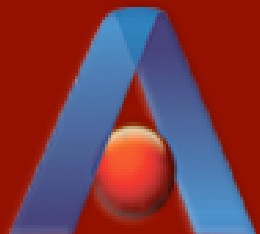


Advanced tools for cyber-physical systems and digital twins

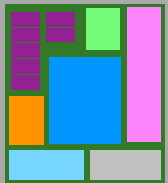
Principal Investigator:	Dr. Mark Bryden
Co-Principal Investigator	Dr. Paolo Pezzini
Date:	08/26/2020
DOE Award Number	DE-AC02-07CH11358
Period of Performance	10/01/2018 – 09/30/2020



AMES LABORATORY

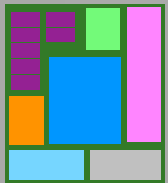
Simulation, Modeling, & Decision Science

Development of tools in support of the concept of integrating cyber-physical systems and digital twins into the current energy system research and development process.



Project Goal

1. Middleware architecture to enable digital twin
2. Monitoring and control tools for existing power plants
3. Diagnostic tools using machine learning concept

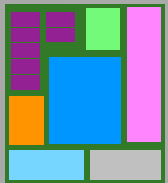
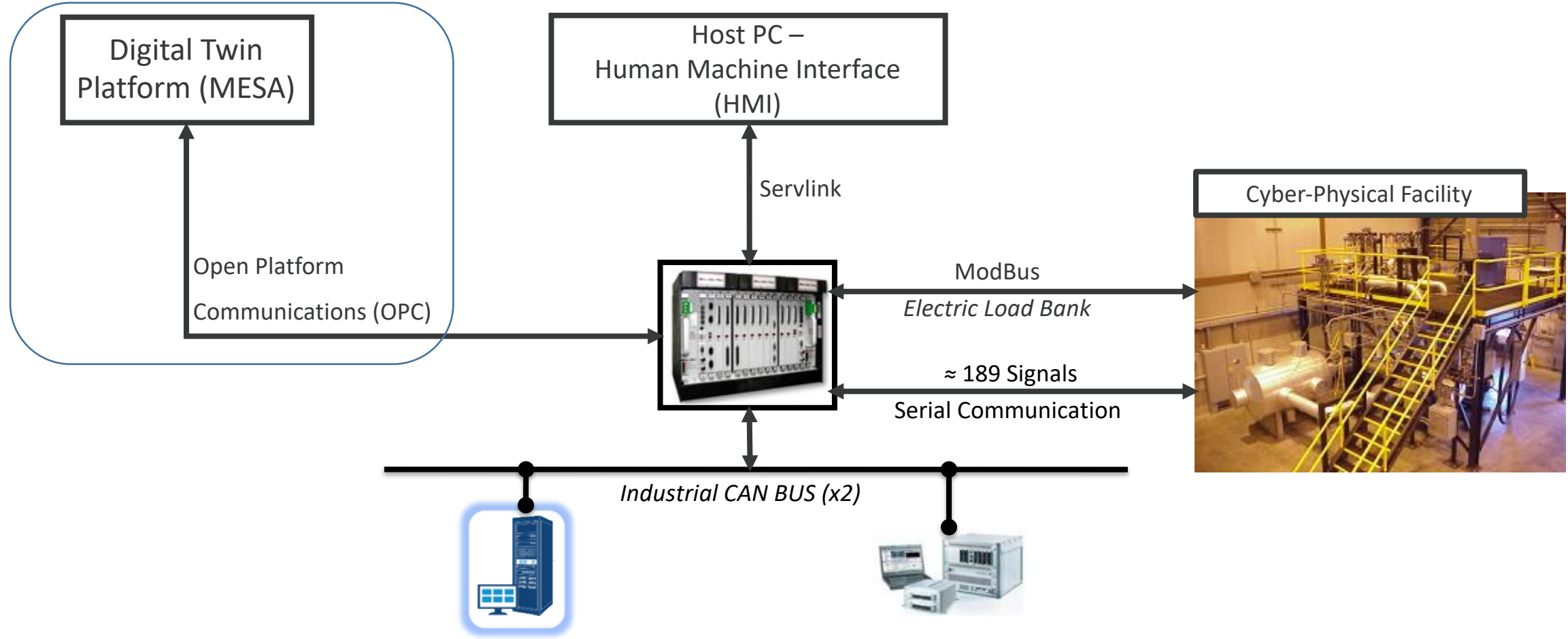




1. Middleware Architecture

Publisher and subscriber architecture used to exchange I/O variables in system automation through open source protocols

Middleware Architecture

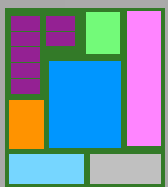
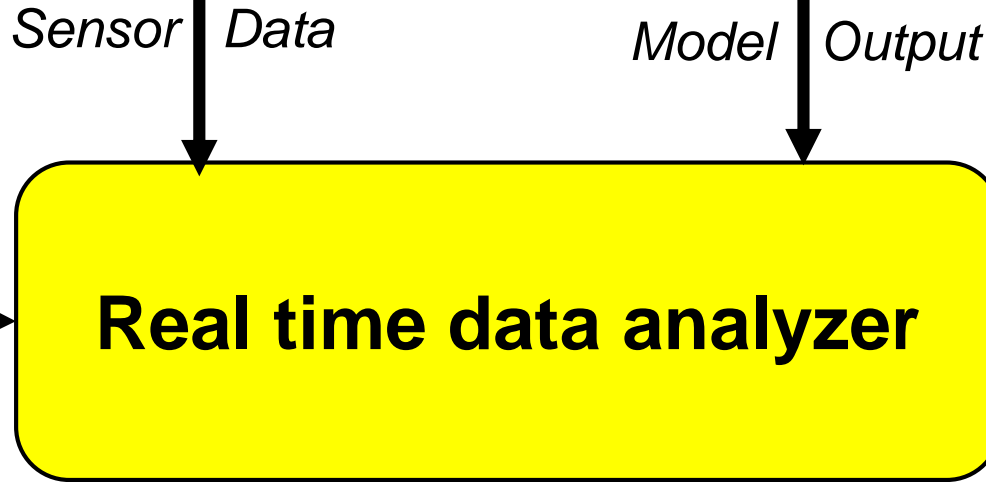
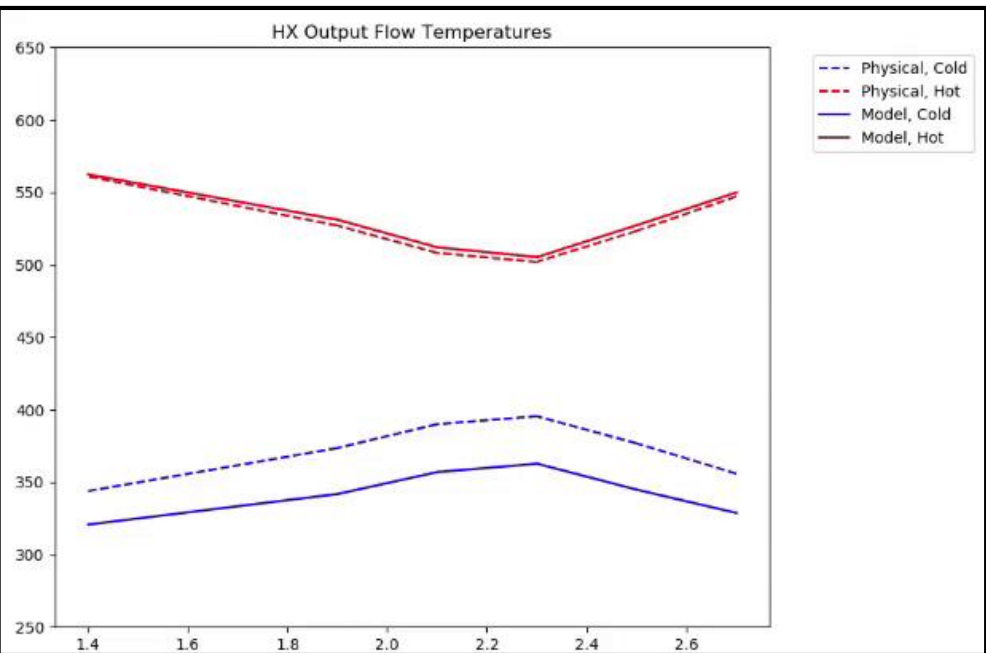
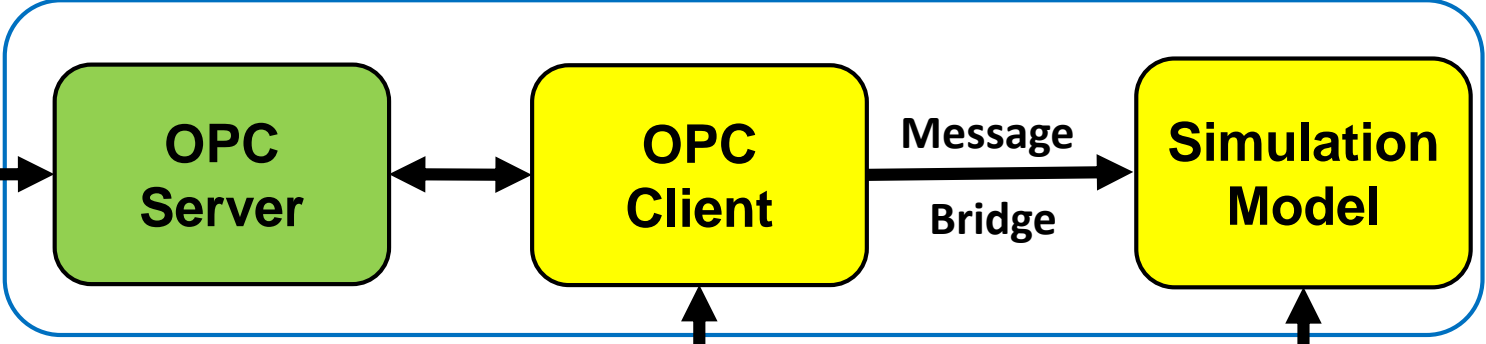


