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Reinforcing Hurst Exponent with Oscillation Detection for Control Performance Analysis: An Industrial Application

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Abstract: Control performance assessment is one of the most important components of control assets monitoring. In the past decades, many different data-based approaches have been presented to assess control performance. Due to the high number of control loops for production industries, the methods requiring less parameters and less priori information became popular in industrial use. Detrended Fluctuation Analysis (DFA) is one of these methods, requiring only closed loop data and a pair of segment length to estimate Hurst exponent based control performance. However, the selection of segment lengths plays an important role in estimation, especially for oscillating control loops. In this paper, we have proposed an additional step (i.e. a step zero) to DFA to estimate control performance. This step uses an autocorrelation based and robust oscillation detection and characterization method to identify the oscillation period. Then, the calculated period is used to select the minimum segment length which leads more robust and precise estimation of control performance based on DFA. The proposed method has been applied and tested on several industrial control loops. The comparisons of the results between two approaches are given.

Keywords: control loop monitoring, control performance assessment (CPA), control loop oscillations, oscillation detection, Hurst exponent, detrended fluctutation analysis (DFA), minimum variance control (MVC)

1. INTRODUCTION

There has been a great interest in the monitoring of control performance as the number of industrial controllers increased rapidly. In general, a typical process plant has vast amount of control loops ranging from hundreds to thousands. Unfortunately, many of these control loops have not been tuned after commissioning. Although most of the plants have dedicated control engineers to maintain these control loops, according to a recent survey conducted among different plants in different industries and even in different continents, a typical control engineer is responsible for 450 control loops in average (Bauer et al., 2016). Industrial experience shows that each control loop requires approximately 1-2 hours of rigorous examination of manual work by a control engineer. In most of the cases, only trending the process data is not enough. Control engineers might need to do some tests to see if the control loop, for example, is able to track the set-point changes or robust to disturbances. Considering the number of components in a typical control loop (control element, controller, transmitter, process etc.), it can be clearly said that assessing control performance is the fundamental need but it does not solve the problem by itself. Besides, diagnostics of low performance plays an important role; since control engineers need to know the root-cause before preparing to fix the low performance. The most common reasons of low control performance in process industries are inappropriate controller tuning, inappropriate control structure design, control valve problems (corrosion, wear, stiction etc.), process dynamics, sensor faults, changing process gains, interactions between loops (Blevins, 2012). Unfortunately, some of these problems reveal themselves in different shape of fingerprints. For example, control valve problems and inappropriate controller tunings reveal themselves as oscillations in process data and in many cases, it is not easy to differentiate them easily by visual inspection (Jelali, 2013). Then, 1-2 hours of examination becomes days or even months for average 450 loops for a control engineer. This clearly states the need of robust, non-destructive and practical performance assessment methods.

Fortunately, the first studies about control performance assessment have been started quite earlier. The most fundamental assessment strategy is to compare the actual performance with a benchmark. Hugo (2001) lists the possible benchmarks as: perfect control (exactly zero variance in control output), best possible non-linear control, minimum variance control, best possible MPC control, best possible PID control and open loop control. Among all, in the process control community, the most popular benchmark is minimum variance control (MVC). It was

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first developed by Åström (1970) as an optimal control solution. Later, Harris (1989) developed this idea and used it as a benchmark for single-input single-output (SISO) controllers. Shortly after that, Desborough and Harris (1992) improved the idea and presented how to assess the performance of univariate feedback control. Ever since that, the method became like an industrial standard to measure the base layer control performance. There are several features of this method which led it to become popular. First, it does not require any plant tests. In other words, routine closed loop process data is enough. Second, the calculated performance index is bounded between 0 and 1. When the index gets closer to 1, it means that the actual performance is close to that of theoretical minimum variance controller. This feature also makes it easier to compare performances of different controllers. Third, it is easy to calculate and does not require much priori information, only process delay is enough. Fourth and final is that, there are not many parameters to be chosen, only the order of ARX model is enough, which is also quite easy to determine.

There are many different and successful applications of the study presented by Desborough and Harris (1992). The most-known application is conducted by Paulonis and Cox (2003) covering 14000 PID controllers in 40 plants at 9 sites worldwide. Another interesting application is implemented by Torres et al. (2006) covering 700 control loops belonging to 12 different companies (petrochemical, pulp and paper, cement, chemical, steel and mining). These applications showed how the work of Desborough and Harris (1992) is robust and easy to estimate the performance of industrial controllers. Despite these successful applications, it is obvious that in many cases, time delays of processes are not readily available (Jelali, 2006). Even though there are many different methods to estimate the time delays of processes such as presented by Bjorklund and Ljung (2003), true process delay estimation is not a trivial task.

