

# Global identification of mechanical and electrical parameters of synchronous motor driven joint with a fast *CLOE* method

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**Abstract**— In many cases of new actuation of compliant controlled or bio-inspired joint driven robot, a global identification of electrical and mechanical coupled dynamics is required. This paper proposes a technique which mixes a closed loop output error method with the inverse dynamic identification model method which allows using linear least-squares technique to estimate the parameters. A first approach which has been validated on a DC motor allows a decoupled identification of the electrical and mechanical dynamics but fails to make a simultaneous identification. A major improvement of that method is proposed to carry out the coupled identification of both mechanical and electrical parameters. A validation on a synchronous motor driven joint shows the effectiveness of the new procedure.

## I. INTRODUCTION

Since a lot of industrial robots still use synchronous motor, this paper is focused on Direct Current motor drive chain identification with a new approach based on the association of two methods. The first one comes from important theoretical results and successful experimentation that have been obtained in the area of identification of dynamic parameters of robot manipulators [1] [2]. This identification method based on the Inverse Dynamic Identification Model (IDIM) and least-squares (LS) technique has been successfully applied to identify parameters of DC electric drive [3], synchronous [4] and asynchronous machines [5]. With a well-tuned derivative bandpass filtering of position to calculate the velocities and accelerations and a well-tuned derivative bandpass filtering of current to calculate current derivative, the method gives good results. This is achieved using exciting trajectories [6] which give rich information to get good noise immunity and to decrease bias and variance of the estimation.

The second method comes from a commonly used identification algorithms: the Output Error (OE) identification [7] [8]. This approach is to minimize a quadratic error between an actual output and a simulated output of the system, assuming both the actual and simulated systems have the same input. A nonlinear optimization algorithm is required which is very sensitive to the choice of initial conditions to get the convergence [9].

The OE method has been used to identify electrical parameters of a synchronous machine, and a comparison with the IDIM method showed very similar results [10]. But

the two methods have a drawback. The IDIM method needs a good tuning of filters [3] [4] [5] while the OE method needs good initial conditions [9] and a powerful algorithm to solve non linear least squares [11]. By mixing these two approaches [12], our method overcomes these drawbacks. The idea is to use the OE structure and the inverse dynamic model at each iteration which dramatically simplifies the non linear LS optimization.

The method proposed in [13] requires only one physical signal measurement, which avoids filtering other values. It works well to get a decoupled identification, but the results of a global identification mainly depend on initial conditions. This paper proposes a new solution to solve this problem. An experimental setup on a synchronous motor driven joint validates the method and is compared to IDIM method.

## II. INVERSE DYNAMIC IDENTIFICATION MODEL (*IDIM*)

Let us consider a joint driven by a voltage source amplifier and a synchronous motor. Electrical and mechanical equations are the following:

$$\begin{bmatrix} V_d \\ V_q \end{bmatrix} = \begin{bmatrix} R_s & -p\dot{q}L_q \\ p\dot{q}L_d & R_s \end{bmatrix} \begin{bmatrix} I_d \\ I_q \end{bmatrix} + \begin{bmatrix} L_d & 0 \\ 0 & L_q \end{bmatrix} \begin{bmatrix} \dot{I}_d \\ \dot{I}_q \end{bmatrix} + \begin{bmatrix} p\dot{q}\phi_{fd} \\ p\dot{q}\phi_{fq} \end{bmatrix} \quad (1)$$

$$\Gamma_m = pI_q[\phi_{fq} + (L_d - L_q)I_d] + pI_d\phi_{fd} = J\ddot{q} + F_v\dot{q} + F_s \text{sign}(\dot{q}) \quad (2)$$

where  $I_{dq} = (I_d, I_q)$ ,  $V_{dq} = (V_d, V_q)$ ,  $R_s$ ,  $L_{dq} = (L_d, L_q)$ ,  $p$ ,  $q_p$ ,  $\phi_f$ ,  $\phi_{fd} = \phi_f \sin(pq_p)$ ,  $\phi_{fq} = \phi_f \cos(pq_p)$ , are respectively into the dq frame : the currents, the voltages, the resistance, the inductances, the number of pole pairs, the rotor field position with respect to the d frame, the maximum flux under a pole, the rotor flux constants. For the mechanical dynamics,  $\Gamma_m, J, F_v, F_s, q, \dot{q}, \ddot{q}$ , are respectively the electromagnetic motor torque, the inertia moment, the viscous friction coefficient, the coulomb friction torque, the motor position, velocity and acceleration. Let us introduce  $p_a, t_s, t_{obs}$ , the number of parameters to identify, the sampling time and the observation range time.

