Asset failure prediction in Sabisu

A 'blind' test

1.1 Problem

What follows is a real-world example of predictive analytics in action, in the downstream oil & gas and petrochemicals sector – in fact, it's how the applicability of Sabisu algorithms to asset management challenges was first tested.

Sabisu's asset failure prediction algorithms were first trialled in 2015 on SABIC UK's Olefins 6. In order to test the algorithms it was agreed that blind tests using process data provided from OLIP21 would be appropriate.

The challenge was to identify and if possible predict possible heat exchanger or Borsig failure. Such failures are hard to anticipate with assets varying in reliability and lifetime. Inner tube failures start small and become increasingly serious until the asset fails, whereas outer tube failures are often immediately catastrophic.

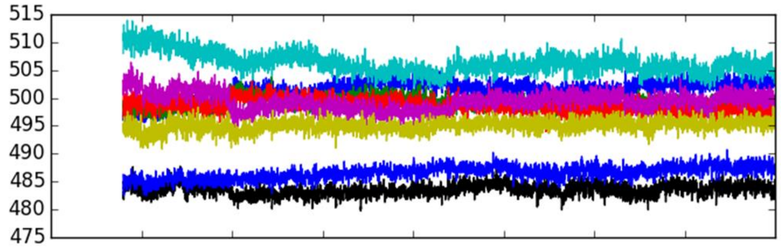
As Sabisu algorithms are designed for broad applications, the following rules were set:

- 'Plug and play', i.e., no tuning of any algorithms, or building of models.
- No knowledge of the manufacturing process
- No help as to what the tags and data represented or their relationship.
- No context as to the performance of the plant, the nature of any failures or any other work that might affect the plant operation and data.

This was a key test. Would the mathematics work with so little to go on? Could we prove we can predict asset behaviour?

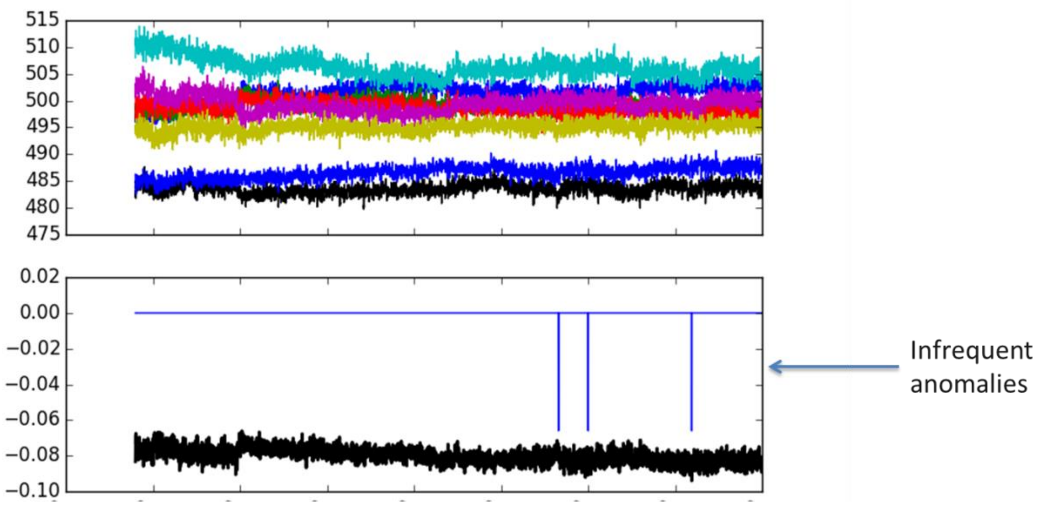
1.2 Solution

Around 12 months of data was made available to Sabisu with readings every minute for 8 tags. The value ranges and tag descriptions implied that they were temperatures but there was no other data available. An example week's worth of data looks like this:



It's noisy data and there are no distinguishing characteristics. In this sense it's common to a lot of continuous process data. The data is within a very narrow range and the process is under Advanced Process Control (APC) schemas to maximise rate and quality, so there's little variation.

