DINAME 2023 - Proceedings of the XIX International Symposium on Dynamic Problems of Mechanics,
A.S. De Paula, A.T. Fabro and M.R. Machado (Editors), ABCM.
Pirenópolis, Go, Brazil, February 26th to March 3rd, 2023

Data-driven Model for Torsional Oscillations in Slender Structures

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Abstract: This work focuses on the parameter identification of a 2-DOF model to study the torsional dynamics. The system studied is a slender structure subjected to friction. In this study, we calibrate the model with experimental data. We utilize an experimental setup composed of a DC motor and two rotating inertias connected by a slender shaft, with friction resulting from braking acting over one of the inertias. The mechanical and friction parameters of the low-dimensional model are inferred using a neural network. Finally, the parameters are compared with those experimentally identified.

Keywords: torsional vibrations, data-driven models, parameter estimation, friction

INTRODUCTION

Excessive drill string vibration leads to loss of the drilling process effectiveness and premature damage to the equipment: this makes the drilling system behavior a challenge to the process enhancement. The drill string vibrations can either be induced by drill bit-formation or drill string-borehole interactions. Due to the drill string's slenderness, torsional vibration is present in most drilling routines, ultimately reaching the stick-slip phenomenon. Stick-slip is characterized by two phases: one in which the drill bit remains stopped due to the resistive torque, and the other that begins when the stored energy overcomes the resistive torque, and the bit is set in motion.

The stick-slip phenomenon is a complex nonlinear problem since static friction rules the motion during the stick phase, while velocity-dependent kinetic friction rules it during the slip phase (Leine *et al.* (1998)). Despite the complexity of the bit-rock interaction, researchers often treat the relationship between torque and bit velocity as a dry friction function. Surveys on drill string modeling and dynamics can be found in Ghasemloonia *et al.* (2015); Saldivar *et al.* (2016). Most of the mathematical models of slender systems, like drill strings were developed analytically.

In this work, we apply system identification, which comprises a set of techniques for building data-based models (Aguirre (2017)), to calibrate a 2-DOF torsional model. We use data-driven identification to provide physically interpretable models. The experimental setup utilized is composed of a DC motor and two rotating inertias connected by a slender shaft, with friction resulting from braking acting over one of the inertias. The mechanical and friction parameters of the low-dimensional model are inferred using a neural network. The parameters estimated are compared with those experimentally identified.

THE EXPERIMENTAL SYSTEM

A DC motor connected to two solid discs by a low-stiffness shaft composes the test rig. Figure 1 shows the schematic of the experimental rig, presenting its main components. The shaft transmits rotary motion to the discs. Bearings are used to support the discs, allowing them to rotate freely while restricting lateral motion. Besides, we may independently apply resistive torques to the discs. There are two braking devices, consisting of pins that pass through the bearing support and touch the discs. The dry contact between the pins and the discs produces friction torque, leading the system to exhibit torsional vibrations (Pires *et al.* (2019)).

The motor and disc are equipped with optical quadrature-type encoders. The angular velocities of the inertia are calculated by numerical differentiation of the angular positions measured by the encoders. Load cells measure the normal force on the disc and the motor torque. We use a National Instruments cDAQ- 9174 as a real-time data acquisition platform. For more details about the test rig, please refer to Cayres *et al.* (2018). For simplicity, in this study, we only consider the subsystem composed of the motor, Disc D2, and the shaft connecting them, the other parts were disconnected.

Dynamical Model

We model the experimental system as a torsional pendulum and assume that the only resistive torque in the system is caused by the friction torque caused by the braking device. The system equations of motion are:

$$\begin{aligned} J_d\ddot{\theta}_d + c(\dot{\theta}_d - \dot{\theta}_m) + c_d\dot{\theta}_d + k(\theta_d - \theta_m) &= -T_f(\dot{\theta}_d), \\ J_m\ddot{\theta}_m + c(\dot{\theta}_m - \dot{\theta}_d) + c_m\dot{\theta}_m + k(\theta_m - \theta_d) &= \tau_m \end{aligned} \tag{1}$$

