HPGe CP5 Predictive Maintenance

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Abstract

Predictive Maintenance is the process of using State of Health (SoH) data to determine when systems require maintenance. Since maintenance may be planned, this approach reduces the amount of unplanned downtime experienced by a system when compared to traditional reactive maintenance. Through collecting SoH data from onboard sensors and collected spectra, predictive maintenance can be performed on HPGe detectors to accurately predict many failure modes and determine the urgency of field or factory servicing.

One failure mode of HPGe detectors is the cooler and through examining multiple parameters such as the Cooler Power, Ambient Temperature, and Crystal Temperature, the behavior of the cooler can be carefully monitored, and vacuum degradation issues can be swiftly and accurately identified. The algorithms developed can give advanced warning of these issues several months to years in advance of required servicing. This will allow for increased uptime of detectors, and flexibility in servicing that is difficult to accomplish with traditional reactive maintenance.

Engineered parameters extracted from spectral data can also be analyzed to determine and respond to the causes of decreased spectroscopic resolution. Common and engineered spectroscopic parameters are analyzed to determine the health of the signal chain. These parameters can identify low-end tailing, high-end tailing, and wings along with the changes of this behavior across various energies. Through this process, these parameters can identify problems in the signal chain from the crystal to the Multi-Channel Analyzer (MCA).

Finally, factory data can be leveraged to detect deviations from baseline performance which can provide early warning indicators of these issues as well.

Overview

HPGe Gamma Ray detectors are used in a variety of environments, from nuclear power plants to continuous environmental assays. Most of these use cases are sensitive to downtime, especially those operating continuously in remote locations. Predictive maintenance mitigates downtime through accurately predicting when service will be required, allowing for maintenance to be scheduled well in advance and for the optimal use of spares.

Predictive maintenance on HPGe detectors can be split into solving two subsets, cooler conditions and spectroscopic conditions. Cooler conditions can include outgassing, vacuum leakage, overheating, or partial warmups and can impact the performance or even cause a failure of the detector. Spectroscopic conditions include charge collection issues, microphonics, or incorrect pole zero, all which can affect the accuracy of the analysis.

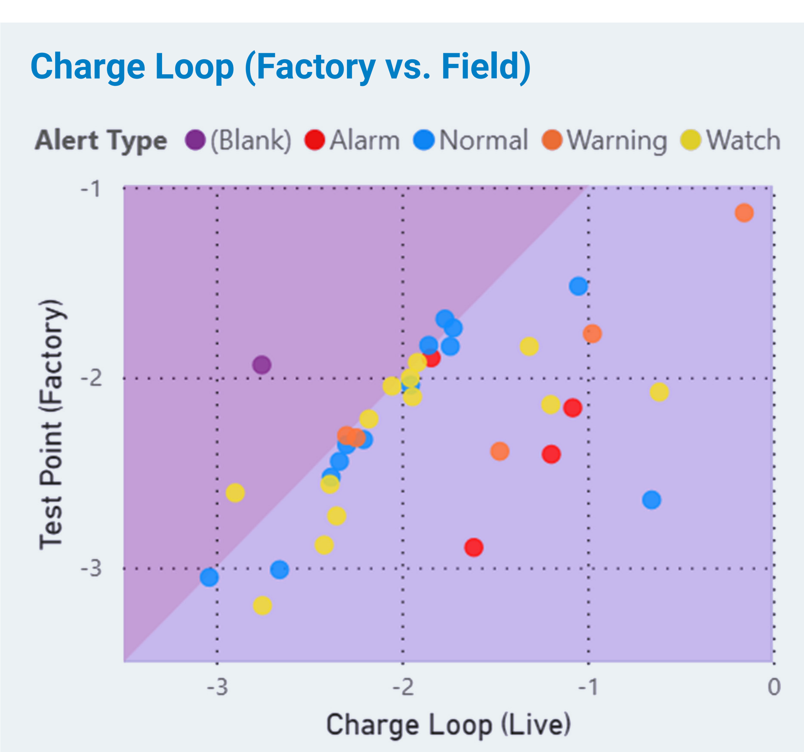

Figure 1 – A) Visualization of Factory baseline data versus live data to identify detectors with poor state of health.