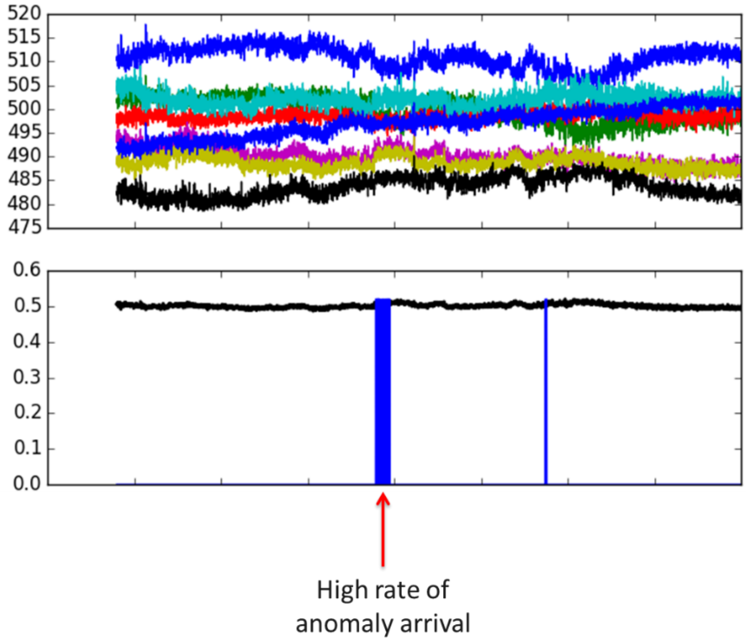
In fact, in normal operation the algorithms flagged occasional anomalies like this:



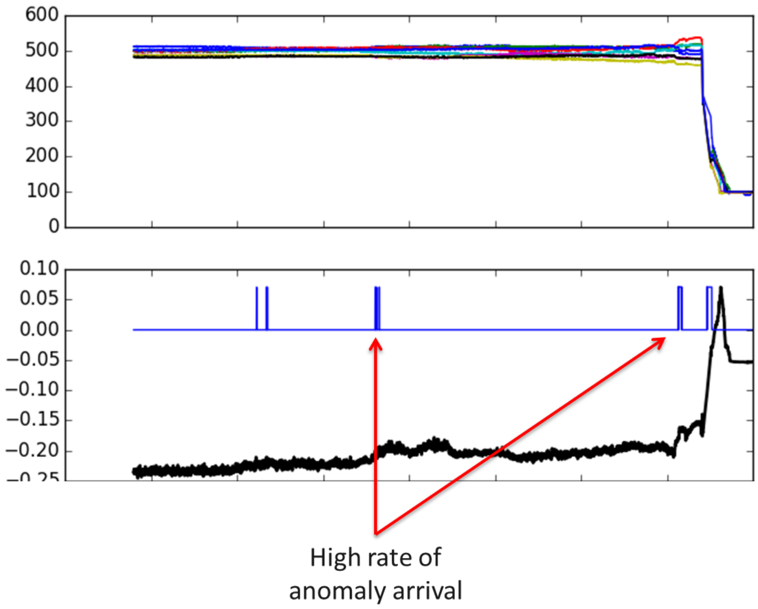
But the algorithms also found some very interesting failure indicators that would be impossible to see in any other way.

The following graph shows a significant number of anomalies arriving together over a period of several hours. The variation in the data is negligible – clear to the human eye but insufficient to cause any alarms, or Process or Reliability Engineers to be notified by any other method.

Signal analysis by the Sabisu algorithms detects sufficient anomalous behaviour to constitute a potential issue:



Some 10 days later we see this failure:



You'll observe a small rise in temperature before the failure; that's useful but too late.

The first anomalous period was highlighted *10 days* ahead of the eventual failure. That's a great result – certainly sufficient for Process & Reliability Engineers to address the issue.

So what happened?

Our understanding that at the first anomalous period, a fissure had opened in a superheater tube. APC or other process controls may seek to resolve this and early in its development the leak is relatively small. However over the next 10 days it grows.

Eventually the various plant controls can't limit the growth of the fissure, or perhaps plant conditions change and it fails – in this case blowing a hole in the tube, taking the instrument with it.

Had other process data been available, this would have been even more obvious as correlations would be seen elsewhere; diverging process and steam gas temperatures for example, strengthening the algorithm's detection of the anomalous behaviour.