2018 UTSR Project Review Meeting

Real-time Health Monitoring of Gas Turbine Components Using Online Learning and High Dimensional Data

Nagi Gabraeel [1], Tim Lieuwen [2], Kamran Paynabar [1], Reid Berdanier [3], Karen Thole [3]

[1]School of Industrial and Systems Engineering, Georgia Tech
[2]School of Aerospace Engineering, Georgia Tech
[3]Department of Mechanical and Nuclear Engineering, Penn State

Background and Motivation

- Gas turbines and combined-cycle plants are equipped with hundreds to thousands of sensors, which are used for monitor turbine performance or physical degradation.
- Due to the large volume of data generated by these sensors, conventional data analytic tools are no longer effective.
  - Large volumes of multivariate time series (correlated variables)
  - Complex data structures (spectral data, image and video data)
- **Big Data Analytics** holds enormous potential for improving the reliable operation of power generating gas turbines and combined cycle plants.

Background and Motivation

- In the energy/power generation sector, multivariate time-series applications involve monitoring variables individually.
  - A normally distributed variable has a 0.27% chance of generating false alarm
    - ***On average a false alarm every 370 observations.***
  - This does not even consider harsh industrial settings
    - ***Equipment dynamics, signal noise, unaccounted sources of randomness, missing/corrupt data, etc.***
- Consider 50 variables monitored independently with $\alpha = 0.27\%$
  - False alarm rate of the monitoring system can be estimated using the expression $1 - \prod_{i=1}^{50}(1-\alpha)$
    - ***Approximately 13% for just 50 variables***

Background and Motivation

- Another limitation relates to the dimensionality of the data.
  - Algorithms used to date by OEMs and utility companies only process aggregated data.
  - For example, although acoustic/vibration spectral signatures are constantly acquired at the plant-level. However, OEM monitoring centers only receive 3 to 4 values every 5 minutes (peak amplitudes at specific frequency ranges).
- Data is prone to being very noisy and contains very little information.
- Although inefficient, this approach has remained the *de facto* tool used at Monitoring and Diagnostics Centers operated by major OEM’s and utilities.

Background and Motivation

- Prognostic models are intended for predicting remaining useful lifetime (RUL).
  - Formally, given the current age and condition of an asset, RUL is defined as a (probabilistic) random variable

$$P(T_k > t|, Z(t), S_1, \ldots, S_k)$$

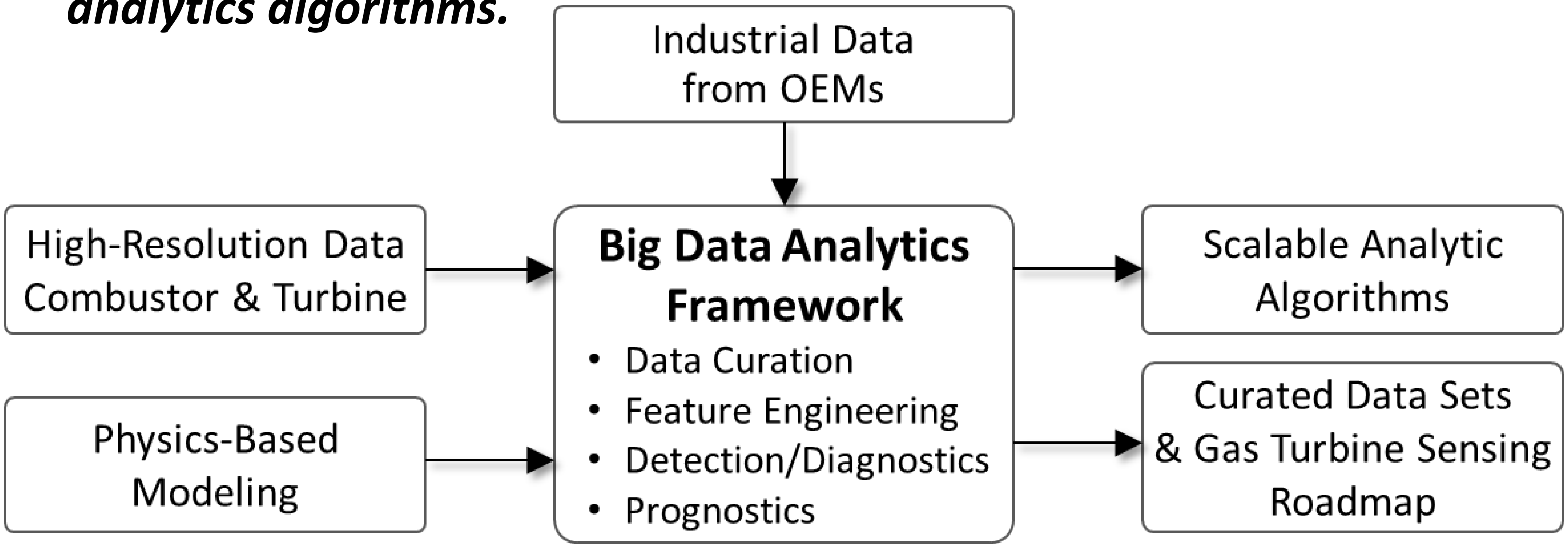
  - Where T represents the RUL, t some future time/age of the asset/component, $S_1, \ldots, S_k$ is observed degradation-based sensor data $Z(t)$ is the operating condition and/or profile.
- At their core, most of the existing techniques used to date are actually detection models (not predictive).
  - Once the detection model flags an anomaly (fault), predictions are generated based on SME experience and *gut instincts*.

Project Objective

- Enable the development of a Big Data analytics framework for fault detection and prognostics of critical gas turbine components through a systematic experimental program that leverages unique industry-class turbine test rigs.
- Advanced gas turbine test facilities will be interrogated using state-of-the-art instrumentation techniques to build an open data collection supporting predictive algorithm development for combustors and turbines.
- Highly-resolved data generated from a combustor test rig (Georgia Tech) and a turbine test rig (Penn State) during both normal operation and with “seeded” faults, will be used as the basis for the Big Data sets. The test conditions in the two test facilities will include common, critical events that occur in the operation of power plants.

Technical Approach

- The technical approach is based on
  - ***Experimental testing to gain knowledge of the physical processes associated with unsteady combustor and turbomachinery dynamics.***
  - ***Data-driven modeling and Machine Learning for development of analytics algorithms.***

