, $\mathrm{Y}_2 = \begin{bmatrix} U_{\mathrm{s}\alpha} & U_{\mathrm{s}\beta} \end{bmatrix}^{\mathrm{T}}$, $Y_2 = \begin{bmatrix} U_{\mathrm{s}\alpha} & U_{\mathrm{s}\beta} \end{bmatrix}^{T}$ and:

$$\begin{aligned} &A_{\mathrm{d2}} = \mathrm{e}^{-R_{\mathrm{r}}N_{\mathrm{r}}T_{\mathrm{e}}}I,\ B_{\mathrm{d2}} = L_{\mathrm{r}}\left(1-\mathrm{e}^{-R_{\mathrm{r}}N_{\mathrm{r}}T_{\mathrm{e}}}\right)I \\ &C_2 = -R_{\mathrm{r}}N_{\mathrm{r}}I + \omega_{\mathrm{m}}J,\ D_2 = \left(R_{\mathrm{s}}+R_{\mathrm{r}}\right)I + L_{\mathrm{fs}}\omega_{\mathrm{m}}J,\ E_2 = L_{\mathrm{fs}}I \end{aligned} \qquad J = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$$

The vector of parameters to be estimated is $\Theta = \begin{bmatrix} R_s & L_{fs} & R_r & N_r \end{bmatrix}^T$. One of the advantages of the reduced order model is to easily enable the analytical calculation of the tangent linearized model:

$$\tilde{A}_{d2} = \frac{\partial F_2}{\partial X_k} = \begin{bmatrix} A_{d2}(\Theta_k) & J_{\Phi 2} \\ 0 & I \end{bmatrix}, \quad \tilde{C}_2 = \frac{\partial G_2}{\partial X_k} = \begin{bmatrix} C_2(\Theta_k) & J_{Y2} \end{bmatrix} \qquad [3.45]$$

By writing $a = e^{-R_r N_r T_e}$, we obtain:

$$\begin{aligned} J_{\Phi 2,k} &= \frac{\partial A_{d2}(\Theta_k)}{\partial \Theta_k}\Phi_{k|k} + \frac{\partial B_{d2}(\Theta_k)}{\partial \Theta_k}U_{2,k'} \\ &= \begin{bmatrix} 0 & 0 & aT_e\left(U_{2,k'} - N_r\Phi_{k|k}\right)\left(\dfrac{a-1}{N_r^2} + \dfrac{a}{N_r}T_eR_r\right)U_{2,k'} - aT_eR_r\Phi_{k|k} \end{bmatrix} \\ J_{Y2,k} &= \frac{\partial C_2(\Theta_k)}{\partial \Theta_k}\Phi_k + \frac{\partial D_2(\Theta_k)}{\partial \Theta_k}U_{2,k} + \frac{\partial E_2(\Theta_k)}{\partial \Theta_k}\dot{U}_{2,k} \\ &= \begin{bmatrix} U_{2,k} & \dot{U}_{2,k} + \omega_m J U_{2,k} & U_{2,k} - N_r\Phi_{k|k} & -R_r\Phi_{k|k} \end{bmatrix} \end{aligned} \qquad [3.46]$$

3.5.3.3. *Covariance matrix adjustment*

Here we will only present the tuning of the Kalman filter, using the reduced order model. For a detailed presentation of the tuning of the fourth order filter, we can refer to [LOR 98] and to [LOR 00]. We will compare different estimations obtained with discretization periods T_e from 1 ms to 20 ms. In order to obtain comparable results, we will define variance-covariance matrices (Q_c and R_c) of continuous time noises before transposing them in discrete time according to [GRE 93]:

$$Q_k = T_e Q_c \quad R_k = T_e^{-1} R_c \qquad [3.47]$$

The first two components of noise W are linked to the rotor flux and according to state equation [3.7], they come from parametric errors or from measuring noises on stator currents. Since parametric errors are evaluated by the Kalman filter itself, we will only take into account current measuring noises. To simplify, we will suppose decorrelated noises on axes as α and β (which is not true because of the transformation of Concordia). From the spectral density of measuring noises $G_{I_s} = 8 \times 10^{-4}$ A^2/Hz, we have deduced by simulation the variance of state noises [LOR 00]. The variance-covariance matrix of state noises in continuous time then equals $Q_{\Phi,c} = 2 \times 10^{-5} I$.

The four last components of the state noise define the dynamics of parameters. We will define a diagonal variance relative matrix: $Q_{\Theta,c} = \sigma_r^2 \operatorname{diag}\left(R_s^2 \quad L_{fs}^2 \quad R_r^2 \quad N_r^2\right)$ with $\sigma_r = 10^{-2}$.

The observation equation of the inverse model is relatively complex, but the main source of error (non-parametric) is the voltage measurements of variance $\Gamma_{U_s} = 2V^2$, we simply take $R_c = \Gamma_{U_s} I$.

3.5.3.4. *Filter initialization and restart*

We must still consider the initialization of state variables and their covariance matrix. For an extended Kalman filter, some precautions must be taken, notably in the case of the induction motor. In fact, as it often happens, if we choose a zero initial state, the Kalman filter diverges immediately. This is completely normal because when the machine is not magnetized, rotor resistance is not sensitized. Before triggering the estimation of parameters, it is therefore necessary to correctly initialize the rotor flux. The simplest way is to use the same Kalman filter, by suspending the estimation of the parameters and their covariance matrix. We thus obtain a non-extended filter that takes into consideration the initial parametric errors and evaluates their incidence on the variation of estimated fluxes. Experience shows that the convergence of this filter is very quick: we simply have to apply it during a few dozen milliseconds, before activating the estimation of the parameters. We then obtain a smooth transition as shown in the next section.

