Edge-Level Predictive Maintenance and QA/QC Optimization with Artificial Intelligence

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Abstract

Predictive Maintenance is the process of using State of Health (SoH) data to determine when systems require maintenance. By integrating predictive maintenance directly into a QA/QC solution, AI algorithms automatically run on the user's QA spectra to assess the state of health of HPGe detectors, accurately predicting many failure modes and determining 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

A Convolutional Neural Network (CNN) classifier assesses spectroscopic health by inputting the QA spectrum directly into a neural network, which classifies the detector's spectral state of health with high accuracy (Figure 5). When an issue is identified through the AI algorithms or a QA limit is exceeded, AI-driven optimization algorithms automatically fine-tune the Rise Time (RT) and Flat Top (FT) of the detector to bring it back within acceptable limits.

Factory data can also be leveraged to detect deviations from baseline performance, providing early warning indicators before they impact measurement quality. All algorithms run directly on the Lynx II with no internet connection required, and can be monitored through the Lynx II web interface.

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. By embedding predictive maintenance and AI-driven optimization directly into a QA/QC solution on the Lynx II, detector health is automatically assessed during routine QA measurements with no internet connection required, allowing for maintenance to be scheduled well in advance and for the optimal use of spares.

Predictive maintenance on HPGe detectors addresses 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. When issues are detected or QA limits are exceeded, AI optimization algorithms can automatically adjust the RT/FT parameters to restore optimal performance, creating a closed-loop system from detection to correction.

Figure 1 – Edge-Level QA & Predictive Maintenance Dashboard hosted on Lynx II. Accommodates easy QA checks and automatic Detector State-Of-Health monitoring, with AI optimization algorithms if a detector ever reaches QA limits.

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. In addition, user QA spectra collected during routine QA/QC measurements serve as a key data source, enabling AI algorithms to assess spectroscopic health directly from the measurement workflow.