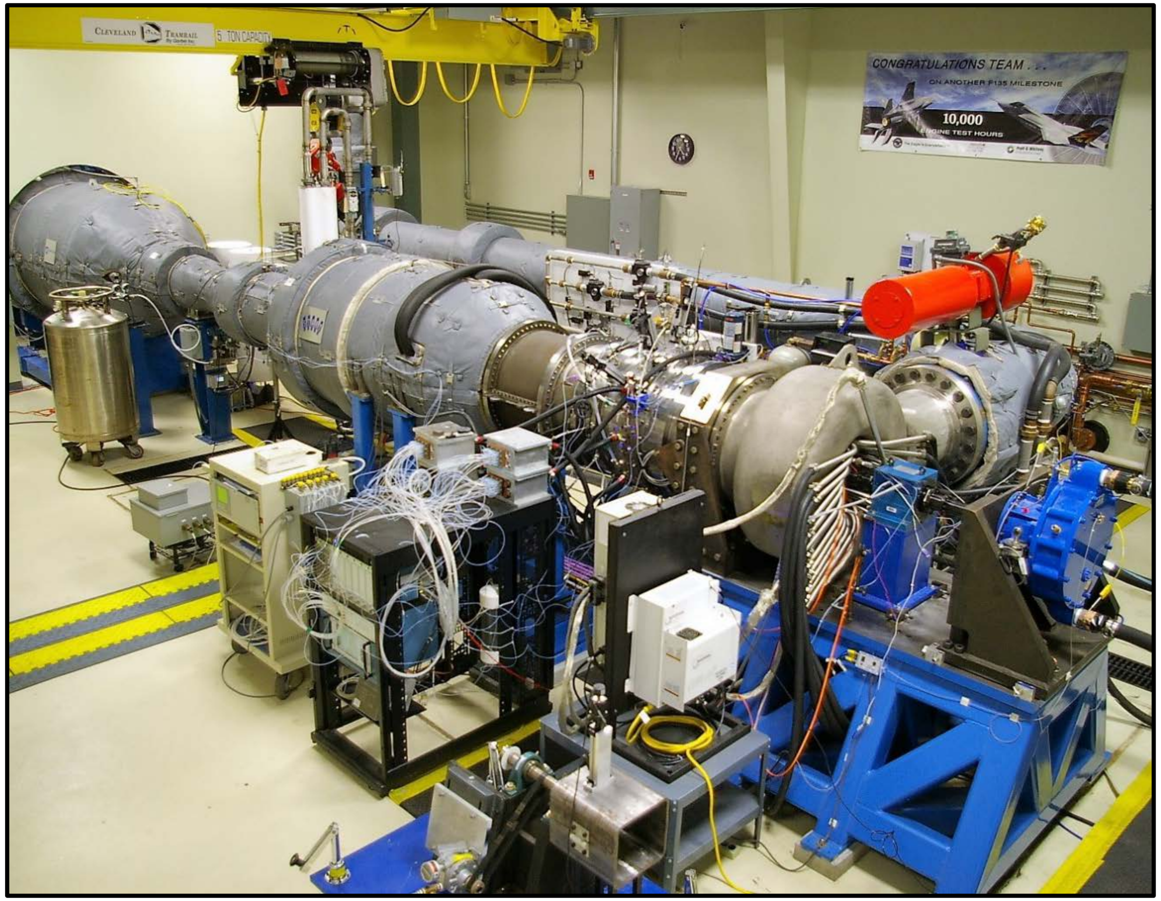


Technical Approach

- Research Tasks:
  - Project Management and Planning
  - Combustion System Faults and Data. (Experimental)
  - Turbine Faults and Data. (Experimental)
  - Virtual Combustor and Turbine Probes.
  - Big Data Analytics for Gas Turbine Health Monitoring

The PSU Steady Thermal Aero Research Turbine (START) Lab addresses four primary research focuses

Georgia Tech
PennState



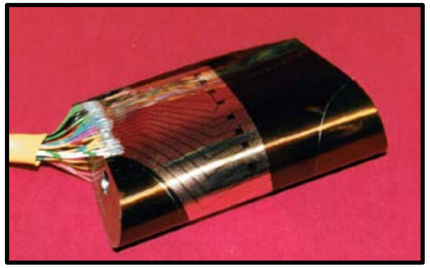
PRATT & WHITNEY DEPENDABLE ENGINES

U.S. DEPARTMENT OF ENERGY | Fossil Energy

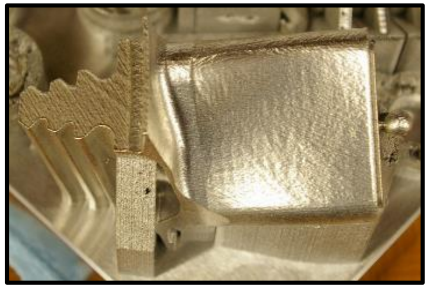
NETL NATIONAL ENERGY TECHNOLOGY LABORATORY

Study turbine performance with engine-relevant hardware

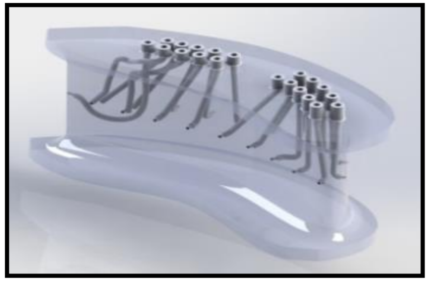
Test bed for instrumentation development



Advance the use of additive manufacturing in turbines

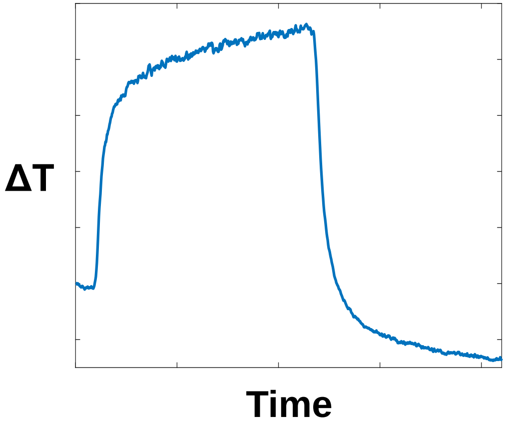


Direct integration of sensors in hardware

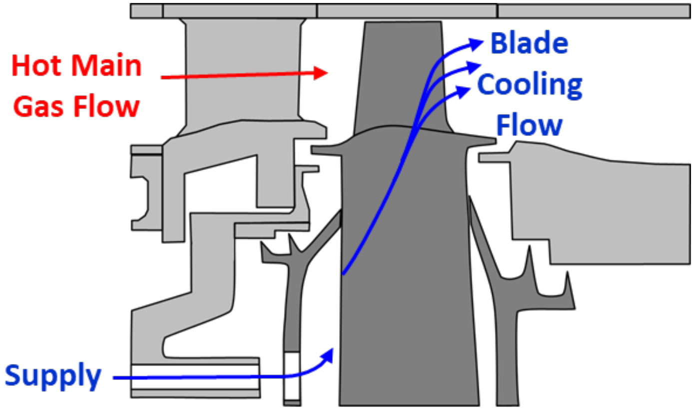


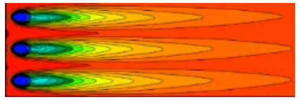
Four turbine faults will be demonstrated for this project

