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MACHINE LEARNING FOR CALIBRATION DRIFT FORECASTING IN SUPERCONDUCTING RF CAVITIES

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Abstract

Superconducting radio frequency (SRF) cavities in particle accelerators rely on accurately calibrated RF signals to assess cavity bandwidth and detuning, ensuring optimal performance. In practice, however, calibration drift due to humidity and temperature fluctuations over time poses a significant challenge, potentially resulting in suboptimal operation and reduced efficiency. This study explores how environmental variables such as humidity and temperature affect this phenomenon. Relative humidity, in particular, is difficult to control and has been shown to impact calibration drift strongly. Building on these insights, we introduce machine learning-based approaches to forecast both relative humidity and calibration drift in SRF cavities. By leveraging advanced algorithms and historical data on cavity operation and performance, we develop predictive models that identify patterns and trends indicative of relative humidity and calibration drift. Two approaches are presented in this work, including a polynomial NARMAX model and an attention-based deep neural network. These models enable real-time compensation and automated recalibration, improving system stability and efficiency.

BACKGROUND

The European XFEL (EuXFEL) is currently the world's largest linear accelerator, featuring a total of 784 superconducting radio-frequency (SRF) cavities—776 operating at 1.3 GHz and 8 at 3.9 GHz. Commissioned in 2017, the EuXFEL accelerator operates at a 10 Hz repetition rate with the energy up to 17.5 GeV. It delivers ultra-short, high-brilliance X-ray pulses through three undulator lines, facilitating advanced research in fields such as physics, chemistry, and biology.

SRF cavities are critical components in particle accelerators, facilitating the acceleration of charged particles by providing high-quality electromagnetic fields. These cavities rely on precisely calibrated RF signals to ensure optimal performance, with key metrics like cavity bandwidth and detuning being closely monitored to avoid inefficiencies. However, over time, calibration drift, caused by environmental factors such as humidity and temperature fluctuations, poses a significant challenge for maintaining optimal cavity performance in SRF systems. Among these environmental variables, relative humidity is particularly difficult to control and has been shown to exert a considerable influence on calibration drift in SRF cavities [1]. This drift, if not managed, can lead to suboptimal cavity operation. For a facility like European XFEL, where high beam quality and reliability are essential for producing stable X-ray pulses, investigating and mitigating calibration drift is crucial to ensure efficient, consistent machine performance over long operational periods. To address this, the Drift Compensation Module (DCM) [2] was developed as part of the Low-Level RF (LLRF) system to track environmental changes and performs real-time calibration corrections.

Since the beginning of operation in 2017, European XFEL has accumulated a large amount of historical RF and beam data, providing a valuable resource for studying long-term system behavior. In particular, the DCM has gathered extensive historical environmental and operational data, including relative humidity, temperature, and applied phase corrections to RF probe signal, which serve as critical indicators of calibration drift. By forecasting of relative humidity and dynamic phase corrections, predictive models can be developed to identify patterns and trends associated with calibration drift.

Building on these insights, this paper presents machine learning-based approaches to forecast relative humidity and dynamic phase corrections to the RF probe signal. These forecasts provide critical insights into patterns associated with environmental fluctuations and calibration drift, enabling early detection of calibration anomalies and the implementation of dynamic correction strategies. Two predictive models are employed: the polynomial NARMAX (Nonlinear Autoregressive Moving Average with Exogenous Inputs) model, representing classical nonlinear statistical modeling, and the attention-based Crossformer, a modern deep learning approach. Both methods aim to capture the underlying dynamics of the system, but they differ in their modeling philosophy, complexity, and interpretability. This work advances the integration of predictive modeling into particle accelerator operations, offering the potential to enhance system stability and operational efficiency.

FORECASTING OF RELATIVE HUMIDITY AND CALIBRATION DRIFT USING A POLYNOMIAL NARMAX MODEL

At the European XFEL, environmental variables such as humidity and temperature at one tunnel location are often

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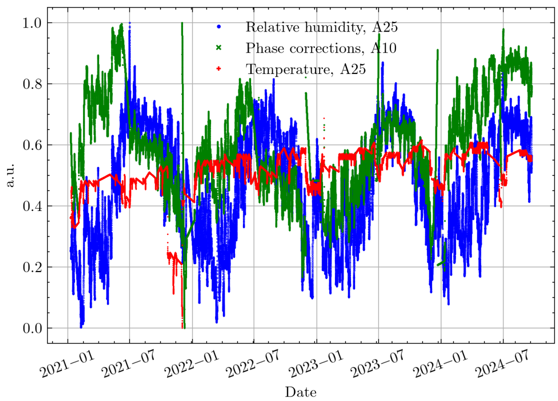

Figure 1: Example historical relative humidity, temperature, and dynamic phase corrections for the past few years.

