UNDER (NO) PRESSURE

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ANALYTICAL CLASSIFICATION OF PRESSURE READINGS

1 ABSTRACT

All along the LHC, vacuum gauges provide valuable pressure readings. With them, the integrity of the vacuum can be confirmed.
Knowing the linear relationship that exists between the temperature and pressure an automatic algorithm has been developed to detect areas where pressure behaviour may infer temperature increase. This divides the gauges into two classes: expected and unexpected. The resulting analytical algorithm correctly classifies pressure responses with very high accuracy.

2 BACKGROUND

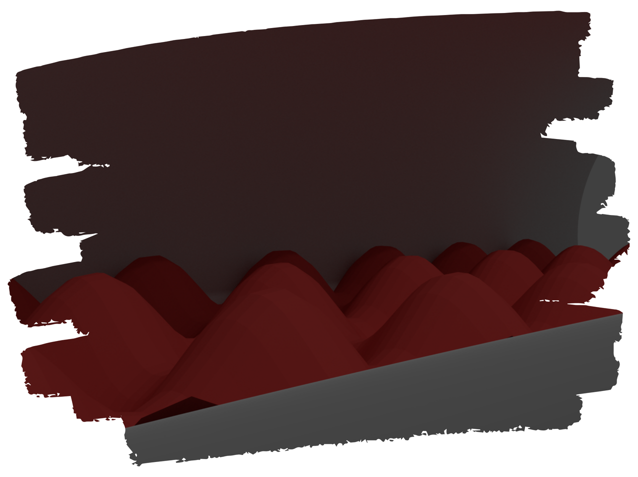


Figure 2: Waves inside the beamline

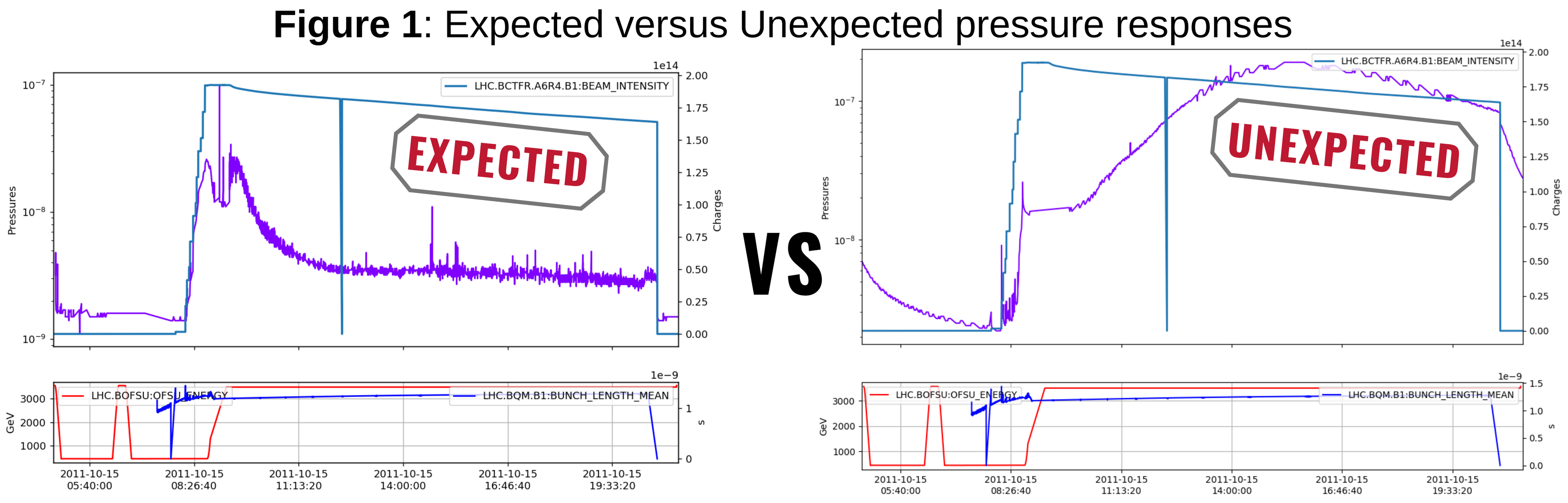
When particles are injected into the LHC, the increase in intensity and energy leads to a pressure increase. This usually stabilizes or decreases after some time.

