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Empirical Modeling of Control Valve Layer with Application to Model Predictive Control-Based Stiction Compensation ⋆

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Abstract: In this work, we develop an empirical modeling procedure for feedback loops comprised of sticky valves and linear controllers for the valves and incorporate the models in a model predictive control (MPC)-based stiction compensation strategy. The empirical models are developed from data on the measured values of the valve outlet flowrates and the set-points for these flowrates. They utilize standard empirical model structures but are defined in a piecewise fashion, with different branches identified for set-point changes that correspond to sticking of the valve and to sliding of the valve, and modifications to account for the effect of the linear controller on the response of the valve outlet flowrate to a set-point change. Through a chemical process example, it is shown that the use of the empirical models in the MPC-based stiction compensation strategy can decrease the computation time of the method without significantly jeopardizing the constraint satisfaction of the closed-loop process, but preventing the need for a valve layer model with parameters and/or details about the valve that are difficult to obtain.

Keywords: Nonlinear process control, empirical models, valves, friction, optimization

1. INTRODUCTION

Stiction is a nonlinear friction effect that negatively impacts control system performance and causes the dynamics between the linear controller input to a sticky valve and the flowrate out of the valve to be described by four major regions: deadband, stickband, slip-jump, and the moving phase (Choudhury et al. (2005)). In the chemical process industries, problems that can result when control valves exhibit stiction include set-point tracking issues or oscillations in a control loop. A variety of methods have been proposed in the valve stiction compensation literature to reduce its negative effects, including both strategies that are not based on a model of the stiction dynamics (e.g., the knocker (Hägglund (2002)) and tuning methods (Li et al. (2014))), and those that are based on a stiction model (e.g., optimization (Srinivasan and Rengaswamy (2008)) or model predictive control (MPC)-based methods (Durand and Christofides (2016))).

Stiction models that are available for use in stiction compensation strategies are generally classified into two categories: first-principles models (e.g., the Classical (Garcia (2008)) and LuGre (Canudas de Wit et al. (1995)) models), which attempt to capture aspects of the friction phenomenon in both presliding and sliding through algebraic or differential equations, and data-driven models, which are empirical models that utilize a decision tree structure to determine the position of the valve based on the current and past inputs (e.g., the Kano (Kano et al. (2004)) and Choudhury (Choudhury et al. (2005)) models). Many strategies that attempt to identify the parameters of an empirical model of valve stiction assume that one of the data-driven models holds and then identify its parameters from data on the control signal sent to the valve and the output of the process on which the flowrate from the valve acts (e.g., Wang and Wang (2009); Jelali (2008); Srinivasan et al. (2005); see also Brásio et al. (2014) for more information on stiction modeling and compensation).

A recently proposed MPC-based stiction compensation strategy (Durand and Christofides (2016)) that computes valve outlet flowrate set-points for a valve layer comprised of valves and linear controllers for each valve requires models of the nonlinear dynamics of sticky valves in the valve layer. In addition, it requires models for other aspects of the valve layer, such as for the linear controllers for the valves and for the relationships between the valve positions and the flowrates out of the valves. The need for such detailed information and the possible stiffness of the dynamic equations for the valve layer when this layer reacts quickly to set-point changes from the MPC are two drawbacks of the stiction compensation strategy that may limit its industrial use. Though a data-driven model could be used in place of a first-principles friction model in this stiction compensation strategy, the output of the linear controller for the valve would still need to be modeled explicitly, and other details about the valve layer may also

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need to be considered or captured during the development of the data-driven model. It would be desirable to develop an empirical model that relates only the set-points for the valves and the valve outputs.

In this work, we propose a procedure for developing empirical models for feedback loops in the valve layer. The models can be developed with structures standard in the chemical process industry, using only valve set-point and valve outlet flowrate data, and they account for the dynamics of stiction by incorporating a logic structure that activates different equations depending on whether the valve is sticking or sliding. The empirical model is then used to replace the first-principles model for the valve layer in the MPC-based stiction compensation strategy developed in Durand and Christofides (2016). Through a chemical process example, we demonstrate that an empirical model may be less stiff than the first-principles valve layer equations and may improve the computation time of the MPC-based stiction compensation strategy with minimal process constraint violation.

2. PRELIMINARIES

2.1 Notation

The notation $t_k = k\Delta$, $k = 0, 1, 2, \ldots$, and the notation $\tilde{t}_j = j\Delta_e$, $j = 0, 1, 2, \ldots$, refer to elements of a time sequence separated by time periods of lengths Δ and Δ_e, respectively. The notation $|\cdot|$ signifies the Euclidean norm of a vector. The notation $S(\Delta)$ signifies the set of all vector functions with m components that are piecewise-constant for time periods of length Δ.

2.2 Class of Systems

We consider a process-valve system controlled by a model predictive controller that computes valve flowrate set-points for a control valve layer. The output of the control valve layer (the flowrates out of the valves) acts on the process. The class of nonlinear processes considered is:

$$\dot{x} = f(x(t), u_a(t), w(t)) \tag{1}$$

where $x \in R^n$ is the state vector, $u_a \in R^m$ is a vector of bounded process inputs ($u_{a,i} \in \{u_{a,i,min} \leq u_{a,i} \leq u_{a,i,max}\}$, $i = 1, \ldots, m$), and $w(t) \in R^w$ is a vector of bounded disturbances ($|w| \leq \theta, \theta > 0$). The process inputs $u_{a,i}$ are outputs of the valve layer.

