A Framework for Improving the Energy Efficiency and Sustainability of Collaborative Robots

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A framework for improving the energy efficiency and sustainability of collaborative robots

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Abstract. On a worldwide scale, industry is responsible for a large part for the overall use of energy and resources: reducing this use is included in the targets of SDG9, one of the Sustainable Development Goals drawn by the United Nations. This work aims to create a framework for better understanding, modelling, and optimizing the energy consumption of industrial robots, with specific reference to the collaborative robot UR5e. The framework comprises a real robot and its electro-dynamic model, the latter being developed on the basis of experimental tests and of data supplied by the manufacturer. The paper presents the main features of the framework, and the future work aimed at improving the accuracy of the proposed energy model.

Keywords: SDG9 · SDG12 · energy efficiency · model identification · collaborative robot · UR5e

1 Introduction

The operation of industrial robots has been traditionally aimed at maximizing productivity, hence by reducing the time needed to complete a work cycle. This practice, however, does not take into account the energy consumption per cycle, whose optimization brings potential economic saving, as well as a clear reduction of the energy efficiency of the production facility. The impact of power consumption of industrial robots and automatic machines is not to be underestimated, as it has been shown that electric motors are responsible for up to 70% of the total energy consumed in industry [1,2].

The importance of improving the energy efficiency in industry is clearly outlined in the SDG9 and SDG12, two of the Sustainable Development Goals formulated in 2015 by the United Nations General Assembly. In particular, the SDG9 at target 4 reads as: "By 2030, upgrade infrastructure and retrofit industries to make them sustainable, with increased resource-use efficiency and greater adoption of clean and environmentally sound technologies and industrial processes, with all countries taking action in accordance with their respective capabilities".

In most cases, industrial robots are programmed to execute mainly motion tasks, hence their performances are largely dictated by the strategy used to plan their trajectories. Therefore, motion planning has largely been investigated as one of the most effective way of boosting the capabilities of robotic systems, leading to an extensive literature [3]. Traditionally, the literature on trajectory planning has focused on the minimization of execution times [4,5], on vibration reduction for improved motion accuracy [6,7], and only more recently, on energy saving [8,9,10]. Using motion planning as a tool to enhance energy efficiency is indeed a very sound option in industry, as it does not require any hardware modification to an existing infrastructure, as in [11], being obtainable just by altering the software that handles the robotic operation. Modifying the motion profile of an existing robotic cell is not only 'simple', but also potentially rewarding, as energy efficiency improvements up to 33% are cited, as in [12].

This paper is aimed at presenting the current and the future development of an hardware/software framework that is a tool to investigate, model and optimize the energy consumption of industrial robots. In particular, the investigation is targeted on the robot UR5 e-Series, produced by Universal Robots [13].

The choice of this robot is motivated by several factors: first of all, it is a device of large use in industry, as well as in education and in research facilities. Moreover, the architecture of the UR5e robot is shared not only with other manipulators produced by the same manufacturers, but with other robot fabricators. Indeed, many collaborative robots are designed, like the UR5e, to be lightweight, to carry small to medium payloads, to use brushless motor of reduced size and strain wave gear reduction.

In the next sections, the dynamic and electric model are outlined, showing the first implementation of the setup used to validate and test the simulator that allows to predict the energy absorption during the execution of a motion task.

2 Energy modelling of a collaborative robot

The estimation of the electric energy consumption of a robot can be conducted through the detailed analysis and use of its dynamic model, which should take into account both a mechanical dynamic model and an electric model. Let us first investigate the mechanical model, which can be formulated, according to the most common procedure, by using the Lagrange formalism as:

$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{F}_f + \mathbf{g}(\mathbf{q}) = \boldsymbol{\tau} - \mathbf{J}^T(\mathbf{q})\mathbf{h} \tag{1}$$

Equation (1) includes the position-dependant mass matrix $\mathbf{M}$, which is a function of the vector of the joint coordinates $\mathbf{q}$. Matrix $\mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})$ accounts for the centrifugal and Coriolis effects, whereas $\mathbf{g}(\mathbf{q})$ accounts for the effects of gravity on the manipulator. $\boldsymbol{\tau}$ is the vector of the joint torques, and $\mathbf{h}$ collects the forces and moments acting on the end-effector, which are weighted by the robot Jacobian matrix $\mathbf{J}$. Finally, the dissipative action due to friction is included in the friction torque vector $\mathbf{F}_f$.

