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STUDIES IN APPLYING MACHINE LEARNING TO RESONANCE CONTROL IN SUPERCONDUCTING RF CAVITIES*

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Abstract

Traditional PID, active resonance and feed-forward controllers are dominant strategies for cavity resonance control, but performance may be limited for systems with tight detuning requirements, as low as 10 Hz peak detuning (few nanometers change in cavity length), that are affected by microphonics and Lorentz Force Detuning. Microphonic sources depend on cavity and cryomodule mechanical couplings with their environment and come from several systems: cryoplant, RF sources, tuners, etc. A promising avenue to overcome the limitations of traditional resonance control techniques is machine learning (ML) due to recent theoretical and practical advances in these fields, and in particular Neural Networks (NN), which are known for their high performance in complex and nonlinear systems with large number of parameters and have been applied successfully in other areas of science and technology. In this paper we introduce ML to LLRF control. An LCLS-II superconducting cavity type system is simulated using the *Cryomodule-on-Chip* (CMOC) model developed by LBNL and is used to produce data for future training of NN. Future work based on the experience and results of the present research will be performed for resonance control systems to overcome microphonics detuning of SRF cavities.

INTRODUCTION

Low Level Radio Frequency (LLRF) control systems aim to control the amplitude and phase of the electric field used in driving the cavities of particle accelerators. For X-ray Free Electron Lasers (FELs), such as the Linac Coherent Light Source II (LCLS-II), the quality of the X-rays produced at the undulators is directly affected by the quality of the electron beam accelerated with Superconductive RF cavities (SRF). Therefore, tight stability requirements for the cavity field's amplitude and phase have to be achieved by the LLRF control system [1].

Typically, amplitude and phase are controlled by the LLRF through Proportional-Integral (PI) controllers implemented in FPGAs. The goal of our research is to explore alternative control techniques based on ML, specifically a Neural Network (NN) based controller, to further improve the performance of the LLRF system. We present simulations of how amplitude stability is impacted by several sources of noise, which are modelled by the *CMOC* software developed at LBNL. The data obtained from these simulations will then be used as training data for a NN-based controller.

Applying ML and controls have been developed in different applications by members of this research team. Reza developed control systems to keep formation between 2 CubeSats [2–4]. He also developed, different ML frameworks to increase the efficiency of the formation control [5–7], similar techniques can be applied to the control of accelerator components.

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LLRF FOR LCLS-II

The LCLS-II upgrade includes a scheme for higher beam energy, this is achieved with the addition of 35 cryomodules, each with 8 superconducting accelerating cavities. The cavities are driven under a Single Source Single Cavity (SSSC) topology, where 280 Solid State Amplifiers (SSA) will deliver RF power to 280 cavities [8].

A LLRF for LCLS-II has been designed and tested. It has proven the ability to regulate the RF amplitude and phase under the aforementioned stability requirements. This system is now in a production phase, and installation will begin at the SLAC gallery soon. The LLRF system is based on a basic PI controller [9], and is depicted in Fig. 1.

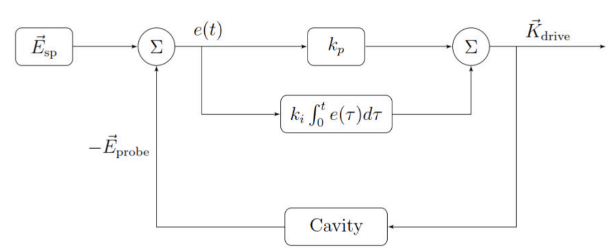

Figure 1: Diagram of a PI Controller.

The proportional gain, k_p, increases the gain of the closed loop and the integral gain, k_i, minimizes the steady state error. A nominal configuration with k_p = 1200 and k_i = $3.8{\times}10^7$ has been chosen for the control system [10].

Cavity Model

A model of the system encompassing the superconducting cavity, the LLRF control system and the cryomodule was developed by the LLRF team at LBNL and has been used to study the performance of electrodynamic system. For a

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cavity with several electromagnetic modes, each mode can be represented by a circuit model [9], see Fig. 2.

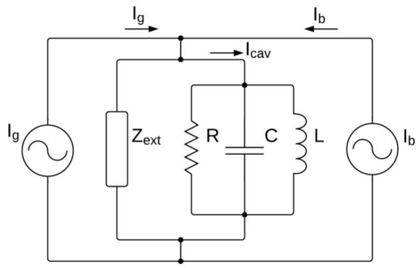

Figure 2: Circuit model of a resonant mode in a cavity.

