Dynamic Analysis and Monitoring of Process Control Loops

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Abstract

Dynamic analysis and monitoring is of great importance in industrial process plant. Very often, a qualitative analysis of process data is enough to analyze the situation of the plant. This paper introduces a methodology to analyze qualitative trend of time series data at first. Based on the methodology, a method to diagnose a control valve in a process control loop is introduced. The proposed diagnosis method is successfully applied to several data sets in industrial chemical processes.

1. Introduction

Monitoring of process control loops is a computer aided task based on the online analysis of process time series data. For the analysis of time series data, many kinds of methods have been developed and used. Typical examples of the methods are spectral analysis, ARMA methodologies and Kalman filters. Among various methods, simple trend analysis is useful in various applications such as the monitoring of process plants.

Dash *et al.* proposed an interval-halving framework to automatically identify the qualitative shapes of sensor trends [1]. This method is based on a polynomial-fit and iteratively halving its approximation interval. It is useful for offline analysis, but it cannot be used online. Charbonnier *et al.* proposed a methodology to extract online temporal trends from a time series [2]. They used the method to several applications such as alarm management in intensive care units, food process monitoring, and abnormal situation management in a simple process simulation.

In this paper, a method of qualitative trend analysis for two variables time series data is described at first [3]. Based on this qualitative trend analysis method, a method of dynamic analysis and monitoring control loops is shown [4]. Then, application results of the method to several industrial plants are shown in detail. The result shows effectiveness of the method as a monitoring method of process control loops.

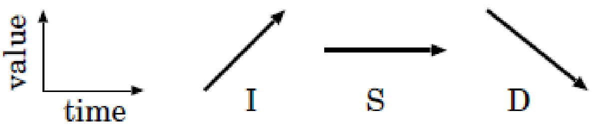

Fig. 1: Symbolic representation of a time series

2. Description of Qualitative Trend

2.1 Qualitative Trend

Trends or shapes of a time series signal can be qualitatively represented as a sequence of symbolic values. Simplest representation is using three symbols: increasing (I), steady (S), and decreasing (D). Figure 1 shows these three primitives in a time value plane. Alternatively, three primitives plus (+), zero (0) and minus (−) are used, corresponding to the signs of their respective derivatives. Although, more complex representation using second derivative is also proposed, only the three symbols representation is used in this paper.

Once a time series data is represented in a sequence of qualitative symbols, many trend analysis problems will be solved effectively. For example, fault diagnosis problem of process systems comes down to a problem of a simple symbolic pattern matching between the current trend and abnormal trends. Then various kinds of pattern matching methods can be used for further analysis.

2.3 Qualitative Movements

For the analysis of time series signals it is often useful to consider two variables simultaneously in a u - y plane. The time axis is not shown explicitly in that plane, but it corresponds to the movement of the behavior.

To represent qualitative movement in a u - y plane, a combination of the three qualitative primitives for each variable is introduced. As shown in Fig. 2, eight symbols can be defined to represent qualitative movement. Other than these eight symbols, SS can also be used for a symbol without any movement. Movement in a u- y

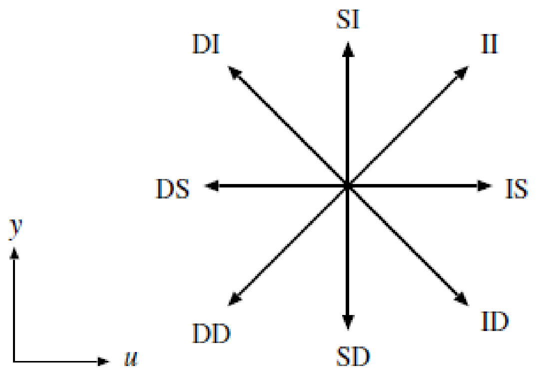

Fig. 2: Qualitative movements in *u*-*y* plane

plane can be represented qualitatively using these nine symbols [3].

A sequence of these symbols represents a movement pattern in the plane. For example, (IS SD DS SI) represents a clockwise rectangular movement. In the sequence of movements, similar movements are combined to form episodes. For example, (IS IS SI SI SI) is equivalent to (IS2 SI3). More sophisticated procedure to extract qualitative movement patterns is investigated [3]. For the analysis of noisy signal, these kinds of method will be required.

Dynamic analysis of a two variables system can be qualitatively analyzed by using this qualitative movement representation. As an example of the application of this representation to an industrial problem, diagnosis of process control valves will be described in the next section.

2.2 Implementation

For the implementation of the method to noisy data, preprocessing of time series is required before symbolizing the data [3]. The proposed procedure of the preprocessing is given below:

(a) Temporal Segmentation; A univariate time series is splitting into successive line segments. Parameter identification is based on the linear least-square method. The detection whether the linear approximation is acceptable or not is based on the cumulative sum (cusum).
(b) Classification of Segments; Temporal patterns are classified into the following six classes: Steady, Increase, Decrease, Positive Step, Negative Step and Transient.
(c) Aggregation of Segments; After the classification of each time segment, if possible, consecutive classes of the shapes are aggregated to abstract temporal patterns.

