Studies in Applying Machine Learning to LLRF Control in Superconducting RF Cavities*

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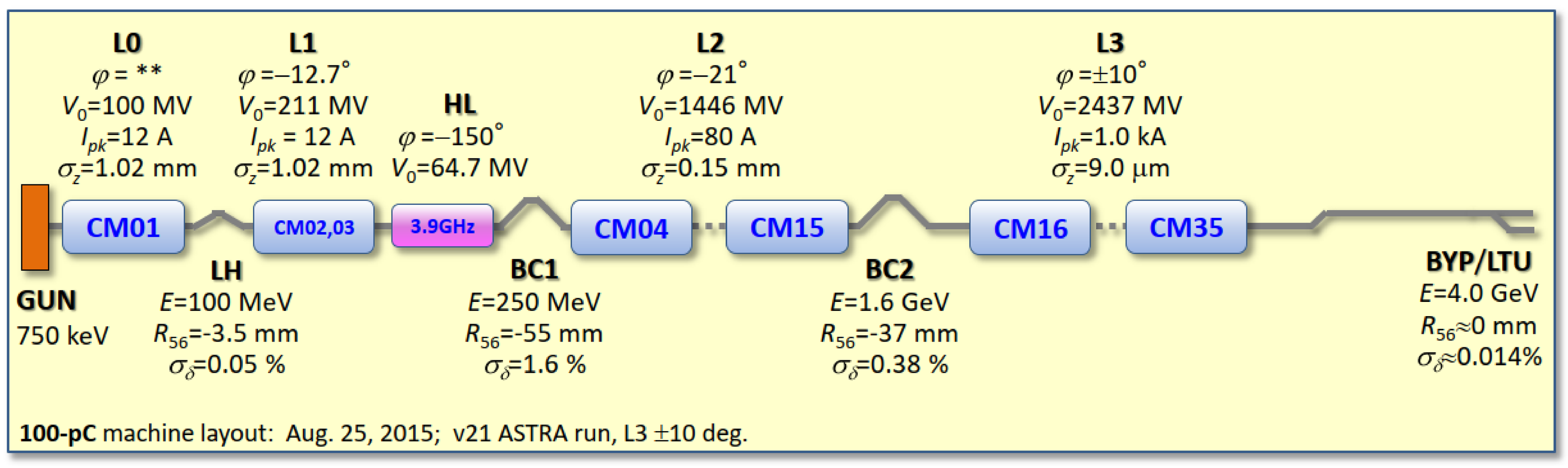
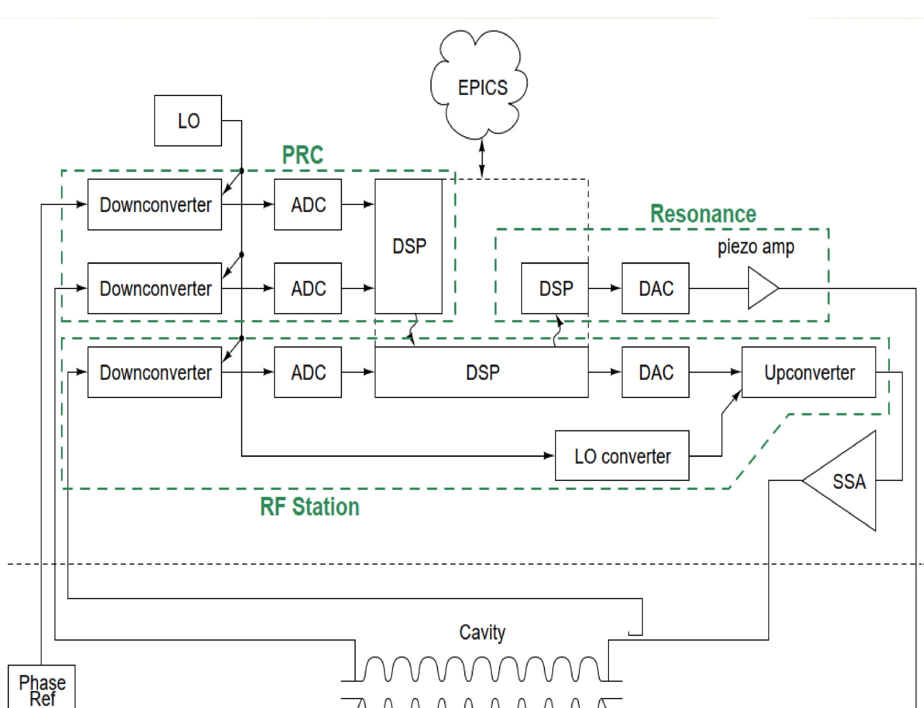
LCLS-II LLRF & Resonance Control





