A Method for Automatic Detection of Controller Tuning Issues

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Abstract: A modern complex industrial process, such as petroleum refinery, petrochemical plant, pulp & paper process and power plant, usually include hundreds or thousands of control loops. It is a well-known fact that many controllers in a process plant are not tuned properly (Desborough and Miller, 2001). Badly tuned controllers would lead to loss in production as well as quality (Bialkowski, 1993; Ender, 1993). Therefore, it is necessary to detect the controllers that are poorly tuned and diagnose their behavior as sluggish or aggressive (oscillatory) and make the operators aware of it so that appropriate retuning actions can be initiated. There are methods in the literature for diagnosing aggressive (Thornhill and Horch, 2007) or sluggish (Hugglund, 1995; Kuehl and Horch, 2005) controller behavior. However, each of these methods has its own limitations and none of them addresses the improper controller tuning issues (sluggish and aggressive behavior) in a unified framework. Here, we have proposed a non-invasive method to automatically detect the badly tuned controller and identify its tuning issue as sluggish or aggressive directly from the routine plant operation data. The effectiveness of the proposed method is demonstrated on both simulated as well as industrial control loop examples.

Keywords: Process and Control Monitoring

1. INTRODUCTION

A modern complex industrial process, such as petroleum refinery, petrochemical plant, pulp & paper process and power plant, usually includes hundreds or thousands of control loops. Various studies indicate that a large percentage (between 66% to 80%) of industrial process controllers have performance problems (Desborough and Miller, 2001; Bialkowski, 1993). These problems arise due to various reasons including use of incorrect controller tuning parameters or inappropriate hardware during installation. Furthermore, the performance of a well-tuned control system can deteriorate over time due to various factors including changes in operating conditions and equipment wear and tear. Nonetheless, these poorly performing controllers has a detrimental effect on plant profitability, both in terms of increased product variance and increased settling time, which can lead to loss in production as well as quality. Therefore, there is a strong motivation to develop a method for automating detecting control loop tuning issues.

Hagglund (1999) proposed a method for detecting the sluggishness of controller tunings directly from routine operation data. It is based on idle index which relies on the length of reverse correlation between *CE* and *OP* in the transition region. Since, the Hagglund's method is based on the correlation of increments in *CE* and *OP*, it is highly sensitive to noise and it works well only with clean, noise free data. Therefore, the practical applicability of this method is very much limited and it is not at all suitable for real industrial dataset where the data are inherently noisy. To overcome this problem and to enable this method to deal with real, noisy data, Kuehl and Horch (2005) proposed a series of data pretreatment procedure which includes a set of filtering techniques, steady state detection and signal quantization. Each of these pretreatment procedures (e.g., filtering, steady state detection, signal quantization) requires a number of parameters, the values of which are to be chosen appropriately to obtain the desired results. An improper choice of any of these parameters may lead to misleading/ erroneous results. The choice of best set of parameter values depends heavily on nature of the signal. In fact, there is no unique set of parameter values that works well for all types of data. Therefore, finding the best set of parameter values for each signal is really a daunting task and demands sufficient domain/process knowledge. Therefore, the data pre-treatment procedures proposed by Kuehl and Horch (2005) to overcome the limitations of Hagglund's method is not ideally suited for the large scale industrial process involving thousands of closed loop controllers. A robust method which can efficiently handle real, noisy industrial data without the need of any pre-treatment is highly desirable as per as practical implementation is concerned. Furthermore, the method proposed by Hagglund (1999) and/or Kuehl and Horch (2005) cannot address all the controller tuning issues,

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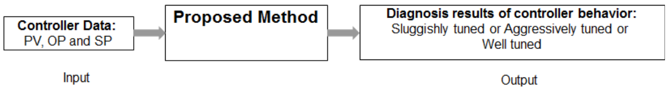
it can only detect whether a controller is tuned conservatively or not. Hence, there is a strong motivation for developing a single unified approach which can detect full range of controller tuning problems and diagnose them either as sluggish or aggressive behavior directly from the routine plant data.