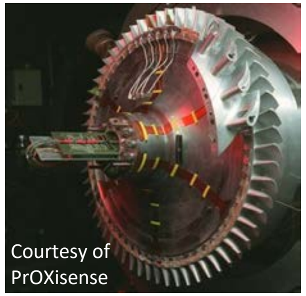
(1) Inlet Temperature Transients



(2) Blade Cooling Loss

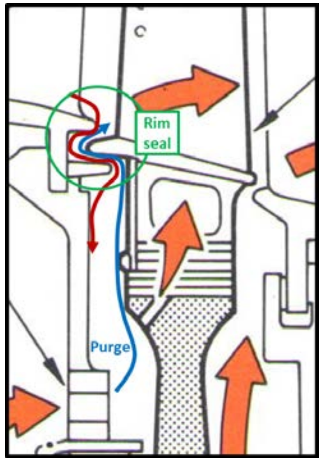


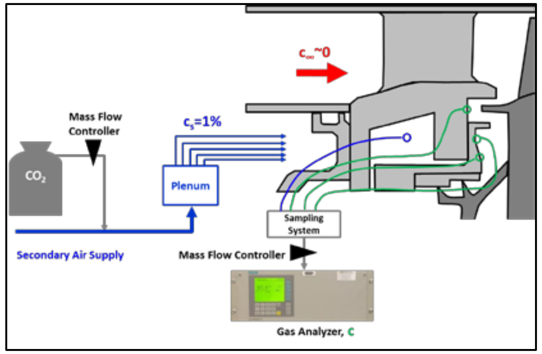




Courtesy of PrOXisense

(3) Inter-Stage Cooling Loss



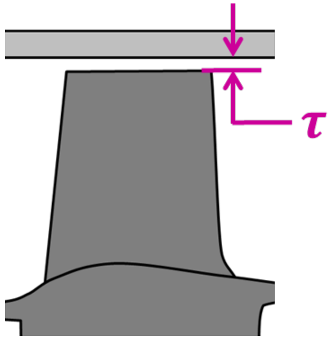


CO_2 tracer gas quantifies sealing effectiveness

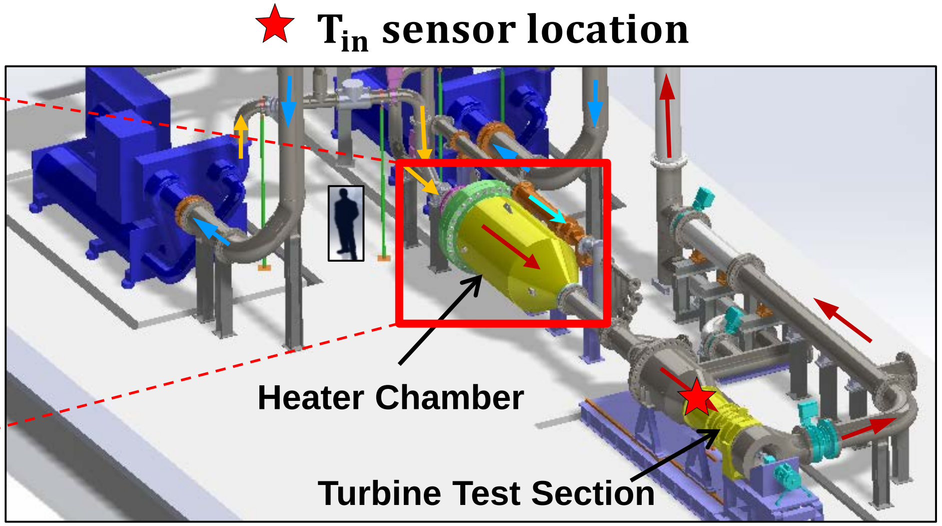
(4) Blade Tip Clearance

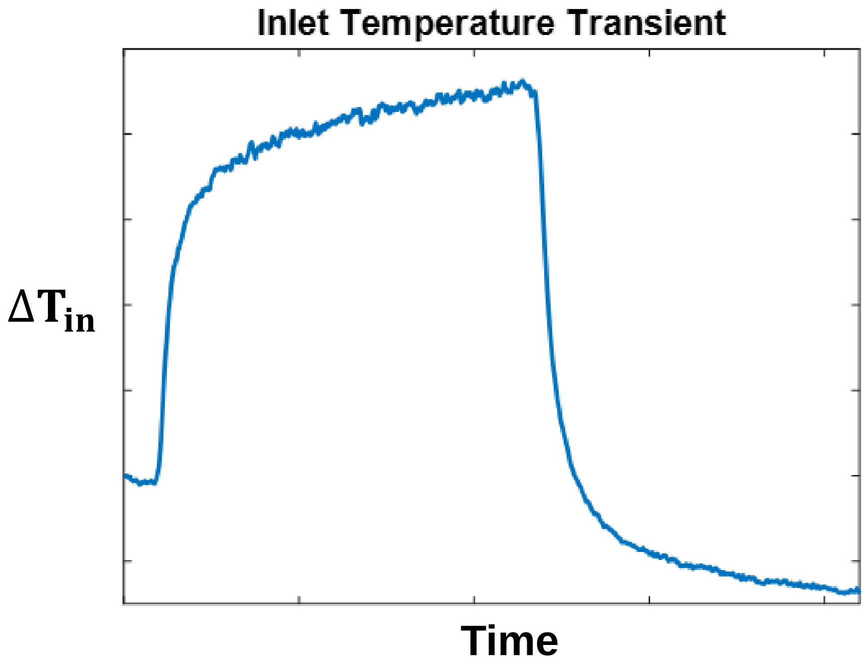
Magnetic bearings enable shaft alignment offsets to simulate local clearance changes

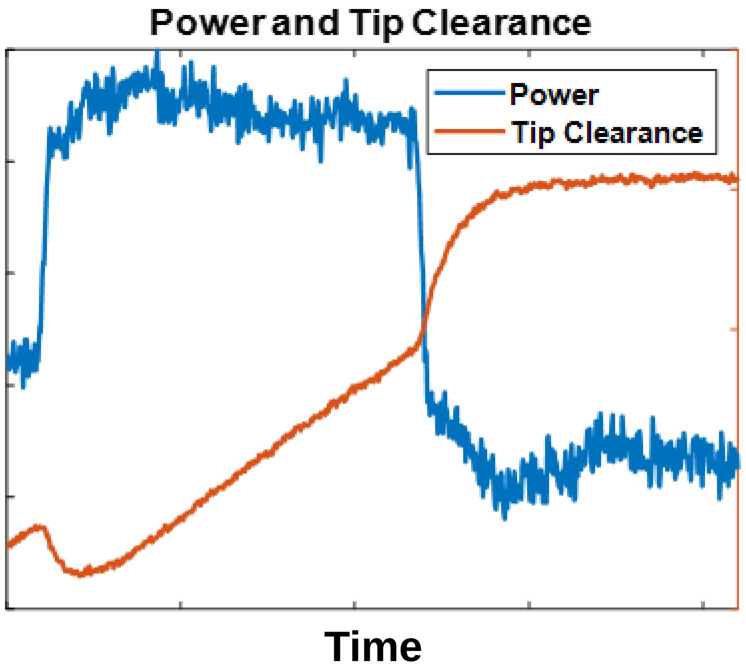
Courtesy of Synchrony



(1) An in-line natural gas heater simulates inlet temperature spikes



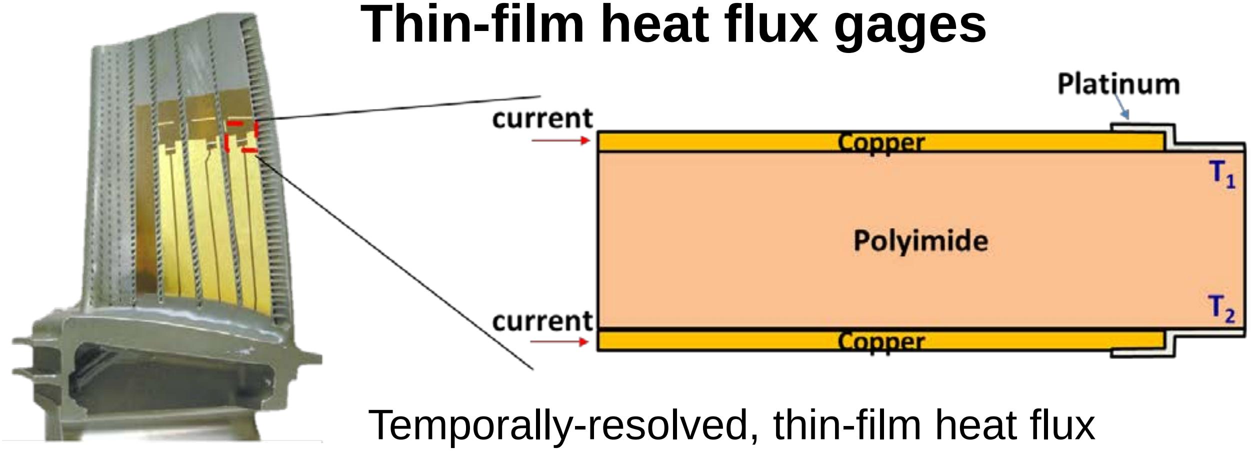




(2) Blade coolant loss detected by advanced measurement systems

Thermal Imaging

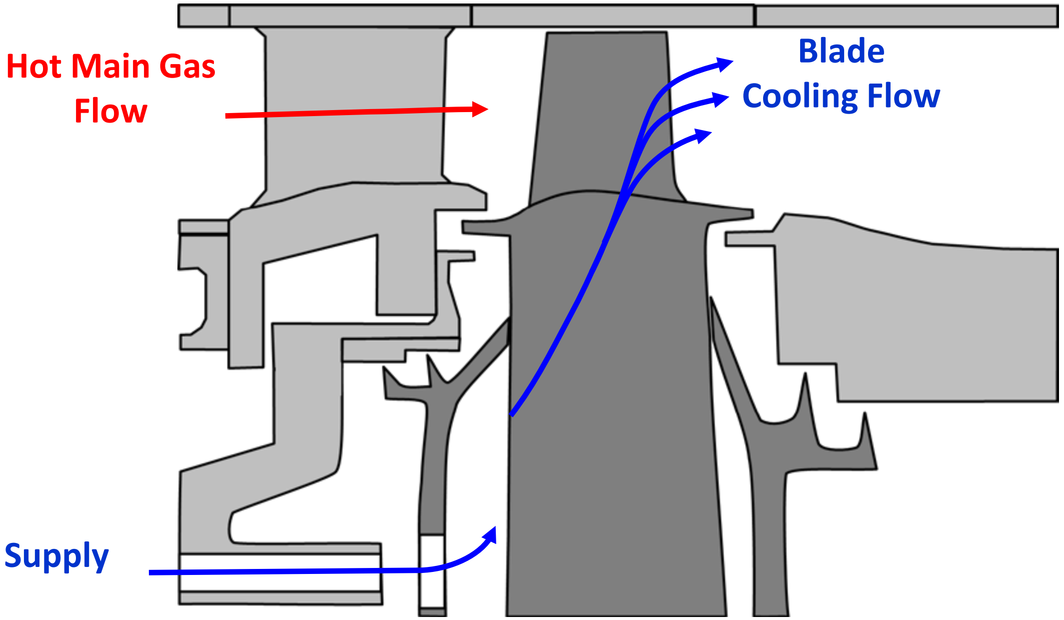
Spatially-resolved component views



Anthony et al. [2011]

