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Regular paper

## Induction motor parameters estimation based on the subspace identification approach

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*In this paper, we are interested in the survey of deterministic identification by subspace approach. To the opposite of classic recursive identification method, this new technique is well adapted to multivariable linear time invariant LTI systems described by a state space model, and of consequent order. Founded on geometric and mathematical tools of linear algebra such as matrix projection, QR decomposition and Singular Value Decomposition SVD, the subspace identification method permits to estimate a state realization directly from the only knowledge of input-output data. One proposes, in this work, to describe the method stages and its application to estimate the induction motor parameters as well as in simulation and experiment. In this purpose, the motor is described by a complex formed model in dq referential. Simulation study and experiment results are presented and discussed.*

**Keywords:** Deterministic identification, Subspace, LTI systems, induction motor, and complex formed model, parameters estimation

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### 1. INTRODUCTION

The determination and the setting in work of control laws of all system requires the knowledge of its dynamic model. The modelling consists then in elaborating, for the system to control a mathematical model allowing describing well its dynamic behaviour [12]. Of by its class and its structure, the parameters model represent one of the main sought-after features, it is for this reason that their identification represents a key stage permitting to act on control qualities. One finds in the literature various approaches of identification that proved their efficiency, one essentially mentions the recursive methods [13], and these techniques are well adapted to monovariable systems described by transfer function models. A new generation of identification techniques appeared these last two decades; it is well appropriate to multivariable systems described by state space models, and of consequent order. These techniques are baptized: the subspace methods [3-6]. The appellation of subspace comes in fact from the method principle which consists, especially, in constructing the subspaces from input-output data. Simple geometric operations are done on these subspaces in order to extract, directly, a realization that describes the system model. The major advantage of these new techniques which are founded on geometric approach consists in no requirement of non-linear optimisation algorithm. They use, also, robust mathematical tools of linear algebra as QR decomposition, Singular Value Decomposition SVD, matrix projection and angles between subspaces. The objective of subspace identification methods is to estimate, directly, a discrete linear time invariant state space model only from input-output data.

The purpose of this work is to study the subspace deterministic identification method for induction motor parameters estimation.

The paper is organised as follows. In the next section, one presents the identification of LTI systems by the subspace approach. A survey of the geometric and mathematical tools is expected. The stages of the new identification technique are analysed. The third section has been focused on the induction motor parameters estimation based on the subspace method. The motor is described by a complex formed Park model written in the  $dq$  referential. The

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parameters estimation has been studied in simulation and in experiment with input-output data extracted from the motor. The obtained results are presented and discussed. A conclusion, on the main works that are developed in this paper, is given in the last section.

## 2. IDENTIFICATION OF LTI SYSTEMS BY SUBSPACE APPROACH

One is interested, especially in this section, to the survey of deterministic identification of LTI systems by subspace method. Geometric and mathematical tools, theorems, as well as subspace identification method are presented.

### 2.1 Geometric tools

One presents, firstly, symbols and mathematical tools used in subspace method [6].

One assumes that the matrices  $A \in \mathbb{R}^{p \times j}$ ,  $B \in \mathbb{R}^{q \times j}$  and  $C \in \mathbb{R}^{r \times j}$  are given.

- $A^\dagger$  denotes the pseudo inverse Moore-Penrose of matrix  $A$ ,
- One defines the operator of orthogonal projection  $\Pi_B$  which projects the row space of a matrix onto the row space of the matrix  $B \in \mathbb{R}^{q \times j}$ .

$$\Pi_B = B^T \cdot (B \cdot B^T)^\dagger \cdot B \quad (1)$$

- The projection of the row space of the matrix  $A \in \mathbb{R}^{p \times j}$  onto the row space of the matrix  $B \in \mathbb{R}^{q \times j}$  is defined by:

$$A/B = A \cdot \Pi_B = A \cdot B^T \cdot (B \cdot B^T)^\dagger \cdot B \quad (2)$$

- $B^\perp$  denotes a base of the orthogonal space to the row space of  $B$ .
- $\Pi_{B^\perp}$  defines the geometric operator that projects the row space of a given matrix onto the orthogonal space to the row space of matrix  $B$

$$\Pi_{B^\perp} = I_j - \Pi_B \quad (3)$$

It results that:

$$A/B^\perp = A \cdot \Pi_{B^\perp} = A \cdot (I_j - \Pi_B) \quad (4)$$

While taking account of equations (2) and (4), one shows easily that all matrix  $A$  can be decomposed in two matrices where their row spaces are orthogonal such as:

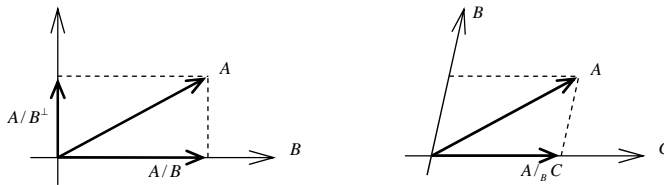
$$A = A \cdot \Pi_B + A \cdot \Pi_{B^\perp} \quad (5)$$

One presents, Figure 1, the geometric interpretation of equation (5).