The valve layer is comprised of m feedback loops (one for each valve); within each there is a linear controller that computes control signals that generate forces that move each valve. The control signals generated are a function of the error between the valve output set-point $u_{m,i}$ and the valve output $u_{a,i}$. The signals may also be a function of the state vector $\zeta_i \in R^{r_i}$ of dynamic states of the linear controller, which evolve as follows:

$$\dot{\zeta}_i = A_i \begin{bmatrix} x_{v,i} \\ \zeta_i \end{bmatrix} + B_i g_{V,i}^{-1}(u_{m,i}) \tag{2}$$

where $x_{v,i}$ is the relative position of the $i - th$ valve with respect to surfaces that cause friction, and $g_{V,i}^{-1}$ is the inverse of the nonlinear one-to-one relationship $u_{a,i} = g_{V,i}(x_{v,i})$ between the position and output of the $i - th$ valve. A_i and B_i are matrices of appropriate dimension, and $u_{m,i}$ is bounded ($u_{m,i,min} \leq u_{m,i} \leq u_{m,i,max}$).

The force generated from the control signal to the valve moves the valve position $x_{v,i}$ through a force balance:

$$\frac{dx_{v,i}}{dt} = v_{v,i} \tag{3}$$

$$\frac{dv_{v,i}}{dt} = \frac{1}{m_{v,i}}[c_i^T F_{O,i} - F_{f,i} - b_i^T F_{I,i}] \tag{4}$$

where $v_{v,i}$ is the relative velocity of the $i - th$ valve, $m_{v,i}$ is the mass of the valve moving parts, $c_i^T F_{O,i}$ comprises forces in the opposite direction to the friction force $F_{f,i}$, and $b_i^T F_{I,i}$ comprises forces in the same direction as the friction force. The function $\hat{v}_{v,i}$ will denote the right-hand side of Eq. 4. The friction force dynamics are described by:

$$F_{f,i} = \hat{F}_{f,i}(x_{v,i}, v_{v,i}, z_{f,i}) \tag{5}$$

$$\dot{z}_{f,i} = \hat{z}_{f,i}(x_{v,i}, v_{v,i}, z_{f,i}) \tag{6}$$

where $z_{f,i} \in R^{z_i}$ is an internal state of the friction model. The full process-valve system has state vector $q = [x^T \ x_v^T \ v_v^T \ z_f^T \ \zeta^T]^T$ and dynamic equation:

$$\dot{q} = \begin{bmatrix} \dot{x} \\ \dot{x}_v \\ \dot{v}_v \\ \dot{z}_f \\ \dot{\zeta} \end{bmatrix} = f_q(q(t), u_m(t), w(t)) = \begin{bmatrix} f(x(t), g_V(x_v(t)), w(t)) \\ v_v(t) \\ \hat{v}_v(c(t), F_O(t), b(t), F_I(t), x_v(t), v_v(t), z_f(t)) \\ \hat{z}_f(x_v(t), v_v(t), z_f(t)) \\ A\begin{bmatrix} x_v(t) \\ \zeta(t) \end{bmatrix} + Bg_V^{-1}(u_m(t)) \end{bmatrix} \tag{7}$$

2.3 Model Predictive Control

Model predictive control (MPC) (Qin and Badgwell (2003); Ellis et al. (2014)) is a control strategy that determines optimal control actions by solving:

$$\min_{u_m(t) \in S(\Delta)} \int_{t_k}^{t_{k+N}} L_e(\tilde{x}(\tau), u_m(\tau))\, d\tau \tag{8a}$$

$$\text{s.t.} \quad \dot{\tilde{x}}(t) = f(\tilde{x}(t), u_m(t), 0) \tag{8b}$$

$$\tilde{x}(t_k) = x(t_k) \tag{8c}$$

$$u_{m,i,min} \leq u_{m,i}(t) \leq u_{m,i,max}, \ i = 1, \ldots, m, \ \forall\, t \in [t_k, t_{k+N}) \tag{8d}$$

$$g_{MPC,1}(\tilde{x}(t), u_m(t)) = 0 \tag{8e}$$

$$g_{MPC,2}(\tilde{x}(t), u_m(t)) \leq 0 \tag{8f}$$

The cost function $L_e(x, u_m)$ is minimized subject to bounds on the inputs (Eq. 8d), equality and inequality constraints (Eqs. 8e-8f), and the restriction that the states must evolve according to the nominal ($w(t) \equiv 0$) dynamic model in Eq. 8b when initialized from a measurement of the state (Eq. 8c). A vector of control actions u_m is computed for each of the N sampling periods of length Δ, and only the first of these vectors is applied to the process in a sample-and-hold fashion according to a receding horizon strategy. The notation $u_m^*(t|t_k)$, $t \in [t_k, t_{k+N})$, signifies the optimal value of u_m for time t for the optimization initiated at time t_k. The MPC shown in Eq. 8 is written without reference to u_a because the MPC literature typically assumes that the valve dynamics are instantaneous