Middleware architecture: NETL's cyber-physical facility

Middleware Architecture

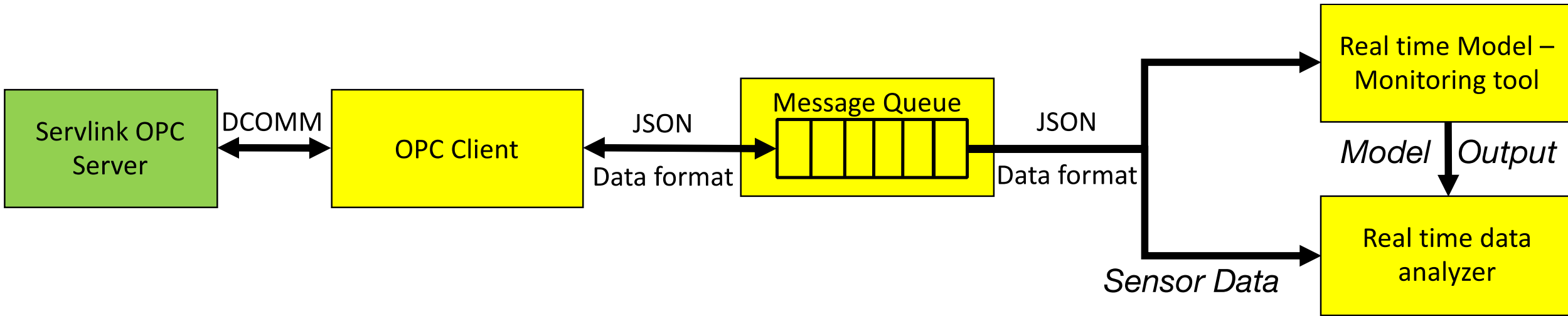


Cyber-Physical Facility

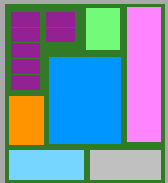


Demonstrate a working environment for a digital twin

Merge Environment Simulation Analysis (MESA)



- OPC Client – Executable using “Go” language to read OPC data
- RabbitMQ - Message broker connecting OPC data to real time model
- Real time model of a Heat Exchanger
- Real time data analyzer

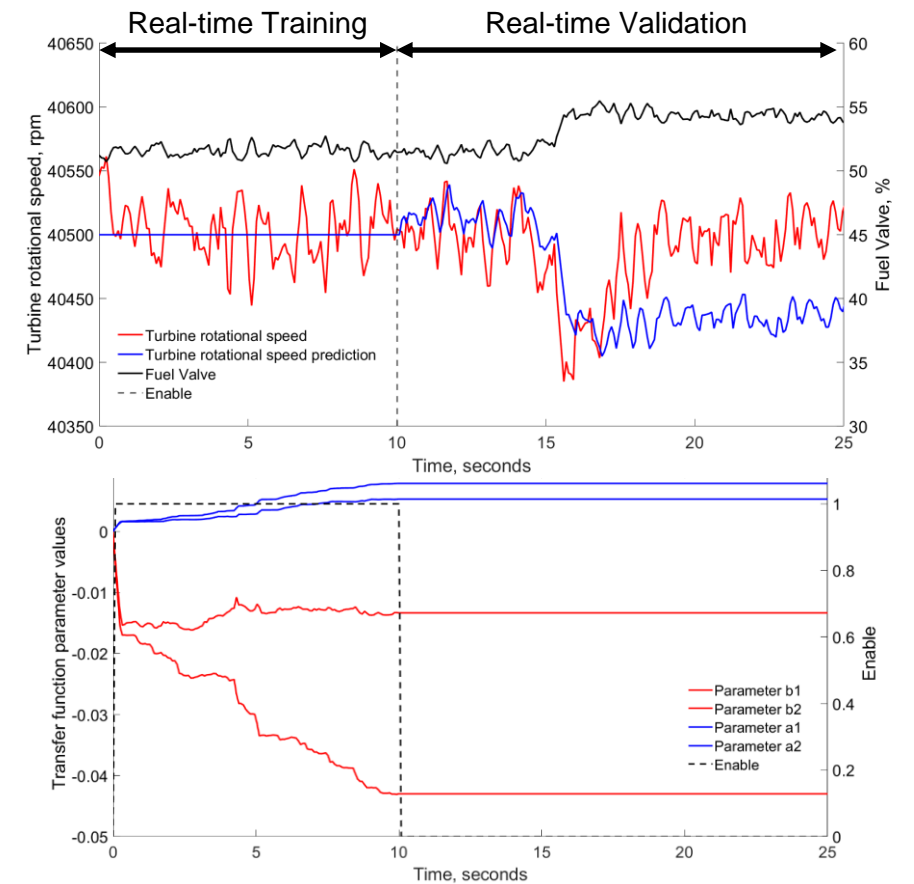
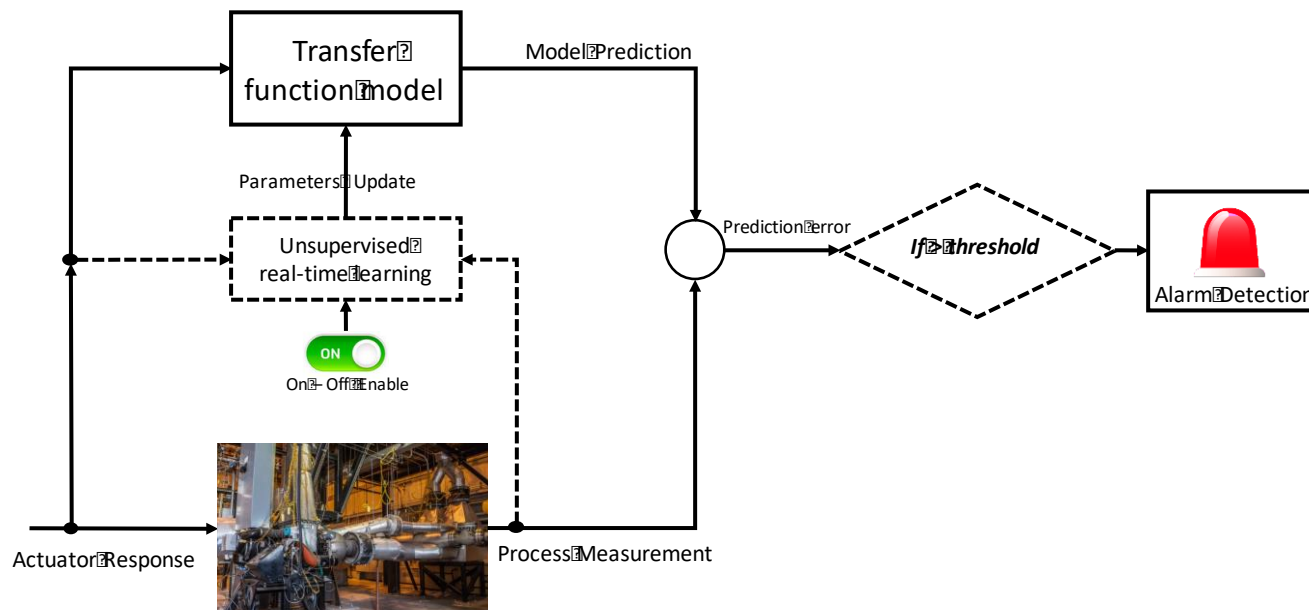