However if there is a source of heat (e.g. power loss), the pressure response may be different.

3 PROPOSAL

Given a set of pressure readings, determine whether the gauge is behaving as expected.

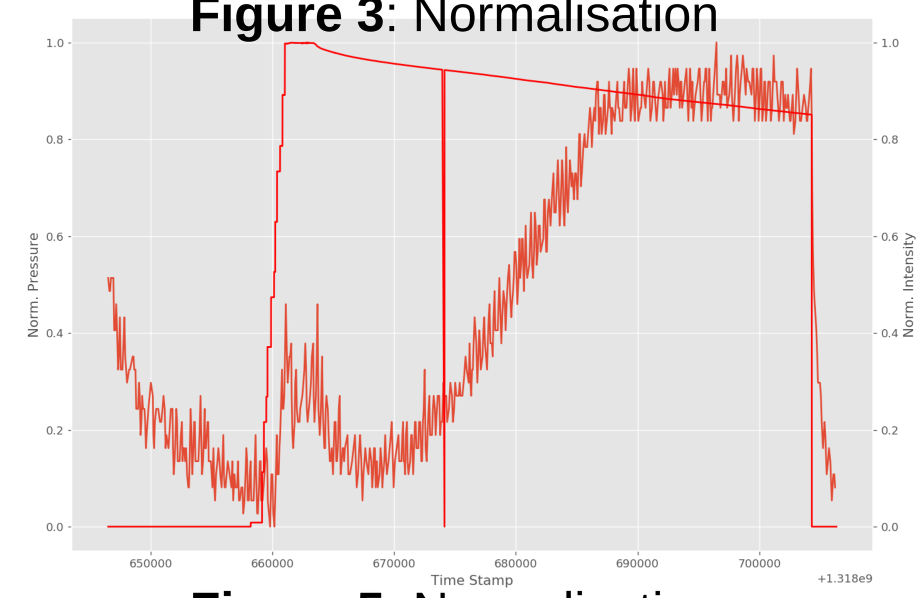
Figure 1: Expected versus Unexpected pressure responses



Unexpected behaviour of the gauge could indicate increased power loss.

4 METHODOLOGY

Figure 3: Normalisation



1) Normalise Data

Translate values to range between 0 and 1. To do so losslessly, we apply **feature scaling** [3]:

$$\frac{x - \min(x)}{\max(x) - \min(x)}$$

Optional: Remove noise in data by replacing them with the median of their neighbours.[4]

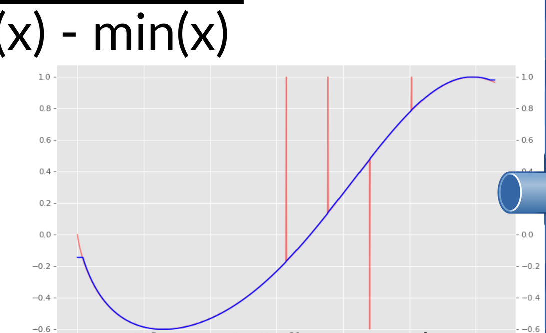
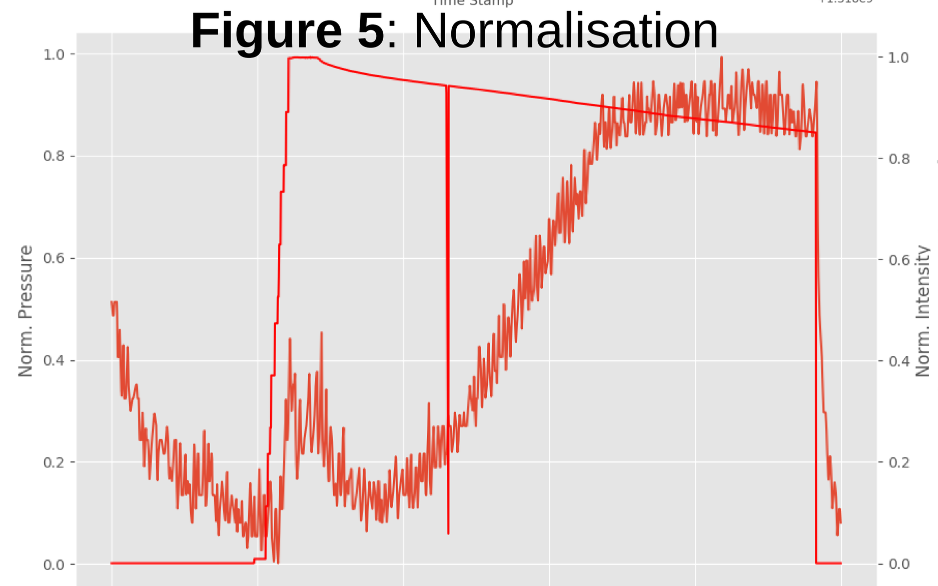


