

# NEURAL NETWORKS FOR MODELING AND CONTROL OF PARTICLE ACCELERATORS

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Auralee Edelen

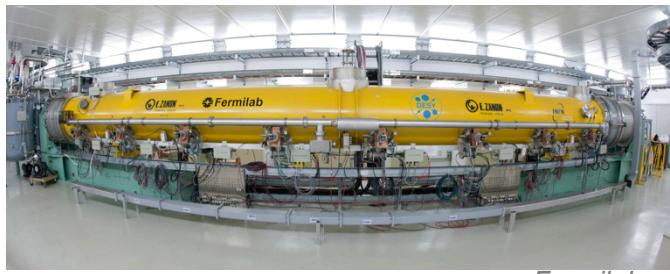
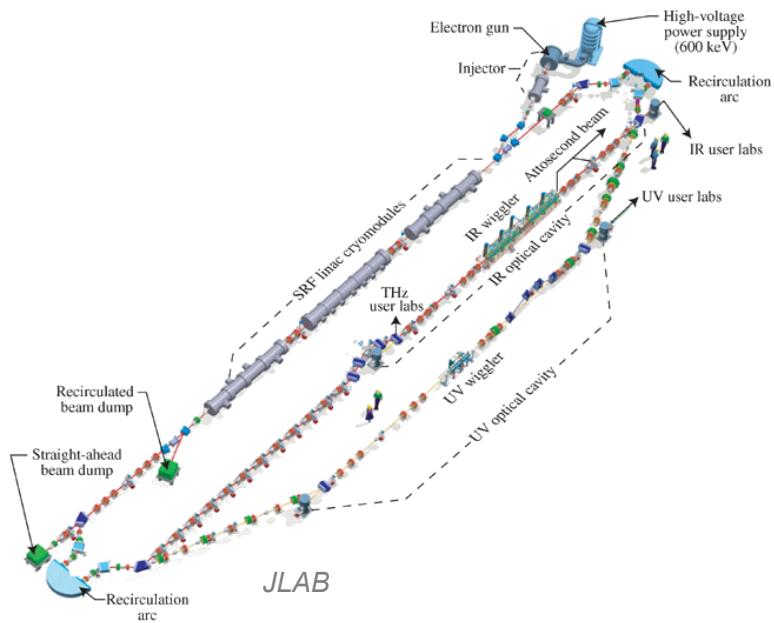
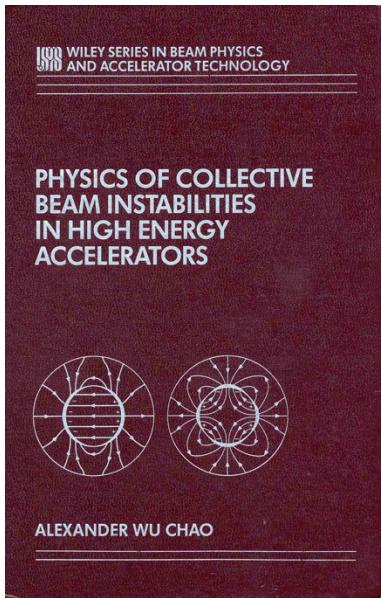
2016-02-02

*Advisors: Sandra Biedron and Stephen Milton*

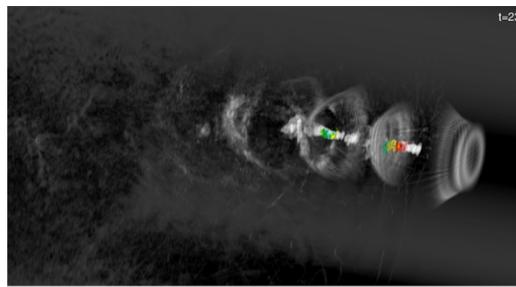
# Published Work

- Edelen, A. et al. *Neural Networks for Modeling and Control of Particle Accelerators*. Submitted to IEEE Transactions in Nuclear Science, Jan. 2015.
- Edelen, A., et al. *Initial Experimental Results of a Machine Learning-Based Temperature Control System for an RF Gun*. Paper for the 6th International Particle Accelerator Conference (IPAC), Richmond, VA, May 3-8, 2015.
- Morin, A., et al. *Trajectory Response Studies at the Jefferson Laboratory Energy Recovery Linac and Free Electron Laser*. Paper for the 16th Annual Directed Energy Symposium, Huntsville, AL, March 10-14, 2014.

# Control Challenges

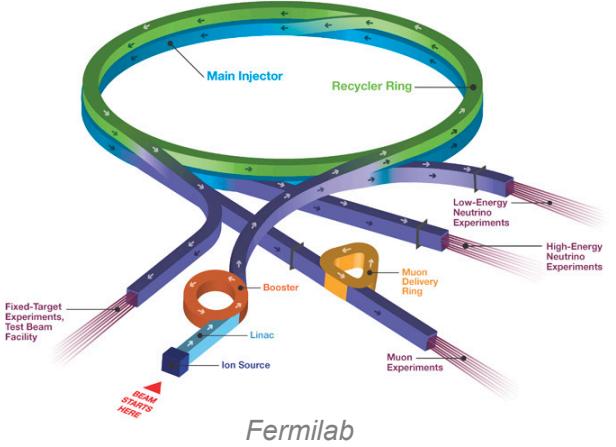


Fermilab

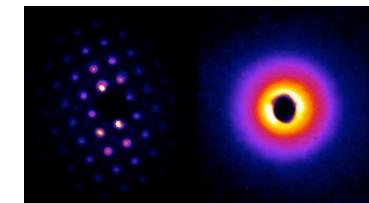


LBNL Visualization Group

Fermilab Accelerator Complex



Fermilab



SLAC



www.tka-architects.com

# Inspiration from Operators



*Control Room Photo: Reidar Hahn, FNAL*

# A trip to the zoo...

Artificial Intelligence

Machine Learning

*Regression  
Classification*

*Clustering*

*Dimensionality reduction*

Learning Theory

*Supervised Learning*

*Unsupervised Learning*

*Reinforcement Learning*

*Reactive search optimization*

Computational Statistics

Support Vector Machines

Neural Networks

Fuzzy Logic

Decision Trees

ICA, PCA

Biological Sciences  
and Psychology  
(*inspiration!*)

Mathematical Optimization

*Gradient descent  
Conjugate gradient  
Newton method  
Quasi-Newton methods*

*Simulated annealing  
Evolutionary algorithms  
Swarm intelligence*

Intelligent Control

Nonlinear Control

Adaptive Control

Optimal Control

Robust Control

Stochastic Control

System Identification

Model-free Methods

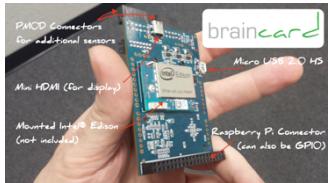
Model-based Methods

Ensemble Methods

# *Many Failures Early On → So Why Try Again Now?*



IBM, ANL



In general:

greater theoretical understanding

+

increased computational capability

+

advantageous co-developments in related fields

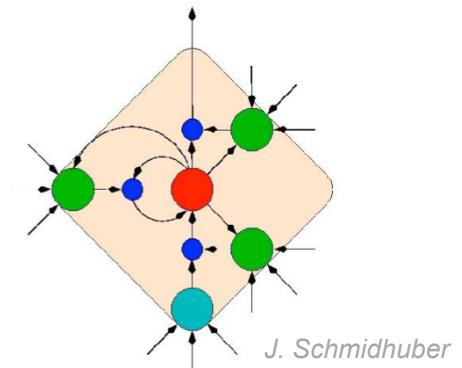
+

feedback from a wider variety of application attempts

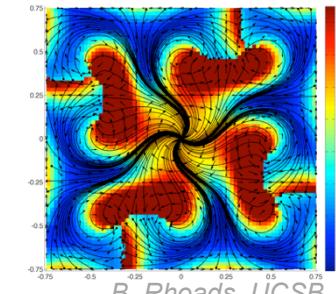


Shutterstock

→**greater overall technological maturity**



J. Schmidhuber



B. Rhoads, UCSB



Google

**But still difficult in the context of nonlinear control → we need R&D!**

# Central Focus:

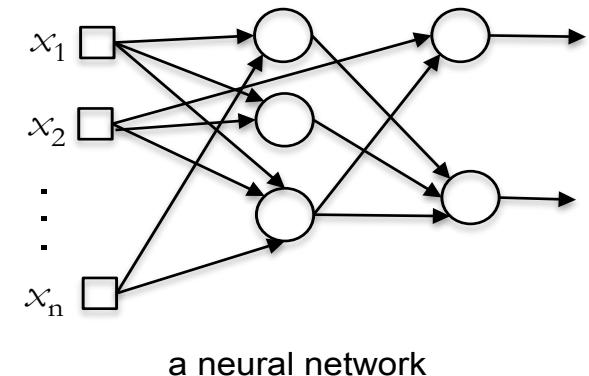
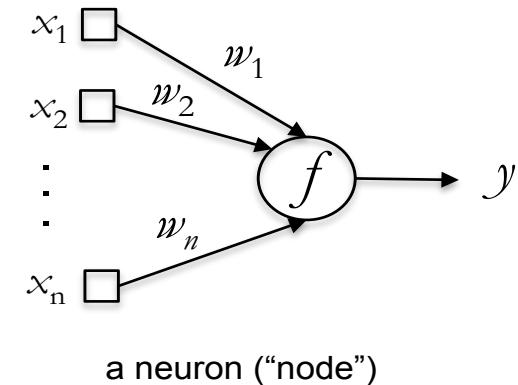
*Let's develop and test some AI-based solutions for control problems in accelerators!*

- Explore the tools and techniques
- Examine some real-world problems, focusing on *process control*
- Need to test on an actual machine; not just in simulation
- Have at it!

# Some Tools

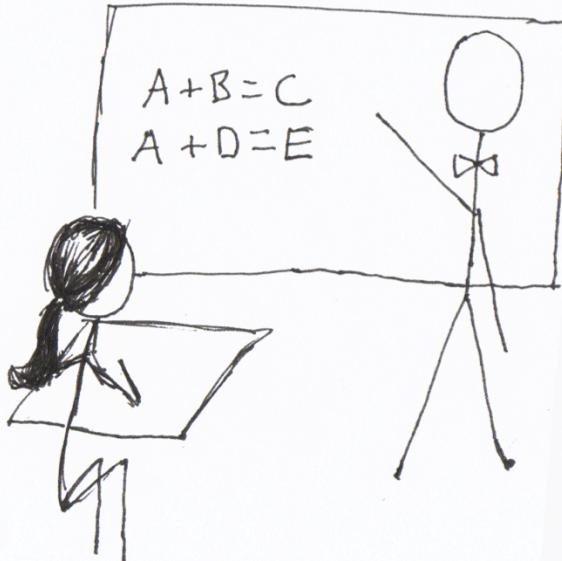
# Neural Networks

- What are they
- How do they learn?
- When are they useful?
- What are the disadvantages?