New tools developed

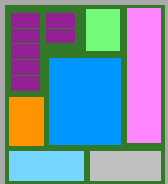


2. Monitoring and controls tools:

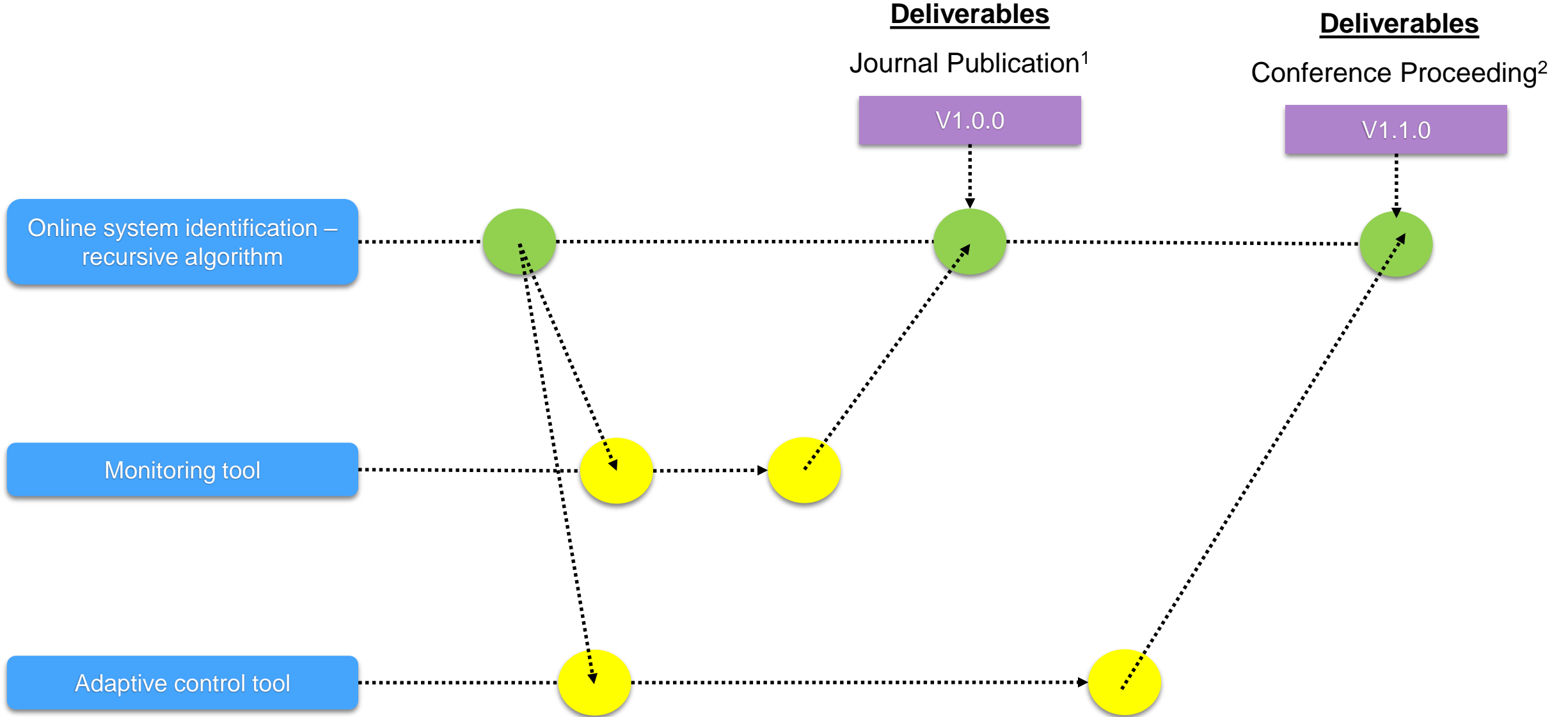
- Online system identification monitoring tool
- Model reference adaptive control (MRAC)
- Agent-based Control



- A sudden leak of 10% in the working fluid was reproduced
- An increase in the fuel flow was detected to maintain normal operation during the leak
- The leak was detected 5-7s after it occurred

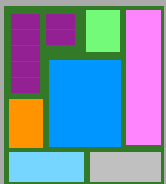


Experimental results – Online system identification tool



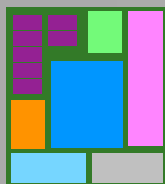
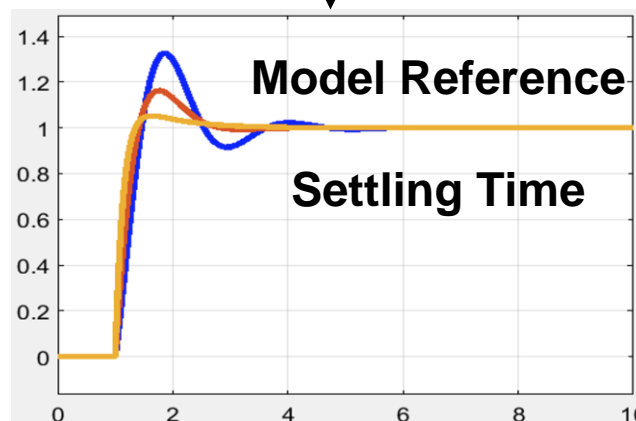
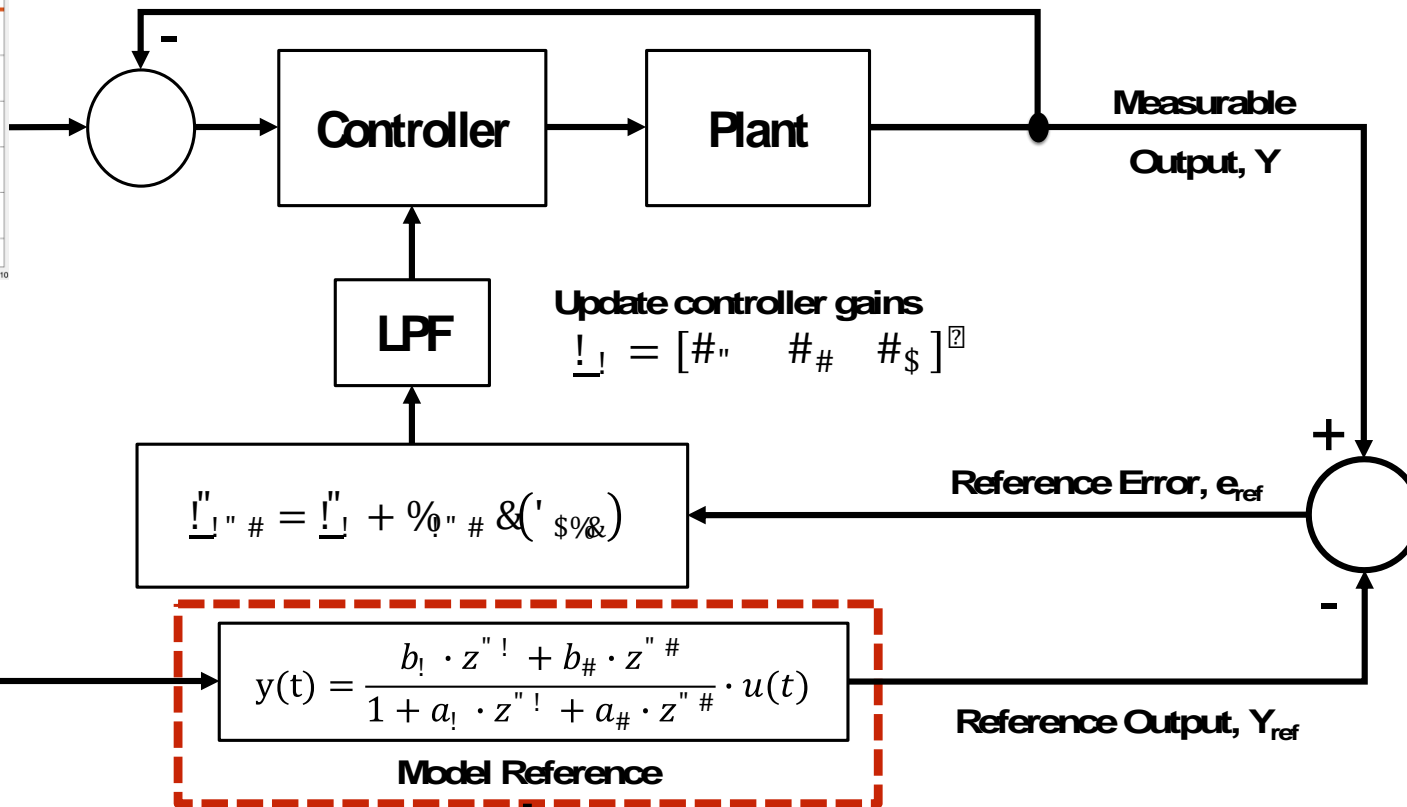
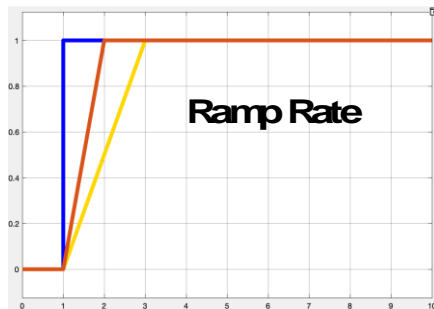
¹ H. Bonilla, K. M. Bryden, L. Shadle, D. Tucker, and P. Pezzini “Development of realtime system identification to detect abnormal operations in a gas turbine cycle,” *ASME Journal of Energy Resources Technology*, JERT-19-1712, Jul 2020, 142(7): 070903 (10 pages), doi.org/10.1115/1.4046144. 3.