The inverse model calculates the control input as a function of the state and its derivative. It is naturally given by the equations of the physics. These equations are non linear in the state because of  $\text{sign}(\dot{q})$ , but they are linear in relation to the parameters to identify and define the identification model as follows:

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$$\begin{bmatrix} V_d \\ V_q \\ 0 \end{bmatrix} = \begin{bmatrix} I_d & I_d & -p\dot{q}I_q & p\dot{q} & 0 & 0 & 0 & 0 \\ p\dot{q}I_d & I_q & \dot{q} & 0 & p\dot{q} & 0 & 0 & 0 \\ -pI_dI_q & 0 & pI_dI_q & -pI_d & -pI_q & \ddot{q} & \dot{q} & \text{sign}(\dot{q}) \end{bmatrix} X \quad (3)$$

$$X = [L_d \ R_s \ L_q \ \phi_{fd} \ \phi_{fq} \ J \ F_v \ F_s]^T$$

$X$  is the  $(p_a \times 1)$  vector of parameters to identify ( $p_a=8$ ).

Let us define:

$$y_{idm} = \begin{bmatrix} V_d \\ V_q \\ 0 \end{bmatrix}, \quad IDIM(I_{dq}, \dot{I}_{dq}, \hat{q}, \ddot{q}) = \begin{bmatrix} \dot{I}_d & I_d & -p\dot{q}I_q & p\dot{q} & 0 & 0 & 0 & 0 \\ p\dot{q}I_d & I_q & \dot{q} & 0 & p\dot{q} & 0 & 0 & 0 \\ -pI_dI_q & 0 & pI_dI_q & -pI_d & -pI_q & \ddot{q} & \dot{q} & \text{sign}(\dot{q}) \end{bmatrix}$$

Equation (3), can be written as :

$$y_{idm} = IDIM(I_{dq}, \dot{I}_{dq}, \hat{q}, \ddot{q}) X \quad (4)$$

Because of perturbations due to noise measurement and modeling errors, the actual  $y$  differs from  $y_{idm}$  by an error,  $e$ , such that:  $y = y_{idm} + e = IDIM(I_{dq}, \dot{I}_{dq}, \hat{q}, \ddot{q})X + e$

$$y = y_{idm} + e = IDIM(I_{dq}, \dot{I}_{dq}, \hat{q}, \ddot{q})X + e \quad (5)$$

The inverse model (5) is sampled at different times  $t_{s1} = t_{s1}, t_{s2}, t_{s3}, \dots, t_{sn} = t_{obs}$  with  $r_{rows} = 3 \times n_{samples} \geq p_a$ , and filtered to get an over determined linear system:

$$Y = W X + \rho \quad (6)$$

with:

$$Y = \begin{bmatrix} y(t_{s1}) \\ \dots \\ y(t_{obs}) \end{bmatrix}, \quad W = \begin{bmatrix} IDIM(\hat{I}_{dq}(t_{s1}), \hat{I}_{dq}(t_{s1}), \hat{q}(t_{s1}), \hat{q}(t_{s1})) \\ \dots \\ IDIM(\hat{I}_{dq}(t_{obs}), \hat{I}_{dq}(t_{obs}), \hat{q}(t_{obs}), \hat{q}(t_{obs})) \end{bmatrix}$$

where  $(\hat{I}_{dq}, \hat{I}_{dq}, \hat{q}, \hat{q})$  are calculated by band-pass filtering the measures of  $(I_{dq}, q)$ .

Using the base parameters [1] and tracking “exciting” reference trajectories [6],[14], we get a well conditioned matrix  $W$ . The  $LS$  solution  $\hat{X}$  of (6) minimizes  $\|\rho\|^2$  and is given by:

$$\hat{X} = ((W^T W)^{-1} W^T) Y = W^{-1} Y \quad (7)$$

Standard deviation are estimated using classical and simple results from statistics, considering the matrix  $W$  to be a deterministic one, and  $\rho$  to be a zero mean additive independent noise, with standard deviation  $\sigma_\rho$  such that :

$$C_{\rho\rho} = E(\rho\rho^T) = \sigma_\rho^2 I_r$$

where  $E$  is the expectation operator and  $I_r$  is the  $(r \times r)$  identity matrix. An unbiased estimation of  $\sigma_\rho$  is used and given by the expression :

$$\hat{\sigma}_\rho^2 = \frac{\|Y - W\hat{X}\|^2}{r-p_a}$$

The variance-covariance matrix of the estimation error and standard deviations can be calculated by:

$$C_{\hat{X}\hat{X}} = E[(X - \hat{X})(X - \hat{X})^T] = \sigma_\rho^2 (W^T W)^{-1}$$

The relative standard deviation  $\% \sigma_{\hat{X}i}$  is given by the

expression:  $\% \sigma_{\hat{X}i} = 100 \frac{\sigma_{\hat{X}i}}{|\hat{X}i|}$ , where  $\sigma_{\hat{X}i}^2 = C_{\hat{X}\hat{X}}(i, i)$  is the

diagonal coefficient of  $C_{\hat{X}\hat{X}}$ .

$IDIM$  identification procedure is represented on Fig.1.

