Comparison of EKBF-based and Classical Friction Compensation

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In servo control, traditionally, models that attempt to capture the friction-velocity curve and interactions at contacting surfaces have been used to compensate for friction-introduced tracking errors. Recently, however, extended Kalman-Bucy filter (EKBF)-based approaches that do not use a phenomenological or structured model for friction have been proposed. In addition to being cast as a friction estimator, the EKBF can also be used to provide parameter adaptation for simple friction models. In this paper, a traditional motor-driven inertia experiment is used to demonstrate the usefulness of EKBF in friction compensation. In addition, a numerical simulation is used to test the robustness of the new methods to normal force variations. Using root mean square position tracking error as the performance metric, comparisons to traditional model-based approaches are provided.

1 Introduction

The motion control precision of many mechanical systems is severely compromised due to friction. Precise positioning systems that involve repeated velocity reversals are particularly vulnerable. Examples of such systems include airborne navigation systems, systems used in computer controlled manufacturing, semiconductor manufacturing and inspection systems, robotics, and automated surgical instruments. A primary feature of these applications is low velocity, bidirectional position tracking.

In cases where it is feasible to measure or estimate friction accurately in real time, it is possible to use the measurement or estimate to provide instantaneous feedforward compensation.Friction is thus monitored in real time, and corrective action is taken simultaneously. Optimized proportional-integral-derivative (PID) control combined with feedforward friction compensation provides high tracking accuracy with smaller control gains. In general, real-time friction modeling is difficult and an observer is used to estimate friction using measured quantities, such as position, velocity, and input torque. This estimate is then used to provide a compensating torque at the input of the machine (Fig. 1). This topology is considered in a number of previous studies [1–5].

Friction observers are typically model-based, i.e., phenomenological or empirical modeling is used to characterize the surface interactions leading to friction. Dahl developed the first successful friction model for use in servo machines and used it to cancel bearing friction [1]. This model accounts for presliding displacement (sometimes referred to as the “Dahl effect”). Bliman studied the Dahl model as a map between the displacement or velocity and friction force and showed the existence of bounded hysteresis.

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ment idea is illustrated using friction compensation in a DC motor-driven inertia as an example. The system equations typically take the form

\[
J \ddot{\theta} + B \dot{\theta} = U_{\text{in}} - T_f
\]

(1)

where \( J \) is the moment of inertia, \( B \) is the viscous damping, \( U_{\text{in}} \) is the input torque, and \( T_f \) is the opposing friction torque. \( \dot{\theta} \) and \( \ddot{\theta} \) denote the angular velocity and acceleration, respectively, and are time derivatives of the angular position \( \theta \). Usually, it is simple to determine \( J \) and a nominal value for \( B \) from the physical properties (density and geometry of the inertia) of the system along with a measured response to a step input torque. For a position control system, \( U_{\text{in}} \) is the output of a PID-type controller and is also known. If velocity and acceleration are measured perfectly, friction in is the only unknown in Eq. (1) and a time history of \( T_f \) may be extracted. In practice, however, measurements are prone to measurement noise, system parameters are not perfectly known and multiple sensors (acceleration and velocity) are expensive. When an accurate position measurement is available, state estimation techniques are used to extract friction from Eq. (1) in real time.

A Gauss-Markov (GM) formulation is used to append the friction torque, and the state estimator is written as

\[
\begin{bmatrix}
\dot{z} \\
\dot{\theta} \\
\dot{T_f} \\
\dot{T_f}
\end{bmatrix} =
\begin{bmatrix}
B & 0 & -1 & 0 \\
-\frac{1}{J} & 0 & -\frac{1}{J} & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0
\end{bmatrix}
\begin{bmatrix}
\dot{z} \\
\dot{\theta} \\
\dot{T_f} \\
\dot{T_f}
\end{bmatrix}
+ \begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
w_1 \\
w_2 \\
w_3 \\
w_4
\end{bmatrix}
+ \frac{1}{J} \begin{bmatrix}
\dot{\theta} \\
\dot{\theta}
\end{bmatrix}
+ \begin{bmatrix}
U_{\text{in}} \\
0
\end{bmatrix}
\]

(2)

where the first two states are from the system dynamic model (Eq. (1)), whereas the next two denote the friction states. \( w_1, w_2, w_3, w_4 \) are zero-mean Gaussian distributed random variables included to represent the uncertainty in each state element (see discussion below).