A relatively recent study published by Srinivasan et al. (2012) have presented a different approach to this problem. They have used Hurst exponent estimated by detrended fluctuation analysis (DFA), which is a well-known index in fractal analysis, to assess the control performance without any priori information. Similar to MVC based control performance assessment, DFA utilizes closed loop operating data. Hurst exponent of that data is calculated with a predefined minimum and maximum segment length. Then, calculated Hurst exponent is transformed into controller performance index with a certain correlation. Srinivasan et al. (2012) showed that DFA based control performance assessment provides almost same results with MVC based assessment along with no requirement of defining the time delay of the process. This makes DFA easier to apply for many controllers and reduces the priori requirements only to parameter selection, the minimum and maximum segment lengths. Especially in case of oscillatory process data, DFA based performance assessment is known to be more sensitive to segment length selection (Srinivasan et al., 2012).

The motivation of this paper is to increase the robustness of DFA based performance assessment. For that purpose, we propose an additional step, a step zero, to DFA calculation steps to choose the minimum segment length accordingly. In step zero, an oscillation detection method, developed originally by Thornhill et al. (2003), is applied to the closed loop controller data to check for oscillation and if any, to determine its period. Then, the estimated period and the regularity of the oscillation are used to define the optimal minimum segment size of the DFA. This provides significant robustness to DFA based performance assessment. With this improvement, the proposed method can be fully automated without any concerns of sensitivity.

The outline of the paper is as follows. In Section 2.1, a brief introduction to Hurst Exponent and DFA is given. Then, in Section 2.2, the use of DFA in performance assessment is described. Later, Section 2.3 explains the difficulties of estimating DFA based performance in the existence of oscillations. After that, in Section 2.4, the oscillation detection method introduced as the step zero is described. Then, Section 3.1 presents our modified approach to estimate DFA based control performance. Finally in Section 3.2, the results of the application to real industrial control loop data are given.

2. PERFORMANCE ASSESSMENT AND OSCILLATION DETECTION

2.1 A Review of Hurst Exponent and Detrended Fluctuation Analysis (DFA)

Hurst exponent is widely used as a metric to measure the long-term memory of time series. It was first developed by Hurst (1951) as an outcome of a project of determining the optimum dam size of Nile river. Later, it became one of the fundamental methods of fractal geometry. There have been many successful applications of Hurst exponent in stock market analysis (Carbone et al., 2004; Matos et al., 2008; Bui and Ślepaczuk, 2022), dam construction (Hurst, 1951; Li et al., 2015), meteorology (Rehman and Siddiqi, 2009; Chandrasekaran et al., 2019; Fu et al., 2022), material science (Wawszczak, 2005; Martinez et al., 2013; Duan et al., 2022), bio-statistics and bio-engineering (Peng et al., 1994; Chen et al., 2013; Diógenes Pinto et al., 2022).

In fractal analysis, a self-similar process holds $y_t(k) \equiv a^\alpha y(k/a)$, where a is the scaling factor of x-axis, and a^α is the scaling factor of y-axis. Then, the exponent α is called as the self-similarity parameter or Hurst exponent (Srinivasan et al., 2012). There are several methods to estimate α, such as rescaled range (R/S) analysis (Mandelbrot and Wallis, 1968), periodogram regression (Geweke and Porter-Hudak, 1983), wavelet analysis (Simonsen et al., 1998) and detrended fluctuation analysis (DFA) (Peng et al., 1992). In this paper, DFA is used to estimate α. The most crucial property of α, which is also utilized in control performance assessment, is:

- $\alpha < 0.5 \rightarrow$ the data is anti-correlated
- $\alpha \simeq 0.5 \rightarrow$ the data is uncorrelated (white noise)
- $\alpha > 0.5 \rightarrow$ the data is correlated
- $\alpha \simeq 1.0 \rightarrow$ the data is pink noise
- $\alpha > 1.0 \rightarrow$ the data is non-stationary
- $\alpha \simeq 1.5 \rightarrow$ the data is Brownian noise

Having this property of α, it becomes possible to measure the stationarity of the signals. Peng et al. (1992) described the steps to estimate α with DFA as:

(1) Given signal y_t is mapped to a self-similar process $Y(k)$,

$$Y(k) = \sum_{i=0}^{k-1} (y_t(i) - \bar{y}), \tag{1}$$

where $\bar{y}$ is the mean of y_t, $k = (0, 1, ..., N-1)$ and N being the total number of samples.

