Applications of Machine Learning for RF Systems

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Low Level RF 2022

radiasoft

U.S. DEPARTMENT OF ENERGY | Office of Science

Controls Landscape for LLRF

”Low Level” RF

- Cryogenic systems
- Water cooling systems
- Environmental controls
- High level RF systems
- Beam instrumentation

Fast or Real-time Controls

- RF waveform generation and reference system
- Phase and amplitude control
- Pulse-to-pulse corrections
- Beam-loading compensation
- Filling / stacking / synchronous transfer / timing

Slow Controls

- Amplifier stabilization / linearization
- RF distribution drifts (phase and amplitude)
- Beam-based feedback

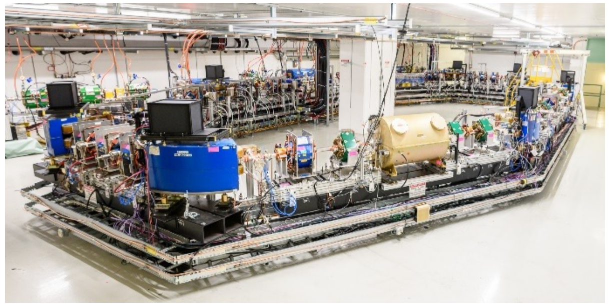
- Room temperature resonance control
- Lorentz force detuning (SRF)
- Microphonics compensation cavities (SRF)
- Frequency tracking / SEL-GDR

Machine Learning Landscape

Problem Spaces	Methods	Tools
Model Building	Supervised Learning	Neural Networks
Anomaly Detection	Semi-supervised Learning	Gaussian Processes
Control	Unsupervised Learning	Clustering
Signal Processing	Reinforcement Learning	Linear Models

Machine Learning Applications for Accelerators

Accelerator R+D



Beam for Experimentalists

Down Time

Tuning
- Inverse Models
- Neural Network + Optimization

Surrogate Modeling
- Neural Network
- Neural Network + Optimization

Anomaly Detection
- Inverse Models
- Autoencoders

Machine Learning Efforts for LLRF

”Low Level” RF

- Cryogenic control (SPIRAL 2)
- Beam instrumentation (virtual diagnostics and on-line modeling, many)

Fast or Real-time Controls

- Extremum seeking for beam loading compensation (LANL)

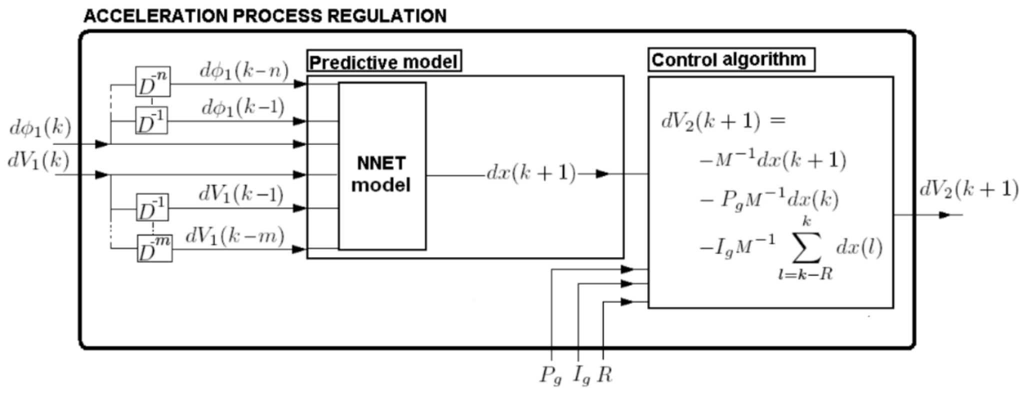
Slow Controls

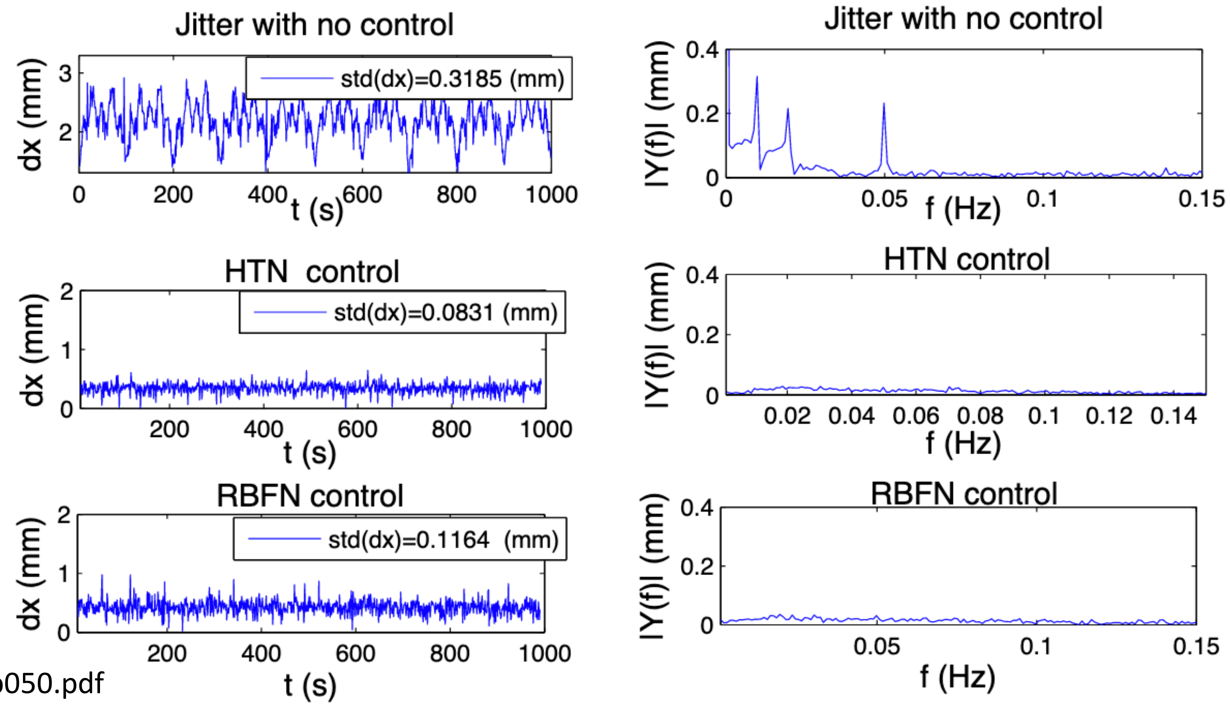
- Energy jitter correction (Australian synchrotron)
- Anomaly detection (RadiaSoft and others)
- Quench classification (Jlab)
- Breakdown modeling (CERN)

- Room temperature resonance control (FAST and PIP-II IT)
- Gain scheduling / optimization (UNM)
- Quench detection (DESY)

