Preprints of the 19th World Congress
The International Federation of Automatic Control
Cape Town, South Africa. August 24-29, 2014

Dynamic identification of the Kuka LWR robot using motor torques and joint torque sensors data

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Abstract: Off-line robot dynamic identification methods use the Inverse Dynamic Identification Model (*IDIM*), which calculates the motor torques that are linear in relation to the dynamic parameters of both links and drive chains, and use linear least squares technique (*IDIM-LS* technique). For most robots, the only available data are the motor position and the motor torques which are calculated as the product of the known current reference signal by the joint drive gains. Then the accuracy of links parameters may be limited by noise and error modeling in the drive chains. The Kuka *LWR* robot (industrial version *IIWA*: Intelligent Industrial Work Assistant) gives the possibility for an industrial robot to investigate this problem using the joint torque sensors data, measured at the output of the harmonic drive geared drive chains, to identify only the links inertial parameters without the errors coming from the drive chains. This paper focuses on the comparison of the accuracy of the identification of the dynamic parameters of the rigid model of the *LWR4+* version, which is very popular in robotics research, using measures of the motor positions and the motor currents, or the torque sensors measurements or both side data. This paper is giving a first complete and reliable identified rigid dynamic model of the *LWR4+*, publicly available for the robotics community. Moreover, this work shows for the first time the strong result that motor torques calculated from motor currents can identify the links inertial parameters with the same accuracy than using joint torque sensors at the output of the joint drive chains.

Keywords: Identification, robot, dynamic parameters, torque sensor, drive chain.

1. Introduction

The usual identification process is based on the Inverse Dynamic Model (*IDM*) and Least Squares (*LS*) estimation. This method, called *IDIM-LS* (Inverse Dynamic Identification Model with Least Squares), has been performed on several prototypes and industrial robots with accurate results (Hollerbach et al., 2008). This method needs the measurement of joint positions and the motor torques. These latter are computed as the product of the measurement of motor currents by the joint drive gains. Thus the accuracy of links parameters may be limited by noise and error modeling in the drive chains.

The Institute of Robotics and Mechatronics at German Aerospace Center (*DLR*) collaborated with Kuka Roboter has manufactured a new generation of lightweight robot: the Kuka *LWR 4+* (LightWeight Robot or *LBR*) (Albu-Schäffer et al., 2007)(Bischoff et al., 2010)(Rackl et al., 2012). It is mainly designed for collaborative work with humans. Consequently, the robot is provided with joint torque sensors located at the output of the drive chains, after the gearboxes. They measure joint torques without the drive chains effects for accurate and sensitive collision and failure detection. This robot gives the possibility to study the effect of noise and error modeling in the drive chains on the accuracy of links parameters by the use of the joint torque sensors data, measured at the output of the harmonic drive geared drive chains, to identify only the links inertial parameters. Futhermore, the manufacturer don't give any information about dynamic parameters of the robot and this paper is giving a first complete and reliable identified rigid dynamic model of the LWR4+, publicly available for the robotics community.

A parameter identification of the robot is performed in (Rackl et al., 2012) and (Bargsten et al., 2013) with the joint torque sensors measurement. But some identified parameters are not given and the authors do not compare their results with the identified parameters using the motor torques. The use of motor torques allows to identify the complete dynamic model with drive chain inertias and frictions parameters.

In this paper, a comparison of the dynamic identification of the Kuka *LWR*4+ Robot using measures of the motor currents or/and the the joint torque sensors measurements is performed with *IDIM-LS* method. So four models are compared from measurement of the actual robot: one with only the motor currents and motor positions, one with joint torque sensors measurement and motor positions, one with joint torque sensors measurement, motor currents and motor positions and the last with the same data of the previous one but for identify only the drive chains parameters.

This paper is divided into six sections. Section 2 describes the modeling of robots and the four models. Section 3 presents the usual method for dynamic identification based on *IDIM-LS* method. Section 4 is devoted to the experimental identification on the Kuka *LWR*. Section 5 is the conclusion.

2. Modeling

The *IDM* of a robot calculates the torques τ_{idm} as a function the motor positions, velocities and accelerations. It can be obtained from the Newton-Euler or the Lagrangian equations (Khalil and Dombre, 2002). In this paper, only the rigid model is studied, not the flexible model (Albu-Schaffer and Hirzinger, 2001). It is noticed that the Kuka *LWR* is provided with torque sensors located after the gearbox of each joint (see figure 1).

