# Data-driven Model Predictive Controller for SRF Cavity Resonance Control

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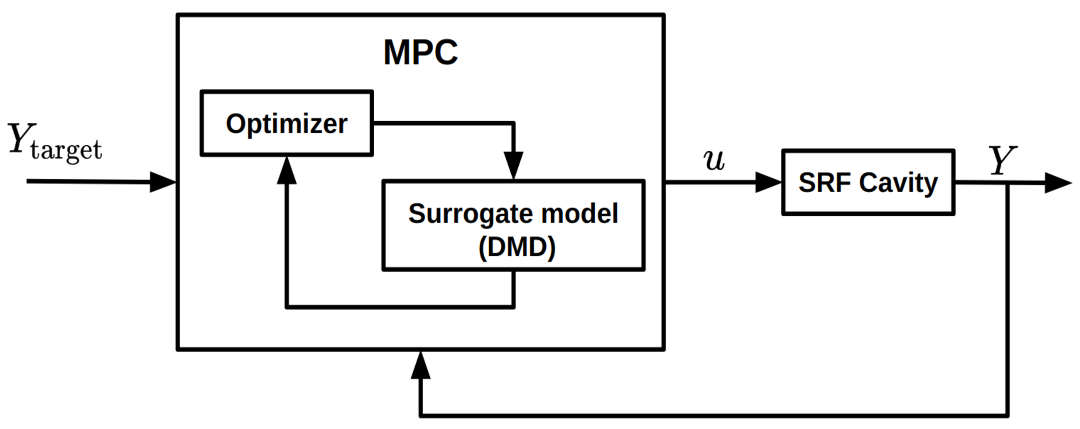
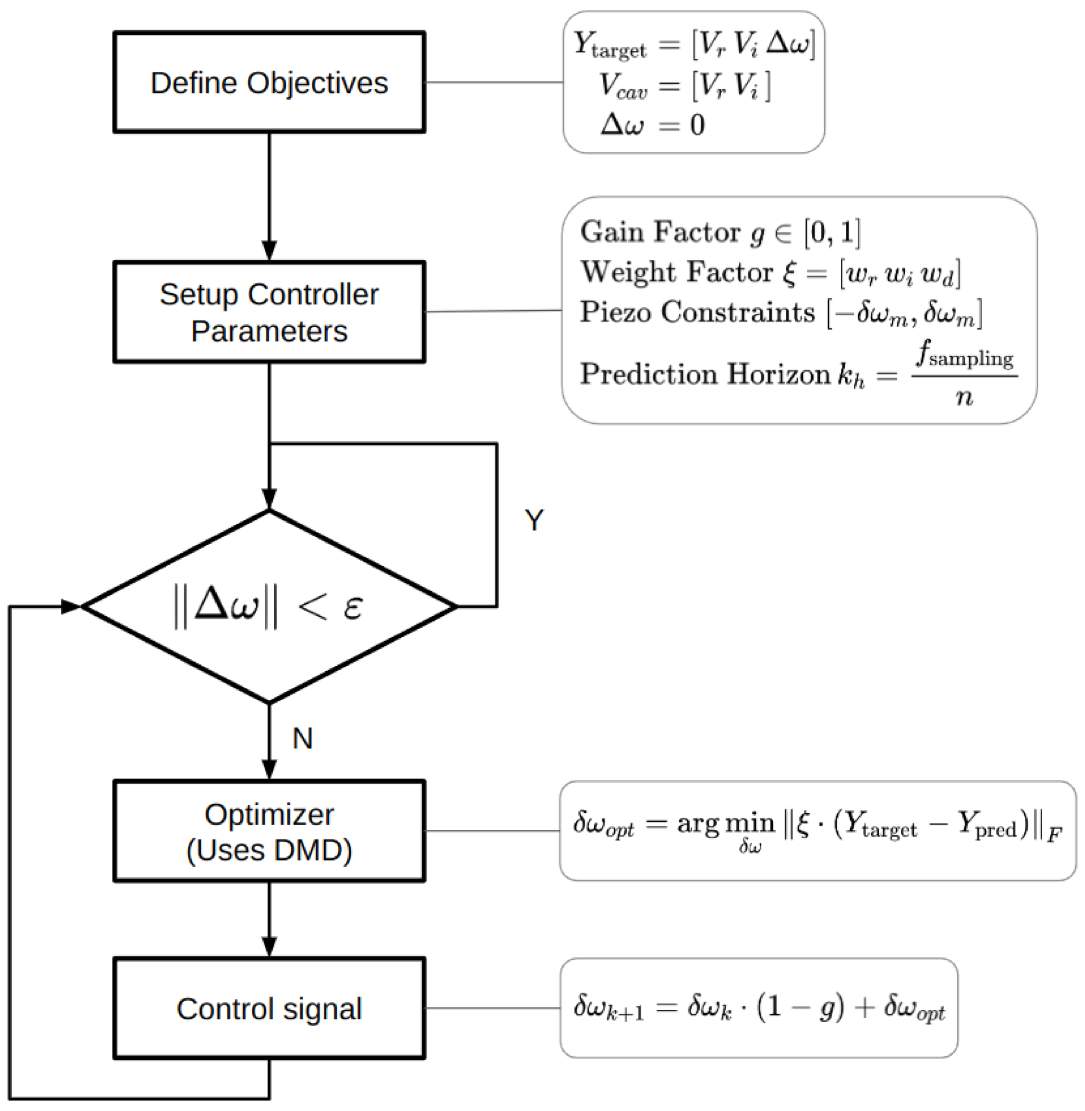
## ABSTRACT