Energy Jitter Compensation Using Neural Networks

- One of the common sources of energy jitter is from variations in the RF system that manifest themselves as changes in the acceleration of the beam
- This effort utilized a neural network model to provide a feed-forward correction to the RF system based on measurements in the system
- Right shows the jitter without control and with control
- The jitter is significantly reduced with this technique





Proceedings of PAC09, Vancouver, BC, Canada TU5RFP050

ELECTRON BEAM ENERGY STABILIZATION USING A NEURAL NETWORK HYBRID CONTROLLER AT THE AUSTRALIAN SYNCHROTRON LINAC*

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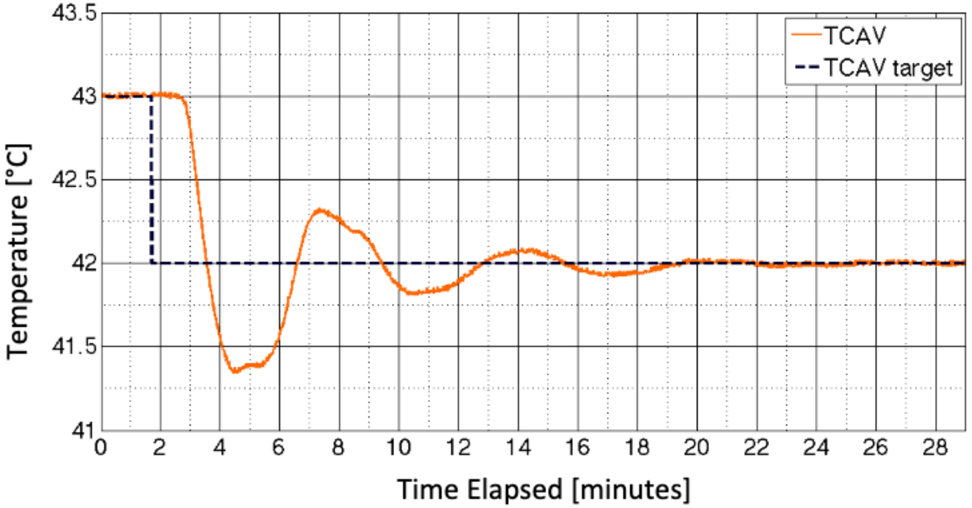
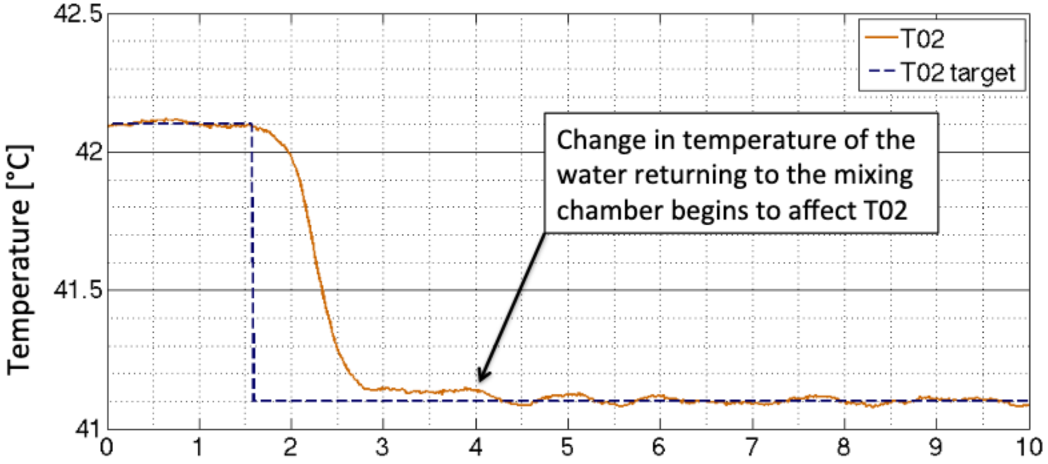
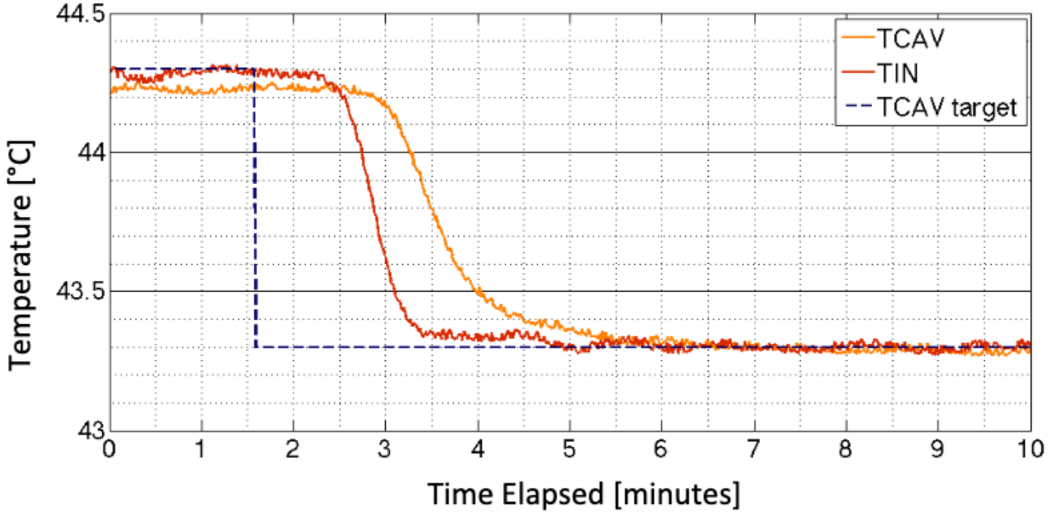
https://accelconf.web.cern.ch/PAC2009/papers/tu5rfp050.pdf?n=PAC2009/papers/tu5rfp050.pdf

ML Based MPC for Room Temperature Cavities

- Long delay times in the cooling system leads to oscillations when PID is used to stabilize the cavity temperature
- Model predictive control can account for this by encoding the time dynamics of the system into the controller and optimizing the control trajectory.
- Machine learning models are a fast executing and flexible tool for this purpose