The dynamics of the system is described with the following system of differential equations [9]:

$$V = Se^{j\theta}, \tag{1}$$

$$\frac{d\theta}{dt} = w_d, \tag{2}$$

$$\frac{dS}{dt} = -w_f S + w_f e^{-j\theta}(2K_g\sqrt{R_g} - R_b I), \tag{3}$$

where V is a representative measure of energy stored in each mode with magnitude S and phase θ, w_d is the detuning frequency, w_f is the cavity's bandwidth, K_g is the incident wave amplitude, R_g is the coupling impedance of the beam and I is the beam current.

CMOC SIMULATION RESULTS

Using the *CMOC* code, simulations of amplitude control have been performed with different sources of noise. Figures 3 and 4 show the cavity field amplitude when the beam is active. Upper and lower limits are shown as references for the stability requirements on the LLRF system. It can be seen how under feed-forward control, the amplitude lies inside the limits during the beam activation time. In Fig. 5 we can see the effect of detuning the cavity, still the amplitude is controlled and stays under the specified limits. Finally, Fig. 6 shows the effect of measurement noise in the amplitude: higher levels of noise will be amplified by the LLRF and that noise will be send to the SSA.

Figure 7 shows measurement noise levels in the range 130 to 260 dBc/Hz, where three different gain configurations [10] and amplitude error where simulated. As expected, higher noise levels produce higher error and higher gain also produces higher error due to amplification of the noise in the feedback loop. Data produced under different conditions and configurations will be used to feed the ML block, which is described in the following section.

EXPLORATION OF NEW AI CONTROL TECHNIQUES

Particle accelerators and most of their subcomponents, the LLRF for example, are complex systems with multiple variables and time-scales. These variables dictate both the

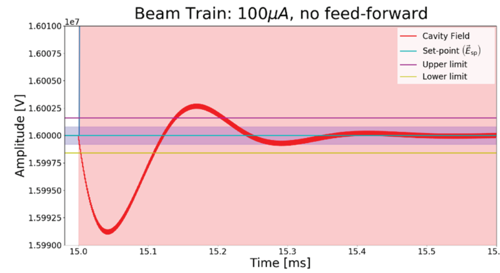

Figure 3: Beam loading noise without feed-forward.

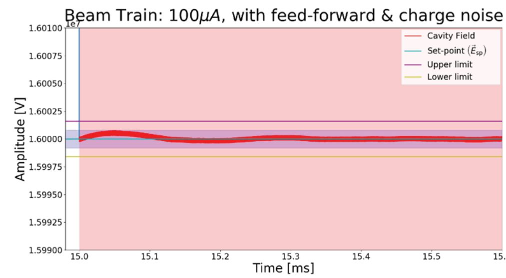

Figure 4: Beam loading noise with feed-forward.

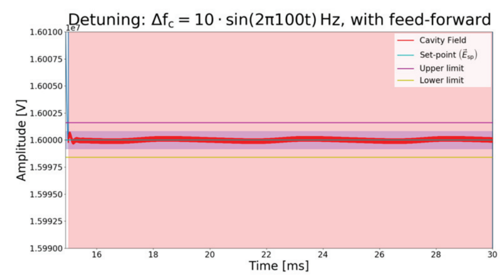

Figure 5: Detuning with feed-forward.

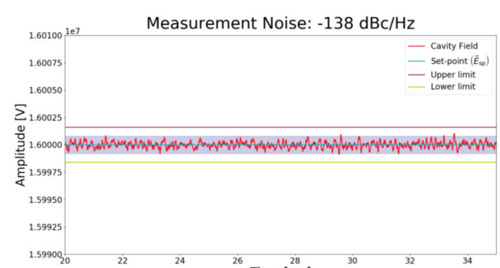

Figure 6: Measurement noise.

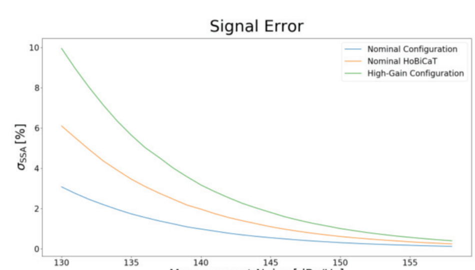

Figure 7: Signal error under different levels of measurement noise and gain configurations.

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complexity of the system and the performance of the machine. Artificial Intelligence (AI), understanding by it a set of learning and optimization algorithms, can potentially provide us with new techniques for controlling accelerator components in a more efficient way. The increase in accelerator performance is a direct result of the algorithm optimizing a set of driving parameters given the complex correlations that may be present in the diagnostic data available from the machine or simulations. With the goal of further increasing the performance of SRF accelerators and in particular, to increase the RF field stability of cavities, we are exploring different control techniques based on ML.