For high-Q over-coupled SRF cavities like those used in the LCLS-II Linac, precise cavity resonance control is crucial for ensuring stable operations. Inadequate control can lead to an increase in RF power demands, escalating both operational and capital expenses due to the need for additional RF power. To address this challenge, we have developed an innovative data-driven model predictive controller that incorporates a highly efficient surrogate model, based on dynamic mode decomposition. This model is designed to manage the complex dynamics of cavities affected by microphonics and nonlinear Lorentz forces.




## MODEL PREDICTIVE CONTROL (MPC)

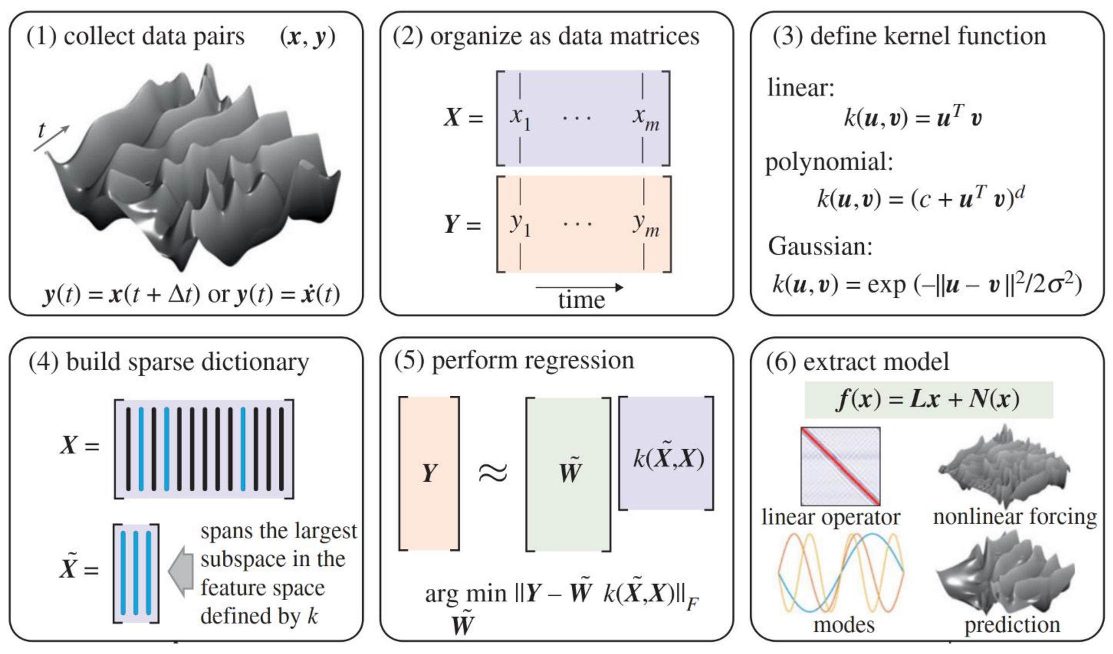
The MPC algorithm is shown in the diagram below. It has 3 targets (cavity I&Q and detuning), and one control signal (piezo output). The optimization step is based on grid search and the minimum of a cost function. A gain factor is included to generate a smooth control signal. A lightweight model based on DMD is used since MPC requires extensive computation. **MPC uses the predictions of DMD to find the optimum piezo voltage that minimizes the error in cavity amplitude and detuning.**