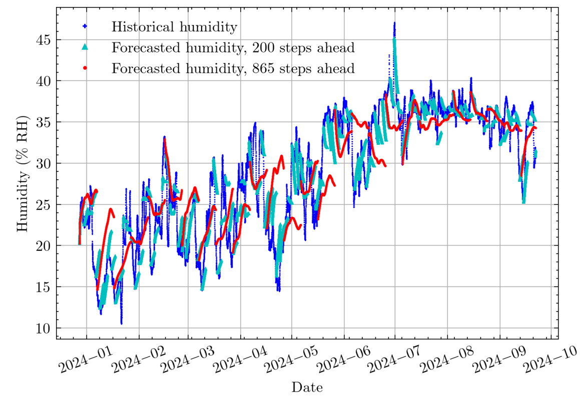

Figure 2: Forecasted relative humidity at station A25 over the next 200/865 time steps (2.3/10.0 days).

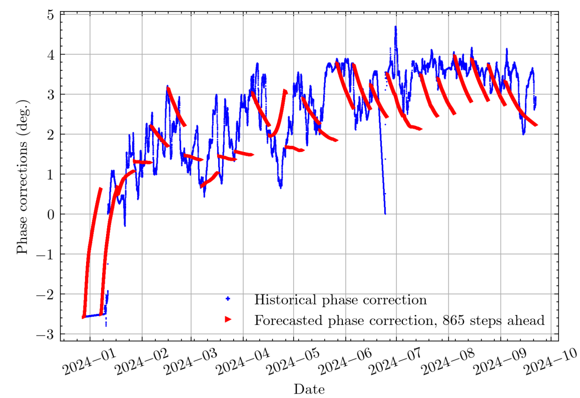

Figure 3: Forecasted phase corrections at station A10 over the next 865 steps (10-day).

strongly correlated with those at other locations, and the applied phase corrections in the LLRF system are primarily influenced by these environmental factors. To capture these interdependencies and nonlinear relationships, we adopt the Polynomial NARMAX model in a MISO (Multiple Inputs, Single Output) setting. This model structure enables effective short-term forecasting by capturing temporal dependencies, incorporating multiple correlated inputs, and modeling their nonlinear influence on target outputs like relative humidity and phase corrections.

The data used in this study consist of historical measurements of relative humidity and temperature collected from the manager LLRF subsystem (Cryomodules 1 and 2) at stations A7, A10, A11, A13, A19, and A25. For phase correction analysis, only historical data from station A10 are used. Prior to modeling, the data were preprocessed by removing outliers and applying linear interpolation to handle missing values. After preprocessing, the data points have a uniform time interval of 16 minutes and 40 seconds. Figure 1 illustrates representative normalized time series of relative humidity, temperature, and dynamic phase corrections recorded over the past four years, revealing clear periodic patterns and strong inter-variable correlations that support the potential for accurate forecasting.

For the forecasting task, the dataset was split chronologically, with 80% allocated for training and 20% for testing. The model was trained to perform multi-step ahead prediction, where each training instance consisted of input sequences from multiple variables, and the target was the corresponding output variable shifted forward by n steps in time. Specifically, for each time step t, the model uses historical values of the input variables to predict the target variable at time $t + n$. Here, $n = 865$ corresponds to a forecasting horizon of 10 days.

By framing the task as a system identification problem, this setup allows the model to learn how environmental variations influence the evolution of calibration corrections and, consequently, calibration drift. Relative humidity is forecasted using humidity data from other RF stations, while phase correction uses both humidity and temperature inputs. Model identification is performed using the Forward Regression Orthogonal Least Squares (FROLS) algorithm [3], implemented in the Python package SysIdentPy [4]. Example forecasting results for relative humidity and phase corrections are presented in Fig. 2 and Fig. 3, respectively. The results indicate that forecasting using the NARMAX model, trained on historical environmental and operational data, successfully captures overall trends and seasonal dynamics. However, its ability to resolve fine-scale variations is limited, likely due to the nonlinear and partially stochastic behavior of the underlying physical processes. This indicates that while it performs well in predicting long-term trends, additional methods may be required to enhance short-term forecasting accuracy.

FORECASTING BASED ON DEEP LEARNING MODEL

While the Polynomial NARMAX model provides a solid foundation for forecasting by capturing nonlinear relationships between system inputs and outputs, it may struggle with long-range dependencies and multiscale temporal patterns. In contrast, the Crossformer model (Fig. 4) employs a Two-Stage Attention (TSA) mechanism [5] to capture both cross-time and cross-dimensional dependencies in multivariate time series (MTS). This enhances its ability to model seasonal trends and inter-variable correlations, making it

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well-suited for long-term forecasting in the LLRF environment.