- One defines the oblique projection of a matrix  $A \in \mathbb{R}^{p \times j}$  along the row space of  $B \in \mathbb{R}^{q \times j}$  on the row space of matrix  $C \in \mathbb{R}^{r \times j}$ :

$$A/B_C = \left[ A/B^\perp \right] \cdot \left[ A/C^\perp \right]^\dagger \cdot C = A \cdot \Pi_{B^\perp} \cdot (C \cdot \Pi_{B^\perp})^\dagger \cdot C \quad (6)$$

A geometric interpretation of equation (6) is illustrated, Figure 1.



**Fig. 1:** Orthogonal and oblique projection in two dimensional space.

One is interested, in the next subsection, to the study of subspace method.

## 2.2 Subspace deterministic identification method

### 2.2.1 Problem formulation

Let consider  $q$  input measurements  $u_k \in \mathbb{R}^m$  and of output  $y_k \in \mathbb{R}^l$  generated by an unknown deterministic system of order  $n$  and described by the following discrete equations:

$$\begin{cases} x_{k+1} = A.x_k + B.u_k \\ y_k = C.x_k + D.u_k \end{cases} \quad (7)$$

One proposes to determine:

- the order  $n$  of unknown system
- the realization  $(ABCD)$  up to a within similarity transformation; with  $A \in \mathbb{R}^{n \times n}$ ,  $B \in \mathbb{R}^{n \times m}$ ,  $C \in \mathbb{R}^{l \times n}$  and  $D \in \mathbb{R}^{l \times m}$

### 2.2.2 Mathematical tools

Let  $U$  a vector such as  $U = (u_0 \ u_1 \ \dots \ u_{q-1})^T$ . The matrix of Hankel associated to the vector  $U$  is given by:

$$U_{0|2i-1} = \begin{pmatrix} u_0 & u_1 & \dots & u_{j-1} \\ u_1 & u_2 & \dots & u_j \\ \vdots & \vdots & \vdots & \vdots \\ \frac{u_{i-1}}{u_i} & \frac{u_i}{u_{i+1}} & \dots & \frac{u_{i+j-2}}{u_{i+j-1}} \\ u_{i+1} & u_{i+2} & \dots & u_{i+j} \\ \vdots & \vdots & \dots & \vdots \\ u_{2i-1} & u_{2i} & \dots & u_{2i+j-2} \end{pmatrix} \quad \begin{array}{c} \uparrow \\ \text{Past} \\ \downarrow \\ \uparrow \\ \text{Future} \\ \downarrow \end{array} \quad (8)$$

with:  $q = 2i + j - 2$  and  $i < j$

One defines respectively the matrices of Hankel of past and future inputs.

$$U_p = \begin{pmatrix} u_0 & u_1 & \dots & u_{j-1} \\ u_1 & u_2 & \dots & u_j \\ \vdots & \vdots & \vdots & \vdots \\ u_{i-1} & u_i & \dots & u_{i+j-2} \end{pmatrix} \quad \text{and} \quad U_f = \begin{pmatrix} u_i & u_{i+1} & \dots & u_{i+j-1} \\ u_{i+1} & u_{i+2} & \dots & u_{i+j} \\ \vdots & \vdots & \vdots & \vdots \\ u_{2i-1} & u_{2i} & \dots & u_{2i+j-2} \end{pmatrix} \quad (9)$$

In the same way one denotes respectively  $Y_p$  and  $Y_f$  the Hankel matrices of past and future outputs.

The instrumental variable matrix (or Hankel matrix of past data) is given by:

$$Z_p = (U_p \ Y_p)^T \quad (10)$$

The matrix of past state sequence is:

$$X_p = (x_0 \ x_1 \ \dots \ x_{j-1}) \in \mathbb{R}^{n \times j} \quad (11)$$

And the matrix of future state sequence:

$$X_f = (x_i \ x_{i+1} \ \dots \ x_{i+j-1}) \in \mathbb{R}^{n \times j} \quad (12)$$

The extended observability matrix (one extends the observability to an order that is superior to the one of the system):

$$\Gamma_i = (C \ CA \ \dots \ CA^{i-1})^T \in \mathbb{R}^{l \times ni} \quad (13)$$

and the reversed extended controllability matrix :

$$\Delta_i = (A^{i-1}B \ A^{i-2}B \ \dots \ B) \in \mathbb{R}^{n \times mi} \quad (14)$$

$$H_i = \begin{pmatrix} D & 0 & 0 & \dots & 0 \\ CB & D & 0 & \dots & 0 \\ CAB & CB & D & \dots & 0 \\ \vdots & \vdots & \vdots & \dots & \vdots \\ CA^{i-2}B & CA^{i-3}B & CA^{i-4}B & \dots & D \end{pmatrix} \in \mathbb{R}^{l \times mi} \quad (15)$$

### Theorem 1: input-output matrix equations

$$X_f = A^i X_p + \Delta_i U_p \quad (16)$$

$$Y_p = \Gamma_i X_p + H_i U_p \quad (17)$$

$$Y_f = \Gamma_i X_f + H_i U_f \quad (18)$$

### Theorem 2: Deterministic identification

While assuming that:

1 – the inputs excitation is persistent of order  $2i$ ,  
 $(r \text{ an } k \left( U_{0|2i-1} U_{0|2i-1}^T \right) = 2.mi)$

2 – no intersection between the row space of matrix  $U_f$  and the one of matrix  $X_p$ ,

