Eliminating Valve Stiction Nonlinearities for Control Performance Assessment ⋆

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Abstract: Control performance assessment or CPA is a useful tool to establish the quality of industrial feedback control loops, but this requires establishing the minimum variance lower bound. While reliable algorithms have been developed for linear systems, common nonlinearities such as valve stiction require modifications to the basic strategy.
If the valve gets stuck due to stiction, for stable plants the output will reach steady state until the valve again moves. During this time the nonlinearity due to stiction is essentially removed from the system, and it is possible to compute performance assessment indices in the standard manner.
This paper describes an automated strategy to reliably identify these linear steady-state periods and subsequently compute the minimum variance lower bounds. The results of a simulation example illustrate that the proposed methodology is efficient and accurate enough for the classes of systems and nonlinearities considered to provide statistics for control performance assessment for linear systems with nonlinearities caused by valves.

Keywords: Control performance assessment, Valve stiction, Steady state.

1. INTRODUCTION

It is perhaps not surprising that instrument and control engineers are overwhelmed by the sheer number of loops that need attention on any typical industrial processing plant. Many loops are mis-tuned, if tuned at all, as noted by Bialkowski (1998) and other practitioners, and many control valves are only maintained when something catastrophic occurs. However the economic benefits from improving the performance of control loops, even those operating at a cursory glance acceptably, is often grossly under estimated.

In this paper, we present a strategy to compute the minimum variance lower bound, which is arguably the difficult step in quantifying the performance improvement of a typical control loop that suffers from the specific nonlinear phenomena of valve stiction being a very common cause for poor control performance.

Control performance assessment, or CPA, is a technology to diagnose and maintain operational efficiency of control systems. CPA is routinely applied in the refining, petrochemicals, pulp and paper and the mineral processing industry as noted by Qin (1998), Harris (1999), Huang and Shah (1999), Jelali (2006), although these, and many other publications, are mainly restricted to linear systems.

In the case of nonlinear systems, Harris and Yu (2007) superimposes the nonlinear dynamic model to an additive linear or partially nonlinear disturbance. It is shown that a minimum variance feedback invariant exists and the minimum variance performance can be estimated from routine operating data. Continuing this idea, a semi-parametric method was proposed in Yu et al. (2008) to find the minimum variance lower bound for linear systems with valve stiction. In that work a local smoothing spline approximated the stiction nonlinearity, but given the complexity of the nonlinearity, and the heuristic approach, it must be expected that this strategy will fail for some cases.

In this paper, we will extend CPA to a important practical nonlinear problem, that of control valve stiction. The performance degradation due to stiction prompted Horch (1999), Choudhury et al. (2005, 2006), Thornhill and Horch (2007) to investigate ways to diagnose the issue, while Jelali (2008) and the references therein, attempt the estimation of parametric stiction models, but few have continued the analysis to quantify the performance loss. Consequently, rather than attempt to approximate the nonlinearity, the approach taken here is to develop an automated strategy that extracts the steady state periods resultant once the valve is stuck fast. Based

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on readily available input/output data collected during these periods, the minimum variance lower performance bound is computed in the standard manner. This gives an indication of how the control loop, even one suffering from stiction, would perform if it was serviced. Of course this presupposes that one is not allowed the luxury of setting the valve under consideration in manual, or one is charged with assessing many hundreds of operating loops.

The incentive to compute this control performance index is that it delivers a benchmark giving the engineer an idea of the improvement potential if the valve was to be serviced. For example, it could well be that of the hundreds of valves on site that required maintenance, the expected performance improvement, even if the stiction was entirely removed, would not be worth the time and effort.

The layout of the paper is as follows. In Section 2, the problem statement and model including valve stiction is introduced. Section 3 describes the methodology proposed in this paper to first extract, then check the validity of the steady-state linear periods. Section 4 illustrates by way of simulation the performance of the proposed methodology. This is followed by a discussion and conclusions highlighting both the limitations and potential of the method.