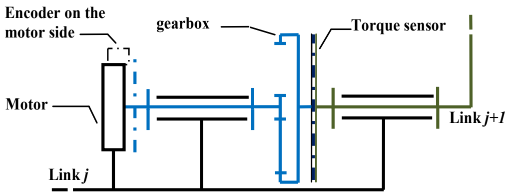

Figure 1. Scheme of a joint of robot

The complete *IDM* of the robot is given by the following relation with the consideration of motor torques and torque sensors measurements :

$$\tau_{idm\_m} = diag(\ddot{q})Iam + M(q)\ddot{q} + H(q,\dot{q}) + \tau_{fm} + \tau_{fl} \quad (1)$$

$$\tau_{idm\_l} = M(q)\ddot{q} + H(q,\dot{q}) + \tau_{fl} \quad (2)$$

$$\tau_{idm\_m} - \tau_{idm\_l} = diag(\ddot{q})Iam + \tau_{fm} \quad (3)$$

with:

$$\begin{aligned} \tau_{fm} &= diag(\dot{q})Fvm + diag(sign(\dot{q}))Fcm + offm \\ \tau_{fl} &= diag(\dot{q})Fvl + diag(sign(\dot{q}))Fcl + offl \end{aligned} \quad (4)$$

Where q, $\dot{q}$ and $\ddot{q}$ are respectively the (nx1) vectors of motor positions, velocities and accelerations; τ_{idm_m} is the (nx1) vector of motor torques; τ_{idm_l} is the (nx1) vector of joint torque sensors measurement; $M(q)$ is the (nxn) robot inertia matrix; $H(q,\dot{q})$ is the (nx1) vector of Coriolis, centrifugal, gravitational and friction forces/torques; *Iam* is the (nx1) vector of total inertia moments for rotors and gears; *Fvm* and *Fcm* are the (nx1) vector of viscous and Coulomb friction parameters of motor side; *Offm* is the (nx1) vector of motor current amplifier offset parameters; *Fvl* and *Fcl* are the (nx1) vector of viscous and Coulomb friction parameters of link side; *Offl* is the (nx1) vector of torque sensor offset parameters; n is the number of moving links. All measurement and mechanical variables are given in S.I. unit in joint side.

Four sets of parameters can be identified with this *IDM*, the first called 'A' uses only the measurement of motor torques (equation (1)), the second called 'B' uses only the joint torque sensors measurement (equation (2)), the third called ' C' uses both the motor torques and the joint torque sensors measurement (equations (1) and (2)) and the last called 'D' uses difference between the motor torques and the joint torque sensors measurement to identify only the drive chain parameters (equation (3)).

The choice of the modified Denavit and Hartenberg frames attached to each link allows a dynamic model that is linear in relation to a set of standard dynamic parameters χ_{ST} (Hollerbach et al., 2008) (Gautier and Khalil, 1990):

$$\begin{aligned} &\tau_{idm} = IDM_{st}(q,\dot{q},\ddot{q})\chi_{st} \text{ with } \chi_{st} = \begin{bmatrix} \chi_{st1}^T & \chi_{st2}^T & \cdots & \chi_{stn}^T \end{bmatrix}^T \\ &\text{with: } \tau_{idm/\mathrm{A}} = \tau_{idm\_m} \text{ , } \tau_{idm/\mathrm{B}} = \tau_{idm\_l} \\ &\tau_{idm/\mathrm{C}} = \begin{bmatrix} \tau_{idm\_m}^T & \tau_{idm\_l}^T \end{bmatrix}^T, \tau_{idm/\mathrm{D}} = \tau_{idm\_m} - \tau_{idm\_l} \end{aligned} \quad (5)$$

Where $IDM_{st}(q,\dot{q},\ddot{q})$ is the (nxNs) jacobian matrix of τ_{idm}, with respect to the (Nsx1) vector χ_{st} of the standard parameters. χ_{stj} is composed of the following standard dynamic parameters of axis j :

$$\begin{aligned} &\chi_{stj}^{ms} = \begin{bmatrix} Ia_j & Fvm_j & Fcm_j & Offm_j \end{bmatrix}^T \\ &\chi_{stj}^{ls} = [XX_j \quad XY_j \quad XZ_j \quad YY_j \quad YZ_j \quad ZZ_j \\ &\quad MX_j \quad MY_j \quad MZ_j \quad M_j \quad Fvl_j \quad Fcl_j \quad Offl_j]^T \\ &\text{with } \chi_{stj} = \begin{bmatrix} \chi_{stj}^{ms\,T} & \chi_{stj}^{ls\,T} \end{bmatrix}^T \text{ with measure A and C} \\ &\chi_{stj} = \chi_{stj}^{ls} \text{ with measure B ,} \\ &\chi_{stj} = \chi_{stj}^{ms} \text{ with measure D} \end{aligned} \quad (6)$$

Where Iam_j is a total inertia moment for rotor and gears of actuator of link j (to simplify: it is named drive inertia moment) ; Fvm_j and Fcm_j are the viscous and Coulomb friction parameters of joint j (motor side); $Offm_j$ is the motor current amplifier offset of joint j ; XX_j, XY_j, XZ_j, YY_j, YZ_j, ZZ_j are the six components of the robot inertia matrix of link j; MX_j, MY_j, MZ_j, are the components of the first moments of link j; M_j is the mass of link j; Fvl_j and Fcl_j are the (nx1) vector of viscous and Coulomb friction parameters of joint j (link side); $Offl_j$ is the torque sensor offset of joint j . The maximum number of standard parameters is Ns=17xn.