In this paper we propose a novel method, which is able to automatically detect the badly tuned controller and identify its tuning issue as sluggish or aggressive directly from the routine plant operation data. Rest of the paper is organized as follows: the proposed method for detecting controller tuning issues is presented in section 2. The proposed method requires automatic detection of the steady state and transition regions in the controller time series data. In section 3, a novel and efficient technique for detecting the steady state and transition regions in the controller time series data is proposed. The efficacy of the proposed method for detecting controller tuning issues is demonstrated through various simulated and industrial control loop examples in Section 4.

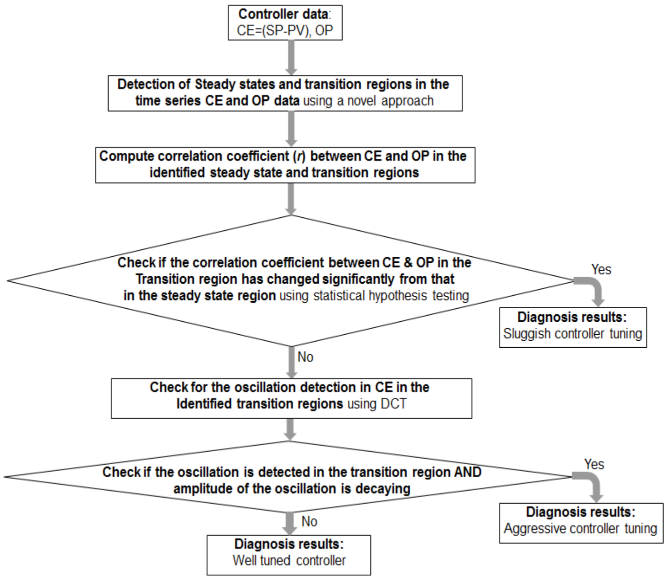
2. PROPOSED APPROACH FOR DETECTING CONTROLLER TUNING ISSUES

When a closed loop control system is at the steady state a strong correlation – either positive (in case of reverse acting controller) or negative (for direct acting controller) exists between the controller input i.e., Control Error (*CE* = *SP* – *MV*) and controller output (*OP*). The closed loop system undergoes through a transition in response to a step change in the set point (*SP*) or in load disturbance and ultimately settles down to a new steady state. The behavior of the system during this transition can be analyzed for detecting the controller tuning issues. If the controller is tuned sluggishly, the strong correlation (either positive or negative) that exists between controller input (*CE*) and output (*OP*) in the steady states is expected to break significantly during the transition periods. For the aggressively tuned controller, on the other hand, the transition regions would exhibit clear oscillatory behavior in both *CE* and *OP* with decaying oscillation amplitude. However, Presence of oscillation in the time series data cannot be used as a basis for the diagnosis of aggressive controller tuning, since several other problems – such as valve stiction, external disturbance can also lead to oscillation in *MV* and/or *OP* data. Hence, the presence of oscillation in the *MV* and/or *OP* signal does not necessarily indicate that the oscillation is due to the aggressive controller tuning. However, as discussed before, when a system undergoes transition in response to a step change in SP or load disturbance, the presence of aggressive controller tuning would result in clear oscillation with decaying amplitude in the transition region. Therefore, presence of oscillatory behavior with decaying amplitude in transition region of time series *CE* and/or *OP* data forms a strong basis for the diagnosis of aggressive controller tuning issue.

In this paper, we have proposed a unique approach for diagnosing both sluggish as well as aggressive controller behaviors in a unified framework. The proposed approach is depicted in Fig. 1. The input to the system is the routine time series operation data of a controller, i.e., *MV*, *OP* and *SP* data and the output is the diagnosis results of controller tuning problem (see Fig. 1a). The output could be sluggish or aggressive controller behavior or it could be well tuned controller. The major steps involved in the proposed method are shown in Fig. 1b.



(a)



(b)

Fig. 1(a). Input and output, and (b). Major steps in the proposed method.

