Fault Detection and Diagnosis Method for a Process Control Valve

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Abstract

In this paper is presented a simple fault detection and diagnosis (FDD) method. This model based method is especially suitable for embedded systems because need for computing power is minimal. The static model scheme is utilized to model inherent system nonlinearities in the method. Model is obtained during system normal operation after the explanatory variables are specified. Separate fault learning is not need. The introduced method is applicable for all the systems where feedback control is utilized and some of system's internal variables are measurable.

In this method the faults can be detected through detecting internal variables operation point changes. These operation point changes are consequences of the faults since feedback control tries to compensate them.

Eight typical faults (leakages, friction changes and backlash) for a process control valve were simulated in the process control valve fault simulator and proposed method tested. The results indicate that all the faults can be detected and diagnosed before severe impact to control performance of the system. Some of the faults were tested also in the real process control valve test bench in the laboratory. The results in the real environment are consistent with the simulator results.

KEYWORDS: fault detection, fault diagnosis, process control valve

1. Introduction

Predictive maintenance is one of the tools to increase productivity in the process industry by decreasing unwanted shutdowns and loss of product quality. A process control valve as the most usual final control element in the control loop has huge potential to support predictive maintenance. For this reason it has to have fault detection and diagnosis capabilities. Currently intelligent valve controllers can detect some symptoms or faults, but not diagnose them. Thus there is need to research methods to detect and diagnose specified control valve faults. Active research has done in last years in the field of soft computing diagnostic methods for the control valves, like neural networks (e.g. /1/, /2/, /3/, /4/,) and fuzzy systems (e.g. /5/, /6/, /7/, /8/, /9/). These soft computing methods are applicable for the software applications on the distributed control system level, not for the field device level, because they require much computing power. Therefore research related to methods more suitable for embedded systems such as intelligent valve controllers are needed.

2. Fault simulator

The pneumatic process control valve fault simulator presented by author in the previous paper /10/ gives the base for this research. Utilizing the simulator different fault cases can be simulated, consequences analysed and data generated for fault detection and diagnosis research.

The fault simulator was essential to realize because implementing all the faults to real environment is not possible in means of fault repeatability and without interfering original system performance.

The simulator consists of the following models: an intelligent valve controller (nozzle – flapper and spool valve), a pneumatic spring return cylinder actuator, a segment type process control valve, medium flow in the process pipe and the flow control loop as seen in **Figure 1**. The models are from first principals but fitted with nonlinear fitting parameters such as position related spring coefficients. A physics based model scheme was chosen to make fault modelling and location possible. Some relevant faults for each component are modeled to make fault impact simulations possible. These faults are presented with red arrows in Figure 1.



Figure 1: Intelligent control valve in flow control loop and modeled faults

The derived models have been verified with measurements and the modeling error is found to be acceptable for fault simulations. Some typical faults have been simulated in

different use cases (high cycle, flow control and off-line performance test) and impacts to the flow control loop internal variables and control performance analyzed.

2.1. Fault detection and diagnosis method

In this introduced method the faults can be detected through detecting internal variables operation point changes. That was observed analysing behaviour of the internal variables and system internal transfer functions during the fault simulations. Operation point shifts are consequences of the faults since feedback control tries to compensate them. All the internal variables before the fault impact location in the internal variables chain are part of compensation done by the controller as seen in **Figure 2**. That mechanism enables fault localization by detecting the last internal variable affected by the fault. Size of operation point change is proportional to fault size as seen also in Figure 2.





In Figure 2 can be seen how the internal variable operation points are shifted by the fault. The fault considered in this case is prestage pressure leakage presented in **Figure 3**. With this fault feedback controller compensates leakage by moving the flapper closer to the nozzle in the nozzle-flapper system to decreases mass flow though the nozzle to maintain required prestage pressure and spool valve position.



Figure 3: Nozzle-flapper schematics including leakage

Also other system input variables (e.g. set point, supply pressure, temperature) than the faults can affect to the internal variables operation point. Therefore relations between these other system input variables and the internal variables have to be modelled to separate the effects of the input variables from the faults. A pneumatic control valve is highly nonlinear system related to the system input variables. That can be seen from **Figure 4** where effect of supply pressure and valve set point to the flapper operation point is presented. In this introduced method nonlinear relations are modelled through multi-variable histograms.



Figure 4: System nonlinearities

2.2. Multi-variable histogram models

Multi-variable histogram models are simple statistical nonlinear models of variable relations. Advantages of multi-variable histogram models are simplicity, easy learning and nonlinearity /11/.

Multi-variable histograms models are based on schematics where system operation point is taken account within operation point space as seen in **Figure 5**. In the figure the system input variables (Valve Set Point and Supply Pressure) define operation

point space for this observed variable. In the figure one bin represents one operation point of the system. In this example operation point space is dived to the 64 bins.