2. PROCESS DESCRIPTION

We assume the plant can be adequately modelled by

$$y_t = \frac{B(q^{-1})}{A(q^{-1})} q^{-b} u_t + d_t \quad (1)$$

where $A(q^{-1})$ and $B(q^{-1})$ are polynomials in the backshift operator q^{-1}, and b is the time delay of the system. The disturbance d_t is modelled as the output of a linear Autoregressive-Integrated-Moving-Average (ARIMA) filter driven by white noise a_t of zero mean and variance σ_a^2 of the form

$$d_t = \frac{\theta(q^{-1})}{\phi(q^{-1})\nabla^d} a_t = \psi(q^{-1}) a_t \quad (2)$$

where $\nabla \stackrel{\text{def}}{=} (1 - q^{-1})$ is the difference operator and d is a non-negative integer, typically less than 2. The polynomials $\theta(q^{-1})$ and $\phi(q^{-1})$ are monic and stable.

A common process nonlinearity afflicting control valves is known as ‘stiction’ which exhibits a range of of nonlinear behaviour including hysteresis, backslash and deadzones, both dynamic and static, and is summarised in de Wit et al. (1995), Lampaert et al. (2004).

Fig. 1 illustrates the typical sawtooth characteristic behaviour of a poorly maintained valve suffering from stick/slip friction using the stiction model developed in Choudhury et al. (2004). It is important to note that under normal industrial operations, the manipulated variable (MV) signal injected into the plant, here denoted as u^v, is unobservable.

We include the nonlinear stiction function $f(\cdot)$ (which represents the relationship between the manipulated variable and the actual valve output), into Eqn. 1 giving

$$y_t = \frac{B(q^{-1})}{A(q^{-1})} q^{-b} f(u_t) + d_t \quad (3)$$

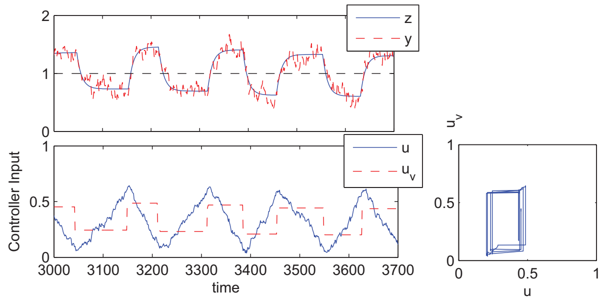

Fig. 1. The output of the controller, u, and the subsequent output of the control valve, u^v, suffering from slip/stick stiction.

Fig. 2 summarises the system considered in this paper. The intended controller output, u, (sometimes referred to as OP), is typically different from the actual valve position, u^v, due to the stiction. In the ideal case however, we can simply assume $u_t^v = f(u_t) = u_t$.

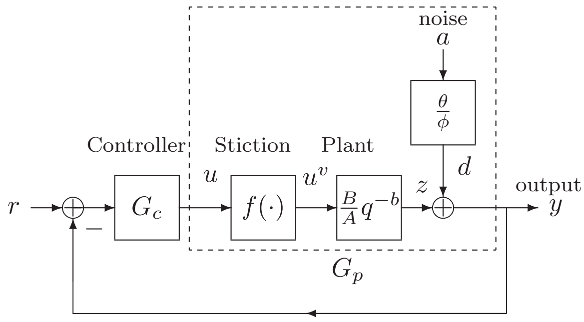

Fig. 2. Closed loop system with valve stiction under consideration

3. MINIMUM VARIANCE PERFORMANCE BOUNDS: VALVE STICTION CASES

The basis for minimum variance performance bounds was developed by Harris (1989) where it was was shown that the minimum variance performance bound for linear systems could be estimated from routine closed-loop data provided the process delay is known in advance. For the system described by Eqn. 1, the minimum variance performance lower bound is simply

$$\sigma_{MV}^2 = (1 + \varphi_1^2 + \cdots + \varphi_{b-1}^2)\sigma_a^2 \quad (4)$$

where the φ weights are the first $b-1$ impulse coefficients of the disturbance transfer function in Eqn. 2.

The minimum variance performance bounds for a class of nonlinear systems described by Eqn. 3 have been reported in Harris and Yu (2007) which used a nonlinear polynomial-AR or polynomial-ARX model to estimate the b-step ahead prediction. The drawback for this application is that it is difficult to find a general function to adequately approximate the valve stiction. Notwithstanding, the non-parametric spline method to approximate the nonlinearity proposed in Yu et al. (2008) partially overcomes the issue of modelling valve stiction/friction, but it too will fail for some cases.