Thin-film heat flux gages

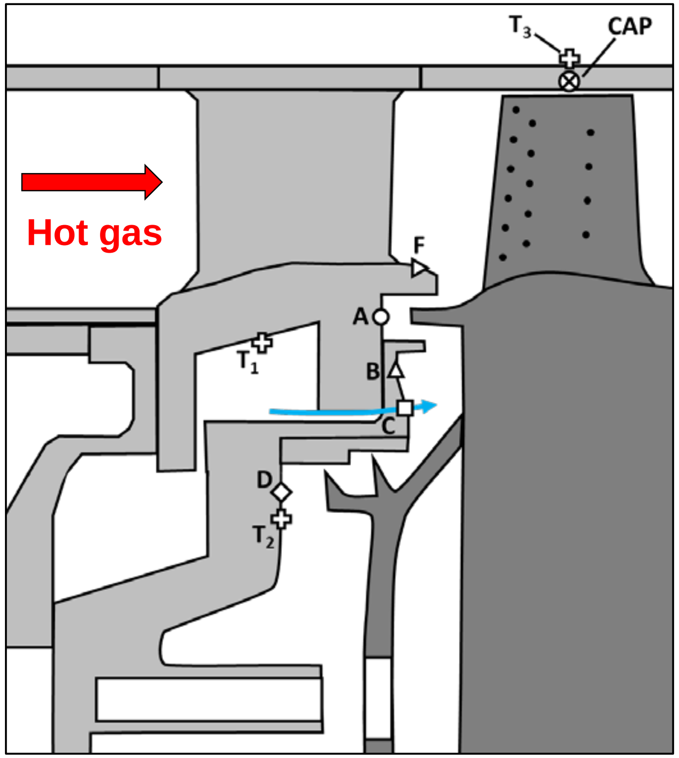
Temporally-resolved, thin-film heat flux gages mounted directly to blade surface

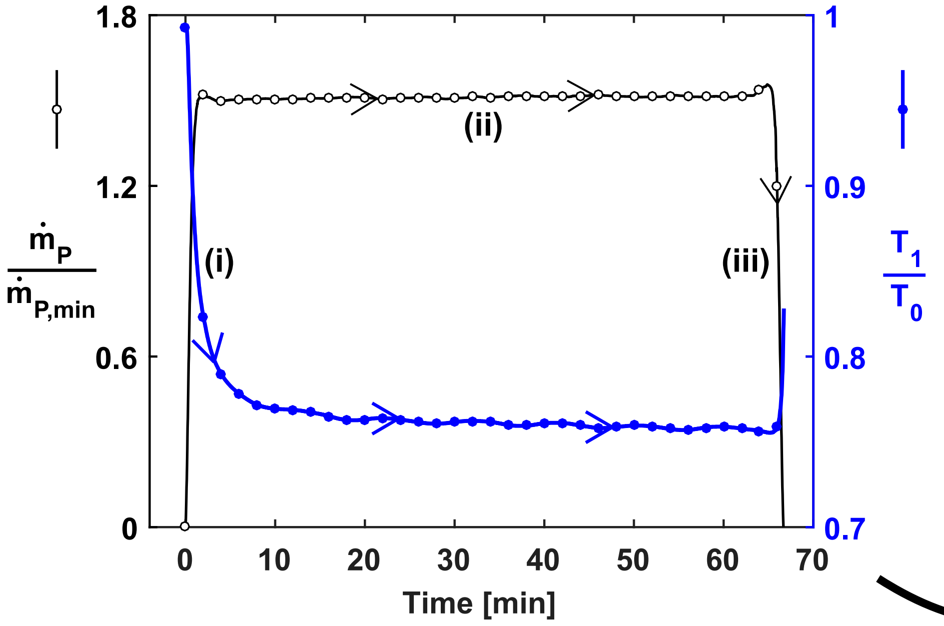


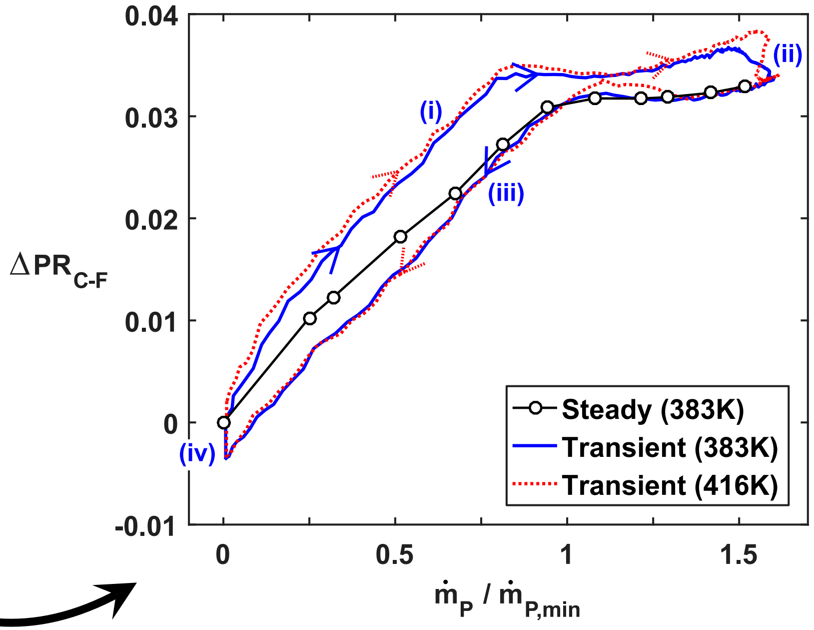
Coupling advanced measurement systems with simple turbine performance measurements can indicate the root cause of changes in turbine performance

These high fidelity datasets can be related back to simpler in service engine measurements