INITIAL EXPERIMENTAL RESULTS OF A MACHINE LEARNING-BASED TEMPERATURE CONTROL SYSTEM FOR AN RF GUN

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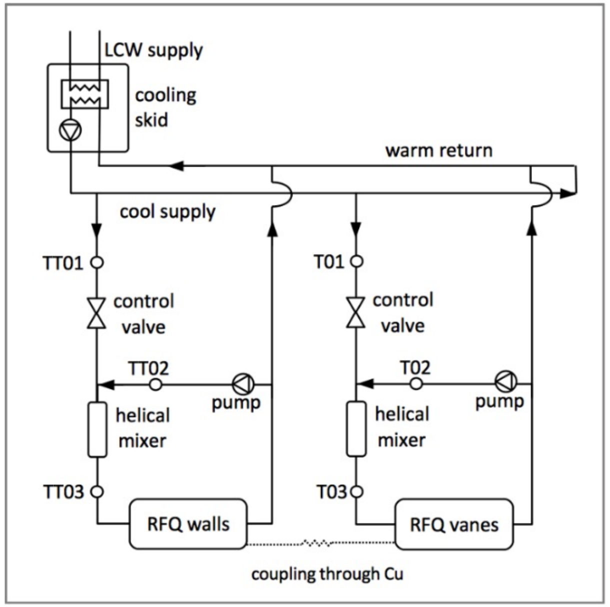
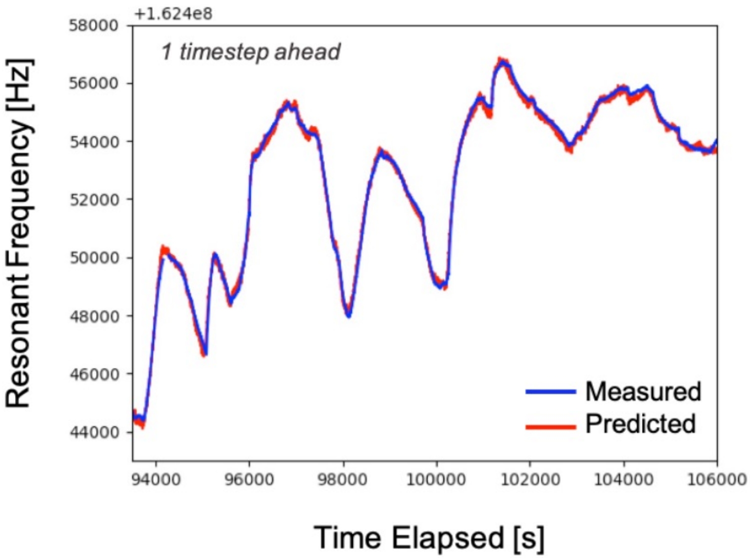
https://arxiv.org/ftp/arxiv/papers/1511/1511.01883.pdf
https://ieeexplore.ieee.org/document/7454846

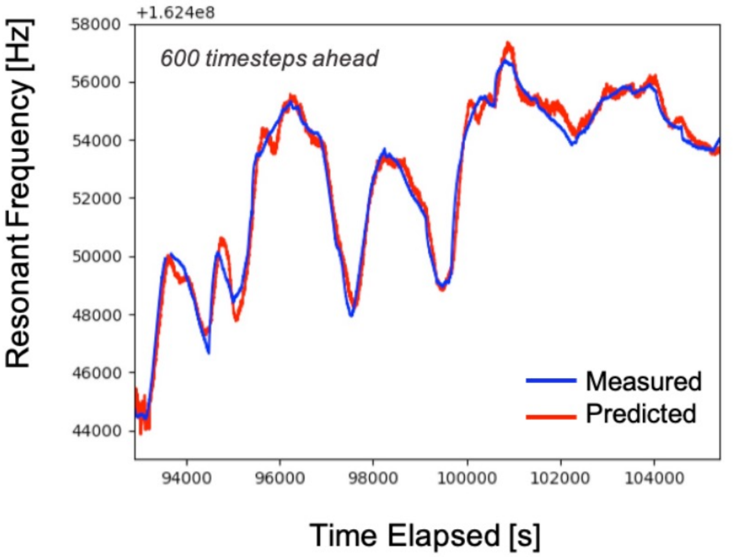
Temperature / Frequency Modeling

- Prediction of resonant frequency changes using neural network model
- Being able to predict one timestep in the future is helpful for some applications but in long timescale systems with coupled dynamics a longer prediction window is necessary
- This work shows the efficacy of predicting up to 600 timesteps in the future, which is impressive even by today's standards.
- Model used conventional feed-forward neural networks: LSTMs were also investigated



Variable	Min	Max	Units
Wall Valve Setting	0	99	[% open]
Vane Valve Setting	0	99	[% open]
Cavity Field	0	70	[kV]
Wall Supply Temp	19.1	20.5	[C]
Vane Supply Temp	18.9	20.4	[C]
Wall Entrance Temp	19.8	22.8	[C]
Vane Entrance Temp	19.5	21.9	[C]
Resonant Frequency	162.4403	162.4738	[MHz]
Cave Temp	23.3	25.5	[C]
Cave Humidity	19.1	36.6	[%]





https://arxiv.org/abs/1612.07237

A. Edelen, Dissertation: https://www.leelinska.com/wp-content/uploads/2021/06/Auralee_Edelen_Dissertation.pdf

SRF Quench Classification

- Data collected from the CEBAF accelerator and labeled with different quench types or cavity or origin
- Machine learning tools were used to classify the different types of quenches or the cavity of origin.
- The distribution of cavity quenches and types are shown on the top right
- Bottom right is the confusion matrix for the classifier.
  - The confusion matrix highlights the quality of the classifier.
  - A perfectly diagonal confusion matrix would be an ideal classifier

PHYSICAL REVIEW ACCELERATORS AND BEAMS **23,** 114601 (2020)

Editors' Suggestion

Superconducting radio-frequency cavity fault classification using machine learning at Jefferson Laboratory