3. IDIM-LS: Inverse Dynamic Identification Model with Least Squares Method

1. Theory

Because of perturbations due to noise measurement and modeling errors, the actual torque τ differs from τ_{idm} by an error e, such that:

$$\begin{aligned} &\tau = \tau_{idm} + e = IDM_{ST}(q,\dot{q},\ddot{q})\chi_{st} + e \\ &\text{with: } \tau_{\mathrm{A}} = \tau_m \text{ , } \tau_{\mathrm{B}} = \tau_l \text{ ,} \\ &\tau_{\mathrm{C}} = \begin{bmatrix} \tau_m & \tau_l \end{bmatrix}^T \text{, } \tau_{\mathrm{D}} = \tau_m - \tau_l \end{aligned} \quad (7)$$

Where τ_l is the joint torque sensors measurement and τ_m is the actual motor torques computed as the product of the measured motor currents by the joint drive gains:

$$\tau_m^j = g_{\tau j} I_j \quad (8)$$

Where τ_m^j , ,$g_{\tau j}$ and I_j, are respectively the motor torque, the manufacturer's joint drive gain and the motor current of joint j.

The vector $\hat{\chi}_{st}$ is the least squares (*LS*) solution of an over determined system built from the sampling of (7), while the robot is tracking exciting trajectories (Gautier and Khalil, 1991):

$$Y = W_{st}\chi_{st} + \rho \quad (9)$$

Where: Y is the (rx1) measurement vector, W_{st} the (rxn_{st}) observation matrix, and ρ is the (rx1) vector of errors. The number of rows is $r=nxn_e$, where the number of recorded samples is n_e. When W_{st} is not a full rank matrix, the *LS* solution is not unique. The system (9) is rewritten:

$$Y = W\chi + \rho \tag{10}$$

Where a subset W of b independent columns of W_{st} is calculated, which defines the vector χ of b base parameters (Gautier and Khalil, 1990)(Mayeda et al., 1990). The base parameters are obtained from standard dynamic parameters by regrouping some of them with linear relation (Gautier and Khalil, 1990)(Mayeda et al., 1990).

ρ is assumed to have zero mean, be serially uncorrelated and be heteroskedastic, i.ie., to have a diagonal covariance matrix Ω partitioned so that (Gautier, 1997)(Janot et al., 2014):

$$\Omega = diag\left(\sigma_1^2 I_{ne} \ldots \sigma_j^2 I_{ne} \ldots \sigma_n^2 I_{ne}\right) \tag{11}$$

where I_{ne} is the (n_exn_e) identity matrix. The heteroskedasticity hythesis is based on the fact that robots are nonlinear multi-input multi-output (*MIMO*).

σ_j^2 is the error variance calculated from subsystem j ordinary *LS* (*OLS*) solution:

$$Y^j = W^j \chi + \rho^j \tag{12}$$

Thus, the weighted *LS* (*WLS*) estimator is used to estimate χ. The *WLS* solution of (10) is given by:

$$\hat{\chi} = \left(W^T \Omega^{-1} W\right)^{-1} W^T \Omega^{-1} Y \tag{13}$$

Usually, such weighting operations normalize the error terms in (10). Indeed, with:

$$\overline{\rho} = \Omega^{-1/2} \rho \tag{14}$$

one obtains $\sum_{\overline{\rho}\rho} = E(\overline{\rho}\rho^{\mathrm{T}}) = \Omega^{-1/2} E(\rho\rho^{\mathrm{T}}) \Omega^{-1/2} = I_r$.

The estimated covariance matrix of *WLS* estimates is:

$$\sum_{LS} = \left(W^T \Omega^{-1} W\right)^{-1} \tag{15}$$

$\hat{\sigma}_{\hat{\chi}(i)}^2 = \sum_{LS}(i,i)$ is the i^{th} diagonal coefficient of $\sum_{LS}$. The relative standard deviation $\%\hat{\sigma}_{\hat{\chi}(i)}$ of $\hat{\chi}$ (the i^{th} component of $\hat{\chi}$) is given by:

$$\%\hat{\sigma}_{\hat{\chi}(i)} = 100\hat{\sigma}_{\hat{\chi}(i)} / \hat{\chi}(i) \text{ with } \left|\hat{\chi}(i)\right| \neq 0 \tag{16}$$

2. Identification of the payload inertial parameters

In order to identify the payload parameters, it is necessary that the robot carried out two sets of trajectories: without the payload and with the payload fixed to the end-effector (Khalil et al., 2007). The payload is considered as a link $n+1$ fixed to the link n of the robot (Khalil et al., 2007).