Diagram of a Detector with CP5 Plus Configuration

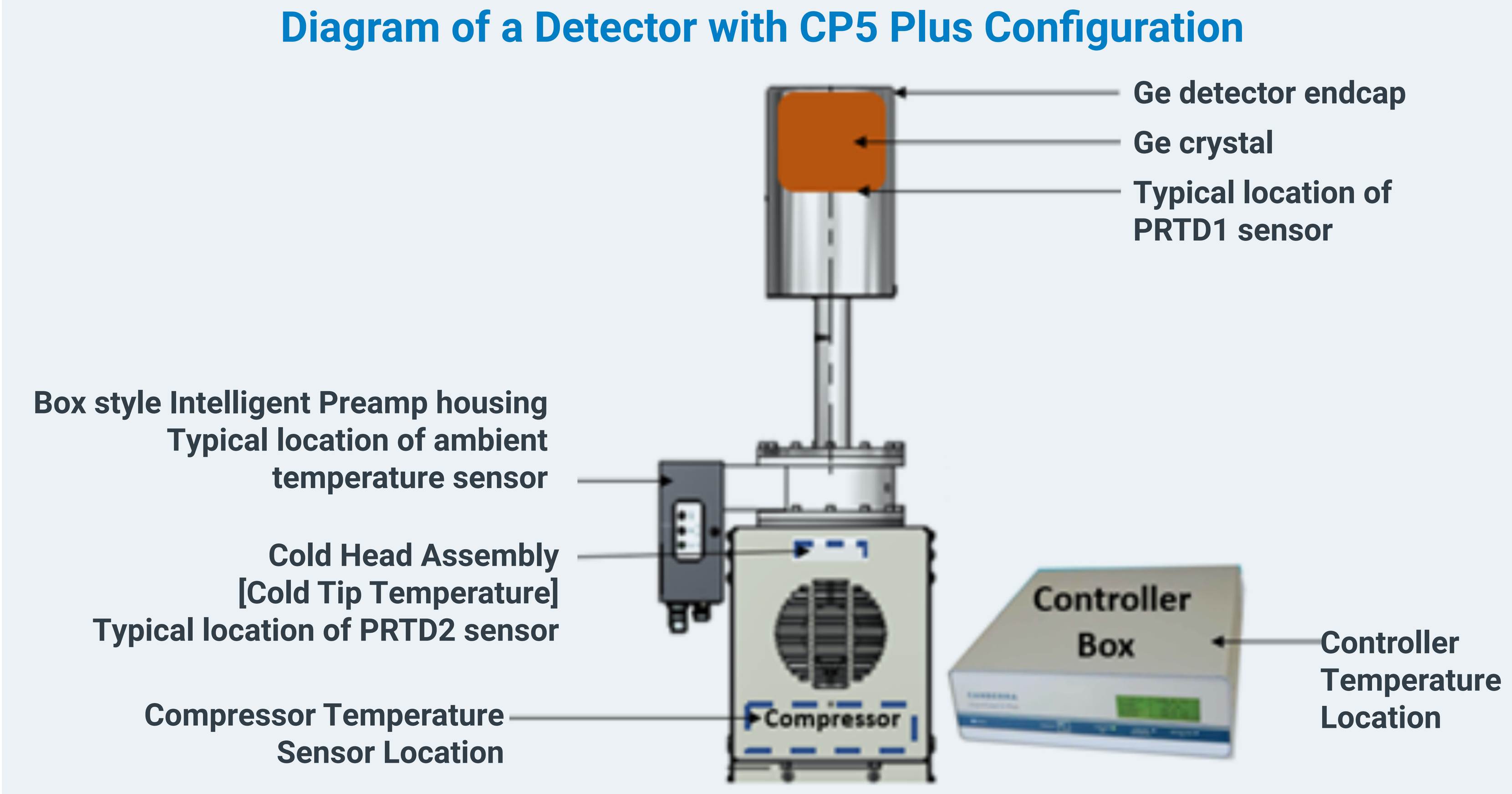


Figure 2 – A diagram of the onboard sensors on a detector with a CP5 setup, used to stream live data for analysis.

Algorithms

Four algorithm types are employed: live data, factory data, AI State-of-Health, and AI-driven RT/FT optimization.

Live data algorithms detect anomalies over days to months by correlating parameters such as cooler power and ambient temperature; weak correlation indicates a likely cooler issue (Figure 1B), enabling remaining service life estimation.

Factory data algorithms compare pre-shipment baselines to live values, identifying systematic deviations indicative of detector degradation.

An LSTM network (Figure 3) trained on hand-labelled time series data augments these algorithms by automatically classifying detector behavior during routine QA measurements.

Additionally, a CNN-based spectral health classifier (Figure 5) inputs the QA spectrum directly into a convolutional neural network to assess the detector's spectroscopic state of health, accurately flagging issues caused by charge collection degradation, microphonics, and pole zero errors.

When issues are detected or QA limits surpassed, optimization algorithms search the RT/FT parameter space to restore performance. All processing runs on the Lynx II with no internet required.