² H. Bonilla, P. Pezzini, L. Shadle, D. Tucker, and K. M. Bryden “Online Adaptive Control Tuning in a Gas Turbine Hybrid System,” Proceeding of the 2020 ASME Power Conference, ICONE28-POWER2020-16534, Anaheim, California, USA



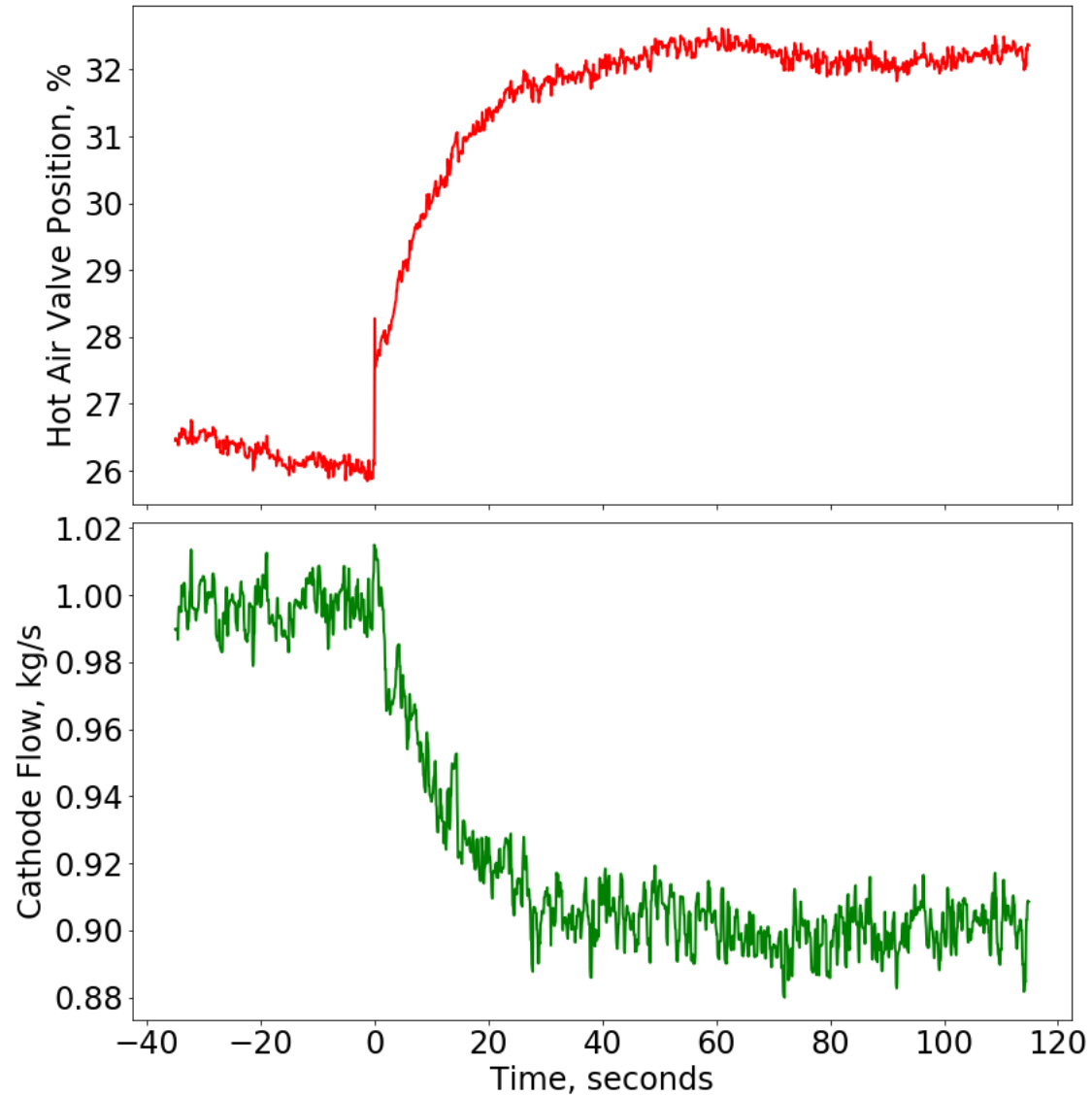
Recursive Algorithm implementation

Reference Setpoint, R

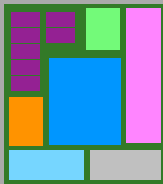
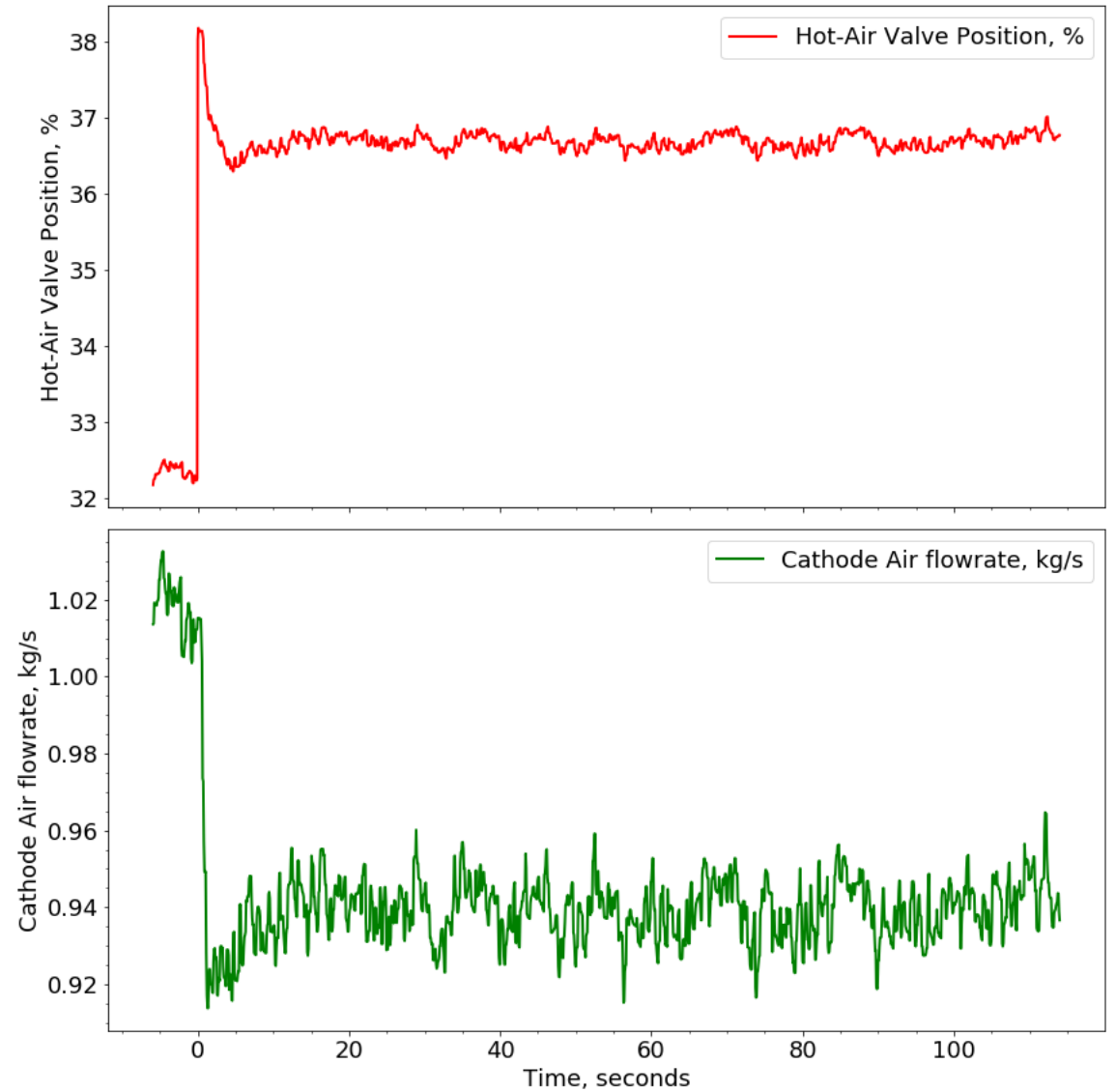


Adaptive control tool (MRAC)

