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Fault Detection of Actuator with Digital Positioner Based on Trend Analysis Method

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1. Introduction

The demanding on high safety, performance and reliability in controlled processes has becoming increasingly stringent in recent years. Control valves (or actuators) are widely used in industrial processes. As the final control elements, they are often installed in the technology nodes working in the harsh environment: high temperature, high pressure, humidity, pollution, chemical solvents, etc. Their malfunctions usually lead to poor control performance or process disturbance, even result in unqualified product. Therefore, the on-line detection and diagnosis of control valve should be applied to preserve the high-reliability of control valves due to the severity of its possible effects of failure on the processes.

The malfunctions of actuator mainly include fully failure, offset and bias, change of gain, serious hysteresis, and stick-slip fault. In the past two decades, there has existed a number of fault detection and diagnosis methods for actuators in process control systems. Some efforts involved model-based approaches: state estimation (Hoefling et al.,1995; Park T.G. et al., 2000; Edwin Engin Yaz & Asad Azemi,1998); parity equation (Massoumia et al.,1998; Mediavilla et al.,1997). These methods require relatively accurate mathematic models about the processes. However, it is very difficult to obtain accurate mathematic models in most industrial processes. Other studies focused on using neural networks (Patan,2001; Patan & Parisini,2003; Pawel et al.,2003), fuzzy logic, and signal analysis (Deibert,1994). An important issue that should be highlighted is that, there is no a method that can detect and diagnose all kinds of faults because various fault types may occur in control valves. most existing method requires process knowledge or user-interaction (Forsman & Stattin 1999; Hagglund,1995; Wallen,1997). Only few approaches do not need prior knowledge about the process (Horch, 1999).

In process control systems, actuators with digital positioner are widely used. Generally, few related signals can be sampled to process monitor systems. These signals are: the input and output signals related to the component itself, and the flow signal that controlled by the industrial actuator. In fact, these signals provide useful information about the operation of the actuator.

In this chapter, a series of methods based on trend analysis are proposed to detect typical faults of industrial actuators with digital positioners by using these three signals. Because

there is no need to have prior knowledge about the control processes, these methods provided can be easily applied to the real processes.

2. Description of Actuator with Digital Positioners and Its Typical Faults

2.1 Description of actuators with digital positioners in process control systems

As a typical example, Fig.1 shows the air-operated actuator with digital positioner in most process control systems. It consists of three primary parts: digital positoner, air-driven part(or executive body), and valve body. The digital positoner receives valve travel setting signal (control signal U_d) from the controller in a control system, and set the actual valve travel (x) according to the valve travel setting signal by supplying air to the driven part. The valve steam is then driven by air pressure and moves to a specified position to achieve flow control.
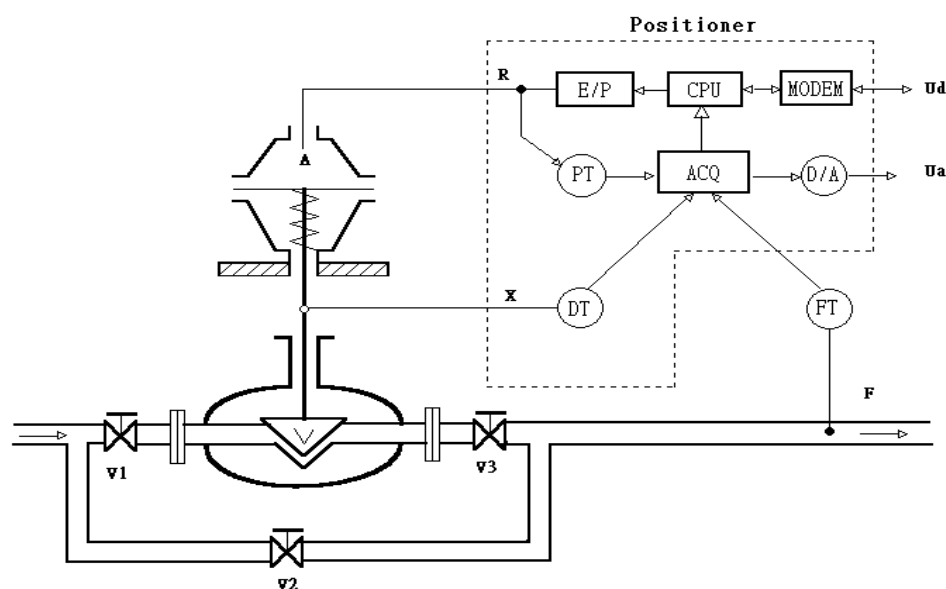

Fig. 1. Diagram of the air-operated actuator with digital positioner

The valve body is a liquid-limit component which includes valve seat and valve spool. When the valve stem moves to a specific position, the valve spool will also reach a corresponding opening point. The model of valve body can be described as follows:

$$Q/Q_{max} = f(x/L) \tag{1}$$

where Q_{max} is the maximum flow rate and L is the spool displacement when the valve spool is fully open, Q is the real flow rate, , x is the real spool displacement, x/L represents the spool opening, and Q_{max} represents relative flow rate.

2.2 Generalized model of actuator with digital positioner

In actuator with digital positioner, important signals for fault detection are: valve travel setting signal, the actual valve travel, air pressure of driven part, inlet pressure of valve body, outlet pressure of valve body, and the flow rate through valve body. However, in

most cases, only few signals can be sampled by DCS (distributed control system) or SCADA system. They are:

a)   valve travel setting signal: CV
b)   actual valve travel:X
c)   flow rate through valve body: Q

For other kinds of actuator, such as electric valve actuators and hydraulic actuator, we get the same result: the three signals can be easily obtained. Because the three signals can represent most important running state of actuator, a generalized model of actuator with digital positoner is given in Fig.2.
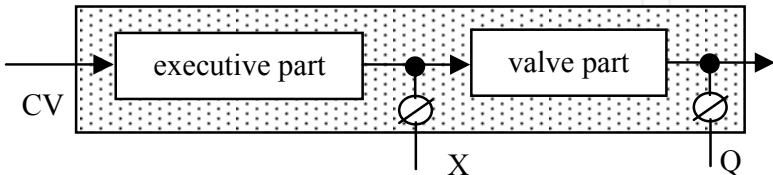
Fig. 2. Generalized model of actuator with digital positioner

When the actuator works well, the X will trace CV rapidly and smoothly, and the flow rate will keep a corresponding value to X. Once there are some malfunctions, the relationship among CV, X, and Q will change. Fault detection can be made by detecting these changes with the three signals.

2.3 Typical malfunctions of digital positioners

Malfunctions may occur in every part of the actuator. As an example, 19 typical fault types of the membrane air-operated actuator are given in table 1.