3 – the weighting matrices  $W_1 \in \mathbb{R}^{l \times li}$  and  $W_2 \in \mathbb{R}^{j \times ji}$  are such as  $W_1$  is of full rank and  $W_2$  verifies :

$$\text{rank}(Z_p) = \text{rank}(Z_p \cdot W_2) \quad (19)$$

with  $O_i$  is the oblique projection:

$$\mathcal{O}_i = Y_f /_{U_f} Z_p \quad (20)$$

and

$$W_1 \mathcal{O}_i W_2 = (U_1 \ U_2) \cdot \begin{pmatrix} S_1 & 0 \\ 0 & 0 \end{pmatrix} \cdot \begin{pmatrix} V_1^T \\ V_2^T \end{pmatrix} = U_1 \cdot S_1 \cdot V_1^T \quad (21)$$

It results :

$$1 - \quad \mathcal{O}_i = \Gamma_i \cdot X_f \quad (22)$$

2 – the order of the model defined by the system of equations (7) is equal to the number of singular values different from zero, given by the matrix  $S_1$

3 – the extended observability matrix  $\Gamma_i$  is given :

$$\Gamma_i = W_1^{-1} U_1 S_1^{1/2} T \quad (23)$$

$$4 - \quad X_f W_2 = T^{-1} S_1^{1/2} V_1^T \quad (24)$$

$$5 - \quad X_f = \Gamma_i^\dagger \mathcal{O}_i \quad (25)$$

$T \in \mathbb{R}^{n \times n}$  is a non-singular similarity transformation matrix.

### 2.2.3 The system realization determination method

#### System order determination

• From a finite number  $q$  of input-output data  $(u_k, y_k)$ , one forms the following Hankel matrices  $(Y_p \ Y_f)^T$  and  $(U_p \ U_f)^T$  then, one deduces the instrumental variable matrix  $Z_p = (Y_p \ U_p)^T$ . One computes the oblique projection:

$$\mathcal{O}_i = Y_f /_{U_f} Z_p \quad (26)$$

• One multiplies  $\mathcal{O}_i$  at left and at right, respectively, by the matrices  $W_1$  and  $W_2$ .

$$W_1 \mathcal{O}_i W_2 = U_1 \cdot S_1 \cdot V_1^T \quad (27)$$

$W_1$  and  $W_2$  are the weighting matrices which are used for improving the estimation of  $\Gamma_i \cdot X_f$ . Their choice defines the computation algorithm [8].

Table 1: Different algorithms with their weighting matrices.

| Algorithm    | $W_1$  | $W_2$   |
|--------------|--|---|
| 4SID-basique | $I_{li}$   | $I_i$   |
| N4SID        | $I_{li}$   | $(Z_p \Pi_{U_i^\perp})^\dagger Z_p$                   |
| MOESP        | $I_{li}$   | $(Z_p \Pi_{U_i^\perp})^\dagger (Z_p \Pi_{U_i^\perp})$ |
| CVA          | $\left( Y_f \Pi_{U_f^\perp} \left( Y_f \Pi_{U_f^\perp} \right)^T \right)^{-1/2}$ | $(Z_p \Pi_{U_i^\perp})^\dagger (Z_p \Pi_{U_i^\perp})$ |

Many algorithms have been developed in the literature and regrouped in three big families. One cites then the Numerical algorithm for Subspace Space State System IDentification N4SID, the Multivariable Output Error State sPace MOESP and the Canonical Variate Analysis CVA [4-7]. One presents, Table 1, some algorithms and their weighting matrices.

•One computes the SVD of  $W_1 \mathcal{C}_i W_2$

$S_i$  is a diagonal matrix formed by  $n$  singular values different of zero. The order of the system is then  $n$ .

**Determination of matrices  $A$  and  $C$  through  $\Gamma_i$**

Once  $\Gamma_i = \begin{pmatrix} C & CA & \dots & CA^{i-1} \end{pmatrix}^T$  is computed, the matrix  $C$  is extracted directly from the  $l$  first rows of  $\Gamma_i$ .

One designs by :

$$\underline{\Gamma}_i = \begin{pmatrix} CA & CA^2 & \dots & CA^{i-1} \end{pmatrix}^T \text{ and } \bar{\Gamma}_i = \begin{pmatrix} C & CA & \dots & CA^{i-2} \end{pmatrix}^T$$

The matrix  $A$  is such as :

$$A = \underline{\Gamma}_i^\dagger \bar{\Gamma}_i \quad (28)$$

**Determination of matrices  $B$  and  $D$**

While multiplying the equation (18) at left by  $\Gamma_i^\perp$  and at right by  $U_f^\dagger$  one obtains then :

$$\Gamma_i^\perp Y_f U_f^\dagger = \Gamma_i^\perp \Gamma_i X_f U_f^\dagger + \Gamma_i^\perp H_i U_f U_f^\dagger \quad (29)$$

and knowing that the product  $\Gamma_i^\perp \Gamma_i$  is null, it results:

$$\Gamma_i^\perp Y_f U_f^\dagger = \Gamma_i^\perp H_i \quad (30)$$

one poses :

$$\mathcal{L} = \Gamma_i^\perp; \mathcal{M} = \Gamma_i^\perp Y_f U_f^\dagger \quad (31)$$

The equation (31) becomes:

$$\mathcal{M} = \mathcal{L} H_i \quad (32)$$

A system of equations which are function of  $B$  and  $D$  is resolved by a linear regression algorithm.

