A Novel Engineering Method for the Power Flow Assessment in Servo-actuated Automated Machinery

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ABSTRACT

Multipurpose and programmable servo-actuated mechanisms may be envisaged as the key technology for increasing flexibility and re-configurability of modern automated machinery. Unfortunately, based on the current state-of-the-art, these mechatronic devices are extremely flexible but generally energy intensive, thus compromising the overall system sustainability. Nonetheless, the system power consumption can be partially reduced if energy optimality is introduced as a design goal along with the global productivity. Naturally, as a first step towards the practical implementation of any energy-optimality criterion, the end user should be capable of predicting the system power flow, including the major sources of energy loss. In this context, this paper firstly presents a reliable model of a servo-actuated mechanism accounting for linkage, electric motor and power converter behavior. Then, a novel identification method is discussed, which allows the separate determination of the models parameters by means of non-invasive experimental measures. The method is finally validated by comparing predicted and actual power flows in a simple mechatronic system, which is composed of a slider-crank mechanism directly coupled with a position-controlled permanent magnet synchronous motor.

1. INTRODUCTION

The reduction of the Energy Consumption in automated production systems is currently becoming a topic of primary importance for both large manufacturing companies and small/medium enterprises [1]. In particular, a growing attention has been recently focused on the development of novel methods and tools for the energy consumption optimization in position-controlled Servo-actuated Mechanisms (SM) [2] and industrial robot [3-5], whose behavior can be improved by either selecting energy-efficient components or by simply employing energy-optimal motions law whenever possible. Naturally, the practical implementation of the aforementioned energy-saving strategies requires a reliable model of the SM power flow, which is the direct consequence of several interacting factors, namely mechanical system and electric motor dynamics, controller performance, and power converter architecture. Even though several SM models may be easily found in the literature [6], the numerical parameters describing the system behavior are usually either unknown, rather inaccurate or covered by confidentiality agreements. For instance, the numerical parameters describing the mechanical hardware (e.g. link masses and moments of inertia) can be directly measured if the linkage structure is disassembled. Nonetheless, this procedure would require extensive time and effort or may also end up being impossible (due, for instance, to warranty issues). Similarly, the torque constant and the motor efficiency at the nominal operating point can be found in the component data-sheets. However, these data are often very roughly defined and useful only for approximate models, so that appropriate identification methods become necessary [7]. Within this scenario, the dynamic identification of serial and parallel mechanisms has been widely studied in the past literature, both in the field of robotics [8-10] and automated machinery [11]. In parallel, proper techniques for the identification of accurate electric motor models have been proposed [12,13]. However, these techniques are rarely integrated into one single identification procedure [14].

In this context, the purpose of the present paper is to outline a simple and fast method for the power flow assessment in linkage systems actuated by means of a permanent magnet synchronous motor. The proposed method is based on the separate study of power converter, motor and mechanical hardware, which is possible thanks to the use of a power meter at the entrance (network side) and exit (motor side) of the converter. In particular, the identification of a simple Slider-Crank (SC) servo-mechanism is carried out as a case study. First, the mechanism Dynamic Model (DM), the electric Motor Model (MM) and the Converter Model (CM) are derived in Linear-in-Parameters formulations. Then, the dynamic parameters are identified, together with the torque constant [15]. Once these

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parameters are known, also the MM and the CM are identified, focusing on the system power flow. Finally, all the estimated models are recasted into reliable formulations of ingoing and outgoing converter powers.

2. IDENTIFICATION METHOD

The whole identification process is conceptually summarized in Figure 1 (quantities between blocks simply represent the outputs and the inputs of the previous and consecutive blocks respectively). Initially, the DM of the servo-mechanism is derived, assuming only the SC geometric parameters as known. This model, that describes the relation between crank position, q, velocity, $\dot{q}$, acceleration, $\ddot{q}$ (hereafter referred to as kinematic variables), and motor current, i_{mot}, is obtained in an identifiable linear-in-parameters formulation. The DM is excited using a suitable trajectory, performed with and without a known payload applied on the slider. The optimal trajectory, whose choice is explained in Section 4, is requested to comply well-defined constraints on maximum velocities and accelerations. During the motions, the useful variables are sampled, employing several measurement instruments and two different software, namely TwinCAT and Matlab Data Acquisition Toolbox. These values are then accurately processed, as explained in Section 6, and the experimental kinematic variables and motor current are obtained. Similarly to [15], the torque constant and the dynamic parameters are estimated together. Once these parameters are identified, the derivation of the motor and power converter models can begin. The MM and the CM are derived focusing the attention on the power flows, as explained in Section 3. Both MM and CM are excited employing optimal trajectories, which are enforced without any payload applied to the slider. The sampled data, acquired during these motions, are accurately processed again. The experimental variables are finally used to estimate both motor and converter parameters. As far as all the model parameters are estimated, they are recasted into a predictive formulation of the ingoing (network side, P_{in}) and outgoing (motor side, P_{out}) converter powers (see Figure. 2). These formulations are finally used to forecast the power flows on a test trajectory different from the ones used during the estimation phases. In Section 8, the predictive capability of the identified models is finally analyzed.