Valve body	Air-driven part	Digital positioner	Other fault
F1: valve body blocked	F8: valve stem bending	F12: electro- peumatic convertor failure	F16: air feed pressure declining
F2: Sediment in valve seat or valve spool	F9: overshadowed tight membrane	F13: position feedback sensor failure	F17: abnormal differential pressure of valve body
F3: valve body eroded	F10: membrane damage	F14: pressure sensor failure	F18: bypass valve open
F4: friction force increase in valve or bush	F11: spring failure	F15: positioner spring failure	F19:flow sensor failure
F5:external leakage (bush or valve cover			
F6: internal leakage(tight valve)			
F7: fluid evaporation			

Table 1. Typical malfunctions of the membrane air-operated actuator

These fault types F1 to F19 will make the actuator work in faulty state. Meanwhile, the relationship between the three signal CV, X, and Q will change in an abnormal way. These different faulty state of actuators can be classified generally into the following types: "Stick-

slip" fault, "constant bias" fault, "change of gain" fault, "serious hysteresis" fault,"stuck" fault. Fig.3. to Fig.8 show the above typical fault types, in which the three signals behave in different ways.
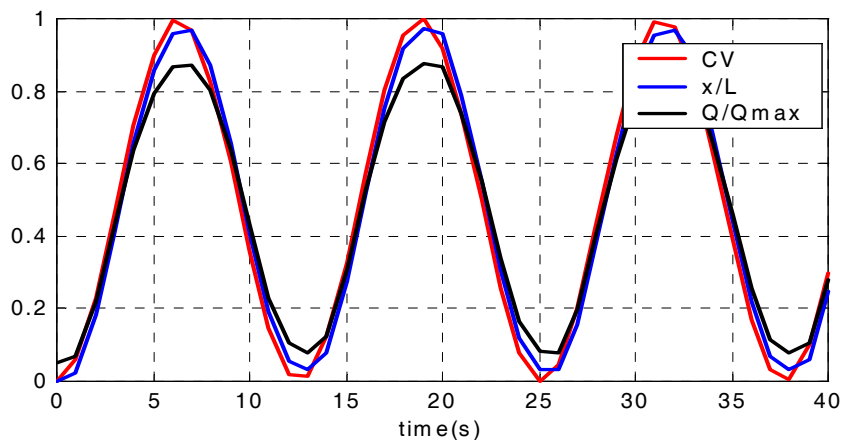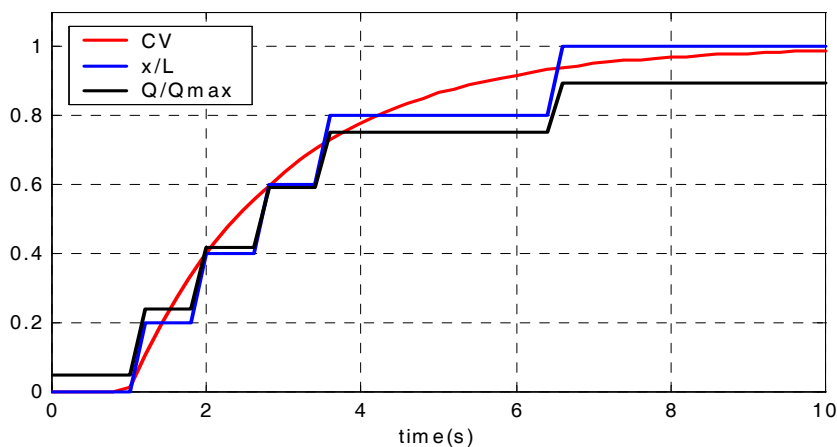

Fig. 3. Actuator works in fault-free state

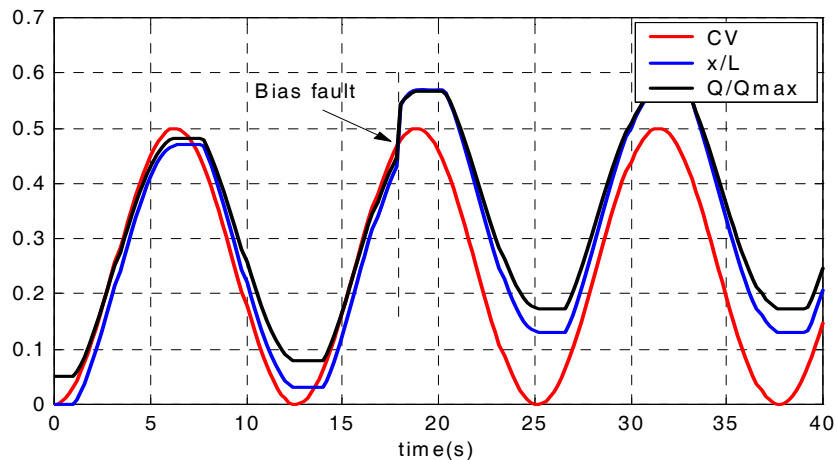Fig. 4. Actuator works in "stick-slip" state

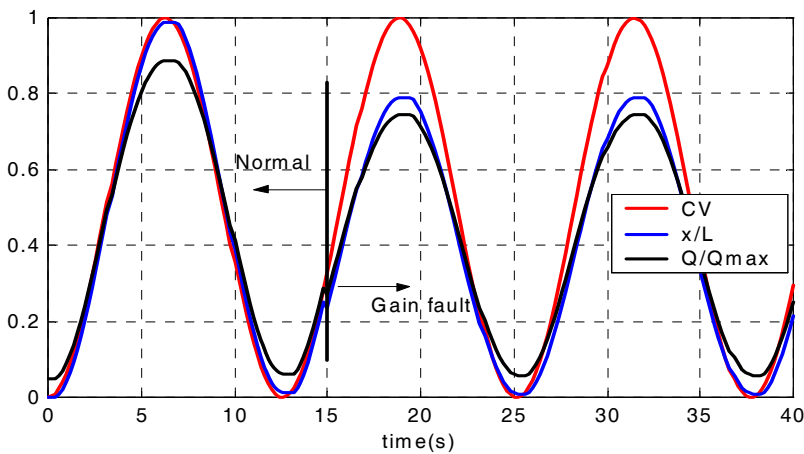Fig. 5. Actuator works in "constant bias" state
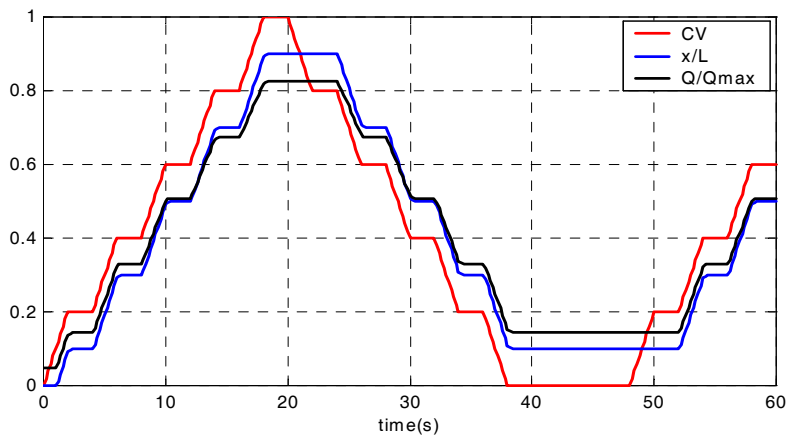
Fig. 6. Actuator works in "change of gain" state