Figure 4: Spike removal

Figure 5: Normalisation



2) Interpolate

To guarantee even-spacing, construct new data points based on the existing data by fitting different low-order polynomials to set intervals.[5] This prevents mis-fitting due to 'holes' in the data.

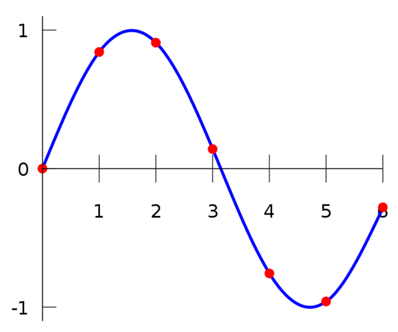
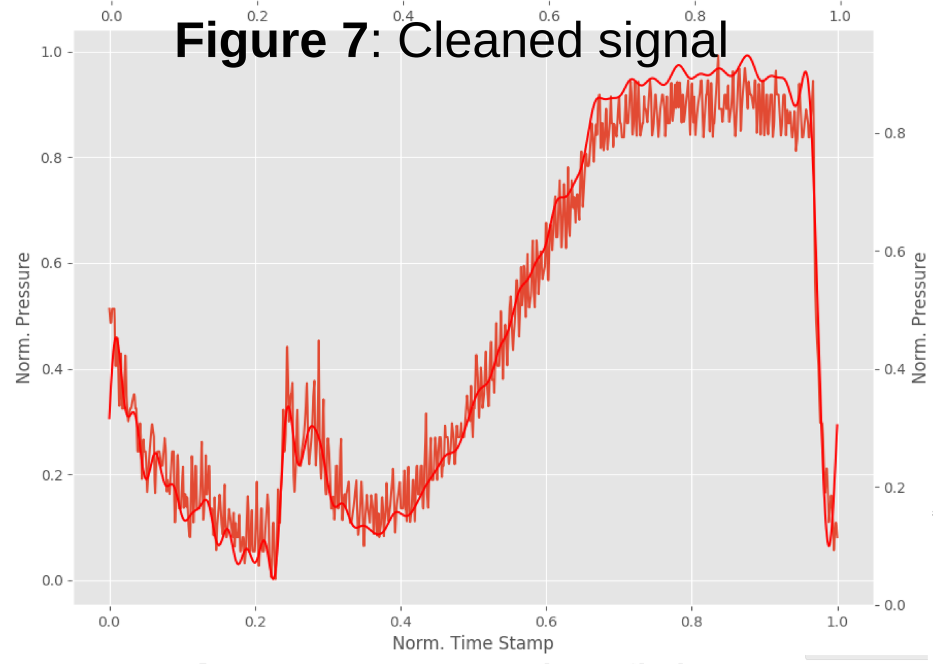


Figure 6: Spline interpolation

Figure 7: Cleaned signal



3) Low Pass filter

Cut off terms above 40Hz in Fourier domain to reduce noise [6]