A first-order GM formulation \((\dot{T}_f=0)\) treats the friction torque as a random constant during each sampling interval. The EKBF is a state estimator that estimates this constant, along with the other states, during each time increment. It is noted that using a Gauss-Markov formulation in this manner is merely a method to append the system state for estimation. It does not mean that we are constraining the first time derivative of the friction torque to be zero during the entire time history. The second-order GM formulation \((\dot{T}_f=0, \text{ used in Eq. (2)})\) treats the derivative of the friction torque as a random constant during each sampling interval. The optimal order is chosen based on the computational cost and performance improvement over the uncompensated case for a DC motor-driven inertia. The GM formulation is sometimes referred to as a “random walk model” and has been used in previous studies to append the system states to estimate aerodynamic forces [10,15] and tire forces [11].

A distinction needs to be made between the process noise sequences \( w_1, w_2 \) and the process noise sequences \( w_3, w_4 \). The first two sequences represent actual unknown disturbances that affect the position and velocity. For instance, the input torque, \( U_{\text{in}} \), could contain electrical noise that could affect position and velocity. The latter two sequences are not physical entities but are required to drive the two friction state elements. These noise sources are internal to the EKBF and only their covariance needs to be specified.\(^2\) Used in this way, these do not represent unknown external inputs, but rather quantify the amount of uncertainty in the augmented states. The entries of the process noise covariance matrix associated with \( T_f \) and \( \dot{T}_f \) therefore become tuning parameters. The tuned parameters used in this study are as follows:

- Experimental apparatus: \( Q_c(T_f)=Q_c(\dot{T}_f)=2 \times 10^{-4} \). All other \( Q_c \) matrix entries=0.
- Simulated apparatus: \( Q_c(T_f)=Q_c(\dot{T}_f)=300 \). All other \( Q_c \) matrix entries=0.

where \( Q_c(T_f) \) is the entry in the process noise covariance matrix \( Q_c \) corresponding to \( T_f \). This method is denoted by the term “KF estimator” to differentiate it from the adaptive Dahl model, which also utilizes the EKBF.

### 2.2 Classical Friction Compensation Methods.

#### 2.2.1 Adaptive LuGre Model (ALM)

The LuGre model [8] is a system of differential equations that captures several observed friction traits, such as presliding displacement, stick-slip, and friction hysteresis. The contact surfaces are thought to contain bristles, the interaction between which leads to friction. A first-order nonlinear differential equation governs the average bristle deflection \( z \), and a function \( g(\dot{\theta}) \) characterizes the different friction regimes and the Stribeck effect:

\(^2\)Note that the \( w_4 \) are not injected into the system in the manner persistent excitation is injected in some adaptive methods (e.g., [4]).
\[ \frac{dz}{dt} = \theta - \frac{\dot{\theta}}{g(\dot{\theta})}, \quad \alpha_0 g(\dot{\theta}) = T_c + (T_s - T_f) e^{-(\#^4 \phi)^2} \]  
(3)

where \( T_c \) and \( T_s \) are the levels of Coulomb and static friction and \( \dot{\theta} \) is the Stribeck velocity. The friction torque is given by

\[ T_f = \alpha_0 z + \alpha_1 \frac{dz}{dt} + \alpha_2 \dot{\theta} \]  
(4)

where \( \alpha_0 \) is the bristle stiffness, \( \alpha_1 \) is the bristle damping coefficient, and \( \alpha_2 \) is the viscous friction coefficient. The procedure to estimate the static parameters \( (T_c, T_s, \alpha_0, \text{and} \ \dot{\theta}) \), and the dynamic parameters \( (\alpha_0 \text{and} \ \alpha_1) \) is described in Ref. 5.