For an online application, the previous problem occurs at each restart of the parametric identification. In fact, we cannot continue to attempt to estimate the parameters if they are no longer sensitized. We can then use a similar strategy as that described previously. When we detect a loss of identifiability, we lock the parameter(s) involved with their covariance matrix and we continue to estimate the state and possibly the remaining identifiable parameters. We come back to the complete extended Kalman filter, by ensuring the continuity of estimated variables and variance-covariance matrices. The ideal would be to have a modular Kalman filter in order to be able to selectively activate the estimation of each parameter.

3.5.3.5. *Results*

In order to compare the performances obtained with each model, we will use experimental data and simulations based on a 3 kW squirrel-cage machine powered by a PWM inverter with a modulation frequency of 3 kHz. The results of this section were obtained in the context of a doctoral degree by I. Zein [ZEI 00]. The measurement signals are represented in Figure 3.7.

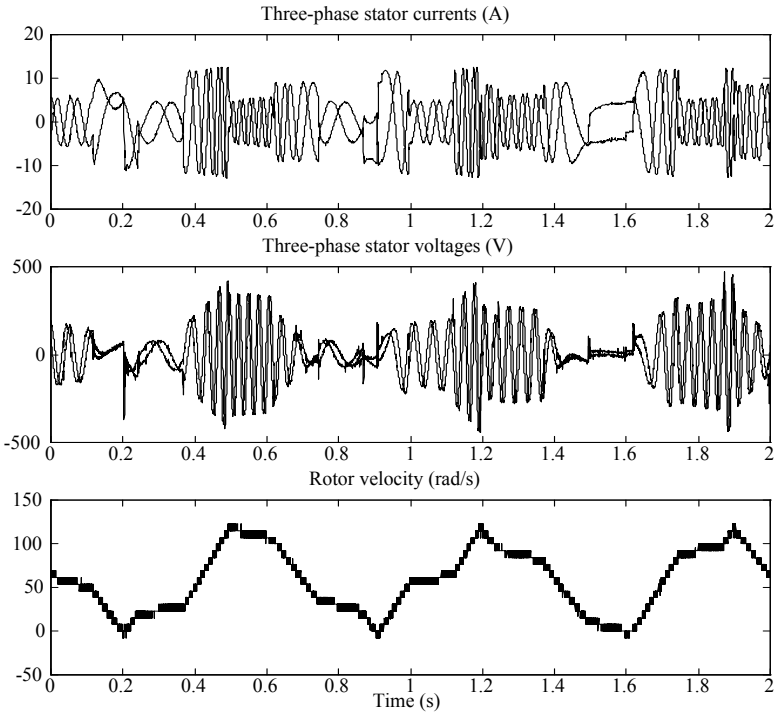

Figure 3.7. *Measured signals*

Line currents and interphase voltages were measured by Hall sensors. The angular velocity of the machine was deducted from a position measurement by incremental encoder (2,000 points/rev). Electrical signals were filtered by an anti-aliasing filter with a cut-off frequency of 500 Hz. The period of acquisition of signals is $T_{acq} = 0.2$ ms.

3.5.3.5.1. Simulation results

To evaluate the intrinsic precision of estimated parameters with each model, we will first use a simulation that reproduces the test in Figure 3.7. In order to do this, we recalculate stator currents by integrating the order four model by the order four Runge-Kutta method (algorithm RK45 from Simulink), with a fixed step equaling $T_{acq} = 0.2$ ms. This simulation uses the parameters that we presume are those of the machine (R_S = 2.6 Ω, L_{fs} = 10 mH, R_r = 1.7 Ω, L_r = 170 mH) and white and Gaussian noises are added to voltages ($G_{U_s} = 25\times10^{-3}$ Hz) and currents ($\Gamma_{I_s} = 8\times10^{-4}$ A^2/Hz). The Kalman filters will be initialized with a significant error (50%) to reveal their initial behavior.

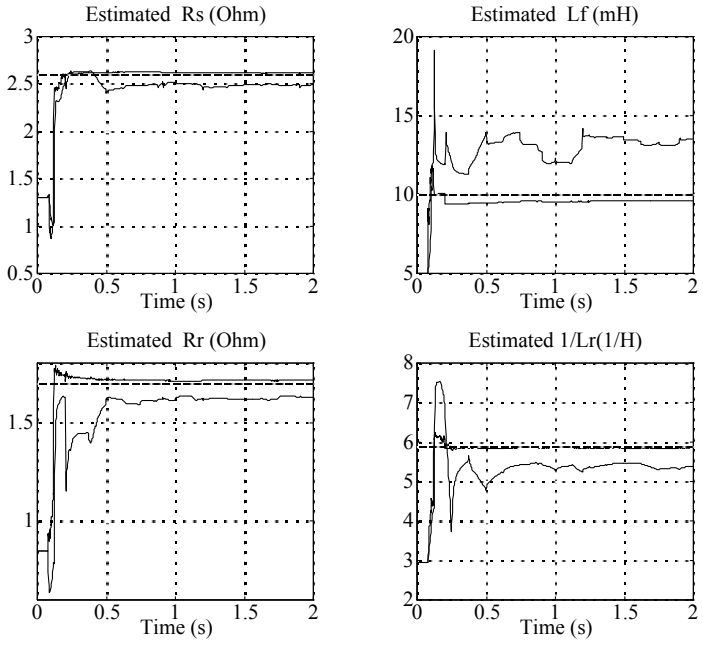

Figure 3.8. *Estimation of parameters with fourth order model T_e = 1 ms (thin line) and 2.8 ms (thick line)*

Figure 3.8 shows the estimation provided by a Kalman filter using the fourth order model for two steps of discretization: 1 ms and 2.8 ms. The dotted line indicates the exact value of the parameter. The results are good for 1 ms, but not at 2.8 ms, notably involving inductances (the model becomes unstable for a sampling period exceeding 3 ms).

By comparison, Figure 3.9 shows that the second order model enables the use of much greater periods: with this model and a 20 ms period, we obtain better precision than with the fourth order model at 1 ms. We can also observe the speed of convergence of estimations and the quality of the initial transient. Remember that the beginning of the data is used to initialize the rotor flux and its covariance matrix. The estimation of parameters only starts at 0.1 s.