In the proposed approach, first, the steady state and transition regions in the time series data are identified. For this we have proposed a novel steady state detection approach. The steady state detection method is discussed in the next section. After detecting the steady state regions, the transition regions are identified as the segments in the time series in between two steady states. The correlation coefficient (r) between *CE* and *OP* are computed in the identified steady state as well as in the transition regions. *CE* and *OP* would be strongly correlated in the identified steady state regions i.e., the value of correlation coefficient (r) would be positive (for reverse acting controllers) or negative (for direct acting controllers) at the steady states. A significant change (reversal) in correlation structure between *CE* and *OP* in the transition region compared to that in the steady state region is a clear indication of sluggish controller tuning. The sluggish controller behavior is diagnosed if the correlation coefficient (r) between *CE* and *OP* in the transition region differs significantly and becomes reverse from that in the steady state. To determine whether the correlation coefficient in the transition region has changed significantly from that in the steady state we use statistical hypothesis testing which is based on the p-value associated with the computed correlation coefficient (r) (Taylor, 1990). A low p-value ($p<0.01$) indicates that the correlation is statistically significant. If the slow control is not detected through the above procedure, then the identified transition segment in the time series data is further tested for the presence of oscillation. The *CE* data in the identified transition region is tested with auto-correlation based oscillation detection method (Thornhill *et al.* 2003). Aggressive controller tuning is diagnosed if the oscillation is detected in *CE* data and the amplitude of detected oscillation is decaying. Otherwise, the controller would be diagnosed as well tuned if neither sluggish nor aggressive behavior can be detected.

In this work, we propose a novel steady state detection method for identifying the steady state and transition regions automatically in the time series *CE* and *OP* data of control loop. The proposed steady state detection method is discussed next.

3. A NOVEL STEADY STATE DECTION METHOD

Most of the steady state detection methods (Narashiman et al. 1987; Cao and Rhinehart, 1995; Jiang et al. 2003) proposed in the literature are uni-variate in nature. Here, we have proposed a novel bivariate based steady state detection method that can identify the regions in the time series at which a closed loop control system is at the steady state by taking the time series data of both *CE* and *OP* together into the consideration.

In case of a PID controller Control Error (*CE*) and controller output (*OP*) are related through the following equation

$$OP(t) = K_c CE(t) + K_i \int_0^t CE(\tau)d\tau + K_d \frac{d}{dt} CE(t) \quad (1)$$

In Eq (1), K_c, K_i and K_d are proportional, integral and derivative gain respectively. The term t represents time or instantaneous time (the present) and τ is the variable of integration; takes on values from time 0 to the present t. In the regions where the closed loop system is at steady state both the magnitude of $CE(t)$ as well as changes in *CE* (ΔCE) become very small. Because of this, in the steady state regions, the term $\int_0^t CE(\tau)d\tau$ in Eq 1 does not vary much (stays nearly constant), also the derivative action (3rd term in Eq 1) becomes negligible. As a result of this, *CE* and *OP* become almost linearly correlated with a slope close to K_c in *CE - OP* space when the system is at steady state. Therefore, when time series *CE* and *OP* data are transformed into a new coordinate system, $x' - y'$ by rotating the original *CE – OP* coordinate system by an angle $\theta = \left(\tan^{-1}(K_c)\right)$ in anticlockwise direction (shown in Fig. 2) and a histogram of y' coordinate values of all the data points is obtained (see Fig 3), then the peaks in the histogram would typically correspond to the samples that are at the steady state regions while the transitions are typically represented by the valleys or flat regions in the histogram. Thus, the steady state region in bivariate *CE* and *OP* can be identified by finding a time-series segment in which the y' coordinate values lie within the peak region of the histogram (say, within 2 bins on both sides of a peak). This forms the basis of steady state detection in bivariate *CE-OP* data in this paper. The various steps involved in the proposed steady state detection method are presented in Fig. 4. Once the steady states regions are determined in the time series data, a transition region can be easily identified as the region that lies in between two steady states.

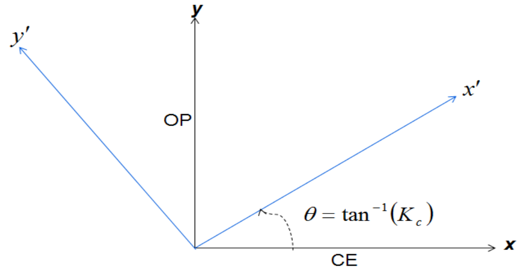


Fig. 2. Original and transformed coordinate system.