In the next section, one is interested to present the application of the subspace approach to the induction motor parameters estimation and this in simulation and experiment ways. The identification results will be presented and discussed.

### 3. INDUCTION MOTOR PARAMETERS ESTIMATION BY SUBSPACE APPROACH

One proposes to estimate the induction motor parameters by the subspace approach while using input-output data from a simulated model (complex formed Park model) and then from measured data carried out from the motor [2-5].

In the first stage, one presents briefly the complex formed Park model.

#### 3.1 Complex formed Park model of induction motor

In the literature many models for describing the induction motor behaviour have been proposed and which differ by the kind of envisaged application [5]. In the goal to estimate the parameters of an induction motor; one proposes to use the complex formed Park model in the stator referential [9]:

$$\begin{cases} \frac{d}{dt} X = A_c X + B_c U \\ Y = C_c X + D_c U \end{cases} \quad (33)$$

with:

$$X = \begin{pmatrix} \bar{I} \\ \bar{\Phi} \end{pmatrix}; U = \bar{V}; Y = \bar{I}$$

and

$$A_c = \begin{pmatrix} -\left(\frac{1}{\sigma\tau_s} + \frac{1-\sigma}{\sigma\tau_r}\right) & \frac{L_m}{\sigma L_s L_r \tau_r} + j \frac{L_m}{\sigma L_s L_r} p\omega_r \\ \frac{L_m}{\tau_r} & -\frac{1}{\tau_r} + j.p\omega_r \end{pmatrix}, B_c = \begin{pmatrix} 1 \\ \sigma L_s \\ 0 \end{pmatrix}, C_c = \begin{pmatrix} 1 & 0 \end{pmatrix} \text{ and } D_c = 0$$

One remarks that all the model matrices coefficients are invariant in the time except the rotor speed. At permanent regime, this size is assumed to be constant, what allows describing the induction motor, in this case, by a Linear Time Invariant LTI model.

### 3.2 Induction motor parameters estimation in simulation way

#### Motor parameters Identification from model input-output data

One presents the different phases followed for induction motor parameters estimation. The used input-output data (stator voltages and currents, Fig. 2) are carried out from a model simulation using a sample frequency of 10 kHz. Two uncertain sequences of white noise (with a 40 dB signal to noise ratio) have been added to the input and the output.

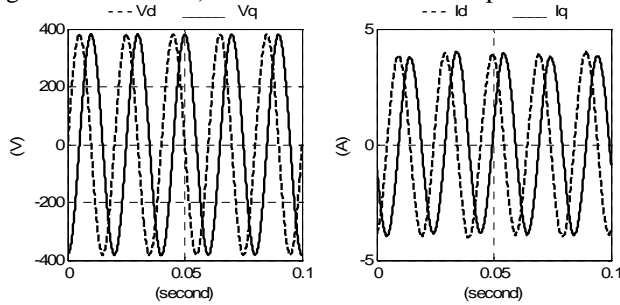


Fig. 2: Curves of voltages and currents in  $dq$  axis.

#### Determination of the system order

The Singular Value Decomposition SVD of  $W_1 \mathcal{O}_i W_2$  with different number  $q$  of input-output data while using the N4SID algorithm is given Fig 3.

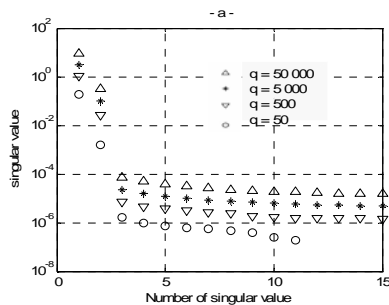
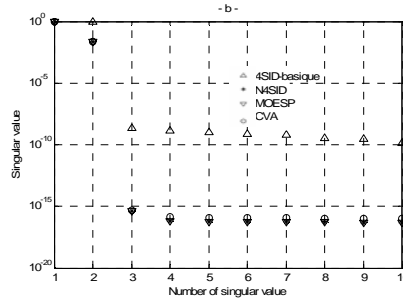


Fig. 3: singular values of  $W_1 \mathcal{O}_i W_2$  computed with different number  $q$  of input-output data.

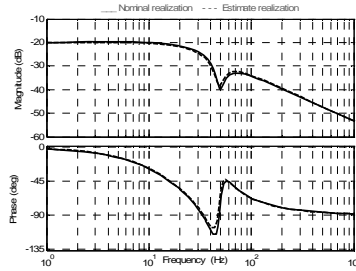
One notes that two singular values are dominant. They become more dominant when  $q$  grows to be higher. The model is then of order two. One presents, Fig. 4, the singular values for an identification carried out with the four algorithms (4SID-basique, N4SID, MOESP and CVA) and for  $q = 2000$ .



**Fig. 4:** The singular values of  $W_1 C_i W_2$  computed with different algorithms for  $q = 2000$ .

The model order estimation is quite improved by a choice of  $W_1$  and  $W_2$  different of the identity matrix (case of N4SID, MOESP and CVA).

