Internship in data science for accelerator physics

Explainable state observers and interpretable classification of faults in RF superconducting cavities

SPIRAL2 is a state-of-the-art superconducting LINAC, housing 26 cavities cooled at 4.2 K. These cavities are subject to faults such as quenches, microphonics, and thermoacoustic oscillations, which compromise beam availability and reliability. The current monitoring chain is based on FPGA-triggered LLRF post-mortem buffers, generating high-dimensional time series of RF, cryogenic, and control signals. While operators can diagnose obvious failures, many events remain ambiguous [4,5].

In control theory, state observers (Kalman filters, Luenberger observers, Unknown Input Observers) have long been used for fault detection: they reconstruct hidden states and generate residuals—differences between predicted and measured outputs—that act as natural indicators of anomalies [1-3]. In anomaly detection, residuals are analyzed through statistical tests, clustering, or machine learning. Modern extensions combine observer-based prediction with data-driven self-supervised classifiers, producing both timely alarms and interpretable diagnostics [6].

This internship will explore this classical but under-used connection in accelerator physics: building simple observers for SPIRAL2 cavities, generating residuals, and testing how they can feed anomaly detection and classification pipelines, paving the way for larger-scale developments in a PhD [4,5].

Explainability focus: Depending on progress and in addition to implementing observers and classifiers, this internship will explore post-hoc explainability methods (e.g. SHAP, LIME) on observer residuals and classification outputs. The aim is to identify which RF and cryogenic signals contribute most to a failure class. This aligns with insights from recent accelerator AI research that feature attribution, and causal graphs make anomaly detection usable and trustworthy for operators [6].

Objectives

- Implement a simple virtual state observer (Luenberger/Kalman) for cavity RF signals [1-3].
- Extract residuals and test anomaly detection methods (thresholds, clustering, first self-supervised models) [4-6].
- Focus case: discriminate between true quenches and false alarms.
- Produce a demonstration dashboard for visualizing observer states, residuals, and classifications.

Expected outcome

- Feasibility study of observer-based anomaly detection.
- First dataset benchmarks and candidate methods.
- Deliverables that pave the way for the PhD (advanced observers, explainability, generalisation).

Expected skills

Python, signal processing, ML basics, control/observer theory

This work leads to a PhD-thesis.

Contact: Adnan Ghribi
Phone: +33 (0)2 31 45 46 80
mail: adnan.ghribi@ganil.fr

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