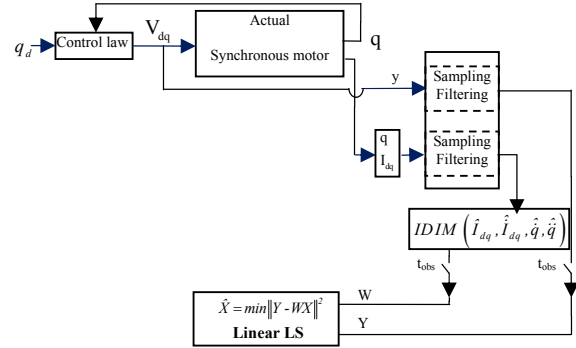


Fig.1  $IDIM$  identification scheme

### III. THE OUTPUT ERROR IDENTIFICATION METHOD ( $OE$ )

The  $OE$  identification methods minimize a quadratic error between an actual output  $y$ , and a simulated output  $y_s$  of the system, assuming both the actual and the simulated systems have the same input. This approach can be implemented in an open-loop form [15] [16] or in a closed-loop form [17] [18]. It is more suitable to choose the closed-loop output error ( $CLOE$ ) form, because the open loop simulation can be unstable and very sensitive to the initial state conditions and to the errors in numerical algorithms which solve the differential equations. With the open or the closed-loop, the output is given by the integration of a non linear state-space model output equation. The direct dynamic model can be obtained by writing the inverse dynamic model equation (3) as following:

$$\begin{bmatrix} L_d & 0 & 0 \\ 0 & L_q & 0 \\ 0 & 0 & J \end{bmatrix} \begin{bmatrix} \dot{I}_d \\ \dot{I}_q \\ \dot{q} \end{bmatrix} = \begin{bmatrix} V_d \\ V_q \\ 0 \end{bmatrix} - \begin{bmatrix} R_s & -p\dot{q}L_q & p\dot{q}\phi_{fd} \\ p\dot{q}L_d & R_s & p\dot{q}\phi_{fq} \\ -p\phi_{fd} & -p\phi_{fq} & F_v \end{bmatrix} \begin{bmatrix} I_d \\ I_q \\ \dot{q} \end{bmatrix} - \begin{bmatrix} 0 \\ 0 \\ F_s \text{sign}(\dot{q}) - pI_dI_q(L_d - L_q) \end{bmatrix} \quad (8)$$

The state  $x_s = [I_d, I_q, \dot{q}, q]^T$  is the result of the integration of the linear implicit differential equation (8). Usually, for mechanical system where the joint position is measured by encoders,  $y = q$  and  $y_s = q_s$ .

The  $CLOE$  identification method is based on the the minimization of the quadratic criterion  $J(X) = \|Y - Y_s\|^2$ , where  $Y$  and  $Y_s$  are vectors of samples of  $y$  and  $y_s$  respectively. This is a nonlinear least-squares problem. The estimation of the parameters can be computed using algorithms such as the gradient method, the Newton methods or the Levenberg Marquardt method. These methods are based on a first or second order Taylor's expansion of  $J(X)$ . The Gauss-Newton regression is a simple way to

calculate the optimal solution [19]. It is based on a Taylor series expansion of  $y_s$  at a current estimate  $\hat{X}^k$ , of the parameters at iteration  $k$ :

$$y_s(X^{k+1}) = y_s(\hat{X}^k) + \left( \frac{\partial y_s(\hat{X}^k)}{\partial X} \right)_{\hat{X}^k} (X^{k+1} - \hat{X}^k) + o \quad (9)$$

$$\text{where: } \left( \frac{\partial y_s(\hat{X}^k)}{\partial X} \right)_{\hat{X}^k} = \delta_{y_s/\hat{X}} \quad (10)$$

$\delta_{y_s/\hat{X}}$  is the  $(n \times b)$ , Jacobian matrix of  $y_s$ , with respect to  $\hat{X}$ , evaluated at  $\hat{X}^k$ .

$o$  is the residual of the Taylor series expansion.

Each coefficient of  $\delta_{y_s/\hat{X}}$ , defines a sensitivity function.

Let us define:  $y = y_s(X^{k+1}) + e$

(11)

From(9), it becomes:

$$y - y_s(\hat{X}^k) = \left( \frac{\partial y_s(\hat{X}^k)}{\partial X} \right)_{\hat{X}^k} (X^{k+1} - \hat{X}^k) + o + e \quad (12)$$

With the previous equation, it is possible to get an over-determined linear system over the time window  $t_{obs}$ . The sensitivity functions  $\delta_{y_s/\hat{X}}$  characterize the variation of the output function  $y_s$ , with respect to a variation of the parameter  $\hat{X}$ . The sensitivity functions are the solutions of a differential system calculated from (8). This technique is time-consuming and the sensitivity functions must be integrated many times at each step of the iterative nonlinear optimization method. The *CLOE* method is represented on the following scheme:

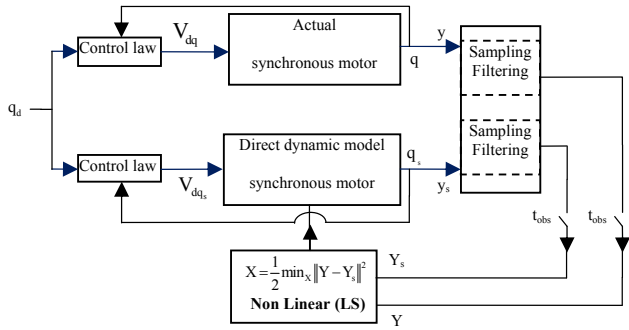


Fig. 2 *CLOE* identification scheme

#### IV. DIRECT AND INVERSE DYNAMIC IDENTIFICATION MODEL TECHNIQUE (*DIDIM*)

Into the *OE* equations, let us replace  $q$  into  $y$  by  $V_{dq}$  and  $q_s$  into  $y_s$  by  $V_{dq_s}$ . Then, looking toward *OE* equation and *IDIM* equation, a straightforward result comes [12]. With the *OE* method, from (12), it comes:

$$y = y_s(\hat{X}^k) - \left( \frac{\partial y_s(\hat{X}^k)}{\partial X} \right)_{\hat{X}^k} \hat{X}^k + \left( \frac{\partial y_s(\hat{X}^k)}{\partial X} \right)_{\hat{X}^k} X^{k+1} + o + e \quad (13)$$

And from the *IDIM* method, at each step of the parameter estimation, (4) becomes:

$$y_s(\hat{X}^k) = IDIM(I_{dq_s}(\hat{X}^k), \dot{I}_{dq_s}(\hat{X}^k), \dot{q}_s(\hat{X}^k), \ddot{q}_s(\hat{X}^k)) \hat{X}^k \quad (14)$$

Substituting  $y_s(\hat{X}^k)$  by its value in (13) gives:

$$y = IDIM(I_{dq_s}(\hat{X}^k), \dot{I}_{dq_s}(\hat{X}^k), \dot{q}_s(\hat{X}^k), \ddot{q}_s(\hat{X}^k)) \hat{X}^k - \left( \frac{\partial y_s(\hat{X}^k)}{\partial X} \right)_{\hat{X}^k} \hat{X}^k + \left( \frac{\partial y_s(\hat{X}^k)}{\partial X} \right)_{\hat{X}^k} X^{k+1} + o + e \quad (15)$$

Let us make the hypothesis that

$$\left( \frac{\partial y_s(\hat{X}^k)}{\partial X} \right)_{\hat{X}^k} = IDIM(I_{dq_s}(\hat{X}^k), \dot{I}_{dq_s}(\hat{X}^k), \dot{q}_s(\hat{X}^k), \ddot{q}_s(\hat{X}^k)) \quad (16)$$

So that (15) is simplified to :

$$y = IDIM(I_{dq_s}(\hat{X}^k), \dot{I}_{dq_s}(\hat{X}^k), \dot{q}_s(\hat{X}^k), \ddot{q}_s(\hat{X}^k)) X^{k+1} + o + e \quad (17)$$

This equation is similar to the Inverse Dynamic Identification Model (3) where  $(I_{dq}, \dot{I}_{dq}, \dot{q}, \ddot{q})$  is no more calculated with the actual measured and filtered data but with the simulated ones  $(I_{dq_s}, \dot{I}_{dq_s}, \dot{q}_s, \ddot{q}_s, \hat{X}^k)$  and the estimation  $\hat{X}^{k+1}$  at step  $k+1$  is obtained with the *IDIM* procedure of section II.

The *IDIM* (17) is sampled and filtered to get an over-determined linear system:

$$Y = WX + \rho \quad (18)$$

where

$$Y = \begin{bmatrix} y(t_{s1}) \\ \dots \\ y(t_{obs}) \end{bmatrix}, \quad W = \begin{bmatrix} IDIM(I_{dq_s}(t_{s1}), \dot{I}_{dq_s}(t_{s1}), \dot{q}_s(t_{s1}), \ddot{q}_s(t_{s1})) \\ \dots \\ IDIM(I_{dq_s}(t_{obs}), \dot{I}_{dq_s}(t_{obs}), \dot{q}_s(t_{obs}), \ddot{q}_s(t_{obs})) \end{bmatrix}$$

The *LS* solution of (18) gives  $\hat{X}^{k+1}$ . This process is iterated with a new simulation using  $\hat{X}^{k+1}$ , until:

$$\frac{\|\rho_{k+1}\| - \|\rho_k\|}{\|\rho_k\|} \leq tol_1, \text{ and, } \max_{i=1, \dots, p} \left| \frac{\hat{X}_i^{k+1} - \hat{X}_i^k}{\hat{X}_i^k} \right| \leq tol_2.$$

where,  $tol_1$  and  $tol_2$  are values ideally chosen to be small numbers to get fast convergence with good accuracy. A good compromise consists in choosing  $tol_1$  and  $tol_2$  between 2.0% and 5.0%.

This identification method is based on a closed-loop simulation using the direct dynamic model *DDM* while the optimal parameters minimize the squared 2-norm of the error between  $y$ , and the simulated  $y_s$ , over an observation window time  $t_{obs}$ . This technique overcomes the problems of nonlinear optimization in *OE* method and the difficulty of filter tuning with the *IDIM* method. Because this method uses both models *DDM* and *IDIM*, it is named the *DIDIM* method: **D**irect and **I**nverse **D**ynamic **I**dentification **M**odels technique.