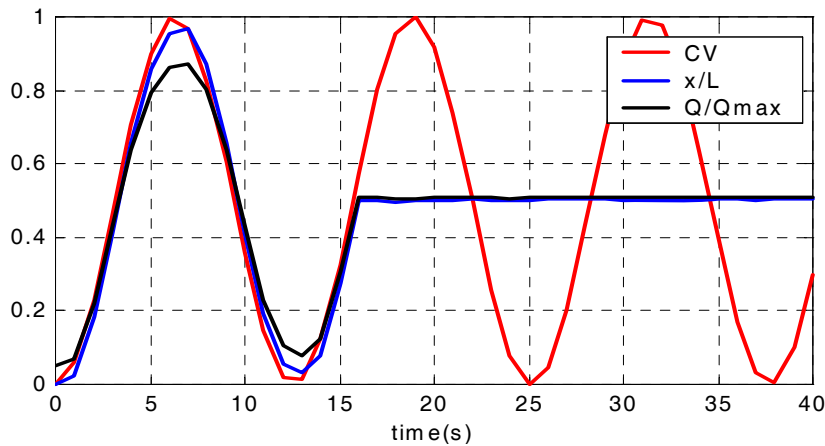
Fig. 7. Actuator works in "serious hysteresis" state

Fig. 8. Actuator works in "stuck" state

3. Online Fault Detection Methods Based on Trend Analysis

The online fault detection based on trend analysis methods adopts the three signals in the generalized model of actuator with digital positioner. In the real-world data is always noisy. It is necessary to filter the sampled data. Here, a first-order filter is used for data pre-

processing. Sliding window is use to handle data of the three signals to accomplish online fault detection tasks.

3.1 "stick-slip" fault detection by trend analysis method

Under normal conditions, the valve stem moves smoothly; when "stick-slip" fault occurs, the valve travel varies in steps. Fig.9 shows simulation data of the valve travel variations during stick-slippage against time. The enlarged part in it is the behavior of the valve stem at the transition from sticking to slipping. Stick-slip fault is often caused by several factors (seal degradation, lubricant depletion, inclusion of foreign matter, and activation at metal sliding surfaces at high temperatures) that lead to change of friction characteristics of the valve stem when moving. Its seriousness is determined by the friction characteristics. Detailed analysis of this phenomenon can be seen in the past studies (Li C.B., 1982; Kagawa et al. 1993).
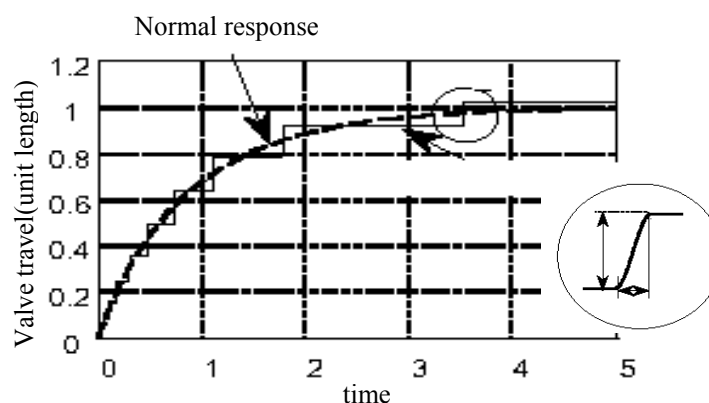

Fig. 9. Behavior of the valve travel during stick-slippage against time

It is very disadvantageous for the control valve when in the stick-slippage condition. In addition to its influence on control performance, such as oscillation in control loops, this 'moving-stopping-moving' state will damage the actuator and reduce its lifetime.

3.1.1 Principle of fault detection of stick-slippage

In order to detect the stick-slip fault, two signals are needed: actual valve travel signal and valve travel setting signal. There is an assumption that the above two measurement signals are fault -free. There is no need to have prior knowledge about the control processes.

The detection method is derived from the previously-described studies around stick-slip phenomena. Under normal operational state, since the movement period is extremely short compared with the response rate of the control valve, the valve stem moves smoothly, and its speed of movement is generally distributed as shown in Fig.10 corresponding to the normal response in Fig.9. When the valve malfunctions due to stick-slippage, the movement of the valve steam is just like "moving-stopping-moving", Fig.4 gives the speed distribution of the valve stem, where the valve stem speed is divided into two moving and stationary states, reflecting repetition of slipping and sticking conditions. From Fig.10 and Fig.11 we can see that at different speed (from small to large), the speed occurrence frequency shows different characteristics. This difference can be represented by the relationship between the mean and root mean square of the stem valve speed magnitudes. In the case of no stick-

slippage, the mean is very close to the root mean square of the speed, but they distance from each other when stick-slip fault exists. It is therefore possible to detect valve malfunctions caused by stick-slippage, using the relationship between the differences in shape of these occurrence-frequency distributions.
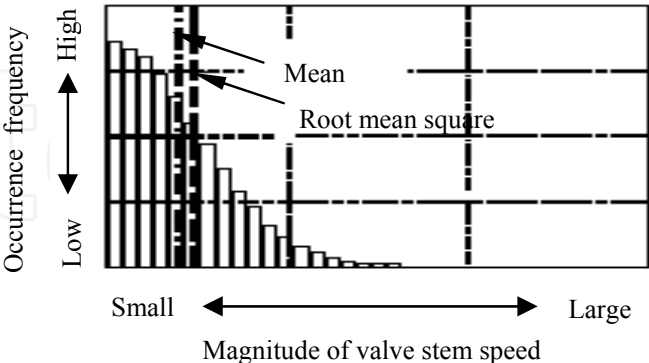

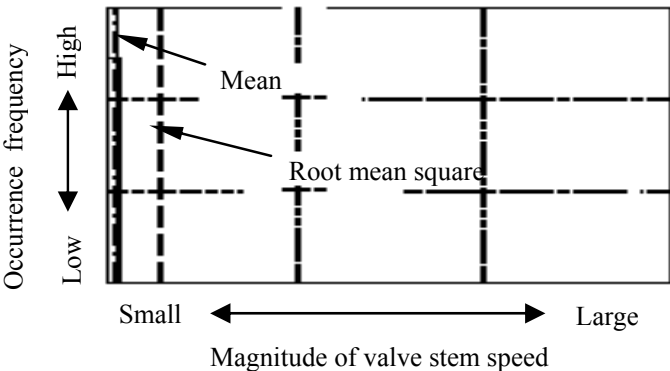Fig. 10. Speed distribution of the valve stem when no stick-slip fault

Fig. 11. Speed distribution of the valve stem when stick-slip fault occurs

After the data is filtered, assume s_i and c_i are respectively the values at the ith sampling time of the valve travel and the valve travel setting signals. For continuous and on-line monitoring the state of control valves, a fixed-length sliding window with N sample data is used to see whether the stick-slippage has occurred during the time from the current sample time to the past N sample time.

