Classifying Valve Stiction Using Features Extracted from Time Series

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ECO-INNOVATION CHESHIRE & WARRINGTON

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The Eco-Innovation Cheshire and Warrington project is part-funded by the European Regional Development Fund. The project is led by the University of Chester who have partnered up with Lancaster University to work with local SMEs in the innovation and adoption of Low Carbon Technologies. In collaboration with Spiro Control Ltd., this particular project aims to reduce carbon in the industrial process control sector through the application of machine learning based performance monitoring and fault detection algorithms.

INTRODUCTION & BACKGROUND

Control Valve Stiction

Stiction in a control valve is a fault that frequently occurs due to a combination of seal degradation, insufficient lubrication, foreign debris and tight packing around the stem, all of which limit the response of the valve to a given control signal. This restriction in valve movement causes oscillations in the form of periodic finite-amplitude instabilities, known as limit cycles (seen clearly in the PV variable in Fig. 3). The result is an increase in variability of product quality, accelerated equipment wear and overall system instability.

The friction surrounding the stem is often considered as the main cause of stiction, and is an indirect consequence of the strict regulations on volatile organic compound (VOC) emissions. In many plants, a team monitors each valve for VOC emissions, usually between the packing and the stem. If any leakage is detected, the packing in the valve is excessively tightened, resulting in stiction.

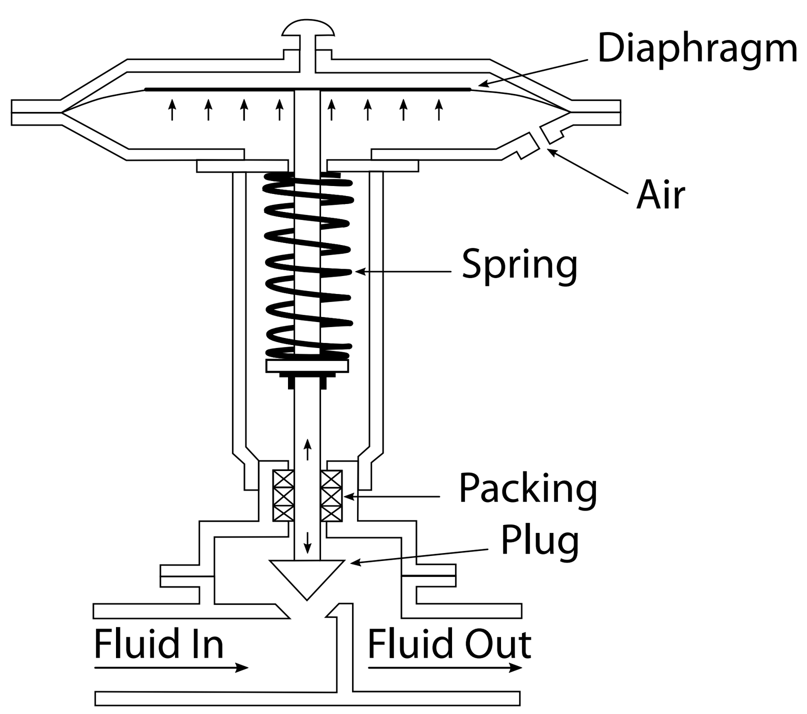

Figure 2: Typical pneumatic control valve schematic.

Over the last few decades several algorithms have been developed for the detection and quantification of valve stiction in control loops [1]. Despite the success of machine learning based fault classification in other industries, there are currently no stiction detection methods that adopt a supervised learning approach to this problem. We address this in our work, where we have trained a support vector machine using simulated examples of stiction to recognise any underlying patterns in the recorded time series data of a given control loop.