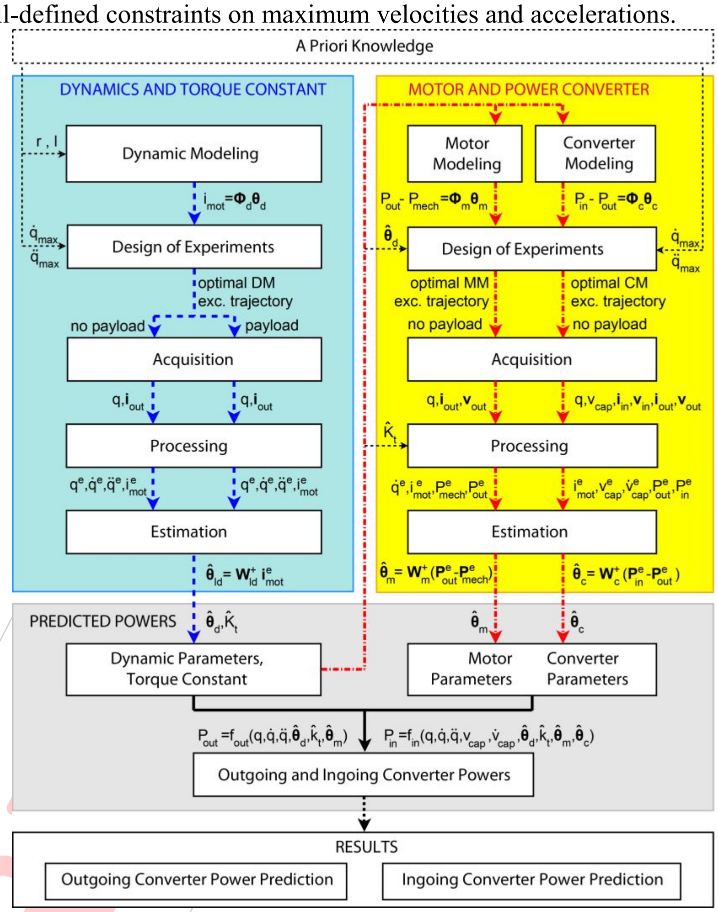

Figure 1. Schematic of the identification method.

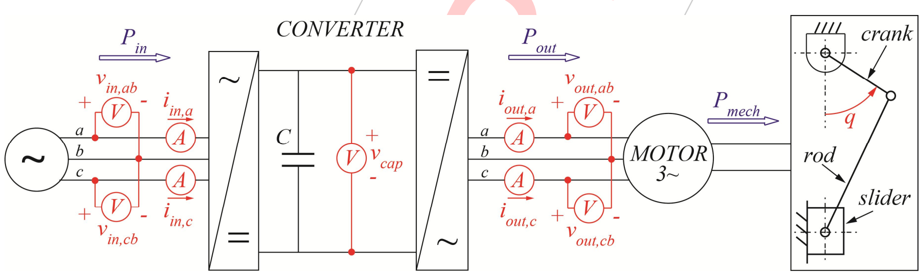

Figure 2. SM schematic with measurements and power flows.

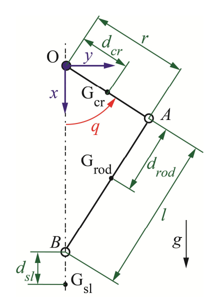

Figure 3. SC geometric scheme.

3. MODELING

3.1. MECHANISM DYNAMIC MODEL

As previously defined, the dynamic model of the SM describes the motor's quadrature current i_{mot} as function of the kinematic variables. The DM is derived in the following identifiable linear formulation:

$$i_{mot} = \boldsymbol{\phi}_d(q, \dot{q}, \ddot{q})\boldsymbol{\theta}_d \tag{1}$$

where $\boldsymbol{\phi}_d$ is the Dynamic Regression Matrix and $\boldsymbol{\theta}_d$ are the Dynamic Parameters.