The ratio of the mean to RMS of the stem speed magnitudes can be then used as an indicator of stick-slippage because it theoretically related to the shape of valve stem speed occurrence frequency distribution. The mean of the stem movement speed $\bar{v}_p$ is calculated as follows:

$$\bar{v}_p = \frac{1}{N} \sum_{i=1}^{N} |v_i| \tag{2}$$

$$v_i = \frac{s_i - s_{i-1}}{dt} \tag{3}$$

where N is the length of observing data, v_i is the speed of ith sample time, dt is the sample time, s_i is the filtered value of the measurement of stem position at ith sample time.

The RMS of the stem speed is:

$$RMS_p = \sqrt{\sum_{i=1}^{N} |v_i|^2 /(N-1)} \tag{4}$$

and the ratio is:

$$r_p = \frac{RMS_p}{\bar{v}_p} \tag{5}$$

In fact, the input command signal to the actuator should be considered because the valve travel setting signal may behave like stick-slippage, even the speed distribution of stem in a healthy actuator will be similar with the case during stick-slippage. Similarly, the mean and RMS of the speed of command signal can be calculated like Equ.(2) to Equ.(4). The r_c is then obtained as:

$$r_c = \frac{RMS_c}{\bar{v}_c} \tag{6}$$

Defining the decision variables D_c and D_p as:

$$D_c = \begin{cases} 1 & r_c > \varepsilon \\ 0 & \text{else} \end{cases} \tag{7}$$

$$D_p = \begin{cases} 1 & r_p > \varepsilon \\ 0 & \text{else} \end{cases} \tag{8}$$

where ε is the tolerance value (or the threshold) to represent the seriousness of stick-slip fault, and the value 1 denotes stick-slip phenomenon, otherwise, the value is 0. The r_p (or r_c) will be close to 1 when no stick-slip fault occurs. When this kind of fault existing, they will increase according to the severity of stick-slip phenomenon. Larger value of r_p (or r_c) means more serious degree of the fault. A tolerance value should be set in order to avoiding frequent alarm in the case of slight stick-slippage, which is not fault. ε can typically be chosen between 2.5~6, and this is also dependent of specific application. The following boolean equation can be used to give a final decision to indicate whether the control valve suffers from stick-slippage fault.

$$\text{Stiction} = D_p \text{ AND (Not } D_c) \tag{9}$$

3.1.2 Experimental result
In this section, the proposed method will be evaluated on real world data sets, collected from different air baffles and control valves from the DCS in a power plant. The illustrative application of the proposed method is made on the steam superheater control system. There are two control valves installed in this control system as the digital positioners to control flex of water to reduce the temperature of the boiler steam. The first control valves is the valve-A which is installed on the left side in the superheated steam system, and the second on the right side is valve-B. Data are sampled during the operation of the process with the

sampling time of 1 second, and calculated on-line. Two cases are illustrated with data related to valve A and B, where the length of sliding window is 100 and ε is chosen as 2.5. Stick-slippage occurs in valve-A while the input signal to the control valve is not like steps. Fig.12 shows 400 sets of sampling data of valve- A. The results of r_p and r_c is shown in Fig.13.
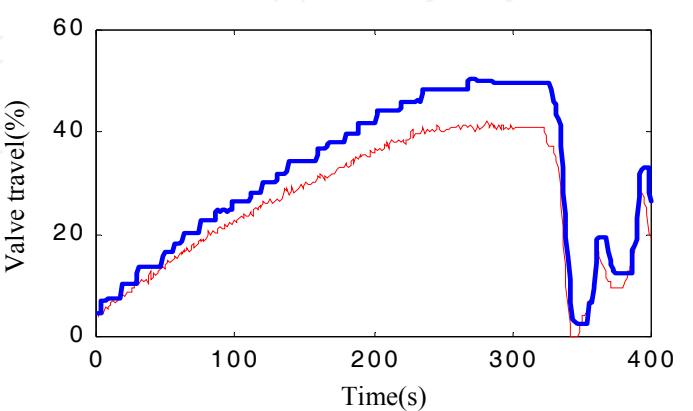

Fig. 12. Valve signals in control valve A, the valve travel setting signal (thin line), the actual valve travel signal (bold line), *dt*=1s
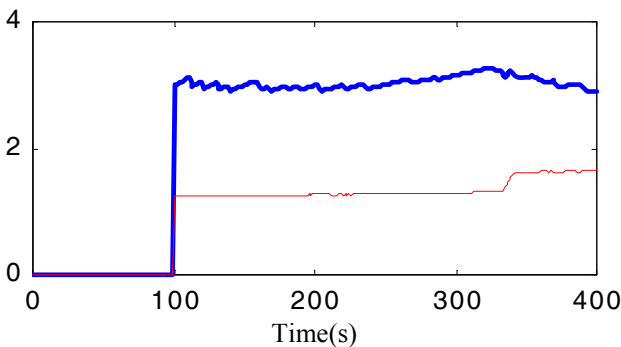

Fig. 13.Results of the ratio of rc (thin line), rp (bold line)

3.2 "serious hysteresis" fault detection by trend analysis method
Serious hysteresis fault comes from too large dead zone with the actuator. Generally, a healthy actuator have little dead zone. This feature shown in Fig.14 is useful for noise suppression, and avoiding frequent movement because of all kinds of signal noise. From Fig.7, obviously, only when the bias between the valve travel setting signal (CV) and the actual valve travel (X) exceeds dead zone (D_z), the valve stem will move. When too large dead zone exists, the actual valve travel cannot trace the valve travel setting signal. It also may result in bad control performance and even oscillation in control loops.
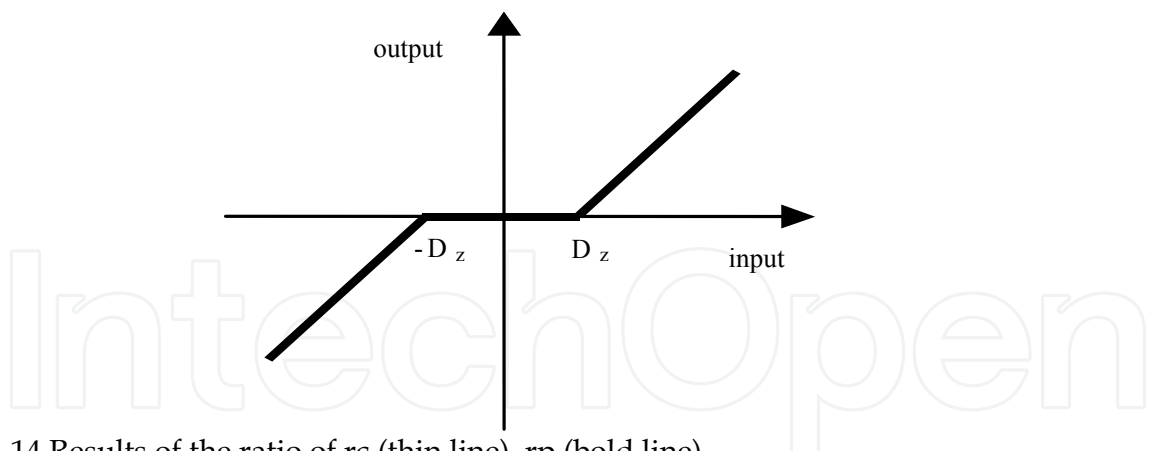
Fig. 14.Results of the ratio of rc (thin line), rp (bold line)