3. Filtering

Calculating the *LS* solution of (10) from perturbed data in W and Y may lead to bias if W is correlated to ρ. Then, it is essential to filter data in Y and W before computing the *WLS* solution. Velocities and accelerations are estimated by means of a band-pass filtering of the positions (with Butterworth filter). More details about the adjustment of cut-off frequency of Butterworth filter can be found in (Gautier, 1997) and (Gautier et al., 2012).

To eliminate high frequency noises and torque ripples and to avoid that W and Y are statistically correlated with error terms, a parallel decimation (decimate filter) is performed on Y and on each column of W. To chose the cut-off frequency of the decimate filter, a Durbin-Watson test is performed (Janot et al., 2014), the *dw* value is computed with the following relation:

$$dw = \frac{\sum_{i=2}^{r}\left(\overline{\rho}(i) - \overline{\rho}(i-1)\right)^2}{\sum_{i=1}^{r}\overline{\rho}(i)^2} \tag{17}$$

The *dw* value must be between 1 and 3 with ideal value at 2. The choice of the cut-off frequency of the decimate filter is a compromise between the minimization of $|dw\text{-}2|$ value and the conservation of the robot dynamics in W and Y.

4. Model reduction

Some parameters have no significant contribution on the robot dynamics. These parameters can be cancelled in order to keep a set of essential parameters of a simplified dynamic model with a good accuracy. Recently, a new model reduction method based on the F-statistic (Davidson and MacKinnon, 1993) was introduced in (Janot et al., 2014).

The F-statistic is run as follows:

- compute the vector of errors $\|\overline{\rho}\|$ with the system (10) which contains the b base parameters,

- for each b base parameter , compute the vector of errors $\|\overline{\rho}_c\|$ with the system (10) reduced to the $b_c=b$-1 base parameters (with removing the current parameter) and computes:

$$\hat{F} = \frac{\left(\|\overline{\rho}_c\|^2 - \|\overline{\rho}\|^2\right)\Big/\left(b-b_c\right)}{\|\overline{\rho}\|^2\Big/\left(r-b\right)} \tag{18}$$

If $\hat{F}$ is less than or compatible with F_d then the F-statistic accepts the model reduction i.e. the current parameter can be deleted from the model; otherwise, the model reduction is rejected, i.e the current parameter is kept in the model. Parameters that show the largest relative standard deviation are eliminated first and the process is executed until the F-statistic fails.

F_d can be read on the Fisher-Snedecor table with α=5%, if $r \gg 1$, F_d is equal to 3.85.

It is noticed that it is needed to perform a Kolmogorov-Smirnov test to verify the normality of $\|\overline{\rho}\|$ before to apply the F-statistic.

4. EXPERIMENTAL VALIDATION

5. Description of the robot and its kinematics

The Kuka *LWR* (see figure 2) robot has a serial structure with n=7 rotational joints. Each motor has encoder which measures the motor position.

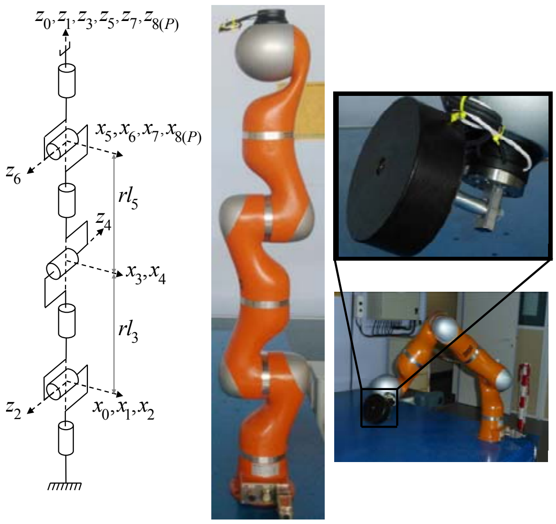

Figure 2. Link frame of the robot and robot without and with payload

The kinematics of serial robots is defined using the Modified Denavit and Hartenberg (*MDH*) notation (Khalil and Dombre, 2002). In this notation, the link *j* fixed frame is defined such that: the z_j axis is taken along joint *j* axis; the x_j axis is along the common normal between z_j and z_{j+1}; α_j and d_j parameterize the angle and distance between z_{j-1} and z_j along x_{j-1}, respectively; θ_j and r_j parameterize the angle and distance between x_{j-1} and x_j along z_j , respectively; *a(j)* denotes the link antecedent to link *j*.