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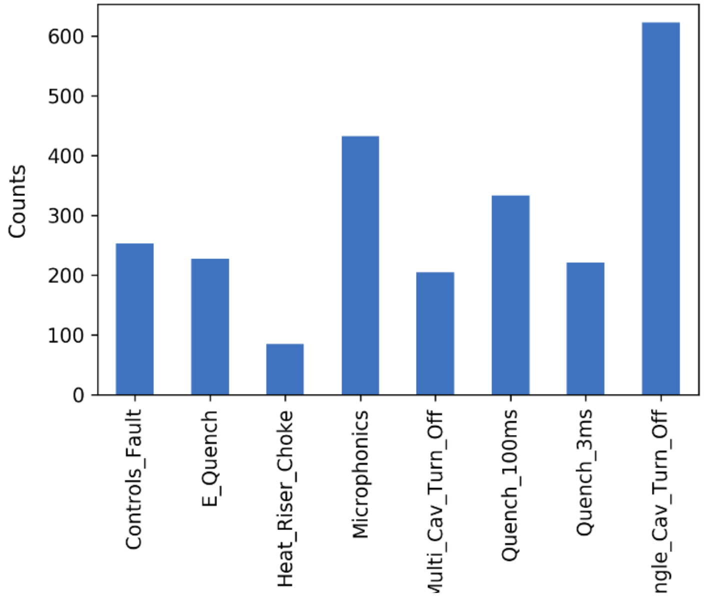
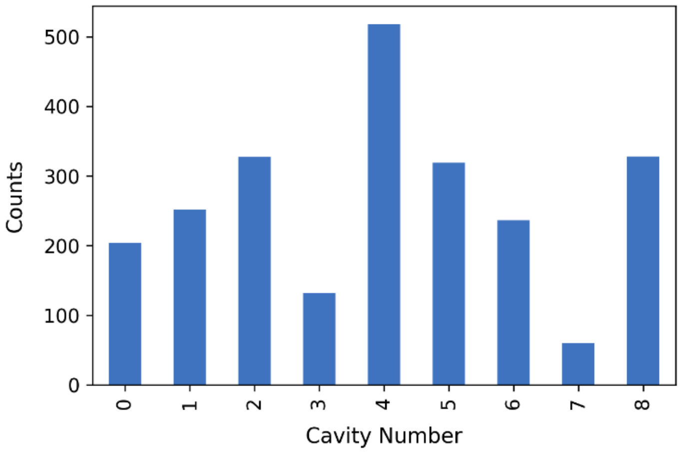
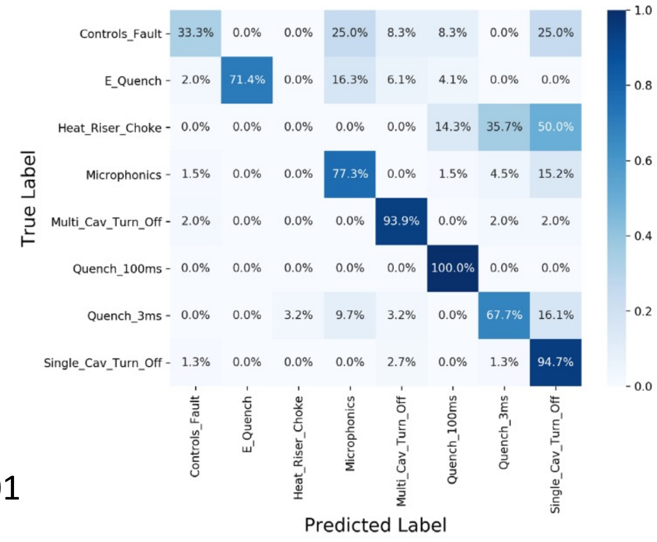
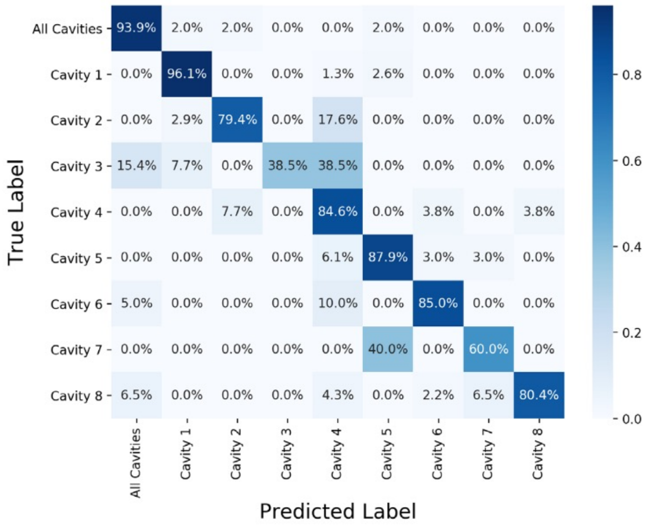
https://journals.aps.org/prab/pdf/10.1103/PhysRevAccelBeams.23.114601









Classification of Breakdown Events

- Using machine learning to a) classify if a breakdown event occurred and b) try and predict if a breakdown event will occur on the next pulse
- t-SNE algorithm used for initial data processing
- Various neural network architectures for analyzing time series data were explored
- Table 2 result uses scalar data including vacuum pressure, temperature, and other diagnostic data
- Table 3 result uses waveform data

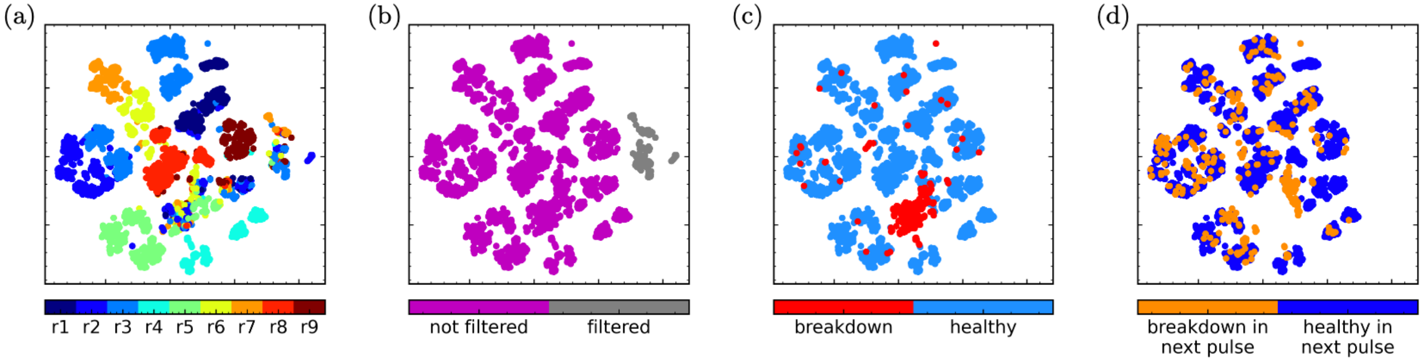


TABLE II: AR score of different models, predicting primary (a), follow-up (b), and all breakdowns (c) with trend data. The best score for each row is highlighted in bold. AR_μ relates to the average AR score of different validation sets and AR_σ to the standard deviation. The trained model is finally tested on the test set with a performance AR_t.

	time-CNN			FCN			FCN-dropout			Inception			ResNet		
breakdowns	AR_μ	AR_σ	AR_t	AR_μ	AR_σ	AR_t	AR_μ	AR_σ	AR_t	AR_μ	AR_σ	AR_t	AR_μ	AR_σ	AR_t
(a) primary	55.2%	11.0%	48.1%	86.1%	8.7%	81.0%	84.9%	9.0%	81.7%	85.4%	8.5%	82.9%	**87.9%**	**7.2%**	**80.4%**
(b) follow-up	92.8%	3.8%	87.6%	98.2%	1.0%	97.8%	95.6%	3.0%	97.3%	**98.7%**	**1.6%**	**98.6%**	98.7%	1.4%	98.0%
(c) all	67.7%	6.3%	66.0%	**93.8%**	**4.2%**	**90.6%**	92.7%	4.6%	90.6%	92.3%	4.8%	90.9%	93.1%	4.6%	90.1%

TABLE III: AR score of different models, predicting primary (a), follow-up (b), and all breakdowns (c) with event data. The best score for each row is highlighted in bold. AR_μ relates to the average AR score of different validation sets and AR_σ to the standard deviation. The trained model is finally tested on the test set with a performance AR_t.