## DYNAMIC MODE DECOMPOSITION (DMD) [1,2]

DMD is formulated as a linear regression problem based on measurement data and is used to predict the future state of the system.

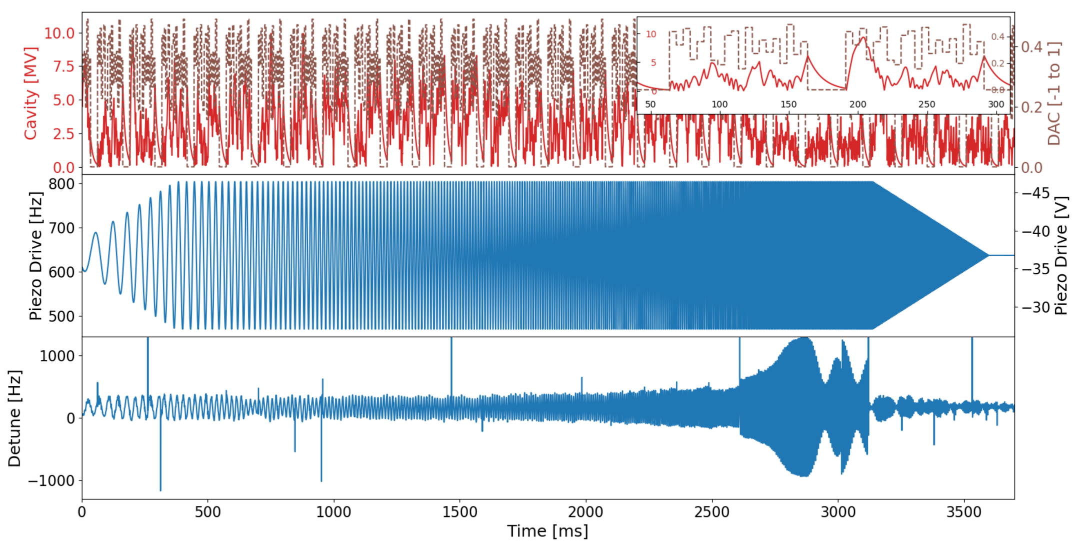
$$x_k = \begin{bmatrix} V_{rk} & V_{ik} & \dot{V}_{rk} & \dot{V}_{ik} & \Delta\omega_k & \dot{\Delta\omega}_k \end{bmatrix}^T$$