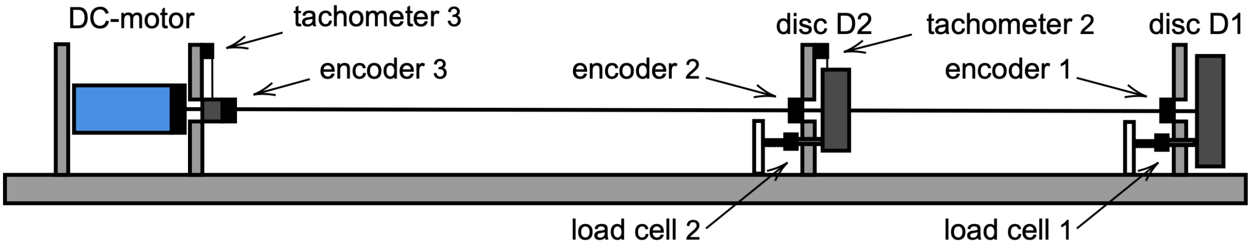

Figure 1 – Schematic diagram of the experimental rig.

where the moments of inertia of the disc and the motor are J_d and J_m. The shaft stiffness is denoted by k and the internal damping by c. c_d and c_m are the external dampings. θ, $\dot{\theta}$, and $\ddot{\theta}$ are the angular displacement, angular velocity, and angular acceleration of the inertias, respectively. The torque transmitted to the mechanical subsystem is denoted by τ_m, and the resistive friction torque on disc D2 is denoted by T_f. T_f is given by:

$$T_f = F_f a, \tag{2}$$

where a is the distance between the disc center and the disc-pin contact point. For simplicity, we consider $T_C = F_C a$ the resistive torque related to the kinetic Coulomb friction.

Friction Model

The study of the complex characteristics of the bit-rock interaction is indispensable to the drill string dynamics analysis. Despite the complexity of this interaction, studies often treat the torque on the bit as dry friction torque. The friction force is the resistance to the relative motion of two contact surfaces (Leine and Nijmeijer (2004)). Marques *et al.* (2016); Wojewoda *et al.* include a review of some of the most common models employed in dynamical systems. In this study, we use the regularized Coulomb friction formulation to obtain the resistive torque T_f that will be used in the dynamical model of the test rig.

The classical Coulomb friction model states that friction opposes the relative motion between contacting surfaces, and its magnitude is proportional to the normal contact force. The following equation defines the unregularized model:

$$F_f = F_C \text{sign}(v), \tag{3}$$

where F_f is the friction force, $F_C = \mu_k F_N$ is the magnitude of Coulomb friction, v is, from the perspective of the body, the relative tangential velocity between the contacting surfaces, F_N is the normal force, and μ_k is the kinetic friction coefficient. This model presents a velocity dependence by the sign function that introduces a discontinuity in the system of ODEs. Instead, in this study we consider a regularized approximation using the hyperbolic tangent with a transition velocity v_t to avoid discontinuities. Therefore, the regularized Coulomb friction is:

$$F_f = F_C \tanh\left(\frac{v}{v_t}\right). \tag{4}$$

Because of its simplicity, the regularized Coulomb model is very suitable for System Identification.

Experimental Results

We measure forces and velocities utilizing a LabView-based Data Acquisition System (DAQ). Figure 2 presents the time histories of the motor torque (a), the motor inertia angular velocity (b), and the disc angular velocity (c). We acquired the measurements for a nominal angular velocity of 55 RPM and an average normal contact force between pin and disc of 50 N. This combination of nominal angular velocity and normal force leads the system to exhibit stick-slip oscillations as we can see from the graphs of Fig. 2.