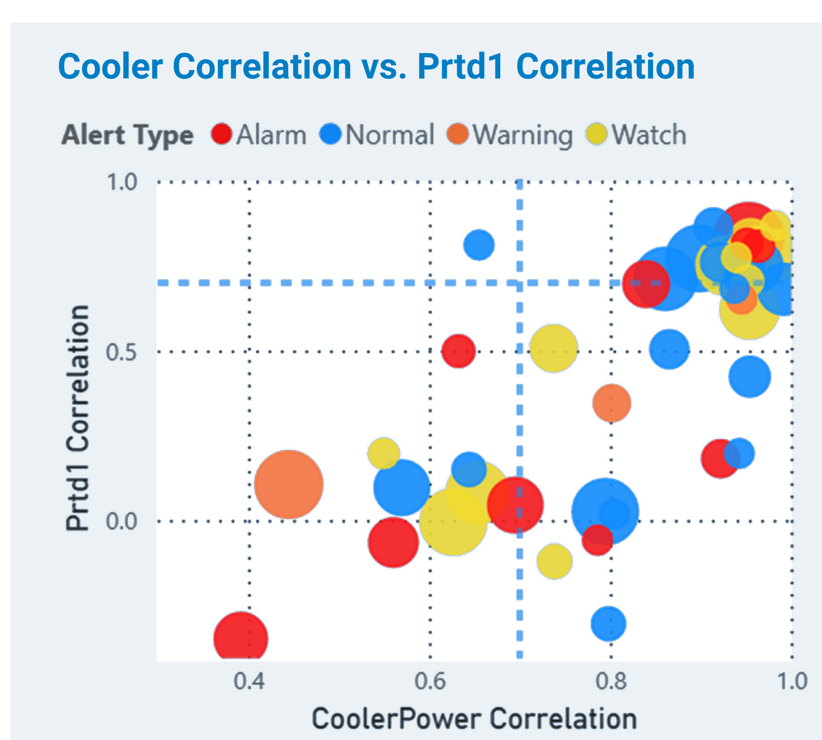

Figure 1 – B) Engineered live parameters which can identify failure modes.

Sensors and Data

The Cryo-Pulse 5 (CP5) Plus Detector Configuration (Figure 2) consists of multiple sensors including sensors for the cooler power, ambient temperature, crystal temperature, compressor temperature, and controller temperature.