#### V. VALIDATION OF HYPHESIS

This section validates the hypothesis given by (16). The current estimate  $\hat{X}^k$  of the parameters  $X$ , at iteration  $k$ , is calculated with the Jacobian matrix  $\left( \frac{\partial y_s(X)}{\partial X} \right)_{\hat{X}^k}$ , using (14):

$$\begin{aligned} \left( \frac{\partial y_s(\hat{X}^k)}{\partial X} \right)_{\hat{X}^k} &= \frac{\partial}{\partial X} \left( IDIM(I_{dq_s}(\hat{X}^k), \dot{I}_{dq_s}(\hat{X}^k), \dot{q}_s(\hat{X}^k), \ddot{q}_s(\hat{X}^k)) \hat{X}^k \right)_{\hat{X}^k} \\ \left( \frac{\partial y_s(\hat{X}^k)}{\partial X} \right)_{\hat{X}^k} &= IDIM(I_{dq_s}(\hat{X}^k), \dot{I}_{dq_s}(\hat{X}^k), \dot{q}_s(\hat{X}^k), \ddot{q}_s(\hat{X}^k)) \frac{\partial \hat{X}^k}{\partial X} \\ &+ \hat{X}^k \frac{\partial}{\partial X} \left( IDIM(I_{dq_s}(\hat{X}^k), \dot{I}_{dq_s}(\hat{X}^k), \dot{q}_s(\hat{X}^k), \ddot{q}_s(\hat{X}^k)) \right)_{\hat{X}^k} \end{aligned} \quad (19)$$

The calculation of the second term of (19) is given by:

$$\begin{aligned} \frac{\partial}{\partial X} \left( IDIM(I_{dq_s}(\hat{X}^k), \dot{I}_{dq_s}(\hat{X}^k), \dot{q}_s(\hat{X}^k), \ddot{q}_s(\hat{X}^k)) \right)_{\hat{X}^k} &= \\ \frac{\partial}{\partial I_{dq_s}} \left( IDIM(I_{dq_s}(\hat{X}^k), \dot{I}_{dq_s}(\hat{X}^k), \dot{q}_s(\hat{X}^k), \ddot{q}_s(\hat{X}^k)) \right) \frac{\partial I_{dq_s}}{\partial X} & \\ + \frac{\partial}{\partial \dot{I}_{dq_s}} \left( IDIM(I_{dq_s}(\hat{X}^k), \dot{I}_{dq_s}(\hat{X}^k), \dot{q}_s(\hat{X}^k), \ddot{q}_s(\hat{X}^k)) \right) \frac{\partial \dot{I}_{dq_s}}{\partial X} & \quad (20) \\ + \frac{\partial}{\partial \dot{q}_s} \left( IDIM(I_{dq_s}(\hat{X}^k), \dot{I}_{dq_s}(\hat{X}^k), \dot{q}_s(\hat{X}^k), \ddot{q}_s(\hat{X}^k)) \right) \frac{\partial \dot{q}_s}{\partial X} & \\ + \frac{\partial}{\partial \ddot{q}_s} \left( IDIM(I_{dq_s}(\hat{X}^k), \dot{I}_{dq_s}(\hat{X}^k), \dot{q}_s(\hat{X}^k), \ddot{q}_s(\hat{X}^k)) \right) \frac{\partial \ddot{q}_s}{\partial X} & \end{aligned}$$

Equation (20) is equal to zero if

$$\frac{\partial I_{dq_s}}{\partial X} = \frac{\partial \dot{I}_{dq_s}}{\partial X} = \frac{\partial \dot{q}_s}{\partial X} = \frac{\partial \ddot{q}_s}{\partial X} = 0 \quad (21)$$

Let us introduce  $I_{dq_d}, \dot{I}_{dq_d}, \dot{q}_d, \ddot{q}_d$  the desired values obtained with a reference trajectory so that  $I_{dq_s}, \dot{I}_{dq_s}, \dot{q}_s, \ddot{q}_s$  assumes for the simulated tracking error  $e_{I_{dq_s}}, e_{\dot{I}_{dq_s}}, e_{\dot{q}_s}, e_{\ddot{q}_s}$  keep close to

the actual one for any  $\hat{X}^k$ . This means that:

$$I_{dq_s}(\hat{X}^k) = I_{dq_d} + e_{I_{dq_s}}, \dot{I}_{dq_s}(\hat{X}^k) = \dot{I}_{dq_d} + e_{\dot{I}_{dq_s}}, \dot{q}_s(\hat{X}^k) = \dot{q}_d + e_{\dot{q}_s}, \ddot{q}_s(\hat{X}^k) = \ddot{q}_d + e_{\ddot{q}_s}$$

In others words  $(I_{dq_s}, \dot{I}_{dq_s}, \dot{q}_s, \ddot{q}_s)$  have little dependence on  $X$ , such that (21) becomes:

$$\frac{\partial (I_{dq_d} + e_{I_{dq_s}})}{\partial X} = \frac{\partial (\dot{I}_{dq_d} + e_{\dot{I}_{dq_s}})}{\partial X} = \frac{\partial (\dot{q}_d + e_{\dot{q}_s})}{\partial X} = \frac{\partial (\ddot{q}_d + e_{\ddot{q}_s})}{\partial X} = 0$$

The tracking error doesn't need to be zero, we will use simple P or PD control laws to drive the current and the position in the synchronous motor to get the *DIDIM* constraint.