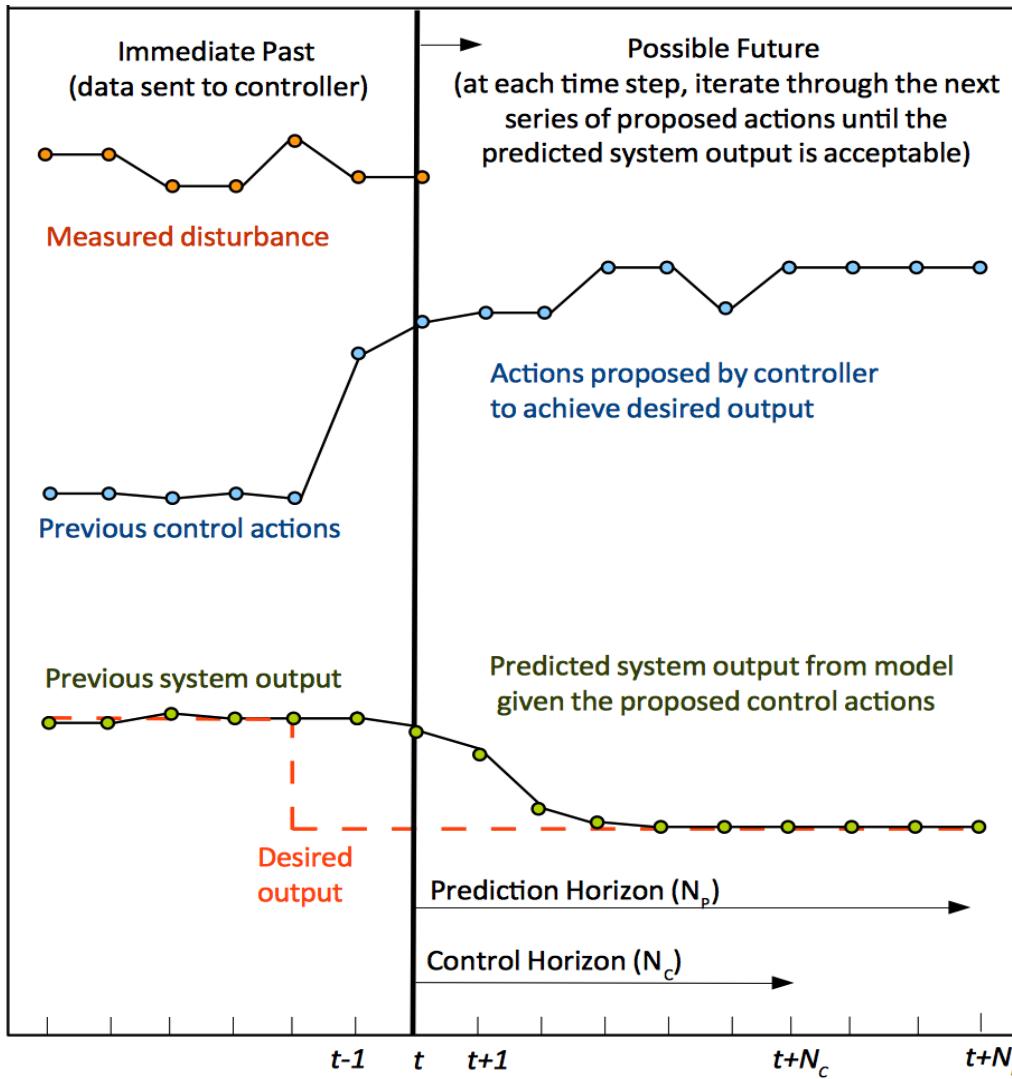


→ *How can we use these things in particle accelerators?*

# Learning Paradigms

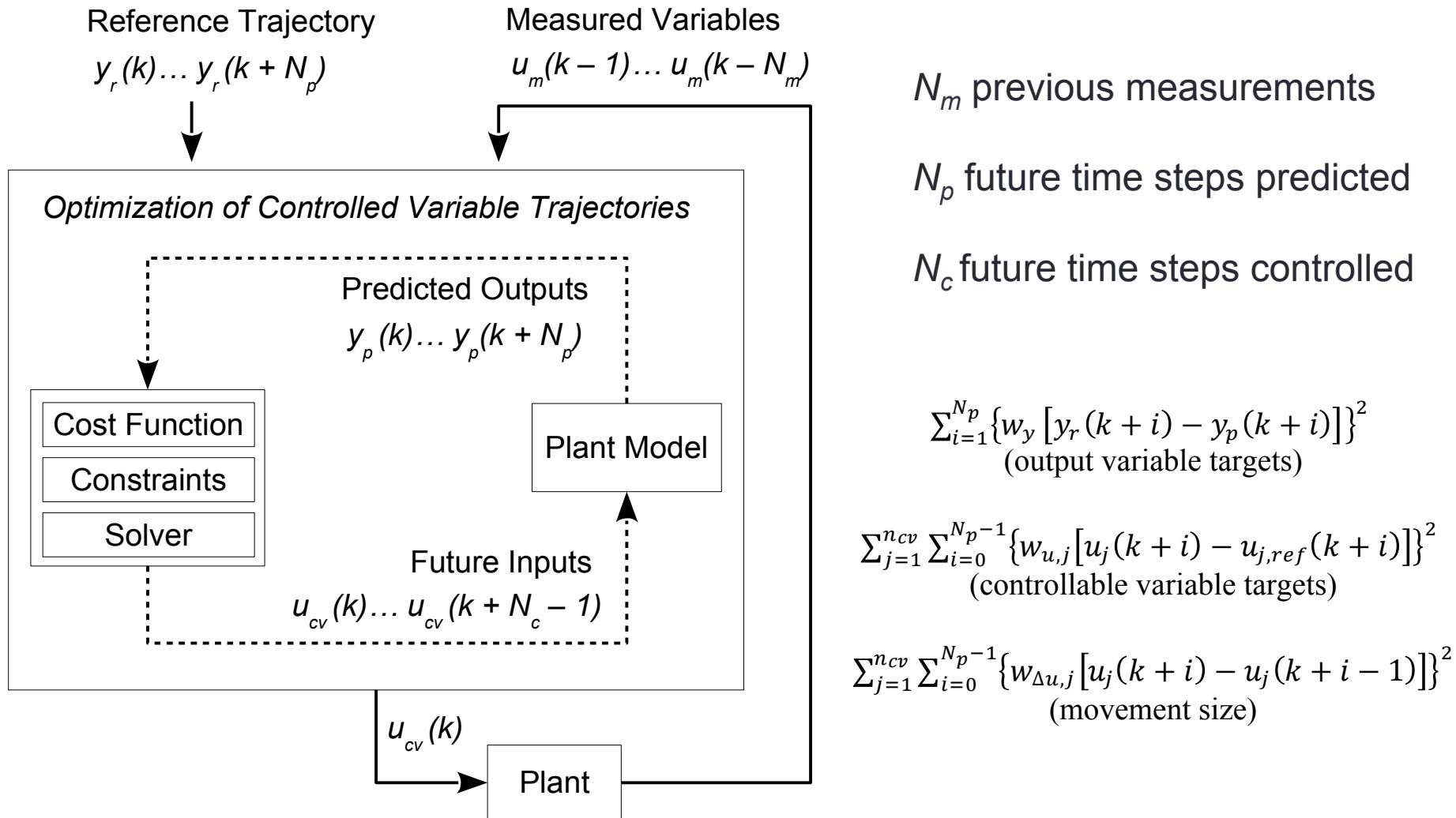


# Model Predictive Control

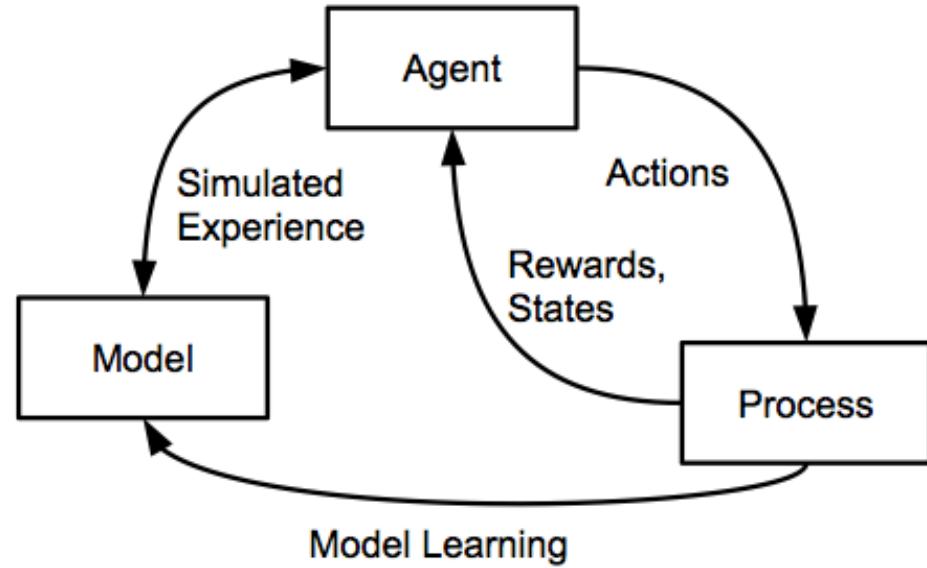
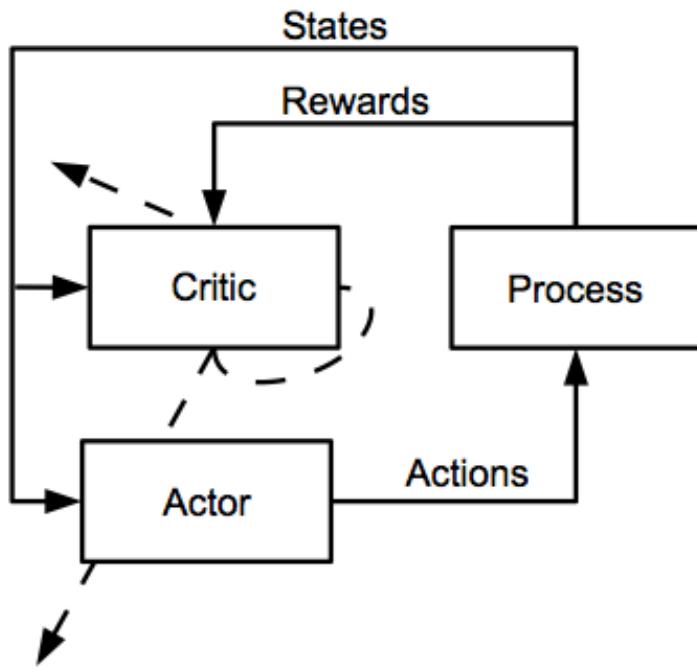
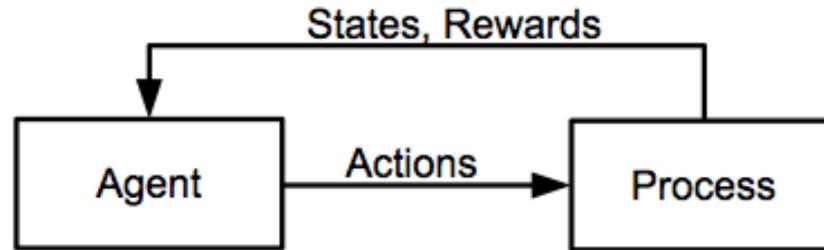


