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INFLUENCE OF ENVIRONMENTAL PARAMETERS ON CALIBRATION DRIFT IN SUPERCONDUCTING RF CAVITIES

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Abstract

Precisely calibrating superconducting Radio-Frequency (RF) linear accelerators is crucial for accurately assessing cavity bandwidth and detuning, which provides valuable insights into cavity performance, facilitates optimal accelerator operation, and enables effective fault detection and diagnosis. In practice, however, calibration of RF signals can present several challenges, with calibration drift being a significant issue, especially in settings prone to humidity and temperature fluctuations. In this paper, we delve into the effect of environmental factors on the calibration drift of superconducting RF cavities. Specifically, we examine long-term calibration drifts and explore how environmental variables such as humidity, temperature, and environmental noise affect this phenomenon. The results show that environmental factors, particularly relative humidity, significantly influence calibration drifts. By analyzing these correlations, appropriate compensation algorithms can be designed to mitigate and eliminate these effects, thus optimizing calibration accuracy and stability.

BACKGROUND

The European X-ray Free-Electron Laser (European XFEL) is one of the most advanced facilities utilizing Superconducting Radio Frequency (SRF) technology, providing researchers with unprecedented capabilities in probing the structure and dynamics of matter at the atomic scale. The European XFEL relies heavily on the stability and accuracy of the SRF cavities to ensure the high quality of the X-ray pulses. Precisely calibrating RF cavities is crucial for accurately assessing cavity bandwidth and detuning, which provides valuable insights into cavity performance, facilitating optimal accelerator operation.

A key challenge in the operation of SRF cavities is the phenomenon of calibration drift, which, if not managed properly, can lead to significant performance degradation. Various environmental parameters, such as temperature and humidity fluctuations, and mechanical vibrations, can influence this drift, necessitating robust calibration and compensation mechanisms.

The Low-Level RF (LLRF) control system plays a crucial role in maintaining the stability of the RF fields within the SRF cavities. The LLRF system continuously monitors and controls the RF signals to generate precise and stable RF fields required for X-ray free-electron laser pulses, including the compensation for any deviations caused by environmental factors. However, calibration drift remains a persistent issue despite the advanced control algorithms employed as they rely on the calibration.

The Drift Compensation Module (DCM) [1] has been developed as part of the LLRF system to address this challenge. It is specifically designed to mitigate the effects of calibration drift by dynamically adjusting the calibration parameters in real-time. However, it is important to note that DCM only calibrates the probe signal, not the drift of forward and reflected signals.

Accurate measurements of the RF forward V_F^m and the reflected signals V_R^m are critical for calculating cavity bandwidth and detuning. Ideally, the sum of V_F^m and V_R^m should equal the RF probe signal V_P^m. However, in practice, the finite directivity of waveguide directional couplers and the drift caused by environmental parameters impact the accuracy of the RF forward and reflected signals, thus degrading the performance of the accelerator.

This paper investigates the long-term calibration drift in superconducting RF cavities and examines the influence of environmental factors on this phenomenon. By analyzing the correlation between these variables, we found that the calibration error or drift could be predicted based on environmental factors. Additionally, calibration coefficients can be accurately forecasted, offering a promising calibration method for SRF cavities operating in Continuous Wave (CW) mode.

RF SIGNAL CALIBRATION AND CALIBRATION DRIFT

Long-term Calibration Drift

The original virtual probe is defined by the sum of the measured forward $V_F^m \in \mathbb{C}$ and reflected $V_R^m \in \mathbb{C}$ RF signals, expressed in In-phase and Quadrature (I&Q) form as

$$V_P^v = V_F^m + V_R^m \tag{1}$$

Ideally, the virtual probe V_P^v should be equal to the measured RF probe signal $V_P^m \in \mathbb{C}$. However, as mentioned above, in practice, the finite directivity of waveguide directional couplers and drift due to environmental parameters can affect the measurement of the RF forward and reflected signals, leading to calibration errors. Formally, calibration error is defined as the difference between the measured probe signal V_P^m and the virtual probe V_P^v, denoted as:

$$E_C = V_P^m - V_P^v = V_P^m - \left(V_F^m + V_R^m\right) \tag{2}$$

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Specifically, the amplitude and phase of the calibration error are defined as E_C^A and E_C^P, respectively

$$
\begin{aligned}
E_C^A &= \frac{\sum_{i=0}^{K} \left| V_{P\,i}^{m} - V_{P\,i}^{v} \right|}{K} \\
E_C^P &= \frac{\sum_{i=0}^{K} \angle \left(V_{P\,i}^{m} - V_{P\,i}^{v} \right)}{K}
\end{aligned}
\tag{3}
$$

Here, the K is the number of data points in each RF pulse. The RF pulse at the European XFEL, typically sampled at 9 MHz with around $K = 16000$ data points per pulse, consists of distinct filling, flattop, and decay phases, crucial for precise control of electron acceleration. More detailed insights can be found in [2]. The amplitude of calibration error E_C^A is visualized in Fig. 1. The data used in this study was collected at 10-minute intervals from May 20, 2024, to June 6, 2024, from C1-4.M4.A6.L3 (LINAC 3, RF station 6, cryomodule 4, and SRF cavity 1-4 at European XFEL). Excluding some missing pulses, a total of 2348 R_F^m, R_R^m, and R_P^m RF pulses was used for data analysis. As can be seen from the figure, there is a significant drift in the error.