## VI. EXPERIMENTAL CASE STUDY

A permanent magnet synchronous machine with 2 pole pairs is used. The control system is based on a TMS 320C31 Texas Instruments™ processor and Matlab-Simulink software, in order to get a high rate numerical control with a big computational capacity [20]. All analog and digital signals are directly accessible between the process and Simulink using the C code generator RTW Matlab toolbox [21] and the RTI program from dSPACE.

## VII. GLOBAL IDENTIFICATION WITH VOLTAGE MEASUREMENT

A cascaded-loops controller is used. The control law is realized with a 'P' controller and considering  $sign(\dot{q})$  as a perturbation. Given  $w_{i_{dq}}, w_{\dot{q}}, w_q$  which assume a stable closed loop and no saturation on the synchronous motor, the

gains  $K_{i_{dq}}, K_{\dot{q}}, K_q$  can be calculated assuming an initial set of parameter  $X^0 = X_{ap}^{k=0}$ . Let us chose the following *a priori* set of parameters:  $L_{dap}=1.2E-1H, L_{qap}=7.6E-1H, R_{sap}=32\Omega, \Phi_{fdap}=0V/rad/s, \Phi_{fqap}=1.26V/rad/s, J_{ap}=2.8E-3kgm^2, F_{vap}=2E-3Nm/rd/s, F_{sap}=1E-1Nm$ . The trajectory assumes the constraint of (16) and equilibrates the relative accuracy for parameters [6].

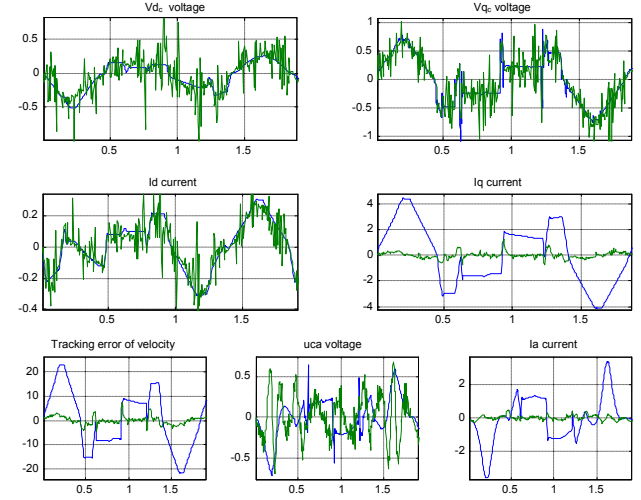


Fig. 3 Global identification with DIDIM (experimental, simulated)

The convergence process takes around 7 steps. On Fig. 3 the  $V_{dq}$  voltage simulated signals match the experimental ones. This is not the case for the  $I_q$  current, the velocity tracking error, the  $u_{ca}$  voltage. In Table I, the bad results for some parameters are due to the large ratio between the electrical and the mechanical dynamics. The gap between the actual and the simulated trajectories is linked to the initial conditions. This example shows the limits of *DIDIM* for a global identification with only one physical signal measurement for two dynamics (electrical, mechanical) separated by a factor greater than 10.

TABLE I. GLOBAL IDENTIFICATION WITH DIDIM

Methods	<i>DIDIM</i>			<i>IDIM</i>		
	$\hat{X}$	$2\sigma_{\hat{X}}$	$\% \sigma_{\hat{X}r}$	$\hat{X}$	$2\sigma_{\hat{X}}$	$\% \sigma_{\hat{X}r}$
$L_d$ (H)	0.48	5.10e-2	5.31	0.372	1.03e-1	13.9
$R_s$ ( $\Omega$ )	0.323	2.18e-2	3.37	30.9	2.91	4.70
$L_q$ (H)	3.75e-3	4.65e-4	6.19	0.214	4.53e-2	10.6
$p\phi_{fd}$ (V/rad/s)	-0.289	1.10e-2	1.91	-0.422	3.32e-2	3.93
$p\phi_{fq}$ (V/rad/s)	0.320	1.56e-2	1.81	0.768	2.99e-2	1.95
$J$ (kg m <sup>2</sup> )	2.94e-4	1.91e-5	3.25	1.76e-3	7.89e-5	2.23
$F_v$ (Nm/rd/s)	5.02e-4	3.56e-4	35.4	2.68e-3	2.30e-3	43.0
$F_s$ (Nm)	3.51e-2	9.00e-3	12.8	7.08e-2	3.63e-2	25.6