*Basic concept: use a predictive model to assess the outcome of possible future actions*

# Model Predictive Control



# Reinforcement Learning



# Real-World Problems

# At Fermilab...

*RF electron gun at the  
Fermilab Accelerator Science  
and Technology (FAST) facility*

- Long, variable time delays
- Tight tolerances
- Recursive behavior
- Two controllable parameters

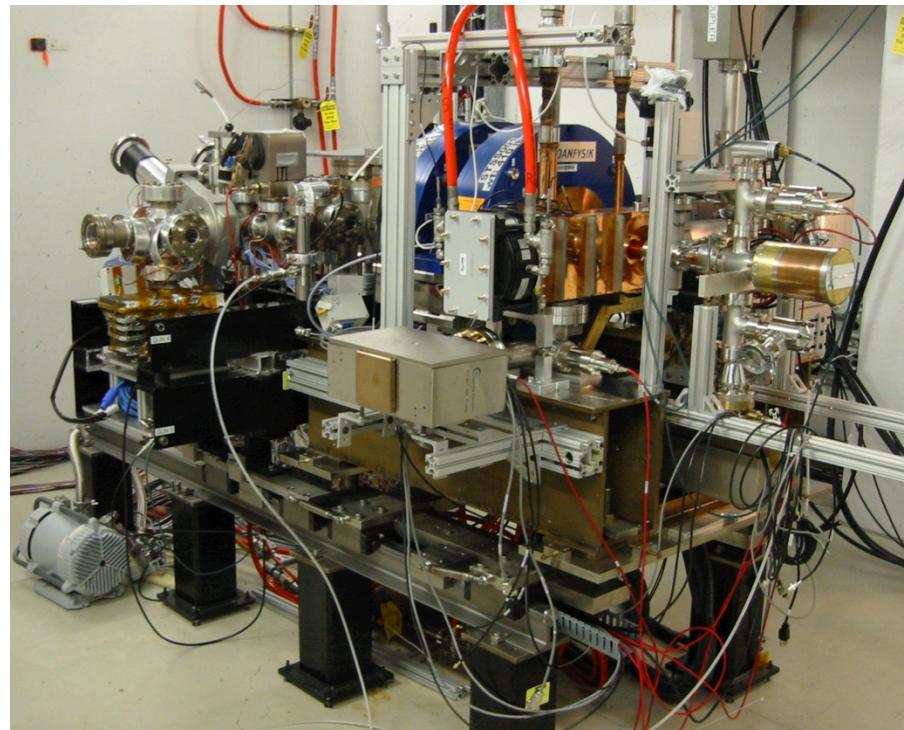


Photo: P. Stabile

*High-intensity RFQ for the  
PIP-II Injector Experiment  
(PXIE)*

- Time delays
- Large, dynamic frequency response
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Photo: J. Steimel

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FAST RF Gun Parameters	
Gun Parameters	
Type	Photoinjector
Number of cells	1½
RF Mode	$\text{TM}_{010,\pi}$
Loaded Q	~11,700
RF Frequency	1.3 GHz
Frequency Shift	23 kHz/ $^{\circ}\text{C}$
Nominal Operating Parameters	
Macropulse Duration	1 ms
Repetition Rate	1–5 Hz
Bunch Frequency	3 MHz
Design Gradient	40–45 MV/m
Power Source	5 MW Klystron

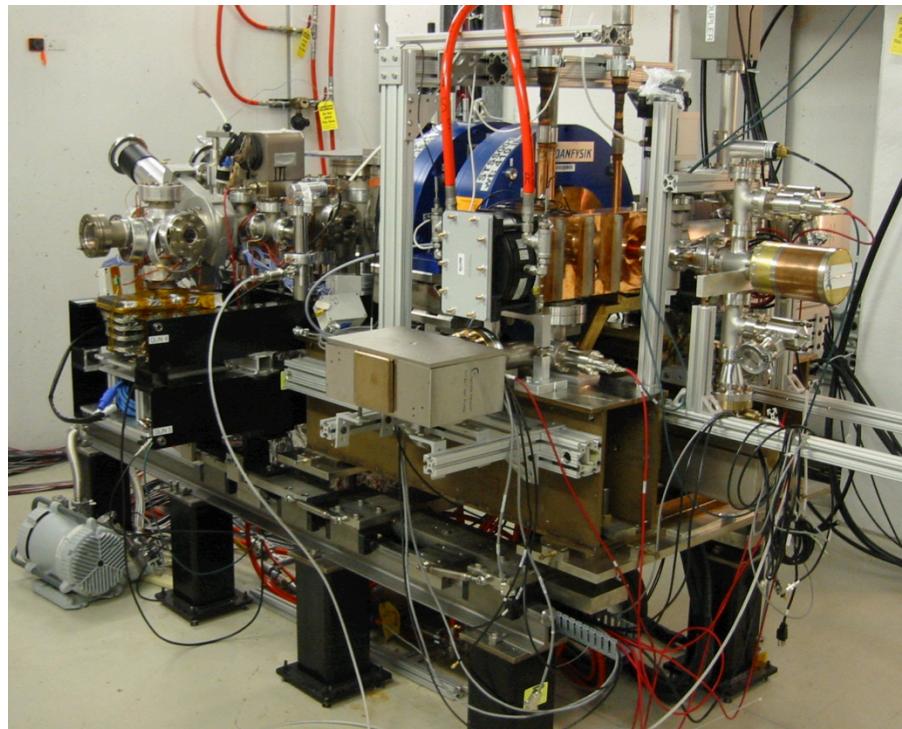
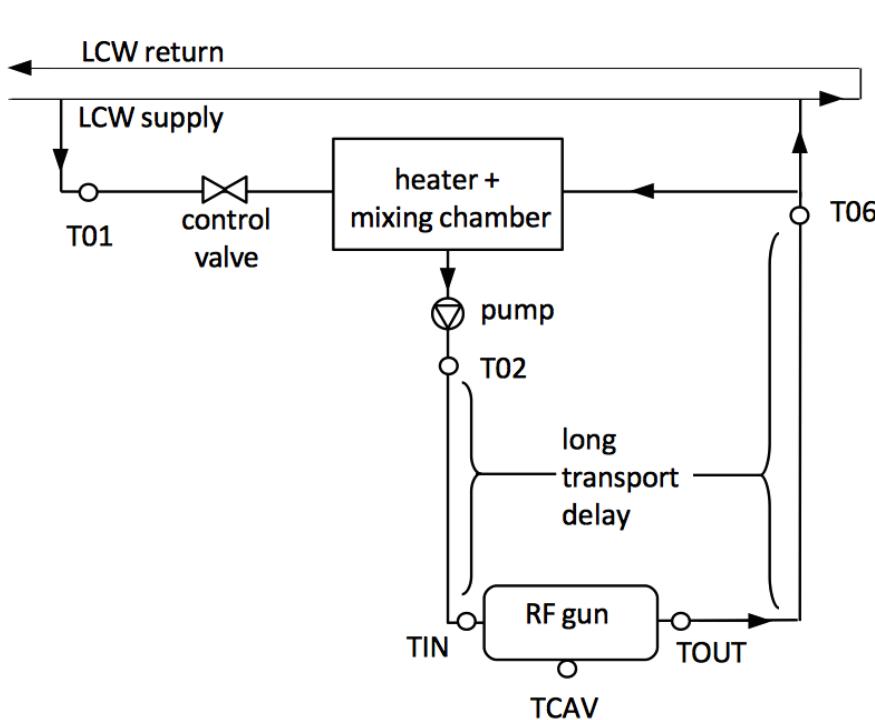