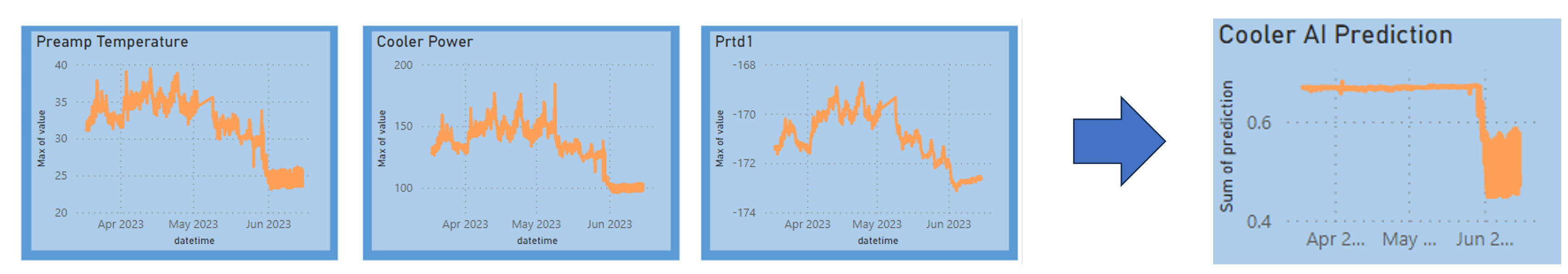


Figure 3 - An LSTM applied to multiple live parameters which accurately predicts the state of health of the detector from multiple input sensors.

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.

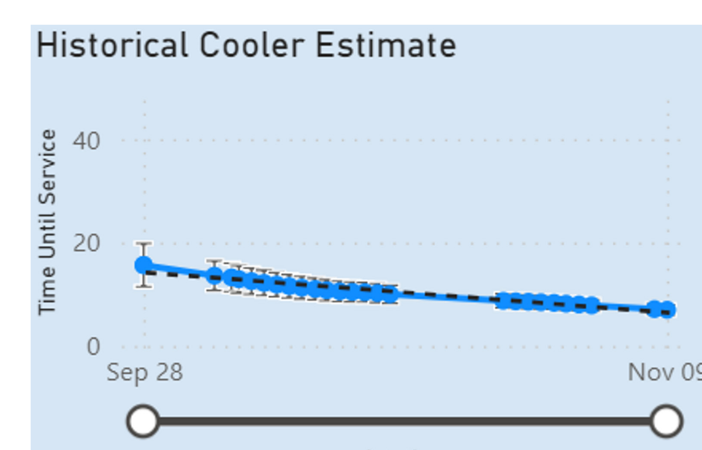
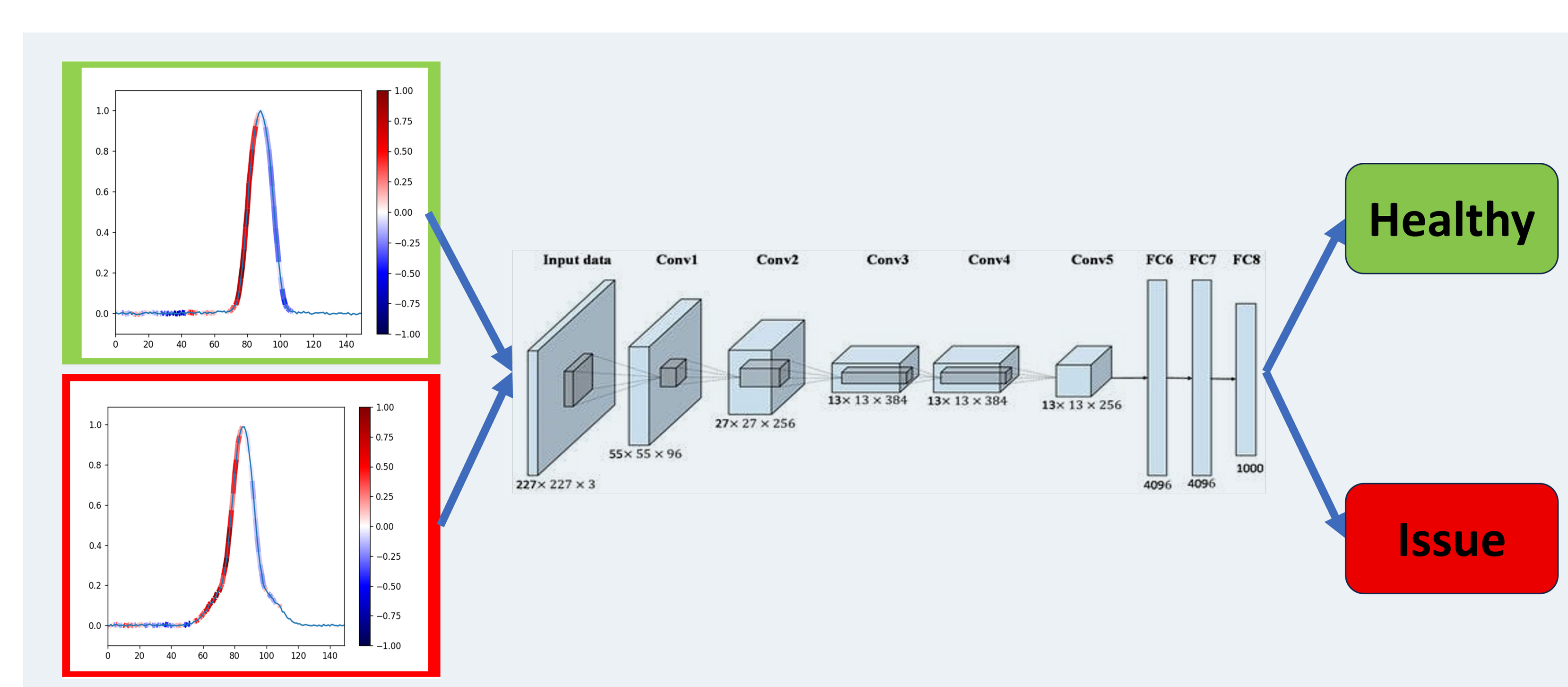