In this paper, we propose a method to find the minimum variance performance bounds for valve stiction cases. Rather than trying to find a parametric or non-parametric function to approximate the nonlinear function as suggested in Yu et al. (2008), we will focus solely on the periods when we know, or at least suspect, that the system is operating in a linear regime. That way, we can simply ignore the now non-existent nonlinearity, and compute the minimum variance lower bound in the standard manner. The success of this strategy depends on how well we can establish that the system is behaving essentially as a linear system.

We can potentially ignore the effects of the nonlinearity by exploiting a unique characteristic of valve stiction. Due to the stick/slip friction, the times that the valve is stuck gives the system a chance to reach steady state and during these periods, we can use linear ARMA techniques to estimate the lower performance bound.

The key problem is how to identify the steady state periods from the closed loop output data. Our approach includes two parts. First we use a heuristic pattern method to select the periods of steady state in the observable time series y, and we validate this by employing a linearity test. Second, given possibly multiple segments of a linear time series, not necessarily contiguous, we can now fit a linear ARMA model and subsequently compute the minimum variance performance bound. The details of the methodology are discussed in the following sections.

3.1 Identifying steady-state periods

The presence of valve stiction induces a limit cycle with a characteristic triangular shape in the controller output as is shown in Fig. 1. This cycling is exacerbated by the integral component of the controller which eventually increases to such an extent that the stuck valve again moves. Unfortunately the valve moves too far, and the cycle begins again as demonstrated in Fig. 3.

Since the information of the actual valve output position, u^v, is not available for most industrial implementations, (if it was, we could simply use this series for the computation), the steady state periods must be identified from the data consisting solely of the process output y and controller output u.

Under the cycling conditions due to stiction, the scaled difference between u and y will describe a sawtooth trend as given in Fig. 4. The discontinuous turning points of the triangle wave indicate when the valve actually moves and it is these instances, (depicted as the vertical dashed and dotted lines) that we need to identify.

Given that most industrial plants have a stable low-pass frequency response that attenuates high frequency noise, and that the plant measurement is disturbed by d, it may be necessary to weight the subtraction to better highlight the trend. Fig. 4 actually trends $cu - y$ where the scale factor c is in this case 10.

After the periods of steady state are identified, an initial segment in each period will be discarded so that the previous input effects will be removed. Then subsequently

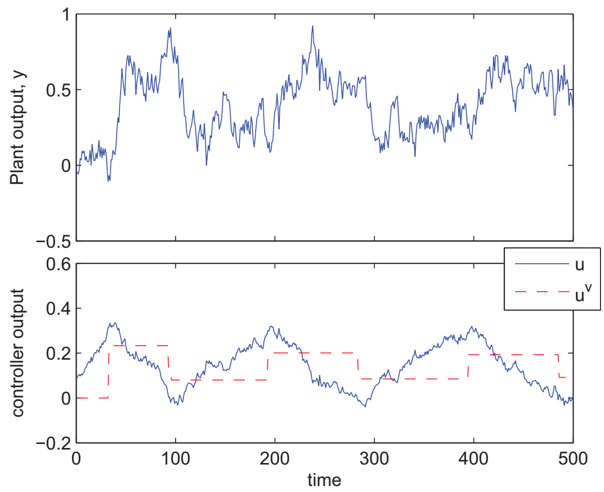

Fig. 3. The plant output, y, the controller output u, and the output of the valve suffering from stiction, u^v.

we can derive a minimum variance controller performance lower bound using these periods of data.

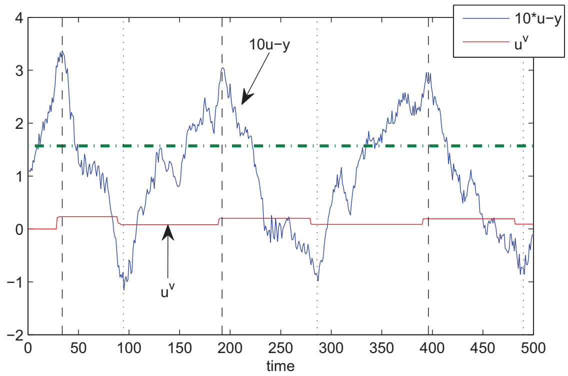

Fig. 4. Establishing the steady-state periods by computing $cu - y$.