For the LLRF system, an AI framework includes an optimization phase and a learning phase in order to define the optimal parameters for the system. Figure 8 represents this approach.

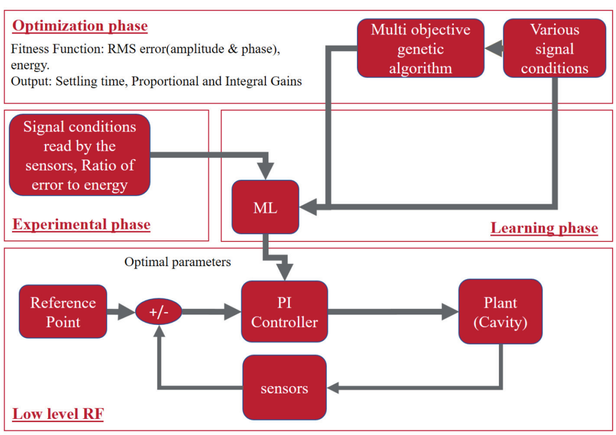

Figure 8: Artificial Intelligence framework.

In the optimization phase, a loss function, composed by the measurement of the RMS error and energy, is minimized through a multi-objective genetic algorithm (GA) [11]. The inputs to the optimization algorithm are the signals of the cavity. The outputs of this optimization are the settling time, the RMS steady state error, and the energy. The minimization of the cost fuction gives optimum values of the proportional and integral gains in the control systems for each of the input signals. The data produced by this algorithm is a set of inputs and their corresponding optimal parameters, which are fed into the ML algorithms. Figure 9 represents the ML algorithms in more detail.

The first component of the ML algorithm is a Gaussian process (GP) regression [12], which estimates the energy corresponding to the signal conditions and achieved error, together with a confidence interval of the estimation. The second one is a deep learning (DL) [13] structure that estimates then optimal parameters for these signal conditions. The network also estimates a confidence interval of the predicted parameters.

Finally, Fig. 10 shows the algorithm used in the DL framework. This will be implemented in *TensorFlow* and processed using High Performance Computer (HPC) resources. *TensorFlow* is a *Python* based toolwork for AI and can optimally implement the learning algorithm with the huge amounts of data on the many cores of an HPC. The DL architecture is designed where the fitness function for this optimization process is the Mean Absolute Percentage Error (MAPE).

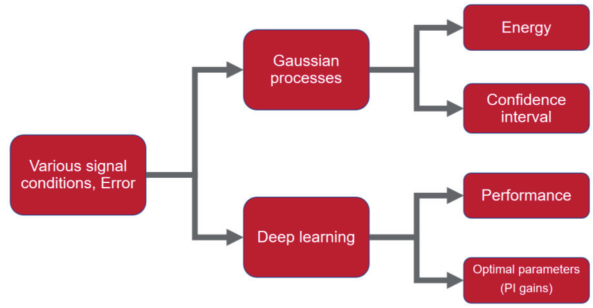

Figure 9: Deep learning and GP learning.

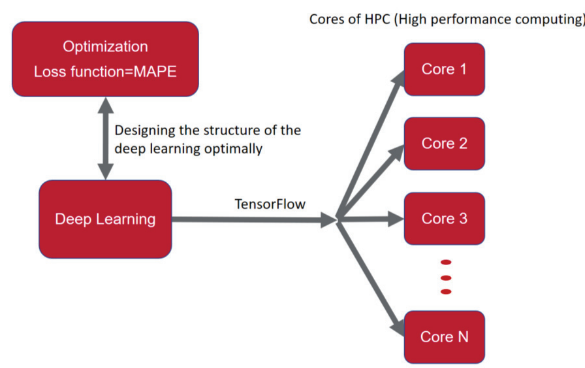

Figure 10: Deep learning architecture.

SUMMARY AND FUTURE WORK

In this research, an advanced control technique is being developed based on ML algorithms to improve the performance of existing PI controllers for LLRF systems. A ML algorithm can select the optimal proportional and integral gains with a more satisfactory performance. The applicaltion of AI in general and ML techniques in particular to improve control systems that require high performance is a relatively new approach that benefits of the superior performance in data driven estimation of some ML techniques due to their high complexity and efficient modern training criteria and algorithms. In particular we have seen that DL and GP can help to reduce the effect of noise in the control system with a short computational time with respect to other traditional approaches. Future work will include the development of more advanced control techniques with the help of Machine Learning and Artificial Intelligence. Additionally, these techniques will be applied to other challenging problems like microphonics, where current control approaches show limited performance.

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