SEAMLESS IMPLEMENTATION OF A NOVEL VALVES STICTION DETECTION ALGORITHM USING SEEQ DATA LAB

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Abstract

Data analytic methods to identify process faults developed by researchers are a dime a dozen. Shortcomings that many of these methods have is that (1) are not robust, that is, detect faults where there are none and (2) that productization takes time. Here, we develop a new method that is tested for false positives and show how it can be productized within a very short time period as an open source add on in the Seeq Workbench environment. Thus, both shortcomings are addressed.

Keywords

Data analytics, implementation, fault detection and diagnosis, process industry, valve stiction.

Introduction

During operation of a continuous production process, data is generated from the sensors as well as control loops that act on the process. This data is stored in the data historian and can be analyzed with tools that allow easy visual representation and data handling. In the past two decades, access to process data has become easier as has the handling of the tools that allow the analysis of the data. As a result, many new methods to analyze the data in the chemical and process industry have been developed. Chiang et al. (2017) state that data analytics is the journey to turn data into insight for more informed business and operational decision.

Very often, it is necessary to have process knowledge in the form of a process schematic, more detailed piping and instrumentation diagram and general knowledge of the process dynamics as well as of material and energy balances. However, there are examples where data can be analyzed without any process knowledge. In particular, control loop performance monitoring is an area where the controller data is inspected for common observations regarding to the quality of operation (Jelali, 2006, Thornhill et al., 2007).

One vital piece of information that we have for process data is that we usually have four measurements for each control loop: controller output, process variable, setpoint and the mode, that is, whether the controller is in automatic mode (closed loop control) or manual mode (open loop).

Fig. 1 shows an example of industrial process data. While we expect the setpoint and mode to constant signals, the process variable (PV) and the controller output (OP) are oscillating. A well performing control loop will have some minor random noise. In Fig. 1 the setpoint changes repeatedly because the controller is under a multivariate scheme, that is, there is a model predictive control algorithm that determines the setpoint. In addition, there appears to be an oscillation affecting both the PV and the OP.

Many think that the oscillation occurs because of poor tuning settings: if you tune your controller too tightly, then you will introduce oscillations to a process that is normally not of oscillatory behavior. However, in the process

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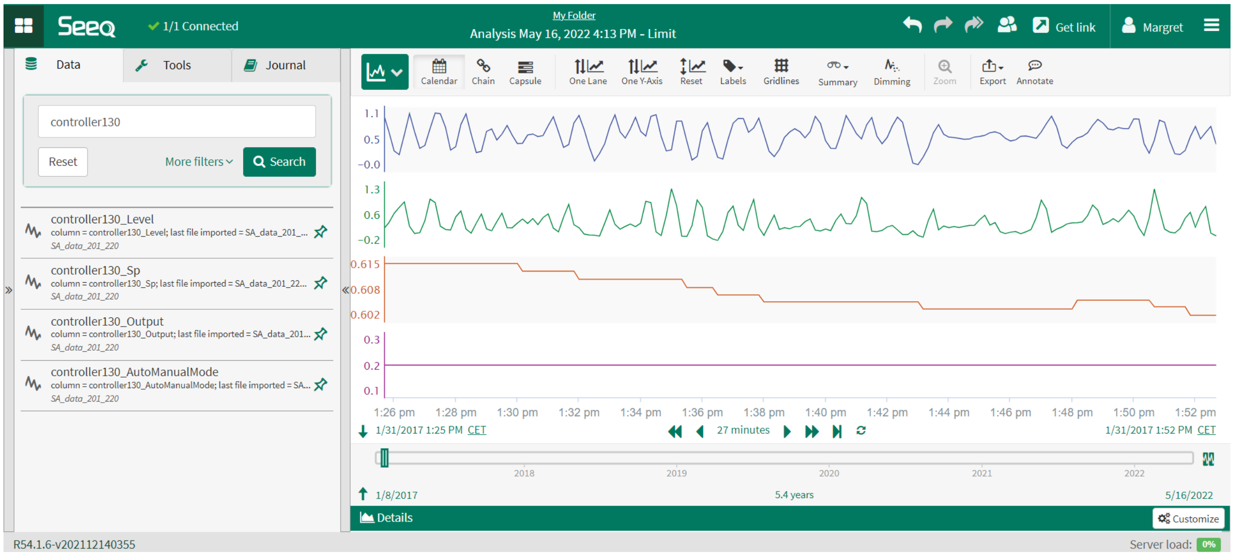


Figure 1. Oscillatory control loop data of a level loop in the Seeq software environment. All data is scaled to zero mean and unit variance.

industries most PID controllers are tuned very conservatively, that is, most of the time there is no derivative part active and only little proportional and integrative control action is applied. The arguably most common cause of oscillation is in fact valve stiction.