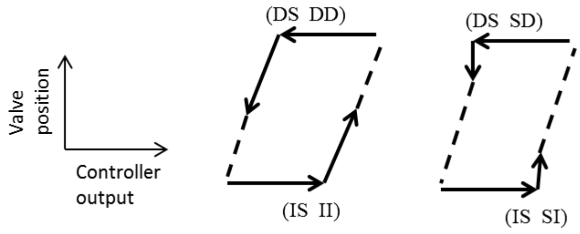

Fig. 3: Typical stiction patterns

3. Diagnosis of Process Control Loops

3.1 Control Loop Monitoring

Process Monitoring is very important to ensure safety, product quality, energy conservation and so on. A usual process plant has hundreds or thousands of control loops. Quite a few loops have oscillatory behavior. Industrial engineers highly demand a tool to facilitate loop monitoring. Poor control performance can be caused by improper controller tuning, external disturbances, and so-called stiction in a control valve, which is often the only moving part in the loop.

Input-output characteristics of a valve in oscillating loop are investigated by visual inspection of typical oscillating data sets. The valve output is the valve position; the valve input is the controller output. If a control valve has high static friction, the valve position does not change from small changes of the controller output. The controller then increases the set-point to the valve. Then the valve breaks off and moves to a new position with a slip-jump. Figure 4 shows idealized typical shapes for the dynamic input-output characteristics of a sticky valve [4, 5].

3.2 Index to Detect Valve Stiction

Several researchers have investigated methods to diagnose likely causes of oscillations in process control loops. Horch proposed a method of diagnosing oscillations based on the cross correlation between the controller output and the process output [6]. We proposed several shape-based methods to diagnose stiction using input-output characteristics of control valves [7].

A fragment of the movement sequence can be represented by a sequence of two successive patterns. For example, if pattern II follows the pattern IS, the movement is represented as (IS II). Using this representation, typical movement for valve stiction can be represented as four fragments (IS II), (DS DD), (IS SI), and (DS SD) as shown in Fig. 3. All sticky motions of valve stiction, IS and DS, should be a part of these patterns. The degree of stiction can be evaluated by counting the time period of IS and DS in these four fragments of patterns. Subsequently, an index ρ can be defined as

$$\rho = \frac{\tau_{\text{IS II}} + \tau_{\text{IS SI}} + \tau_{\text{DS DD}} + \tau_{\text{DS SD}}}{\tau_{\text{total}}}$$

where τ_{total} is the duration of the observation period, and $\tau_{\text{IS II}}$ and $\tau_{\text{DS DD}}$ are time periods for patterns (IS II) and (DS DD), respectively. This index will become large if the valve has severe stiction. As an extreme case, the index ρ becomes close to unity if the valve does not move for changes of controller output. If the signals are random, the value of ρ is likely to become 0.25 because it represents two out of eight patterns. Therefore, one can infer that the loop is likely to have valve stiction if the index value is greater than 0.25. Before applying this method, it is recommended to select adequate sampling interval so as to reduce the effect of noise. If an oscillating frequency of the signal is available, a sampling interval corresponding to about 16 times of the oscillating frequency is recommended.

To qualify the stiction, the width of the sticky movement can also be calculated for the found typical sticky patterns. The width is defined by the mean value of the maximum differences of controller-output during each IS and DS period in sticky patterns.

3.2 Industrial Example

This section presents an evaluation of the proposed method using real-world data sets collected from an industrial chemical plan [4]. All these data sets have 1440 samples at one-minute intervals; all the samples were used for the analysis. All the variables are normalized based on their standard deviation and mean value. A normalized time series of four single input single output (SISO) control loops is shown in Fig. 4. In this figure solid lines are flowrates, which correspond to valve positions. Dotted lines represent for controller outputs. Input-output characteristics of the valve for each loop are also depicted in the same figure.

Consider first the level control case with valve stiction (Loop 1). An input-output plot of the valve and the loop are shown in the figure. To clarify details, fewer points are indicated in these figures. Table 1 lists numerical values of the detection indices. The index for this case has a relatively large value, correctly indicating stiction. This loop is for a level control, which is an integrator process; the cross-correlation method proposed by Horch [6] can not be used for this loop.