(2) The integrated time series in Eq. 1 is divided into segments of equal length n.

(3) For each segment, a linear least squares fit is applied.

(4) Each segment is detrended with the linear fit obtained in step 3, where $Y_n(k)$ becomes the y-coordinate of the linear fit.

(5) The root-mean-square (RMS) fluctuation of the integrated and segmented data is calculated,

$$F(n) = \sqrt{\frac{1}{N} \times \sum_{k=0}^{N-1} (Y(k) - Y_n(k))^2}, \tag{2}$$

where $F(n)$ is the RMS value for segment size of n.

(6) Steps from 2 to 5 are repeated for different segment sizes of $n = (S_{\min}, S_{\min}+1, ..., S_{\max}-1, S_{\max})$ where $S_{\min}$ is minimum and $S_{\max}$ is maximum segment length.

(7) The log-log plot of the root-mean-square $F(n)$ vs. the segment size n (also known as DFA plot) is expected to yield a straight line. The slope of that line is the Hurst exponent, α.

2.2 *Use Hurst Exponent for Performance Assessment*

DFA is a method easy to apply and interpret for estimating Hurst exponent. Later, the study of Srinivasan et al. (2012) showed that there is a strong correlation of Hurst exponent with the control performance. In their work, N being the number of the total samples, it is proposed to choose $S_{\min} = 10$ and $S_{\max} = N/4$. Then, based on the estimated Hurst exponent α, they have proposed a performance measure similar to MVC benchmark, bounded between 0-1. In the work of Desborough and Harris (1992), it was stated that as the performance index gets closer to 1, the controller can be said to be close to MVC benchmark. Similar to MVC, DFA based performance CPI (controller performance index) was defined as (Srinivasan et al., 2012):

$$CPI = \begin{cases} 2\alpha, & \text{if } \alpha \leq 0.5, \\ 1.5 - \alpha, & \text{if } \alpha > 0.5. \end{cases} \tag{3}$$

Later, this idea was applied to set-point tracking aimed PID controllers by Pillay and Govender (2014). In their approach, the control error signal has been used to estimate the Hurst exponent. Several simulation examples were provided under minimum variance control, sluggish control and oscillatory control.

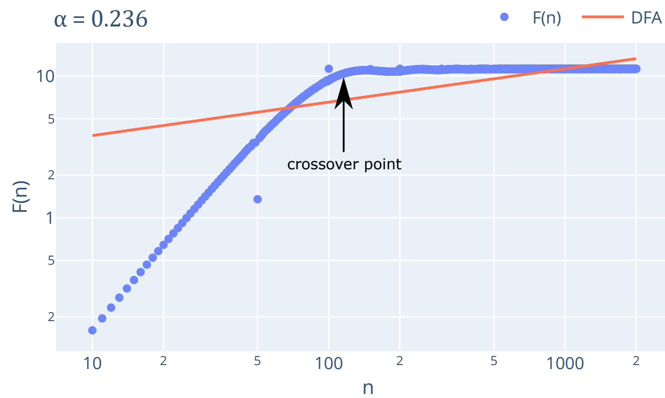

Fig. 1. Sinusoidal Signal with Period of 100 samples/cycle ($S_{\max} = 2000$)

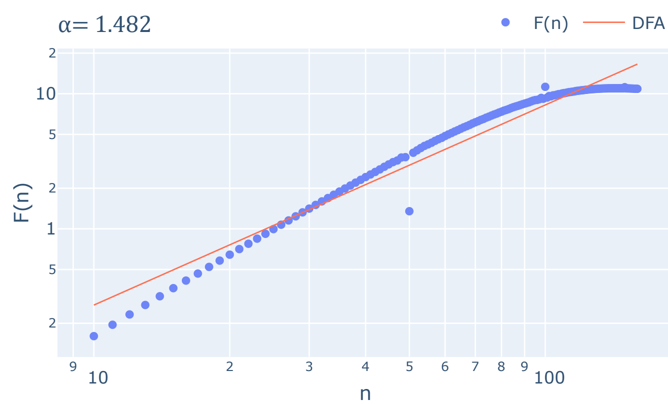

Fig. 2. Sinusoidal Signal with Period of 100 samples/cycle ($S_{\max} = 160$)