An automated procedure to establish the stuck periods relies on reliably identifying the maxima and minima of the sawtooth shaped $cu - y$ trend in Fig. 4. First the times of the zero-crossings and their directions (falling, or raising edges) are established. Then, between each crossing instance, a search is made for the corresponding maximum or minimum.

Of course using such a heuristic approach, this simple algorithm is suspectable to false positives and correspondingly derives estimates of the steady-state periods shorter than the actual period. In cases of excessive suspected false crossings, standard techniques such as data smoothing or a Fourier identification of the dominant period could be applied to the noisy data series. However since these erroneous short periods will not be used for the minimum variance calculation anyway, they do not overly deteriorate the quality of the computed result. They do however, lower the efficiency of the data use.

3.2 Ensuring the removal of any nonlinearities

Notwithstanding the expectation that the valve stiction nonlinearity exhibits little memory, we need to be assured that the selected period is in fact linear. One way is to do this is to apply a statistical test of linearity proposed by Subba and Gabar (1980), Hinich (1982) and previously used in this context by Choudhury et al. (2004) and Yu et al. (2008). This test, known as the Hinich test, is both nonparametric and reasonably robust.

In the simulations subsequently presented in section 4 it was obvious that the periods were linear so the nonlinear test was not actually employed. However if one is still in doubt, Yu et al. (2008) illustrates how such a validation could be performed.

3.3 Establishing the limit cycle

The proposed strategy works best when the valve is stuck for relatively long periods allowing the system to reach steady state. That is, periods larger than about 10 dominant time constants since we discard the first 3–4 to allow the system to reach steady-state, and then use the remaining data for the ARMAX model identification. Consequently we desire that the period of oscillation due to the valve nonlinearity is long compared to the settling time of the compensated loop and therefore we need to *a priori* establish reasonable conditions when that is likely to occur.

From the literature, and our simulation experience detailed further in section 4, it is found that there are three main factors which will affect the period of oscillation, namely the tuning of the PI controller, the magnitude of the disturbance, and the valve characteristics of the valve stiction.

4. SIMULATION EXPERIMENTS

The purpose of this section is to demonstrate the proposed method for the minimum variance performance assessment for valve stiction cases. A second order single-input, single-output (SISO) system with time constants 10 and 2, and steady-state gain of 3 is sampled at $T_s = 1$ to give

$$G_p = \frac{B}{A} = \frac{0.04338 + 0.03755q^{-1}}{1 - 1.621q^{-1} + 0.6483q^{-2}} \tag{5}$$

with time delay $b = 4$ under feedback control with controller

$$G_c = \frac{0.11 - 0.1q^{-1}}{1 - q^{-1}} \tag{6}$$

was used for generating simulated data. An additive disturbance of

$$d_t = \frac{0.2a_t}{1 - 0.8q^{-1}} \tag{7}$$

where a_t is a sequence of independent and identically distributed Gaussian random variables with zero mean and nominal variance $\sigma_a^2 = 0.1$.

A data-driven model for valve stiction proposed by Choudhury et al. (2004) is used to simulate the valve stiction. The model is characterised by two parameters, s for the valve stickiness and j for the magnitude of the valve jump. The closed loop behaviour with various combinations of s and j are plotted in Fig. 5. Pure deadband occurs when $j = 0$, (b) represents the undershoot case of a sticky valve, $s < j$, (c) illustrates the pure stick-slip situation, $s = j$ and (d) shows the valve output overshooting case, $s < j$. Note that the oscillation period decreases while the j value increases.