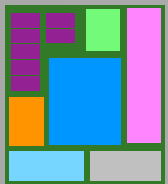
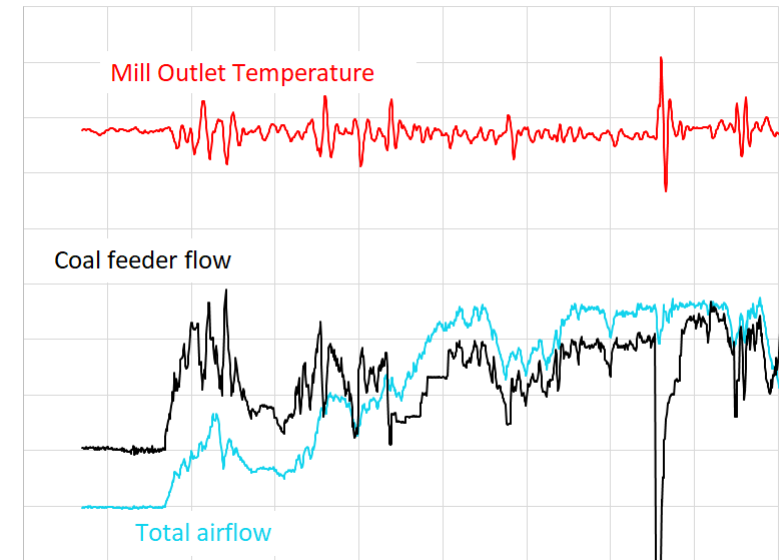
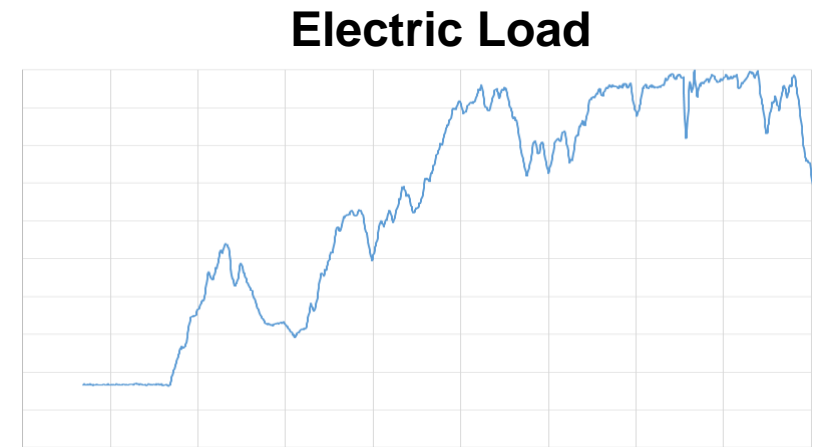
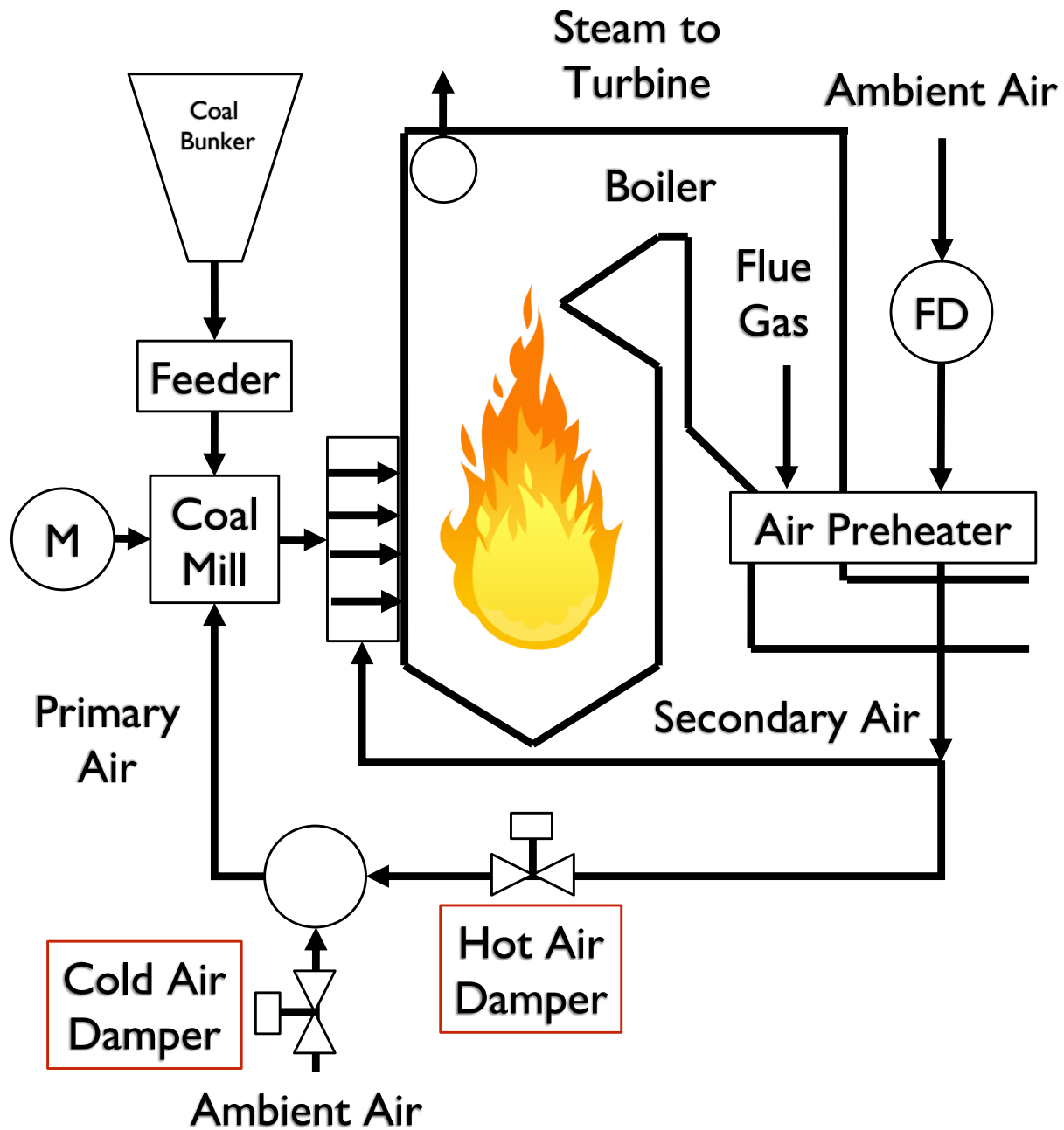
Existing PID Controller



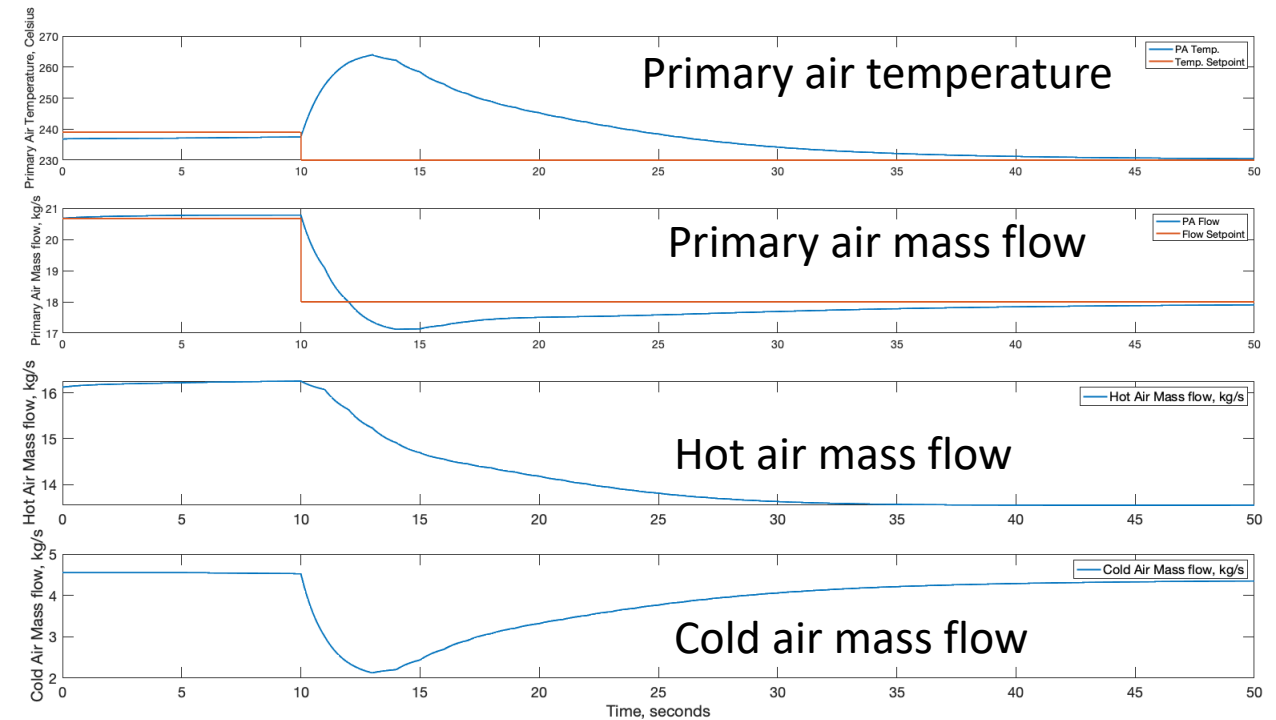
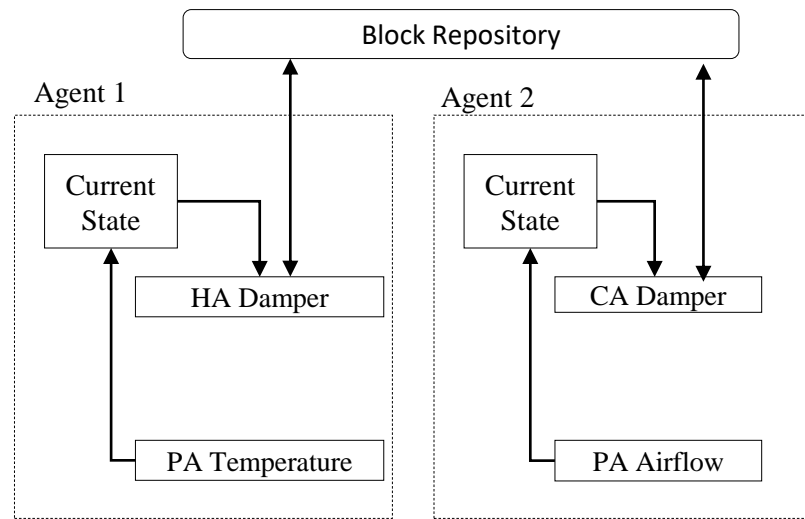
Model Reference Adaptive Controller