(3) Effects of inter-stage coolant transients have been identified



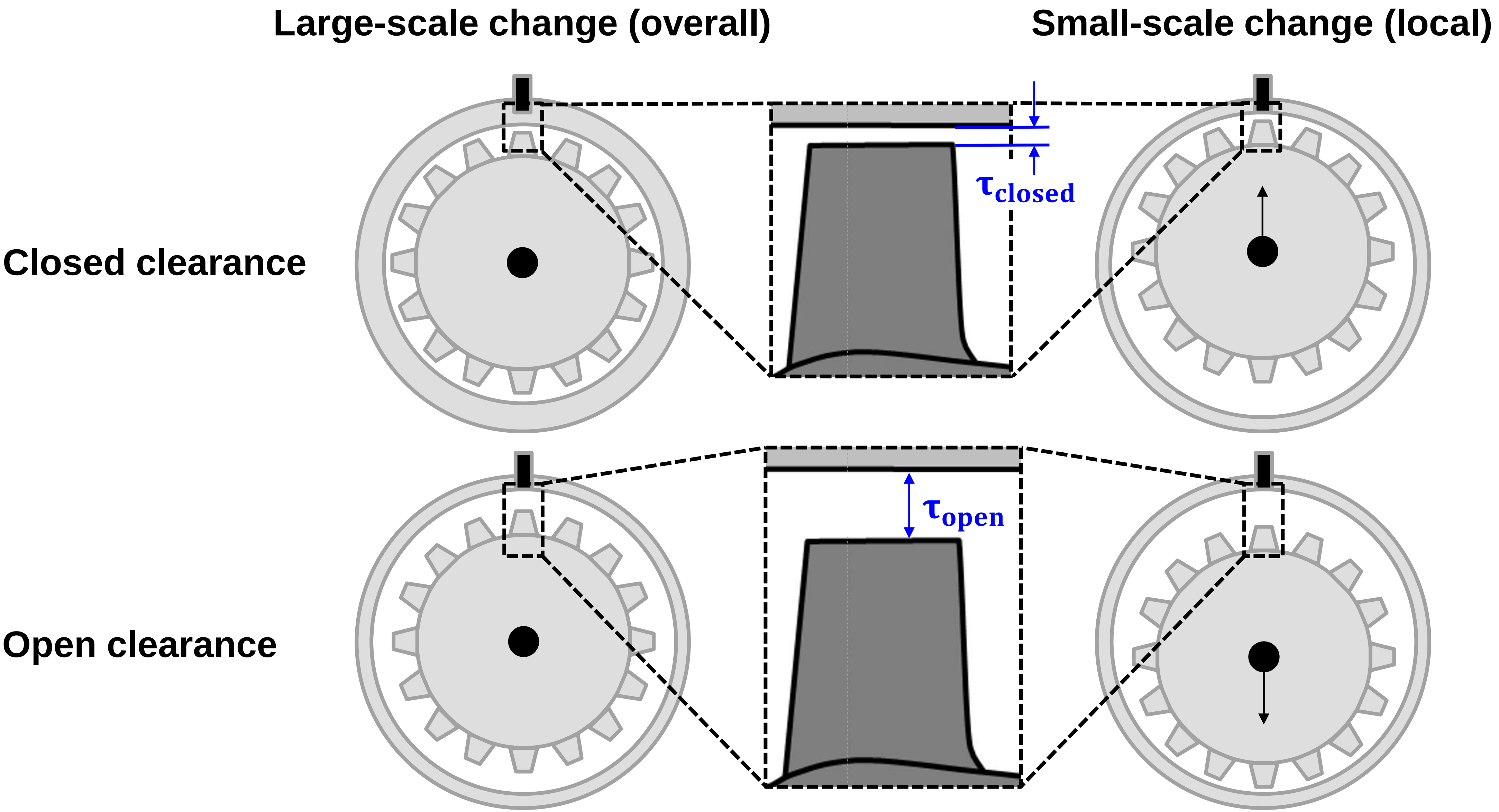




Hysteresis of measured cavity parameters caused by changing hardware temperature through transient event

Steady measurements + Transient measurements	→	Combined assessment of "slow" and "fast" coolant loss effects	→	Improved component lifing models including cavity flow physics changes

(4) Large- and small-scale tip clearance changes are demonstrated



Combustion Background: Hardware Faults

- Combustion system faults threaten entire hot section
  - Damage initiates with combustor/transition piece.
  - Liberated parts travel downstream and damage power turbine
- Common hardware faults:
  - Combustor liner cracks
  - Transition piece cracks
  - Melted fuel/air swirlers
  - **These failures alter flow paths!**

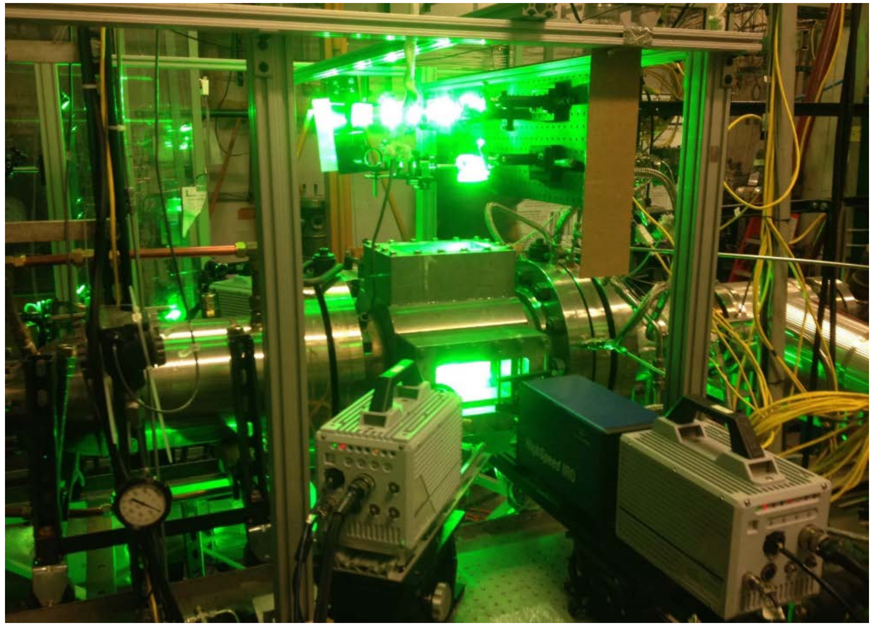
Goy *et al.*, in *Combustion instabilities in gas turbine engines: operational experience, fundamental mechanisms, and modeling*,
T. Lieuwen and V. Yang, Editors. 2005. p. 163-175.

Image courtesy of B. Igoe, Siemens

Combustion Background: Instrumentation

- In-engine instrumentation limited to basic point measurements
  - Single-point pressures, temperatures
  - Harsh conditions prevent instrumentation
- Combustor test rigs enable over-instrumentation
  - Optical accessibility admits optical diagnostics
  - Spatio-temporally resolved data
- Faults associated with altered flow paths and fluid dynamics
  - Directly detectable with over-instrumentation
  - Learn fault fingerprints in single-point data

https://www.omega.com



Over-instrumented blowout experiment in optically accessible combustion test rig at Georgia Tech

Combustion Background: Lean Blowout

Georgia Tech PennState

- Low NOx systems are particularly prone to lean blowout
- Lean blowout trips plant
  - Plant offline for lengthy shutdown, purge, restart cycle
- Substantial body of research on lean blowout precursor detection
  - Often detect precursors too late
  - Limited success with traditional approaches

NERC
NORTH AMERICAN ELECTRIC RELIABILITY CORPORATION

Industry Advisory

June 26, 2008

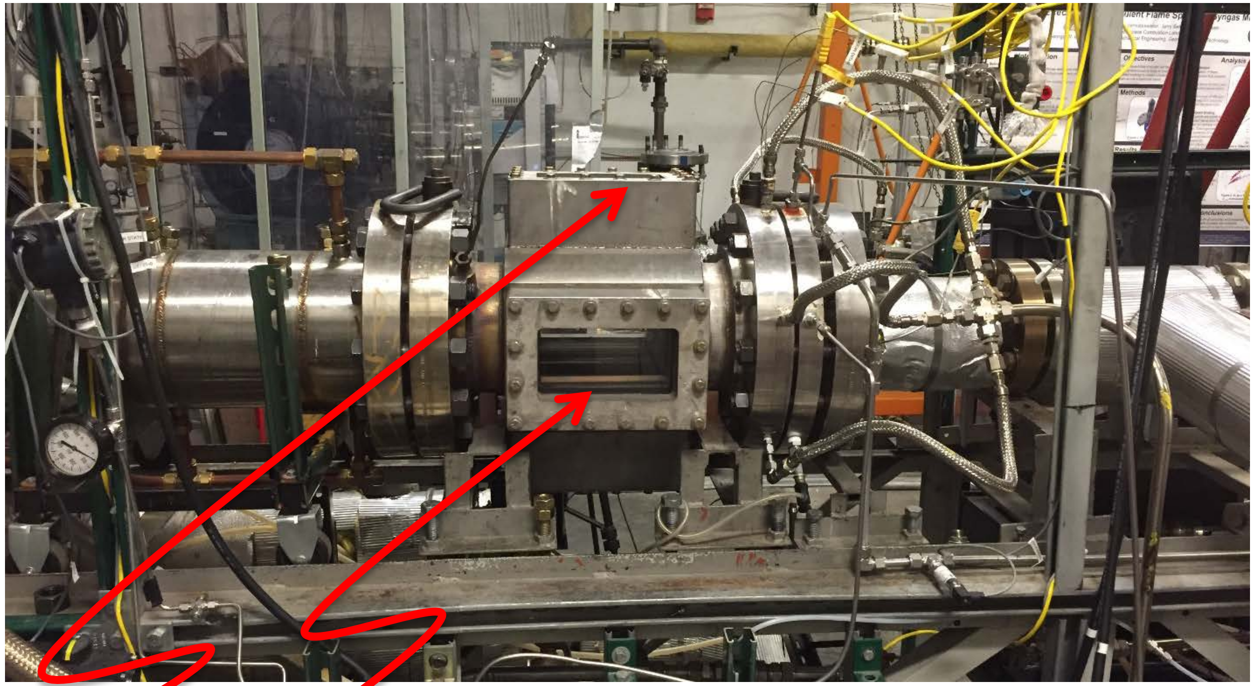
Background:

On Tuesday February 26th, 2008, the FRCC Bulk Power System experienced a system disturbance initiated by a138 kV transmission system fault that remained on the system for approximately 1.7 seconds. The fault and subsequent delayed clearing led to the loss of approximately 2,300 MW of load concentrated in South Florida along with the loss of approximately 4,300 MW of generation within the Region. Approximately 2,200 MW of under-frequency load shedding subsequently operated and was scattered across the peninsular part of Florida.