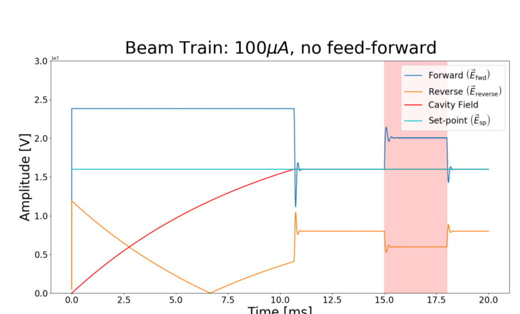
Frequency:	1.3 GHz and 3.9 GHz
Cavity Q_L	$4.1x10^7$
Beam Current	0.3 mA
Beam Macro Pulse	Up 1 MHz
RF Power	3.8 kW (1 dB compression)
Cavity Microphonic detuning (max)	2 Hz sigma and 10 Hz peak
Lorentz detuning coefficient (max)	1 Hz/ $[MV/m]^2$
Cavity Probe Qext	$2.5x10^{11}$ to $7x10^{11}$, nominal: $4x10^{11}$
1.3 GHz SC Cavities (number)	280
3.9 GHz SC Cavities (number)	16
1.3 GHz NC Buncher Cavity	1
186 MHz E-Gun cavity	1

Motivation

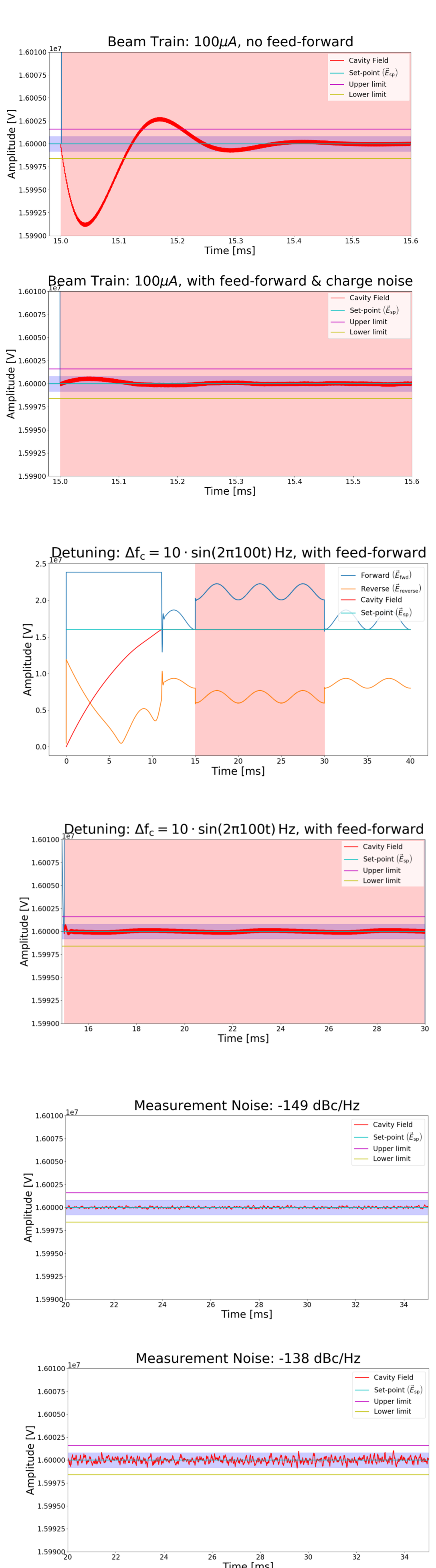
Traditional techniques to deal with microphonics involve characterization of the resonant modes of the structure and identification of sources of microphonics, to then be able to isolate and damp by mechanical modifications. Active Resonance Control (ARC) has shown promising results in compensation of microphonics with piezo tuners. In this research we explore Machine Learning techniques to improve actual control techniques for LLRF systems.