The geometric parameters defining the robot frames are given in table I. The 8[th] joint '*L*' corresponds to the payload. The model A of the Kuka *LWR* has b=79 base parameters with payload parameters (b=74 for model B, b=102 for model C and b=28 for model D). The regrouped parameters are detailed in appendix 1 for models A,B and C. There are no regrouped parameters for model D.

TABLE I. MDH PARAMETERS OF THE KUKA LWR4+

j	$a(j)$	α_j	d_j	θ_j	r_j
1	0	0	0	q_1	0
2	0	$\pi/2$	0	q_2	0
3	0	$-\pi/2$	0	q_3	rl_3(= 0.400 m)
4	0	$-\pi/2$	0	q_4	0
5	0	$\pi/2$	0	q_5	rl_5(= 0.390 m)
6	0	$\pi/2$	0	q_6	0
7	0	$-\pi/2$	0	q_7	0
8(*P*)	2	0	0	0	0

6. Data acquisition, exciting trajectories and filtering

The *KRL* controller of the Kuka *LWR* provides motor positions, motor currents and joint torque sensors measurement using an internal special function called "*Recorder*" in S.I unit in joint side. The sample acquisition frequency is 1(KHz). The exciting trajectories *PTP* (Point-To-Point) consist of 44 points additional of start and stop positions chosen that make the robot moving in most of its workspace areas. The motion profiles are trapezoidal acceleration profiles and the total motion has duration of 90 seconds by trajectories.

In order to identify the payload parameters, it is necessary that the robot carried out two sets of trajectories: without the payload and with the payload fixed to the end-effector (see figure 2). The mass of payload has been measured with an weighing machine at M_L=4.6136 (Kg)±0.1(gr). The robot has severable possible control law. In this paper, only the joint position control is used with a decentralized feedback controller (Albu-Schäffer et al., 2007).

For each axis *j*, Kuka controller estimates the joint position q_{aj} from the joint torque sensor measurement τ_{cj} , motor position q_j and an *a priori* stiffness value $k^{ap}{}_j$: $q_{aj}=q_j-\tau_{cj}/k^{ap}{}_j$ with $k^{ap}{}_j$ is 10000(Nm/rad) for axis 1 to 5 and 7500(Nm/rad) for axis 6 and 7. In this paper, only the motor positions q are used for the four models. A brief comparison between using of motor positions and joint positions on model B is performed in appendix 2.

The cut-off frequency of the Butterworth filter is fixed at 10(Hz) . The cut-off frequency of the decimate filter is fixed at 0.8(Hz) and allows to have dw=1.7 .

7. Dynamic identification

The identification of dynamic parameters of the Kuka LWR with payload is performed for the four models. The results are given in table II with relative errors $||e\%||$ between the identified values of model B, C and D to model A.

The Fvm_j and Fcm_j identified value of model A are respectively the regrouped parameters Fvm_j+ Fvl_j and Fcm_j+ Fvl_j (see appendix 1). The parameters with the subscript R stand for the regrouped parameters (see appendix 1).

The relative error between measured and reconstructed torques are respectively 9.0%, 2.6%, 3.2% and 12% for the four models. The torque of the axis 1 and 2 are show on figure 4 to 7.

Only 34 essential parameters are identified for model A, 23 for model B, 44 for model C and 21 for model D. The payload is well identified for the first three models (<1% error). The relative standard deviations are low and the histogram of error on figure 3 show us that the errors terms are normalized thus the identification is relevant.