Indications are that six combustion turbine (CT) generators within the Region that were operating in a lean-burn mode (used for reducing emissions) tripped offline as result of a phenomenon known as “turbine combustor lean blowout.” As the CT generators accelerated in response to the frequency excursion, the direct-coupled turbine compressors forced more air into their associated combustion chambers at the same time as the governor speed control function reduced fuel input in response to the increase in speed. This resulted in what is known as a CT “blowout,” or loss of flame, causing the units to trip offline.

Blowout Rig

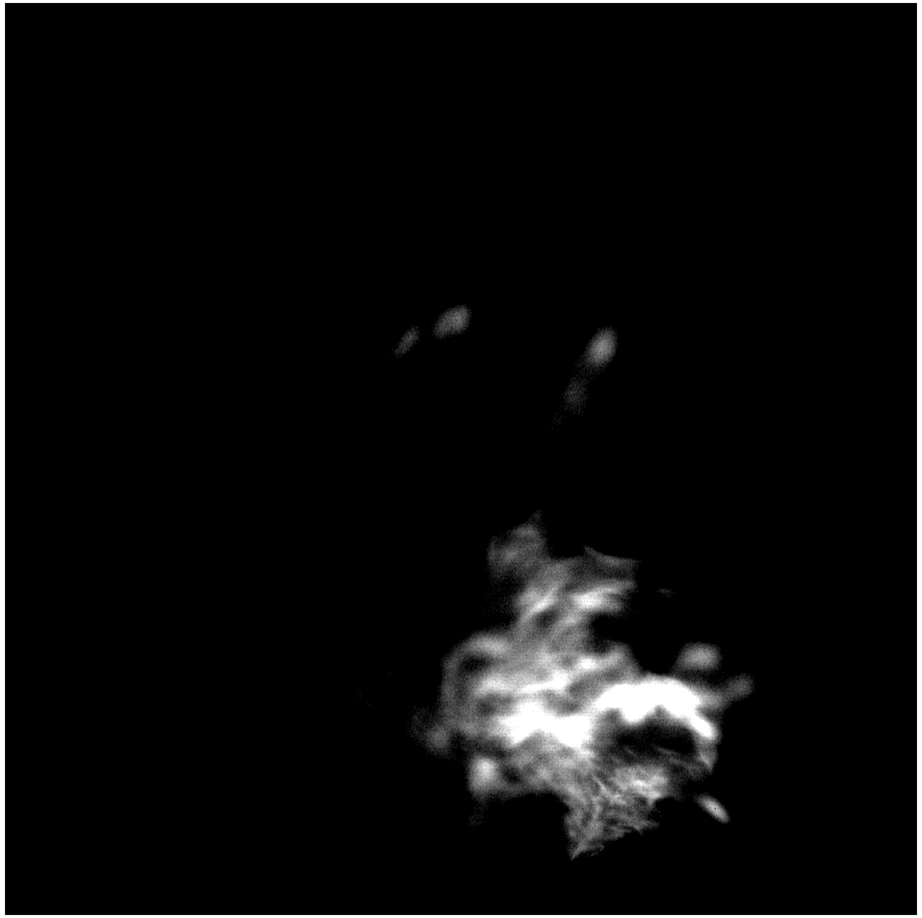
- Single-injector combustor test rig
- Relevant operating conditions
  - Inlet air temperatures up to 700 F
  - Gas turbine relevant pressures
- Substantial optical access for advanced diagnostics
- Acoustic probes (typical fielded single-point measurement)



Windows for lasers and high speed cameras

What does Blowout Look Like?

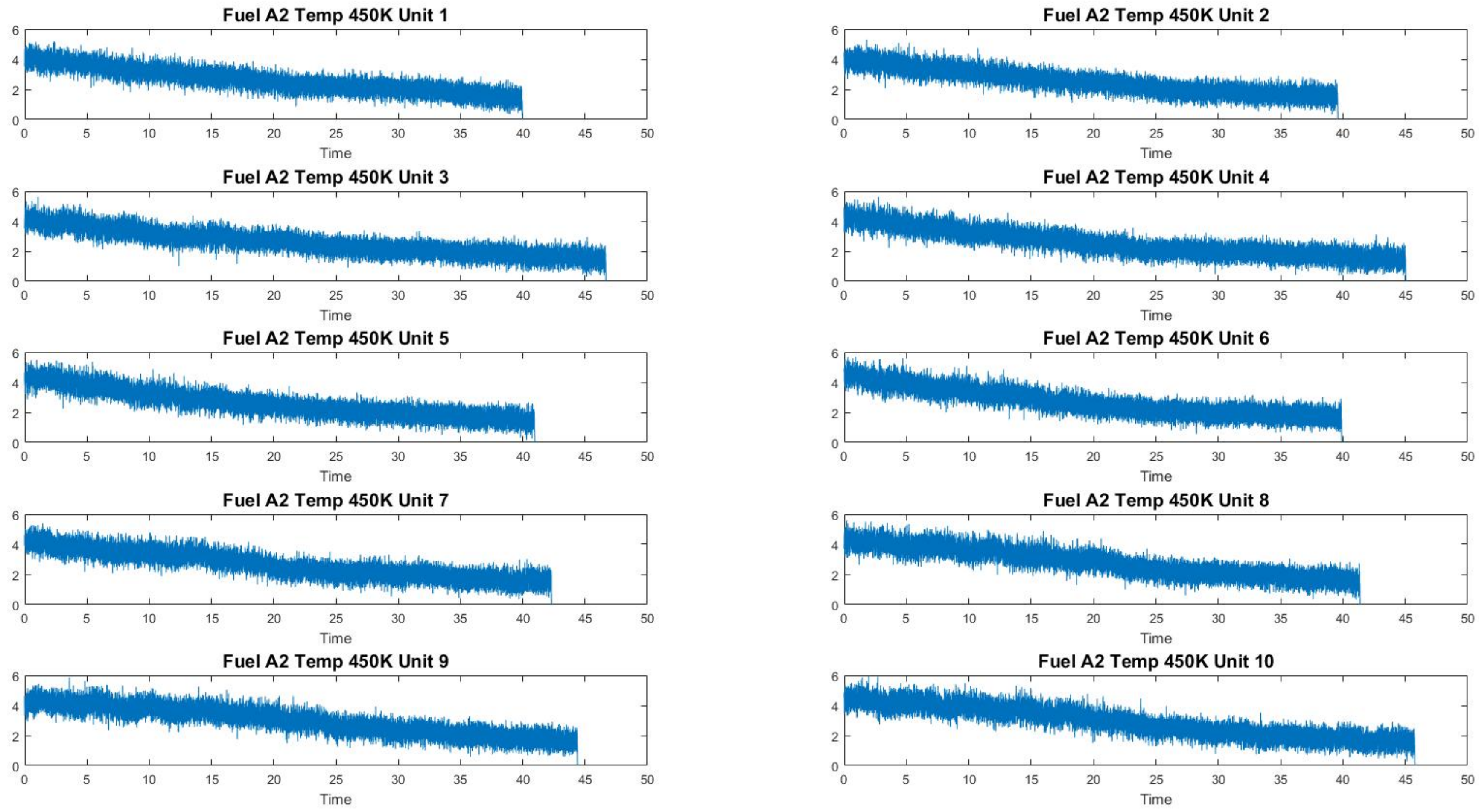
- High speed images shown near-blowout physics
  - Flame burns robustly
  - Large holes in flame
  - Flame is nearly extinguished, but reignites
- Intermittent stage can be sustained indefinitely
  - Eventually, when fuel/air ratio is low enough, flame doesn't recover
- Can we identify patterns in this extinction/re-ignition that provide blowout precursors?