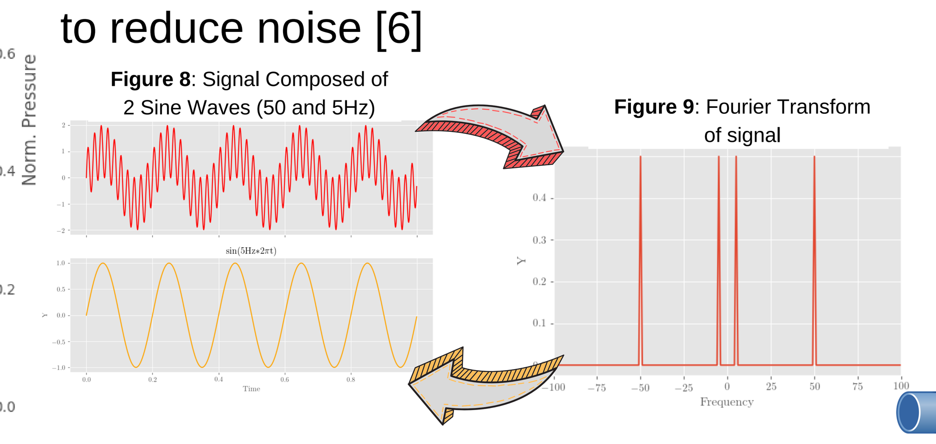
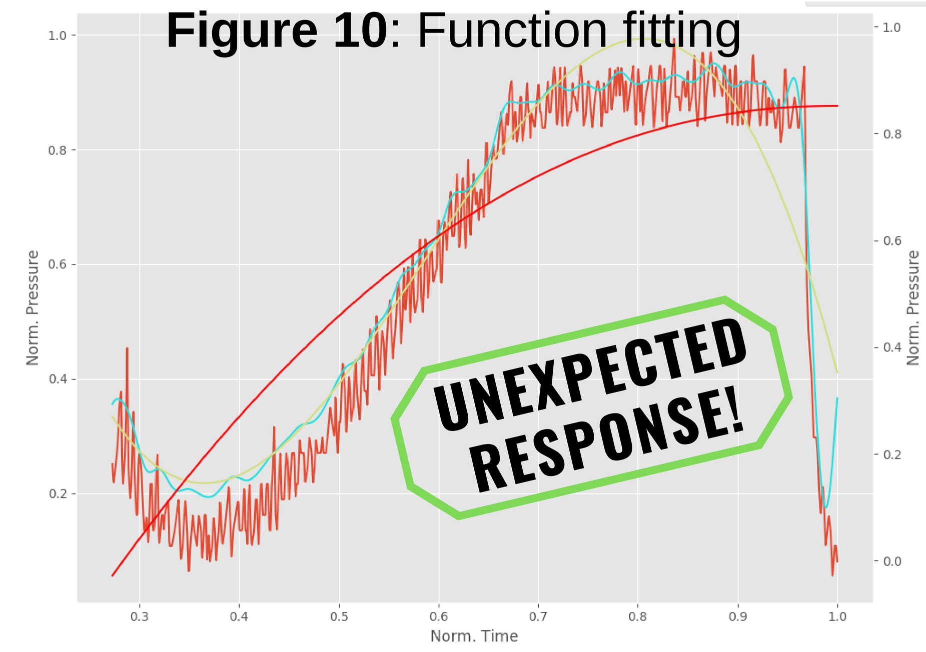


Figure 8: Signal Composed of 2 Sine Waves (50 and 5Hz)

Figure 9: Fourier Transform of signal

Figure 10: Function fitting



4) Fit functions

Fit a decay function (expected) and a 3rd order polynomial (unexpected)