	time-CNN			FCN			FCN-dropout			Inception			ResNet		
breakdowns	AR_μ	AR_σ	AR_t	AR_μ	AR_σ	AR_t	AR_μ	AR_σ	AR_t	AR_μ	AR_σ	AR_t	AR_μ	AR_σ	AR_t
(a) primary	52.7%	3.4%	51.9%	54.7%	9.8%	52.8%	**56.6%**	**8.3%**	**54.0%**	52.6%	3.6%	49.9%	51.9%	7.0%	53.5%
(b) followup	79.2%	12.8%	82.1%	**89.7%**	**8.1%**	**91.1**	89.1%	5.3%	83.7%	87.9%	8.4%	90.5%	88.7%	7.7%	89.9%
(c) all	59.8%	7.7%	66.6%	66.8%	12.5%	68.7%	**65.2%**	**7.3%**	**67.3%**	65.9%	13.6%	67.1%	67.2%	14.3%	68.5%

Explainable Machine Learning for Breakdown Prediction in High Gradient RF Cavities

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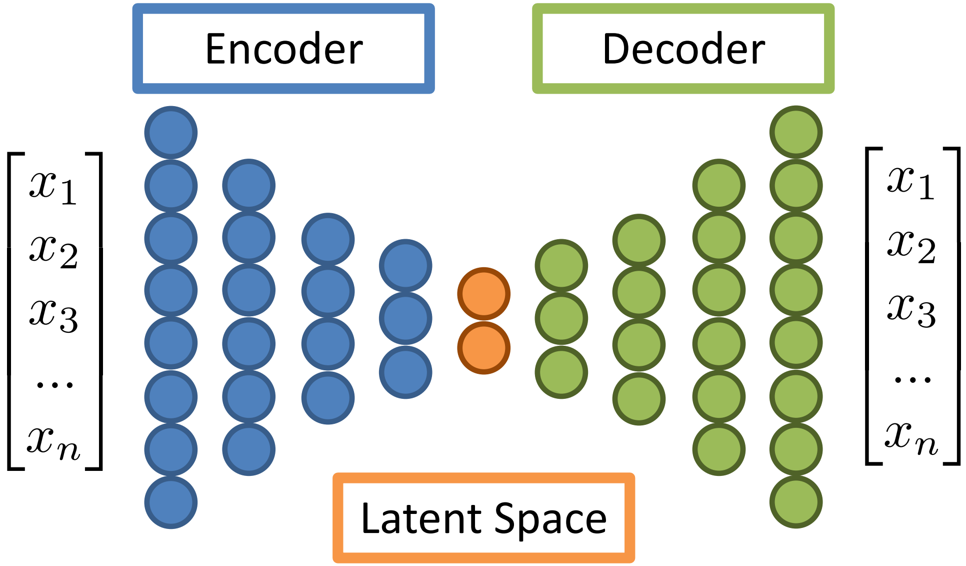
Cockcroft Institute, Lancaster University, Lancaster, United Kingdom

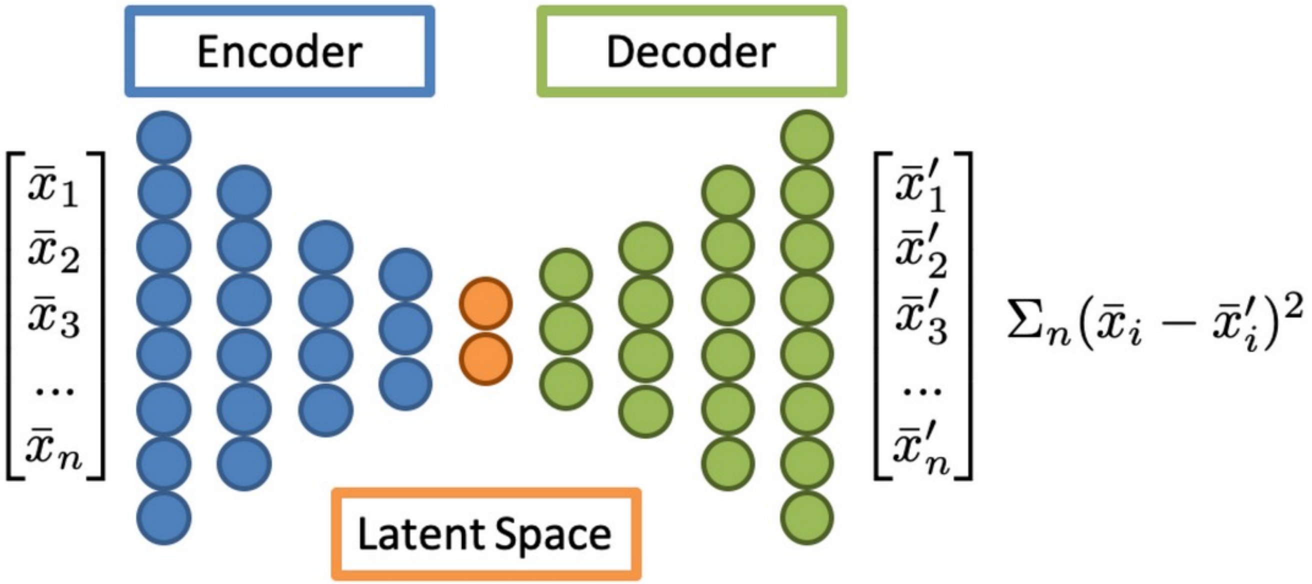
(Dated: February 14, 2022)

https://arxiv.org/pdf/2202.05610.pdf

Autoencoders

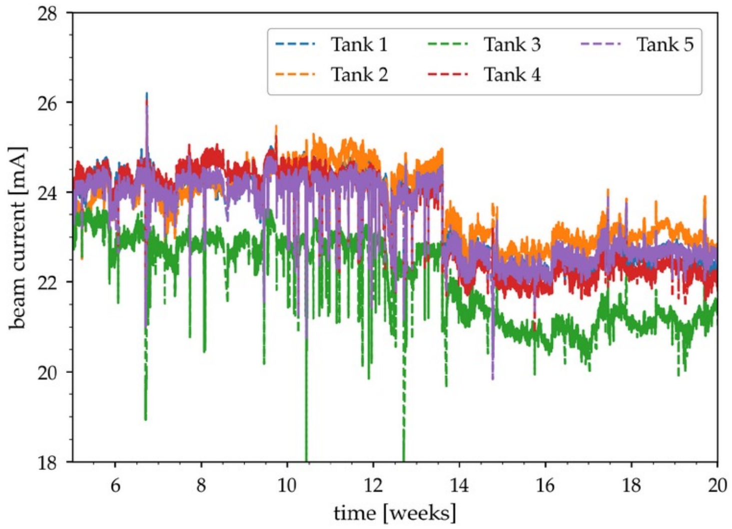
- An autoencoder is a neural network that creates an identity transformation for a given dataset (i.e. the inputs and outputs are identical)
- Typically the dimension of the dataset also decreases
- Autoencoders:
  - Provide a metric for identifying similarities between datasets
  - Perform dimensionality reduction through query of the latent space