This expression is obtained employing proper dynamic parameters and making the following assumptions:

- Linear relation between motor torque, τ_{mot}, and motor current, i_{mot}. Denoting K_t as the torque constant, this relation is modeled as: $\tau_{mot} = K_t i_{mot}$.
- Simple friction formulations for the crank's actuated rotational joint and the slider's prismatic joint:

  $$\tau_{f,cr} = f_{C,cr}\, sign(\dot{q}) + f_{v,cr}\, \dot{q} \quad (2); \qquad \tau_{f,sl} = f_{C,sl}\, sign(\dot{x}_B) + f_{v,sl}\, \dot{x}_B \quad (3)$$

  where $f_{C,cr}$, $f_{v,cr}$, $f_{C,sl}$ and $f_{v,sl}$ are the Coulomb and viscous friction coefficients for crank and slider respectively, whereas $\dot{x}_B$ is the slider velocity (point *B* in Fig. 3) in the vertical direction x.
- Negligible friction torques for passive rotational joints, namely crank-rod and rod-slider joints.

Grounding on these suppositions, Eq. 1 is derived employing the Euler-Lagrange equation, the virtual work principle, the motor torque-current relation, and a proper definition of the dynamic parameters. All the passages that led to the definition of the DM will not be discussed here for brevity (the interest reader can refer to [8] for further details of the general method). Nonetheless, it can be verified that the Dynamic Parameters and Dynamic Regression Matrix can be expressed as:

$$\boldsymbol{\theta}_d = \frac{1}{K_t}\begin{bmatrix} J_{cr} + m_{cr}d_{cr}^2 + m_{rod}r^2 + m_{sl}r^2 \\ J_{rod} + m_{rod}d_{rod}^2 + m_{sl}l^2 \\ m_{cr}d_{cr} + m_{rod}r + m_{sl}l \\ m_{rod}d_{rod} + m_{sl}l \\ f_{C,cr} \\ f_{v,cr} \\ f_{C,sl} \\ f_{v,sl} \end{bmatrix} \quad (5); \qquad \boldsymbol{\phi}_d = \begin{bmatrix} \ddot{q} \\ c_q r^2(\ddot{q}{c_q}^3 r^2 + \ddot{q}c_q l^2 - \ddot{q}c_q r^2 - s_q\dot{q}^2 l^2 + s_q\dot{q}^2 r^2)/\square^4 \\ s_q\, g \\ r^2[(-4\ddot{q}c_q^5 r^3 + 4c_q^4 s_q\dot{q}^2 r^3 - 4\ddot{q}\square c_q^4 r^2 + 4\square c_q^3 s_q \dot{q}^2 r^2 + 2gc_q^3 s_q r^2 - 4\ddot{q}{c_q}^3 l^2 r) + \\ +(8\ddot{q}c_q^3 r^3 - 4\ddot{q}\square c_q^2 l^2 + 4\ddot{q}\square c_q^2 r^2 + 4\ddot{q}c_q l^2 r - 4\ddot{q}c_q r^3 - 6s_q^3\dot{q}^2 l^2 r + 6s_q^3\dot{q}^2 r^3) + \\ +(4s_q\dot{q}^2 l^2 r - 4s_q\dot{q}^2 r^3 + 2s_{2q}\square\dot{q}^2 l^2 - 2s_{2q}\square\dot{q}^2 r^2 + s_{2q}gl^2 - s_{2q}gr^2)]/(2\square^3 l^2) \\ sign(\dot{q}) \\ \dot{q} \\ sign(\dot{q})\left|r\, s_q[1 + (r\, c_q)/\square]\right| \\ \dot{q}\left\{r\, s_q[1 + (r\, c_q)/\square]\right\}^2 \end{bmatrix}^T \tag{6}$$

where m_{cr}, m_{rod} and m_{sl} are the crank, rod and slider masses, J_{cr} and J_{rod} are the crank and rod barycentric inertias, g is the gravity acceleration, r and l are the known crank and rod lengths, d_{cr} and d_{rod} are the unknown distances of crank and rod center of gravity from the crank-frame and crank-rod revolute pairs respectively (as shown in Figure 3), s_x and c_x stand for the sine and cosine of x, and $\square$ is defined as $\square = \sqrt{l^2 - r^2\sin^2(q)}$.