Table 3.1 recaps estimation errors obtained for each configuration (average errors calculated at the end of the test). The values obtained show that the precision has very little deterioration at T_e = 20 ms for the reduced order model.

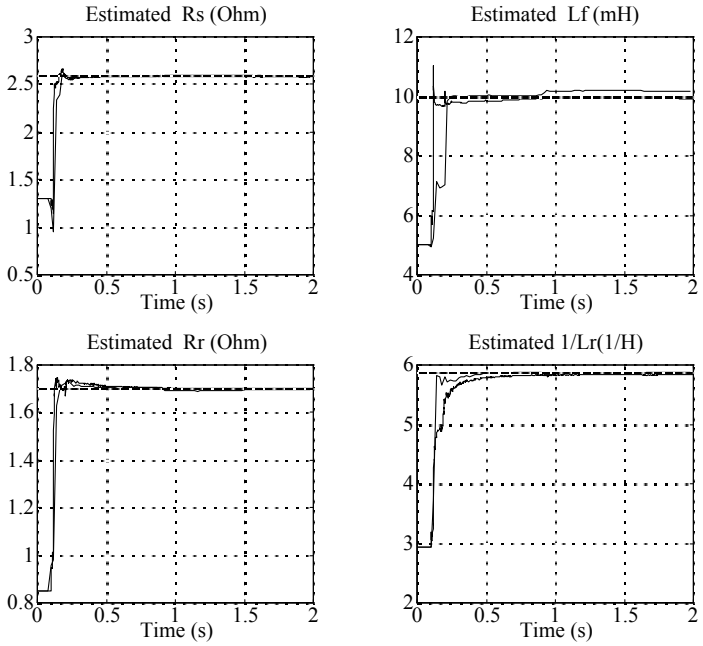

Figure 3.9. *Estimation of parameters with second order model T_e = 1 ms (thin line) and 20 ms (thick line)*

Model	R_s(%)	L_{fs}(%)	R_r(%)	L_r(%)
Order 4 – T_e = 1 ms	0.5	–4.2	0.9	0.2
Order 4 – T_e = 2.8 ms	–4.5	34.7	–4.2	9.7
Order 2 – T_e = 1 ms	–0.8	–0.5	0.06	0.8
Order 2 – T_e = 20 ms	–0.6	1.7	–0.3	0.2

Table 3.1. *Relative estimation error (by simulation)*

3.5.3.5.2. Experimental results

We will now compare the performances of the two filters against the original experimental data. We find very similar behaviors to what was observed during simulations.

Figure 3.10 confirms that the fourth order model is very sensitive to the sampling period when it exceeds 1 ms whereas the second order model provides estimations almost identical to 1 and 20 ms (see Figure 3.11). Table 3.2 lists the different

estimations obtained. Even in a real situation, that is, with modeling noises and errors that do not totally respect the hypotheses of the Kalman filter, the precision of the second order model remains excellent at 20 ms.

The reduced order model therefore combines all the advantages: it is simple and precise while allowing for long sampling periods. In addition, it is perfectly adapted to the implementation of an extended Kalman filter. In the following section, we will see that it can also be used in an extended Luenberger observer.

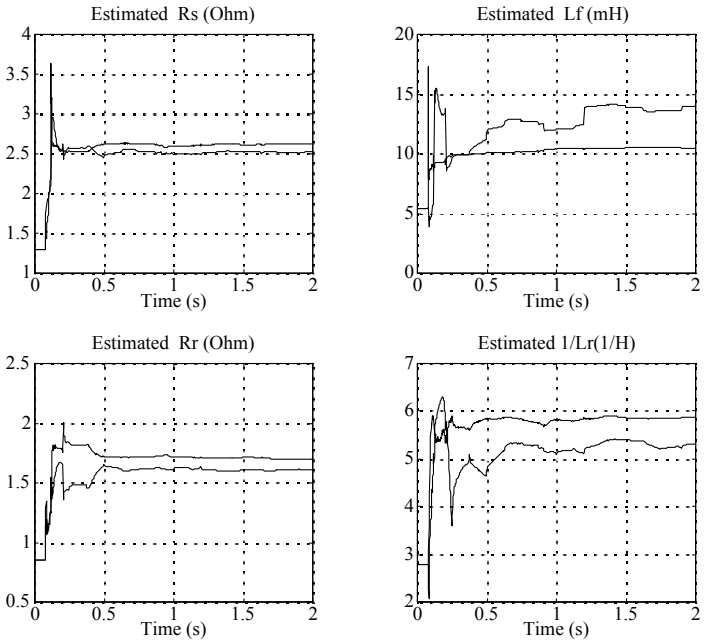

Figure 3.10. *Estimation of parameters with fourth order model T_e = 1 ms (thin line) and 2.8 ms (thick line)*

Model	R_s **(Ω)**	L_{fs} **(mH)**	R_r **(Ω)**	L_r **(mH)**
Order 4 – T_e = 1 ms	2.6	10.5	1.70	170
Order 4 – T_e = 2.8 ms	2.5	**14**	1.60	**190**
Order 2 – T_e = 1 ms	2.59	10.5	1.69	170
Order 2 – T_e = 20 ms	2.57	10.6	1.66	171