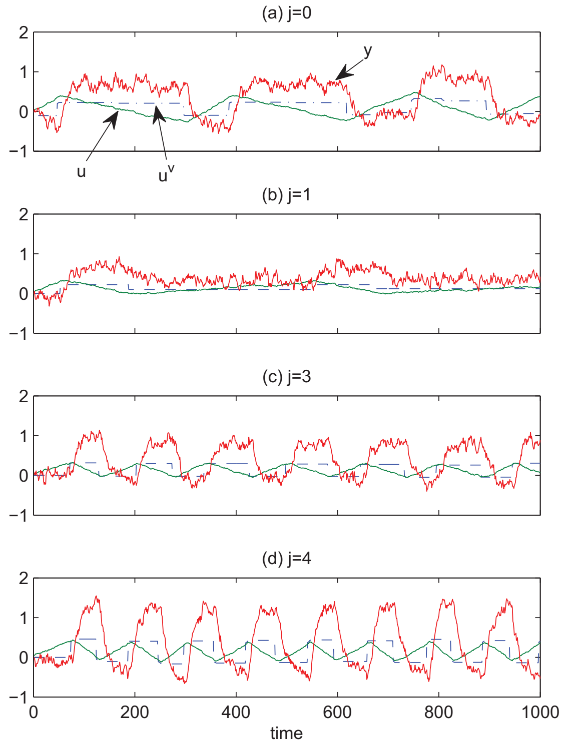

Fig. 5. The closed-loop behavior for $s = 3$ and with various values of j: (a) $j = 0$ (b) $j = 1$ (c) $j = 3$ (d) $j = 4$.

As noted in the pervious section, this strategy is reliant on relatively long periods when the valve is stuck. Given a fixed PI controller, we can vary the magnitude of the disturbance and the stiction jump/slip parameters, j, s and use a Monte-Carlo simulation to establish the largest period on average of the oscillation for each (σ_a^2, s, j) triplet. The resultant contour plots of periods are shown in Fig. 6.

In all cases we are most interested in the 'islands' of high periods apparent in all three examples given in Fig. 6.

Areas with periods less than about 100 are not interesting and are not plotted in Fig. 6. This is because since the plant in Fig. 6 has a dominant time constant of 10 sampled at 1, ten dominant time constants correspond to about 100 samples. We discard 30 to 40 samples to allow time for the system to reach steady-state, leaving a minimum of 60 samples in which to do the ARMA model identification. This data series length is about at the minimum recommended by Ljung (1987).

As expected the 'islands' of large periods occur when both the noise, σ_a^2, and jump parameters are not too big. This makes sense because if both s and j are zero, there is no stiction, and there is no self sustained oscillation due to the nonlinearity. Also for a given stiction, as the noise variance increases beyond the deadband limit, the valve will continually move, lowering, or completely eliminating, the potential steady-state periods.

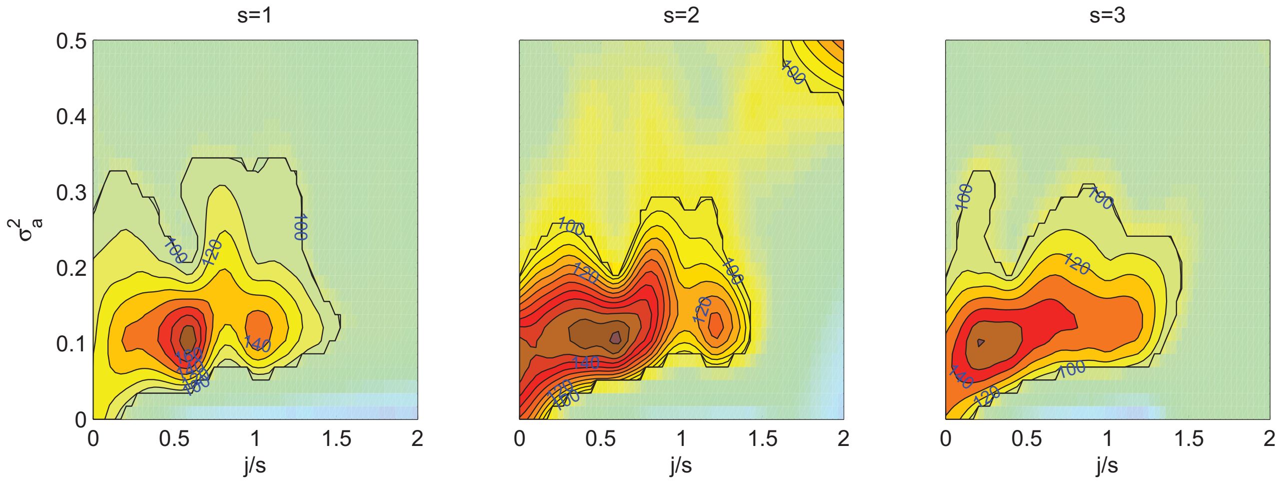

Fig. 6. The period of oscillation as a function stiction jump parameter j, and noise disturbance variance σ_a^2, at differing levels of stiction slip parameter s. Areas where the period is less than about 100 samples are not interesting for t his specific application because they are too short to perform a meaningful identification.