Friction torques are included in the formulation of Eq. (1) by means of a general expression, with the specific aim of implementing one of the many friction models that have been developed for describing harmonic drives, which are the main source of friction dissipation in the setup under consideration [14]. As a preliminary result, the experimental data gathered for this work has shown that a rather good approximation of $\mathbf{F}_f$ can be obtained by setting Coulomb friction forces as the dominant source of friction torque in the reducers, while friction in motors is modeled also according to a viscous friction effect. In both cases, the discontinuity of the theoretical Coulomb model is avoided by the hyperbolic tangent smoothing approach [15]. This model has been motivated in the work [16], through the analysis of the manufacturers' technical sheets. The estimated friction parameters are reported in Tab. 1: Coulomb friction torque is identified by T_C, with the superscript m indicating the motor and the superscript r indicating the reducer, whereas the viscous friction coefficient acting on the motor shaft is represented by f_v^m.

Table 1: Estimated friction parameters from [16].

Joint k	f_v^m $[Nms/rad]$	T_C^m $[Nm]$	T_C^r $[Nm]$
$1:3$	$6.6 \cdot 10^{-5}$	$7.4 \cdot 10^{-2}$	0.069
$4:6$	$3.4 \cdot 10^{-5}$	$3.4 \cdot 10^{-2}$	0.029

Equation (1) is of paramount importance for the estimation of the energy consumption of a manipulator, as it can be used as an inverse dynamic model to estimate the joint torques to be generated to exert the required speeds and accelerations, as well as to balance eventual external forces and gravity. By applying Eq. (1) to the whole time frame that records the robot performing a task, it is possible to estimate both the instantaneous mechanical power required by the task, as well as the mechanical energy expenditure associated with the task, after time integration.

However, the energy dissipation operated by friction forces is not the only one to be accounted for when computing an energy balance of the robot, as also the electric energy dissipation in the actuators significantly concurs in estimating the overall energy losses. As such, the mechanical model of Eq. (1) must be complemented by an electric model, which relates the speed and torque generation with the electric power absorption for each electric motor of the robot.

Brushless motors can effectively be modeled using the Clarke-Park transform as equivalent DC motors, which use the torque constant k_t, the back-emf constant k_b and the winding resistance R to relate current i, voltage drop V, speed ω_m, and torque τ_m as:

$$\begin{aligned} \tau_m(t) &= k_t\, i(t) \\ V(t) &= R\, i(t) + k_b\, \omega_m(t) \end{aligned} \tag{2}$$

The coefficients k_t, k_b and R can either be measured, gathered form technical sheets [16], or from experimental data [17], according to the available information. The two approaches have been combined to estimate the parameters used in the robot simulator: a detailed description of the developed procedure is here omitted to comply with the space limitations of the manuscript.

Equation (2) provides both the current and the voltage drop across the motor leads: their product describes the instantaneous power absorption $W_m(t) = V(t)\,i(t)$, which, through time integration, provides an estimation of the energy consumption associated with the execution of a task. Thus, it is possible to relate to it an energy figure, which can then be the subject of additional analysis and improvement through thoughtful motion planning. In the next section, the main features of the setup used to tune and preliminary validate the energy model of the UR5e robot are described.

3 Experimental results

The experimental setup, which has been used to guide the development of the energy model of the UR5e robot, is based on a minimal hardware configuration. The hardware setup requires just the robot (Fig. 1) and a computer that interfaces with the robot controller to define the robot motion and to log the experimental data during the robot operation. The control of the robot, as well as the data logging, is performed through ROS Melodic Morenia and Python 3.6. The communication between the robot and the PC running ROS is performed through a TCP/IP connection.

Fig. 1: The experimental setup.