Table 3.2. *Final value of estimations (experimental data)*

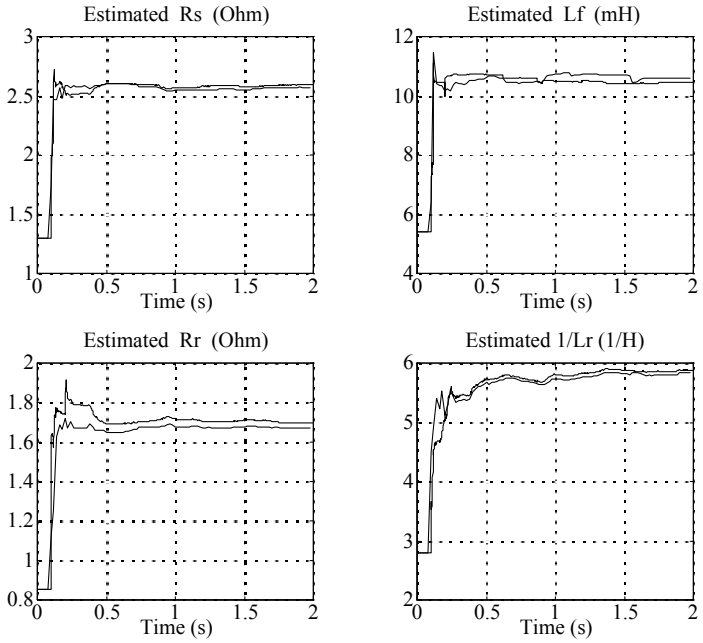

Figure 3.11. *Estimation of parameters with second order model T_e = 1 ms (thin line) and 20 ms (thick line)*

3.6. Extended Luenberger observer

The extended Luenberger observer is a deterministic alternative to the extended Kalman filter. Its main characteristic is that it does not use a stochastic system model but a pole placement strategy. We can observe in practice that this strategy is not simple to define and to implement, notably in the case of a multivariate system. Following the structure and adjustment of the extended Luenberger observer, we will compare its performances with that of an extended Kalman filter, with an induction motor application.

3.6.1. *Principle*

3.6.1.1. *Discrete time observer*

There are different possible implementations of a discrete observer, depending on the way we sequence calculations and how we use output signals [BOR 90]. We will use the observer-corrector form which is the closest to the Kalman filter. Consider the discrete system traditionally defined by:

$$\begin{cases} X_{k+1} = A_{\mathrm{d}} X_k + B_{\mathrm{d}} U_k \\ Y_k = C X_k + D U_k \end{cases} \quad [3.48]$$

We then build a two-step observer. The first one is a prediction step (that we will note as $k+1|k$, by analogy with the Kalman filter):

$$\begin{cases} \hat{X}_{k+1|k} = A_{\mathrm{d}} \hat{X}_{k|k} + B_{\mathrm{d}} U_k \\ \hat{Y}_{k+1|k} = C \hat{X}_{k+1|k} + D U_{k+1} \end{cases} \quad [3.49]$$

The second one is an correction step (noted $k+1|k+1$) based on the output measurement and on gain L which determination will be clarified later:

$$\begin{aligned} \hat{X}_{k+1|k+1} &= \hat{X}_{k+1|k} + L\left(Y_{k+1} - \hat{Y}_{k+1|k}\right) \\ &= \left(A_{\mathrm{d}} - LCA_{\mathrm{d}}\right)\hat{X}_{k|k} + \left(B - LCB\right)U_k - LDU_{k+1} + LY_{k+1} \end{aligned} \quad [3.50]$$

The dynamic of this observer is therefore defined by the matrix ($A_{\mathrm{d}} - LCA_{\mathrm{d}}$).

3.6.1.2. *Extended observer*

We use the extended non-linear state [3.36] used for the Kalman filter without taking into consideration state and output noises:

$$\begin{cases} X_{k+1} = \begin{bmatrix} \Phi_{k+1} \\ \Theta_{k+1} \end{bmatrix} = \begin{bmatrix} F_{\Phi}\left(\Phi_k, \Theta_k, U_k\right) \\ F_{\Theta}\left(\Phi_k, \Theta_k, U_k\right) \end{bmatrix} = F\left(X_k, U_k\right) \\ Y_k = G\left(X_k, U_k\right) \end{cases} \quad [3.51]$$

where, as before, vectors Φ and Θ express the state and parameters to estimate.

This model must also be linearized around the current point before building the observer. We then define a tangent linearized model similar to the one used for the extended Kalman filter:

$$\tilde{A}_{\mathrm{d}} = \frac{\partial F}{\partial X_k} = \begin{bmatrix} \dfrac{\partial F_{\Phi}}{\partial \Phi_k} & \dfrac{\partial F_{\Phi}}{\partial \Theta_k} \\ \dfrac{\partial F_{\Theta}}{\partial \Phi_k} & \dfrac{\partial F_{\Theta}}{\partial \Theta_k} \end{bmatrix}, \quad \tilde{C} = \frac{\partial G}{\partial X_k} = \begin{bmatrix} \dfrac{\partial G}{\partial \Phi_k} & \dfrac{\partial G}{\partial \Theta_k} \end{bmatrix} \quad [3.52]$$

If we apply the previously seen observer-equalizer, we obtain an algorithm with similarities to the Kalman filter:

$$\text{Prediction: } \begin{cases} \hat{X}_{k+1|k} = F\left(\hat{X}_{k+1|k}, U_k\right) \\ \hat{Y}_{k+1|k} = G\left(\hat{X}_{k+1|k}, U_k\right) \end{cases} \qquad [3.53]$$

$$\text{Correction: } \hat{X}_{k+1|k+1} = \hat{X}_{k+1|k} + L\left(Y_k - \hat{Y}_{k+1|k}\right)$$

The only difference is in the determination of gain L obtained by choosing the eigenvalues of:

$$\tilde{A}_{\mathrm{d}} - L\tilde{C}\tilde{A}_{\mathrm{d}} = \left(\frac{\partial F}{\partial X_k} - L\frac{\partial G}{\partial X_k}\frac{\partial F}{\partial X_k}\right) \qquad [3.54]$$

3.6.1.3. *Tuning (pole placement)*

The tuning of a deterministic observer, such as the Luenberger observer, is based on the choice of its poles, that is, on the eigenvalues of its dynamic matrix defined by [3.54]. When it is an observer applied to a linear and stationary model, this choice only affects the dynamic of the initial error. In this case, the introduction of an observer has no incidence on performance in reference tracking, but only on that of its disturbance rejection if it is variable, whereas it was assumed to be constant (a step variation of this disturbance equals a change in its initial condition). This result also applies to an extended observer assuming constant or slowly variable parameters, as the dynamic of poles directly conditions that of estimated parameters.