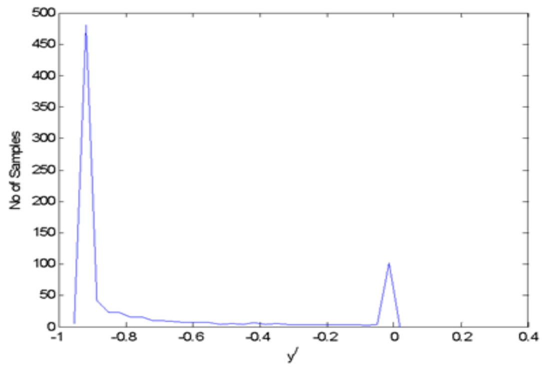


Fig. 3. Histogram of y' coordinate values.

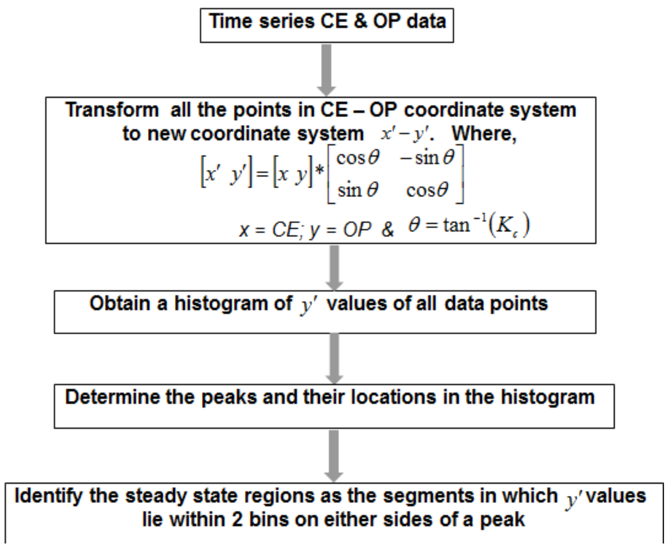


Fig. 4. Flow chart of proposed steady state detection method.

4. ILLUSTRATIVE EXAMPLES

This section presents some simulated as well as real industrial examples, where the proposed method for detecting controller tuning issues is demonstrated.

4.1 Simulated sluggishly tuned controller

First, the proposed method is applied to the simulated sluggishly tuned controller example reported in Kuehl and Horch (2005), wherein a simple process model described as $G(s) = \frac{1}{(s+1)^2}$ is perturbed with a single stepwise load disturbance of amplitude 1. White noise with a variance of 0.01 has been added to the disturbance. The process is controlled with a sluggishly tuned PI controller $\left(F(s) = K_c + K_i \frac{1}{s}\right)$ with K_c = 0.4 and K_i = 0.02. The *MV*, *SP* and *OP* data of this simulated loop are shown in Fig. 5. The results of the proposed method are summarized in Table 1.

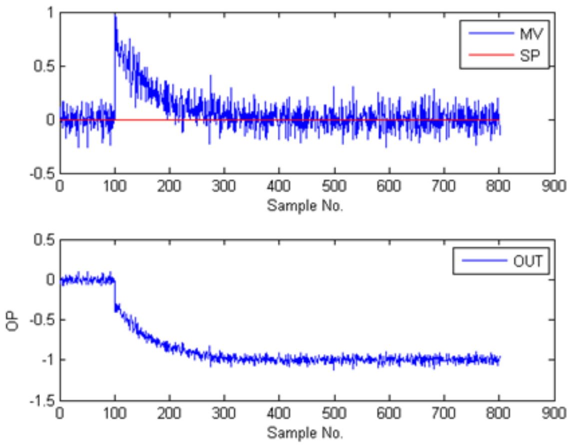


Fig. 5. Time series plot of *MV, SP* and *OP* data in the simulated sluggish controller example in Kuehl and Horch (2005).