Due to the intractable nature of the nonlinearity, a Monte Carlo method is used to estimate the performance of the proposed strategy to estimate the minimum variance, σ_{MV}^2. 1000 observations generated from the valve stiction simulation are passed to the automated steady-state period identifier described in section 3.1 from which suitable periods are extracted. An ARMA model is fitted to the longest period from which σ_{MV}^2 is directly computed from the parametric model. This procedure is repeated 500 times.

The estimates of σ_{MV}^2 and associated uncertainties for different valve slip/jump conditions are shown in the comparative box plot in Fig. 7 again as in Fig. 5 for the case where $s = 3$ and various values for j. The true value of the minimum performance lower bound for this example is $\sigma_{MV}^2 = 9.2 \times 10^{-3}$.

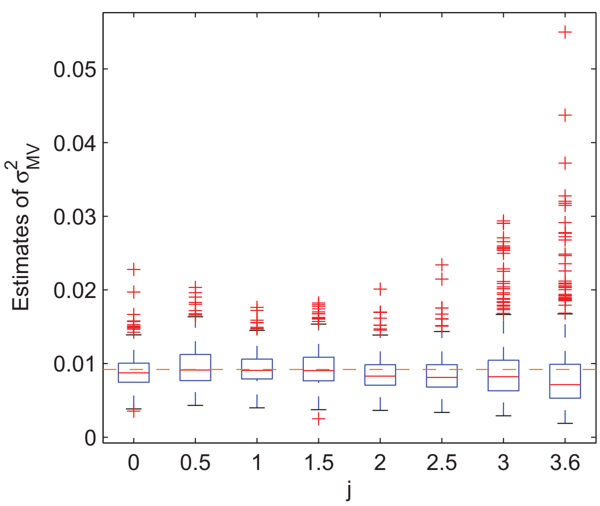

Fig. 7. Comparative box plots of the quality estimates of σ_{MV}^2 for $s = 3$ and for different j models. The horizontal dashed line is the true value of $\sigma_{MV}^2 = 9.2 \cdot 10^{-3}$.

5. DISCUSSION

The results from the numerical experiments to establish the minimum variance performance lower bound from normal operating data given in Fig. 7 show that the proposed strategy does reconstruct the correct σ_{MV}^2. Furthermore it is interesting to note that the quality of the estimate is best for the jump parameter $j \approx 1$, while for values smaller, and particularly larger, it begins to deteriorate. This is consistent with the results presented in Fig. 6 reinforcing the requirement to have reasonably long periods of steady-state to extract statistically significant results.

In the cases where the jump parameter j is larger than the slip s, we experience short periods of the stuck valve coupled with a comparatively large nonlinearity that contributes to the obvious deterioration in the confidence of the estimated minimum variance lower bound.

Similarly, if the zero-crossings are too frequent (and therefore the period available for steady-state consideration is too short compared to the anticipated dominant time constant), then we suggest that the strategy proposed in Yu et al. (2008) which uses smoothing splines to remove the nonlinearity might be more appropriate.

The proposed strategy has some limitations. First of all, as developed, we assume that the plant is stable, and reasonably well-damped. For type 1 plants with integrators, it is of course possible to differentiate the output. Furthermore, we assume that the dominant time constant is approximately known in order to discard the appropriate amount of data while waiting for steady-state. This is unlikely to be an overly onerous requirement for any processing plant. Finally we restrict our attention to those cases with moderate extent of stiction, since of course excessive stiction *must* be addressed, and minimal stiction would probably not be noticed anyway.

6. CONCLUSIONS

Valve stiction is a debilitating feature of many control loops that cannot, nor should not, be corrected by controller tuning. However given the time and energy required to service the valve, it may be prudent for the instrument engineer to first establish what the best controlled performance would be if the valve was serviced.

The strategy proposed in this paper establishes the minimum performance lower bound in the case of excessive valve stiction using only observable signals and estimates of the plant dominant time constants and plant delay. In the case of rapid oscillation in the limit cycle, it is possible to stitch the short periods together to build up enough input/output data to make a reasonable identification.

While the examples considered only nonlinearities introduced by valve stiction, this strategy will work for any system which reaches steady states and stays there for a while.

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