Figure 5: Operation point space of the observed variable

Contrary to many other modelling schemes multi-variable model output is distribution (histogram) as seen in **Figure 6**, not a single value. This means together with operation point space modelling scheme, that unique histogram is located in every bin in operation point space.

When effects of other input variables than faults are taken account, faults are seen as distribution changes as presented in Figure 6. In the figure, flapper position distribution is shifted by prestage pressure leakage.

Reference histogram is model where forgetting factor is high. Therefore this model is adapted to normal operation of the system. Reference model can be obtained also from the simulation results. When it is obtained during normal operation, faults are not allowed to be present in the system.



Figure 6: Histogram models in one operation point

It is essential to research which input variables are the dominating variables for the observed variables. Only the dominating variables are reasonable to include to the model to keep model structure as simple as possible. In this case, the dominating variables for each observed variable are seen in **Table 1**. These dominating variables were searched by information entropy functions.

Internal Variable	Explanatory input variables						
Spool SP	Valve SP						
Control	Temperature	Valve SP					
Flapper Position	Supply Pressure	Valve SP					
Prestage Pressure	Supply Pressure	Valve SP					
Spool Position	Valve SP						
Cylinder Pressure	Valve SP						
Valve Load Torque	Valve SP						
Valve Position	Valve SP						
Flow	Valve SP						

Table 1: Explanatory input variables for observed variables

As noticed before, the model outputs are distributions. This makes possible to use statistical approach for alarm limit generation. In the introduced FDD method, alarm limits are generated from reference model distributions. For example high and low limits can be calculated as limits were 90% of the samples of the distribution are covered around average of the distribution. Then can be assumed moving average of the observed variable stays between the limits during system normal operation. These alarms limits are generated for all reference models located in all bins in operation point space to achieve alarm limit adaptation to the system operating point. Effect of the operating point to the alarm limits can be seen from **Figure 7** where red lines are alarm limits and blue line is moving average of the observed variable. In the figure can be seen also how prestage leakage affects to flapper position.



Figure 7: Flapper position and alarm limits during prestage leakage simulation

The introduced method was evaluated with the fault simulator generated data including 8 different faults seen in Figure 1. As seen in **Figure 8**, noisy stepwise excitation signal was used in these flow control loop simulations. During the simulation environmental variables supply pressure and temperature were varying as sinusoidal signals to simulate real operation environment variations and to verify robustness of the introduced FDD method.



Figure 8: Flow control loop simulation

Every tested fault was simulated as a linearly increasing fault. Size of the fault was kept small enough to maintain system performance in good level. In **Figure 9** are presented the results of prestage leakage simulation as an example. There can be seen the percentile values of the internal variables in upmost figure. The percentile value represents difference between reference and present model as seen in Figure 6. As

noticed before, the flapper compensates prestage leakage. This can be seen also in the figure below. The alarms generated by introduced FDD method during the simulation are presented in middle figure and size of the fault in lowest figure.



Figure 9: Prestage leakage simulation

3. Results

In Table 2 are seen the results of all fault simulation runs. Markings in the table are:

- The internal variables of the system are listed at left side of the table.
- The simulated faults are listed on top of the table.
- 'REAL' text in the table means data is gathered from the real control valve test bench run in the laboratory.
- Green area in table presents the internal variables which should compensate the fault according FDD principle presented before.
- Grey variables were not used in fault detection and diagnosis.
- Number one stands for high limit and minus one for low limit alarm.

As can be seen from the table, all the faults can be detected and diagnosed to main modules of the system. Generally the internal variable closest to the fault reacts to the fault. Therefore the fault can be detected and diagnosed through detecting affected internal variables. The results from the real control valve test bench within three tested faults are consistent with the simulator results.

	Pre Block	Nozzle Block	Pre Leak	REAL	Spool Fric	Act Leak	REAL	Act Fric	Act Backlash	Valve Fric	REAL	Act Leak And Valve Fric	REAL	Pre Leak And Valve Fric
Spool SP				1		1	1	-1				1	1	
Control	1	-1	1	1	1	1								1
Flapper	-1	1	-1	-1	-1			1						-1
Pre Mass Flow														
Pre Press					1			-1						
Spool						1	1	-1				1	1	
C2 Mass flow														
C2								±1	±1	-1	-1			-1
Torq										±1	±1	±1	±1	±1
Pos														

Table 2: Results of the fault simulations

4. Conclusions

Based on the simulations and the test bench runs it is possible to detect and diagnose typical control valve faults before severe impact to flow control loop performance. The internal variable before fault compensates and reacts first to the fault when utilizing feedback control. That leads to the operation point change for all the internal variables before the fault in the chain of the internal variables in the system. Fault localization resolution is related to the amount of the internal variables available for diagnosis.

5. Acknowledgements

This work has been partly supported by the Neles Inc. 30th anniversary foundation.

6. References

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