Several algorithms have been proposed to adapt the LuGre model parameters, and in this paper, the Canudas de Wit and Lischinsky method [5] is chosen as a representative method. This method addresses variations in \( T_c \) and \( T_s \) when there is a change in the normal load. Equation (3) is modified as

\[ \frac{dz}{dt} = \theta - \Theta \frac{\dot{\theta}}{g(\dot{\theta})} - z \hat{\dot{z}}, \quad k > 0 \]

\[ \frac{d\dot{\theta}}{dt} = -\gamma \frac{\dot{\theta}}{g(\dot{\theta})} \hat{z} + \hat{z} - z_m = u_f - a_f \]  
(5)

where \( \hat{\dot{z}} \) denotes that the average bristle deflection is now being estimated. \( \Theta \) is the parameter to be adapted that denotes a simultaneous uniform change in \( T_c \) and \( T_s \) with time. \( \gamma \) and \( k \) are tunable gains, and \( z_m \) is the position error. \( u_f \) and \( a_f \) are the filtered signals that depend on the system inertia [5].

This compensator was used only in the simulation study. The parameters that are not estimated \( (\dot{\theta}, \sigma_0, \sigma_1, \text{and} \ \sigma_2) \) are set to be the same as that of the LuGre model used to inject friction (see Sec. 3.2). In addition, the two parameters to be estimated, \( T_c \) and \( T_s \), are initialized using their true values. The two gains in the adaptation algorithm \( (\gamma=20,000 \text{and} \ k=1.0) \) are tuned to minimize rms position tracking error for a 0.8 Hz sinusoidal trajectory.

2.2.2 Dahl Model (DM). In this paper, we consider Walrath’s implementation of the Dahl model [2], according to which

\[ T_f + \tau \frac{dT_f}{dt} = \text{sgn}(\dot{\theta})T_c \]  
(6)

where \( T_f \) is the friction torque, \( T_c \) is the level of Coulomb friction, \( \dot{\theta} \) is the angular velocity, and the time constant \( \tau \) is a tuning parameter.

The Dahl model is used only in the experimental study. The value of \( T_c \) during the loaded and unloaded conditions is given in Sec. 3. The parameter \( \tau \) is tuned for each operating condition by minimizing the rms tracking error for a 0.3 Hz driving frequency:

Unloaded: \( \tau = 1/24 \text{ s (0.1 Hz)}, \quad \tau = 1/16 \text{ s (0.3 Hz)}, \)

\[ \tau = 1/40 \text{ s (1.0 Hz)} \]  

Loaded: \( \tau = 1/10 \text{ s (0.1 Hz)}, \quad \tau = 1/20 \text{ s (0.3 Hz)}, \)

\[ \tau = 1/36 \text{ s (1.0 Hz)} \]  

The Dahl model is said to be “quasi adaptive” as the parameters are tuned offline for each loading condition and driving frequency. It is also possible to use the EKBF to provide parameter adaptation for the Dahl model (see below).

2.2.3 Adaptive Dahl Model (ADM). The Dahl model is used to formulate the friction state and a first order Gauss-Markov formulation \( (\hat{T}_c=0, \text{see Sec. 2.1 for more information}) \) is now used to append the system state, which is estimated in real time by the EKBF. The state equations (process noise sequences not shown) now become

\[
\begin{bmatrix}
\dot{z} \\
\dot{\theta}
\end{bmatrix} =
\begin{bmatrix}
\frac{\dot{z}}{J} \\
\frac{\dot{\theta}}{J}
\end{bmatrix} - \begin{bmatrix}
\frac{1}{J} & 0 \\
0 & \frac{1}{\tau}
\end{bmatrix}
\begin{bmatrix}
\dot{z} \\
\dot{\theta}
\end{bmatrix}
+ \begin{bmatrix}
\frac{1}{J} U_{in} \\
0
\end{bmatrix}
\]

(7)

where again the first two state equations are from the system dynamic model (Eq. (1)) and the third equation is the Dahl friction model (Sec. 2.2.2, Eq. (6)). The parameter \( \tau \) is not adapted, but also not changed with operating frequency as in the nonadaptive Dahl model (Sec. 2.2.2). This model was used in both the experimental and the simulation studies with the following parameters:

Experimental apparatus: \( \mathbf{Q}_e(T_f)=0.1, \mathbf{Q}_e(T_c)=0.0001 \). All other \( \mathbf{Q}_e \) matrix entries=0, \( \tau = 1/16 \text{ s} \).

