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Abstract

Precision in controlling and ensuring efficient operation relies heavily on the precise identification of the friction force generated within a hydraulic actuator. Nonetheless, accurately predicting this force poses challenges due to the nonlinearities inherent in modeling friction forces and the complexities associated with estimating diverse physical properties. Data-driven modeling and simulation methods driven by machine learning techniques are increasingly employed to surpass the constraints of traditional approaches in the field of multibody dynamics [1]. In this study, a data-driven methodology using a deep neural networks (DNN) to predict nonlinear friction force is introduced [2]. The capability of the trained friction neural network model to replace the mathematical model in the numerical simulations was also verified.

To model hydraulic actuators, various techniques can be applied. Among them, the lumped fluid theory [3] is widely used due to its efficiency and accuracy. If the volume comprising the hydraulic cylinder is divided into two regions based on the position of the piston, the cross-sectional areas and pressures of each volume can be denoted as p_1, p_2, A_1, and A_2. The actuator force F_a can be expressed as follows:

$$F_\mathrm{a} = p_1 A_1 - p_2 A_2 - F_\mu. \tag{1}$$

The LuGre friction model [4] is a popular choice to describe the friction force F_μ in a hydraulic actuator. Using the bristle deformation $\mathbf{z}$ on the contact surfaces, the bristle deformation rate $\dot{\mathbf{z}}$, and the tangential velocity $\mathbf{v}$, the LuGre friction force can be calculated as

$$\mathbf{F}_\mu = \sigma_0 \mathbf{z} + \sigma_1 \dot{\mathbf{z}} + \sigma_2 \mathbf{v}, \quad \dot{\mathbf{z}} = \mathbf{v} - \frac{\sigma_0 |\mathbf{v}|}{g(\mathbf{v})}\mathbf{z}, \quad g(\mathbf{v}) = F_\mathrm{c} + (F_\mathrm{s} - F_\mathrm{c}) e^{(|\mathbf{v}|/v_\mathrm{s})^\mathrm{n}}, \tag{2}$$

where σ_0, σ_1, σ_2, v_s, n, F_c, and F_s are the stiffness of the bristles, the damping coefficient of the bristles, the coefficient of viscous friction, the Stribeck velocity, the exponent of the Stribeck curve, the Coulomb and static frictions, respectively.

To predict the friction force, a variety of measurable responses can be used in hydraulic actuators, including pressures $\mathbf{p}$, actuator length s, and velocity $\dot{s}$ and acceleration $\ddot{s}$ at the actuator end-point. The nonlinearity and historical dependence of the friction force was reproduced by using the structure of a neural network containing historical information of the responses as shown in Figure 1. The selected responses are used as input variables R for the neural network along with the responses from the K-th previous time step from the current time instance. We employed a numerical single-axis hydraulic actuator model manipulating an object with 200 kg mass to gather training data for 30 random spool signal scenario.

The trained neural network for the LuGre friction force was tested in a four-bar mechanism example [5] shown in Figure 1. The lengths of the bodies L_1, L_2, and L_3 are 9 m, $\sqrt{2}$ m, and 2 m, respectively, with corresponding masses of 225 kg, 35 kg, and 50 kg. The hydraulic actuator operated by applying the reference spool signal U_ref based on the conditions specified in Equation (1).

$$U_\mathrm{ref} = \left\{ \begin{array}{lc} 0 & t < 1s,\ 2s \le t < 3.5s,\ t \ge 4s \\ 10 & 1s \le t < 2s \\ -10 & 3.5s \le t < 4s \end{array} \right\}. \tag{3}$$

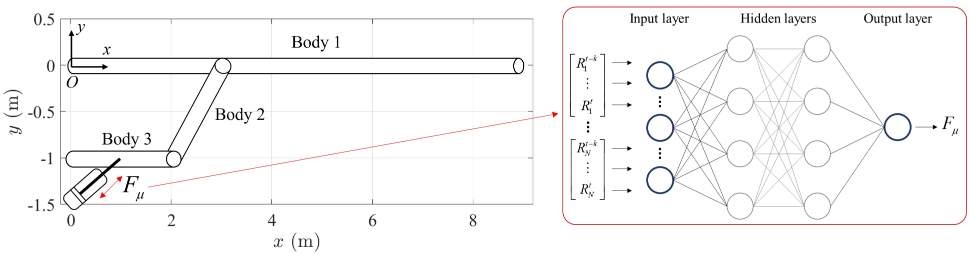

Figure 1: Four-bar mechanism with neural network friction model.

Among the combinations of responses, the four cases of input variables that achieved acceptable prediction performance in the uniaxial hydraulic actuator model was used to replace the LuGre model, and the results are shown in Figure 2. Due to the nature of the LuGre model, which is dominated by the tangential velocity $\mathbf{v}$ and expressed as a function of it, good prediction performance was found in the cases where the input to the neural network are $R = [\dot{s}]$ and $R = [s, \dot{s}, \ddot{s}]$. The limitations of the surrogate model trained by the responses of the uniaxial hydraulic actuator with no changes in mass and moment of inertia caused relatively poor prediction performance in the four-bar mechanism example for two cases where pressures were used as an input variable.

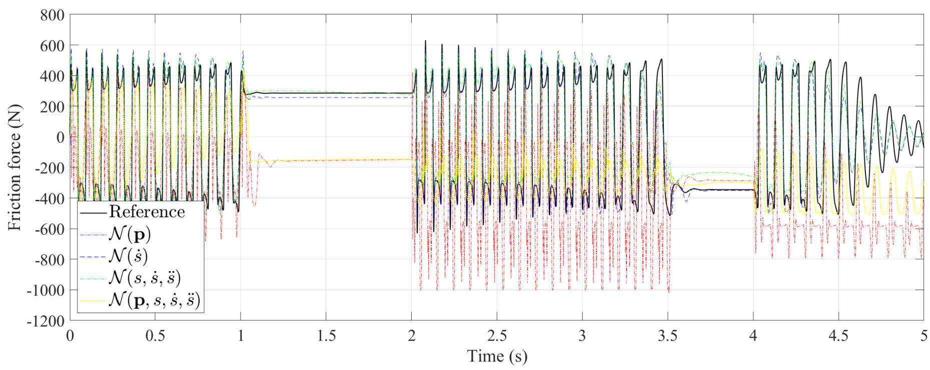

Figure 2: Friction force prediction in the four-bar mechanism system.

In this work, we introduced a data-driven method for predicting the friction force produced by hydraulic actuators during operation. By employing a DNN model trained with LuGre friction force data obtained from a uniaxial hydraulic actuator, the DNN can estimate the current friction force from the responses of the hydraulic actuator. In the numerical simulation of the four-bar mechanism, the well-trained neural network demonstrated its ability to replace the mathematical friction model.

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