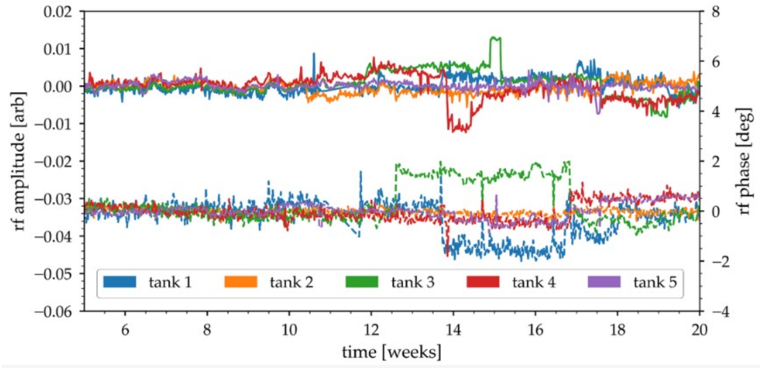


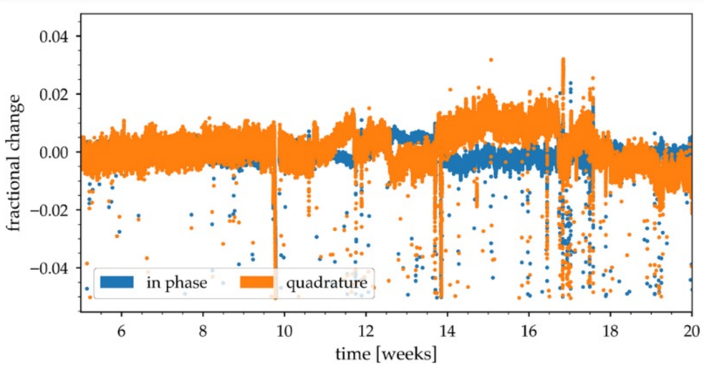


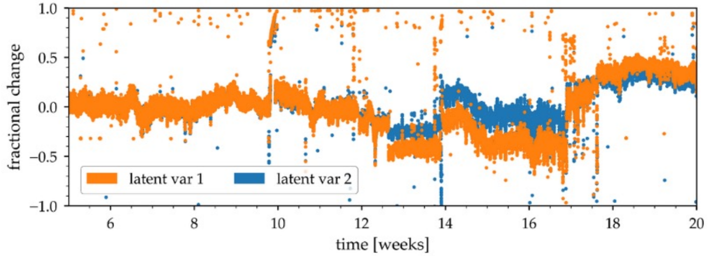
Latent Space Detection of Machine Parameter Changes

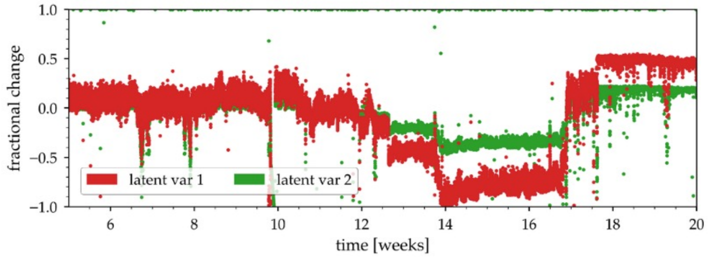
- Consider data from the RF system on the Fermilab low energy LINAC
- A droop in the output current of the LINAC was seen at around week 13 which persisted to the end of the run
- RF parameters change during this period. The vector sum remains constant
- Analysis of the latent space of the autoencoder shows the RF system is in a significantly different state than at the beginning of the run











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Autoencoder Based Analysis of RF Parameters in the Fermilab Low Energy Linac

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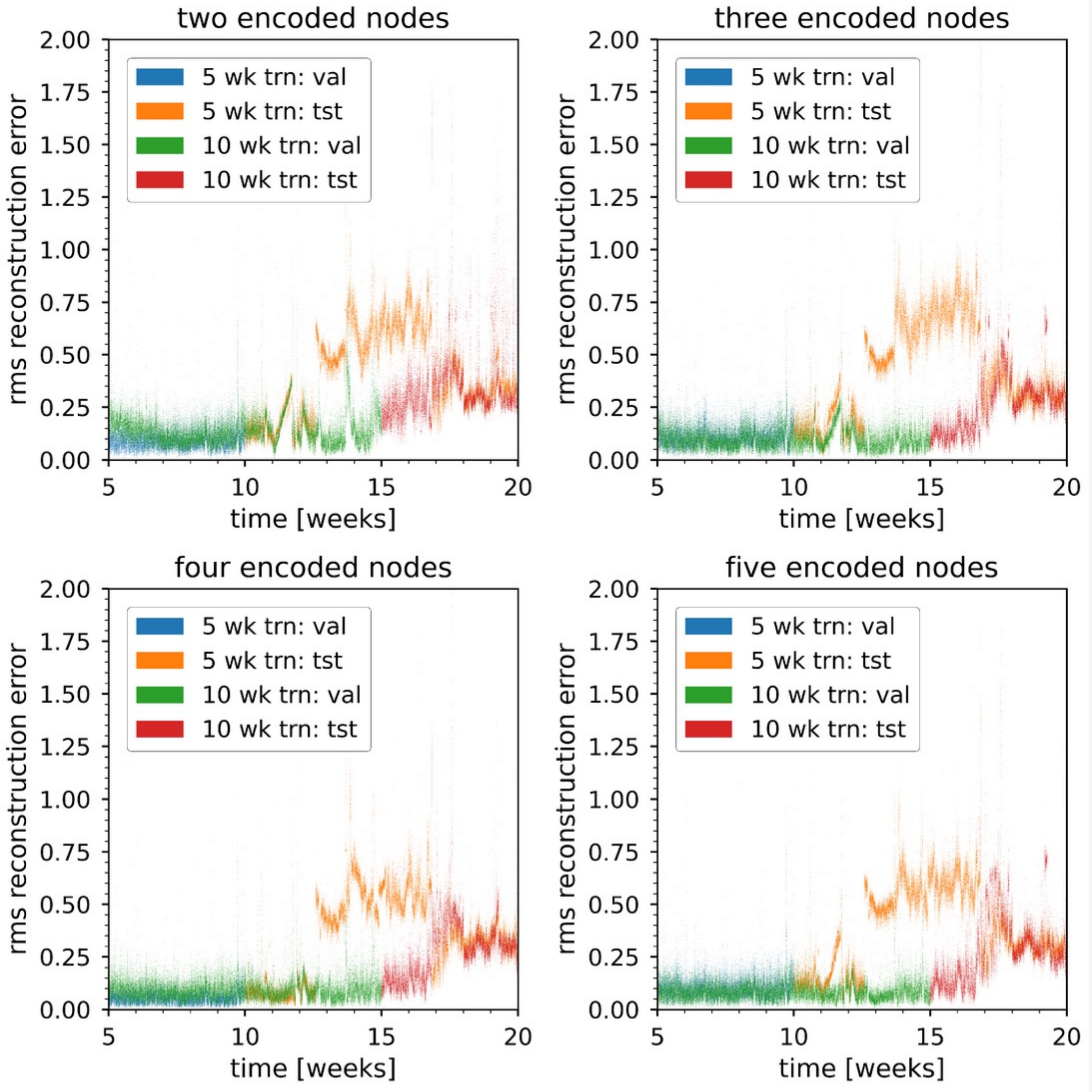
Quantifying a Change in Machine State