Simulated apparatus: \( \mathbf{Q}_e(T_f)=3 \times 10^6, \mathbf{Q}_e(T_c)=3 \times 10^6 \). All other \( \mathbf{Q}_e \) matrix entries=0, \( \tau = 1/20 \text{ s} \).

3 Test Methods for Comparative Study

3.1 Experimental Procedure. The experimental apparatus is very similar to those used in earlier studies involving position tracking [3,5,16]. It consists of a DC motor that drives a heavy disk. The schematic is shown in Fig. 2(a). Two ball bearings support the shaft on which the disk is mounted. The disk was made of 52100 steel (density=7800 kg m\(^{-3}\)) with a Brinell hardness of 192. It was ground to be concentric in its shaft to 2.54 cm. The disk mass is 2.28 kg, and its moment of inertia is 0.0056 kg m\(^2\). In this apparatus, friction exists in two shaft support bearings, as well as in the bearing internal to the motor itself. A cylindrical rider in contact with the disk and under static normal force of 85N was used to provide a variable normal load (Fig. 2).
load provides an additional source of friction (Fig. 2(a)). The motivation behind using additional sources of friction is to elicit a variety of different friction traits in order to thoroughly test each friction compensation scheme. The rider forms a line contact with the disk, and a normal load of up to 2.3 kg (5 lbs) can be placed on the contact. The rider is made of aluminum and is mounted at the end of an l-beam (Fig. 2(a)). The use of a rider in this fashion is similar to the use of a mechanical brake in [5]. The apparatus can be used with and without the rider in contact, and friction levels are higher when the loaded line contact exists. To differentiate between these two cases, we use the term unloaded to refer to the case when the external rider is not in contact with the disk and the term loaded to refer to the case when the loaded external rider is used to introduce additional friction.

The apparatus is modeled as a second-order system driven by a known input torque \( U_{\text{in}} \),

\[
J \ddot{\theta} + B \dot{\theta} = U_{\text{in}} - T_f
\]

(8)

where \( \dot{\theta} \) and \( \ddot{\theta} \) represent the shaft angular velocity and acceleration respectively, \( J \) is the moment of inertia of the disk and motor, and \( B \) is the viscous damping in the bearings. \( T_f \), the unknown friction torque, may include the uncompensated component of viscous damping. An optical encoder (resolution = 6.3 × 10^{-3} rad (or) 1000 points per revolution) is used to measure \( \dot{\theta} \). The plant parameters, \( J = 0.0056 \text{ kg m}^2 \) and \( B = 0.0067 \text{ kg m}^2 \text{s}^{-1} \), are determined using the disk material properties and geometry. The friction characteristics of the apparatus were determined using velocity control experiments as outlined in [5]. The following are the friction parameters of the experimental apparatus:

- **Unloaded:** \( T_c = 0.128 \text{ Nm}, \quad T_s = 0.22 \text{ Nm}, \quad \sigma_2 = 0.0276 \text{ Nms/rad}, \quad \dot{\theta}_r = 0.1 \text{ rad/s} \)

- **Loaded:** \( T_c = 0.26 \text{ Nm}, \quad T_s = 0.80 \text{ Nm}, \quad \sigma_2 = 0.0344 \text{ Nms/rad}, \quad \dot{\theta}_r = 2.4 \text{ rad/s} \)

The friction-velocity curve is shown in Fig. 2(a').

### 3.1.1 Sinusoidal Position Tracking

Position tracking experiments were performed using the apparatus with the feedback control architecture shown in Fig. 1. The position command for the rotating inertia is a sinusoidal tracking reference, \( \theta_m(t) = 0.1745 \sin(2\pi f t) \). This corresponds to a 20 deg peak-to-peak sinusoidal command trajectory. Three different frequencies, \( f = 0.1 \text{ Hz}, 0.3 \text{ Hz}, \) and \( 1.0 \text{ Hz} \) are considered to evoke a wide variety of friction traits. A well-tuned PID controller provides basic compensation to compare the efficacy of various friction compensation schemes. The PID controller gains are \( KP = 200, \quad KD = 100, \quad \) and \( KI = 20 \), leading to a closed-loop bandwidth of \( \sim 25 \text{ Hz} \), which is much higher than the driving frequency used in simulation (0.8 Hz).