3.2. MOTOR AND POWER CONVERTER MODELS

The effect of the electric motor on the power flow is modeled considering the main electrical losses. Taking into account only the copper and iron losses (as defined in [3]), the difference between the outgoing converter power, P_{out}, and the mechanical power, P_{mech}, is expressed as:

$$P_{out} - P_{mech} = L_{mot} = K_{Cu} i_{mot}^2 + K_{Fe}|\dot{q}| \tag{7}$$

where L_{mot} are the electrical losses within the electric motor, and K_{Cu} and K_{Fe} are suitable parameters. This expression is then reformulated stressing the linear structure of the model:

$$P_{out} - P_{mech} = \boldsymbol{\phi}_m(\dot{q}, i_{mot})\boldsymbol{\theta}_m^T \tag{8}$$

where $\boldsymbol{\phi}_m$ and $\boldsymbol{\theta}_m$ are referred to as Motor Regression Matrix and Motor Parameters. Similarly to the motor, also the power converter is modeled considering the main sources of electrical losses. However, in the converter, also the energy storage in the DC-bus capacitor is modeled, such that:

$$P_{in} - P_{out} = \frac{dE_{cap}}{dt} + L_{con} \tag{9}$$

where E_{cap} indicates the energy stored inside the capacitor and L_{con} indicates the converter electrical losses. According to experimental evidence, the power converter losses of the specific case study are modeled considering only the inverter switching losses (as defined in [3]) and a constant loss term. The right hand side terms of Eq. (9) are then defined as:

$$\frac{dE_{cap}}{dt} = Cv_{cap}\frac{dv_{cap}}{dt}\ ; \quad (10); \qquad L_{con} = K_{sw}|i_{mot}| + K_{off} \tag{11}$$

where C is the capacitance and K_{sw} and K_{off} suitable parameters. Equation (9) is then expressed as:

$$P_{in} - P_{out} = Cv_{cap}\dot{v}_{cap} + K_{sw}|i_{mot}| + K_{off} \;\longrightarrow\; P_{in} - P_{out} = \boldsymbol{\phi}_c(i_{mot}, v_{cap}, \dot{v}_{cap})\boldsymbol{\theta}_c \tag{12}$$

where $\boldsymbol{\phi}_c$ and $\boldsymbol{\theta}_c$ are the Converter Regression Matrix and the Converter Parameters.

3.3. Ingoing and Outgoing Converter Powers

First, the mechanical power is obtained by simply multiplying the motor torque, τ_{mot}, by the motor velocity, ω_{mot}. Exploiting also the linear relation between torque and current, the following equation is obtained:

$$P_{mech} = \omega_{mot}\tau_{mot} \;\longrightarrow\; P_{mech} = \dot{q}K_t i_{mot} \tag{13}$$

where $\omega_{mot} = \dot{q}$ since the SC mechanism is directly coupled to the electric motor (absence of gear reducer).

Once the mechanical power has been defined, the expression of the outgoing converter power is derived employing the MM. Exploiting Eqs. (7) and (13), the following equation is derived:

$$P_{out} = P_{mech} + L_{mot} \;\longrightarrow\; P_{out} = \dot{q}K_t i_{mot} + K_{Cu}i_{mot}^2 + K_{Fe}|\dot{q}| \tag{14}$$

Substituting the motor current with its formulation described in Eq. (1), Eq. (14) is rephrased as:

$$P_{out} = f_{out}(q, \dot{q}, \ddot{q}, \boldsymbol{\theta}_d, K_t, \boldsymbol{\theta}_m) \tag{15}$$

obtaining a formulation that depends only on the kinematic variables $q, \dot{q}, \ddot{q}$ and on the parameters $\boldsymbol{\theta}_d$, K_t and $\boldsymbol{\theta}_m$.