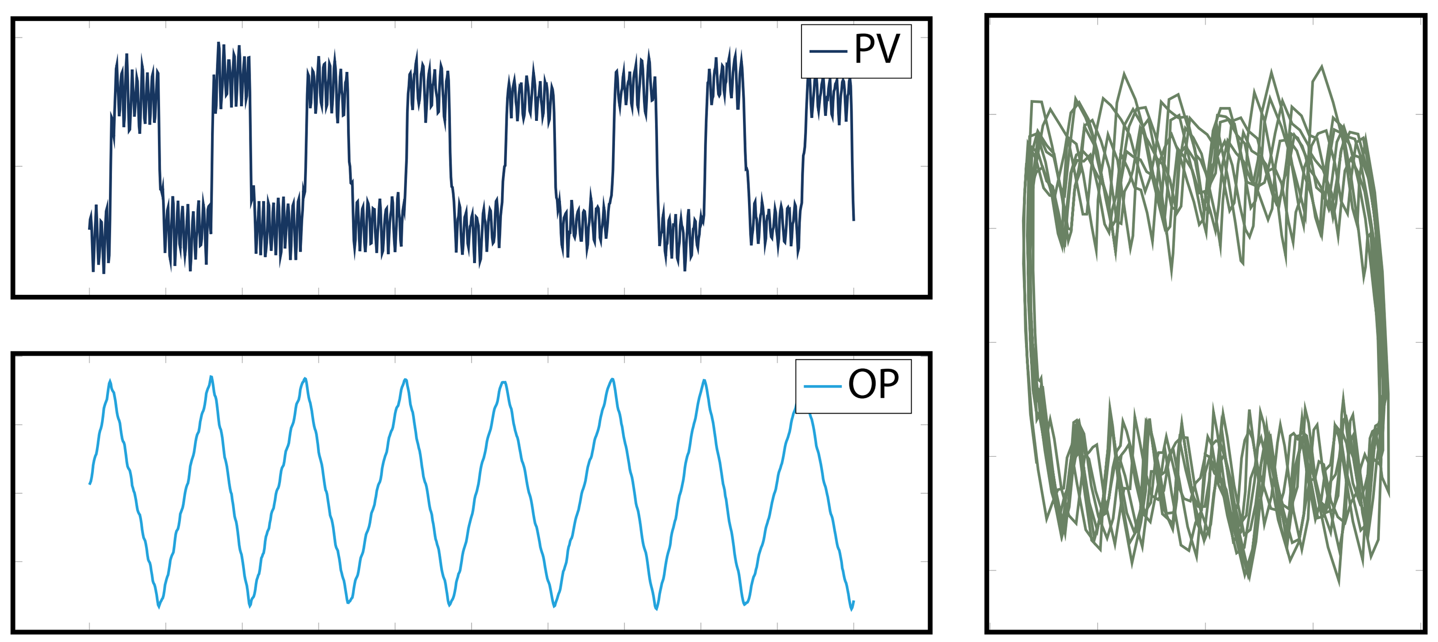

Figure 3: CHEM23 (FC) from the Industrial Stiction Database.

GENERATING DATA

Valve Stiction Model & Simulation

Due to the small number of real stiction examples that are available, we are required to generate our own training data using Simulink. Fortunately there exist many stiction models which produce excellent accuracy when directly compared with real cases [1].

Most research in this field is conducted using data-driven models such as the popular Choudhury model [2]. For our simulations we use the more recent XCH model [3], a modification of the original Choudhury model aimed at improving performance on a series control valve tests set by the International Society of Automation (ISA).

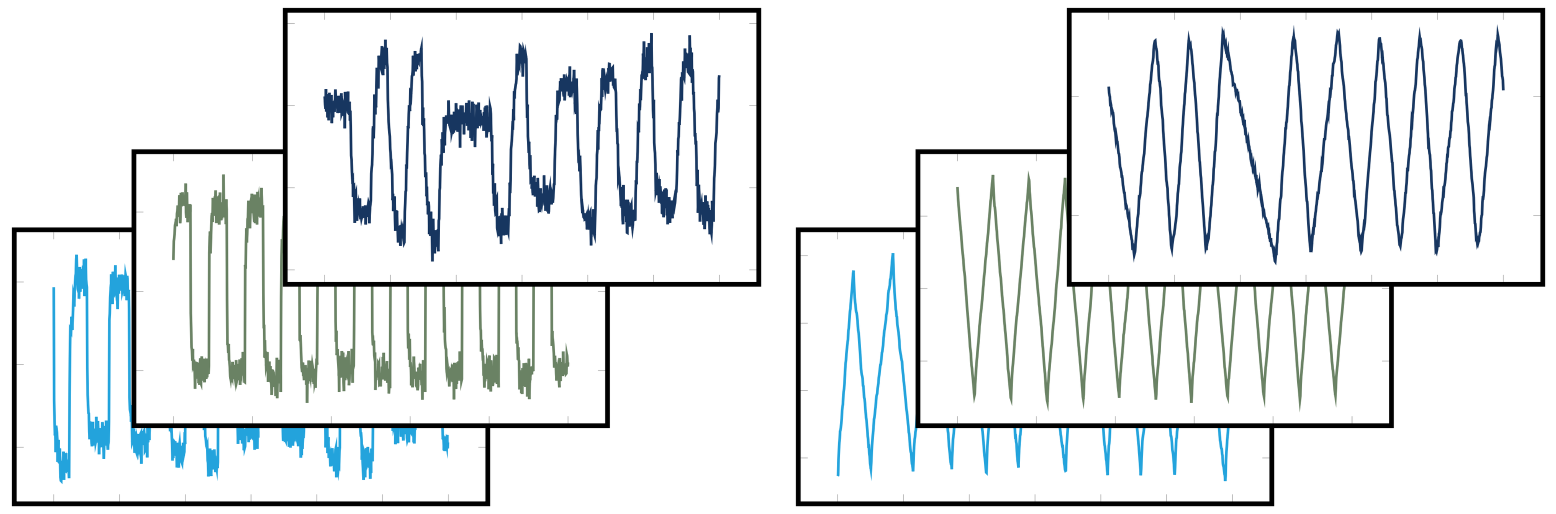

Figure 4: Phase and time plots for a selection of simulated examples of valve stiction.