After the first excitement in the 1990s and early 2000s, control loop performance assessment is not as widely used. A survey among industry practitioners (Bauer et al., 2016) gave reasons why the methods are not always implemented:

1. **Robustness of the methods**: Here, robustness refers to false positives and false negatives, that is, a case of a process fault could be detected incorrectly by either detecting a fault when there is none (false positive) or missing a fault when there is one (false negative). Unlike process alarms which must never miss a fault and should always sound an alarm if a threshold is exceeded (no false negatives), control performance monitoring method must be robust towards the false positives. This means that the method should be very certain that a fault is present before alert an operator.
2. **Workflow and ease of use**: Data today is much easier accessible than before. Conducting an analysis with advanced algorithms to detect disturbances, however, still requires engineering effort and often consulting a specialized department within and outside the company. The interaction between the operating personnel and the specialists who can apply the monitoring methods must be formalized in a workflow that is supported by all parties involved.

A further reason is that computing the financial benefit of control loop performance monitoring is not as easy to assess.

In this contribution, we address the two problems by proposing a novel method to detect valve stiction that can be fully automated. This new method is tested for false positives as well as false negatives using confirmed process data that is publicly available. An improved workflow and ease of use is demonstrated by implementing the novel method in the Seeq Data Lab environment. A seamless integration of the development to the final product is now available as a Seeq Workbench add-on that is free to download from a GitHub repository.

The article is organized as follows. Section 2 describes the problem of valve stiction detection and existing approaches for detecting it. The novel method is explained in Section 4. Section 5 gives the results of applying the method to verified cases of valve stiction as well as other oscillatory signals that did not have valve stiction as a root cause. Section 6 describes the implementation in the Seeq Data Lab environment.

Valve Stiction Detection

In continuous processing, the dominant method of actuation is through control valves. Control valves are expected to have a linear relationship, that is, the applied controller output is exactly equal to the manipulated variable, i.e. resulting flow. This in reality is never the case. Valves can be nonlinear, that is, a change in the stem position does not impact linearly on the flow. In addition, valves can age and the stem may not travel as expected. In particular, valve stems get ‘stuck’ at a certain level and will not move even when a larger controller output is applied. If they overcome a certain inertia, they will start to travel again. Fig. 2 (a) shows the dead band relationship between the applied controller output and the manipulated variable. The phenomena of valve stiction is well described and can be simulated (Choudhury et al., 2005). The interchanging ‘stuck’ movement of the valve stem and the hysteresis or

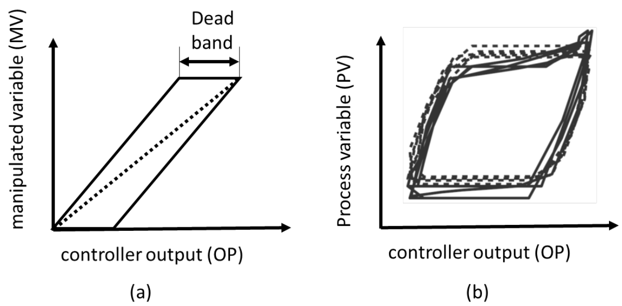


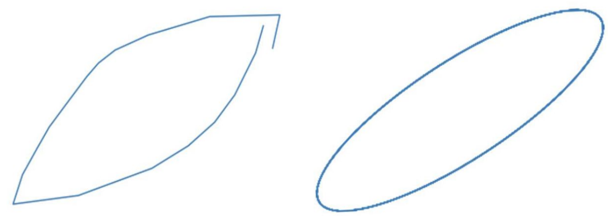
Figure 2. PV/OP plot of an ideal linear behavior of a control valve (a, dotted line) and a control valve behavior with dead band (a, solid line). The plot on the right (b) shows examples of valve stictions PV/OP-plots in industrial data.

dead band shown in Fig. 2 (a) result in an oscillatory time trend that can be observed in both the PV and the OP signal of a control loop.

Ideally, one would plot the manipulated variable against the controller output as shown in Fig. 2 (a). In flow loops, the valve stem position impacts directly on the measured flow. In all other control loops, such as pressure, temperature, level or others, a dynamic process acts between the manipulated variable and the process variable, PV. Usually, the manipulated variable is not available recorded and available as a measurement. Instead, one can use the PV under the assumption that the process is comparatively slow compared to the oscillation introduced because of the nonlinearity of the control valve.