Photo: P. Stabile



Photo: E. Harms

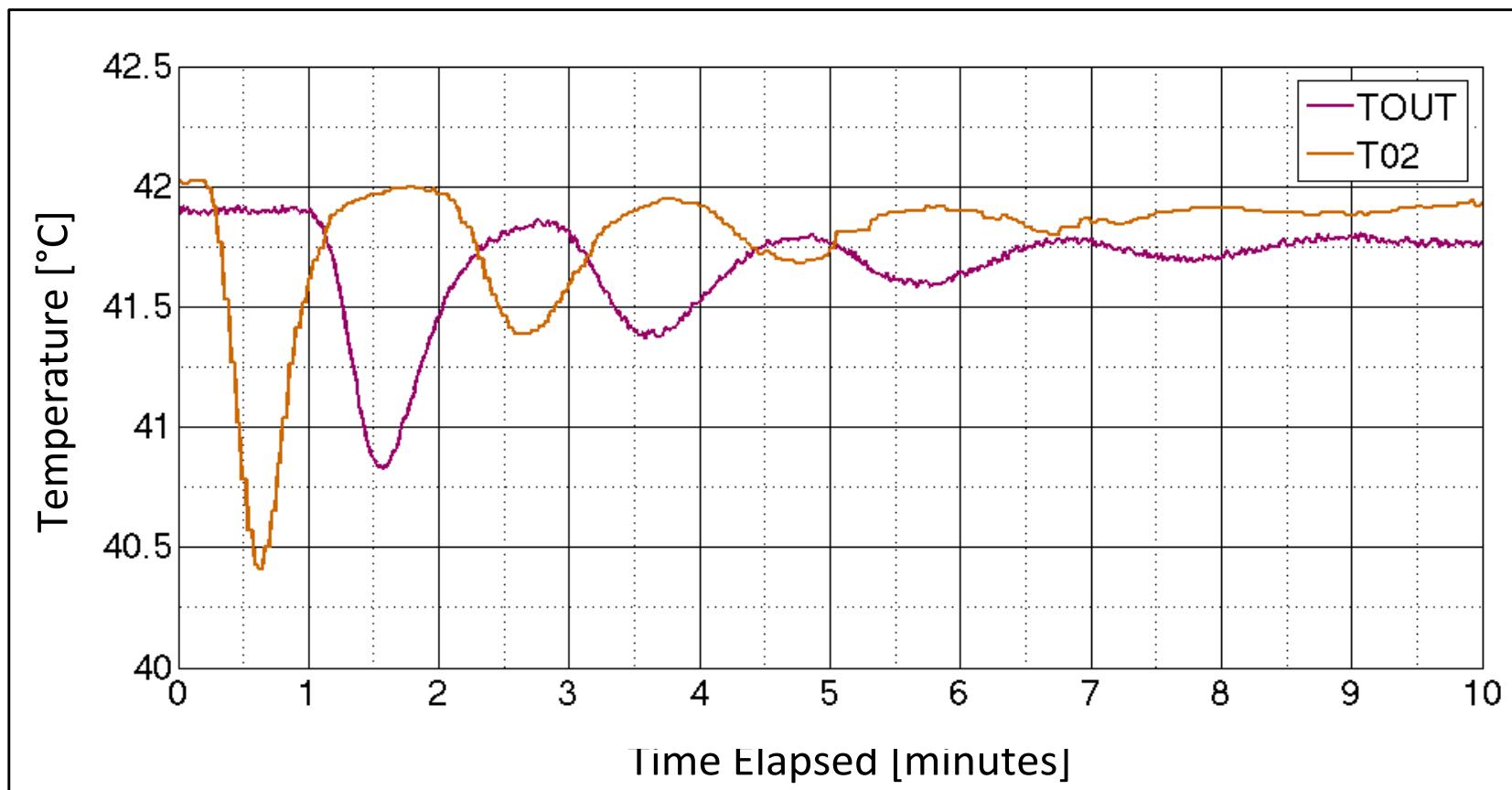
# Gun Water Cooling System



TYPICAL TIME DELAYS BETWEEN SYSTEM ELEMENTS

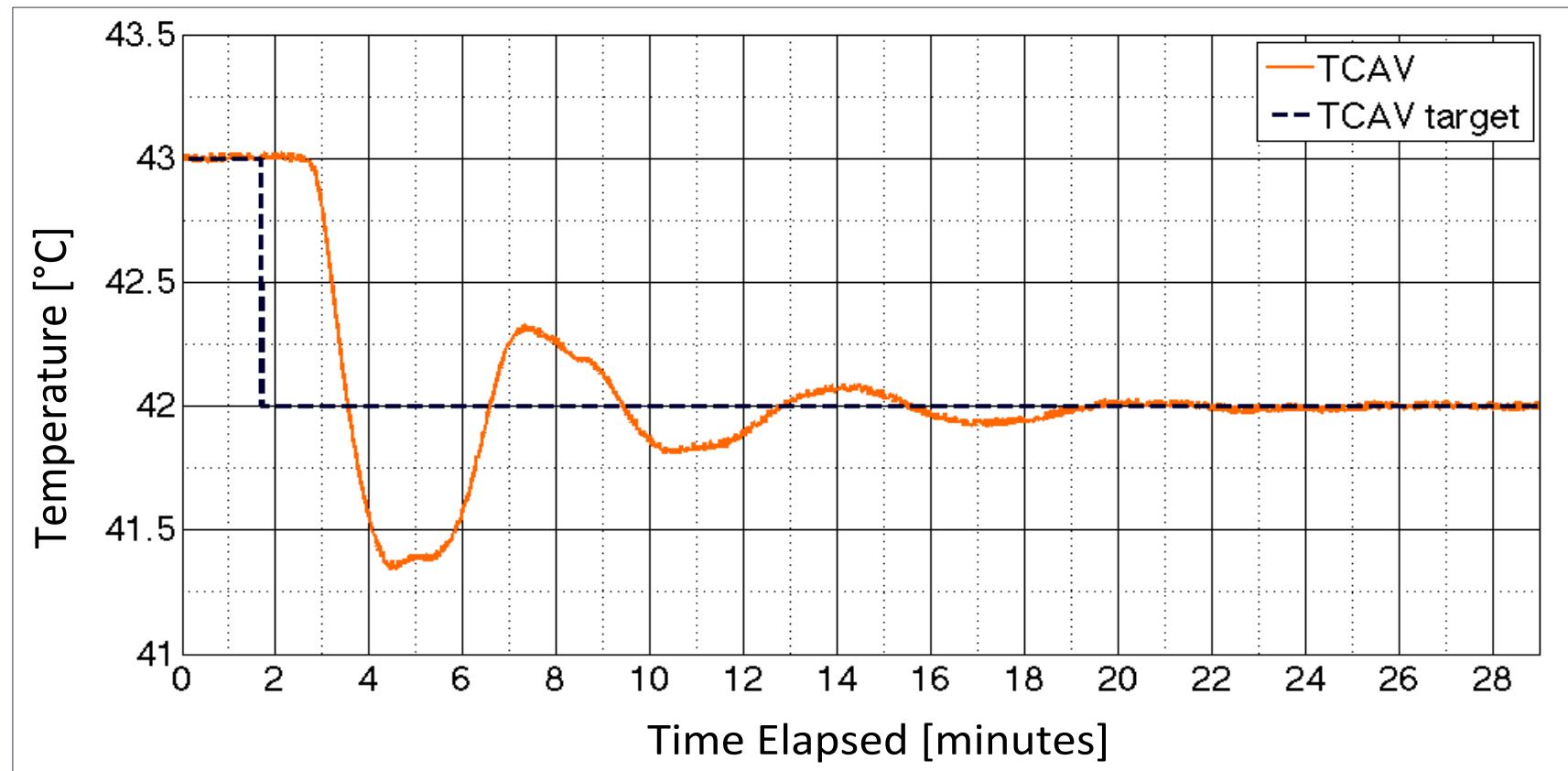
System Segment	Approximate Time [s]
Flow valve to T02	8-10
Heater to T02	5-10
T02 to TIN	32
TIN to TCAV	19-23
TOUT to T06	55-65
TIN to cavity frequency	16-18

# Water Temperatures — Open Loop



*impulse response from a 20-second decrease in the heater power setting from 7 kW to 2.5 kW*

# Existing feed-forward/PI Control of the Gun Temperature



1-°C step change in temperature set point

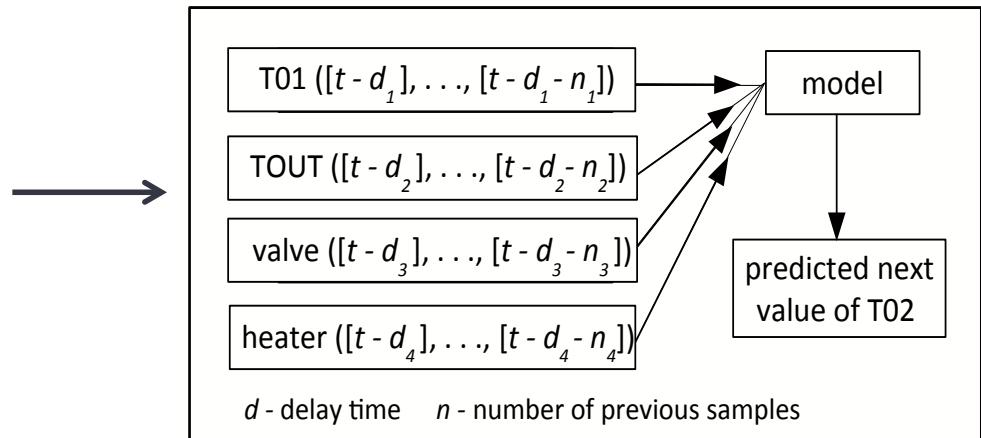
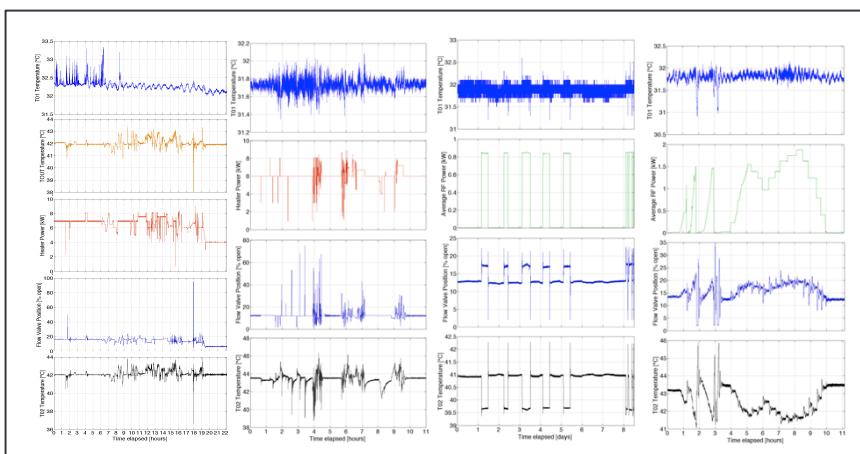
→ Oscillation is NOT due to poorly tune PI gains!

# Initial Solution

- Neural network model
- Model predictive control

→ *Serves as a simple benchmark for future studies*

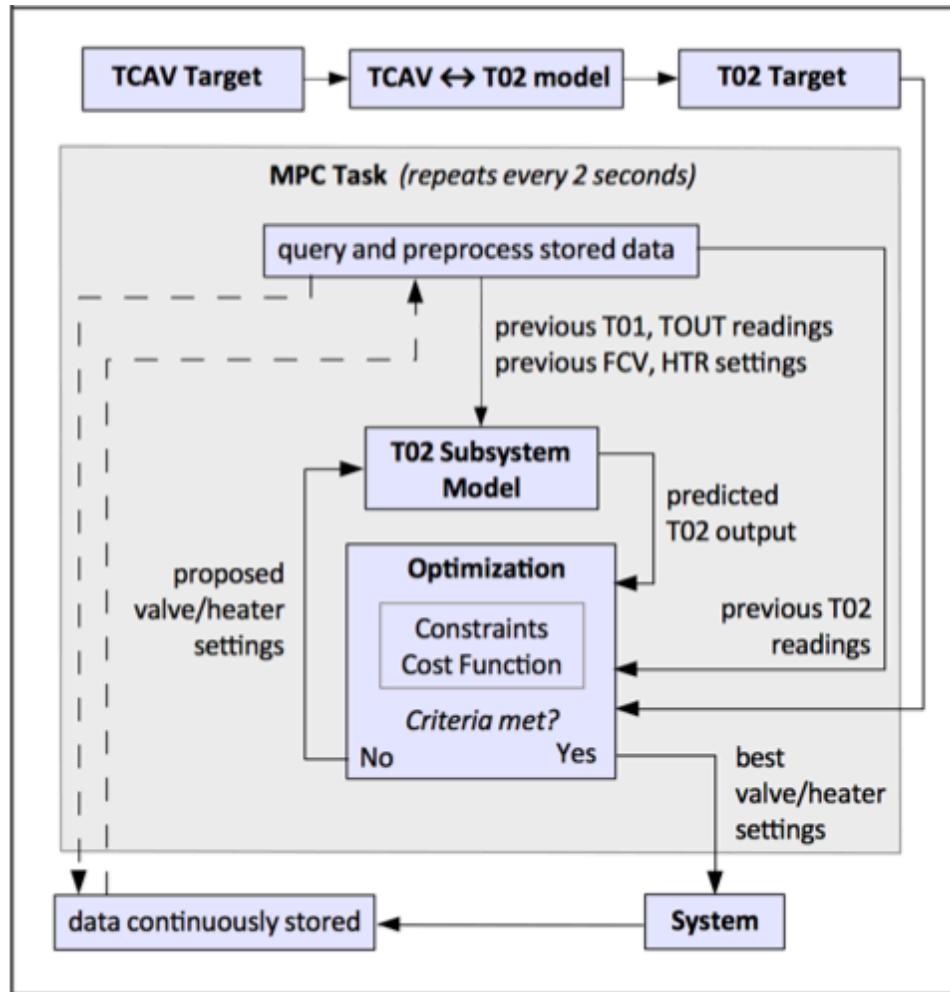
# Neural Network Modeling



AVERAGE PERFORMANCE OF SELECTED NEURAL NETWORK MODEL DESIGNS

NN Model	Mean Absolute Error	STD of Error	Max. Error
T02 with sigmoid act. function	0.018	0.037	1.049
T02 with sigmoid act. function and ambient temperature	0.022	0.043	1.317
T02 with linear act. function	0.058	0.266	2.915
TCAV with sigmoid act. function (tested without power)	0.011	0.012	0.131
TCAV with sigmoid act. function (tested with power)	0.259	0.287	1.390