2.3 *Crossover Phenomena of DFA and Its Effect on Performance Assessment*

Despite the fact that DFA based Hurst exponent provides a performance measure aligned with MVC benchmark, the selection of $S_{\min}$ and $S_{\max}$ is quite important. Hu et al. (2001) presented an excellent work discussing the effects of different trends on DFA. They have applied DFA to different signals and showed the trends of the RMS fluctuations. One observed phenomena is the crossover. Let's consider a pure sinusoidal signal with a period of 100 samples/cycle and 8000 data points, $y(t) = \sin(2\pi \times 0.01 \times t)$. Its DFA plot is given in Fig. 1.

It is quite obvious that the linear trend of DFA plot starts to bend at a certain point close to the oscillation period of 100 samples/cycle. This point is called as the *crossover point* (Hu et al., 2001). The importance of crossover is that the x-coordinate of this point dominates the linear fit and as a result, the Hurst exponent estimation. Let's see the sensitivity of the segment size on the Hurst exponent by decreasing $S_{\max}$ to 160, a value close to the oscillation period of the signal. The estimated Hurst exponent for this DFA (Fig. 2) becomes 1.482. If this signal was a control signal and analyzed with the method proposed by Srinivasan et al. (2012) and also described in Section 2.1, CPI would be calculated as 0.472 for $S_{\max} = 2000$, and 0.018 for $S_{\max} = 160$, even though the signal is identical after 160 samples.

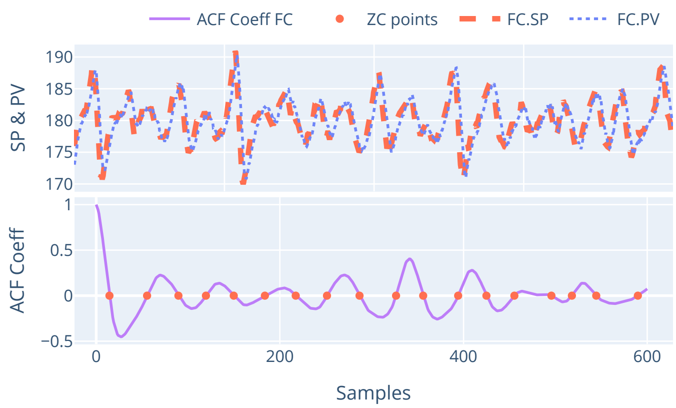

Fig. 3. Process Trend and Control Error Autocorrelation Function of the Industrial Flow Controller

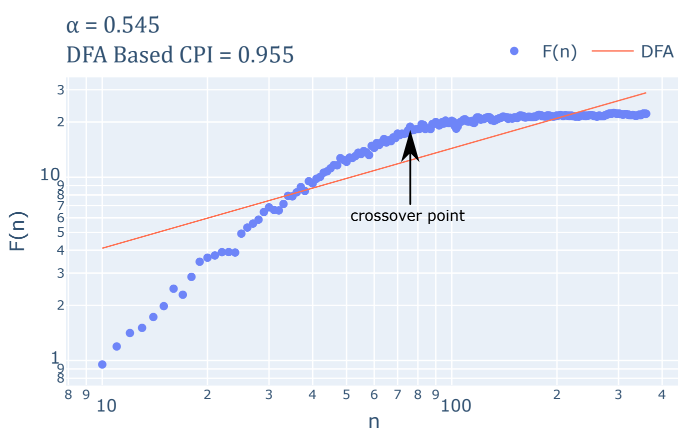

Fig. 4. DFA Plot for Industrial Flow Controller, $S_{\min}, S_{\max} = 10, 360$

It is also worth to display the crossover phenomena in an industrial controller. Here, we use a dataset of a flow controller having 1440 sample points from a Neste refinery. The controller is known to be suffering from the aggressive tuning of its master controller. Fig. 3 shows the process value (FC.PV), set-point (FC.SP) and its autocorrelation function (ACF) to better illustrate its oscillation profile. ZC stands for zero-crossing point, which will be discussed later in Section 2.4. The conventional MVC based CPI estimation presented by Desborough and Harris (1992) yields 0.26 for this particular controller, a poor performing controller as expected. On the other hand, DFA based CPI presented by Srinivasan et al. (2012) yields 0.96, an excellent performing controller. When the DFA plot given in Fig. 4 is analyzed, it is seen that due to the oscillating behaviour of the signal, the crossover phenomena takes place and affects the slope of the linear fit, and eventually DFA based CPI estimation. In many industrial applications, CPI is the first and most fundamental indicator of control performance. Therefore, the use of DFA based CPI without any optimal selection of segment length can be misleading in case of oscillating control loops.