Decay Function	Polynomial Function
$a(1-x)^b + c$	$ax^3 + bx^2 + cx + d$

Compare their Mean Square error to classify the probe's response

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5 NUMERICAL RESULTS

Figure 11: Classification in action

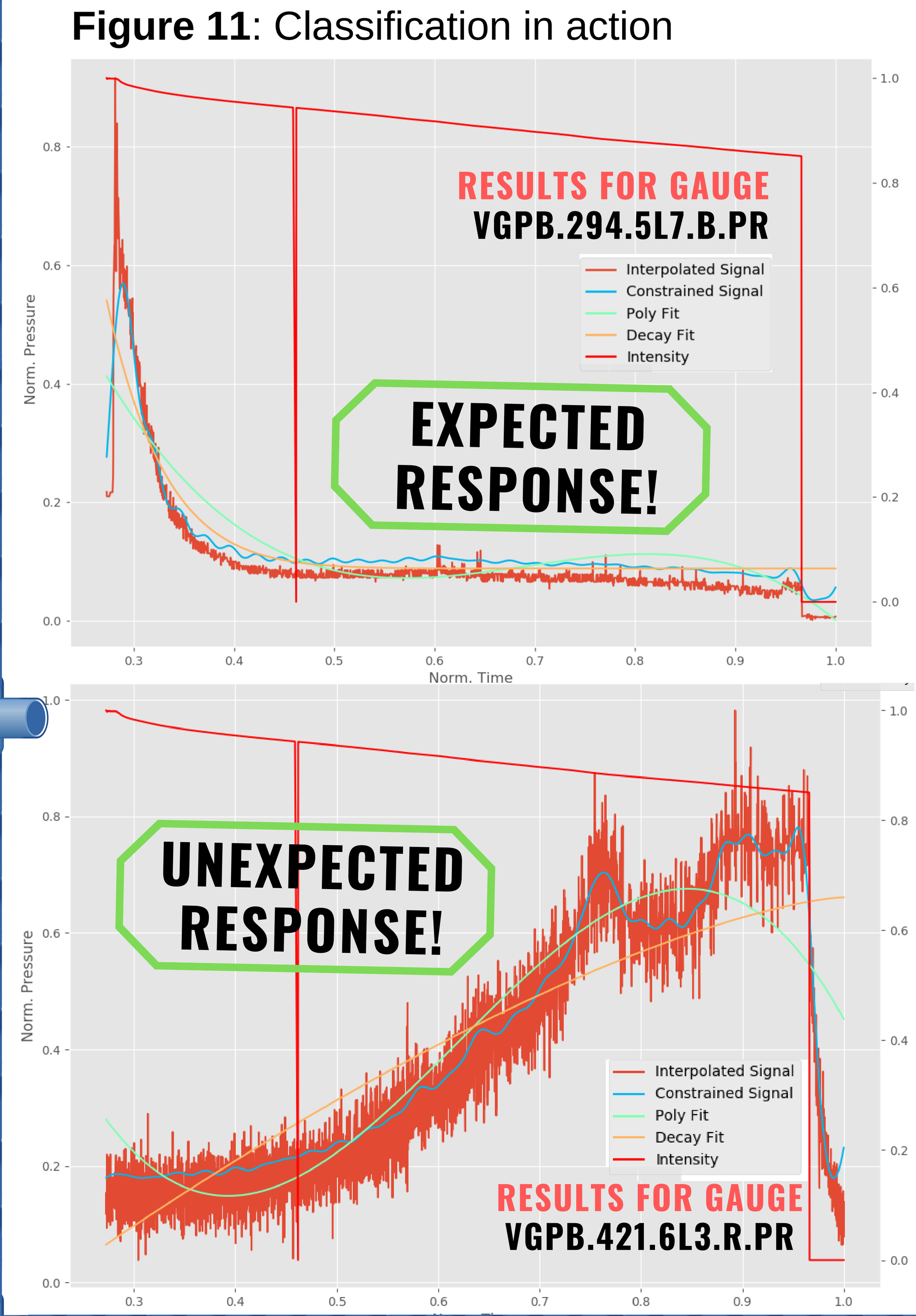
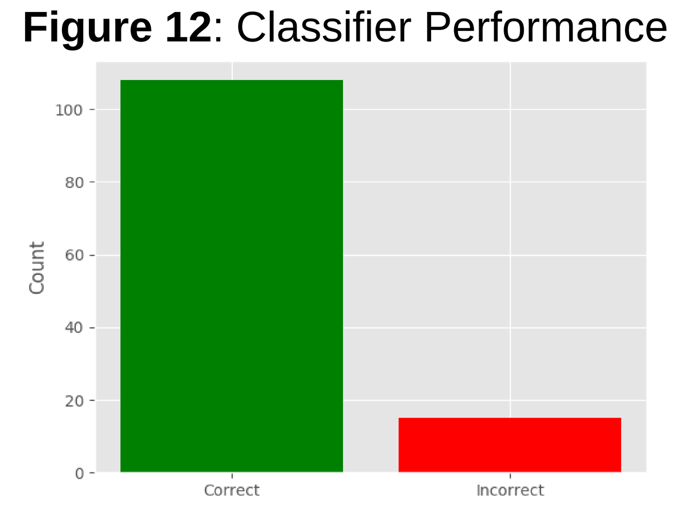