The transfer functions Bode tracing associated to  $(A_d \ B_d \ C_d \ D_d)$  and to  $(\hat{A}_d \ \hat{B}_d \ \hat{C}_d \ \hat{D}_d)$  is given, figure 5.



**Fig. 5:** Bode tracing of transfer functions associated, respectively, to  $(A_d \ B_d \ C_d \ D_d)$  and  $(\hat{A}_d \ \hat{B}_d \ \hat{C}_d \ \hat{D}_d)$ .

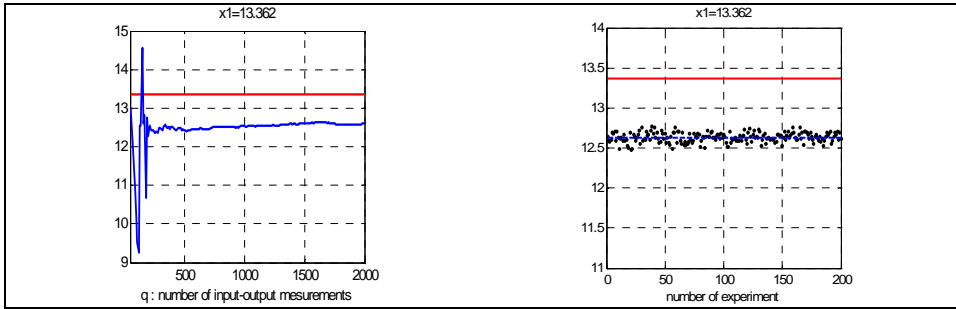
The Bode tracing represented, Figure 5, shows that the realizations  $(A_d \ B_d \ C_d \ D_d)$  and  $(\hat{A}_d \ \hat{B}_d \ \hat{C}_d \ \hat{D}_d)$  describe roughly the same model.

The continuous time reconstituted estimated realization  $(\hat{A}_c \ \hat{B}_c \ \hat{C}_c \ \hat{D}_c)$  is carried out with the ZOH method at a sample frequency  $f_e = 10kHz$ . In the goal to conduct a return on the motor parameters, one uses the properties of similarity transformation. Indeed, it is to recall that the realizations  $(A_c \ B_c \ C_c \ D_c)$  and  $(\hat{A}_c \ \hat{B}_c \ \hat{C}_c \ \hat{D}_c)$  are, generally, different but they are rather similar. These properties are:

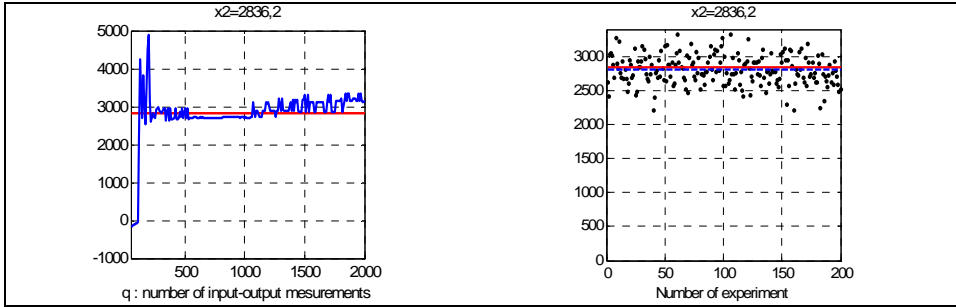
$$\left\{ \begin{array}{l} C_c B_c = \text{Re}(\widehat{C}_c \widehat{B}_c) = \widehat{x}_1 \\ \det(A_c) = \det(\widehat{A}_c) = \widehat{x}_2 + j\widehat{x}_3 \\ \text{trace}(A_c) = \text{trace}(\widehat{A}_c) = \widehat{x}_4 + j\widehat{x}_5 \end{array} \right. \quad (34)$$

One presents on the tracing, Figures 6, 7, 8, 9 and 10, at the left the curves of the estimates of  $\widehat{x}_1, \widehat{x}_2, \widehat{x}_3, \widehat{x}_4$  and  $\widehat{x}_5$  according to the number  $q$  and at the right their curves for 200 experiments where each one is done with 2000 input-output data. The average of the 200 estimated values (discontinuous line) has been computed while assuming that their dispersion follows a Gaussian law.

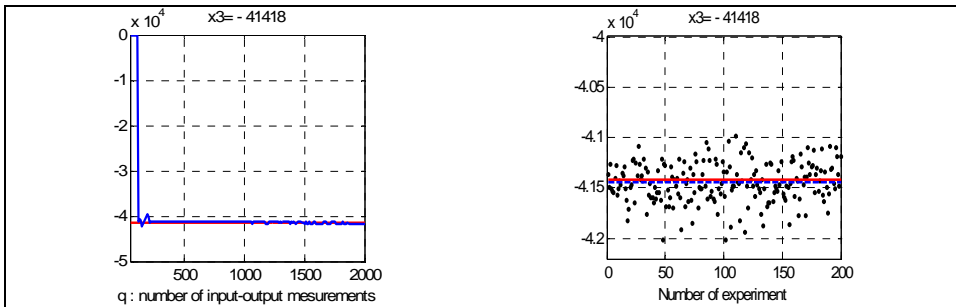
— Estimated value    - - - Average of the 200 estimated values    — Nominal value.