It is quite clear that from the correlation coefficient (r) values and their associated p-values in the steady state and transition regions (see Table 1) that the strong positive correlation between *CE* and *OP* that exists in the steady states is completely broken and becomes reverse (negative) in the transition region. Hence, sluggish controller behavior can be successfully diagnosed through the proposed method. As mentioned in Kuehl and Horch (2005), Huglund's idle index based method fails here to detect the sluggish tuning issue in this example. Although, Kuehl and Horch (2005) succeeded to detect this sluggish tuning issue through a series of data pretreatment steps with proper choice of tuning parameters in each step. However, improper choice of tuning parameters in any of the pre-treatment steps may poetically lead to a misleading result.

Table 1. Results of the proposed method on the simulated sluggish controller in Kuehl and Horch (2005)

Identified steady state region 1 (SS1)	**Sample No 1-109**
Correlation coefficient (r) in SS1	0.9880
p-value of correlation in SS1	~ 0
Identified steady state region 2 (SS2)	**Sample No 247-801**
Correlation coefficient (r) in SS2	0.8522
p-value of correlation in SS2	~ 0
Identified Transition Region	**Sample No 109-247**
Correlation coefficient (r) in transition region	-0.6524
p-value of correlation in the transition region	~ 0

4.2 Simulated aggressively tuned controller

Next, the proposed method is applied to the same simple process as described in section 4.1. But unlike in section 4.1, the PI controller is now tuned aggressively with K_c = 2 and K_i = 1.5. A single stepwise load disturbance of amplitude 1 is added to the process while the variance of added white noise is 0.001. The *MV, SP* and *OP* data of this simulated loop are shown in Fig. 6. The results of the proposed method are summarized in Table 2.

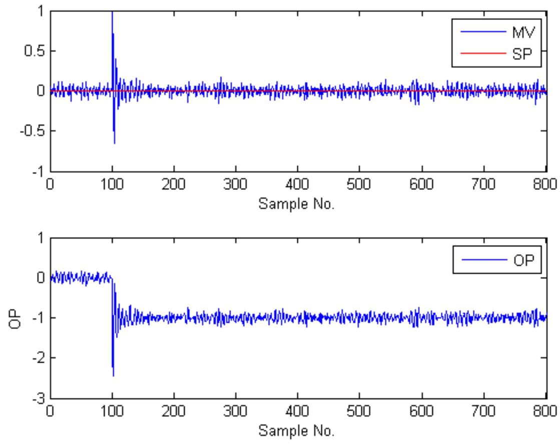


Fig. 6. Time series plot of *MV, SP* and *OP* data in the simulated aggressive controller.

It can be seen from the correlation coefficient (r) values and its associated p-values in the steady state and transition regions that the strong positive correlation between *CE* and *OP* that exists in the steady states is retained even in the transition region as well. Hence, sluggish controller behavior cannot be diagnosed through the proposed method. Therefore, *CE* data in the identified transition region is subsequently tested with DCT based oscillation detection method. Oscillation is detected in the transition region of *CE* and the period regularity of the detected oscillation is ~53%. Oscillation amplitude regularity measure also indicates that the amplitude of this oscillation is decaying since the amplitude irregularity of the detected oscillation is about 65%. Consequently, the controller can be correctly diagnosed as an aggressive one.

Table 2. Results of the proposed method on a simulated aggressive controller

Identified steady state region 1 (SS1)	Sample No 1-100
Correlation coefficient (r) in SS1	0.7291
p-value of correlation in SS1	~ 0
Identified steady state region 2 (SS2)	**Sample No 116-801**
Correlation coefficient (r) in SS2	0.7295
p-value of correlation in SS2	~ 0
Identified Transition Region	**Sample No 100-116**
Correlation coefficient (r) in transition region	0.6416
p-value of correlation in the transition region	0.0055
Oscillation in the transition region	Detected
Amplitude Irregularity of Oscillation in the transition region	64.65%

4.3 Simulated Well-tuned controller

Finally, the proposed method is applied to a simulated well-tuned controller. Here, the same simple process model as discussed above is used with a well-tuned PI controller. The controller parameters are K_c = 0.4 and K_i = 0.4. As mentioned in section 4.1, the process is perturbed with a single stepwise load disturbance of amplitude 1 and a white noise with a variance of 0.01 has been added to it. The *MV, SP* and *OP* data of this simulated loop are shown in Fig. 7. The results of the proposed method are summarized in Table 3.