Many methods have been developed to detect and diagnose valve stiction from industrial process data. An overview of existing methods is given in the textbook edited by Jelali and Huang (2010). Many methods investigate the relationship of the process variable by plotting the oscillatory time trends of the process variable against the controller output as shown in Fig. 2 (b) (Yamashita, 2006, Choudhury et al., 2006, Kano et al., 2004). A comparison of the different approaches is provided by di Capaci and Scali (2018). However, the overview was conducted on false negatives and not on false positives. Recently, methods have been proposed that investigate the time trends, by analyzing the shape of the oscillation (Hägglund, 2011) and by applying pattern recognition and neural networks (Amiruddin et al., 2019).

The proposed method combines several of these recent approaches by first detecting oscillations, then plotting a single oscillation circle as shown in Fig. 2 (b) and finally applying pattern recognition to the shapes. The approach is described in more detail in the next section. The method is applied to confirmed valve stiction data contained a repository (Bauer et al., 2019).



A new stiction detection method using shape detection

The new detection method has at its core a similarity index that compares shapes to known examples of valve stiction. This is described in the following. Fig. 3 shows the shape PV/OP plot of Fig. 2 after travelling through the process and therefore inevitable lowpass filtering. In addition, care has to be taken to pre-process the data and detect the oscillation. The complete procedure is given after the description of the similarity index.

Shape similarity index

The principle of the stiction detection method is that the oscillation with stiction has a nonlinear shape, that is, when plotting the process variable against the controller output, the resulting ellipsoid shape has sharp edges for stiction while an oscillation caused by an outside disturbance, or a poorly tuned controller will have round edges, as shown in Fig. 3. A shape is detected by using the connected pixels approach which is a fundamental approach in the binary image analysis (Suzuki and Abe, 1985). Wang et al. (2004) build on this approach by developing a structural similarity index by distinguishing between luminance, contrast and structural values when comparing two images. A simplified version of the method by Wang et al. can be implemented by only focusing on the structural similarity of two images x and y. The structural similarity is defined as

$$s(\mathbf{x}, \boldsymbol{y}) = \frac{\sigma_{xy} + C_3}{\sigma_x \sigma_y + C_3}$$

Where σ_x and σ_y are the standard deviations of x and y respectively and σ_{xy} is the correlation coefficient that can be estimated as

$$\sigma_{xy} = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \mu_x)(y_i - \mu_y)$$

The constant C3 is a small value that is added to instability when σ_x σ_y is close to zero. The similarity is then assessed for a number of images that are known to show valve stiction. Images are compared to existing images in the data base.

Valve stiction detection procedure

In order to fully automate the method, the controller output and process variable of a control loop should be entered for a long period of time. Several steps need to be

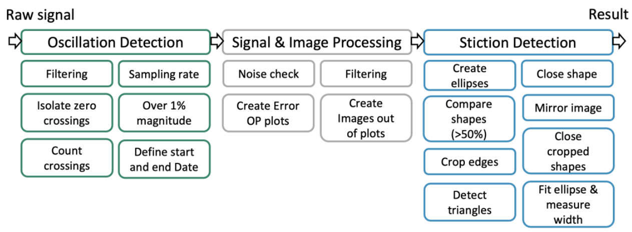


Fig. 4. Valve stiction detection method steps.

Step 1: Enter start and end time and date for the signals of a specified control loop (PV, OP).

Step 2: Pre-process the data by filtering out low frequency components in the signal.

Step 2: Detect start and end of an oscillation present in the selected data.

Step 3: Slice data into oscillation cycles between start and end period of oscillation.

Step 4: Create OP/PV images for each slice.

Step 5: Conduct similarity analysis to detect shape, compute magnitude of similarity.

The last step is the core of the analysis and can be divided into further steps as shown in Fig. 4. The ellipses have to be formed and the connection has to be closed. The shapes are compared and possibly have to be mirrored because the ellipsoid shape can be from bottom right to top left corner or from top right to bottom left corner. Edges will be cropped and shapes have to be closed again. Note that it may be necessary create a mirror image of the ellipsoid. The similarity looks for sharp corners or 'triangles'. The ellipse width is then identified to estimate the dead band of valve stiction.

Examples of shapes of existing loops with valve stiction are shown in Fig. 5. These figures are the input images on which the detection algorithm is based.