The setup does not include any additional sensors or devices other than the bare minimum: the data used to drive the model identification and to validate the model has to rely only on data made available by the robot controller. The latter supports the so-called Real-Time Data Exchange (RTDE) interface, which can be used to establish a real-time two-directional communication between the robot and and the supervisor/datalogger computer over a bus at 500 Hz. Actual and reference joint position, velocities, accelerations, as well as reference torques and actual motor currents can be retrieved from the robot controller. The kinematic state of the robot can be fed to the energy model defined in Sect. 2 to estimate actual joint torques, motor current and voltages, from which the electric power absorption by each motor can be assessed and the overall energy expenditure associated with the execution of a task can be evaluated.

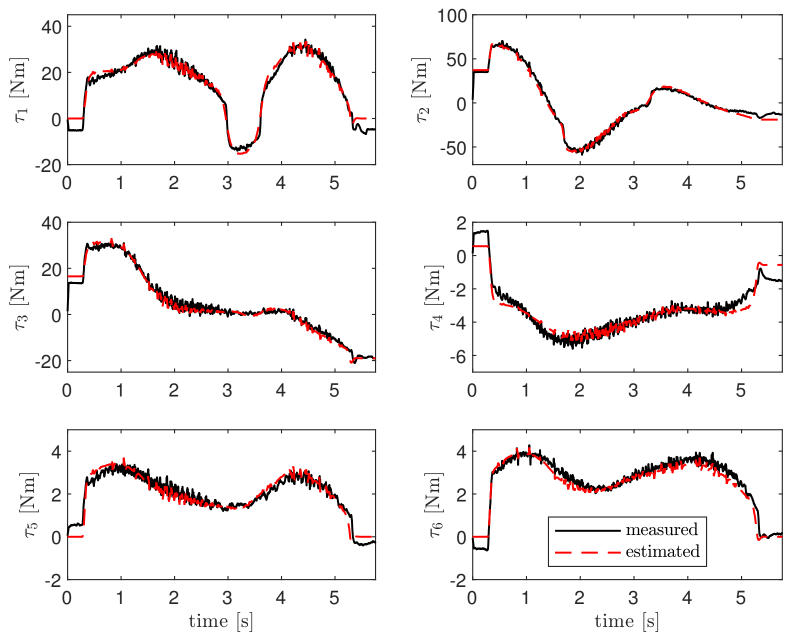

Fig. 2: Dynamic model validation: measured vs. computed joint torques.

The first part of the model to be tuned is the mechanical model of Eq. (1), for which the inertial parameters have yet to be discussed. The analysis of the data collected by executing several motion tasks have shown that the inertial parameters provided by the robot manufacturer, which are also reported in Tab. 2, provide a sufficiently accurate description of the robot dynamics. The latter can be improved even more by including also the moments of inertia of the motors and of the reducers, again according to the data presented in [16].

The good accuracy of the proposed model is supported by the data presented in Fig. 2, which compares the estimated joint torques provided by the robot

Table 2: Estimated inertial parameters from [16].

Joint k	m_i $[kg]$	Center of mass pos. $[m]$	J_m $[kg\,m^2]$	J_r $[kg\,m^2]$
1	3.7	$[0, -0.02561, 0.00193]$	$8.8 \cdot 10^{-5}$	$1.07 \cdot 10^{-4}$
2	8.393	$[0.2125, 0, 0.11336]$	$8.8 \cdot 10^{-5}$	$1.07 \cdot 10^{-4}$
3	2.33	$[0.15, 0.0, 0.0265]$	$8.8 \cdot 10^{-5}$	$1.07 \cdot 10^{-4}$
4	1.219	$[0, -0.0018, 0.01634]$	$2 \cdot 10^{-5}$	$0.19 \cdot 10^{-4}$
5	1.219	$[0, 0.0018, 0.01634]$	$2 \cdot 10^{-5}$	$0.19 \cdot 10^{-4}$
6	0.1879	$[0, 0, -0.001159]$	$2 \cdot 10^{-5}$	$0.19 \cdot 10^{-4}$

controller with the one obtained by solving Eq. (1). The two traces overlap almost perfectly, showing a very good agreement between the theoretical model and the behavior of the real manipulator. The electric power absorption for the six actuators (Fig. 3) can then be computed for the same trajectory from the the torque estimations together with Eq. (2). The resulting power signals, summed and integrated over time, provide the energy consumption that is shown in Fig. 4 divided in the inertial, friction, and gravity contributions.