The level of Coulomb friction \( T_c \) and the level of static friction \( T_s \) were allowed to vary with time

\[
T_{\text{coul}}(t) = \frac{T_c}{2} \left[ 1 + \sin(2\pi f_2 t) \right]
\]

(14)

\[
T_{\text{coul}}(t) = \frac{T_c}{2} \left[ 1 + \sin(2\pi f_2 t) \right]
\]

(15)

where \( T_{\text{coul}} \) and \( T_{\text{coul}} \) are the time-varying Coulomb and static friction levels used in the plant. Each parameter varies sinusoidally about its nominal value by 50%. This corresponds to a simu-
GM formulation is chosen for comparison to other methods. The computational cost that increases with the EKBF order, the second-order gain by going from second to third order. Given the computational cost that increases with the EKBF order, the second-order GM formulation is chosen for comparison to other methods.

4 Results

4.1 Experimental Results

4.1.1 Optimal GM Order for KF Estimator. Table 1 shows the percent improvements in RMS tracking error over the uncompensated PID controller for the a first-order ($T_f=0$), second-order ($T_f=0$), and third-order ($T_f=0$) Gauss-Markov formulations for the EKBF estimator. For each contact condition and frequency, five different data points were taken and a mean was computed. Note that for most cases, the improvement going from first to second order is significantly higher compared to the improvement gained by going from second to third order. Given the computational cost that increases with the EKBF order, the second-order GM formulation is chosen for comparison to other methods.

4.1.2 Comparative Study. Figures 3(a)–3(c) show the RMS tracking error data points for each of the four compensators tested under the unloaded condition. The following four methods are tested: no friction compensation (PID), nonadaptive Dahl model (DM), adaptive Dahl model (ADM), and KF estimator (KF). It is noted that all three compensators provide significant reduction in the tracking error over the uncompensated case. For instance, at the 0.1 Hz driving frequency, the Dahl model reduces the tracking error by as much as 73%. At this frequency, performance of all three compensators is statistically similar. At higher frequencies, performance of the nonadaptive Dahl model (DM) deteriorates compared to that of adaptive Dahl model (ADM) and the KF estimator (KF) (Figs. 3(b) and 3(c)). The two EKBF-based approaches, ADM and KF estimator, have statistically similar performance for all cases.

Figures 3(a)–3(c) show the RMS tracking error data points for the loaded condition. Note that the data show a larger variance than the unloaded case. As a consequence of friction levels being higher, the RMS error values are also higher under this condition. It is noted that ADM and KF improve performance compared to baseline PID for all three driving frequencies. For instance, at 0.1 Hz, the KF estimator reduces the baseline tracking error by as much as 70%. Also, as in the unloaded case, all compensators perform statistically similar for the lowest frequency and DM performance deteriorates at higher frequencies, with performance dropping below baseline PID at 1.0 Hz. The two EKBF-based compensators have statistically similar performance for the lower two frequencies. ADM has slightly better performance at 1.0 Hz. Note that for all cases, parameter adaptation improves DM performance.

Table 1 Improvements (percentages) over uncompensated PID system for different GM orders for the KF estimator

<table>
<thead>
<tr>
<th>EKBF Order</th>
<th>Unloaded</th>
<th>Loaded</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.1 Hz</td>
<td>0.3 Hz</td>
</tr>
<tr>
<td>I</td>
<td>46.97</td>
<td>41.90</td>
</tr>
<tr>
<td>II</td>
<td>65.15</td>
<td>62.86</td>
</tr>
<tr>
<td>III</td>
<td>65.15</td>
<td>67.62</td>
</tr>
</tbody>
</table>

Note that for all cases, parameter adaptation improves DM performance.

4.2 Simulation Results. Figure 4(a) shows the results from the simulation to test compensator performance when friction levels change with time. The dotted line in Fig. 4(a) shows the actual friction torque and the solid line shows the friction torque estimated by the adaptive LuGre compensator. The estimation algorithm takes ~1 s to converge. It is observed that this compensator is unable to properly track the time varying friction level. The estimate does not deviate significantly from the initial value of 0.52 Nm. Note also the high-frequency content in the estimate (arrows in Fig. 4(a)). The RMS tracking error for this case was $8.72 \times 10^{-4}$ rad.