Figure 4 - Historical predictions from the analysis algorithms.

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). A CNN-based spectral health classifier inputs the QA spectrum directly into a neural network during routine QA measurements to accurately classify the detector's state of health. When QA limits are exceeded, the AI optimization algorithms leverages this CNN to automatically fine-tune the RT/FT parameters directly on the Lynx II, bringing the detector back within limits without manual intervention, field visits, or the detector being returned.



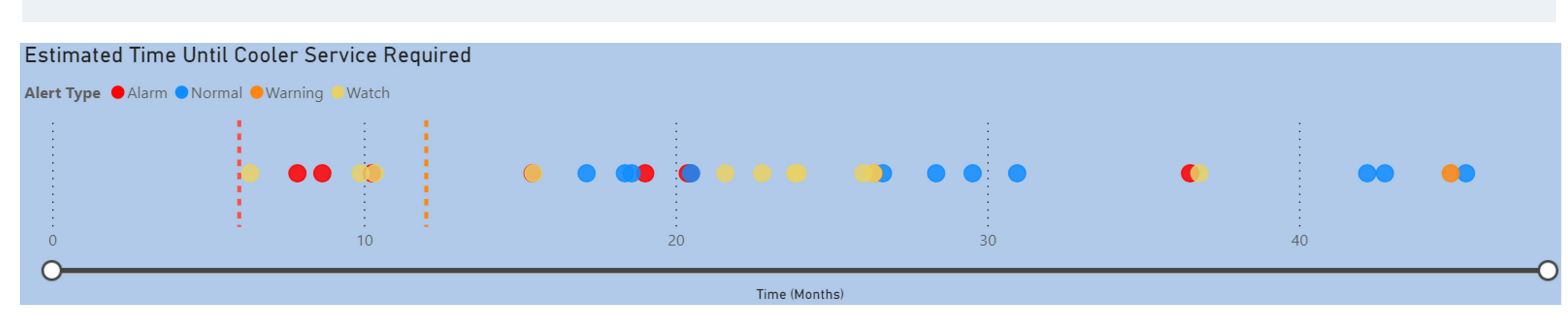


Figure 6 - The output of the analysis algorithms, which predicts the time until servicing is required for each detector using live data, factory baseline data, and artificial intelligence algorithm.

Conclusions

By combining factory baselines, correlation analysis, AI classification, and automated RT/FT optimization, this system identifies and corrects detector issues—including cryostat leaks, outgassing, and peak distortions. Running entirely on the Lynx II with no internet required, this closed-loop solution increases flexibility, decreases downtime, and reduces manual intervention.

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