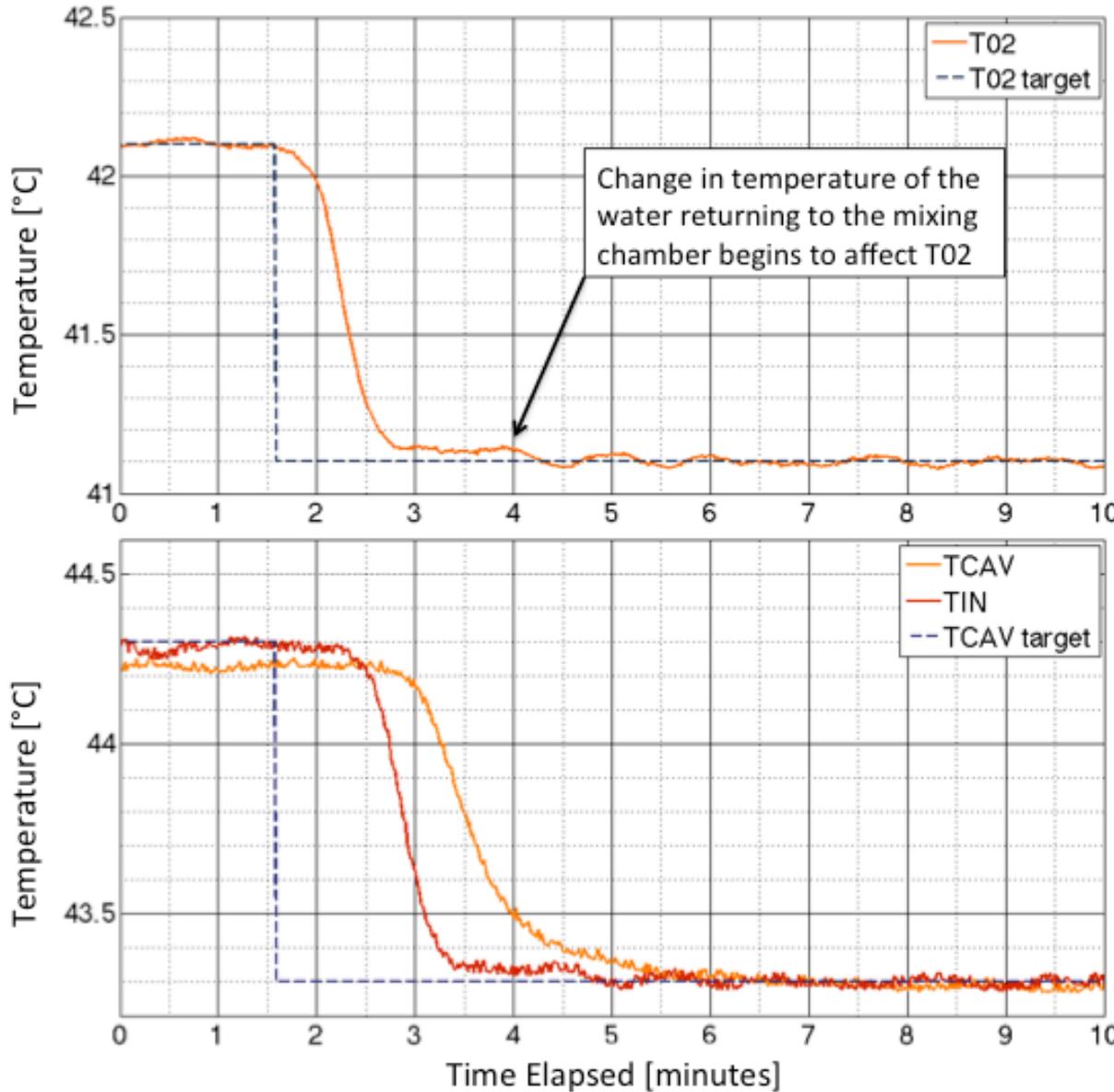
# Benchmark Controller



BENCHMARK MPC PARAMETERS

Parameter	Value	Units
Valve max rate	10	% open/sec
Valve upper limit	70	% open
Valve lower limit	2	% open
Heater max rate	4	kW/sec
Heater upper limit	9	kW
Heater lower limit	1	kW
Prediction horizon	100	s
Control horizon	20	s
Control interval	2	s
Valve rate weight	0.4	-
Heater rate weight	0.5	-
T02 output weight	0.3	-

# MPC Benchmark Controller



*Note: different horizontal and vertical scale than for PI loop*

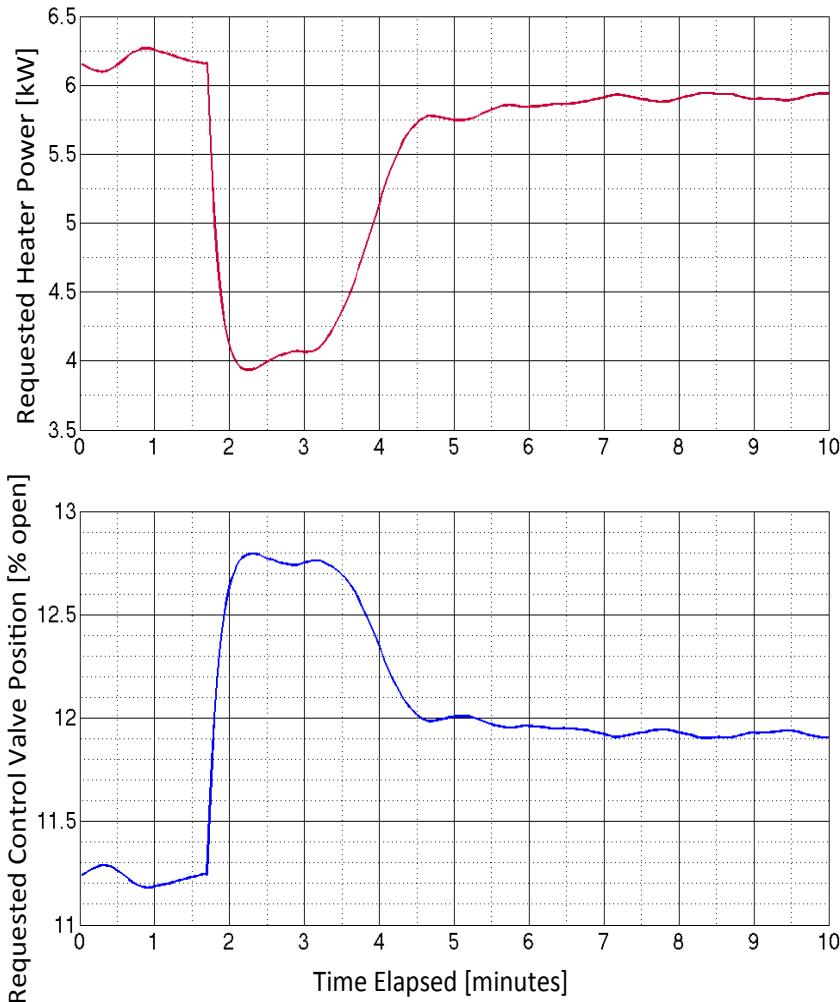
~5x faster settling time

no more overshoot

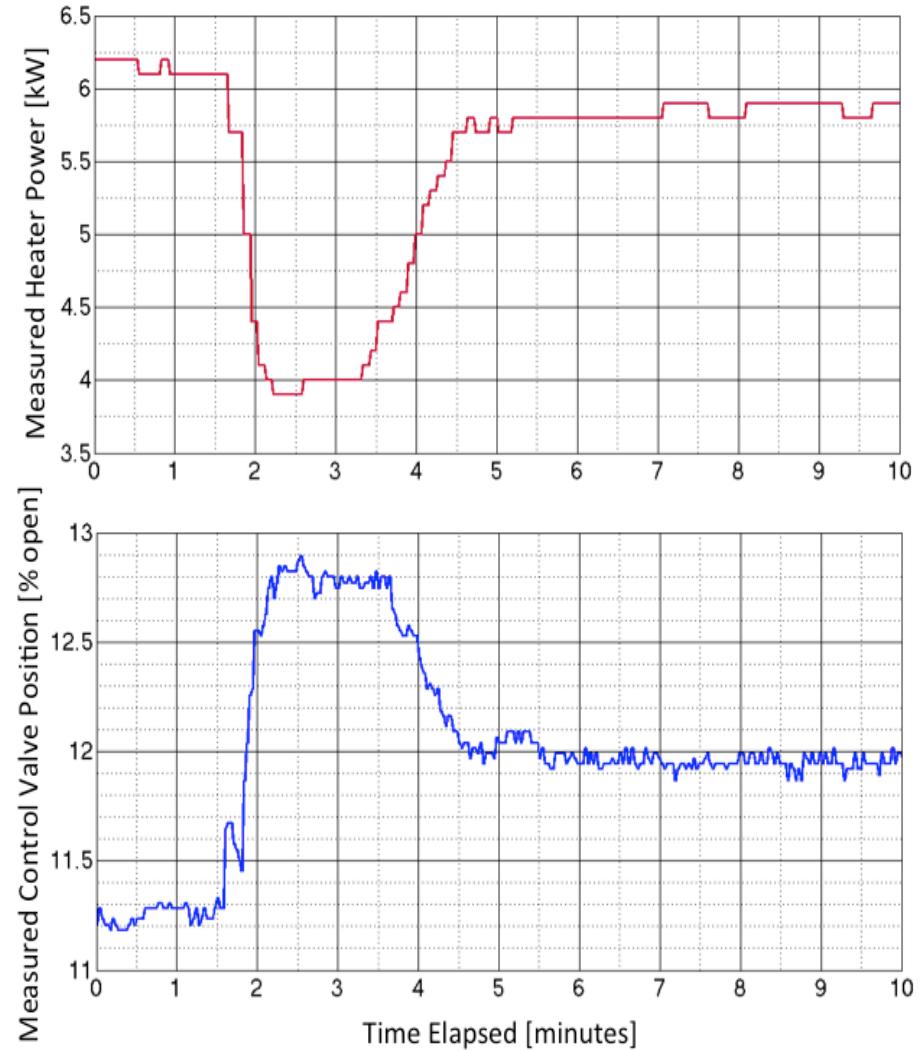
still needs work...  
(esp. T02-to-TCAV model)