Testing the method

The method requires both data for training and also for testing. Here, we test for both data sets that are confirmed cases of valve stiction and cases where there are other problems causing the oscillation. This is because we want to test both false negatives and false positives. All time trends analyzed here can be found in the data repository given earlier (Bauer et al., 2019). Unfortunately, data is not readily available confirmed cases of valve stiction because production companies have no interested and financial benefit of putting the data out into the public domain. The benefit of slicing the data into sections is that several images can be generated for each confirmed case.

The algorithm was applied to the data and Table 1 shows the results for time trends with signals that are confirmed cases of valve stiction. All but one case was

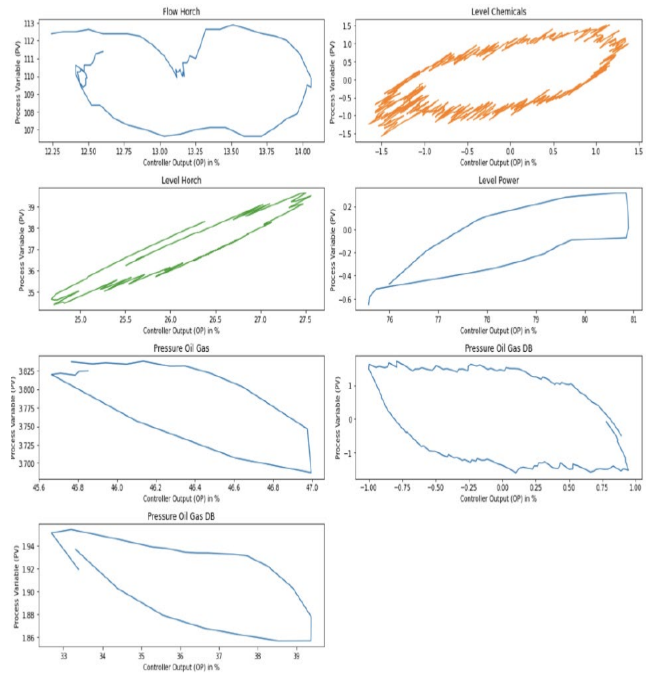


Figure 5. Examples of PV/OP shapes of time series signals with valve stiction as given by Bauer et al., 2019.

correctly detected. The reason for not detecting this data set could be that there were not many cycles detected.

Table 1. Control loops with confirmed cases of valve stiction as described in Bauer et al. (2019).

Stiction control loops	Oscillation cycles	Measurement accuracy	Stiction
Flow Horch	16	97	Yes
Level Chemicals	38	81	Yes
Level Horch	9	-	No
Level Power	169	62	Yes
Pressure Oil&Gas	24	74	Yes
Pressure Chemicals	4	85	Yes
Pressure Oil&Gas DB	12	79	Yes

Table 2. Control loops with disturbances that were not attributed to valve stiction as described in Bauer et al. (2019).

Other control loops	Oscillation cycles	Measurement accuracy	Stiction
Level Minerals	-	-	No
Temperature Oil & Gas	16	0	No
Flow Oil & Gas	53	4.73	Yes
Flow Chemicals	-	-	No
Level Horch	-	-	No
Quality Horch	32	-	No

Arguably the most important test for any method is to avoid false positives. The reason is that there should be a clear indication of valve stiction before an operator or other plant personal is alerted. This is different to process alarms that should avoid false negatives at all cost. The detection of stiction using process data is not part of the basic process operation and generally does not directly impact on the safety of the operation. Any plant personnel who experiences a number of false alerts regarding the valve stiction.

Architecture, User Interface and Implementation

In addition to the algorithm development, a key requirement for this project is to provide an easy-to-use interface to analyze and monitor results. Integration with Seeq Workbench allowed for easy access to data and trending results.

The user interface was designed in accordance with the guidelines of the Seeq Workbench tool. The interface is shown in Fig. 6 and the individual items that can be selected are marked with 1. to 8.

As a first step, the controller error has to be selected. The controller error is the setpoint minus the process variable in the control loop. If the controller error is not available, the process variable can be selected instead. The benefit of using the controller error is that this choice eliminates any fluctuations that stems from setpoint changes. In step 2. the start and end date must be selected by the user. The default is the inclusion of the selected timeframe in the main visual representation as shown in Fig. 1. In step 3. the condition to be analyzed is chosen. The choice is between detecting an oscillation only and detecting valve stiction. In future developments, further conditions such as poor controller tuning can be included. If steps 1 to 3 are selected it is possible to carry out the analysis by clicking the 'Analyze' button. The results will then be displayed in the top right corner, see 5. To incorporate the results into the existing worksheet, both oscillation and stiction signals can be sent to the existing workbook from where the analysis was started, see 6. It is possible to change the name to any name preferred in the analysis. The default names are given in Fig. 6. Further documentation is available to the user to explain the analysis and the problem of valve stiction.