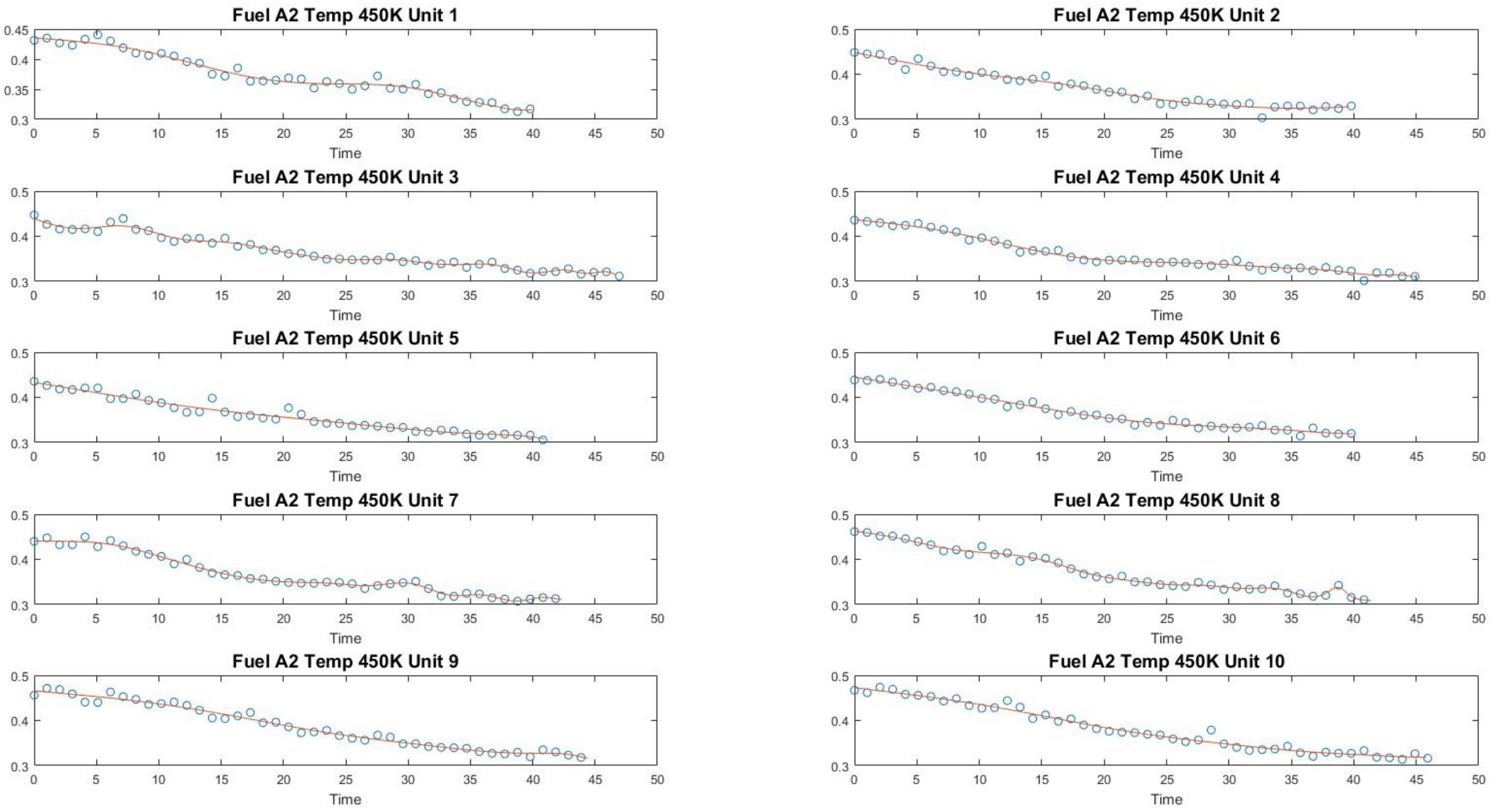
Lean Blowout Experiments and Data

- Combustion flame is maintained while an operator lowers the EQR until the flame is extinguished.
- Air Temperature and fuel type are kept constant at 450 K, and A2, respectively.
- Experiment is repeated for 10 units.
- Flame is monitored using a photomultiplier tube (PMT)
  - Provides a univariate measure of flame intensity
  - PMT Sampling rate of 10 kHz
    - Reduced to 1 kHz using non-overlapping moving average for denoising
- EQR is controlled by the operator
  - EQR Sampling rate of 1 Hz

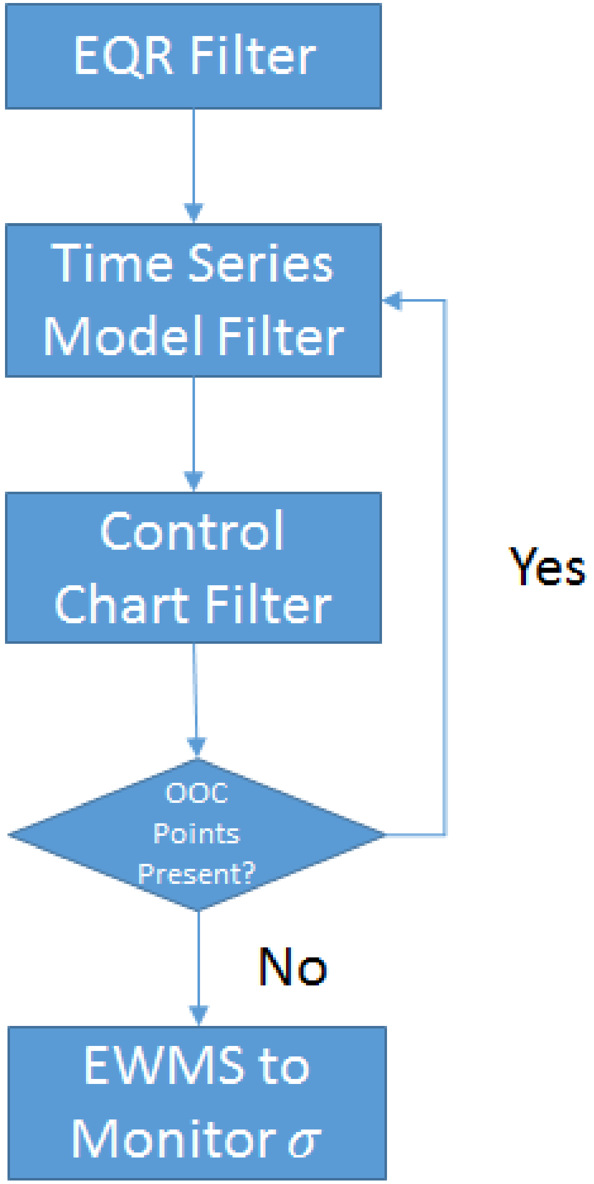
PMT Data – Visualization



EQR Data - Visualization



Methodology Overview

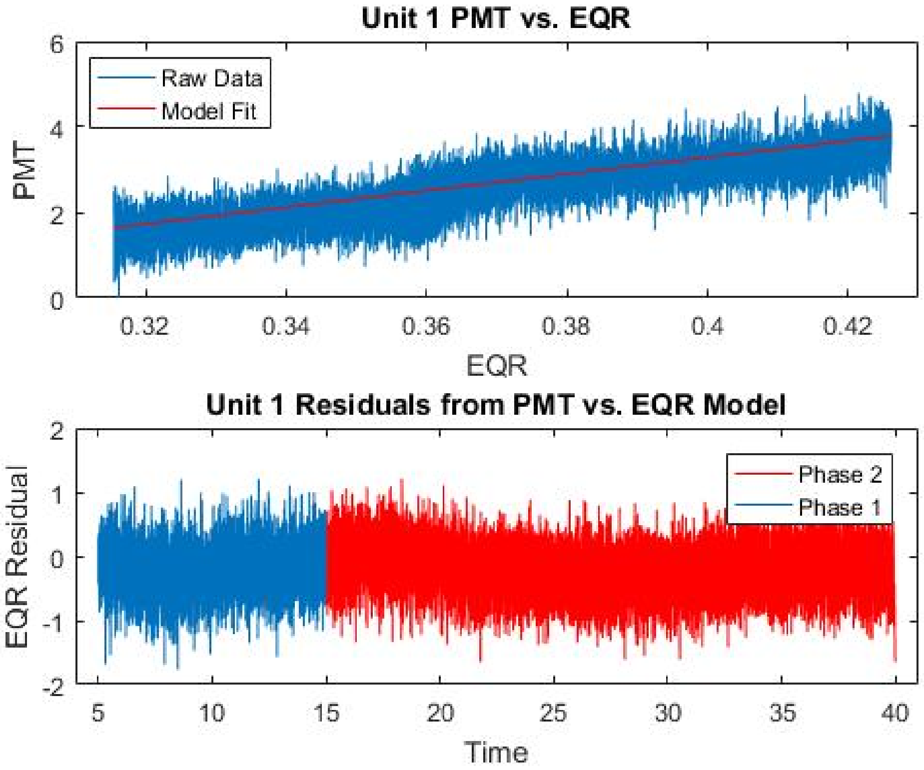


1. As the trend in the PMT signal is direct consequence of the EQR change, we filter out the effect of the EQR on the PMT.
2. The autocorrelation of regression residuals is removed using time-series models.
3. The outliers in training data are detected and removed using Shewhart control charts.
4. As PMT signals become more volatile close to lean blowout, an EWMS control chart is used to detect change in the variance.