# MPC Benchmark Controller: Actions

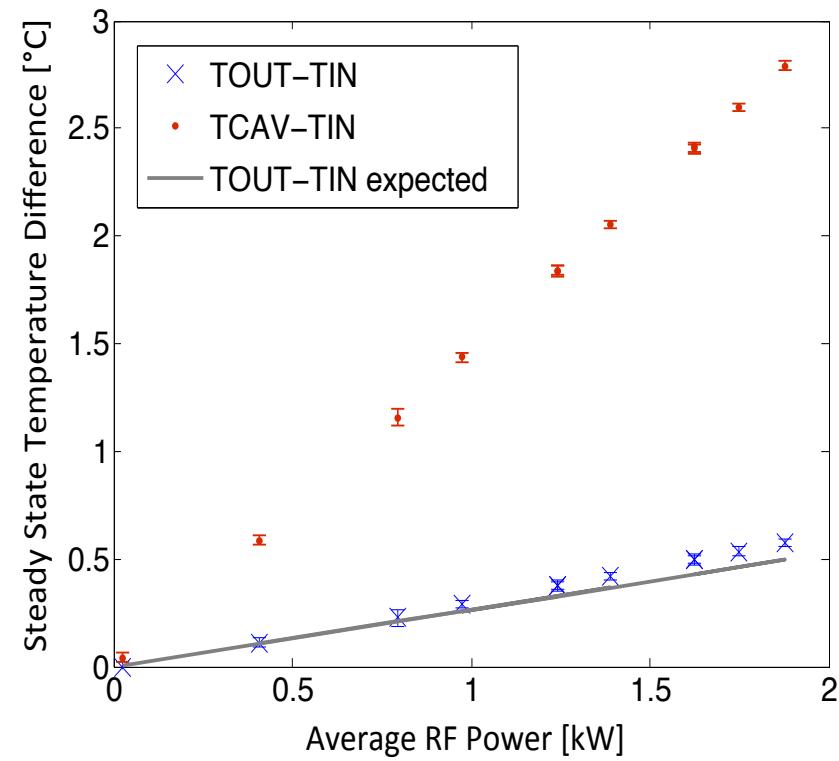
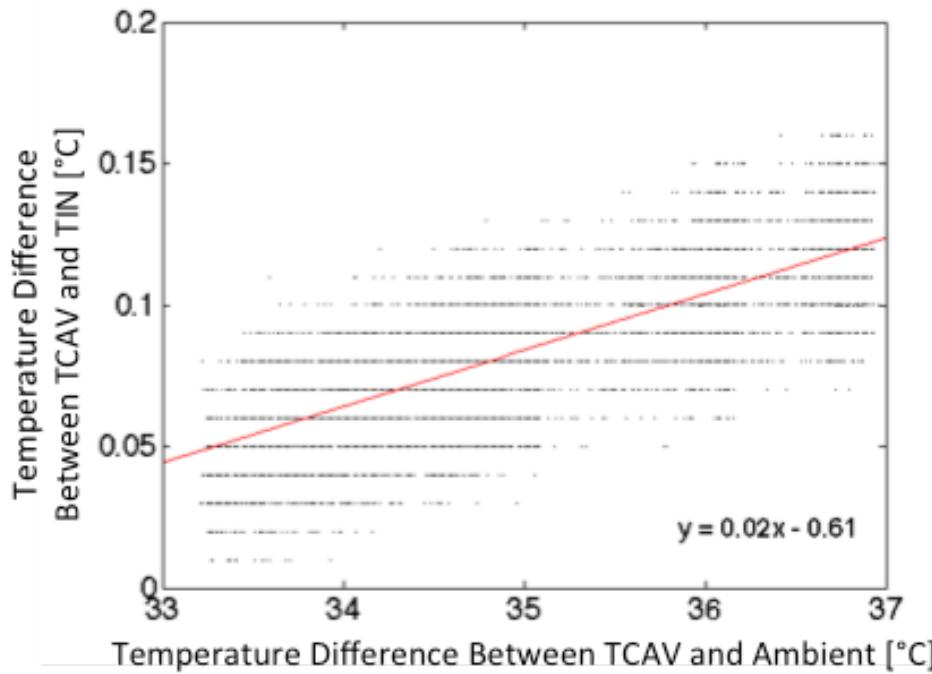
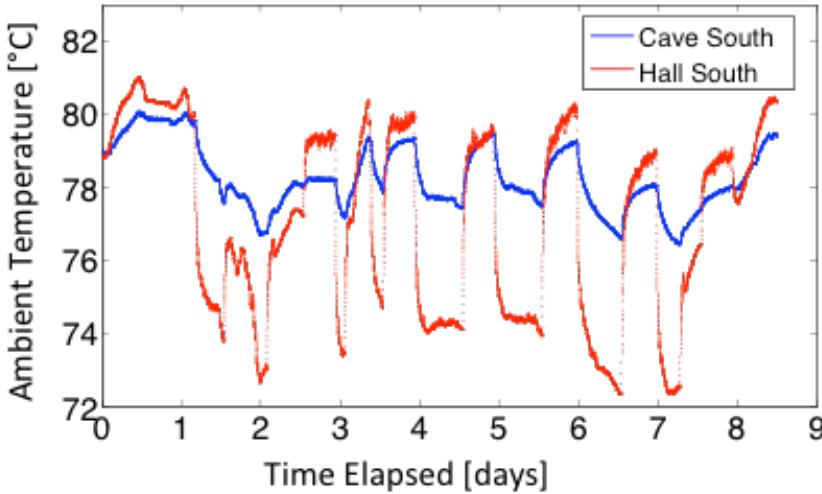
*Requested by Controller*



*Actual Read-backs*



# Of course, there's more to the story....



$$P_{cool} = \frac{(T_{OUT}[\text{°C}] - T_{IN}[\text{°C}]) \times (\text{Flow [GPM]})}{\text{Water Cooling Capacity } \left[ \frac{\text{GPM} \cdot \text{°C}}{\text{kW}} \right]}$$

$$P_{cool} = P_{IN} \approx P_{RF_{avg.}}$$

# FAST Next Steps

- Neural network model predictive control
- Extension to direct resonance control
- Reinforcement learning control

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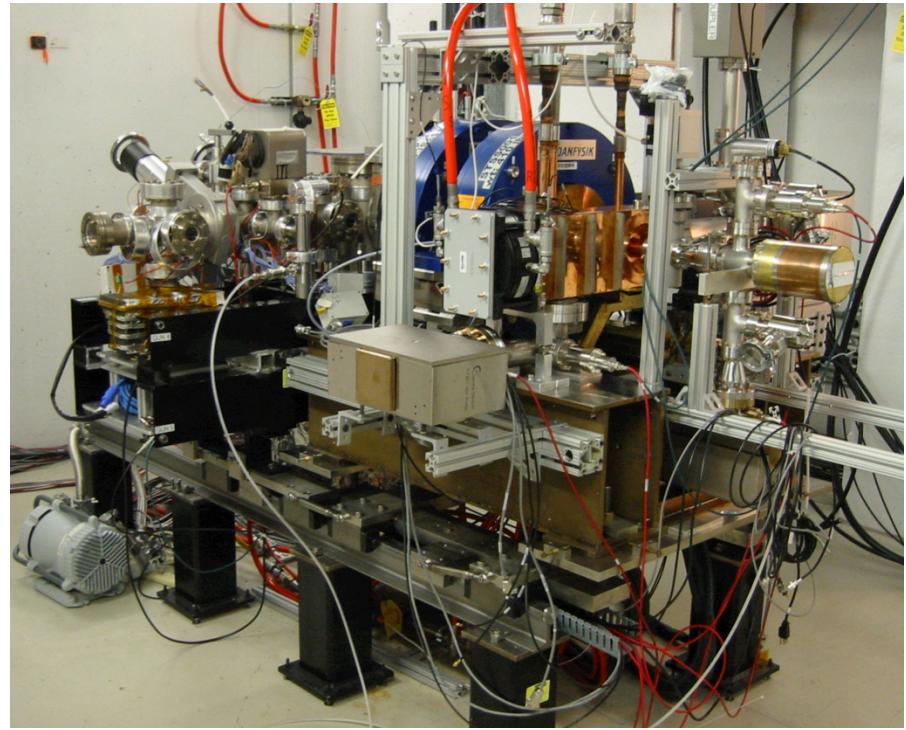


Photo: P. Stabile

*High-intensity RFQ for the  
PIP-II Injector Experiment  
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Photo: J. Steimel

# PXIE RFQ

Constructed by LBNL

PXIE RFQ Parameters	
<b>RFQ Design Parameters</b>	
RF frequency	162.5 MHz
Q-factor	~13,900
Loaded Q	~7,000
Physical Length	4.45 m (2.4 wavelengths)
Vane-to-Vane Voltage	60 kV
Estimated Power Dissipation	< 100 kW
RF Repetition Rate	pulsed – CW
<b>Beam Parameters</b>	
Current	0.5 – 10 mA (nominal 5 mA)
Input Energy	30 keV
Output Energy	2.1 MeV