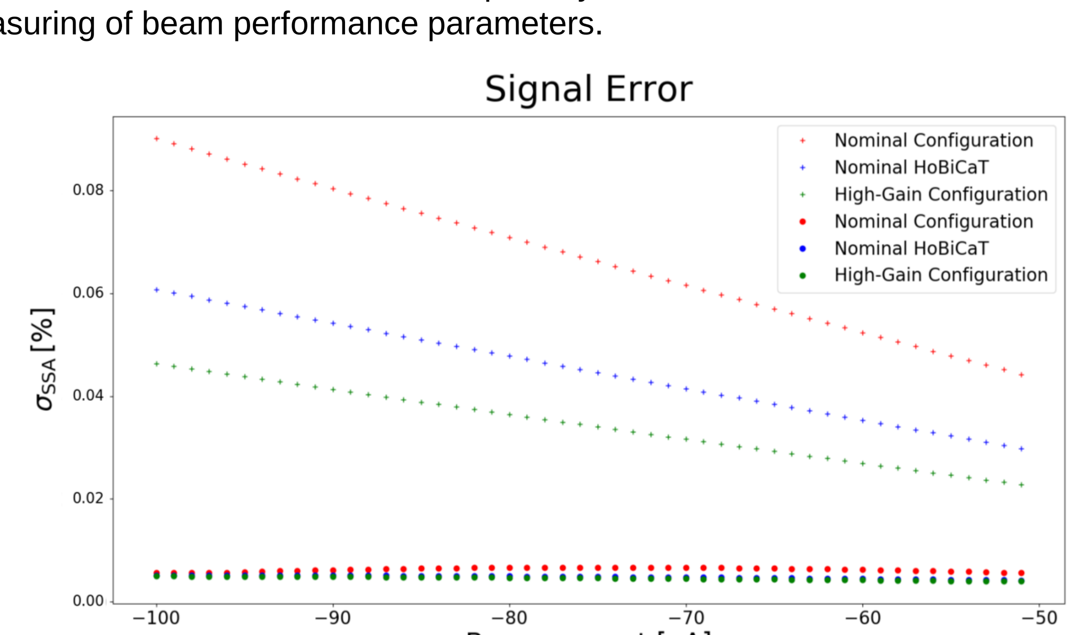
Simulation Results

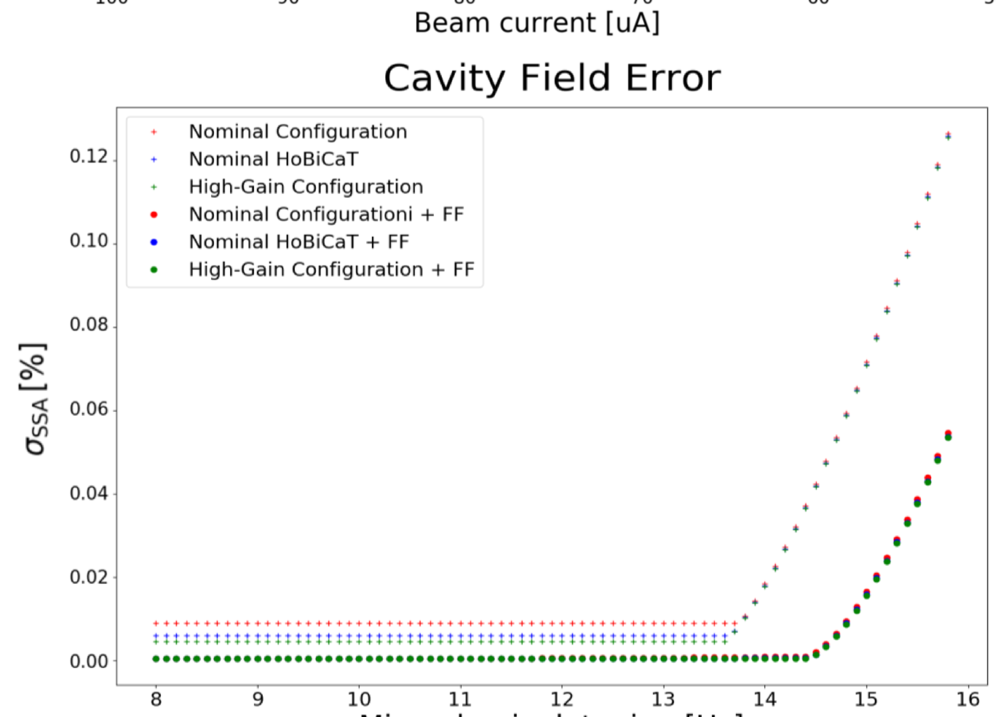
CMOC

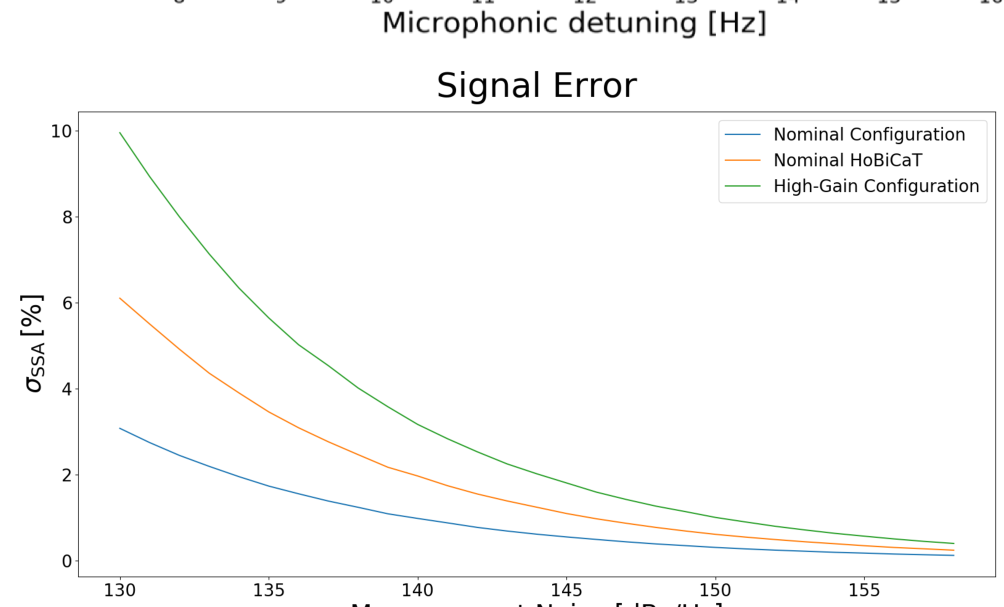


The CryoModule-On-Chip (CMOC) is a simulation engine developed at LBNL to model LLRF and beam-based feedback systems for Linac-driven FELs. The software includes models of cavities (with electromagnetic eigen-modes), of RF stations (RF source + Cavity + FPGA Controller), of cryomodules (Piezo tuners + RF Stations + mechanical modes) and of Linac sections (cryomodules + bunch compressor). It considers beam instrumentation, loop delays and sources of noise. Also allows for measuring of beam performance parameters.