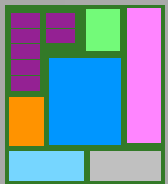
MRAC – Results



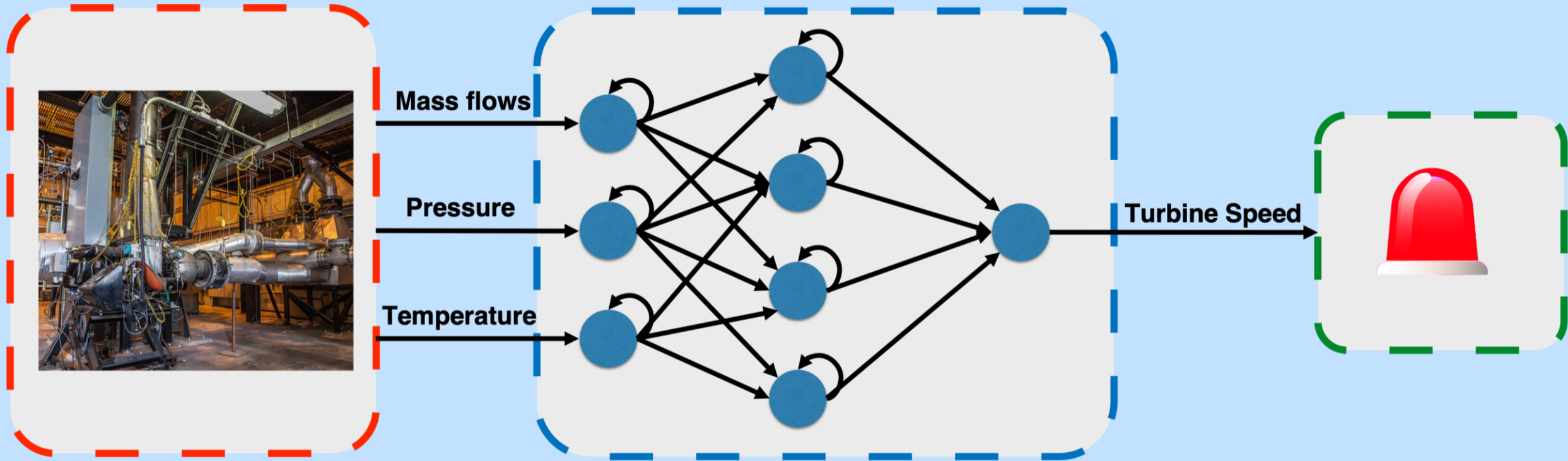
Coal mill outlet temperature control



- Multi-agents emulates intelligent control
- Agents can coordinate their behavior
- Agents are not limited to a set of models



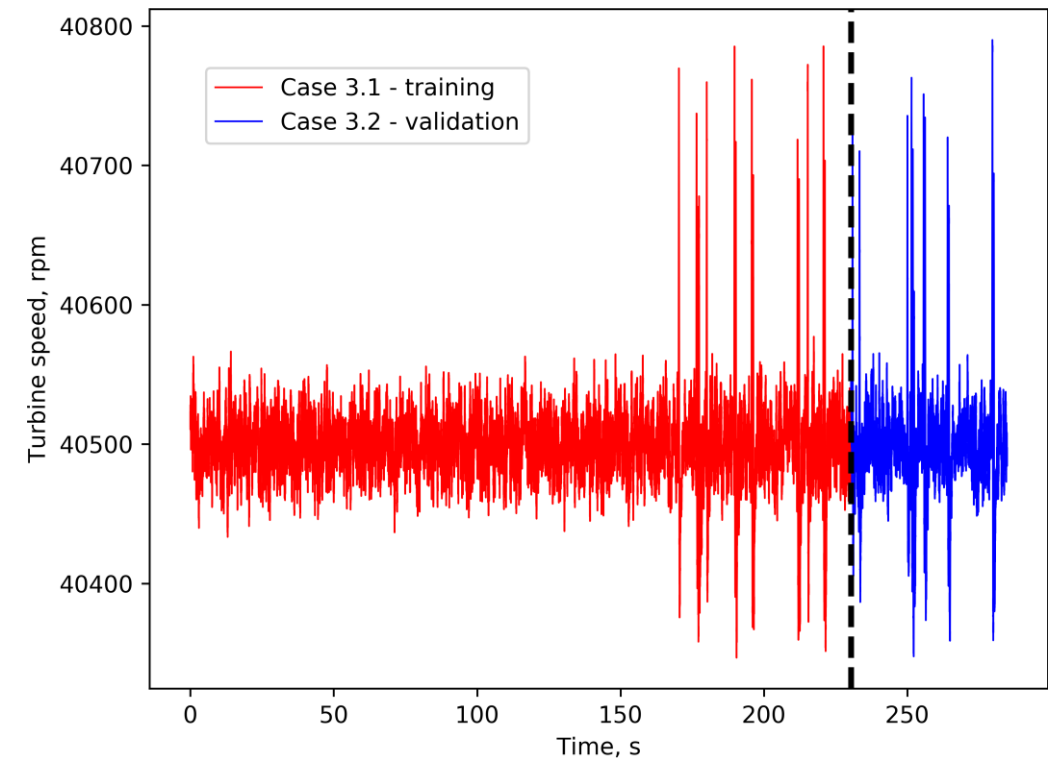
Preliminary results - Coal mill outlet temperature model



3. Machine Learning Diagnostic tools

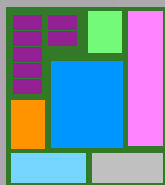
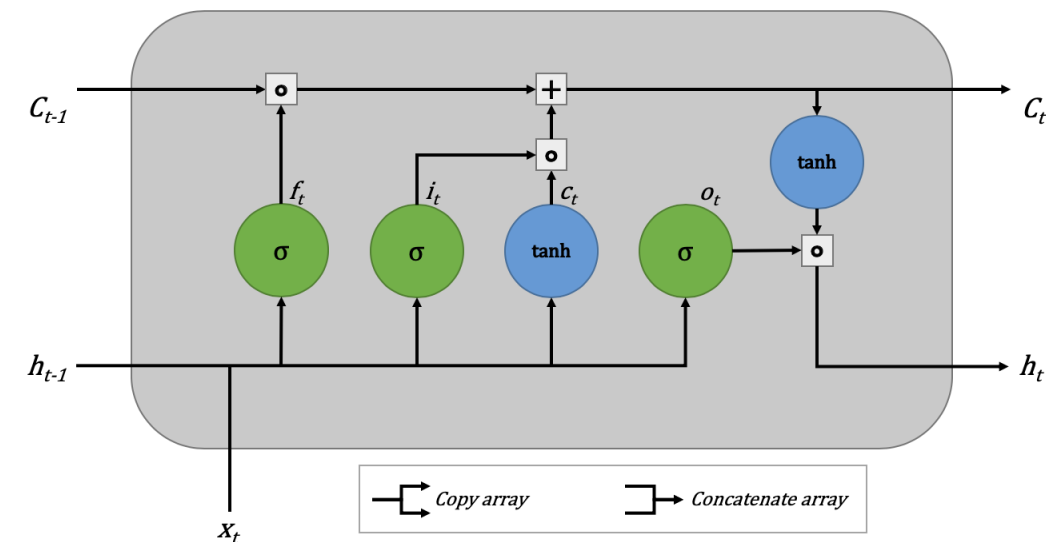
- Detection of unstable turbomachinery performance
- Increase model performance for a gas turbine system

Test Case	Data Points	Incipient Stall Events	Operating Conditions	Use in ML Model
1	7,692	2	Near stall	Training
2	9,216	0	Nominal	Training
3.1	46,080	8	Nominal to near stall	Training
3.2	10,880	7	Near stall	Testing



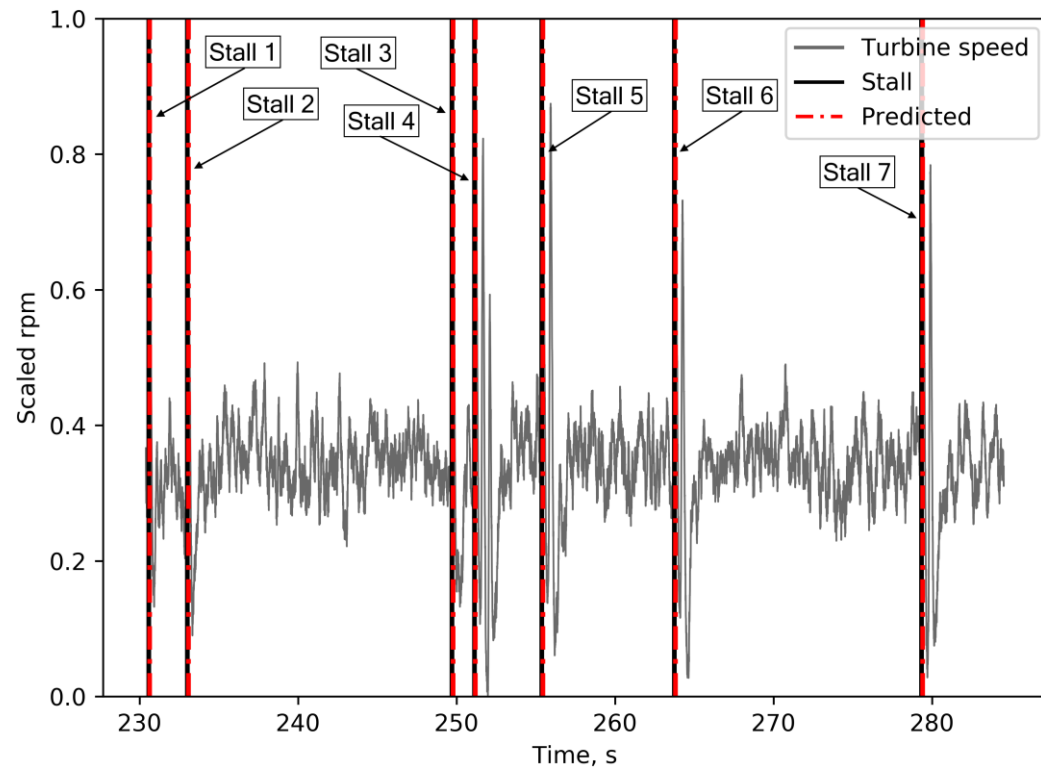
LSTM Hyperparameters

Input steps	40
Output steps	15 (75ms)
First layer size	32
Second layer size	64
Third layer size	32
Batch size	64
Learning rate	0.001
Dropout	20%