## VIII. GLOBAL IDENTIFICATION WITH VOLTAGE AND CURRENT MEASUREMENT

From (2), the synchronous motor torque is calculated with the electrical parameters and can be written as :

$$pI_q\phi_{jq} + L_d pI_q I_d - L_q pI_q I_d + pI_d\phi_{fd} = \Gamma_m(X_e, I_{dq})$$

$$\text{where } X_e = [L_d \ R_s \ L_q \ \phi_{fd} \ \phi_{jq}]^T$$

Let us define:

$$IDIM(I_{dq}, \dot{I}_{dq}, \dot{q}, \ddot{q}) = \begin{bmatrix} \dot{I}_d & I_d & -p\dot{q}I_q & p\dot{q} & 0 & 0 & 0 & 0 \\ p\dot{q}I_d & I_q & \dot{I}_q & 0 & p\dot{q} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \dot{q} & \ddot{q} & \text{sign}(\dot{q}) \end{bmatrix}$$

which can be written as:

$$IDIM(I_{dq}, \dot{I}_{dq}, \dot{q}, \ddot{q}) = \begin{bmatrix} IDIM(I_{dq}, \dot{I}_{dq}, \dot{q}) & 0_{2 \times 3} \\ 0_{1 \times 5} & IDIM(\dot{q}, \ddot{q}) \end{bmatrix}$$

The first step is to rewrite (3) so that:

$$y_{idm} = IDIM(I_{dq}, \dot{I}_{dq}, \dot{q}, \ddot{q}) X \quad (22)$$

$$\text{with } X = [L_d \ R_s \ L_q \ \phi_{fd} \ \phi_{jq} \ J \ F_v \ F_s]^T \text{ and}$$

$$y_{idm} = [V_d \ V_q \ \Gamma_m(X_e, I_{dq})]^T$$

The second step is to rewrite (17) taking into account the lack of information into the voltage which is mainly depending of the motor speed. To bring more information, let us take the current as second input into *DIDIM* method so

$$\text{that into (17) } y = \begin{bmatrix} V_d \\ V_q \\ 0 \end{bmatrix} \text{ becomes: } y = \begin{bmatrix} V_d \\ V_q \\ \Gamma_m(X_e, I_{dq}) \end{bmatrix}$$

By taking  $I_{dq}$  we get a faster convergence, because  $I_{dq}$  drives the torque of mechanical equation and keeps the advantage of not derivation of the position  $q$  to get actual velocity  $\dot{q}$  and acceleration  $\ddot{q}$ .

The new *IDIM* equation at step  $k+1$  is:

$$y = IDIM(I_{dq_s}(\hat{X}^k), \dot{I}_{dq_s}(\hat{X}^k), \dot{q}_s(\hat{X}^k), \ddot{q}_s(\hat{X}^k)) \hat{X}^{k+1} + o + e \quad (23)$$

As previously into (17),

$$IDIM(I_{dq_s}(\hat{X}^k), \dot{I}_{dq_s}(\hat{X}^k), \dot{q}_s(\hat{X}^k), \ddot{q}_s(\hat{X}^k))$$

is calculated with the simulated data while  $y$  is the vector of actual current and voltage. It is possible to go deeply into (23), to show that we obtain a decoupled identification process by introducing the current as a second input. Equation (23) can be rewritten with two separated equations:

$$\begin{bmatrix} y_e \\ y_m(\hat{X}^k) \end{bmatrix} = \begin{bmatrix} IDIM(I_{dq_s}(\hat{X}^k), \dot{I}_{dq_s}(\hat{X}^k), \dot{q}_s(\hat{X}^k)) & 0_{2 \times 3} \\ 0_{1 \times 5} & IDIM(\dot{q}_s(\hat{X}^k), \ddot{q}_s(\hat{X}^k)) \end{bmatrix} \begin{bmatrix} \hat{X}_e^{k+1} \\ \hat{X}_m^{k+1} \end{bmatrix} + o + e$$

The first row equation gives the electrical parameters:

$$y_e = IDIM(I_{dq_s}(\hat{X}^k), \dot{I}_{dq_s}(\hat{X}^k), \dot{q}_s(\hat{X}^k)) X_e^{k+1} + o_e + e_e$$

$$\text{where } y_e = \begin{bmatrix} V_d \\ V_q \end{bmatrix} \text{ and } X_e = [L_d \ R_s \ L_q \ \phi_{fd} \ \phi_{jq}]^T$$

With the results of the electrical parameters at step  $k+1$ , the mechanical parameters at step  $k+1$  are given by:

$$y_m(\hat{X}_e^{k+1}) = IDIM(\dot{q}_s(\hat{X}_m^k), \ddot{q}_s(\hat{X}_m^k)) X_m^{k+1} + o_m + e_m$$

$$\text{where } y_m(\hat{X}_e^{k+1}) = \Gamma_m(\hat{X}_e^{k+1}, I_{dq}) \text{ and } X_m = [J \ F_v \ F_s]^T$$

Under this form, it appears that a global identification is similar to a decoupled identification which performs

separately the electrical dynamic and the mechanical dynamic parameters identification. This is a *DIDIM* method with 2 inputs with a  $k+1$  step obtained in two phases. This is while it is named *DIDIM2*.