For an Nth order system, there are N poles to define. When this system can be completely observed, this choice is totally free. Even for the simple case of a stationary single output system, the placement of poles is not simple because a clumsy adjustment can compromise the robustness of the closed-loop system [LAR 93]. In order to resolve this problem, robust strategies of pole placement were proposed. These are mainly based on the results of the optimal control and consist of connecting the choice of closed loop poles (control and observer) to those of the process and to dynamic objectives (response time or bandwidth) [LAR 93]. When the system is non-stationary, as is the case for the linearized model, we no longer define N poles, but N trajectories. In addition, in many cases, and notably in electrical engineering applications involving static converters, we must take into account the influence of measurement noises in the setup of observers. In general, when we increase the speed of its poles, we increase the

components of gain L, which tends to increase the sensitivity of the observer to output measuring noises.

Moreover in the multi-output case ($n_S > 1$), the choice of observer poles is not sufficient to determine gain L: we arrive at an under-determined problem containing N equations (one per pole) for n_sN unknowns (L components). We can then consider a generic approach, which is often complex such as the placement of an inherent structure [RAC 97], or a specific approach adapted to a specific system, such as the Verghese observer for the induction machine [VER 88]. In fact, to define the control of a multivariable system, it is often more efficient and intuitive to use an optimal control approach (Gaussian quadratic linear control). In this case, we no longer speak of observer, but of optimal filtering, as the latter is simply a Kalman filter used in a deterministic context. Covariance Q and R matrices are then considered as setup parameters for adjusting the compromise between the dynamic of the observer and its sensitivity to output noises.

3.6.2. *Estimation of induction machine velocity*

We now consider the estimation of a specific parameter, the mechanical velocity, of the induction motor model. Nevertheless, insofar as it intervenes as a factor of the machine state model, an approach similar to the estimation of an electrical parameter can be used. In addition, velocity has a very interesting characteristic because it can no longer be observed when it is constant and the frequency of stator currents is zero. Figure 3.12 illustrates a test that will enable testing of the extended Luenberger observer in different situations and notably during loss of speed observability: for $t \geq 6.2$ s, we notice that all signals are constant. We then apply this test to an extended Kalman filter in order to compare the behaviors of both estimators.

3.6.2.1. *Machine model*

Since we do not have a mechanical position measurement we will work in a reference point based on the stator current. The choice of a synchronous reference ($\omega_x = \omega_S$) guarantees an exact discrete model in steady-state since the signals are constant. We also modify the output equation by grouping the terms independent from the velocity to the left:

$$\begin{cases} \dot{X}_2 = A_2\left(\omega_m\right) X_2 + B_2 U_2 \\ Z = Y_2 - \left(D_2 U_2 + E_2 \dot{U}_2\right) = C_2\left(\omega_m\right) X_2 \end{cases} \quad [3.55]$$

where $X_2 = \begin{bmatrix} \Phi_{r\alpha} & \Phi_{r\beta} \end{bmatrix}^T$, $X_2 = \begin{bmatrix} \Phi_{r\alpha} & \Phi_{r\beta} \end{bmatrix}^T$, $U_2 = \begin{bmatrix} I_s & 0 \end{bmatrix}^T$, $Y_2 = \begin{bmatrix} U_{s\alpha} & U_{s\beta} \end{bmatrix}^T$, $\rho_r = \dfrac{R_r}{L_r}$ and

$$A_2 = \rho_r I + (\omega_m - \omega_s) J, \quad B_2 = R_r I, \quad C_2 = \rho_r I + \omega_m J,$$
$$B_2 = (R_s + R_r) I + \omega_s L_{fs} J, \quad E_2 = L_{fs} J, \quad \rho_r = \frac{R_r}{L_r}$$

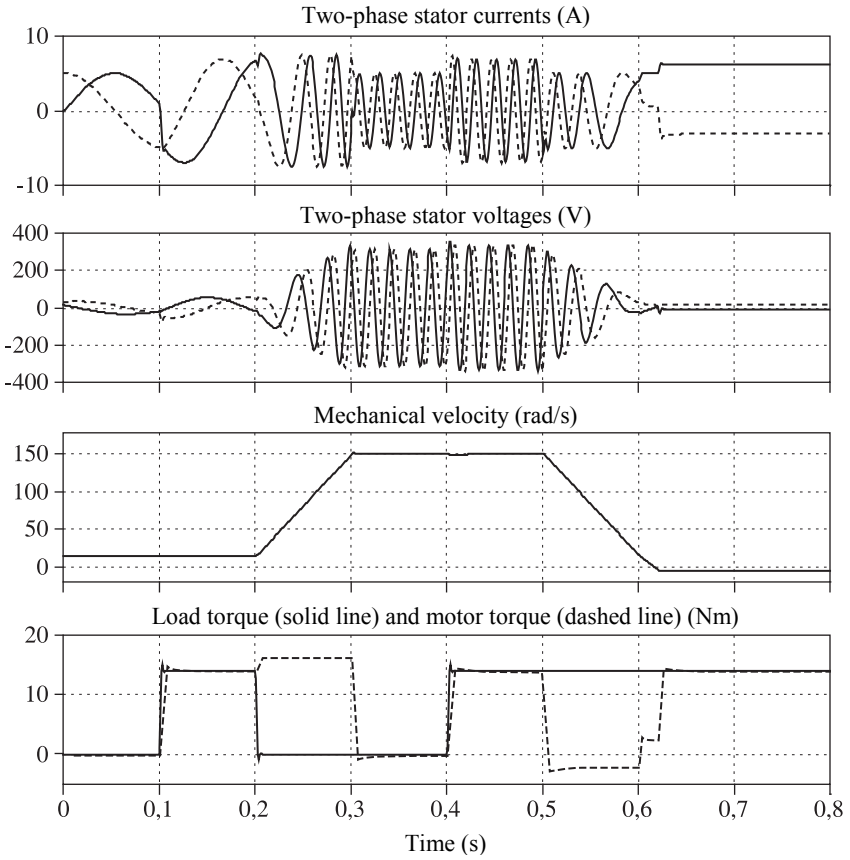

Figure 3.12. *Test with velocity observability loss at t = 0.62 s*

Even though it is possible to exactly discretize this model, we will use a second order approximation, which will be simpler to use:

$$\begin{cases} A_{\mathrm{d2}} = \left(1-\rho_{\mathrm{r}}T_{\mathrm{e}}+0.5\rho_{\mathrm{r}}^2T_{\mathrm{e}}^2\right)I - T_{\mathrm{e}}\left(\omega_{\mathrm{s},k}-\omega_{\mathrm{m},k}\right)\left(1-\rho_{\mathrm{r}}T_{\mathrm{e}}\right)J \\ B_{\mathrm{d2}} = T_{\mathrm{e}}R_{\mathrm{r}}\left(\left(1-0.5\rho_{\mathrm{r}}T_{\mathrm{e}}\right)I - 0.5T_{\mathrm{e}}\left(\omega_{\mathrm{s},k}-\omega_{\mathrm{m},k}\right)J\right) \\ C_2 = -\rho_{\mathrm{r}}I + \omega_{\mathrm{m},k}J \end{cases} \quad [3.56]$$

3.6.2.2. *Extended Luenberger observer*

The discrete extended model is obtained by combining the discrete machine model and the speed model that we will presume is slowly variable with respect to the electric variables:

$$\begin{cases} \Phi_{\mathrm{r},k+1} = A_{\mathrm{d2}}\left(\omega_{\mathrm{m},k}\right)\Phi_{\mathrm{r},k} + B_{\mathrm{d2}}\left(\omega_{\mathrm{m},k}\right)U_{2,k}, \\ \omega_{\mathrm{m},k+1} = \omega_{\mathrm{m},k} \\ Z_{k+1} = C_2\left(\omega_{\mathrm{m},k+1}\right)\Phi_{r,k+1} \end{cases} \quad [3.57]$$

The discrete observer estimating the rotor flux and mechanical velocity is then as given below. In accordance to [3.53], the first step consists of the prediction of the flux, speed and output:

$$\begin{cases} \hat{\Phi}_{r,k+1|k} = A_{\mathrm{d2}}\left(\hat{\omega}_{\mathrm{m},k|k}\right)\hat{\Phi}_{\mathrm{r},k|k} + B_{\mathrm{d2}}\left(\hat{\omega}_{\mathrm{m},k|k}\right)U_{2,k}, \\ \hat{\omega}_{\mathrm{m},k+1|k} = \hat{\omega}_{\mathrm{m},k|k} \\ \hat{Z}_{k+1|k} = C_2\left(\hat{\omega}_{\mathrm{m},k+1|k}\right)\hat{\Phi}_{r,k+1|k} \end{cases} \quad [3.58]$$

where matrices A_{d2}, B_{d2} and C_2 are calculated according to [3.56]. The second step executes a correction of the flux and speed:

$$\begin{cases} \hat{\mathrm{F}}_{\mathrm{r},k+1|k+1} = \hat{\mathrm{F}}_{\mathrm{r},k+1|k} + L_{\mathrm{F},k+1}\left(Z_{k+1}-\hat{Z}_{k+1|k}\right) \\ \hat{\omega}_{\mathrm{m},k+1|k+1} = \hat{\omega}_{\mathrm{m},k+1|k} + L_{\omega,k+1}\left(Z_{k+1}-\hat{Z}_{k+1|k}\right) \end{cases} \quad [3.59]$$

Correction gain $L_{\mathrm{k+1}} = [L_{\Phi,\mathrm{k+1}}, L_{\omega,\mathrm{k+1}}]^T$ is evaluated from the eigenvalues of the transition matrix of the linearized observer $\tilde{A}_{\mathrm{d},k} - L_{k+1}\tilde{C}_{k+1}\tilde{A}_{\mathrm{d},k}$.

Thus:

$$\tilde{A}_{\mathrm{d},k} = \left[\begin{array}{cc} \dfrac{\partial F_\Phi}{\partial \Phi_k} & \dfrac{\partial F_\Phi}{\partial \Theta_k} \\ \dfrac{\partial F_\Theta}{\partial \Phi_k} & \dfrac{\partial F_\Theta}{\partial \Theta_k} \end{array}\right]_{\substack{\hat{\Phi}_{k|k} \\ \hat{\omega}_{\mathrm{m},k|k}}} = \left[\begin{array}{c|c} A_{\mathrm{d}2}\left(\hat{\omega}_{\mathrm{m},k|k}\right) & T_\mathrm{e}\left(1-\rho_\mathrm{r}T_\mathrm{e}\right)J\hat{\Phi}_{\mathrm{r},k|k} + 0.5T_\mathrm{e}^2 R_r J U_{2,k'} \\ \hline 0 & 1 \end{array}\right] \quad [3.60]$$

$$\tilde{C}_{\mathrm{d},k+1} = \left[\begin{array}{cc} \dfrac{\partial G}{\partial \Phi_k} & \dfrac{\partial G}{\partial \Theta_k} \end{array}\right]_{\substack{\hat{\Phi}_{k+1|k} \\ \hat{\omega}_{\mathrm{m},k+1|k}}} = \left[\begin{array}{cc|c} -\rho_r & -\hat{\omega}_{\mathrm{m},k+1|k} & -\hat{\Phi}_{\mathrm{r}\beta,k+1|k} \\ \hat{\omega}_{\mathrm{m},k+1|k} & -\rho_\mathrm{r} & \hat{\Phi}_{\mathrm{r}\alpha,k+1|k} \end{array}\right] \quad [3.61]$$

The following results were obtained from simulations in the Matlab environment. In order to accomplish pole placement, we used function "place" from the "Control" toolbox. This function is based on the Kautsky-Nichols-Van Dooren algorithm [KAU 85], which uses the degrees of freedom offered by the multiple outputs to optimize the robustness of the observer adjustment and minimize numerical problems. We chose constant and relatively fast poles: $-25\ \rho_\mathrm{r}$, $-25\ \rho_\mathrm{r}$, and $-40\ \rho_\mathrm{r}$ (since the output vector is of dimension two, the "place" command does not allow us to place three identical poles).