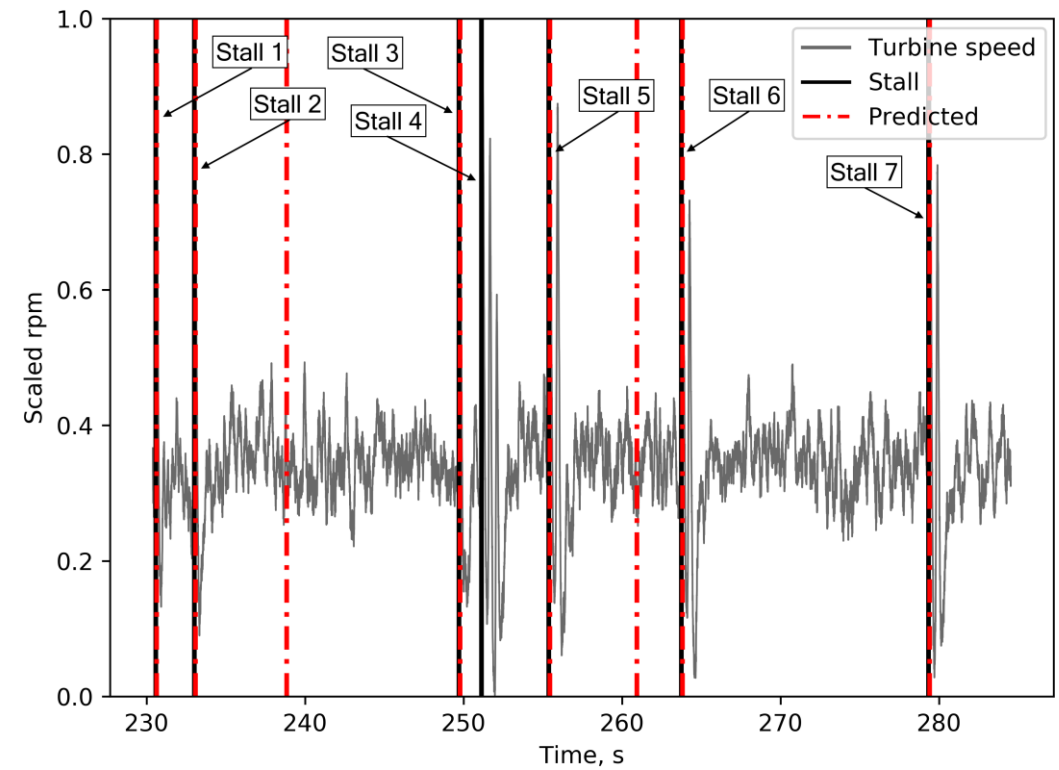


Long short-term memory (LSTM) implementation

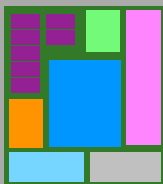
16 epochs



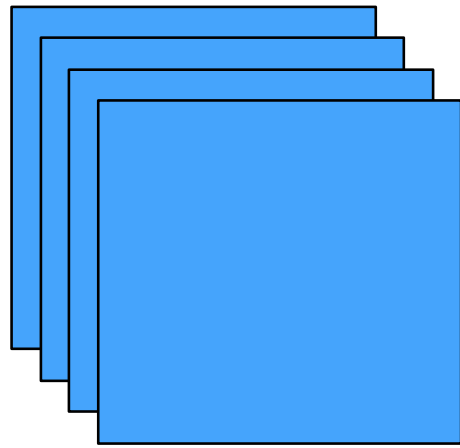
32 epochs



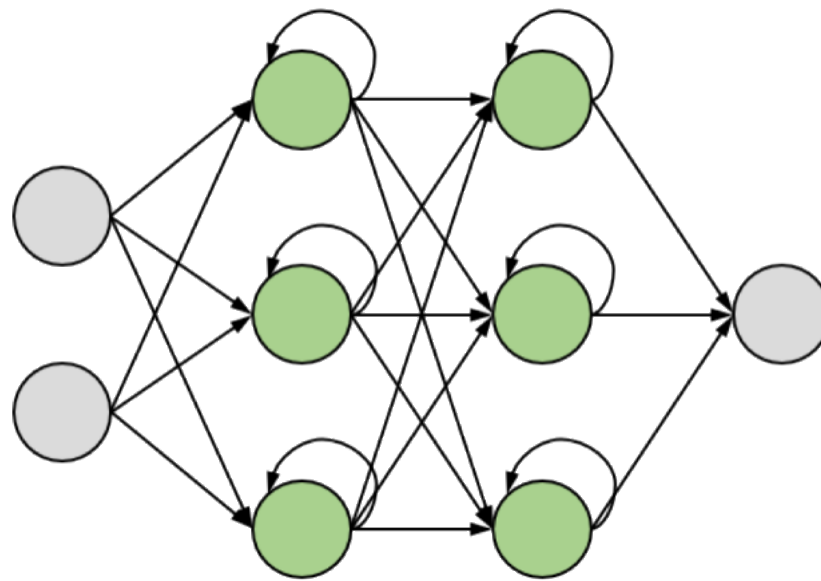
- Stall prediction tool enables 5 to 20 ms reaction time
- Configured for online implementation in a digital twin concept



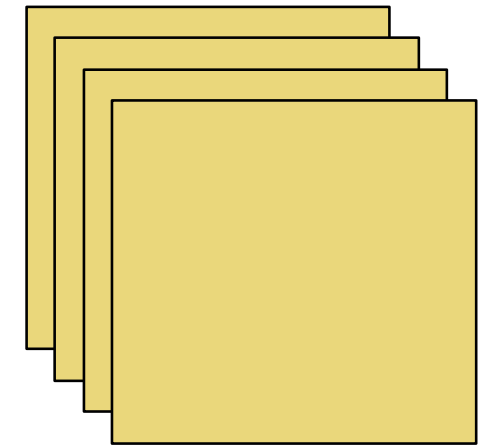
Detection Results



Operational Data

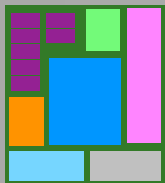
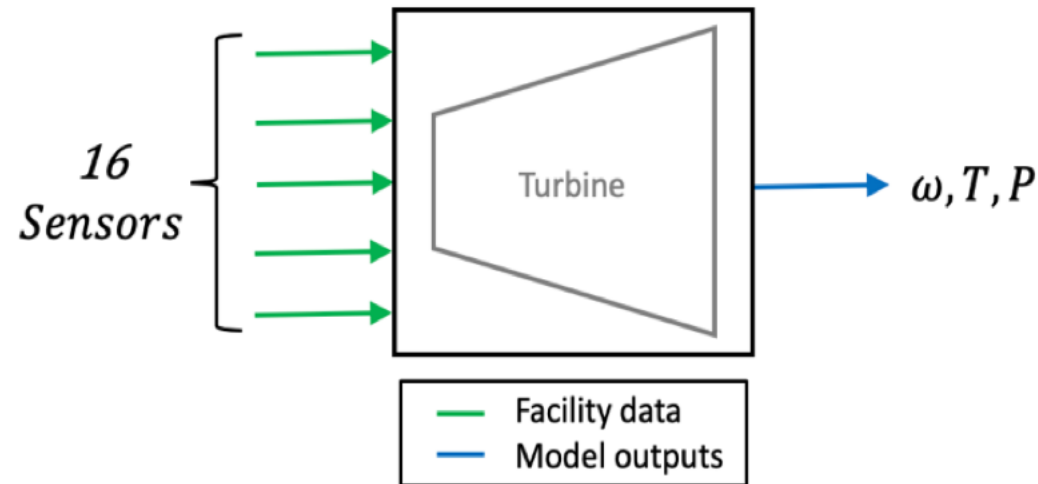


Neural Network

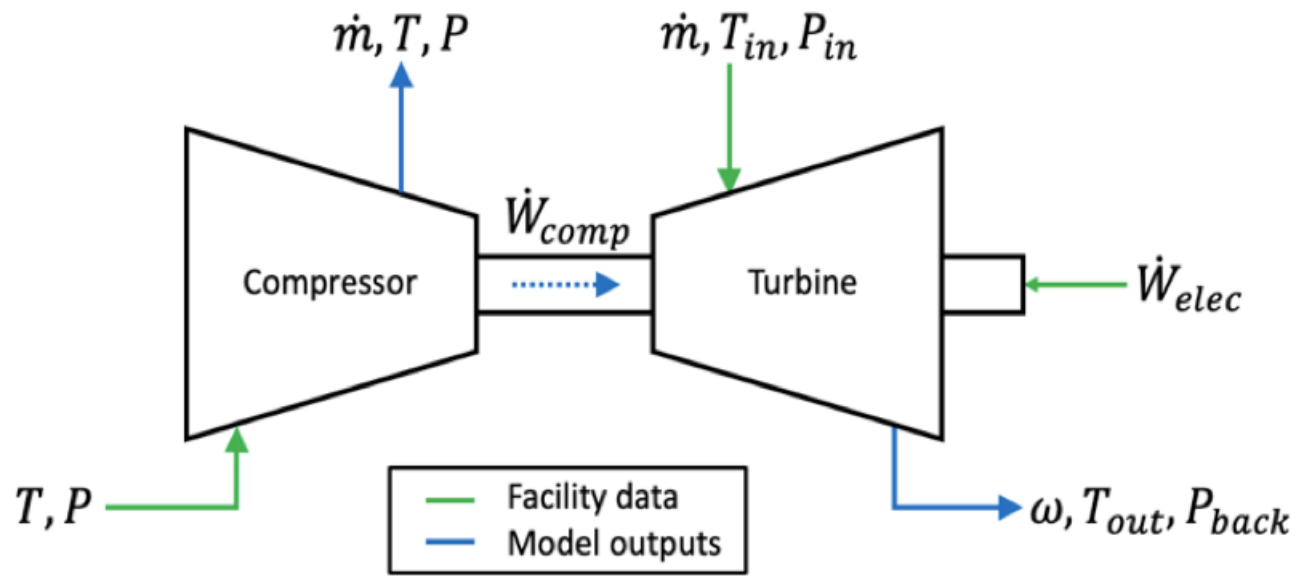


Performance predictions

	Test Case	Data Points	Incipient Stall Events	Operating Conditions	Use in Models
Steady-State	1	9,216	0	Nominal	Training
	2.1	475,000	0	Nominal	Training
	2.2	10,400	0	Nominal	Testing
Stall	3	7,692	2	Near surge line	Training
	4.1	46,080	8	Nominal to near surge line	Training
	4.2	10,880	7	Near surge line	Testing