- Utilize autoencoder reconstruction error to evaluate the difference between segments of the time series
  - Train on either first 5 weeks or first 10 weeks
  - Test on either last 10 weeks or last 5 weeks
  - Both cases show significant offset in the final machine state relative to the first 5 weeks of operation



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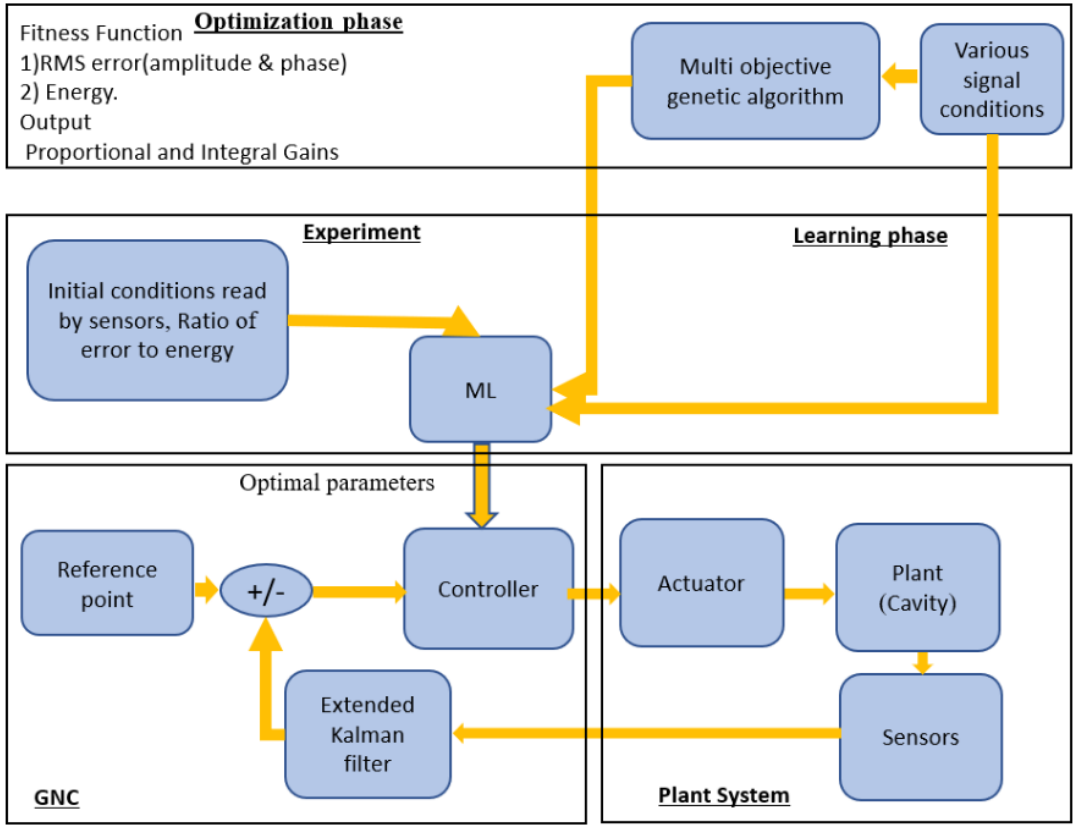
Gain Scheduling with ML

- Machine learning to optimize the control loop parameters for LLRF
- Application of deep learning using neural networks and Gaussian Process
- Simulation studies were conducted using a lumped circuit model for the RF cavity
- Noise was included in the simulation
- The ML methods showed promise for optimizing the gains used in LLRF systems on SRF cavities



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ACHIEVING OPTIMAL CONTROL OF LLRF CONTROL SYSTEM WITH ARTIFICIAL INTELLIGENCE *

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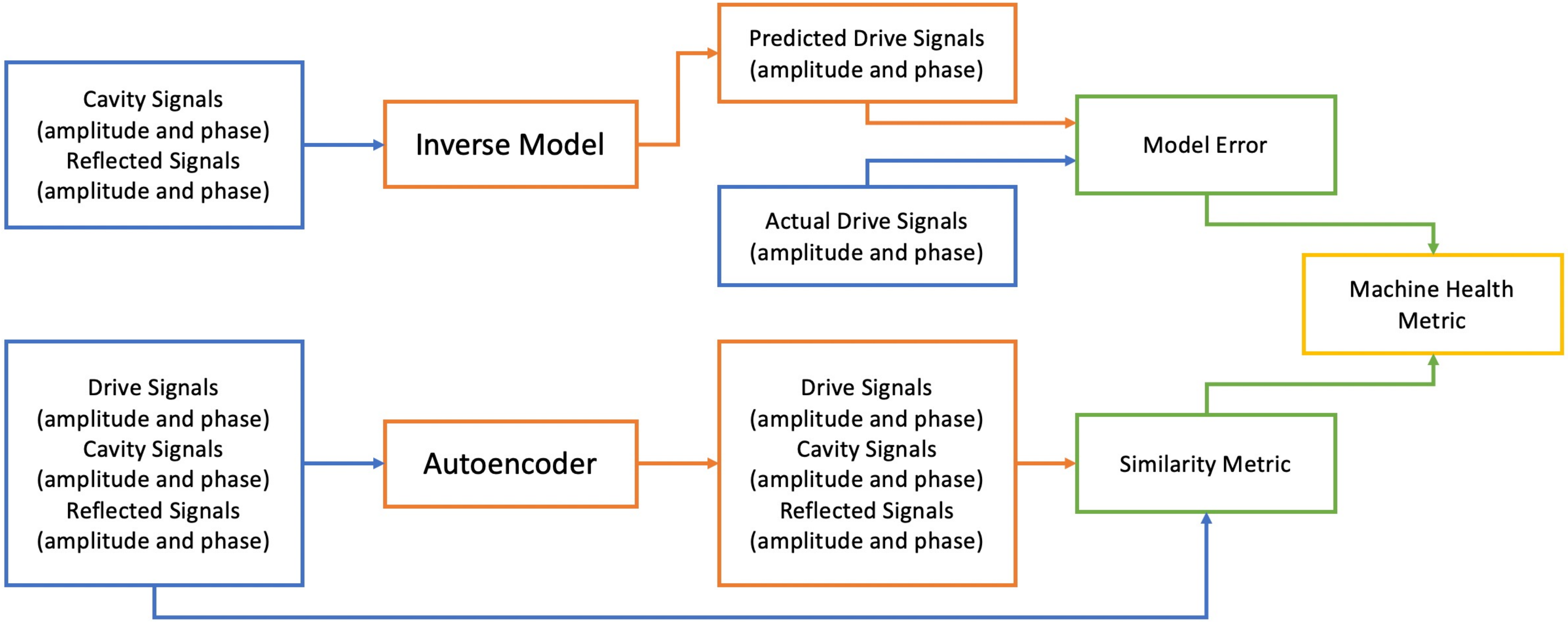
https://epaper.kek.jp/icalepcs2019/papers/mopha114.pdf