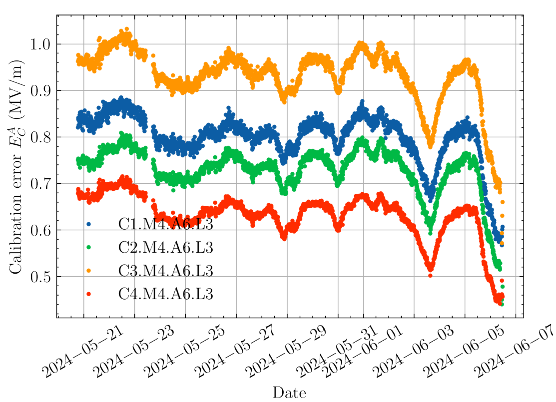

Figure 1: Calibration error and the long-term calibration drift. Shown is the absolute average amplitude error.

During the experiments, operators noticed that these drifts were mainly caused by environmental parameters such as humidity and temperature fluctuations, as shown in Fig. 2. The correlation between the calibration errors and environmental parameters will be analyzed in the next section.

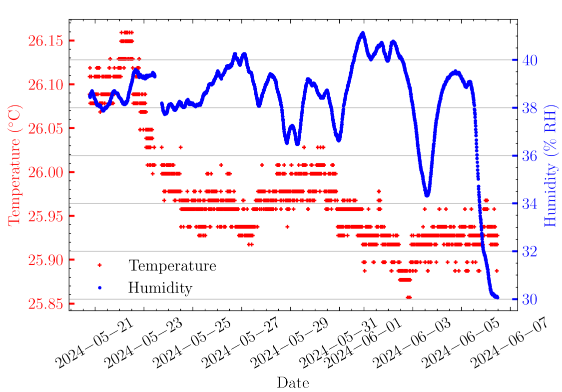

Figure 2: Humidity and temperature fluctuations.

Calibration of RF Signals

If well calibrated, the virtual probe can be utilized for precise RF field control in case the probe signal is missing or corrupted [3]. In this paper, the forward and reflected RF signals are calibrated using Eq. (4), which is based on superconducting cavity system dynamics. This calibration is achieved by performing a nonlinear least square optimization constrained by the law of energy conservation, as detailed in [2, 4].

Then the calibrated virtual probe could be expressed as

$$V_P^{vc} = X V_F^m + Y V_R^m \tag{4}$$

where X and Y correspond to the calibration factors applied to V_F^m and V_R^m, respectively.

Calibration is performed for each RF V_F^m and V_R^m pulse. The long-term analysis of the calibration coefficients X and Y reveals that the amplitude of the applied calibration coefficients X and Y is essentially stable, while the phase of the calibration coefficients varies considerably, with a trend similar to that of the calibration error amplitudes in Fig. 1. After calibration, the magnitude of the calibration error is greatly reduced, by a factor of 5 up to 10 for some cavities.

RESULTS

Correlation Analysis

To better understand the correlation between the environmental parameters, calibration drift and calibration coefficients, we analyzed the correlation coefficients between these signals, and found that humidity has the greatest effect on calibration drift. Each signal is normalized to a range of 0 to 1 by linear scaling for correlation analysis. The visualization of the normalized signals in Fig. 3 also indicated a strong correlation.

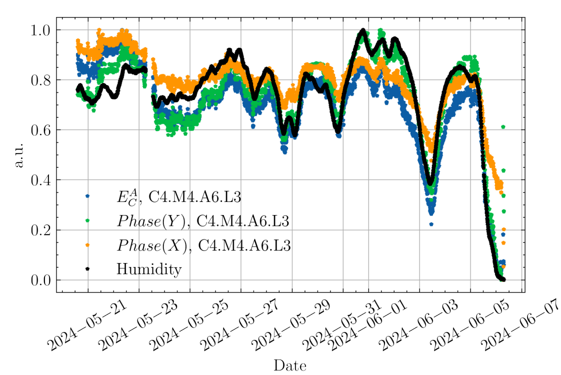

Figure 3: Visualization of the normalized data.

Prediction of Calibration Errors and Calibration Coefficients based on Environmental Parameters

When the LLRF system operates in pulsed mode, pulse-based calibration can effectively calibrate the system. However, when the system operates in a CW mode, the signal V_P^m remains almost constant over time, and therefore the

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existing calibration models in pulsed mode are no longer applicable. One possible solution is to utilize the strong correlation between the signals and then predict the calibration error and the required calibration coefficients based on the environmental factors.