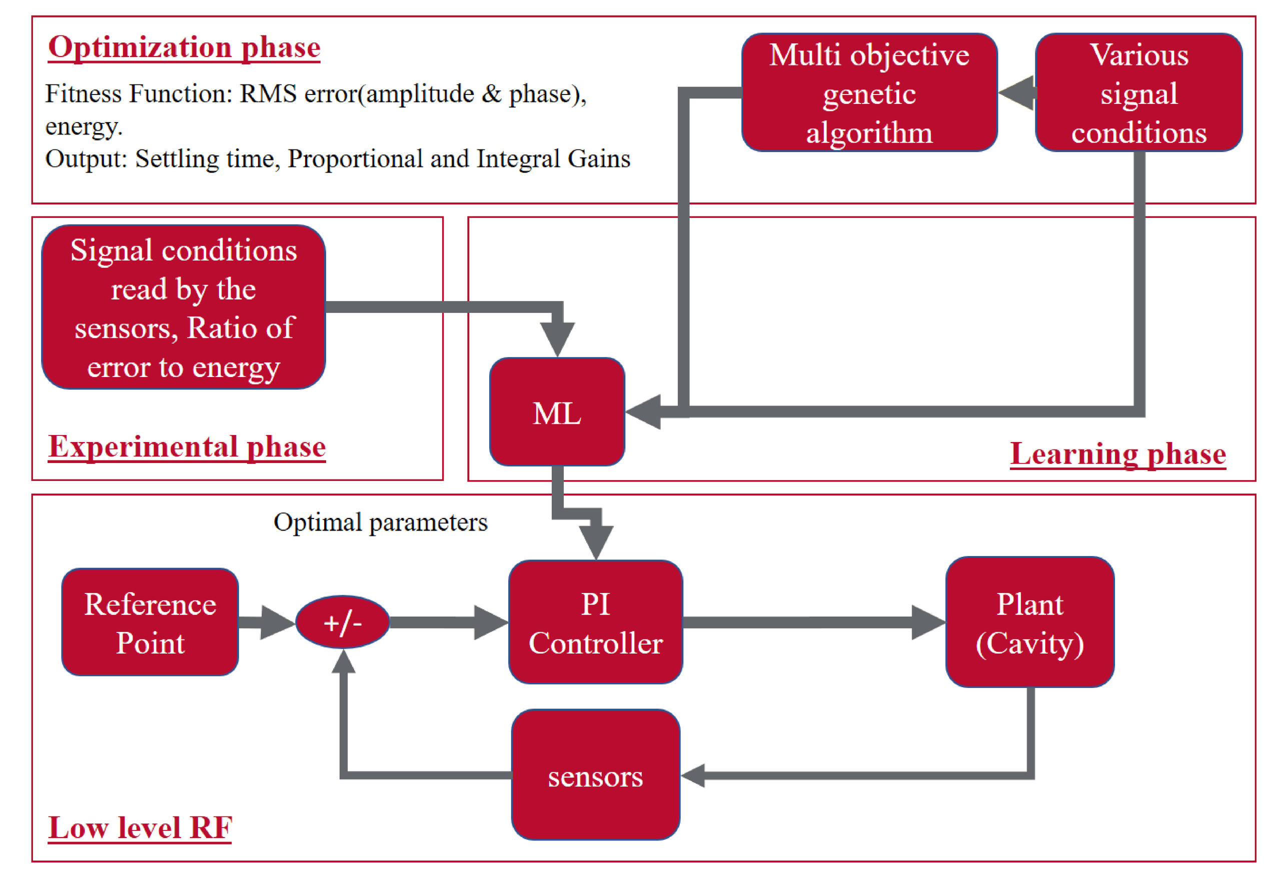


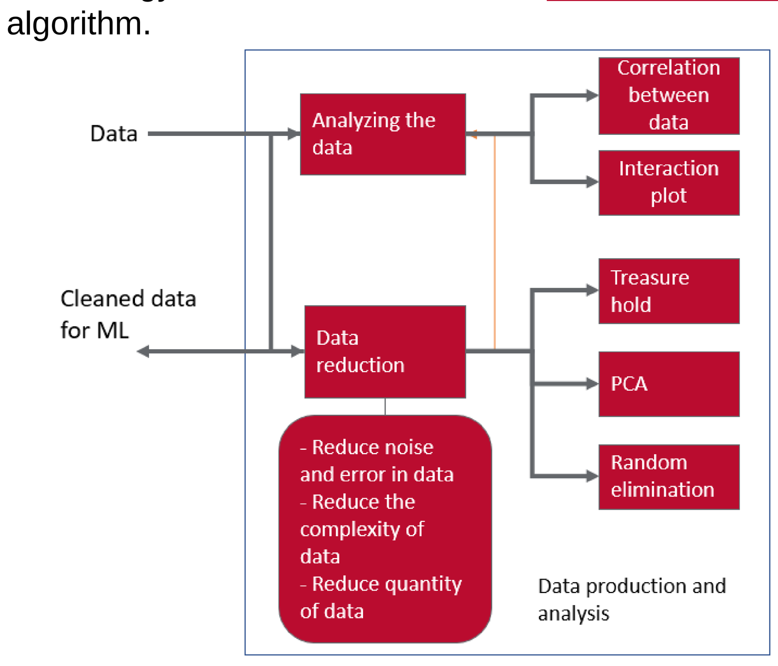


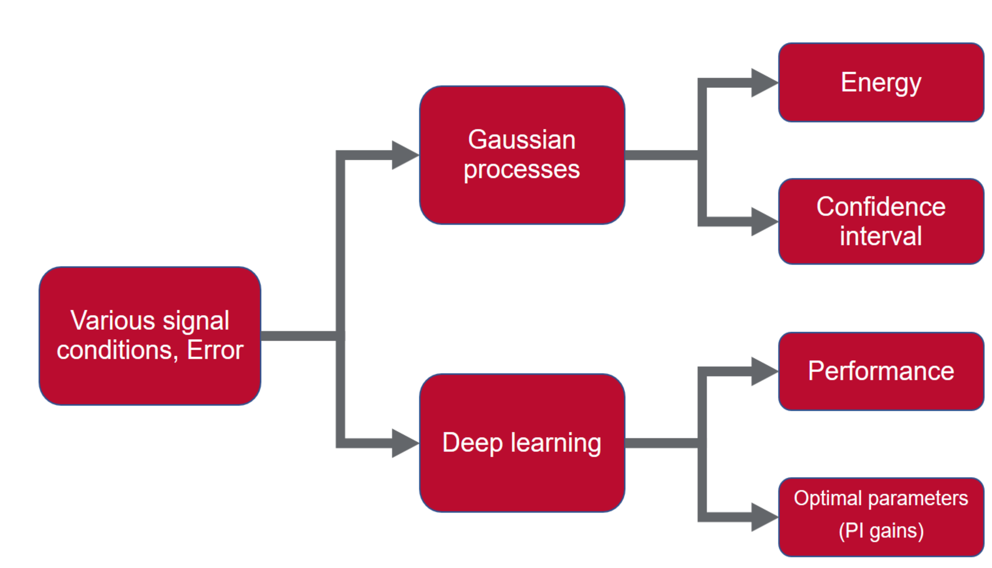
Beam current is active between 15 and 17.5 seconds. Froward, reverse and cavity signals are perturbed and can go beyond the limits. Feed forward control keeps the cavity signal between limits. Error in the cavity signal is simulated under values of beam current, gain configurations and with and without feed forward control. Similar simulations are performed for microphonic detuning and measurement noise

Artificial Intelligence Framework

The artificial intelligence procedure in the LLRF consists of an optimization phase and a machine learning (ML) phase. They together define the optimal parameters for the control system. In the optimization phase, the RMS error of voltage amplitude and phase is minimized through a multi objective genetic algorithm (GA) to optimize the proportional and integral gains of the PI controller. The inputs to the optimization algorithm are the signal of the cavity and the signal change rate, which are fed to the control systems. After the optimization, the PI is used to produce measurements of the settling time, RMS steady state error, and energy to be used in the ML algorithm.



