Predicting compressor failure using Sabisu analytics

1.1 Problem

Sabisu Analytics are intended to apply to a wide range of scenarios. When a customer approached us with a challenge in asset monitoring it provided the ideal opportunity to tune the Sabisu anomaly detection algorithms.

Operating one of the largest LDPE plants in the world is challenging. Scaling up the production processes has pushed assets to the limits of their performance, particularly the compressors. Any compressor failure stops production.

Process data shows that a specific event corresponds to the degradation of the compressor packing rings. There are around 20 packing boxes, each containing 5 rings which over time wear and eventually fail. If all 5 rings in a packing box fail then the compressor fails, causing the plant to trip with significant down-time and costs of around £1m/yr.

Ideally the rings are replaced before this point but the packing boxes are sealed and there is no way to inspect the boxes to determine how many rings are left intact. Instrumentation is also limited to a handful of key process parameters.

The challenge is to identify the ring failures from the data to ensure that

- total failure does not occur
- healthy boxes are not replaced prematurely

1.2 Solution

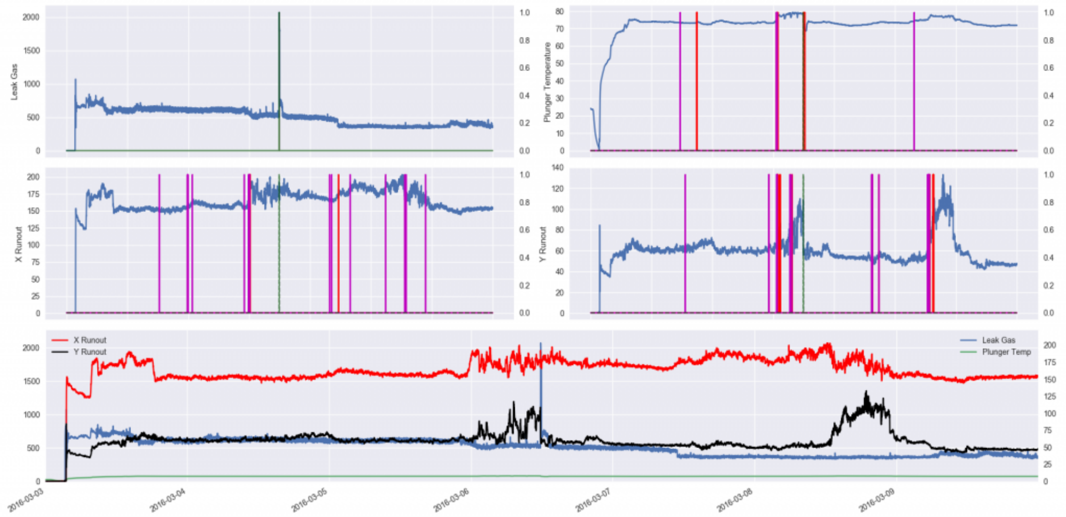
Looking at the data it was clear that our anomaly detection system would form an ideal base for the solution.

An increase in leak gas is the first clue that a ring has failed somewhere in the compressor. This is confirmed by analysing three more signals per packing box.

If an anomaly is detected in one of these signals which correlates to the leak gas increase then the failure can be confirmed and the affected box identified.

Combining two different anomaly detection configurations produces excellent results; reliable, fast and with acceptable compute resource requirements.

The following image shows the raw anomaly results from the first anomaly detection process:



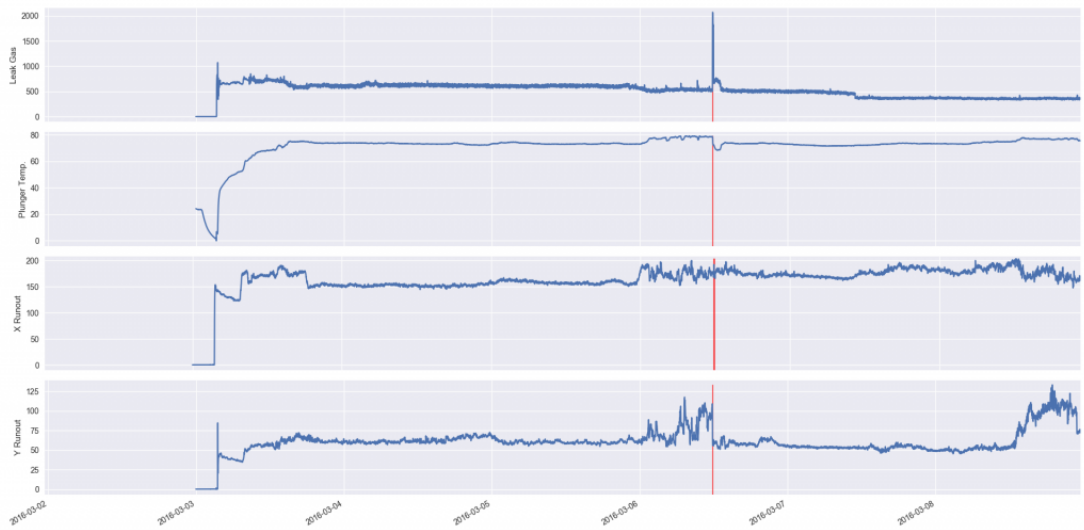
Anomaly Detection Results

The spike in leak gas output indicates a potential ring failure, and is accurately identified by the system.

A less sensitive threshold is used for leak gas detection to avoid false positives.

More sensitive settings are then used to identify any changes in behaviour of the secondary signals, i.e., those which identify the specific box that contains the failed ring.

The following image shows anomalies detected on multiple signals which correlate with the gas leak – meaning this must be the box containing the failed ring.



Aggregated Results

Shows the correlation between the leak gas peak and the features in the signals from a particular packing box.

The aggregation and alignment of these anomalies allows the specific box to be identified and the appropriate preventative maintenance activity carried out.

This approach means that total failure does not occur and ‘healthy’ boxes are not replaced prematurely.

The tight aggregation window means that this approach gives great performance whilst still being extremely lean in terms of compute resources.

1.3 Next Steps

With algorithm performance proven, attention will now be given to how this data is presented to using Sabisu, including pro-actively alerting users when a packing ring failure has taken place using Sabisu Pipelines.

Sabisu Pipelines also support the automatic initiation of maintenance processes in response to a series of events, e.g., triggering box replacement when 4 of 5 rings have failed.

While a gas leak is a useful leading indicator of packing ring failure, Sabisu machine learning can help Process Engineers examine other correlations and contributory factors. Sabisu will pattern match every single previous ring failure to build up a failure signature and library of ‘Events’ for investigation.

In the same way, packing boxes can be compared over time to identify patterns which suggest excessive wear in a particular box, or to predict the lifetime of the box.

User input remains crucial and Sabisu Events permit false positives to be identified and taken into account in the machine learning process, e.g., where the failure is partial, or different kind of event has taken place.

Using this insight, applying machine learning and statistical techniques, further anomaly detection and machine learning configurations can be evaluated to improve management and maintenance of S18’s secondary compressor.

1.4 Related Links

Sabisu Pipelines

Finding Events with Sabisu Machine Learning

Machine Learning in Sabisu – Finding Patterns in Data

Sabisu Workflow

Workflow Management with Sabisu Processes

Sabisu Advisories: Steering you to action

When do I use Sabisu instead of my historian/DCS process viewer?