This can be formulated as a system identification problem with multiple inputs and single output. We choose polynomial NARMAX (Nonlinear AutoRegressive Moving Average with eXogenous input) models and for identification we use FROLS [5] (Forward Regression Orthogonal Least Squares), implemented by the Sysidentpy [6] package in Python. Excluding the first 600 pulses due to some missing signal between them, 1748 pulses were used for model prediction. Specifically, the data is divided into a training set and a validation set, where 80% is used to train the model and 20% is used for validation. The predictions are based on humidity, temperature, and the Loaded Quality factor (Q_L) of the RF cavity. The order of the polynomial model is set to 3 and the number of regressors to 7 or 8. For example, the prediction model for the calibration error of cavity C4.M4.A6.L3 can be expressed as

$$\begin{aligned} E^A_{Cp}(k) &= a_0 E^A_{Cp}(k-1) + a_1 E^A_{Cp}(k-2) \\ &+ a_2 E^A_{Cp}(k-3) + a_3 x_3(k-1) x_2(k-1) x_1(k-1) \\ &+ a_4 x_3(k-1) x_2(k-3) E^A_{Cp}(k-26) + a_5 E^A_{Cp}(k-9) \\ &+ a_6 x_3(k-1) x_2(k-1) x_1(k-3) \end{aligned} \tag{5}$$

where $E^A_{Cp}(k)$ denotes the predicted amplitude of calibration error at discrete time k, and x_1, x_2, and x_3 correspond to the normalized humidity, temperature, and Q_L, respectively. The individual regressor coefficients are listed in Table 1. The root relative mean square error for this model is 0.209.

Table 1: Regressor Coefficients

Coefficients	Values			
a_{0-3}	0.556	0.191	0.121	3.200
a_{4-6}	-0.152	0.124	-3.021	

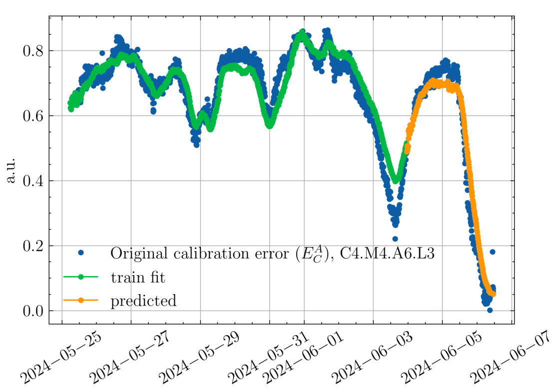

Figure 4: Predicting normalized calibration error.

The corresponding predicted calibration errors for cavity C4.M4.A6.L3 are shown in Fig. 4. In addition, the difference between the predicted calibration amplitude error and the original calibration amplitude error is less than 0.05 MV/m. This encouraging result will help in deciding when to recalibrate the RF system.

Furthermore, taking cavity C4.M4.A6.L3 as an example, we predicted the amplitude and phase of calibration coefficients X and Y using the prediction model based on FROLS algorithm and obtained virtual probe signals based on the predicted calibration coefficients, which further provided the calibration errors, as shown in Fig. 5. The results show that it is possible to achieve a level of accuracy comparable to the pulse-based calibration method, except for the last few data points caused by the warming up of the external quality factor Q_{ext} after the machine interruption. This suggests a promising calibration method for RF cavities operating in CW mode.

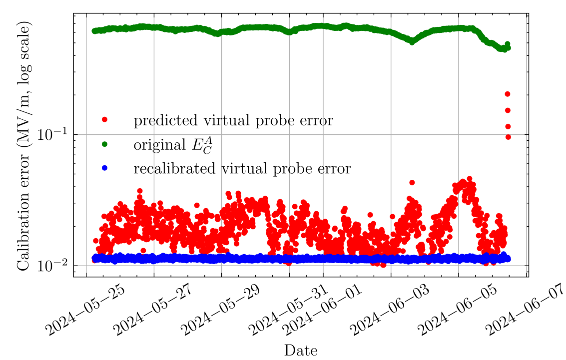

Figure 5: Calibration error based on the predicted calibration coefficients.

CONCLUSION

The contribution focuses on the long-term calibration drift of superconducting RF cavities and analyzes how environmental factors such as humidity and temperature affect this drift. In addition, the correlation between environmental factors and the calibration coefficients obtained by the pulsed-based calibration method was analyzed. Based on the strong correlation between the signals, a model is presented for predicting calibration errors and applied amplitude and phase corrections for RF signals based on environmental factors. This provides a viable method for calibrating RF cavities operating in CW mode.

Future work should include the validation of longer-term data analysis. Furthermore, an automatic method for determining when to recalibrate the RF system should be explored. Additionally, the validity of the fitting and prediction periods of the model should be assessed and confirmed.

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