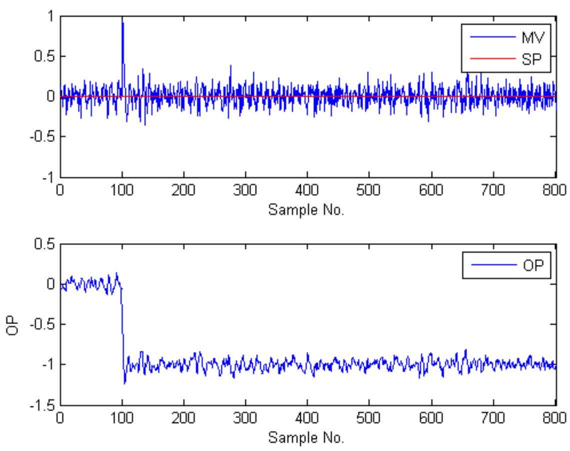


Fig. 7. Time series plot of *MV, SP* and *OP* data in the simulated well-tuned controller.

It can be seen from Table 3 that significant positive correlation exist between *CE* and *OP* in both the identified steady state regions since the correlation coefficient (r) values are positive with their associated p-values close to 0 (<0.01) in both the steady states. While a high p-value, close to 0.04 (>0.01), clearly indicates that the negative correlation (r = -0.6925) between *CE* and *OP* in the identified transition region is not statistically significant. Hence, the clear reversal of correlation between *CE* and *OP* cannot be observed in the transition region of this simulated data and consequently, the presence of sluggish controller tuning cannot be diagnosed. Then, the presence of oscillatory behavior in the identified transition region is checked. But the DCT based oscillation detection algorithm could not detect any oscillation in the transition region. Therefore, the presence of aggressive controller tuning is also ruled out. Finally, this control loop is correctly diagnosed as a well-tuned one since neither the presence of sluggish or not the aggressive tuning can be diagnosed.

Table 3. Results of the proposed method on a simulated well-tuned controller

Identified steady state region 1 (SS1)	Sample No 1-101
Correlation coefficient (r) in SS1	0.6282
p-value of correlation in SS1	~ 0
Identified steady state region 2 (SS2)	**Sample No 109-801**
Correlation coefficient (r) in SS2	0.3810
p-value of correlation in SS2	~ 0
Identified Transition Region	**Sample No 101-109**
Correlation coefficient (r) in transition region	-0.6925
p-value of correlation in the transition region	0.04
Oscillation in the transition region	Not detected

4.4 Industrial Data

The proposed method was tested on the data from three industrial control loops (c.f. Fig 8-10) known to have sluggish, aggressive and well-tuned behaviours respectively. In all the three cases, the proposed method was successful in correctly detecting the controller tuning issues. For example, as can be seen in the flow control loop data (c.f. Fig. 8) that the correlation between *CE* and *OP* is negative in the transition region (sample no 3284 to 3615), while the correlation between *CE* and *OP* is positive in the steady state region (sample no 1 to 3283). Therefore, clearly there is a reversal in correlation in the transition region w.r.t the steady state region. Thus, indicating the presence of sluggish controller tuning. On the other hand, in the level control loop (see Fig. 9) there are 4 identified transition regions (sample no 364 to 550, 674 to 850, 3540 to 3700, and 3871 to 4000) and correlation between *CE* and *OP* in all these transition regions remains negative as it is in the steady state regions. Furthermore, all the transitions are exhibiting oscillatory behavior with decaying amplitude. Hence, our proposed method successfully diagnoses the aggressive tuning issue for this level loop. Again, for the flow control loop shown in Fig. 10 there is no significant change in the *CE-OP* correlation in the identified transition region (sample no 1053 to 1486) as compared to that in the steady state region (sample no 1 to 1052) and the transition is non-oscillatory in nature. Hence, this flow loop is tuned properly, which can be diagnosed correctly by our method.