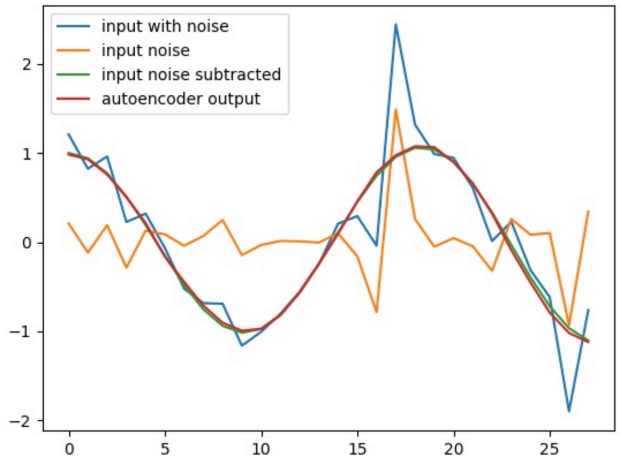
Opportunities: Anomaly Detection

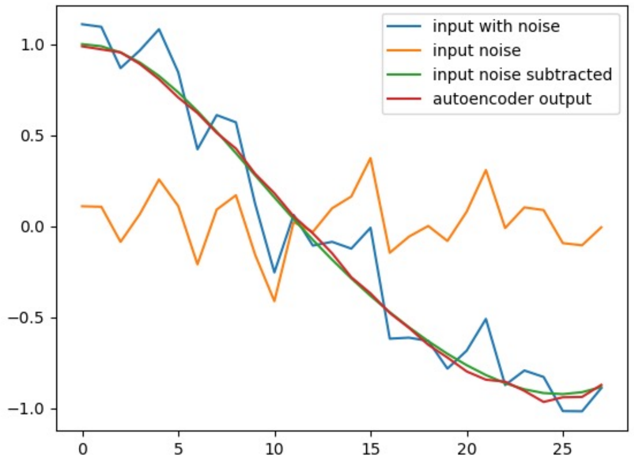
- Combining inverse models and autoencoders to build a high level application that can evaluate the overall health of the RF system
- Inverse models provide information on where the anomalies are occurring
- Autoencoders provide a confidence estimate and a cross check for the inverse model

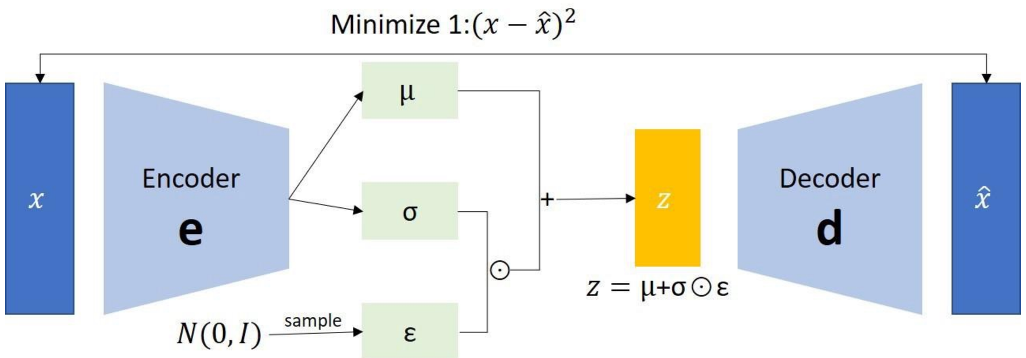


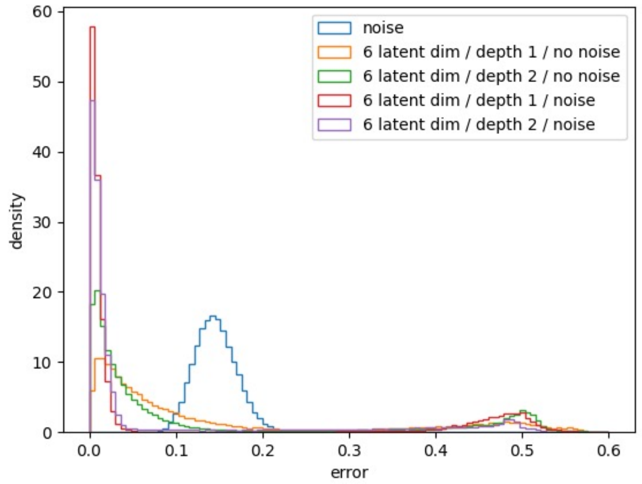
Opportunities: Signal Processing

- Noise reduction using autoencoders
  - Variational autoencoders enforce smoothness condition in the latent space
  - Dimensionality reduction removes complexity of noise
  - Tests done using simulated BPM data
  - Logically extended to RF data
  - Could implement the autoencoder on a FPGA for near-real-time noise reduction









Opportunities: Real Time Control

- Time domain signal processing using neural networks is a maturing field
  - ECG classification (https://ieeexplore.ieee.org/abstract/document/8682194)
  - Gravitational wave identification and classification (https://journals.aps.org/prd/abstract/10.1103/PhysRevD.97.044039)
  - Real-time speech enhancement (https://ieeexplore.ieee.org/abstract/document/8683634)
  - FPGA deployed classifier for jet classification at LHC (100ns latency) (https://cds.cern.ch/record/2316331)
  - Neural network for feature extraction in NP experiments (https://link.springer.com/article/10.1007/s41365-020-00756-z)
- Specialized neural networks and adaptive learning could benefit LLRF
  - Resonance control
  - Amplitude and field control for pulsed copper systems (pulse-to-pulse stabilization)
  - Key benefit is in automation

Challenges and Conclusions

- ~~When should we use ML?~~ → What problems do we need to solve?
  - ML is just one aspect of the toolbox
  - Solutions should be tailored based on the needs of the system
- Compact systems that support industry / security / defense
  - Requires a higher level of automation
  - Automation must scale well (each system can't require lengthy study time to build automation)
- Large facilities
  - Accelerator facilities generate huge amounts of data
    - Dimensionality reduction is going to play a key role
    - Bringing more processing closer the data source
  - Machine complexity is increasing
    - Increased control requirements necessitates new approaches
    - New tools for identifying and diagnosing the machine state
    - Improved diagnostics and modeling capabilities are required

Disclaimer