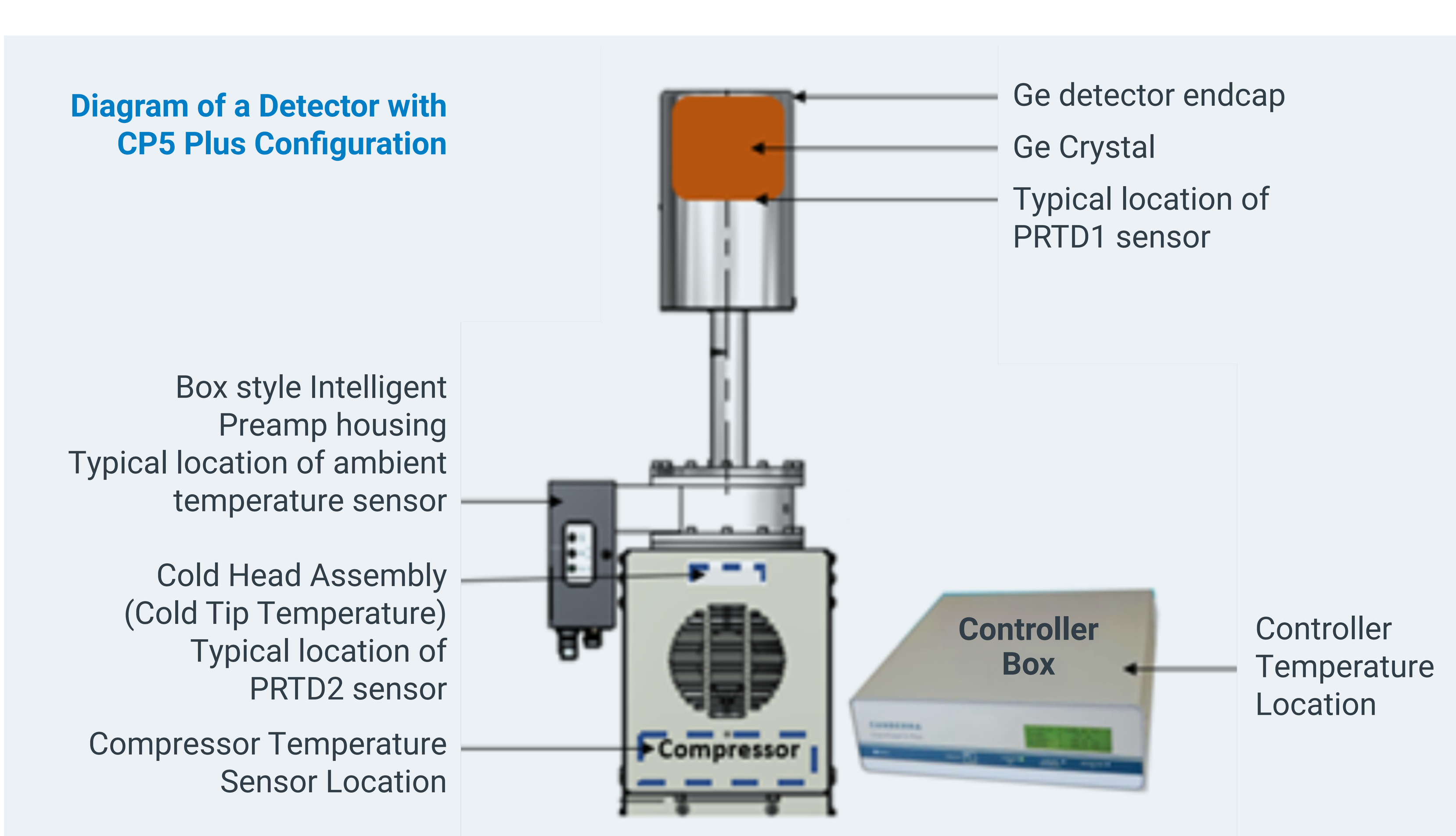

Figure 2 – A diagram of the onboard sensors on a detector with a CP5 setup, used to stream live data for analysis.

Algorithms

There are three types of algorithms which we can leverage for predictive maintenance: live data algorithms, factory data algorithms, and Artificial Intelligence (AI).

Live data algorithms use live streaming data to detect anomalies or systematic issues over days, weeks, or months. For an example, a change in ambient temperature will be closely reflected by an increase in the cooler power. Detectors which have cooler power more weakly correlated with the ambient temperature indicates a likely cooler issue (Figure 1B). This insight can be used to provide an estimate of the remaining time until service will be required on the detector.

Factory data algorithms use baseline testing data collected at the factory prior to shipment to detect deviations in cooler or detector performance. For example, comparing metrics such as the factory leakage current to the live leakage current (Figure 1A) can identify systematic increases from baseline performance which are strong indicators of detector issues.

Artificial intelligence models can be trained on the data collected to automatically identify problematic detector behavior, augmenting the performance of the previously outlined algorithms. As this model was trained on time series data, a Long Short-Term Memory Network (LSTM) was employed on hand-labelled detector data shown in Figure 3.