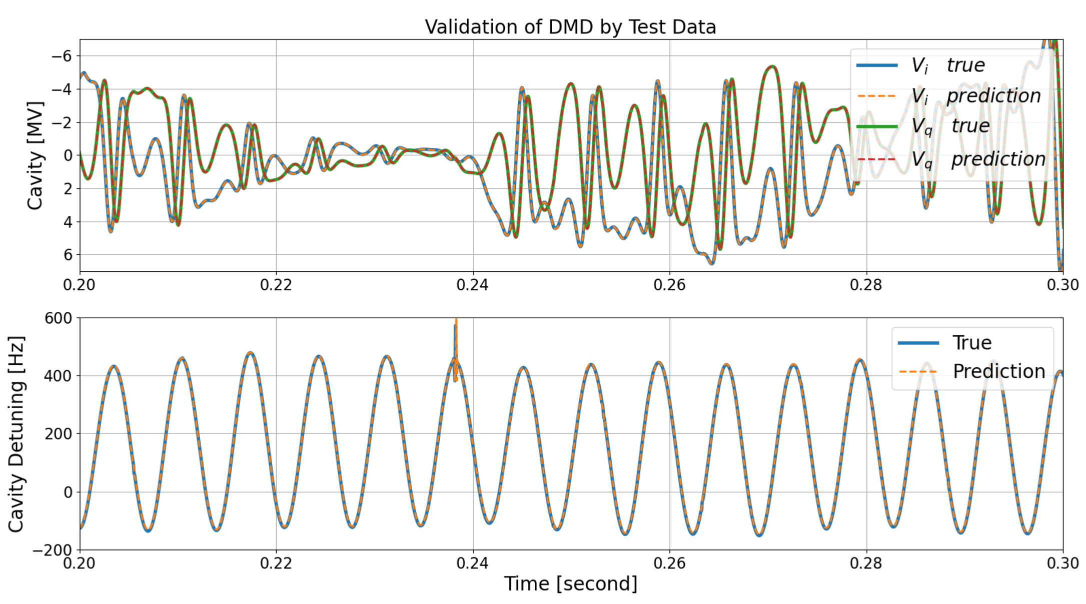

Peter J. Baddoo et al. Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences 478.2260 (2022)

## DMD TRAINING

To maximize the hidden features extracted by the DMD model, it is essential to diversify the training data as much as possible. The cavity drive signal is randomized to cover the operational range, and a chirp is used to drive the piezo to cover the microphonics frequency range and its amplitude



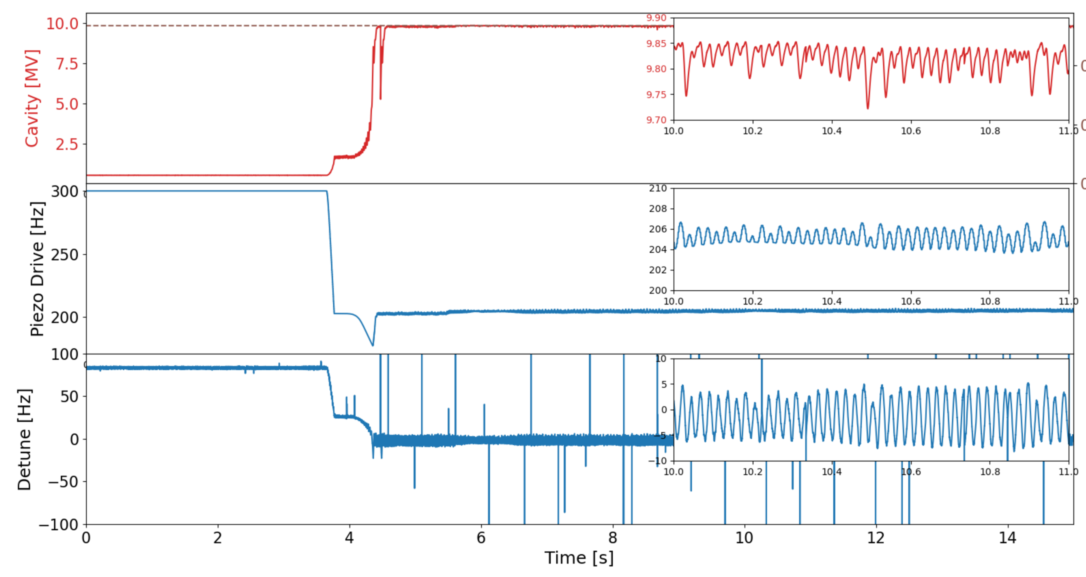

Using the "almost linearly dependent" test, the training data becomes a sparse subset of samples that spans the largest subspace in the original dataset. The performance of the DMD is evaluated using predictions on cavity voltage (I&Q) and detuning. Results show errors of less than 2%