In Figure 3.13, we can compare the estimated rotor flux and its true value, as well as calculated and real electromagnetic torque (the calculated torque is evaluated from the estimated rotor flux and the measured stator current). The components of the rotor flux are initialized at 50% of their true value. We must initialize the flux to a non-zero value or otherwise the observer diverges. The speed cannot be observed if the machine is not magnetized. Whereas, the speed can be initialized at zero. In Figure 3.13, we first notice the strong influence of noises on the estimation when the machine runs on slow speed. The estimations are correct only when the speed is constant and fast. During the acceleration and deceleration phases, the transient error is approximately 11 rad/s. It would be possible to decrease this error by increasing pole speed. Unfortunately, this would amplify noises at slow speed. The curves in Figure 3.13 stop at $t = 0.62$ s at the beginning of the loss of observability. When the stator frequency leans toward zero, some components of the observer gain

become very large because the observability matrix becomes singular. We then observe an abrupt divergence of the observer.

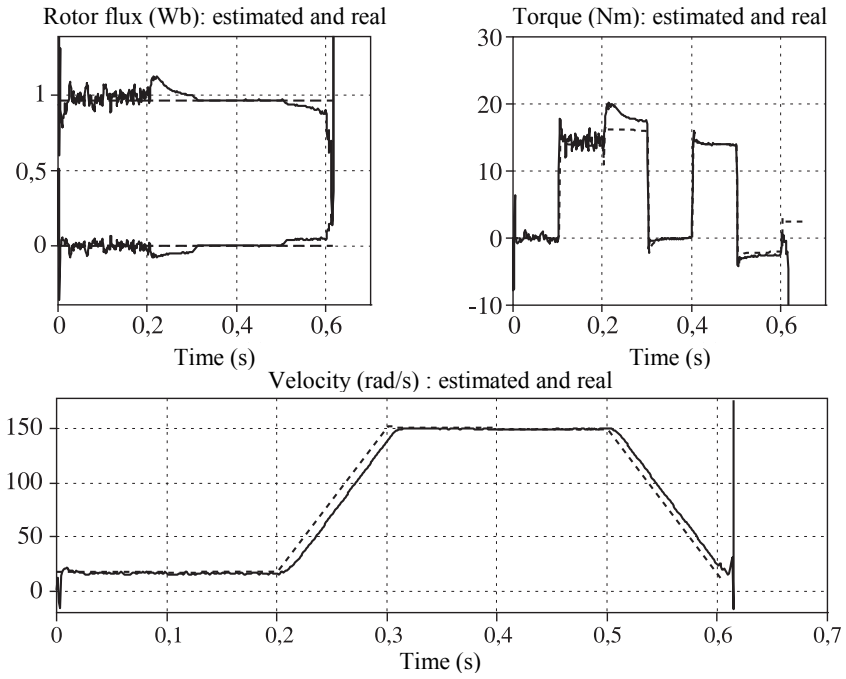

Figure 3.13. *Estimation of rotor flux and velocity*

3.6.2.3. *Extended Kalman filter*

For comparison's sake, we will apply the extended Kalman filter defined in the previous section (equations [3.40] and [3.41]) to the extended model at velocity level [3.57]. As already mentioned, the only difference with the extended observer is in the calculation of the correction gain. In the case of the Kalman filter, this gain depends on the adjustment of covariance matrices of state Q and output noises R.

For this application, we adopted a deterministic approach by choosing an identity R matrix and defining Q by:

$$Q = \begin{bmatrix} \sigma_\Phi^2 & 0 & 0 \\ 0 & \sigma_\Phi^2 & 0 \\ 0 & 0 & \sigma_\omega^2 \end{bmatrix} \qquad [3.62]$$

with σ_Φ = 10–4 Wb. As with the Luenberger observer, we initialized the speed estimated at zero and flux components at half their true value.

Figure 3.14 illustrates the estimation of the rotor flux and velocity. We have set the standard deviation σ_ω of velocity noise at 2 rad/s. This value makes it possible to correctly follow the speed during acceleration-deceleration phases: the average transient error then approximately equals 2 rad/s, which is much lower than the 11 rad/s obtained with the Luenberger observer. In addition, we can observe that the estimation remains correct when the model can no longer be observed. We will analyze this surprising result. We can already note that contrary to the Luenberger observer, the Kalman filter does not necessarily diverge when the model can no longer be observed.