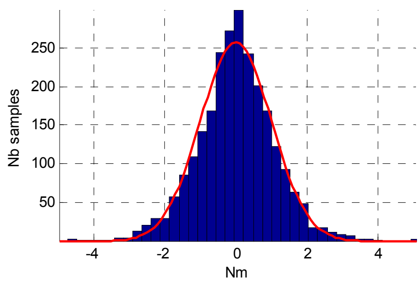

Figure 3. Histogram of error and estimated Gaussian

TABLE II. *IDIM-LS* identified values with motor positions

	Model A		Model B			Model C			Model D		
Par.	$\hat{\chi}$	$\%\sigma_{\hat{\chi}_r}$	$\hat{\chi}$	$\%\sigma_{\hat{\chi}_r}$	||e%||	$\hat{\chi}$	$\%\sigma_{\hat{\chi}_r}$	||e%||	$\hat{\chi}$	$\%\sigma_{\hat{\chi}_r}$	||e%||
Iam_1	-	-	-	-	-	**3.19**	2.8	-	**3.20**	1.9	-
Fvm_1	**14.4**	1.5	-	-	-	**14.4**	2.0	-	**14.3**	1.3	0.7
Fcm_1	**11.9**	2.2	-	-	-	**11.6**	3.0	-	**11.6**	2.0	2.5
Iam_2	-	-	-	-	-	**3.05**	6.5	-	**3.05**	4.9	-
Fvm_2	**15.3**	2.6	-	-	-	**15.1**	3.5	-	**15.5**	2.6	1.3
Fcm_2	**11.5**	3.3	-	-	-	**11.1**	4.5	-	**10.7**	3.6	7.0
Iam_3	**2.01**	2.5	-	-	-	**1.98**	2.9	-	**1.98**	2.3	1.5
Fvm_3	**6.55**	2.1	-	-	-	**6.51**	2.5	-	**6.50**	2.0	0.8
Fcm_3	**8.98**	1.9	-	-	-	**8.58**	2.4	-	**8.60**	1.9	4.2
Iam_4	**1.92**	4.3	-	-	-	**2.05**	4.3	-	**2.06**	3.0	7.3
Fvm_4	**11.0**	1.7	-	-	-	**11.0**	2.3	-	**11.1**	1.6	0.9
Fcm_4	**8.35**	2.1	-	-	-	**8.04**	3.0	-	**8.02**	2.0	4.0
Iam_5	**0.776**	3.3	-	-	-	**0.787**	4.0	-	**0.801**	3.0	3.2
Fvm_5	**4.29**	1.8	-	-	-	**4.38**	2.1	-	**4.37**	1.6	1.9
Fcm_5	**8.31**	1.4	-	-	-	**7.37**	1.9	-	**7.38**	1.4	11
Iam_6	**0.391**	7.4	-	-	-	**0.391**	9.8	-	**0.48**	8.7	23
Fvm_6	**2.26**	3.6	-	-	-	**2.25**	4.9	-	**2.42**	5.0	7.1
Fcm_6	**4.72**	1.3	-	-	-	**4.67**	1.8	-	**4.64**	2.0	1.7
Iam_7	**0.399**	3.2	-	-	-	**0.394**	3.8	-	**0.381**	7.5	4.5
Fvm_7	**1.6**	2.3	-	-	-	**1.6**	3.0	-	**1.75**	5.2	9.4
Fcm_7	**6.04**	0.98	-	-	-	**5.91**	1.3	-	**6.02**	2.4	0.3
Fcl_1	-	-	**0.384**	6.6	-	**0.386**	6.1	-	-	-	-
Fcl_2	-	-	**0.522**	6.1	-	**0.524**	5.5	-	-	-	-
Fcl_3	-	-	**0.452**	3.1	-	**0.452**	2.8	-	-	-	-
Fcl_4	-	-	**0.317**	4.2	-	**0.317**	3.7	-	-	-	-
Fcl_5	-	-	**0.861**	2.5	-	**0.935**	3.0	-	-	-	-
Fcl_7	-	-	**0.080**	6.8	-	**0.079**	5.9	-	-	-	-
ZZ_{1Ra}	**3.20**	2.6	-	-	-	-	-	-	-	-	-
XX_{2R}	**1.31**	11	**1.29**	1.6	1.5	**1.3**	1.5	0.8	-	-	-
ZZ_{2Ra}	**4.46**	4.1	-	-	-	-	-	-	-	-	-
ZZ_{2Rc}	-	-	**1.28**	1.8	-	**1.28**	1.6	-	-	-	-
MY_{2R}	**3.37**	1.6	**3.46**	0.19	2.7	**3.45**	0.18	2.4	-	-	-
XX_{4R}	**0.368**	9.0	**0.441**	1.0	20	**0.441**	0.91	20	-	-	-
ZZ_{4R}	**0.491**	9.2	**0.44**	1.2	10	**0.441**	1.0	10	-	-	-
MY_{4R}	**-1.37**	1.2	**-1.35**	0.21	1.5	**-1.35**	0.18	1.5	-	-	-
MY_{5R}	**0.049**	17	**0.040**	4.2	17	**0.040**	3.6	17	-	-	-
MY_{6R}	**0.042**	17	**0.036**	7.4	15	**0.035**	6.4	17	-	-	-
MY_7	-	-	**0.006**	16	-	**0.006**	14	-	-	-	-
XX_L	**0.118**	19	**0.106**	6.2	10	**0.106**	5.2	10	-	-	-
XZ_L	**-0.037**	20	**-0.037**	5.1	1.6	**-0.037**	4.3	1.3	-	-	-
YZ_L	-	-	**0.025**	8.8	-	**0.025**	7.6	-	-	-	-
ZZ_L	-	-	**0.038**	4.4	-	**0.039**	3.7	-	-	-	-
MX_L	**0.332**	1.9	**0.277**	0.46	17	**0.278**	0.39	16	-	-	-
MY_L	**-0.314**	2.0	**-0.269**	0.58	14	**-0.270**	0.49	14	-	-	-
MZ_L	**0.548**	2.3	**0.544**	0.87	0.7	**0.545**	0.73	0.5	-	-	-
M_L	**4.68**	1.4	**4.60**	0.25	1.7	**4.60**	0.21	1.7	-	-	-