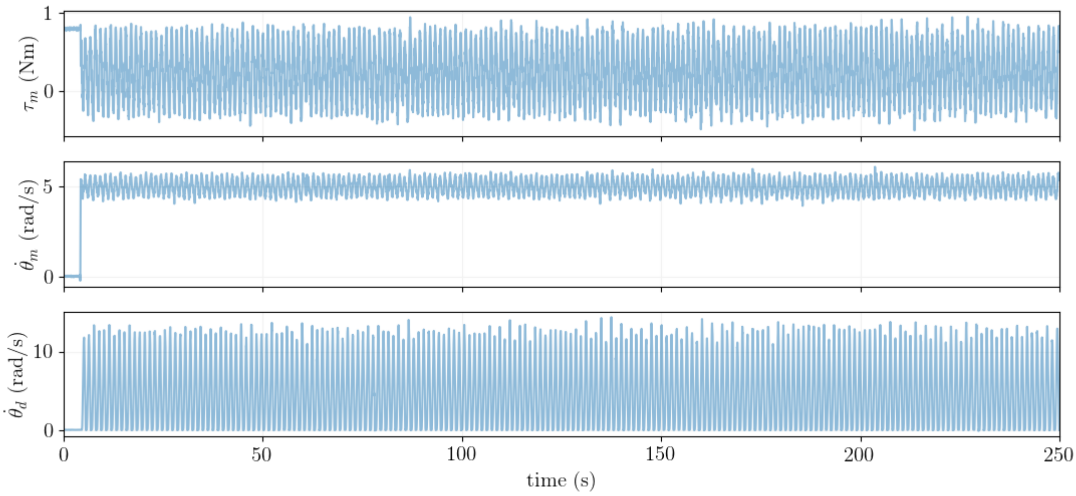

Figure 2 – Measured time history of (a) motor torque, τ_m; (b) motor inertia angular velocity, $\dot{\theta}_m$; (c) disc angular velocity, $\dot{\theta}_d$.

METHODOLOGY

Physical or semi-physical models deal with estimating the physical parameters of a system. To perform the parameter estimation from measurements, we apply a deep learning approach as proposed in Raissi *et al.* (2018). As input and output data, we use the torque transmitted from the motor, τ_m, and the angular velocities $\dot{\theta}_d$ and $\dot{\theta}_m$, respectively.

In this study, the motor and disc inertia are assumed to be known, and stiffness, damping, and friction parameters turn into parameters of the physics-informed neural network.

Both motor and disc angular velocities are approximated by deep neural networks. Therefore, we calculate the required derivatives to compute the residual networks applying automatic differentiation. Finally, we obtain the physics-informed neural network using (1). The parameters of the neural networks and the system mechanical and friction parameters are estimated by minimizing the following sum of squared errors cost function:

$$\sum_{i=1}^{N}(y(t^i)-\hat{y}^i)^2+\sum_{i=1}^{N}(u(t^i)-\hat{u}^i)^2, \quad (5)$$

in this cost function, the first summation corresponds to the training data on the output, $y(t)$, and the second summation carries out the dynamic motion equations. In (5), y_i and $\hat{y}_i$ are the experimental and predicted data, respectively. The use of deep neural networks is motivated by the advances in solving forward and inverse problems (Raissi *et al.* (2018)).

RESULTS AND DISCUSSION

To perform the identification, we employed the measured input and output data of the time interval from 30 to 90 seconds of the recording in Fig. 2. This data set was used to train a deep neural network by minimizing the sum of squared errors (Eq. (5)). We utilize the training network to predict the input and output data, as well as the stiffness, damping, and friction parameters. Table 1 presents the set of estimated parameter values using the neural network and the experimentally identified.

Table 1 – Estimated parameters values

	Deep Learning	Experimental Identification
k (Nm/rad)	0.250	0.3482
c (Ns/m)	0	0.0022
c_d (Ns/m)	0	0
c_m (Ns/m)	0	0
T_C (Nm)	0.222	-

From Table 1, we can see a difference between the values of estimated stiffness. It is worth mentioning, that the friction parameter was not obtained through experimental tests, while in the deep learning identification, all the parameters are attained all at once.

CONCLUDING REMARKS

In this paper, we applied physics-informed deep learning to infer the mechanical and friction parameters of the low-dimensional model. The model describes a laboratory test rig designed to mimic the torsional dynamics of drilling operations, and it is a slender structure subjected to friction. Because of its simplicity, we adopted the regularized Coulomb model for system identification.

Besides the excellent reconstruction of the time series for angular velocity, the methodology employed is capable of identifying the values for stiffness, damping, and friction parameters. The obtained values were compared with those experimentally identified.

ACKNOWLEDGMENTS

This work has been supported by Brazilian research agencies: CAPES and CNPq.

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