## *High-intensity RFQ for the PIP-II Injector Experiment (PXIE)*

- Time delays
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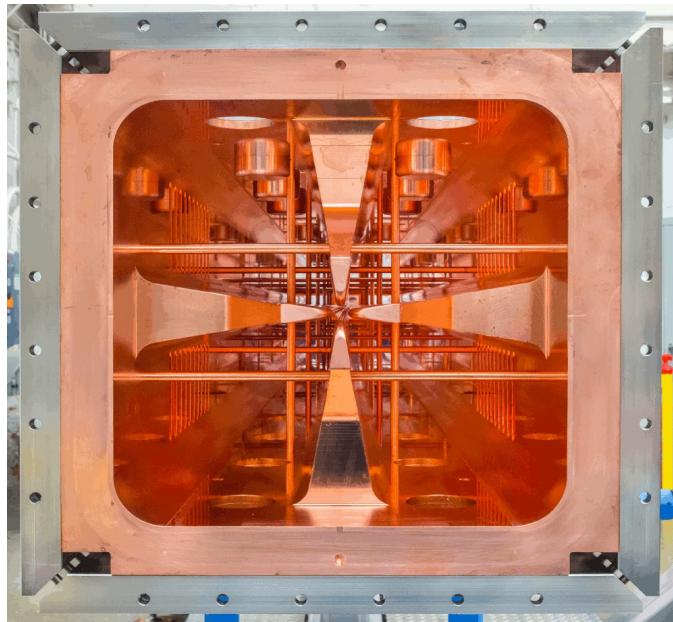
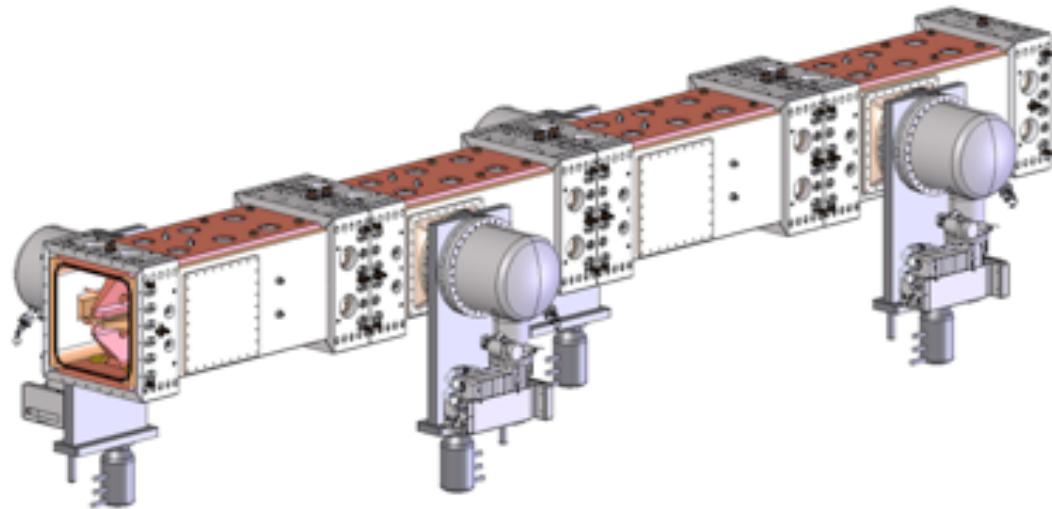