The severity of stiction is controlled by the S and J parameters of the model, where S controls the range of controller output for which the valve sticks, and J the size of the jump once friction is overcome. In order to produce a variety of behaviours, both parameters are varied with each simulation, as well as others such as process gain, time constant, time delay and sample time. Additional sources of oscillation such as aggressive controller tuning and sinusoidal disturbance are also created in an attempt to aid the classifier in identifying patterns that are unique to stiction.

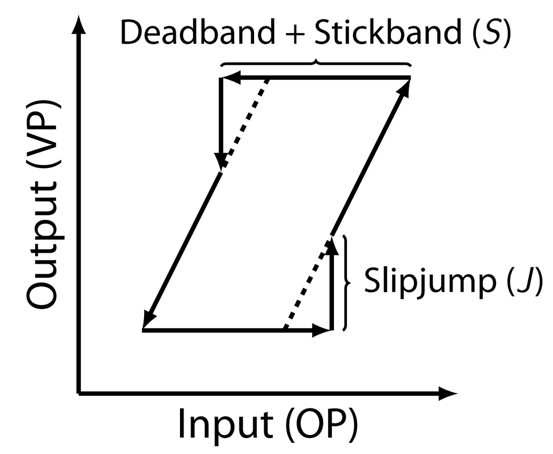

Figure 5: Stiction parameters S and J.

FEATURE EXTRACTION & CLASSIFIER TRAINING

Feature Extraction & Selection

For each of the simulated control loops we consider the standardised PID controller output (OP) and setpoint error (ER). Feature extraction is performed in Python using the time series feature extraction library TSFRESH [4]. The result is a vector of over 1600 features for each simulated control loop. Any irrelevant features are removed using a combination of hypothesis testing (via TSFRESH) and recursive feature elimination (RFE), leaving approximately 500 to be used for prediction. Here are just 3 of the features selected at random:

- OP__agg_autocorrelation__f_agg_"var"__maxlag_40
- ER__change_quantiles__f_agg_"var"__isabs_True__qh_0.8__ql_0.6
- OP__fft_coefficient__coeff_76__attr_"abs".

These would appear meaningless to even a trained engineer, it is only with a computer that we are able to reveal any hidden patterns that aid with stiction diagnosis.

Support Vector Machine Training & Optimisation

Prior to training, all features are first scaled and then labelled as either stiction (1), or not stiction (0). For classification we use the powerful support vector machine (`sklearn.svm.SVC`) from the scikit-learn machine learning library in Python. Optimal parameters for the SVM model are then obtained via grid search and k-fold cross-validation (`sklearn.model_selection.GridSearchCV`).

RESULTS

Results on Simulated Data

We evaluate the performance of the classifier by reserving 30% of the simulated data for testing. The results show that the trained SVM is 96% accurate at distinguishing stiction from the other simulated sources of oscillation. This is a promising result, but we are primarily interested in the outcome when applied to real data, as the simulations cannot capture the minor details present in a real environment.

Comparison with Benchmark Data

In a recent book on the topic of stiction [5], a number of industrial control loops are used as a benchmark for testing several stiction detection algorithms. Where possible we have taken the first 1000 data points from each loop, extracted the relevant features and fed them to our support vector machine classifier. The prediction is compared with the known/suspected verdict given in the book, and the results are presented below.

Table 1: Classification results for non-integrating loops with constant setpoints.

	BIC	CORR	HIST	RELAY	CURVE	AREA	HAMM2	HAMM3	SVM
True Positive	8	6	10	11	8	9	12	13	7
True Negative	14	13	7	4	7	12	4	4	21
False Positive	3	2	8	15	7	4	17	19	2
False Negative	1	8	4	2	5	3	2	1	7
Accuracy	0.846	0.655	0.586	0.469	0.556	0.750	0.457	0.459	0.757
Precision	0.727	0.750	0.556	0.423	0.533	0.692	0.414	0.406	0.778
Recall	0.889	0.429	0.714	0.846	0.615	0.750	0.857	0.929	0.500
F1 Score	0.800	0.545	0.625	0.564	0.571	0.720	0.558	0.565	0.609
# Correct	22	19	17	15	15	21	16	17	28
# Applications	26	29	29	32	27	28	35	37	37

FUTURE WORK

Extension to Other Processes

The simulations used for training in this current iteration are restricted to self-regulating processes with fixed setpoints, which limits the applicability of the method to control loops of this type. Integrating processes and variable setpoints are just as common, so we are currently working on extending our training data to cover such cases.

Stiction Quantification

The current classification procedure is binary, either the loop has stiction or it doesn't. By converting to a regression problem we can use our simulated data with known S and J parameters to make predictions regarding the level of stiction present in a loop. This would allow severe cases of stiction to be prioritised for maintenance.

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