8. Discussion

The relative errors between the parameters of model A (only motor torques) and model B (only joint torque sensors measurement) are between 0.5 and 20%. For axis 2, the relative error between ZZ_{2Ra} and $ZZ_{2Rc}+Ia_{2c}$ is 3% (less than relative standard deviation of ZZ_{2Ra}). The model C allows to separate ZZ_{2R} and Ia_2 . With only using motor torques, the link's parameters (like *XX*, *MX*, *MY*...) are identified as well as when the joint torque sensors measurements are used (relative error between 0.5 and 16%). It shows that only using motor torques is relevant to identify the major part of dynamic parameters of a robot.

The major advantage of using motor currents (model A) is that allows identifying the drive inertia moment and frictions parameters presents before torque sensor (motor side). But some drive inertia moments (2) are regrouping with robot's inertial parameters (see appendix 1). Using only the joint torque sensors measurement (model B) allows identifying only the joint parameters and some frictions parameters presents after torque sensors. The simultaneous use of the motor currents and the joint torque sensors measurement (model C) allows to identify separately all drive inertia moment from the robot inertia parameters additional of frictions parameters and joint parameters, using both measurements allows to identify more parameters compared of the model A and B. However, the simple use of motor torque is relevant because almost all parameters are identified. The model D shows us that it is possible to identify only the drive chain parameters.

5. Conclusion

In this paper, a comparison between using motor currents measurement, using joint torque sensors measurement and using both data for the dynamic identification of a Kuka *LWR* robot was performed. The use of either or both measurements allows to identify all or a subset of dynamic parameters. Only the link's parameters are identifiable when using joint torque sensors measurement while almost all parameters are identifiable using motor torques data. Using both measurements allows separating some drive inertia moment from the robot's inertial parameters. But the main strong result is that motor torques calculated from motor currents can identify the link's inertial parameters with the same accuracy than using joint torques sensors at the output of the drive chain. With the off-line *IDIM-LS* identification technique, the motor currents can measure accurately the dynamics of the links through the geared drive chains.

Appendix 1: Regrouped base parameters of Kuka LWR

The regrouped base parameters (Gautier and Khalil, 1990)(Mayeda et al., 1990) are given in table IV.

TABLE III. Regrouped parameters of the Kuka LWR4+ Robot

Model A	Model B and C
$\boldsymbol{ZZ_{1R}}=ZZ_1+\boldsymbol{Iam_1}+YY_2$	$\boldsymbol{ZZ_{1R}}=ZZ_1+YY_2$
$\boldsymbol{ZZ_{2R}}=ZZ_2+\boldsymbol{Iam_2}+YY_3+2rl_3MZ_3 + rl_3^2\,(M_3+M_4+M_5+M_6+M_7)$	$\boldsymbol{ZZ_{2R}}=ZZ_2+YY_3+2rl_3MZ_3 + rl_3^2\,(M_3+M_4+M_5+M_6+M_7)$
$\boldsymbol{Fvm_{jR}}=Fvm_j+Fvl_j$	
$\boldsymbol{Fcm_{jR}}=Fcm_j+Fvl_j$	
Model A,B and C	
$\boldsymbol{XX_{2R}}=XX_2-YY_2+YY_3+2rl_3MZ_3+rl_3^2\,(M_3+M_4+M_5+M_6+M_7)$	
$\boldsymbol{MY_{2R}}=MY_2+MZ_3+rl_3(M_3+M_4+M_5+M_6+M_7)$	
$\boldsymbol{XX_{3R}}=XX_3-YY_3+YY_4$; $\boldsymbol{ZZ_{3R}}=ZZ_3+YY_4$; $\boldsymbol{MY_{3R}}=MY_3+MZ_4$	
$\boldsymbol{XX_{4R}}=XX_4-YY_4+YY_5+2rl_5MZ_5+rl_5^2(M_5+M_6+M_7)$	
$\boldsymbol{ZZ_{4R}}=ZZ_4+YY_5+2rl_5MZ_5+rl_5^2(M_5+M_6+M_7)$	
$\boldsymbol{MY_{4R}}=MY_4-MZ_5-rl_5(M_5+M_6+M_7)$; $\boldsymbol{XX_{5R}}=XX_5-YY_5+YY_6$	
$\boldsymbol{ZZ_{5R}}=ZZ_5+YY_6$; $\boldsymbol{MY_{5R}}=MY_5-MZ_6$; $\boldsymbol{XX_{6R}}=XX_6-YY_6+YY_7$	
$\boldsymbol{ZZ_{6R}}=ZZ_6+YY_7$; $\boldsymbol{MY_{6R}}=MY_6+MZ_7$; $\boldsymbol{XX_{7R}}=XX_7-YY_7$	