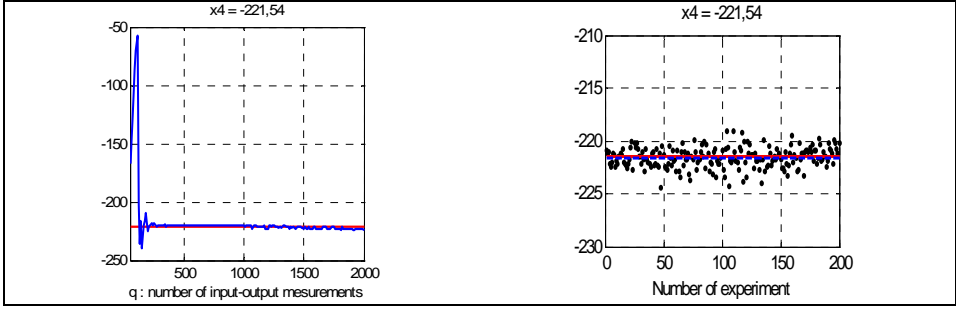
**Fig. 6:** Curves of  $x_1$  and of  $\widehat{x}_1$ .



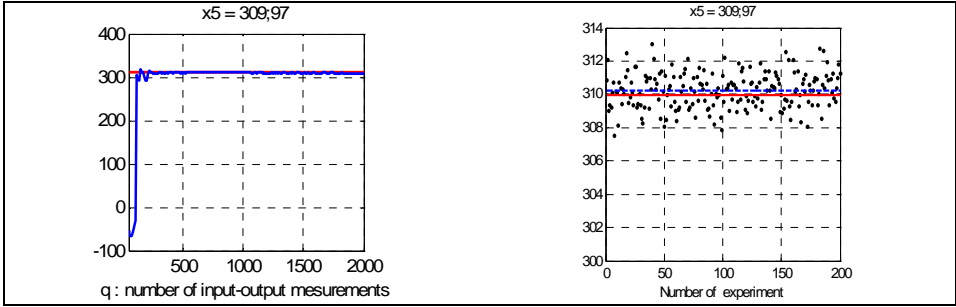
**Fig. 7:** Curves of  $x_2$  and of  $\widehat{x}_2$ .



**Fig. 8:** Curves of  $x_3$  and of  $\widehat{x}_3$ .



**Fig. 9:** Curves of  $x_4$  and of  $\hat{x}_4$ .



**Fig. 10:** Curves of  $x_5$  and of  $\hat{x}_5$ .

On the curves presented, Figures 6, 7, 8, 9, 10, one remarks that the estimated values  $\hat{x}_3$ ,  $\hat{x}_4$  and  $\hat{x}_5$  converge well to their exact values whereas the estimated value  $\hat{x}_2$  oscillates on both sides of the nominal value  $x_2$ . One notes the convergence of the estimated  $\hat{x}_1$  to a biased value. This bias is conserved on the 200 experiments.

Table. 2: Nominal values and estimated average value of product  $\hat{C}_c \hat{B}_c$ , of the trace and of the determinant of the matrix  $\hat{A}_c$ .

|                                | $\text{Re}[\hat{C}_c \hat{B}_c]$ | $\text{Im}[\hat{C}_c \hat{B}_c]$ | $\text{Re}[\det(\hat{A}_c)]$ | $\text{Im}[\det(\hat{A}_c)]$ | $\text{Re}[\text{Trace}(\hat{A}_c)]$ | $\text{Im}[\text{Trace}(\hat{A}_c)]$ |
|--------------------------------|----------------------------------|----------------------------------|------------------------------|------------------------------|--------------------------------------|--------------------------------------|
| <b>Nominal value</b>           | 13,362                           | -                                | 2 836                        | - 41 418                     | - 221,54                             | 309,97                               |
| <b>Estimated average value</b> | 12,631                           | -                                | 2 799                        | - 41 448                     | - 221,61                             | 310,222                              |
| <b>Relative error in %</b>     | 5,4 7%                           | -                                | 1,31 %                       | 0,07 %                       | 0,03 %                               | 0,08 %                               |

One presents, Table 2, a comparison between the nominal values and estimated average value of the product  $\hat{C}_c \hat{B}_c$ , of the trace and of the determinant of the matrix  $\hat{A}_c$ . An evaluation of the relative error is also done.

The obtained equations system is:

$$\left\{ \begin{array}{l} \frac{1}{\sigma L_s} = \hat{x}_1 \\ \left( \frac{1}{\sigma \tau_s} + \frac{1-\sigma}{\sigma \tau_r} \right) \frac{1}{\tau_r} - \frac{L_m}{\tau_r} \frac{L_m}{\sigma L_s L_r \tau_r} = \hat{x}_2 \\ - \left( \frac{1}{\sigma \tau_s} + \frac{1-\sigma}{\sigma \tau_r} \right) p \omega_r - \frac{L_m}{\tau_r} \frac{L_m}{\sigma L_s L_r} p \omega_r = \hat{x}_3 \\ \left( \frac{1}{\sigma \tau_s} + \frac{1-\sigma}{\sigma \tau_r} \right) \frac{1}{\tau_r} = \hat{x}_4 \\ p \omega_r = \hat{x}_5 \end{array} \right. \quad (35)$$

It can be resolved by a non-linear optimisation algorithm. A comparison between the nominal and the estimated parameters is presented Table 3.