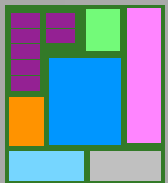


Machine learning model for a gas turbine system

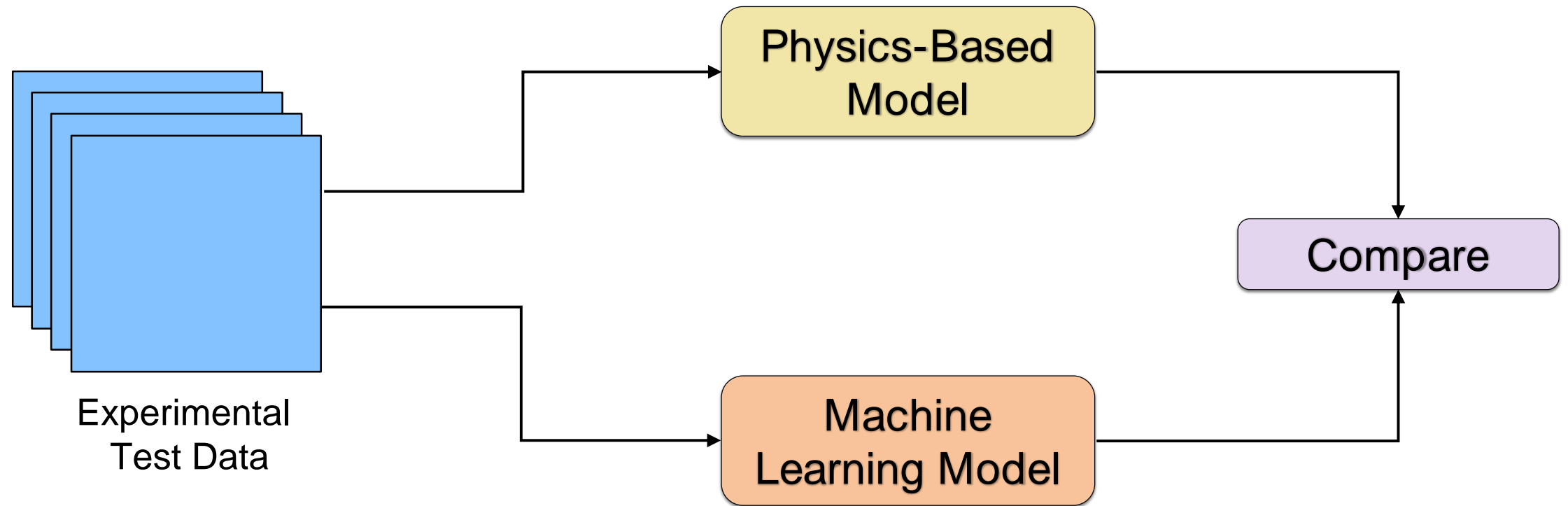


Traditional Euler turbomachinery equations

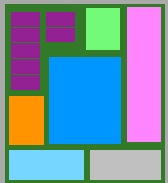
- **Turbine speed** – Turbine work, inertia, shaft load, and rotational losses
- **Rate of turbine work** – Turbine pressure ratio, turbine inlet mass flow, temperature, and specific heat
- **Rate of compressor work** – change in the rate of the angular momentum
- **Temperature outlet** – Pressure ratio and specific heat ratio for compressor and turbine



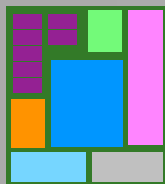
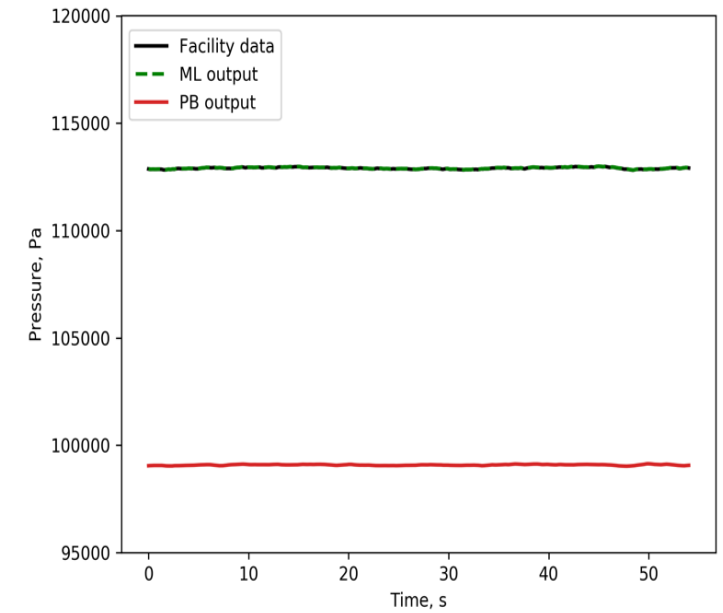
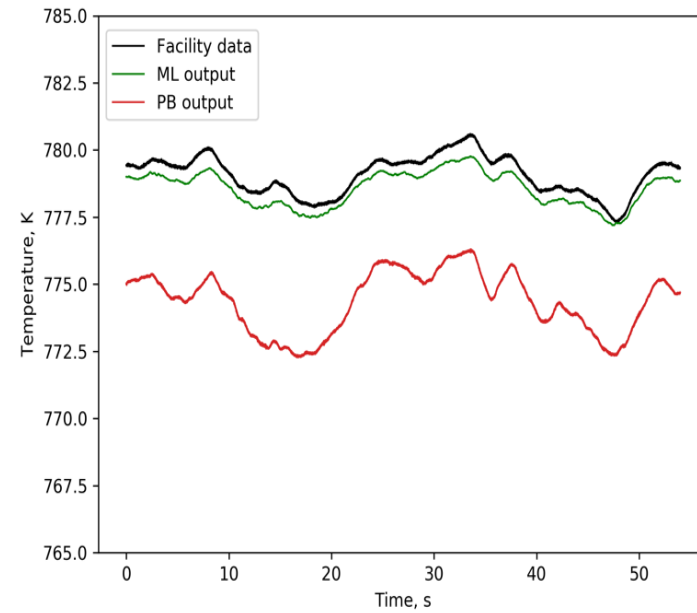
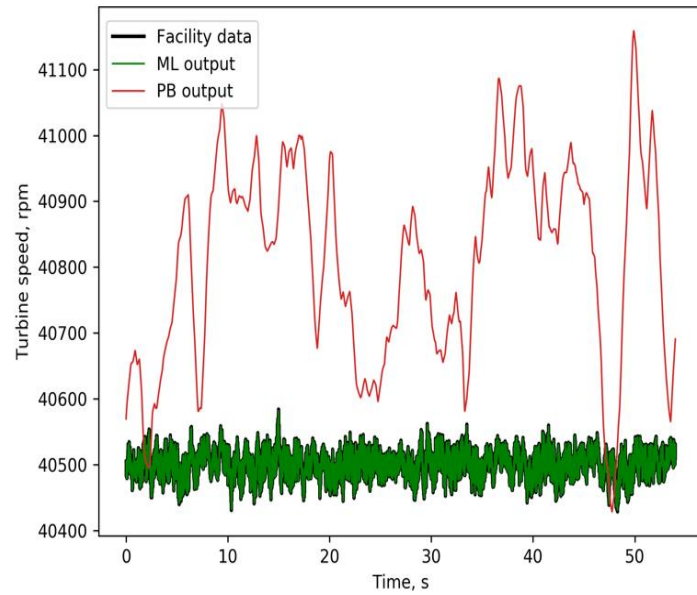
Physics-based model



- Real-time analysis with different computational models
- Performance evaluation during live operation

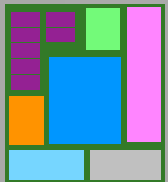


Steady-State Test Data



Results

1. Middleware architecture implemented on a pilot system
2. Monitoring and control tools successfully tested on a pilot system
3. Diagnostic tools using machine learning concept were developed using pilot system data



Summary

MESA Team in Ames

Dr. Peter Finzell

Mr. Harry Bonilla (PhD grad, Iowa State U)

Mr. Zach Reinhard (PhD grad, Iowa State U)

Mr. Sam Hipple (PhD grad, Iowa State U)

Mr. Grant Johnson (Iowa State U)

Hyper Team in NETL

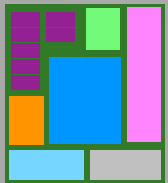
Dr. David Tucker

Dr. Larry Shadle

Dr. Daniel Maloney

Dr. Farida Nor Harun

Dr. Nana Zhou



Acknowledgments