Crossformer Model

Unlike standard Transformers that primarily model temporal patterns, Crossformer is tailored for MTS forecasting, effectively capturing complex temporal and variable interactions in environmental and operational data. The model leverages a Dimension-Segment-Wise (DSW) [5] embedding to enhance locality and reduce computation complexity by dividing each input dimension into local segments of fixed length L_{seg}, which are then embedded using linear projection combined with positional encoding. The resulting DSW embeddings are passed to the TSA layer. Within the TSA layer, the cross-time attention module first computes self-attention along the temporal axis for each variable independently, capturing temporal dependencies. Its encoded representations are then processed by the cross-dimension attention module, which performs self-attention across different input dimensions to capture inter-variable dependencies. A router mechanism, implemented via two multi-head self-attention (MSA) layers, addresses scalability issues with high-dimensional inputs. The TSA layers are used in both the encoder and decoder, each adopting a hierarchical structure to capture multi-scale features effectively. An illustration of the Crossformer model with multiple encoder and decoder layers is shown in Fig. 4. The decoder integrates the encoded representations to generate future predictions, forecasting the same multivariate sequence L_{pred} steps ahead. For more details about this model, refer to Ref. [5].

The model is trained using Adam optimizer [6], with historical sequences of all variables—relative humidity, temperature, and phase corrections—serve as both inputs and prediction targets. In the implementation, the number of routers c in the cross-dimension stage is set to 3 to correspond to the three distinct types of variables. The segment length is set to $L_{seg} = 32$, with input and output sequence lengths of 2000 and 865, respectively. The dataset is divided into training, validation, and testing sets with a split ratio of 80%/10%/10%. Features are standardized to zero mean and unit variance before being passed to the model. The forecasting results are presented in Fig. 5. The results

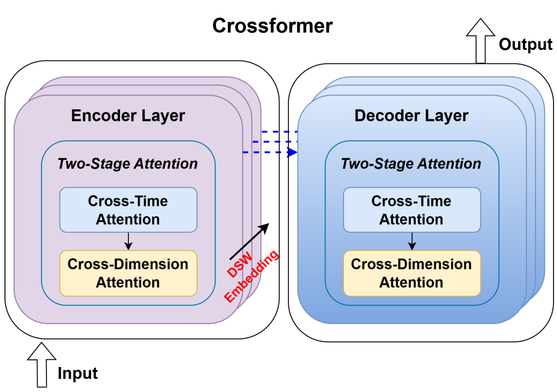

Figure 4: Illustration of the Crossformer model.

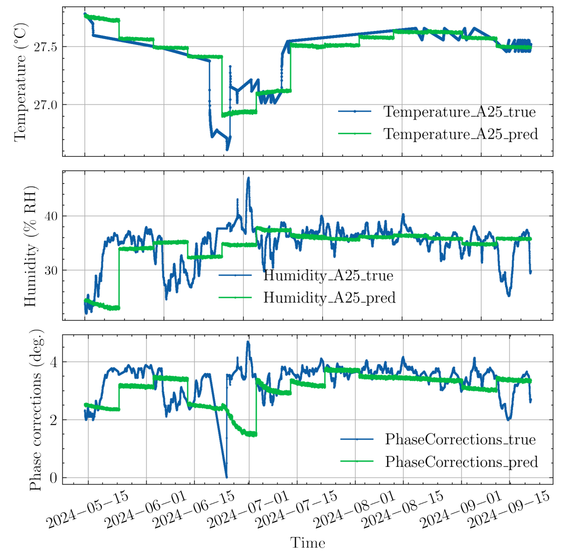

Figure 5: Ten-day forecasts of relative humidity, temperature, and phase corrections using the Crossformer model.

indicate that while the model effectively captures overall trends, many finer-scale variations are not accurately predicted. These limitations, also seen in the NARMAX model, suggest that more expressive models and additional data are needed to better represent the underlying physical dependencies driving environmental conditions and RF behavior in the EuXFEL tunnel.

CONCLUSION

This study investigates the long-term impact of environmental factors on calibration drift in the superconducting RF cavities at the European XFEL. Utilizing historical data from the LLRF drift compensation module, the research employs both the NARMAX method and the Crossformer architecture to model and forecast relative humidity and the applied phase corrections to RF probe signals. These forecasts assist operators in identifying long-term patterns in calibration drift, facilitating timely decisions on when to recalibrate the RF cavities.

However, while the historical environmental and operational data enable the forecasting of general trends, they fall short in providing detailed predictions due to the complex nature of weather systems, which typically require sophisticated physical models for accurate forecasting. Future work aims to incorporate official local weather forecast data to improve prediction accuracy. Additionally, analyzing the long-term calibration error between the measured probe and the virtual probe is essential for a comprehensive understanding of calibration drift.

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