APPENDIX 2: COMPARISON BETWEEN USING MOTOR POSITIONS AND JOINT POSITIONS

The relative difference between the estimation of joint position and the motor position (in S.I. unit on joint side) is between 2 10^{-5} and 3.5 10^{-3}. A brief comparison between the use of motor positions and joint positions is performed for model B. The results are given in table V with the relative error between the parameters identified with motor positions (see table V) and the parameters identified with joint positions with the following model:

$$\tau_{idm\_c} = M\left(q_a\right)\ddot{q}_a + H\left(q_a, \dot{q}_a\right) \quad (19)$$

The results with the use of joint positions are close to the results with the use of motor positions. So if the flexibilities are not excited, the motor positions can be used for performing identification.

TABLE IV. *IDIM-LS* IDENTIFIED OF MODEL B WITH JOINT POSITIONS

Par.	$\hat{\chi}$	$\%\sigma_{\hat{\chi}_r}$	$\lVert e\% \rVert$	Par.	$\hat{\chi}$	$\%\sigma_{\hat{\chi}_r}$	$\lVert e\% \rVert$
Fsl_1	**0.386**	6.7	0.5	MY_{5R}	**0.040**	4.1	1.7
Fsl_2	**0.524**	6.1	0.4	MY_{6R}	**0.036**	7.13	0.8
Fsl_3	**0.451**	3.2	0.2	XX_L	**0.093**	6.75	13
Fsl_4	**0.322**	4.0	1.6	XZ_L	**-0.035**	5.11	3.8
Fsl_5	**0.861**	2.4	0	YY_L	**0.078**	8.15	14
Fsl_7	**0.80**	6.7	0.1	YZ_L	**0.024**	8.72	2.8
XX_{2R}	**1.26**	1.6	2.3	ZZ_L	**0.037**	4.31	2.7
$ZZ_{2R.a.b}$	**1.25**	1.7	2.3	MX_L	**0.276**	0.44	0.4
MY_{2R}	**3.45**	0.19	0.3	MY_L	**-0.269**	0.57	0
XX_{4R}	**0.432**	1.0	2.0	MZ_L	**0.544**	0.83	0
ZZ_{4R}	**0.439**	1.1	0.2	M_L	**4.57**	0.24	0.7
MY_{4R}	**-1.35**	0,21	0				

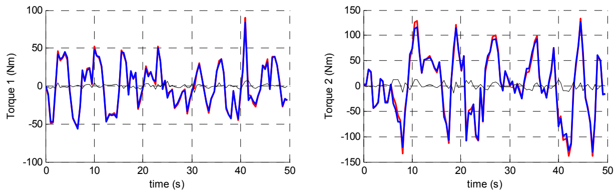

Figure 4. Model A, measured (red) and reconstructed (blue) motor torques with error (black) (motor torques 1 and 2)

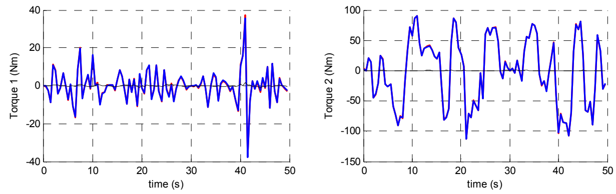

Figure 5. Model B, measured (red) and reconstructed (blue) joint torque sensors measurement with error (black) (joint torques 1 and 2)

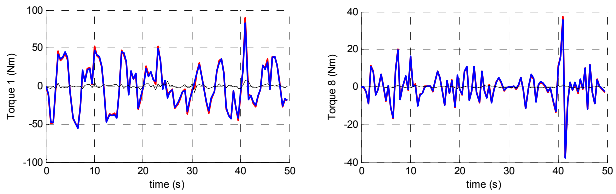

Figure 6. Model B, measured (red) and reconstructed (blue) torques with error (black) (motor torque 1 and joint torque 1)

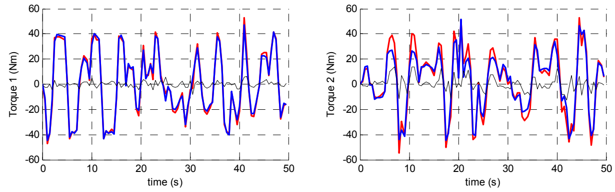

Figure 7. Model D, measured (red) and reconstructed (blue) torques with error (black) (torques 1 and 2)

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