The formulation of the ingoing converter power is finally derived exploiting Eq. (14) and Eq. (12). Using these equations, the following formula is achieved:

$$P_{in} = P_{out} + \frac{dE_{cap}}{dt} + L_{con} \;\longrightarrow\; P_{in} = \dot{q}K_t i_{mot} + K_{Cu}i_{mot}^2 + K_{Fe}|\dot{q}| + Cv_{cap}\dot{v}_{cap} + K_{sw}|i_{mot}| + K_{off} \tag{16}$$

By using Eq. (1), the following formulation is then obtained:

$$P_{in} = f_{in}(q, \dot{q}, \ddot{q}, v_{cap}, \dot{v}_{cap}, \boldsymbol{\theta}_d, K_t, \boldsymbol{\theta}_m, \boldsymbol{\theta}_c) \tag{17}$$

Unluckily, this formulation does not depend only on the kinematic variables and model parameters, but also on the capacitor potential difference, v_{cap}, and its time derivative. Since a reliable formulation of the capacitor voltage has not been detected yet, it is not currently possible to define a totally predictive formulation of P_{in}.

4. Design of Experiments

Proper experiments need to be performed in order to excite adequately all the parameters and to allow an accurate estimation phase. The DOE phase generally includes three different steps: 1) the choice of a certain trajectory; 2) the selection of a proper cost function; 3) the derivation of the best trajectory by means of optimization techniques.

Trajectories are parameterized as Finite Fourier Series:

$$q(t) = q_0 + \sum_{k=1}^{N_h}\left(a_k \sin(k\omega_f t) + b_k \cos(k\omega_f t)\right) \tag{18}$$

where the number of harmonics N_h is set to 5 and the fundamental frequency ω_f is set to 1 rad/s.

As said, the optimal exciting trajectories are selected by minimizing a certain cost function. Different appropriate cost functions can be chosen [8, pp. 296-298]. In the present paper, the Condition Number of the observation matrix **W** is minimized:

$$Cost = cond(\boldsymbol{W}) \tag{19}$$

where each row of the observation matrix is generally defined as the evaluation of the regression matrix in the considered time instant. Note that the cost functions of the MM and CM are defined grounding on the knowledge of the already estimated dynamic parameters and the effect of the capacitor is not included (since a predictive function of the capacitor voltage is not available).

The optimization step is finally carried out employing the *fmincon* Matlab function, which allows the enforcement of the optimization constraints on maximum velocities and accelerations. In particular, these values are set to 30 rad/s and 300 rad/s^2 respectively.

5. Data Acquisition

The employed experimental setup is shown in Figure 4. In particular, the experimental rig is composed of a SC directly coupled with a Beckhoff AM3072 synchronous motor connected to a Beckhoff AX5112 electrical drive. The control system is based on TwinCAT software, i.e. the PC-based control platform owned by Beckhoff, connected to the drive via EtherCAT fieldbus. Positions q are measured using the motor encoder through the TwinCAT software (with a sampling frequency of 2000 Hz). The capacitor voltage, v_{cap}, is also provided by the TwinCAT software, with a sampling frequency of 2000 Hz. A Meetbox power meter [16] is used to measure the ingoing and outgoing converter powers, through the measurement of 2 currents and 2 voltages for each of these powers, as shown in Figures 3 and 4. These measurements, together with a trigger signal, are passed to the NI module in the form of analogue signals. The digital variables are finally obtained employing the Matlab *Data Acquisition Toolbox* with a sampling frequency of 25 kHz.

6. Signal Processing

The signal processing phase is mainly focused on three different aspects: 1) integration of the measures obtained using Meetbox and TwinCAT; 2) derivation of all the needed variables from the measured ones; 3) execution of a good filtering phase.

The integration of the different measures is obtained employing a trigger signal sent from the industrial PC to the NI module. This signal is processed together with the other Meetbox measures and all the variables are then synchronized to the TwinCAT ones.

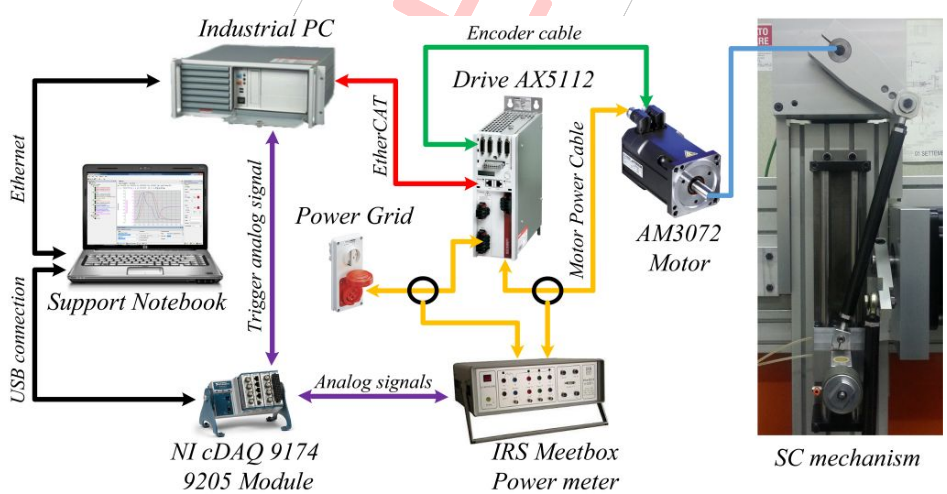

Figure 4. Experimental setup. Power and information flows are highlighted.

