VHI: Valve Health Identification for the Maintenance of Subsea Industrial Equipment

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Abstract. Subsea valves are a key piece of equipment in the extraction process of oil and natural gas. Valves control the flow of fluids by opening and closing passageways. A malfunctioning valve can lead to significant operational losses. In this paper, we describe *VHI*, a system designed to assist maintenance engineers with condition-based monitoring services for valves. *VHI* addresses the challenge of maintenance in two ways: a supervised approach that predicts impending valve failure, and an unsupervised approach that identifies and highlights anomalies i.e., an unusual valve behaviour. While the supervised approach is suitable for valves with long operational history, the unsupervised approach is suitable for valves with no operational history.

1 Introduction

Predictive maintenance techniques are designed to identify developing issues in industrial equipment, alerting the need for maintenance before issues become critical [1,2,4]. These techniques aid hardware maintenance engineers in their maintenance tasks and therefore reduce the cost of condition-based monitoring services for large industrial equipment.

In this paper we present *VHI*, a system that aids hardware maintenance engineers manage subsea equipment in the oil and gas industry using supervised and unsupervised machine learning. The supervised approach makes use of the k nearest neighbour algorithm to classify valves as (*healthy* or *unhealthy*). In the unsupervised scenario, we use anomaly detection to capture abrupt changes in valve behaviour by contrasting the sensor readings of consecutive valve opening and closing events.

The innovative aspect of *VHI* is the convenience that it brings to hardware maintenance engineers. Using the supervised approach the condition of valves can be classified and simultaneously explained through simple nearest neighbour

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signature plots. Using the unsupervised approach the condition of new valves can be visualised with anomaly detection plots from different perspectives.

The *VHI* system is beneficial for the industrial sector where maintenance of equipment is often needed. The system requires time-series data generated by the sensors to monitor the condition of the equipment, and it can benefit industries when a history of operational data is present or otherwise.

There are two similar commercial products available in the market for the maintenance of valves: ValveLink Software from Emerson electric (emerson.com) and the VTScada system (trihedral.com). Both of these systems, however, are generic equipment management tools which lead to complex interfaces. *VHI* is tailor-made for the needs of an oil and gas engineers and kept simple and intuitive to use.

2 System Overview

We now present an overview of the *VHI* system. First, we discuss the dataset description, then we discuss supervised and unsupervised approaches.

Data: The dataset is composed of 583 subsea valves which are monitored over multiple years. These valves have a total of 6,648 open (48.87%) and close (51.12%) events. Each time a valve is opened or closed, the state of the valve is captured by three sensors. Two of the sensors measure pressure, and the third sensor measures cumulative volume. During an event (opening or closing), a sensor records 120 readings at regular intervals and this results in three-time series (one for each sensor).

Supervised Approach: The supervised approach is suitable for valves that have a history of operational data available along with manual assessments. *VHI* uses the k nearest neighbour algorithm [3] for classification and it uses signature plots from the nearest neighbours to help maintenance engineers understand predictions (see Fig. 1).

Unsupervised Approach: The unsupervised approach is suitable for valves for which no operational history is available, making it appropriate for a cold start problem. In the unsupervised approach, we use anomaly detection to capture abrupt changes between consecutive readings from sensors when a valve is either opened or closed. These abrupt changes are calculated by applying distance metrics between consecutive readings. We primarily use dynamic time warping but other distance metrics (e.g. Bray-Curtis and discrete Frechet) are also made available in *VHI*.

3 User Interface

The interface of the supervised approach is composed of four modules (see Fig. 1). The first module is composed of the required inputs. The first input requires a 'csv' file containing the valves' data, where each row contains data captured by