The preliminary results presented in this work have been validated with other trajectories as well, showing overall a good agreement with the data collected during several experimental trials. The final goal of this work has been not yet reached, since some other details of the dynamic and electro-mechanic model are yet to be defined for a complete validation. In particular, the aim of the authors is to incorporate into the model the thermal effects, as it has been shown [18,19] that the energy consumption generally decreases as the whole robot gets warmer. Our aim is to investigate how temperature affects not only friction effects, but also the efficiency of the motors in generating mechanical power, which is expected given that the properties of conductive materials are generally sensitive to temperature changes.

4 Conclusion

In this work the initial development of a testbench for accurately estimating the power consumption of the collaborative robot UR5e has been presented. The proposed model makes use of a combination of nominal parameters provided by the manufacturer, as well as some other data extracted from technical data sheets and available in the literature. The dynamic model has been validated, and complemented with an electric model which describes the electric power absorption by the six brushless motors that move the robot. In order to increase the energy efficiency and sustainability of the industrial applications that use the UR5e robot, future work will focus on refining the model to include the explicit temperature dependence on friction parameters, and on using the model to plan real energy-optimal motion profiles.

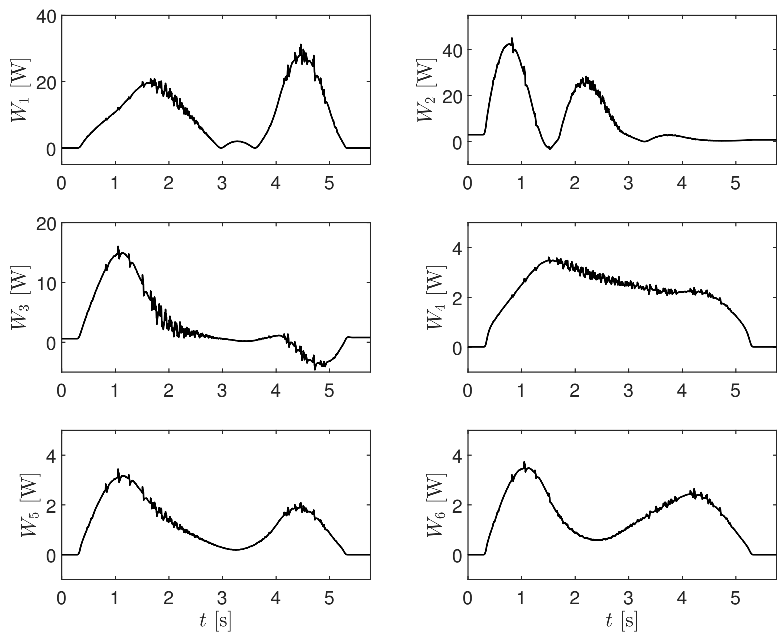

Fig. 3: Estimated motor electric power consumption.

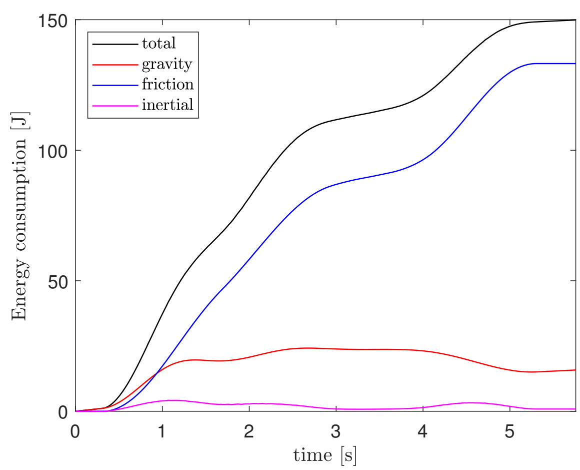

Fig. 4: Estimated electric energy consumption over time.

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