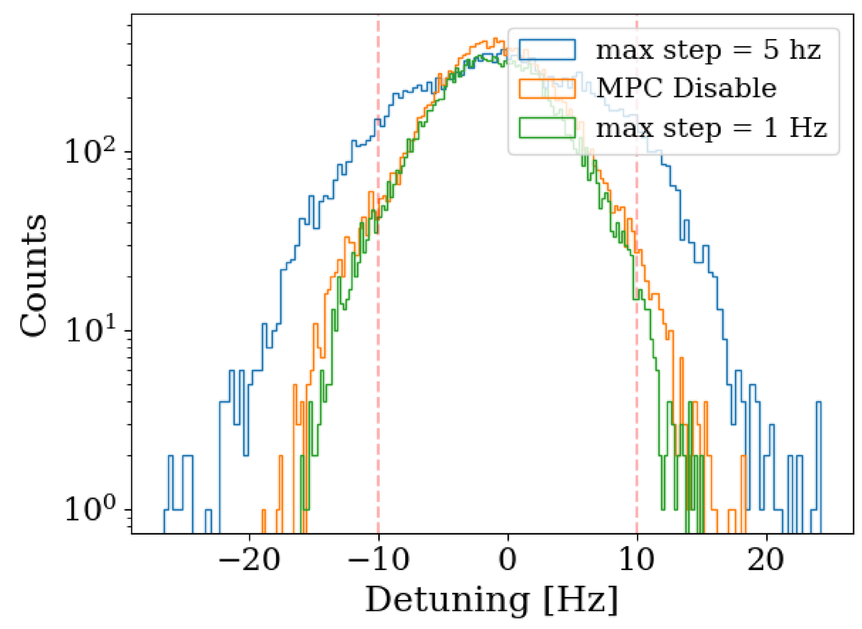

## RESULTS

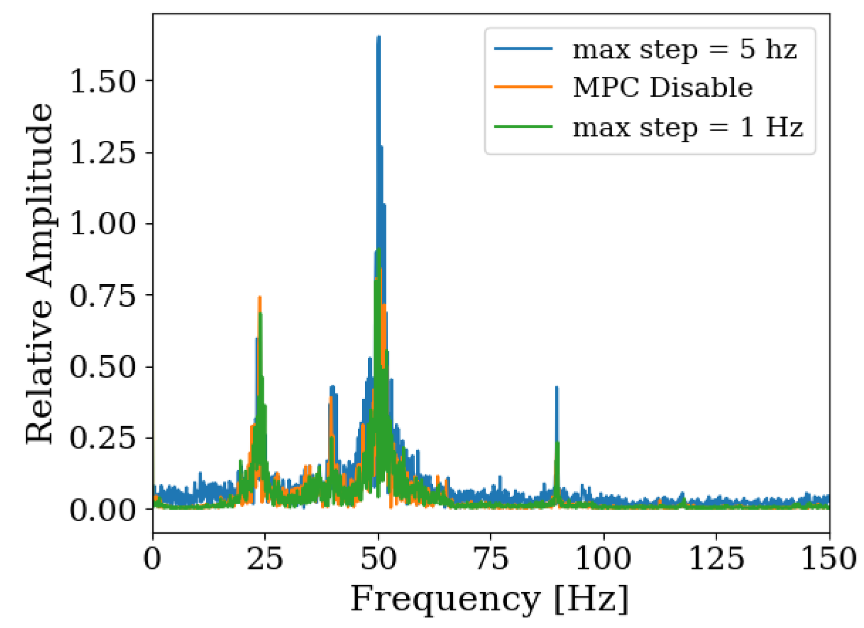
The MPC controller was tested using LCLS-II SRF cavities, that have a nominal $\pi$-mode resonant frequency of 1.3 GHz. We modified the existing LLRF and resonance control systems to enable the implementation of the MPC controller.

**TEST 1:** With the LLRF and resonance control systems disabled, the cavity was driven by a signal of 1.3 GHz and constant amplitude. The MPC controller was enabled (at about 3.5 s in the plot below), and ~1 second latter the cavity amplitude reached the target field. The detuning was also reduced and centered at 0 Hz.




**TEST 2:** The cavity was tuned and driven with the LLRF system enabled (SEL mode) and the resonance control system disabled. Amplitude and phase were stable. Microphonics limited the cavity gradient. We enabled MPC to evaluate the impact on cavity detuning. Factors including the maximum step of the piezo output affected the performance of the controller. If the settings of the MPC are not set correctly, the MPC will induce detuning in the cavity, instead of reducing it.




## ACKNOWLEDGEMENTS

This work was supported by the US Department of Energy, Laboratory Directed Research and Development Program at SLAC National Accelerator Laboratory, under Contract No. DE-AC02-76SF00515.

Thanks to the LCLS-II LLRF team and the SRF team at SLAC, and thanks to the LLRF team at LBNL.

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