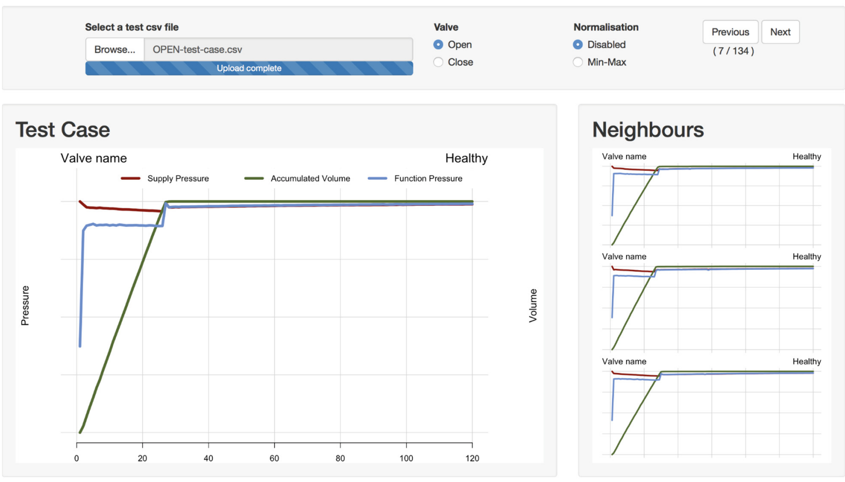

Fig. 1. Screen shot of the supervised approach.

sensors whenever a valve is either opened or closed. The rest of the inputs are to select the event (either open or close), to either apply normalisation to the signals or not, and the last one to navigate between rows of the 'csv' file. The second module (called 'Test Case', see Fig. 1) shows the plots generated by using all three sensors. Each line shows 120 points generated by a sensor. The first plot shows the signature of the predicted valve (on the left side) along with a predicted label (either *healthy* or *unhealthy*). The third module called 'Neighbours' shows the three nearest neighbours (on the right side) along with their respective labels. The prediction is made by majority vote among the three neighbours. The final module is called 'History' which shows a number of previous plots of the valve (being predicted) to demonstrate the evolution of the state of the valve, these plots are not shown due to space limitation.

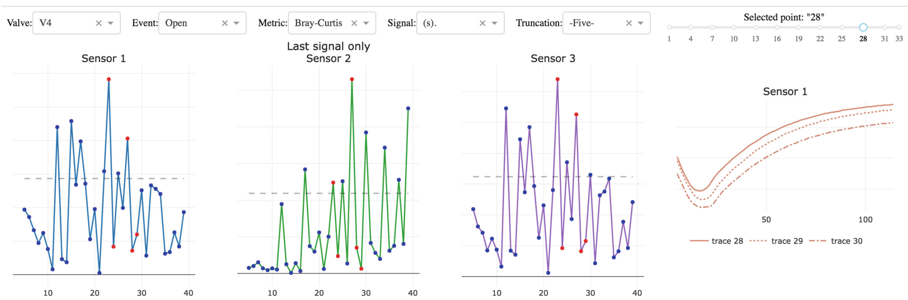

Fig. 2. Screen shot of the unsupervised approach. (Color figure online)

The interface for the unsupervised anomaly detection approach is composed of four modules (see Fig. 2). The first module is composed of the required inputs. The six inputs are to select a valve, an event (opened or closed), a metric (distance), signal transformation (original, first derivative, normalised), truncation of the signal (i.e., eliminating a first few, a last few, or at both sides of the 120 data points), and a slider that controls the instance of a valve progressively over time. The second module shows the anomaly detection plots for each sensor which is calculated by the distance between two consecutive signals (indicated by "Last signal only" in Fig. 2). The colour (which is indicated for demo purposes only) of each point represents the state of the valve at that point (green for *healthy*, blue for *degraded*, and red for *failure*). However, the idea is that a spike in the distance shows an anomaly and needs to be investigated by the engineer. Similar to the second module, the third module shows anomaly detection plots for each sensor but by calculating the distance between the average of three preceding signals and the recent signal (not shown in the Fig. 1 due to space limitation). Finally, the last module shows the original progression of the sensor data over an instance of the valve controlled by the 'Selected point' slider.

The URL https://youtu.be/dueTEovxHqI shows the online video demonstration of the *VHI* system.

4 Conclusions

This paper described *VHI* a novel predictive maintenance system designed to assist oil and gas engineers manage subsea valves. The system uses supervised and unsupervised machine learning techniques to monitor valve health. The system is currently being used by engineers at a number of sites.

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