3.2.1 Principle of fault detection of serious hysteresis

From the point of signal trend analysis, when the input signal to actuator (CV) is not step-like signal, it is very difficult to evaluate the size of dead zone only from the two signals (CV and X). However, the size of dead zone can be easily detect from the X-Y graph between CV and X. When the gain of actuator is linear, when the input signal change from 0% to 100%, and then change from 100% to 0%, we can get a X-Y graph, the relationship between the CV and X is like a parallelogram. The dead zone D_z is just one half of width of the parallelogram.
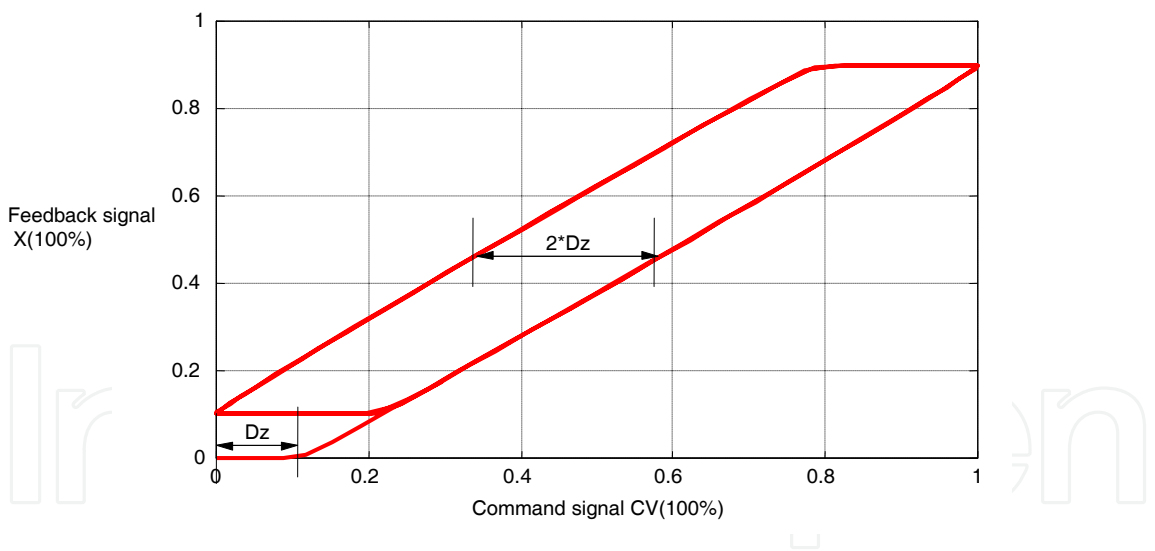

Fig. 15. X-Y graph with dead zone is D_z

Since there must be some non-linearity with practical actuators, the parallelogram representing dead zone will not be a standard graph. In this case, an average value or maximum value can be chosen as the dead zone.

Online fault detection procedure for this kind of fault is done as follows: detecting the CV which changes from a range of increasing and a range of decreasing, online recording the recent data about the actual valve travel signal in this stage. In these data, For each valve of

actual valve travel, finding two CV values v_1 and v_2, one (v_1) is in the stage of increasing and the other is in the stage of descreasing. Assume there are N groups of v_1 and v_2 ea. The online estimation value of dead zone is:

$$D_z = \frac{1}{2N} \sum_{i=1}^{N} |v_{i1} - v_{i2}| \qquad (10)$$

3.2.2 Experimental result
The normal dead zone of the testing actuator is 4%. Simulation result of fault detection method is shown in Fig. 16. In Fig.16, the serious hysteresis occurs at the time of 40 seconds, and the dead zone changes to 12%. After nearly 30 seconds, the estimation value of dead zone is stable at 12%.
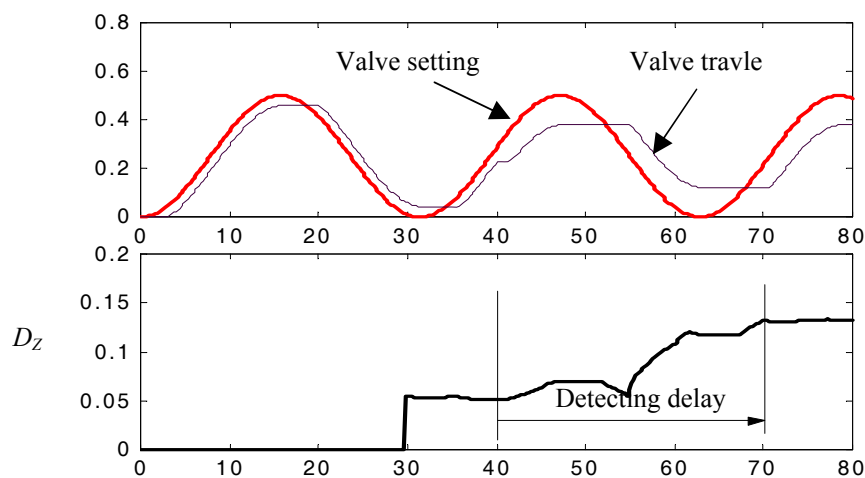

Fig. 16. Estimated dead zone D_z during the fault detection procedure

3.3 "stuck" fault detection by trend analysis method
When the "stuck" fault appears in actuators, the three signals related will change in the following two ways:
a) During a period of time, the valve travel setting changes largely, however, the actual valve travel does not change with the valve travel, and also the flow rate signal does not change.
b) During a period of time, the valve travel setting does not change, and the actual valve travel and flow rate signals keep no change, however, the bias between the valve travel setting and the actual valve become very large.
Online fault detection can be done according to the above two rules.

3.3.1 Principle of fault detection of "stuck" fault
The key point of "stuck" fault detection is how to judge whether one signal is stable or not. Some methods for judging stable state need statistical distribution characteristics of the signal itself. They are not practical in most cases because statistical characteristics can not be

easily obtained. Here, we adopt a method of calculating stable factor of signals for this fault detection task.