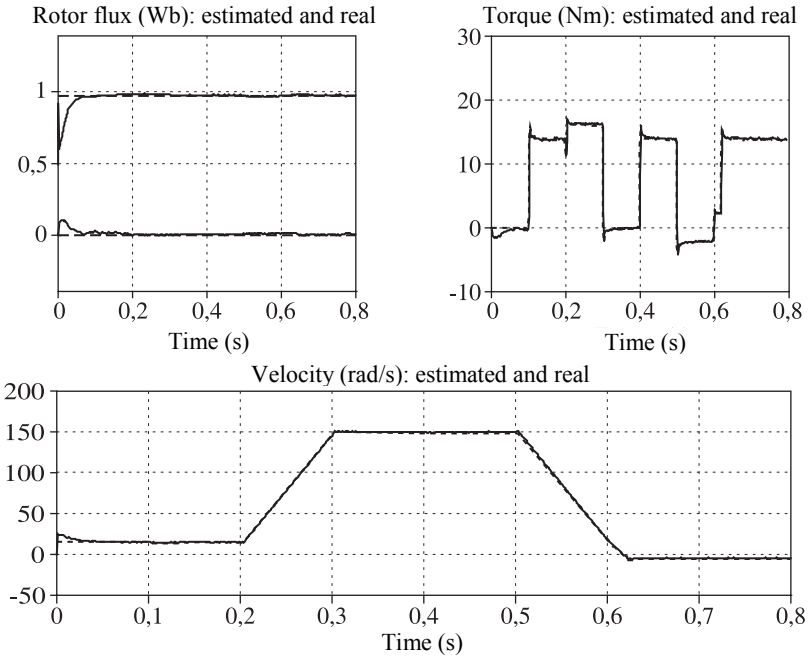

Figure 3.14. *Estimation of flux and velocity –σ_ω = 2 rad/s*

In fact, as we will see, when the model can no longer be observed, the Kalman filter no longer has information to refresh its estimations during the correction phase and it freezes the estimated state (or parameter). Figure 3.15 shows the influence of σ_ω on velocity estimation. For low values (10–3 and 10–2 rad/s), the velocity error is

significant and the estimated speed is greatly biased when the model can no longer be observed. When σ_ω increases, the transient error and bias decrease. For σ_ω = 0.1 rad/s, we obtain a bias of 1.2 rad/s, almost invisible in Figure 3.15, and for $\sigma_\omega \geq 1$ rad/s, this bias is insignificant.

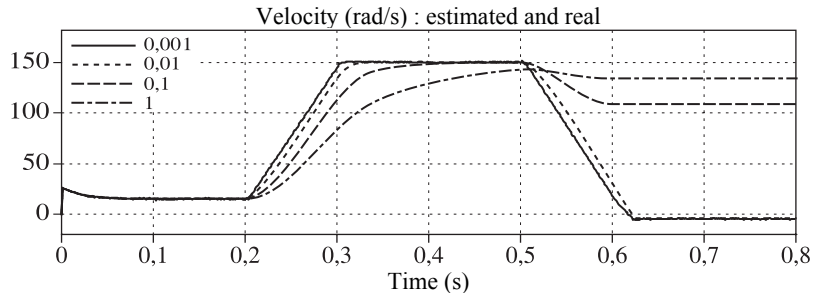

Figure 3.15. *Velocity estimations for different σ_ω settings*

3.6.2.4. *Comparison between Kalman filter and Luenberger observer*

During the 1990s, many authors considered sensorless control of the induction machine by applying different methods, notably the Kalman filters or extended observers. Among these studies, some compared several approaches by highlighting the advantages and disadvantages of each one. We can cite studies by Du and collaborators [DU 94, DU 95] who emphasized the advantages of the deterministic approach over the stochastic approach, which they considered unfounded and too tricky to implement. This opinion is obviously not shared by all. While reading the first articles by Luenberger and the way he describes the Kalman studies, we can feel the antagonism between the two approaches [LUE 66, LUE 71].

Unfortunately, in the studies comparing several approaches, it is often difficult to put the intrinsic qualities of the methods and the expertise of the authors into perspective. When a researcher has spent many years experimenting with an identification technique and he wants to compare this tool that he knows with another one that he is just discovering, the comparison will probably not be objective. This chapter is not intended to establish the superiority of the extended Kalman filter over the Luenberger observer, even in the context of the estimation of the induction machine velocity. It is simply aimed at demonstrating that we can obtain good results with a properly used Kalman filter and that there is nothing trivial about adjusting a Luenberger observer to do just as well. With a non-stationary system, such as the induction machine, a fixed adjustment of poles is not efficient. If we want to decrease the transient error, we must accelerate the observer

poles, but in this case, its sensitivity to noise is amplified which is very cumbersome at slow speed. In addition, and in principle, the Luenberger observer abruptly diverges in the case of loss of observability. The Kalman filter presents a behavior that is much better adapted to this situation since it freezes the estimation by interrupting the correction.

3.7. Conclusion

In this chapter, we addressed the online estimation of the parameters of a dynamic process specifically for an induction machine.

We first recalled the most common objectives and the major problems with this type of identification. These objectives can be divided into two categories mainly involving adaptive control and diagnosis of processes, both interesting for electrical machines. The implementation problems are linked to the diversity of the problems that must be treated simultaneously and coherently if we want to be able to obtain reliable and precise identification. We first have to understand clearly the interactions linking the model, optimization algorithm, and informational content of data. The use of an identification algorithm requires the implementation of a monitoring mechanism. It can be identified with the help of an informational analysis integrated to some identification techniques such as least squares or the extended Kalman filter.

We then presented three approaches of the online parametric identification. The first one is based on least squares or its variations (instrumental variables). These techniques offer several advantages in terms of ease of implementation but they are not compatible with all systems and they are not suitable for the identification of the complete electrical model of the induction motor. The second approach is based on the extended Kalman filter for non-linear systems. Its field of application is much wider, but also leads to greater algorithmic complexity and trickier tuning. Nevertheless, we noticed that because of the use of a specific reduced order model, this technique was perfectly well adapted for the induction machine. Finally, the last approach uses an extended Luenberger observer with an tuning that is based on a pole placement strategy. Unfortunately, it is not simple to define in the case of a non-stationary process such as the induction machine. In addition, in the case of loss of observability, the observer can abruptly diverge, whereas in this situation, the Kalman filter adopts a behavior that is more appropriate by freezing its estimations.

3.8. Appendix: machine characteristics

	Motor 1	Motor 2
Rated output	P_N = 750 W	P_N = 3 kW
Power factor	cos(ϕ) = 0.75	cos(ϕ) = 0.83
Neutral-nominal phase voltage	U_{sN} = 220 V	U_{sN} = 230 V
Rated current (star)	I_{sN} = 2.2 A	I_{sN} = 5.8 A
Rated speed	N_N = 1,420 rev/min	N_N = 1,440 rev/min

Table 3.3. *Rating plates of machines*

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