Table 3: The nominal and the estimated parameters of an induction motor.

| Parameters             | $R_s (\Omega)$ | $R_r$  | $L_s = L_r$ | $L_m$   | $\omega_r$ |
|------------------------|----------------|--------|-------------|---------|------------|
| Nominal value (S.I.)   | 10             | 6,59   | 0,31        | 0,27    | 154,98     |
| Estimated value (S.I.) | 10,026         | 6,5973 | 0,31081     | 0,27071 | 155        |
| Relative error (%)     | 0,26%          | 1,1%   | 0,26%       | 0,26%   | 0,01%      |

The parameters estimation results obtained in simulation are well satisfactory; the relative error on each parameter didn't exceed a value of 1.1%. The subspace deterministic identification method allows giving good parameters estimation with noisy input-output data.

### 3.3. Induction motor parameters estimation based on experiment measures

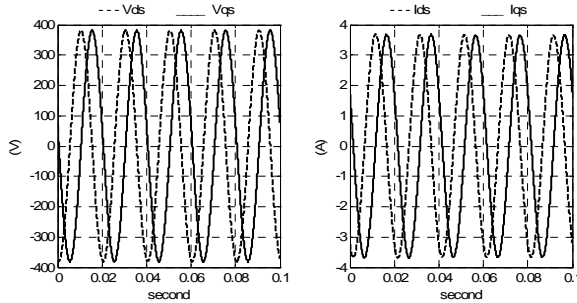
In this section, one is interested to the induction motor parameters estimation while using the measures carried out from experiment. Input-output data are acquired from motors experiment platform, mounted around an acquirement and control card DSPACE 1104 and an inverter, at the automatic control unit of National Engineering School of Sfax. One presents, Figure 12, a general view of the platform as well as the electronic adaptation and measures cards module.



Fig. 12: General view of the platform and the electronic cards module.

#### Input-output data acquirement U and Y

The stator voltages and currents which are acquired [1] in the referential  $dq$  are illustrated Figure 13.



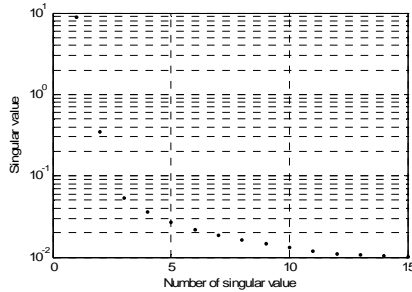
**Fig. 13:** Stator voltages and currents in the referential  $dq$ .

### Motor parameters estimation

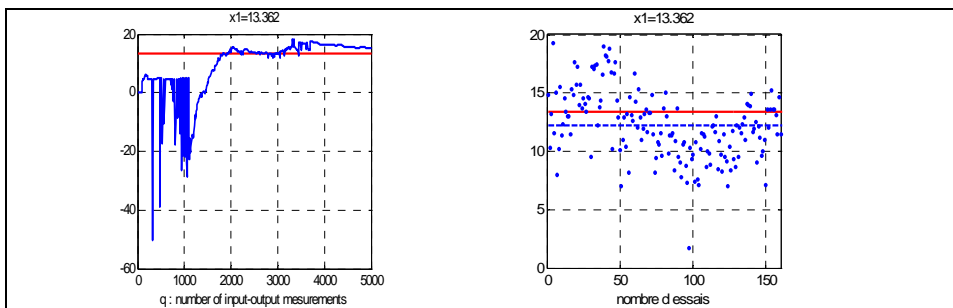
The motor parameters estimation is effected in the same conditions that are adopted in simulation while using the algorithm N4SID. The system order is computed, Figure 14, using SVD method.

### System order

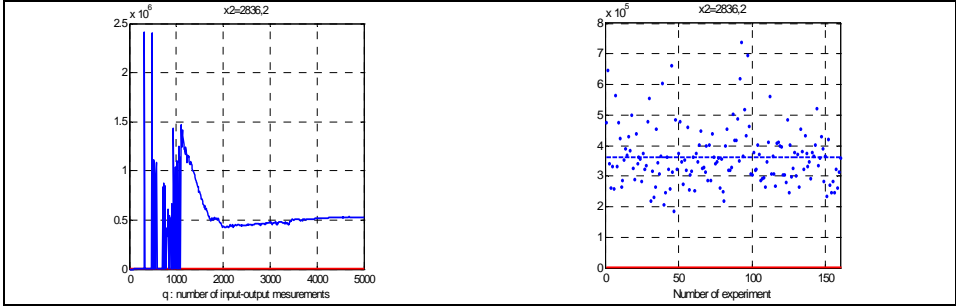
As shows Figure 14, one can assume that there are two dominant singular values, it results that the order system is 2. On the tracings, figures 15-19, one presents, on the left the curve of the estimated values and on the right, the dispersion of the estimated during the 160 experiments with  $q = 5000$ .