For a given process variable Z, the specific steps of calculating stable factor is:

(1) In order to eliminate measurement noise, we can use sliding average filter to filter the process data, then get the filtered data Z_{fi} ;

(2) Get the maximum value Z_1 and the minimum value Z_2 from Z_{fi} :

$$Z_1 = \max_i(Z_{fi}) , Z_2 = \min_i(Z_{fi}) \tag{11}$$

(3) Calculate the average value Z_m of data Z_{fi} ;

(4) Stable factor (SF) is defined as:

$$SF = 100(Z_1 - Z_2) / Z_m \tag{12}$$

Here we use the form of percent to describe the stable degree of signal. For objective comparison between two signals, data size should be the same.

In order to illustrate the effectiveness of SF, some testing experiments on 5 different signals are made, where s_1 is a stable signal with average value 10.0 and standard deviation 0.2; s2 is a signal with average value 10.0 and standard deviation 1.0; s3 a step signal; s4 is a ramp signal; and s5 is a fluctuant signal. These signal are shown respectively in Fig.17. The SF values of s1 to s5 are listed in table2. It can be seen that the stable factor is suitable for judging stable degree of process variables.
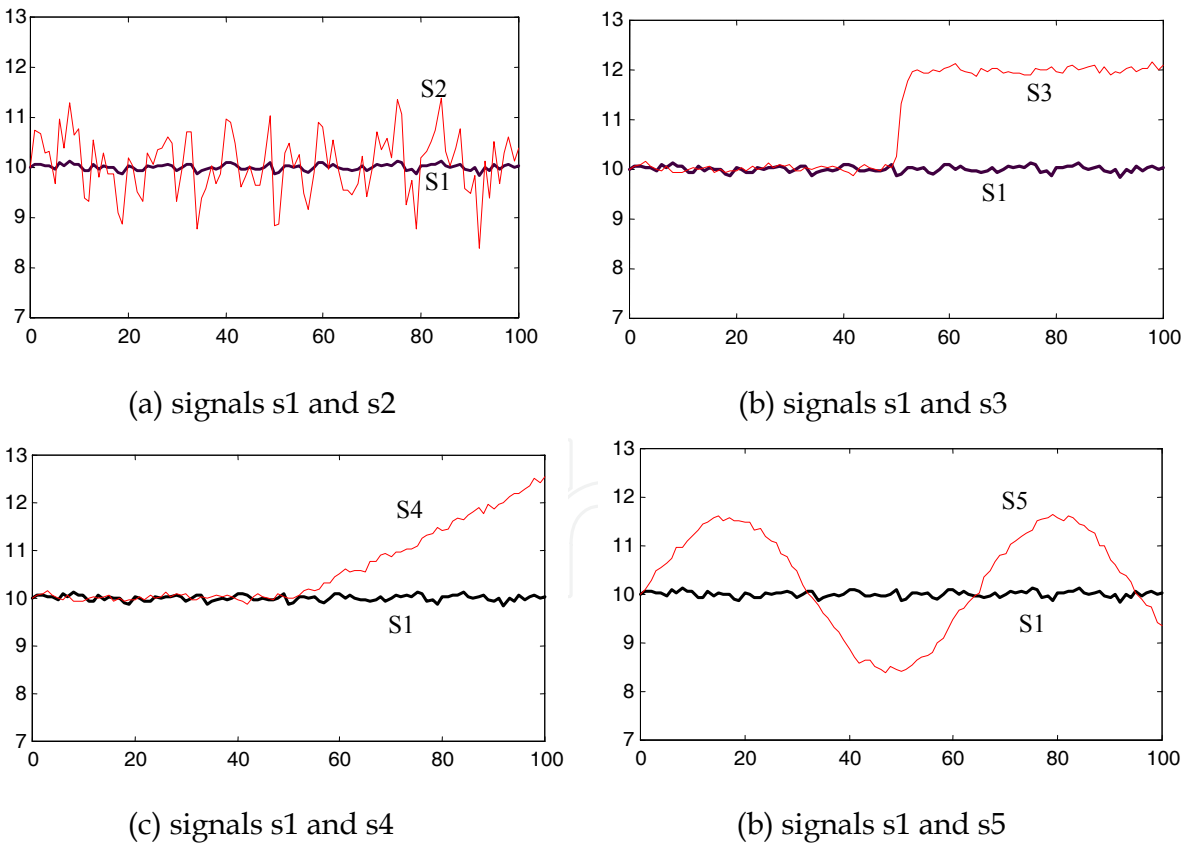

(a) signals s1 and s2

(b) signals s1 and s3

(c) signals s1 and s4

(b) signals s1 and s5

Fig. 17. The five typical signals for testing stable factor

Signal	s_1	s2	s3	s4	s5
SF value	3.02%	29.87%	20.76%	25.08%	31.80%

Table 2. Stable Factor values of s1 to s5

For one sliding window, online fault detection logic is:
(a) If SF of valve travel setting signal is distinctively larger than SF of valve travel, then the "stuck" fault exists;
(b) If the SF values of travel setting signal, valve travel, flow rate are small, but the average bias between valve setting and valve travel is distinctively large, then the "stuck" fault exists.

3.3.2 Experimental result
Fig.18 shows the three signals when stuck fault occurs. Sliding window is use to handle data of the three signals within a period of time, its length is 60 seconds. The fault detection result can be seen in Fig.19.
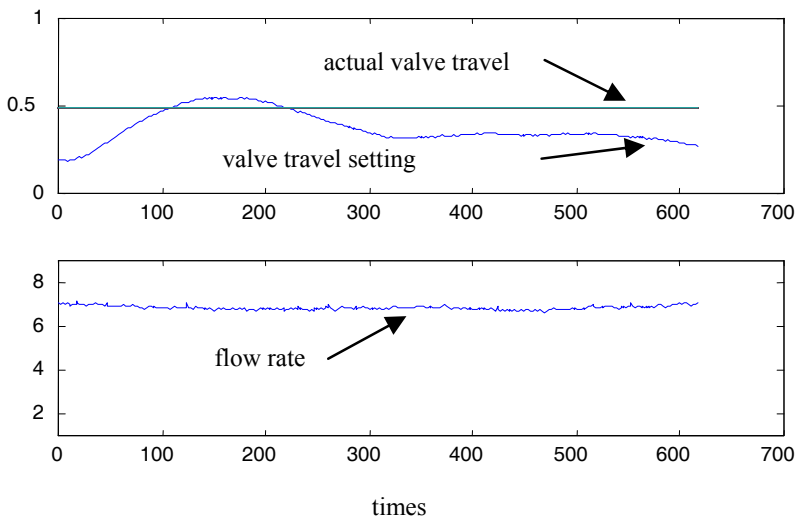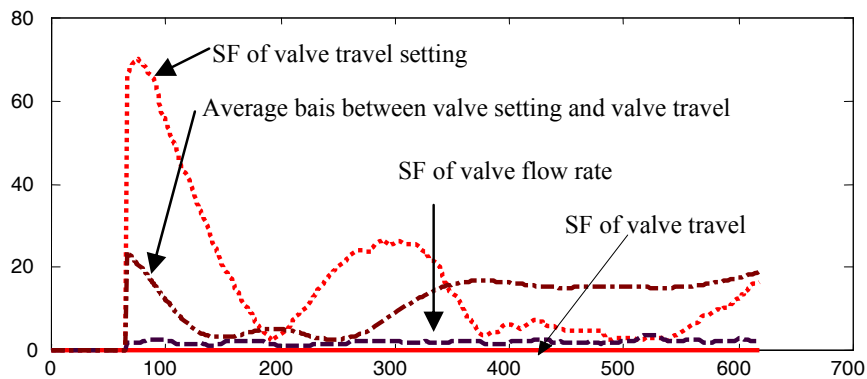