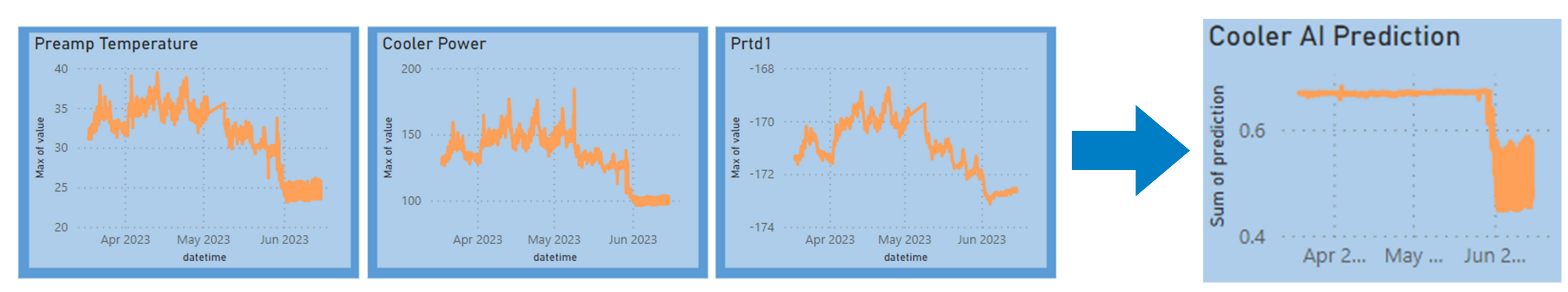

Figure 3 - An LSTM applied to multiple live parameters which accurately predicts the state of health of the detector from multiple input sensors.

Performance

To date, multiple issues have been identified in-the-field months before a detector failure was imminent. For an example, refer to the timeline in Figure 6, which is created by the algorithms previously outlined and predicts the time until service will be required for 45 detectors. With high probability, these algorithms can identify detectors which are likely to fail months to years into the future. These predictions have provided ample time for detector replacement, preventing downtime.

For another example, we can examine the historical predicted time until failure for an individual detector (Figure 4). This example illustrates how the confidence and stability of predictions increases over time, as data is gathered and analyzed.

Additionally, there are a variety of spectroscopic issues which can cause decreased detector performance (Figure 5). Through examining specially engineered spectral parameters across a range of energies, the cause of degraded performance can be accurately identified, and corrective action can be recommended without need for a field visit, or the detector being returned.

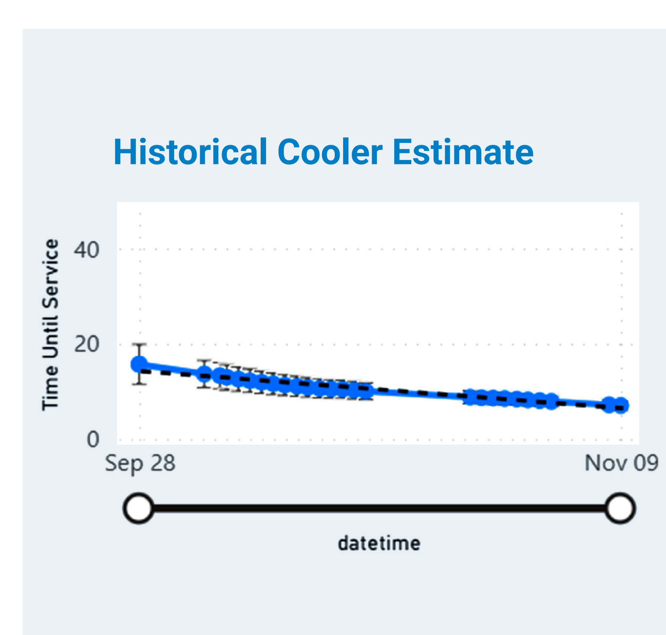

Figure 4 - Historical predictions from the analysis algorithms.