5. CONCLUSIONS

In this paper, we propose a novel non-invasive method to automatically detect the poorly tuned controllers in a process plant directly from the routine plant operation data and identify the tuning issue as sluggish or aggressive. By diagnosing and retuning these loops, control loop performance and the quality of the process can be improved significantly. Some of the novel features of the proposed methods are: (i) it can efficiently handle real, noisy data without the need of any data pretreatment – filtering, quantization etc. which are signal specific; (ii) full range of controller tuning issues (both sluggish as well as aggressive) can be automatically detected using a single unified approach directly from the routine time series data; (iii) The proposed method also incorporates a novel and efficient technique for detecting the steady state and transition regions in the bivariate *CE-OP* time series data of a controller as an integral part of it. The usefulness of the proposed method in detecting controller tuning issues has been demonstrated through various simulated and real industrial examples. However, there are some issues with proposed method - it detects control issues when there is a step change in load or *SP* in the time series data. Successful detection of controller tuning issues are not guaranteed if the change in load or *SP* happens in a non-stepwise manner. This method is generally robust to the presence noise in the data provided the magnitude of load or *SP* change is at least 4 times larger than standard deviation of noise. These issues would be addressed in our future work.

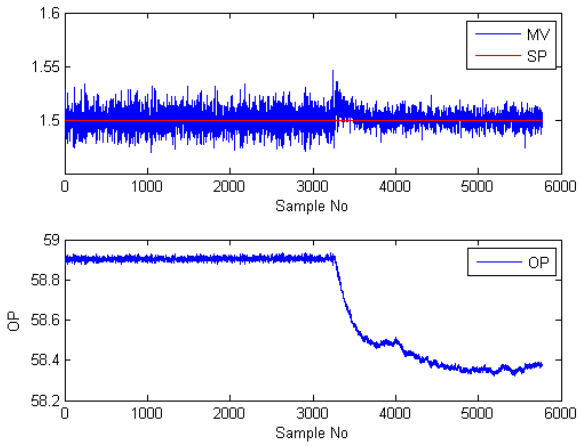


Fig. 8. Data from an industrial flow control loop known to have sluggish behavior.

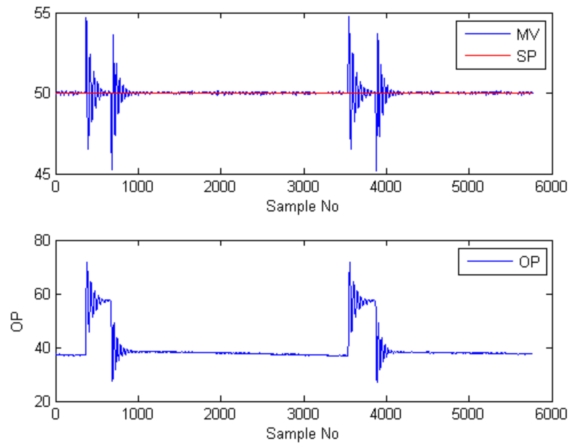


Fig. 9. Data from an industrial level control loop known to have aggressive behavior.

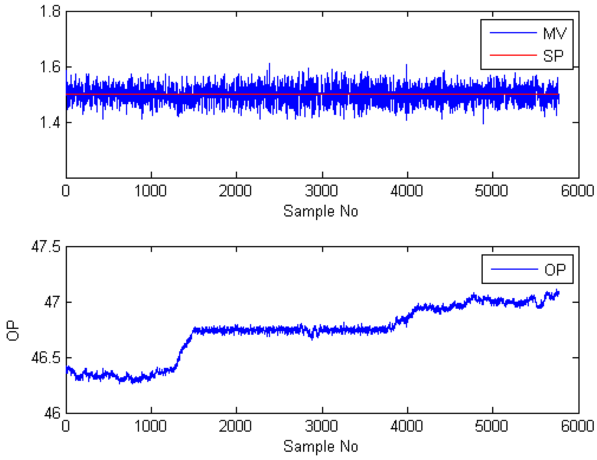


Fig. 10. Data from an industrial flow control loop known to have well-tuned behavior.

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