Fig. 18. Signals when the stuck fault occurs

Fig. 19. Estimated stable factors during the fault detection procedure

3.4 "change of gain" fault detection by trend analysis method

The gain of an actuator describes the ratio relationship between its input and valve travel , and can be defined as follows:

$$a = \frac{\Delta x}{\Delta u} \tag{13}$$

where a is the gain factor, Δx is the change of valve travel, and Δu is the change of valve travel setting signal. Here we assume the actuator have only little nonlinearity, that is to say, the gain is nearly linear at different points within the range of the valve travel.

In normal state , the value of gain factor of actuator is close to 1.0. When the gain of actuator changes, the actual valve travel will not trace valve travel setting very well, it may also lead to poor control performance in control loops.

3.4.1 Principle of fault detection of "change of gain"

The process of fault detection is online calculating the gain factor in a sliding window. The estimated value of a can be defined as follows:

$$\hat{a} = \frac{1}{N-1} \sum_{i=1}^{N-1} \frac{x_{i+1} - x_i}{u_{i+1} - u_i} \tag{14}$$

where N is the length of sliding window, x_i is the i-th value of valve travel, and u_i is i-th value of valve travel setting.

3.4.2 Experimental result

Picture (a) in Fig.20 shows the signals of valve travel setting and valve travel when "change of gain" fault occurs. The gain of actuator changed from 1.0 to 0.7 at the time of 100 seconds. Sliding window is use to handle data of the three signals within a period of time, its length is 60 seconds. The online estimated gain factor result is given in Picture (b) of Fig.20.
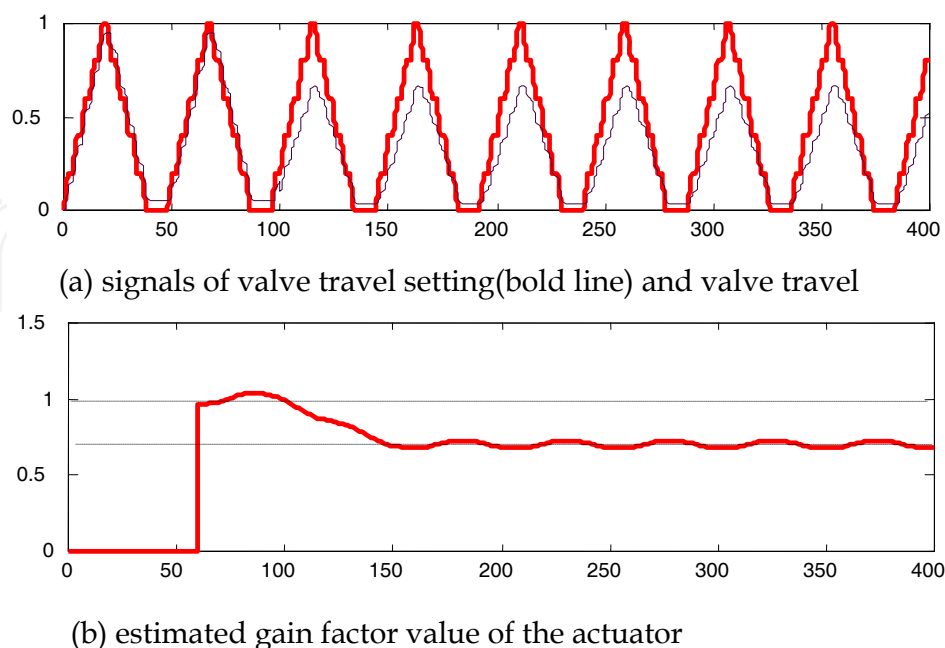

(a) signals of valve travel setting(bold line) and valve travel

(b) estimated gain factor value of the actuator

Fig. 20. Estimated gain factors during the fault detection procedure

This fault is detected at the time of 160 seconds.

3.5 "constant bias" fault detection by trend analysis method

3.5.1 Principle of fault detection of "constant bias"
The process of fault detection is online calculating the
When "constant bias" fault occurs in an actuator, the bias between the valve travel setting signal and the valve travel will outrange the dead zone and keep a fixed value. Fig.5 shows this abnormal working state of an actuator.
The online fault detection is done by calculating between the valve travel setting signal and the valve travel in a sliding window. The estimated value of constant bias C_b can be defined as follows:

$$\hat{C}_b = \frac{1}{N} \sum_{i=1}^{N} |u_i - x_i| \qquad (15)$$

where N is the length of sliding window, x_i is the i-th value of valve travel, and u_i is i-th value of valve travel setting.

3.5.2 Experimental result
Picture (a) in Fig.21 shows the signals of valve travel setting and valve travel when "const bias" fault occurs. When the actuator works healthy, C_b is small, 4% in this example. A const bias fault appeared at the time of 100 seconds, and C_b changes to 20%. The Sliding window is use to handle data of the three signals within a period of time, its length is 60 seconds. The online estimated const bias C_b is given in Picture (b) of Fig.21., and this fault is detected at the time of 160 seconds.
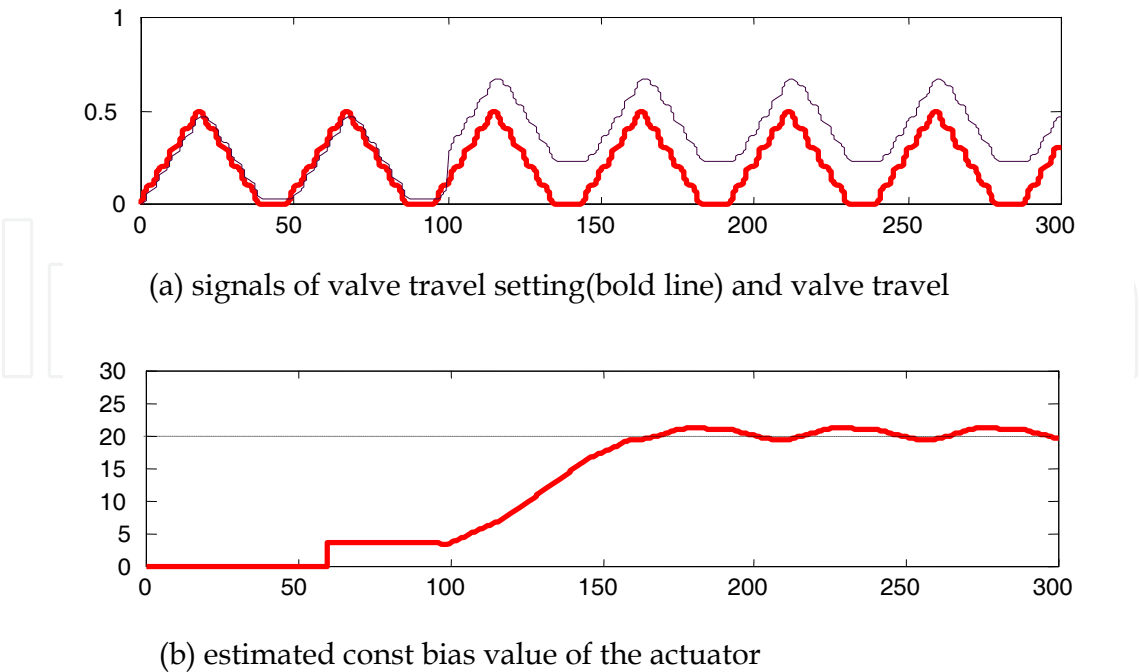