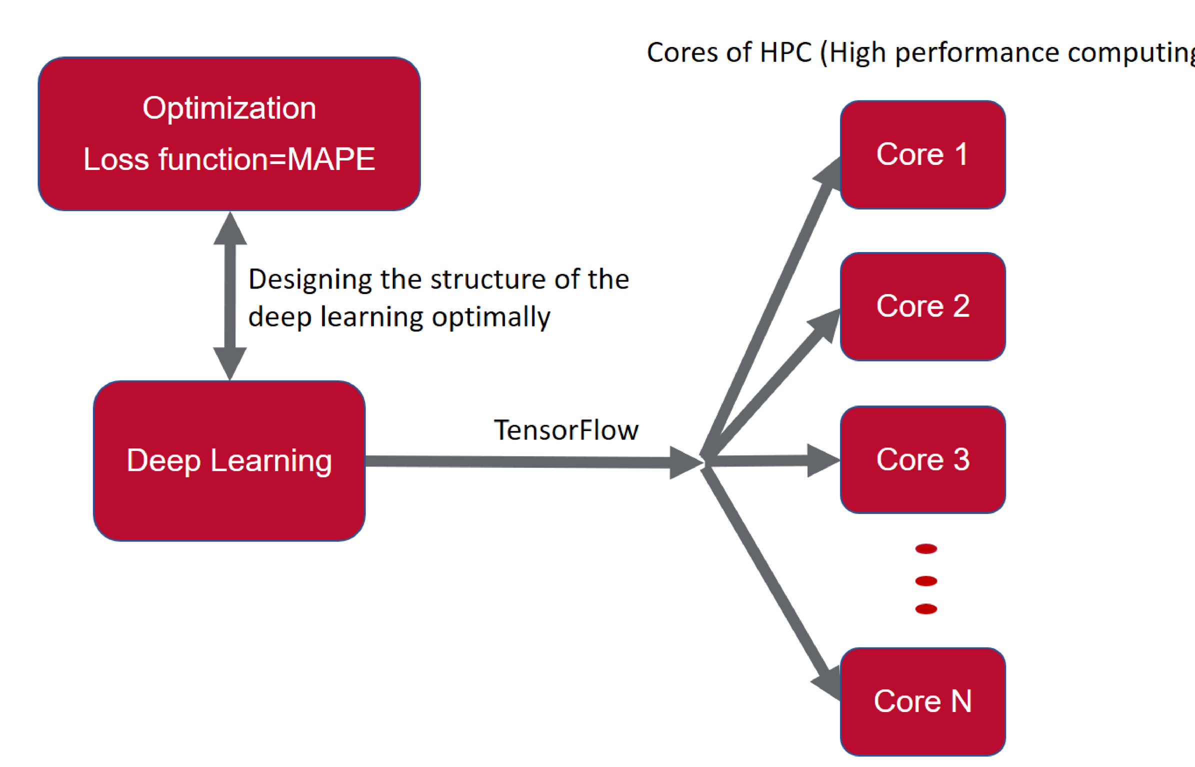




The data are produced by simulation or gathered from test facilities. It is analyzed by plotting features vs other features to see how data are distributed in the parametric space. Different metrics can be implemented to test the data. The data size is also filtered to reduce noise and error, complexity, and the large quantity of data. After each elimination of data, the data are analyzed again to evaluate quality.

The ML algorithms are trained with the data produced by the multi objective GA to find the optimal parameters to be used in the control system of the LLRF. A Gaussian process network is trained to give an estimate of the energy with a confidence interval for the given error, whereas a deep learning (DL) structure finds the optimal parameters with that given confidence interval, so that if the uncertainty is too big in the energy estimation, we select another set of optimal parameters.

The deep learning is implemented on the Argonne National Laboratory high performance computer. It is implemented by TensorFlow, which can efficiently implement the learning in presence of high amounts of training data and high structural complexity. The structure of the deep learning is designed with optimization algorithms. The loss function of this optimization is chosen to be the mean absolute percentage error (MAPE).



Conclusions 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. Our goal is to design a ML algorithm capable of select the optimal proportional and integral gains with a more satisfactory performance.

The application 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 aim to use DL and GP to help reduce the effect of noise in the control system with a short computational time with respect to other traditional approaches.

Future work will integrate the AI framework with the simulation data and real data gather during test of cryomodules. Additionally, these techniques will be applied to other challenging problems like microphonics, where current control approaches show limited performance.

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