The next example illustrates a flow control loop with valve stiction (Loop 2). Table 1 lists the numerical

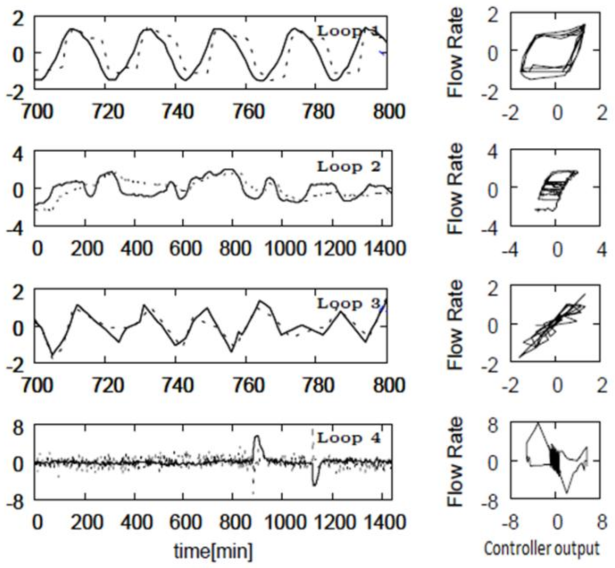

Fig. 4: Industrial data sets

value of the detection index. The index has relatively large value and indicates stiction correctly.

Loop 3 has fluctuations caused by a tuning problem. Calculated index can be found in Table 1. In this example, the index ρ shows a small value and indicates no stiction. As the result, the cause of the oscillation is diagnosed as improper controller tuning or external disturbances. Although the true cause is the poor tuning, in this case, we need another methodology to distinguish these two causes.

Loop 4 is an example of external disturbances in the flowrate. They are visible around 900 and 1150 min. The calculated detection index is shown in Table 1. In this example, index ρ shows a small value and indicates no stiction. The first half part of this data set can be considered a case of normal operation because it has no large disturbance. Therefore, we consider this first half-length data set as Loop 4a. In this case, ρ becomes very small and indicates no stiction.

Table 1. Result of the diagnosis

Case	ρ	width
Loop 1: Level control (stiction)	0.62	1.37
Loop 2: Flow control (stiction)	0.48	1.12
Loop 3: Level control (tuning problem)	0.12	1.01
Loop 4: Flow control (disturbances)	0.14	0.48
Loop 4a: Flow control (normal)	0.07	–

7. Conclusions

In this paper, a methodology to analyze time series data is described at first. Especially, a methodology to extract qualitative movement patterns of time series data in a two variables plane was presented. Nine primitives are used for the qualitative representation of a movement. The method contains the following three steps: segmentation of the movements of the two signals into line segments, classification of the segments into nine primitives, and aggregation of the primitives. This qualitative description formalism is a general method and can be used to identify various kinds of dynamic movements in an input-output plot. If this formalism can describe knowledge regarding the movement of a specific phenomenon, it will be easy to detect the phenomenon.

By using this qualitative description method, a method to diagnose valve stiction in a process control loop was introduced. The diagnosis method was applied to several industrial plant data. The result shows that the characteristic behavior of the signals is well represented by the extracted qualitative movements. It also shows that this method performed excellently for all cases including flow control loops and level control loops.

Detection of sticky valve is useful to find the valve for maintenance. Valve maintenance can reduce the static friction forces and will improve performance of the control loop. Alternatively, stiction compensation methods can mitigate the problem. One of the well konwn compensation methods is to add short pulses, which is called knocker, to the control signal [8]. Diagnosis of valve stiction will help decision making for the actions in plant operation and will effectively improve performance of the control loops.

References

[1] Dash, S., M.R.Maurya, and V.Venkatasubramanian, “A novel interval-halving framework for automated identification of process trends,” *AIChEJ.*, Vol. 50 (2004) pp. 149–162

[2] Charbonnier, S., C.Garcia-Beltan, C. Cadet and S. Gentil, “Trends extraction and analysis for complex system monitoring and decision support,” *Eng. App. Artif. Intel.*, Vol.18 (2005) pp. 21–36

[3] Yamashita, Y., “On-line extraction of qualitative movements for monitoring process plants,” *Lecture Note in Artificial Intelligence*, Vol. 4252 (2006), pp. 595-602

[4] Yamashita, Y., “An Automatic Method for Detection of Stiction in Process Control Loops,” *Control Engineering Practice*, Vol. 14, (2006), pp. 503-510.

[5] Thornhill, N.F. and T. Hägglund, “Detection and Diagnosis of Oscillation in Control Loops,” *Int. J. Adaptive Control and Signal Processing*, Vol. 17 (1997) pp.625-634

[6] Horch, A., “A Simple Method for Detection of Sluggish Control Loops,” *Control Engineering Practice*, Vol. 7 (1999) pp. 1221-1231

[7] Jelali, M. and B. Huang ed., Detection and Diagnosis of Stiction in Control Loops, London, Springer, 2010, Chap. 5, pp.103-113

[8] Hägglund, T., “A friction compensator for pneumatic control valves,” *Journal of Process Control*, Vol. 12 (2002) 897-904