Photo: J. Steimel

# PXIE RFQ

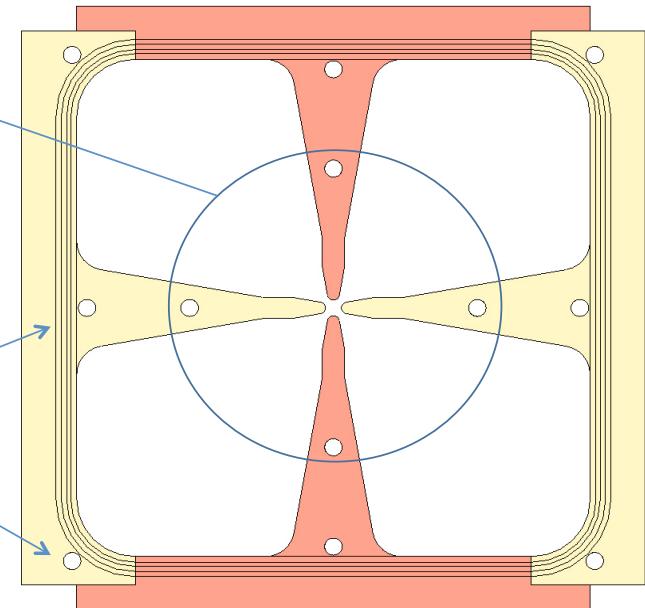
*3-kHz max. freq. shift*

*0.1-°C water stabilization*

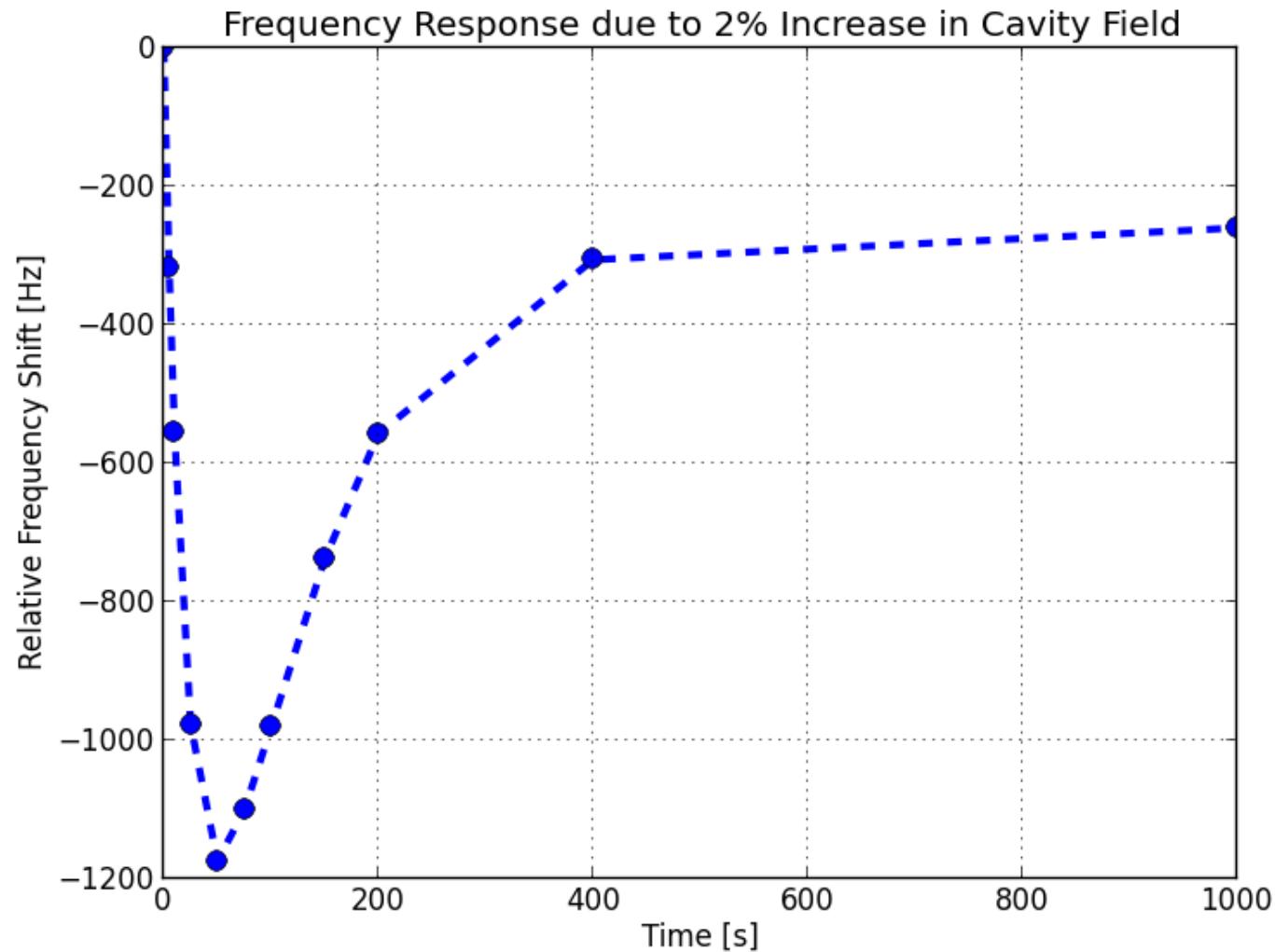


Vane channels

Wall channels

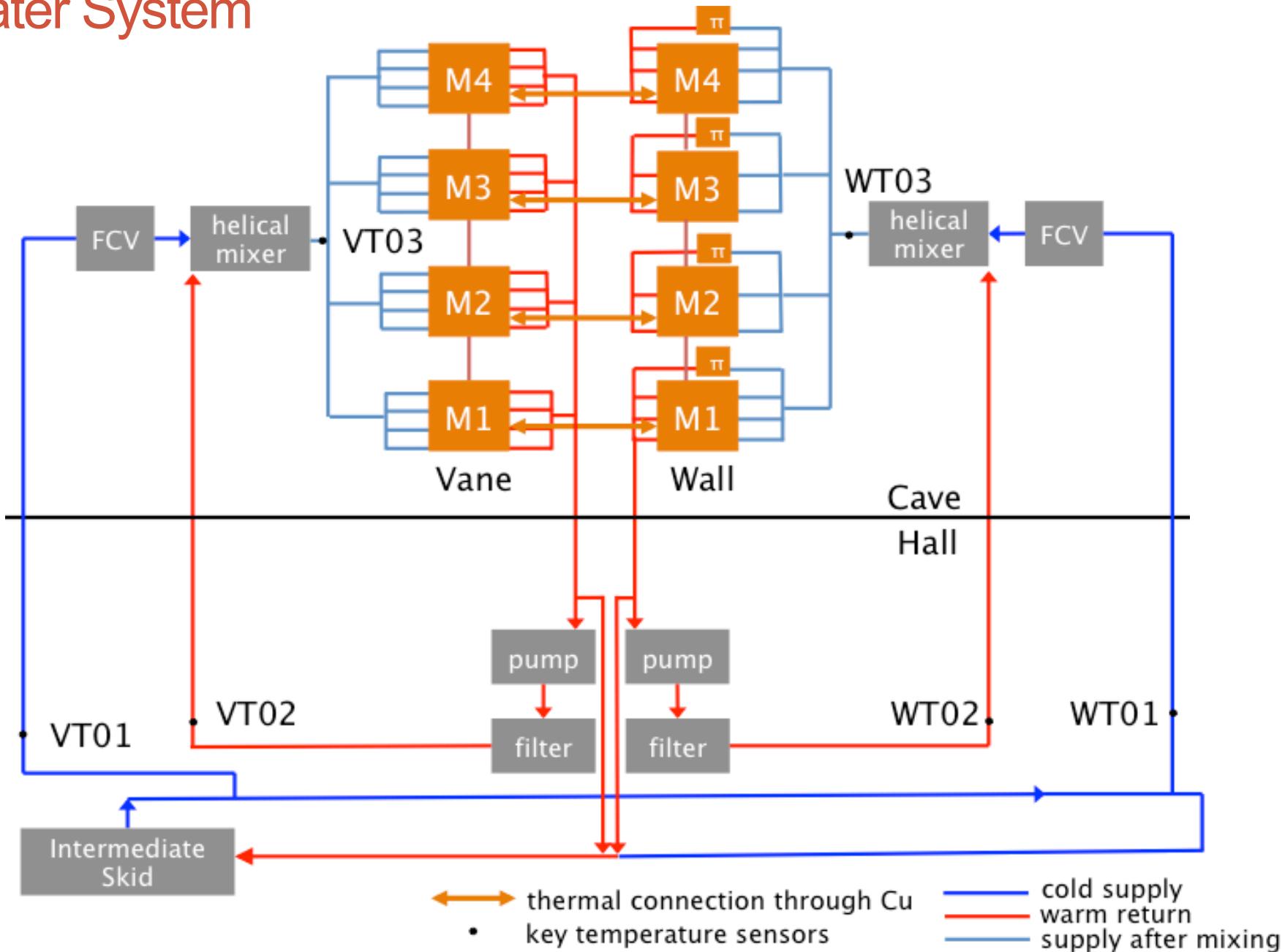


# Expected Frequency Response

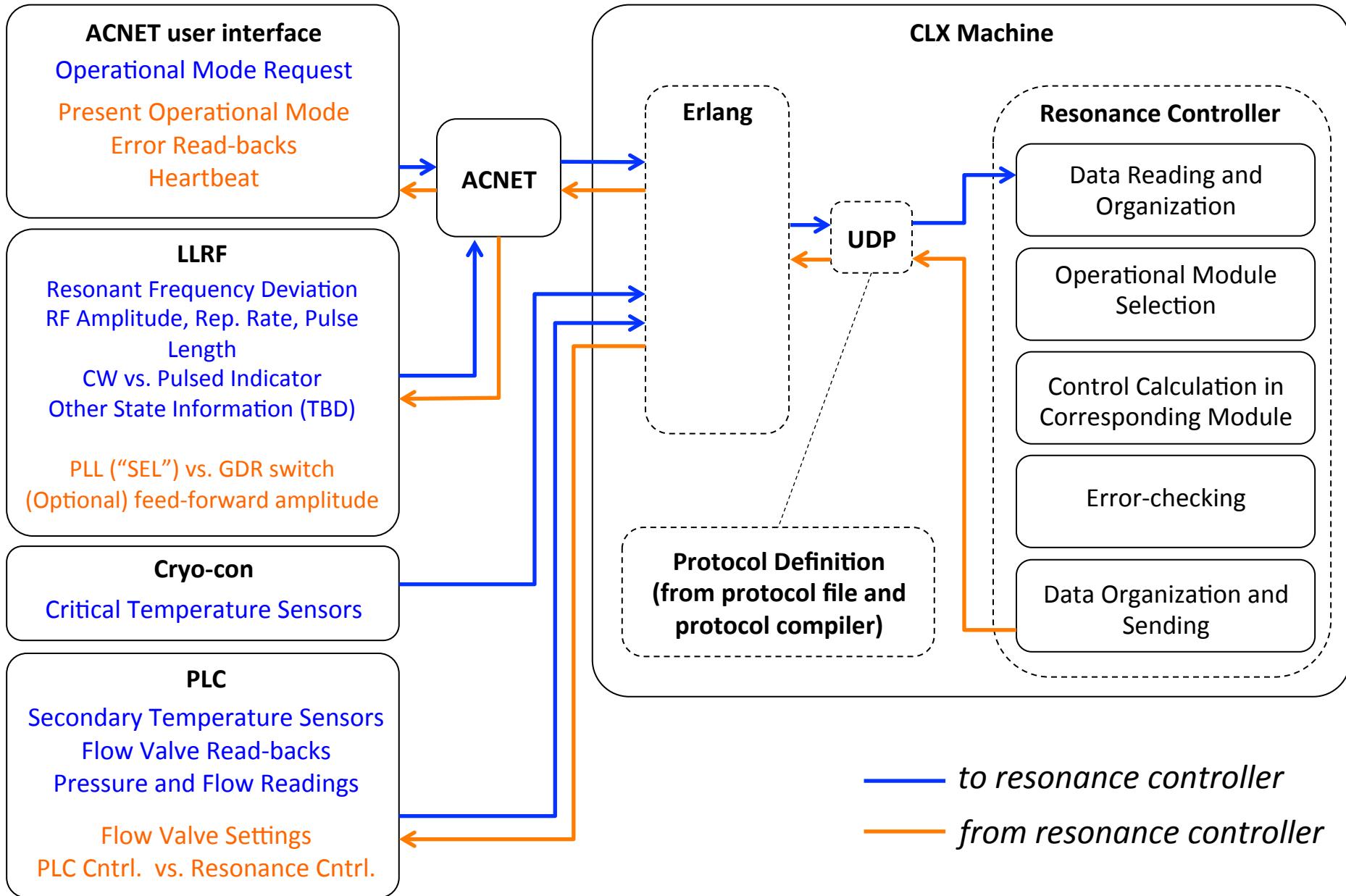


*ANSYS simulation data courtesy A. Lambert, LBNL*

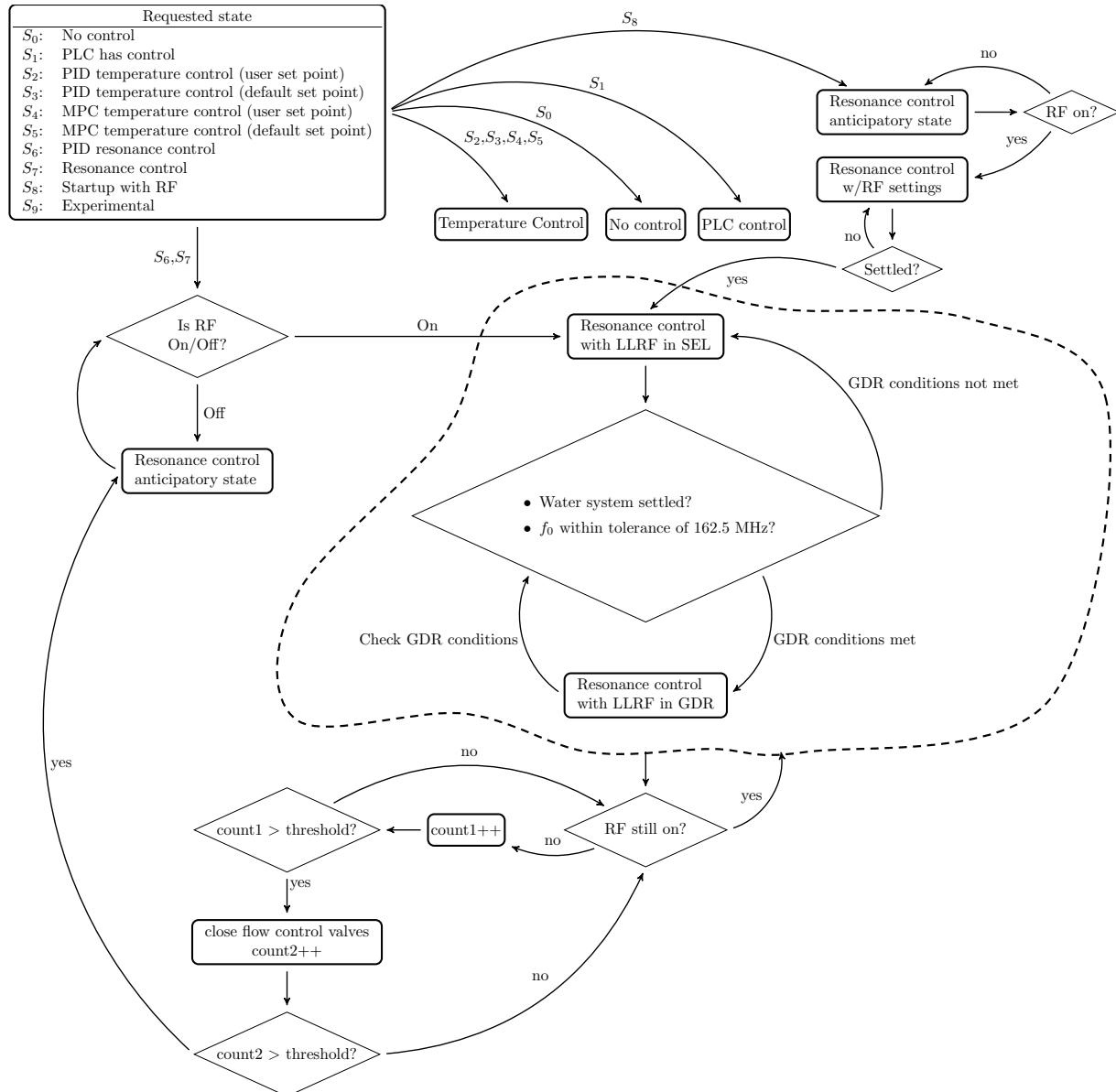
# Water System



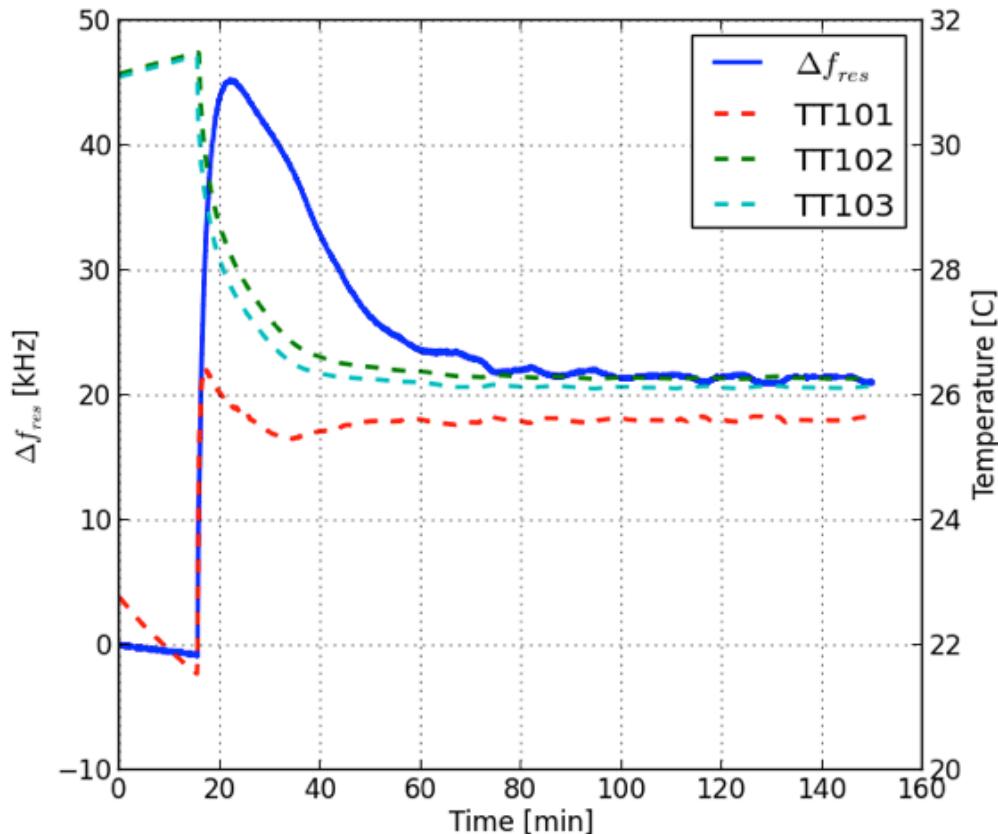
# Resonance Control System Architecture and Component Interfaces



# Resonance Controller State Flow



# Initial Frequency Response Measurements



flow path	time delay [s]
$TT_{101} \rightarrow TT_{103}$	1.0
$TT_{103} \rightarrow TT_{102}$	17.0

# Next Steps for PXIE

- Finish and test control framework
- Characterize and debug water system
- Characterize RFQ and water system under RF power
- Implement basic controllers for contracted work
- Design and test neural network controllers