In contrast, the adaptive Dahl model is able to accurately track the time varying friction level (Fig. 4(b)). The adaptation algorithm converges rapidly and the tracking error ($1.92 \times 10^{-4}$ rad) is much smaller compared to the adaptive LuGre compensator. The error is, in fact, actually very close to tracking with no friction ($1.21 \times 10^{-4}$ rad). With such a small error, it is difficult to differentiate between the actual and estimated friction curves at this scale (Fig. 4(b)). Similar results were obtained with the KF estimator.

5 Discussion

Although EKBF-based methods have been used previously to estimate aerodynamic forces [10,15] and tire forces [11], their use has been limited to gathering data for off-line modeling. In a...
previous study, EKBF-based friction estimates have been used to estimate unknown normal loads [19]. In the current study, EKBF-based friction estimates are applied to provide friction compensation in real time.

Using a standard DC motor-driven inertia experiment, we have shown that EKBF-based approaches provide excellent reduction in friction-related tracking errors for a wide range of operating conditions (Fig. 3). In most cases, EKBF-based methods outperform traditional model-based methods. In a previous study, where a direct friction measurement was available, we have also shown that the friction torque estimated by the Kalman filter was very similar to measured friction [12]. In addition, results from the numerical simulation indicate that EKBF-based methods are able to better track time varying friction (Fig. 4). This is significant because the adaptive Dahl model, which has no knowledge of the LuGre model used to inject friction, is able to outperform the adaptive LuGre model, which has the same structure as the LuGre model used to inject friction, and is initialized with true parameters.

We have also demonstrated that a second-order GM formulation adequately captures the time-varying friction torque (KF estimator), whereas a first-order GM formulation adequately captures variations in the Coulomb friction level (adaptive Dahl model). The success of EKBF-based methods is attributed to the following factors.

Nonadaptive friction models use a fixed set of parameters that are no longer valid when the operating conditions change. No friction model is used in the KF estimator, and therefore, it is not affected by parameter drift. In the adaptive Dahl model, the level of Coulomb friction is estimated by the EKBF and we have found that this type of parameter estimation is superior compared traditional methods, many of which require persistent excitation and carry assumptions such as slowly time-varying parameters [4]. The simulation also shows that EKBF-based estimation converges faster (Fig. 4).

By posing no structure at all (KF estimator) or using a simple friction model structure (adaptive Dahl model), many of the problems associated with models using complex structure, such as the need to estimate multiple parameters in real time, are avoided. In spite of recent advances, friction remains notoriously hard to model. The KF estimator shows that it is possible to circumvent complicated modeling of this time-varying nonlinear phenomenon by using simple Newtonian dynamics, accurate position measurements, and the time-tested Kalman filter.

All compensators have tunable parameters that need to be adjusted for optimal performance. These were set to minimize tracking error for a specific operating condition (0.3 Hz unloaded for the experimental study and 0.8 Hz for the simulation) and were not readjusted for other operating conditions, even though doing so results in substantial performance gains. Overall, the EKBF-based methods were significantly easier to tune. It was relatively easy to select optimal values for entries in the process noise covariance matrix corresponding to the estimated states, and there were no significant performance losses for reasonable perturbations in tuned parameters. Note also that EKBF-based methods do not require the level of Coulomb friction and other friction parameters and, therefore, do not require a separate set of experiments to determine them.

Closed-loop stability for a system under EKBF-based friction compensation was formally investigated in [20]. Using eigenanalysis, a gain margin for the closed-loop system was calculated and verified experimentally. The results indicate that EKBF-based friction compensation is stable under a wide range of operating conditions. In addition, [12] tested the stability characteristics by randomly perturbing the shaft during the experiment. It was found that model-based methods were much more susceptible to such perturbations.

6 Conclusion

The main conclusion of this paper is that EKBF-based methods are able to provide robust friction compensation under a wide range of operating conditions. It is, however, noted that EKBF-based approaches are presented as an addition to and not as a replacement of traditional model-based approaches. We have found that simple models, such as the Dahl model, do perform very well when well tuned and when the underlying assumptions are satisfied. EKBF-based methods work on the assumption that the plant dynamics are very well known. When this is not the case, friction models may be more useful. In addition, we have found that the LuGre model is a very efficient tool to model frictional contact in a numerical simulation.

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