Open Source as an Add-on

For this project, we adopted an approach of bringing academic research and industry vendor together via an open-source model. Open sourcing academic research in the form of a GitHub repository promotes reproducible and collaborative research. Interested parties can examine the details of the algorithm and implementation; the efficacy of the approach can be validated on other data sets. Through pull requests, the user community can contribute to the research and help advance the technology but are also within their rights to fork the repository and strike out on their own. The collaboration with an industrial vendor, Seeq Corporation, has been critical to make this research visible and available for industrial practitioners from an early stage. A link to the Stiction Analyzer GitHub repository is hosted in Seeq's Add-on Gallery https://seeq12.github.io/gallery/. The availability and integration of this research as a ready to use, open-source Seeq Add-on allows industry practitioners to test, validate, and operationalize on their data with minimal overhead.

Conclusions

This paper presented a novel method to detect valve stiction. The emphasis was to detect valve stiction reliably by testing the method for both false positives and false negatives. This was done because the technical value is the savings because of detected valve stiction minus the cost that is incurred because of incorrection action. The method was tested on data that is publicly available. In addition, the method was implemented in an open source add-on made available by the university and used as a package by industrial customers. This gives a seamless integration and shows how the path from developing a new method to productization can be significantly shortened. It also allows research institutions to develop their own products.

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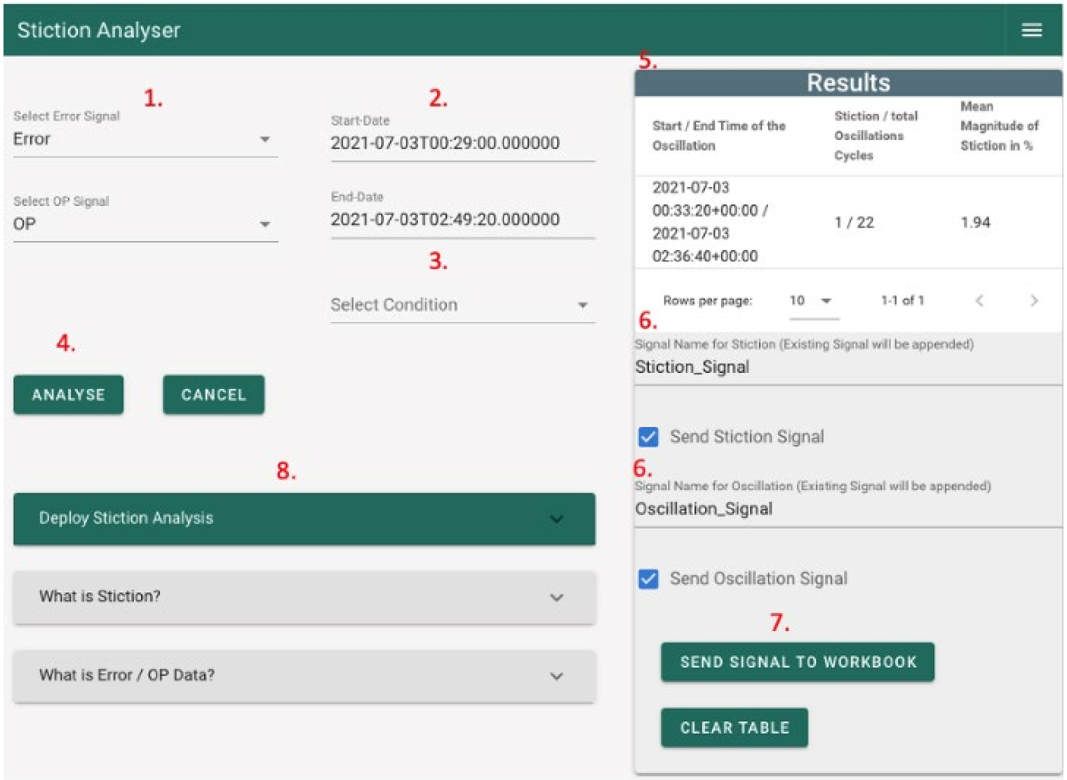

Figure 6. Workflow of the analyzer tool.

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