Figure 12: Classifier Performance



Based on a tally of 123 manually-labeled gauges, an accuracy of ~87.8% is achieved using the classifier.

Attempts at cross-correlating the results with temperature readings are inconclusive.
The positional codes (e.g. 5L7) correspond to ~20m half-cells, which is insufficient.

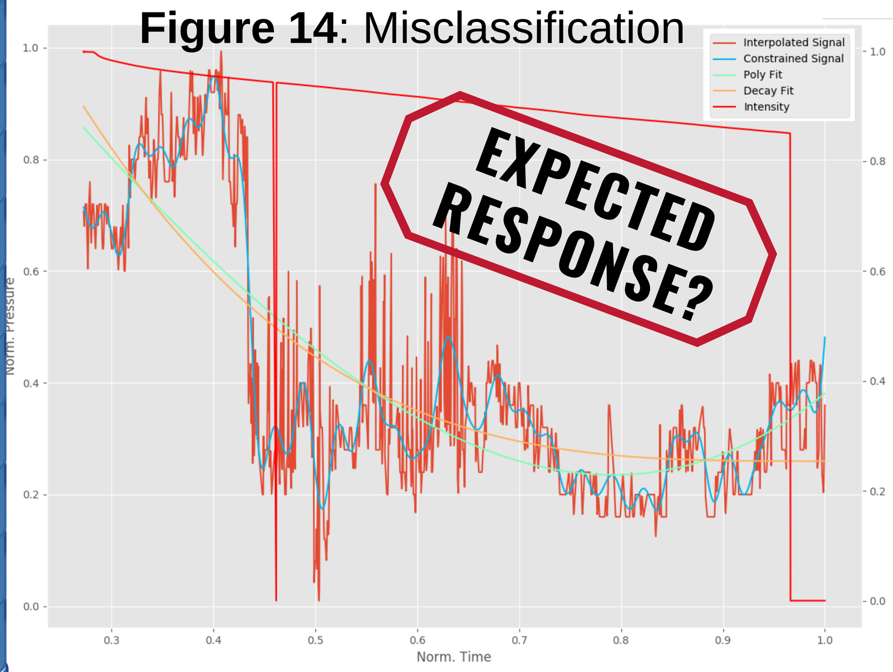
6 CONCLUSION

Based on the results presented here, it is possible to classify vacuum gauges using a completely analytical approach. This works at **87.8% accuracy** for simple responses. However, it does not generalize well to unusual or multi-modal responses.

```
At Fill 2016/7494
s: reload current fill
d: move forward one fill
a: move backward one fill
j: jump to a specific fill
b: step through X fills in specified direction
f: fix selected location until called again
x: to quit this wizard
z: analyze using Analytical Classifier
>>> |
```

Figure 13: Vacuum Gauge explorer

Figure 14: Misclassification



To gain higher accuracy, a Machine Learning (ML) approach is proposed whereby:

- The tuning of parameters such as the cut-off frequency are learned
- Existing ground truths are used to train the ML model

7 BIBLIOGRAPHY

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