2.4 Characterization of Oscillation for Optimal Segment Size Selection

In control loops, oscillations are mainly due to inappropriate controller tuning, control valve stiction, external disturbances and process interactions (Jelali, 2013). Therefore, it is clear that they have negative effect on control performance as partly seen in Section 2.3. There are several methods available in literature to detect the oscillations in control loops. Excellent reviews of the available oscillation detection methods have been presented by Ordys et al. (2006); Jelali (2013). Moreover, a successful implementation of some of the oscillation detection methods to a refinery unit has been presented by Yağcı (2016); Kuşoğlu and Yağcı (2017). The advantages and disadvantages of using different methods are beyond the scope of this paper. However, for the particular purpose of selecting the optimal segment length for DFA, an auto-correlation function (ACF) based method presented by Thornhill et al. (2003) is one of the most robust techniques proposed. The idea in this method is to check if the ACF of control error signal is regular. This is done by first identifying the zero-crossing points of the ACF, and then checking if they are regularly distributed statistically. The half period between each zero-crossing is denoted Tp_n and the average period $\bar{T_p}$ is estimated as

$$\bar{T_p} = \frac{2}{N-1}\sum_{n=1}^{N-1} Tp_n, \quad (4)$$

where N stands for number of zero-crossings. The standard deviation of the average period is calculated according

$$\sigma_{T_p} = 2 \times \sigma_{intervals}. \quad (5)$$

Finally, the regularity of ACF is tested using

$$R = \frac{\bar{T_p}}{3 \times \sigma_{T_p}}, \quad (6)$$

where R stands for the regularity of ACF and values greater than 1 statistically indicate a strong oscillation with a mean period of $\bar{T_p}$. Here, we use this technique to identify the mean oscillation period of the signal under interest. As described earlier in Section 2.3, the oscillation period of the signal is very close to the crossover point. Therefore, the minimum segment size can be selected accordingly to incorporate the oscillating dynamics into DFA plot.

3. PROPOSED APPLICATION AND RESULTS

3.1 Modified DFA Based Performance Assessment

We propose to insert one additional step in the very beginning of the DFA steps given in Section 2.1 as step zero, where the mean oscillation period ($\bar{T_p}$) and the regularity of ACF (R) are calculated first with the method presented by Thornhill et al. (2003), also explained in Section 2.4. Then, the minimum segment size ($S_{\min}$) can be selected such that

$$S_{\min} = \begin{cases} \bar{T_p} \times 1.1, & \text{if } R \geq 0.5, \\ 10, & \text{else.} \end{cases} \quad (7)$$

The reasoning of the parameters in Eq. 7 are as follows: (1) It is a known fact that the intermittent and/or multiple period of oscillations destroy the ACF pattern. In such

Table 1. Metrics for Flow Controller

	CPI (MVC)	Hurst Exp. (α)	CPI (DFA)	$S_{\min}$ $S_{\max}$	$\bar{T}_p$	R
Original Approach	0.26	0.55	0.95	10-360	68	3.57
Modified Approach		0.09	0.18	75-360		

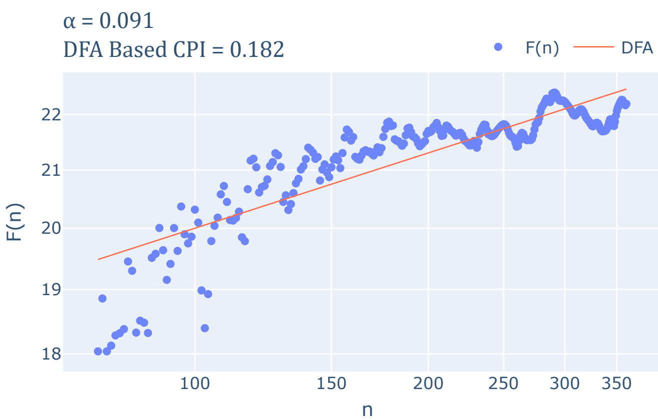

Fig. 5. Modified DFA Plot for Industrial Flow Controller, $S_{\min}, S_{\max} = 75, 360$