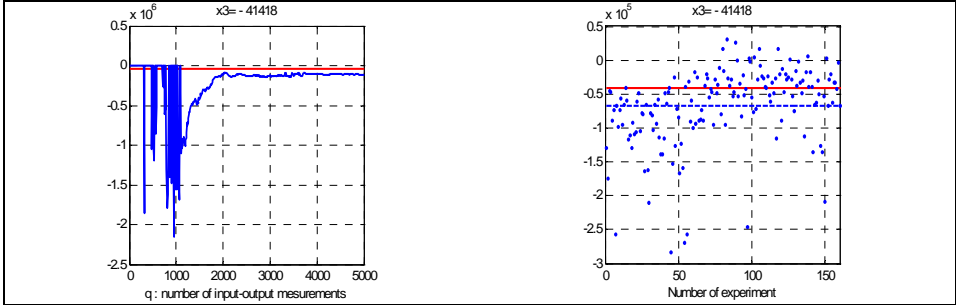
**Fig. 14:** The singular values of  $W_1 \mathcal{O}_i W_2$ .



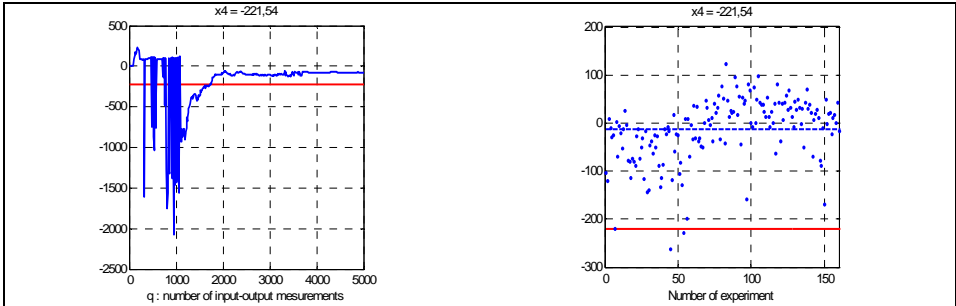
**Fig. 15:** Curves of  $x_1$  and  $\hat{x}_1$ .



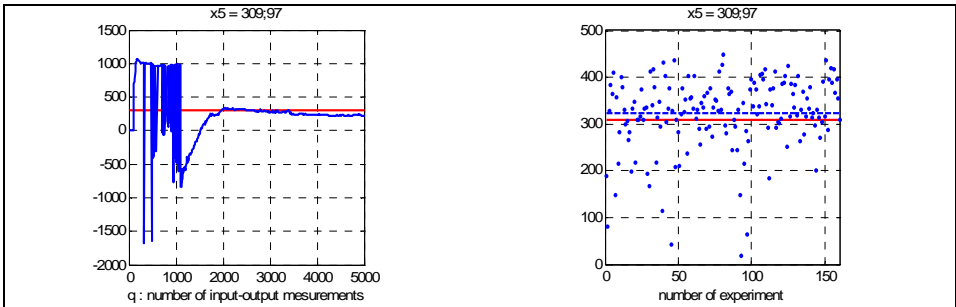
**Fig. 16:** Curves of  $x_2$  and  $\hat{x}_2$ .



**Fig. 17:** Curves of  $x_3$  and  $\hat{x}_3$ .



**Fig. 18:** Curves of  $x_4$  and  $\hat{x}_4$ .



**Fig. 19:** Curves of  $x_5$  and  $\hat{x}_5$ .

In comparison with the estimated parameters, which are obtained from simulation, those of the experiments present relatively important errors. This observation can be explained by the fact that the motor is to time-varying parameters and to noisy operating (process noise,

input noise, modelling noise and measure noise). Indeed, noise can affect considerably some identification properties:

- the estimation convergence: in fact, the simulation foresees an immediate convergence toward the estimated value since the first 200 input-output data, whereas in practice the system converges slowly and this from  $q = 2000$ .
- the estimation bias: the estimated values from simulation present, in one hand, a weak bias, on the other hand, it was shown that in practice the bias has a relatively elevated level.
- the estimated values variance of the 160 experiments: its value in experiment, has an important level in comparison with the one given by simulation.

The table 4 gives the nominal and the estimated values.

Table 4: Nominal and estimated values of induction motor parameters

| Parameters                    | $R_s (\Omega)$ | $R_r$ | $\omega_r$ |
|-------------------------------|----------------|-------|------------|
| <b>Nominal value (S.I.)</b>   | 10             | 6,59  | 154,98     |
| <b>Estimated value (S.I.)</b> | 8,47           | 5,04  | 161,12     |
| <b>Relative error (%)</b>     | 15,3%          | 23,5% | 3,96%      |

In practice the parameters such as the stator and rotor resistors as well as the speed have been estimated with an acceptable relative error.

#### 4. CONCLUSION

The first part of this contribution has been concentrated on the study of the subspace deterministic identification approach for LTI discrete systems. The geometric and the mathematical tools as well as the main theorems which are used by this method have been presented. A description of the different stages of this identification technique has been given. In the second part, one has applied the subspace method to induction motor parameters estimation and this in simulation and experiment. The use of identification algorithm N4SID in simulation, has allowed obtaining a good parameters estimation. The used input-output data have been slightly noisy in order to simulate a case close to the practice one. The experiment results of this approach have showed a degraded accuracy in comparison with the simulation results. This inaccuracy is due to the biased convergence which is mainly caused by the noisy environment in which evolves the system.

The use of the identification approach in its stochastic context would be interesting for the motor parameters estimation because of the addition of different noise forms in practice. We are planning now to study the stochastic algorithms of the subspace identification.

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