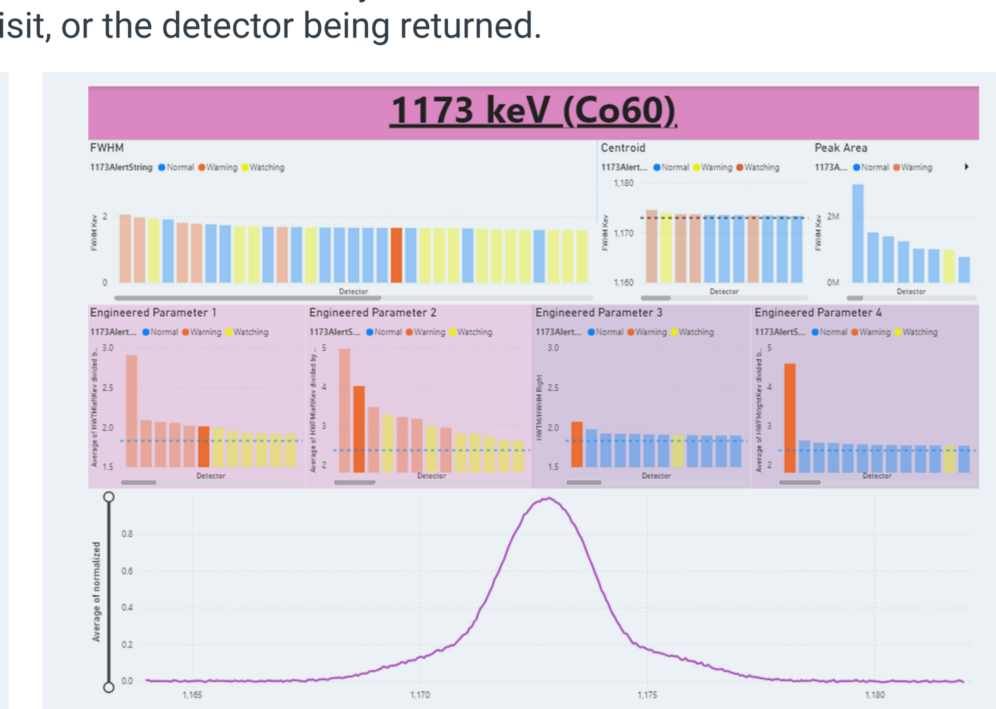

Figure 5 - Spectroscopic analysis algorithms which can predict degradation in resolution through analyzing multiple engineered spectroscopic parameters.

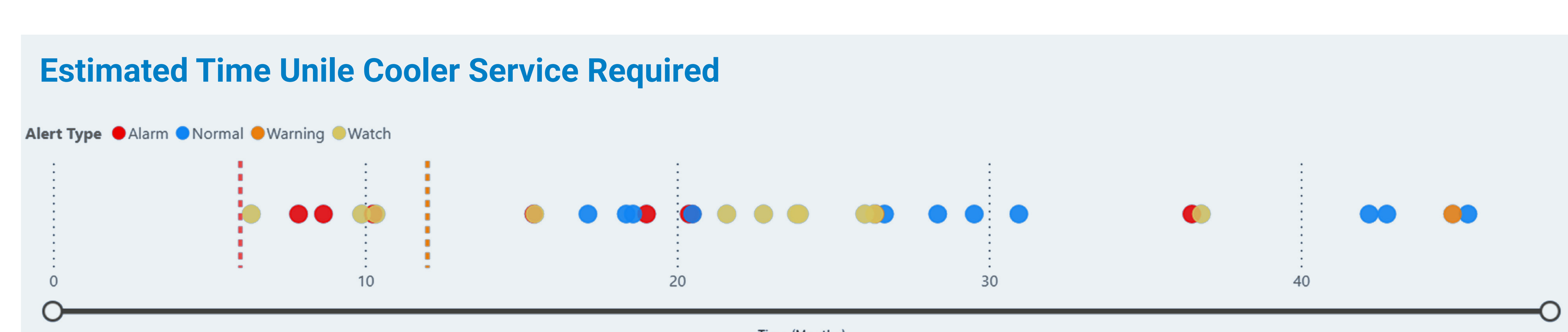

Figure 6 - The output of the analysis algorithms, which predicts the time until servicing is required for each detector using live data, factory baseline data, and artificial intelligence algorithm.

Conclusions

Through leveraging factory data, correlation measures, and artificial intelligence, detector issues can be accurately identified and the time until service is required can be accurately estimated. These algorithms cover many possible failure modes of a detector including a cryostat leak, outgassing, and peak distortions. These predictive maintenance algorithms developed at Mirion allow for increased flexibility and decreased downtime when servicing a detector.

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