(a) signals of valve travel setting(bold line) and valve travel

(b) estimated const bias value of the actuator

Fig. 21. Estimated const bias during the fault detection procedure

4. Discussions about trend analysis methods

4.1 Selection of the length of sliding window

The length of sliding window has an effect on the delay time of fault detection. The delay time will increase when the length of sliding window increases. However, using short sliding window will lead to mistaken fault detection results. The selection of the length of sliding window is a trade-off. Especially, we should chose enough length for the "stuck" fault detection to cover the up and down trip of the valve.

4.2 Selection of fault decision thresholds

How to choose suitable fault decision thresholds is another key point for fault detection. According to many experimental results by using real data sample from control processes, we give some guidance when using these trend analysis methods.

For "stick-slip" fault, ε is between 2.5 to 3.0 means that the actuator suffer minor failure, ε is greater than 4.0 means that the actuator suffer severe failure. For "stuck" fault, the SF is less than 5% means the signal is stable, the threshold of average bias between valve setting and valve travel should be greater than the normal value of dead zone. For "serious hysteresis" fault, the threshold should be 1.5 to 2.0 times of the normal value of dead zone. For "change of gain" fault, the variation should be 15% to 20% of the normal gain value. For "const bias" fault, the threshold should be chosen as 1.5 to 2.0 times of the normal value of dead zone.

4.3 Notes when using different trend analysis methods at the same time

In this chapter, a series of fault detection methods are proposed to deal with different typical fault of the actuator with digital positioner. Since each method is used to extract one kind of fault feature for corresponding fault type, they can be used at the same time. When there are more than one faults existing, they will give respectively fault decision results. In order to make it clear, much experimental work is done and the results are listed in Table3. Table3 shows the relationship between these five trend analysis methods for one same fault.

	stick-slip fault	serious hysteresis fault	const bias fault	change of gain fault	Stuck fault
stick-slip fault	----	no effect	no effect	no effect	minor effect
serious hysteresis fault	have effect when fault is severe	----	no effect	no effect	no effect
const bias fault	no effect	minor effect	----	have effect when fault is severe	minor effect
change of gain fault	minor effect	no effect	no effect	----	no effect
Stuck fault	no effect	no effect	no effect	no effect	----

Table 1. Relationship between these five trend analysis methods for one same fault

5. References

Hoefling, Th.; Pfeufer,Th. & Isermann, R. (1995). Observer and signal-processing approach to FDI for the industrial actuator benchmark test. *Control Engineering Practice*, vol. 3, pp. 1741-1746.

Park T.G.; Ryu J.S. & Lee K. S.(2000). Actuator fault estimation with disturbance decoupling. *IEE Proc. Of Control Theory Appl.*, vol. 147(5), pp.501-508.

Edwin Engin Yaz & Asad Azemi (1998). Actuator fault detection and isolation in nonlinear systems using LMI's and LME's. *Proceedings of American Control Conference* pp.1590-1594, Philadelphia, Pennsylvania, August 1998.

Massoumia, M.A. and W.E. Van der Velde (1998). Generating parity relation for detecting and identifying control systems component failures. *Journal of Guidance, Control and Dynamics*, vol. 11, pp. 60-65.

Mediavilla M., L.J. de Miguel, and P. Vega (1997). Isolation of multiplicative faults in the industrial actuator benchmark. *IFAC Symposium SAFEPROCESS '97*, Kingston Upon Hull, UK, pp. 855-860.

Patan K. (2001). Fault detection of the digital positioners using neural networks. *Proceedings of the 7th IEEE International Conference on Methods and Models in Automation and Robotics*, Porland, pp.1085-1090.

Patan, K., Parisini, T., Dynamic neural networks for actuator fault diagnosis: application to the damadics benchmark problem, *proceedings of IFAC Symposium SAFEPROCESS*, 2003, Washington, USA, pp.1077-1082.

Pawel, R., Syfert, M., Jegorov,S.(2003).On-line actuator diagnosis based on neural models and fuzzy reasoning: the damadics benchmark study, P*roceedings of IFAC Symposium SAFEPROCESS*, 2003, Washington, USA, pp.1083-1088.

Deibert, R. (1994). Model based fault detection of valves in flow control loops. *IFAC Symposium SAFEPROCESS '94*, Espoo, Finland, pp. 445-450.

Forsman, K and Stattin, A. (1999). A new method of detecting oscillation in control loops. *Proc. Of European Control Conference*, Karlsruhe.

Hagglund, T. (1995). A control-loop performance monitor. *Control Eng. Practice*, vol.3(11), 1543–1551.

Wallen, A. (1997). Valve diagnosis and automatic tuning. *Proceedings of the American Control Conference*, Albuquerque, New Mexico. pp. 2930-2934.

Horch, A.(1999). A simple method for oscillation diagnosis in process control loops. *Proceedings of the 1999 IEEE International Conference on Control Applications*, Hawai'i, USA, pp.1284-1289.

Li C.B., Pavelescu, D. (1982). The friction-speed relation and its influence on the critical velocity of stick-slip motion, Wear, vol. 82(3).

Kagawa et al. (1993). Analysis of electro-pneumatic positioner valve system considering non-linear characteristics of pilot valve. *Transition of the Soceity of Instrument and Control Engineerings*, vol. 29(11).

Fault Detection

Edited by Wei Zhang

In this book, a number of innovative fault diagnosis algorithms in recently years are introduced. These methods can detect failures of various types of system effectively, and with a relatively high significance.

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