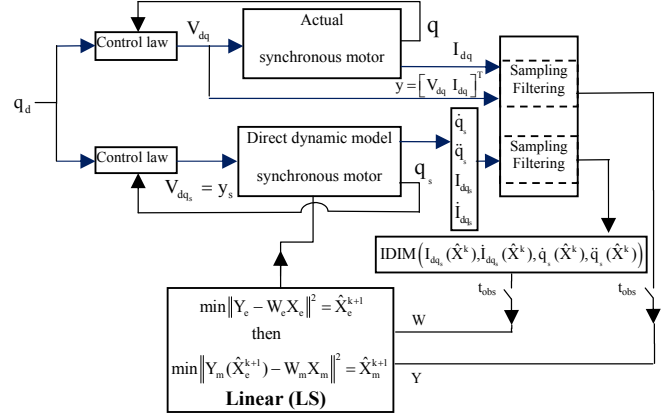


Fig. 4 Global identification with DIDIM2

The proposed experimental identification is realized with the same a priori set of parameters than previously:  $L_{dap}=1.2E-1H$ ,  $L_{qap}=7.6E-1H$ ,  $R_{sap}=32\Omega$ ,  $\Phi_{fdap}=0V/rad/s$ ,  $\Phi_{jqap}=1.26V/rad/s$ ,  $J_{ap}=2.8E-3kgm^2$ ,  $F_{vap}=2E-3Nm/rd/s$ ,  $F_{sap}=1E-1Nm$ . The trajectory assumes the constraint of (16) and equilibrates the relative accuracy for all parameters [6].

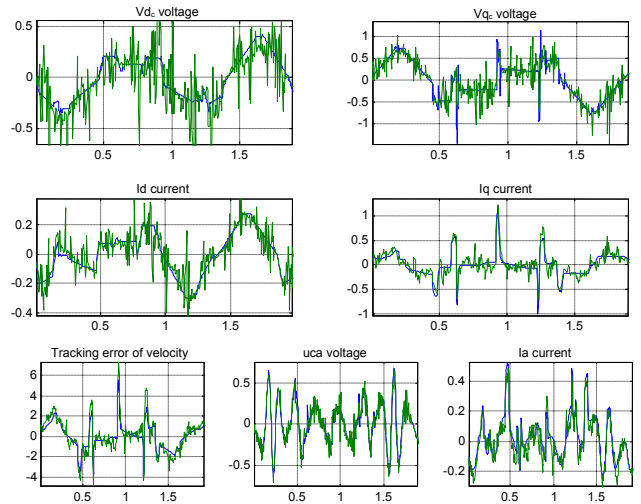


Fig. 5 Global identification with DIDIM2 (experimental, simulated)

In Table II, parameters estimation looks very good and is compared with *IDIM* estimation method [4]. This good result is confirmed by the simulated signals Fig.5 which match the experimental one in less than 7 steps. *DIDIM2* with a global identification is not dependant on the initial conditions.

For simplicity, the minimum a priori parameters to generate the trajectory on the actual system are used as

initial condition, others parameters are set to one on the simulator.

TABLE II GLOBAL IDENTIFICATION WITH DIDIM2

Methods	DIDIM2			IDIM		
	$\hat{X}$	$2\sigma_{\hat{x}}$	$\% \sigma_{\hat{x}r}$	$\hat{X}$	$2\sigma_{\hat{x}}$	$\% \sigma_{\hat{x}r}$
$L_d$ (H)	0.496	6.17e-2	6.22	0.372	1.03e-1	13.9
$R_s$ ( $\Omega$ )	31.3	1.65	2.63	30.9	2.91	4.70
$L_q$ (H)	0.186	2.48e-2	6.6	0.214	4.53e-2	10.6
$p\phi_{ra}$ (V/rad/s)	-0.433	1.74e-2	2.01	-0.422	3.32e-2	3.93
$p\phi_{qa}$ (V/rad/s)	0.749	1.56e-2	1.04	0.768	2.99e-2	1.95
$J$ (kg m <sup>2</sup> )	1.95e-3	3.32e-5	0.85	1.76e-3	7.89e-5	2.23
$F_v$ (Nm/rad/s)	2.92e-3	8.41e-4	14.4	2.68e-3	2.30e-3	43.0
$F_s$ (Nm)	7.74e-2	1.33e-2	8.64	7.08e-2	3.63e-2	25.6

## IX. CONCLUSION

This paper deals with a new off-line global identification technique of electrical and mechanical dynamics of synchronous motor driven joints, called *DIDIM2* for **D**irect and **I**nverse **D**ynamic **I**dentification **M**odels which used **2** inputs with a  $k+1$  step obtained in **2** phases.

This method based on *DIDIM* is a closed-loop Output Error approach mixed with the Inverse Dynamic Identification Model method. Each step of the iterative procedure of the Gauss-Newton non linear regression (*OE* method) is simplified to a linear regression which is solved with the Inverse Dynamic Identification Model technique (*IDIM*). In the case of a global identification, *DIDIM2* avoids convergence problems obtained with *DIDIM* using only the voltage measures. By using both voltage and current, the convergence does not depend on the initial conditions or on the ratio between the electrical and the mechanical dynamics.

The drawback of our method is that we need some experiences to give us an idea of the parameters. Thus a control law can be realized without saturation on the physical system to identify. But this drawback is fully compensated by the simplicity of the method, the speed of the convergence, the absence of derivation of any actual signals and robustness against noisy data. The method validates in the same identification procedure, both models for model based feedforward control and for simulation.

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