cases, the ACF looks regular by visual inspection, however R might be less than the original proposed limit of 1. To account for this fact, R is lowered to 0.5. In other words, weaker or multiple period oscillations are also taken into account in $\bar{T}_p$ calculation. (2) During tests, it has been observed that the crossover point is slightly ahead of the identified mean oscillation period $\bar{T}_p$. The use of exact $\bar{T}_p$ leaded DFA to include the RMS values before the crossover point. Since, in many cases, the slope of the DFA plot before the crossover point tends to be greater than zero, it eventually affects the overall Hurst exponent estimation and gives misleading results.

Below shows the summary of our approach:

(0) $S_{\min}$ *selection*: Calculate ACF of the control error signal and apply Eq. 4, 5 and 6 described in Section 2.4. Choose $S_{\min}$ using Eq. 7 desribed in Section 3.1.

(1-7) *DFA*: Apply regular DFA steps 1-7 described in Section 2.1 with $S_{\min}$ obtained in step zero and $S_{\max} = N/4$, where N is the number of samples.

(8) *DFA based CPI*: Apply Eq. 3 described in Section 2.2.

3.2 Results of the Application to Industrial Process Data

The suggested procedure has been successfully applied and tested on several different controllers in the same plant. To be consistent with the earlier examples, only the results of the already mentioned flow controller is given. As Fig. 5 shows, the linear fit of DFA plot leads reasonable CPI estimation, since the crossover point is out of the segment size range. In addition, the comparison between the original approach vs. the modified approach are given in Table 1. With our modified approach, DFA based CPI gives more consistent results with MVC based CPI.

As the crossover point behaves like a breaking or bending point of linear trend of DFA plot, it is also possible to utilize piecewise linear fitting to DFA as shown in Fig. 6 for the same industrial control loop. Defining two line segments for DFA plot, piecewise linear fitting identifies the break point as 67.5, which is very close to 68.1, the mean period $\bar{T}_p$ calculated by ACF regularity method. In addition, with piecewise linear fitting, the Hurst exponent calculated by the proposed method (for line segment 2) $\alpha_2 = 0.094 \approx 0.091$, which is calculated by the additional oscillation detection step. As a future work, the crossover phenomena of DFA can be used as an oscillation detection and characterization technique.

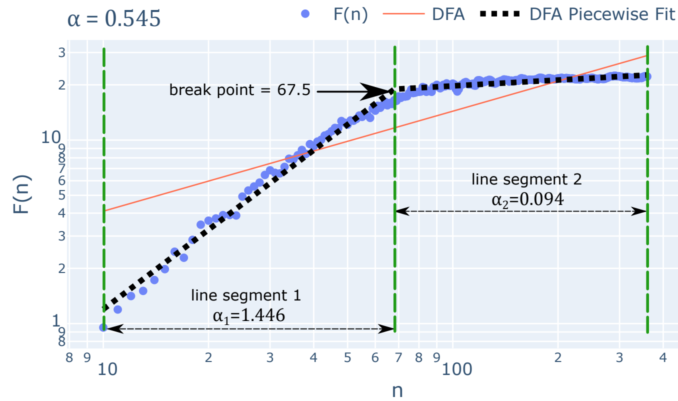

Fig. 6. Piecewise DFA Plot for Industrial Flow Controller

4. CONCLUSIONS

Industries have vast amount of control loops which require automated methods to analyze the control loops. This brings the need of robust and easy to apply control performance assessment methods. DFA based CPI estimation is one of the most promising methods. In contrast to MVC based CPI estimation, DFA based CPI estimation does not require the process delay. However, the segment size selection is sensitive to the datasets having oscillations, because of the fact that oscillations in control loops lead to the crossover effect on DFA plots. This results in misleading CPI estimations if DFA is used. In this study, we propose an additional step to DFA steps. This additional step utilizes a robust oscillation detection method and automatizes the segment length selection of DFA algorithm. With our modified approach, it is possible to fully automatize the CPI estimation without any concerns of reliability and robustness. In our study, simulated signal and also real process data collected from a refinery unit are used to show the effectiveness of the modified approach. The results show the increased robustness of modified approach in control performance assessment.

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