With reference to Figure 2, before performing the filtering phase, the outgoing current on the *b* phase is derived imposing that the sum of the three currents is null. Then, the quadrature motor current i_{mot} is obtained employing the Park transformation [10]. Furthermore, the ingoing and outgoing converter powers are obtained using the Aron insertion [17, section 3.2] and the following formulas are used:

$$P_{in} = \boldsymbol{v}_{in}\boldsymbol{i}_{in}^T \; ; \quad (20); \qquad P_{out} = \boldsymbol{v}_{out}\boldsymbol{i}_{out}^T \quad (21)$$

where $\boldsymbol{v}_{in}$ is defined as $[v_{in,ab}, v_{in,cb}]$, $\boldsymbol{i}_{in}$ is defined as $[i_{in,a}, i_{in,c}]$, $\boldsymbol{v}_{out}$ indicates $[v_{out,ab}, v_{out,cb}]$ and $\boldsymbol{i}_{out}$ is finally defined as $[i_{out,a}, i_{out,c}]$.

Once these variables are defined, the filtering phase is carried out. The sampled variables q and v_{cap} and the derived variables i_{mot}, P_{in} and P_{out} are filtered with a low-pass Butterworth filter. The filtering is applied both in forward and backward direction using the *filtfilt* Matlab function, thus avoiding to add any phase shift to the signal. Velocities and accelerations are then derived applying second order central differences to the filtered positions. Similarly, the capacitor voltage time derivative is derived using the second order central differences. Finally, exploiting Eq. (13), the mechanical power is computed as:

$$P_{mech} = \dot{q}\widehat{K}_t i_{mot} \quad (22)$$

where $\widehat{K}_t$ is the estimated value of the torque constant, and $\dot{q}$ and i_{mot} are the velocity and the filtered motor current respectively. Henceforth, being x a generic variable, its experimental filtered value will be referred to as x^e.

7. Estimation

Since the DM, MM and CM are expressed in linear formulations, all the unknown parameters could be identified using simple linear regression techniques. The proposed method makes use of ordinary un-weighted least squares:

$$\widehat{\boldsymbol{\theta}} = ((\boldsymbol{W}^T\boldsymbol{W})^{-1}\boldsymbol{W}^T)\boldsymbol{Y} = \boldsymbol{W}^{+}\boldsymbol{Y} \quad (23)$$

where $\boldsymbol{Y}$ is the Dependent Variable and $(.)^+$ denotes the Pseudo-inverse. As shown in Figure 1, the dynamic parameters and the torque constant are identified together employing data acquired during the DM exciting trajectory, performed with and without a known payload attached to the slider. The torque contribution due to the known payload mass, m_{pay}, is modeled considering the rate on the motor torque owing to the contribution of a slider mass equaling the payload. Performing a few simple computations, the following equation is found:

$$\tau_{pay} = f_{pay}(q, \dot{q}, \ddot{q}, m_{pay}) \quad \text{with} \quad f_{pay} = m_{pay}(\phi_{d,1}r^2 + \phi_{d,2}l^2 + \phi_{d,3}l + \phi_{d,4}l) \quad (24)$$

The motor current rate due to the payload, i_{pay}, is then obtained simply dividing τ_{pay} by the torque constant K_t. By adding the payload contribution to the dynamic model of Eq. (1), the following relation is found:

$$i_{mot} = \boldsymbol{\phi}_{ld}(q, \dot{q}, \ddot{q}, m_{pay})\boldsymbol{\theta}_{ld} \quad \text{with} \quad (25)$$

$$\boldsymbol{\phi}_{ld}(q, \dot{q}, \ddot{q}, m_{pay}) = [\boldsymbol{\phi}_d(q, \dot{q}, \ddot{q}), f_{pay}(q, \dot{q}, \ddot{q}, m_{pay})] \quad \text{and} \quad \boldsymbol{\theta}_{ld} = \begin{bmatrix} \boldsymbol{\theta}_d \\ 1/K_t \end{bmatrix}$$

where $\boldsymbol{\phi}_{ld}$ and $\boldsymbol{\theta}_{ld}$ are the regression matrix and the parameters of the Loaded Dynamic model. Both dynamic parameters and torque constant are then identified using the following formula:

$$\widehat{\boldsymbol{\theta}}_{ld} = [\boldsymbol{W}_{ld}(\boldsymbol{q}^e, \dot{\boldsymbol{q}}^e, \ddot{\boldsymbol{q}}^e, \boldsymbol{m}_{pay})]^{+}\boldsymbol{i}_{mot}^e \quad (26)$$

where $\boldsymbol{q}^e$, $\dot{\boldsymbol{q}}^e$, $\ddot{\boldsymbol{q}}^e$ and $\boldsymbol{i}_{mot}^e$ are the vectors of experimental variables and $\boldsymbol{m}_{pay}$ is the payload mass vector, whose elements are set to zero when the payload is not mounted.

Similarly, the motor and converter parameters are estimated employing the experimental measures obtained during their exciting trajectories. The following formulas are used:

$$\widehat{\boldsymbol{\theta}}_m = [\boldsymbol{W}_m(\dot{\boldsymbol{q}}^e, \boldsymbol{i}_{mot}^e)]^{+}(\boldsymbol{P}_{out}^e - \boldsymbol{P}_{mech}^e) \quad (27); \qquad \widehat{\boldsymbol{\theta}}_c = [\boldsymbol{W}_c(\boldsymbol{i}_{mot}^e, \boldsymbol{v}_{cap}^e, \dot{\boldsymbol{v}}_{cap}^e)]^{+}(\boldsymbol{P}_{in}^e - \boldsymbol{P}_{out}^e) \quad (28)$$

8. RESULTS

The identified models are validated verifying their predictive accuracy on a test trajectory different from the ones employed during the identification process. The test trajectory, shown in Figure 5, consists in several motions featuring a trapezoidal speed profile and performed between some randomly chosen points. During these trajectories, carried out without any payload, the predicted values are obtained using the following formulations:

$$P_{out}^{p} = f_{out}\left(q^e, \dot{q}^e, \ddot{q}^e, \widehat{\boldsymbol{\theta}}_d, \widehat{K}_t, \widehat{\boldsymbol{\theta}}_m\right) \qquad (29); \qquad P_{in}^{p} = f_{in}\left(q^e, \dot{q}^e, \ddot{q}^e, v_{cap}^e, \dot{v}_{cap}^e, \widehat{\boldsymbol{\theta}}_d, \widehat{K}_t, \widehat{\boldsymbol{\theta}}_m, \widehat{\boldsymbol{\theta}}_c\right) \qquad (30)$$

being $q^e, \dot{q}^e, \ddot{q}^e, v_{cap}^e$ and $\dot{v}_{cap}^e$ the experimental values and $\widehat{\boldsymbol{\theta}}_d, \widehat{K}_t, \widehat{\boldsymbol{\theta}}_m, \widehat{\boldsymbol{\theta}}_c$ the estimated parameters. It is important to notice that, while the outgoing converter power can be predicted once the kinematic variables are known, the ingoing converter power formulation depends on the capacitor voltage and its time derivative. Therefore, the model in Eq. (30) cannot be used to fully predict the ingoing converter power given a certain trajectory. Nevertheless, both motor, L_{mot}, and power converter, L_{con}, electrical losses can be predicted employing:

$$L_{mot}^{p} = \widehat{K}_{Cu}\left(i_{mot}^{p}\right)^2 + \widehat{K}_{Fe}|\dot{q}^e|; \qquad L_{con}^{p} = \widehat{K}_{sw}\left|i_{mot}^{p}\right| + \widehat{K}_{off} \qquad \text{with} \qquad i_{mot}^{p} = \boldsymbol{\phi}_d(q^e, \dot{q}^e, \ddot{q}^e)\widehat{\boldsymbol{\theta}}_d \qquad (31)$$

where $q^e, \dot{q}^e, \ddot{q}^e$ are the experimental kinematic variables and $\widehat{\boldsymbol{\theta}}_d$, $\widehat{K}_{Cu}$, $\widehat{K}_{Fe}$, $\widehat{K}_{sw}$, $\widehat{K}_{off}$ are the estimated parameters. Figure 6 shows the predicted and experimental ingoing and outgoing powers during the test trajectory, where also the influence of the predicted electrical losses is highlighted.

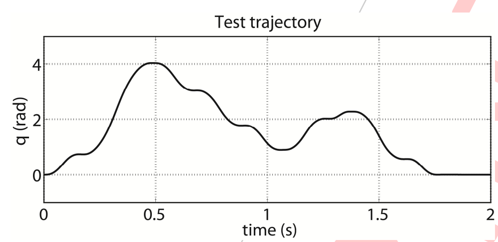

Figure 5. Test trajectory. The test trajectory consists in 9 speed trapezoidal motions, with jerk limitations, passing through 8 randomly chosen motor angles. The waiting time between different motions is set to zero.

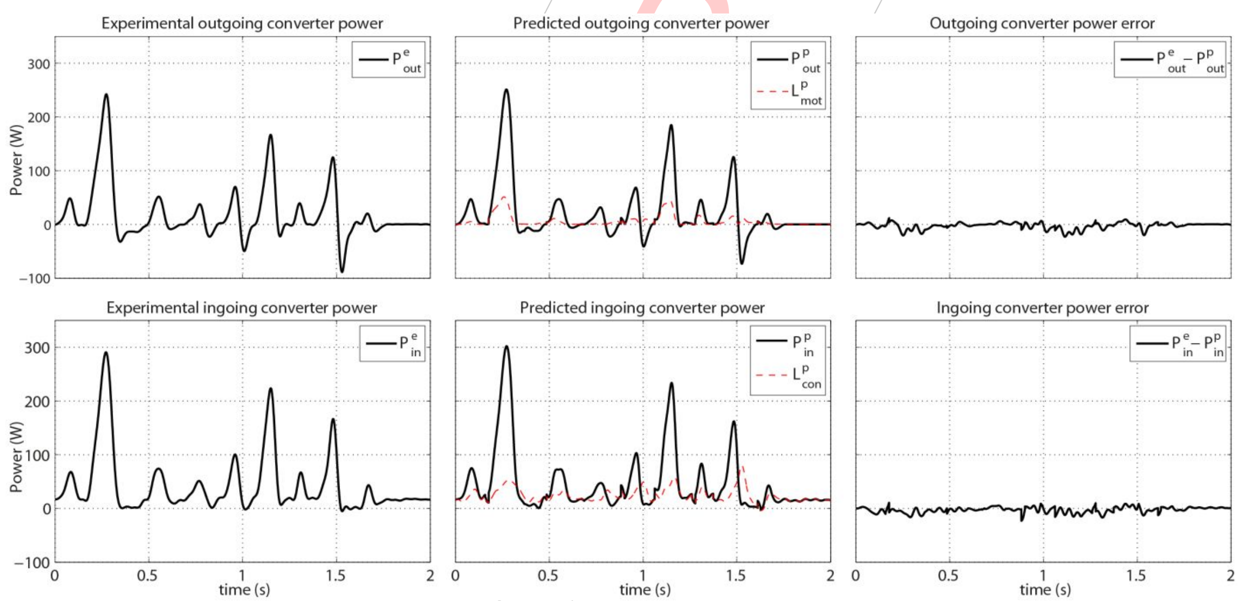

Figure 6. Experimental, P_{in}^{e} and P_{out}^{e}, and predicted, P_{in}^{p} and P_{out}^{p}, ingoing and outgoing converter powers concerning the test trajectory. Predicted motor, L_{mot}^{p}, and power converter, L_{con}^{p} , electrical losses (red dashed lines).

9. Conclusion and Future Works

In this paper, a novel identification method for the power flow assessment of a slider-crank SM has been proposed. The strength of this new method stands in the capability of identifying dynamic, motor and power converter parameters by performing only simple and fast experiments. While the simplicity of the linear structure of the identified models results in a substantial gain in the computational speed, the predictive capability of the derived models is nonetheless excellent. In practice, the proposed models and identification method can be employed as a base for the development of energy optimization methods, which usually require reliable predictive formulations of the SM power losses. Future works will concern the formulation of a predictive model for the capacitor voltage, thus achieving a fully predictive model of the ingoing converter power, and the application of the method to the identification of energy losses in multi degrees-of-freedom SM such as industrial robots.

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