Methodology: EQR Filter

- After filtering the effect of the EQR
  - Split data into Phase 1 and Phase 2
- Phase 1 (training) – System assumed to be working under normal operating conditions with only chance occurrences of outliers
  - All modeling is done in Phase 1
- Phase 2 – At some point, a change in the system occurs and the goal is to detect this change
  - Models applied to Phase 2

$$PMT_t = \beta_0 + \beta_1 EQR_t + \epsilon_{EQR_t}$$



Methodology: Time Series Filter

- Fit ARIMA and GARCH models on the Phase 1 residuals from the PMTI vs. EQR regression model

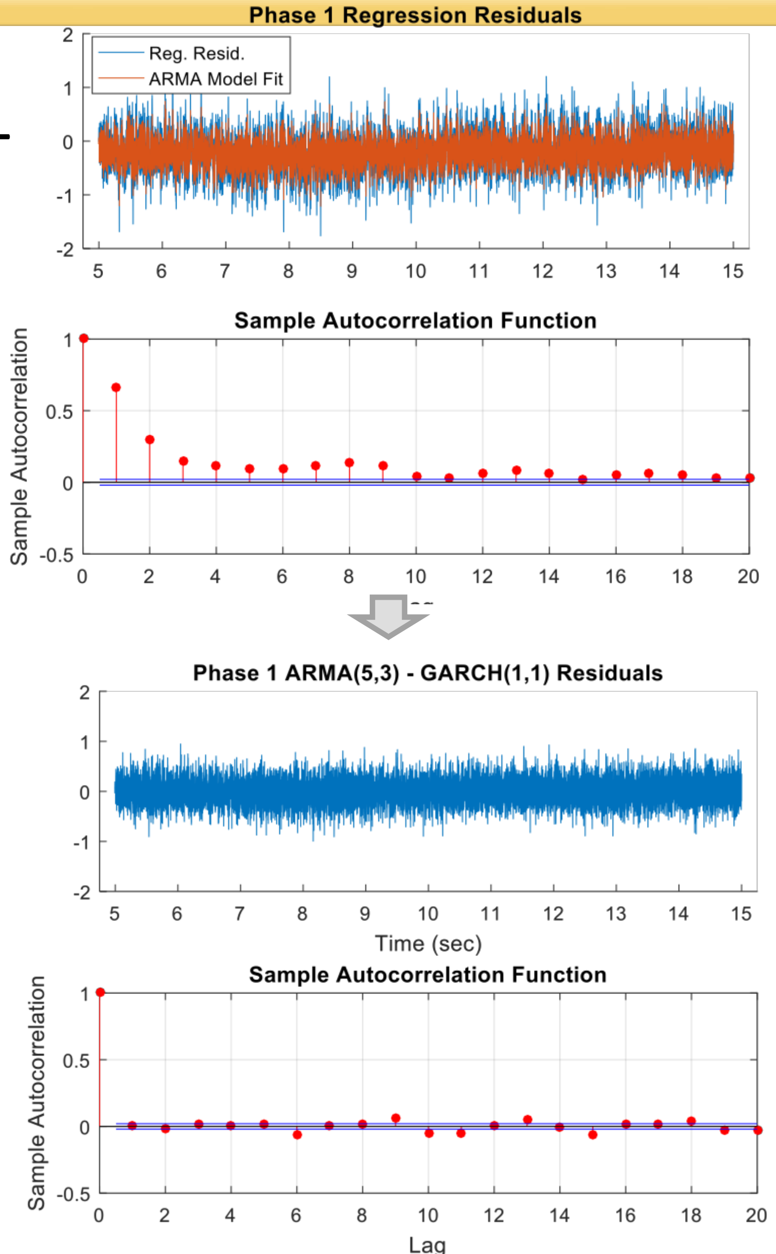
$$X_t = \mu + \sum_{i=1}^{p} \phi_i X_{t-i} + a_t - \sum_{j=1}^{q} \theta_j a_{t-j}$$

$a_t, a_{t-1}, \ldots$ are the prediction errors at time $t, t-1, \ldots$

$\sigma_t^2 = Var(a_t | a_{t-1}) = \alpha_0 + \alpha_1 a_{t-1}^2 + \eta_1 \sigma_{t-1}^2$

- The resulting residuals after ARIMA filter exhibit less autocorrelation.

$$X_t = -0.041 + 0.241X_{t-1} + 0.430X_{t-2} + 0.365X_{t-3} + 0.440X_{t-4}$$
$$+0.210X_{t-5} + a_t - 0.609a_{t-1} + 0.237a_{t-2} + 0.708a_{t-3}$$
$$\sigma_t^2 = 0.0066 + 0.8935a_{t-1}^2 + 0.0139\sigma_{t-1}^2$$



Methodology: Outlier Detection and Removal

- Use x-bar and S Shewhart control charts to detect and filter out outliers in Phase 1

- $\bar{x}$ chart

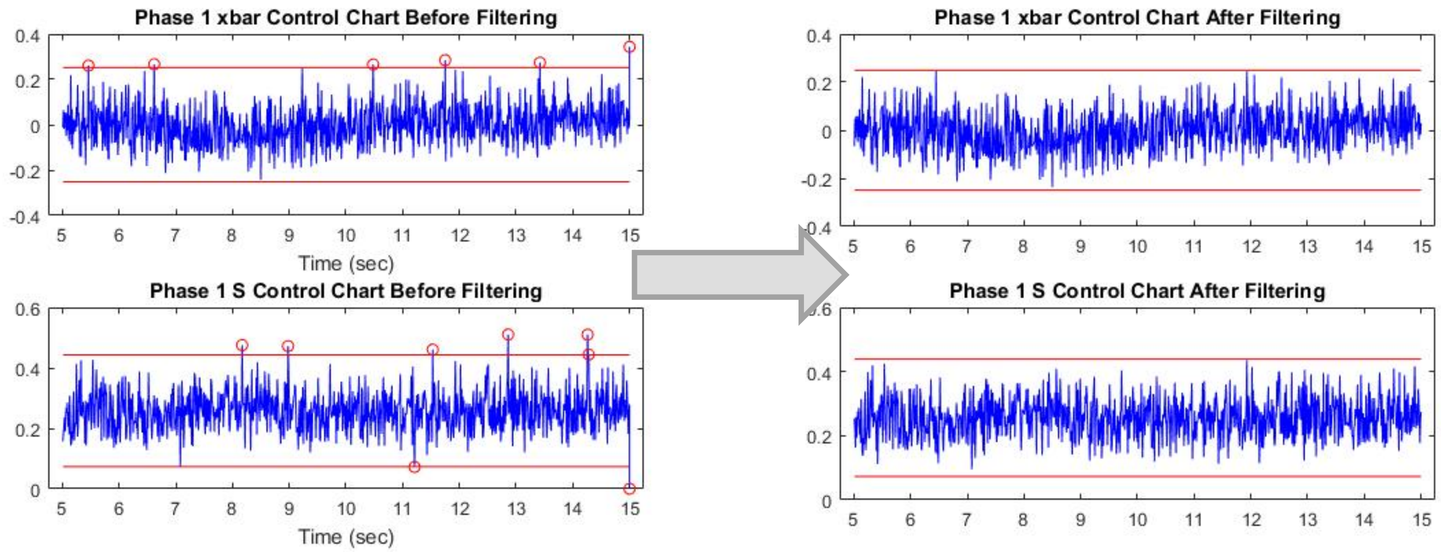
$$[LCL, UCL] = \hat{\mu}_x \mp L\hat{\sigma}$$

- S chart

$$[LCL, UCL] = \bar{s} \mp L\hat{\sigma}\sqrt{1 - c_4^2}$$

$$\hat{\mu}_x = \bar{\bar{x}}$$

$$\hat{\sigma} = \frac{1}{c_4}\left(\frac{1}{m}\sum_{j=1}^{m} s_j\right)$$

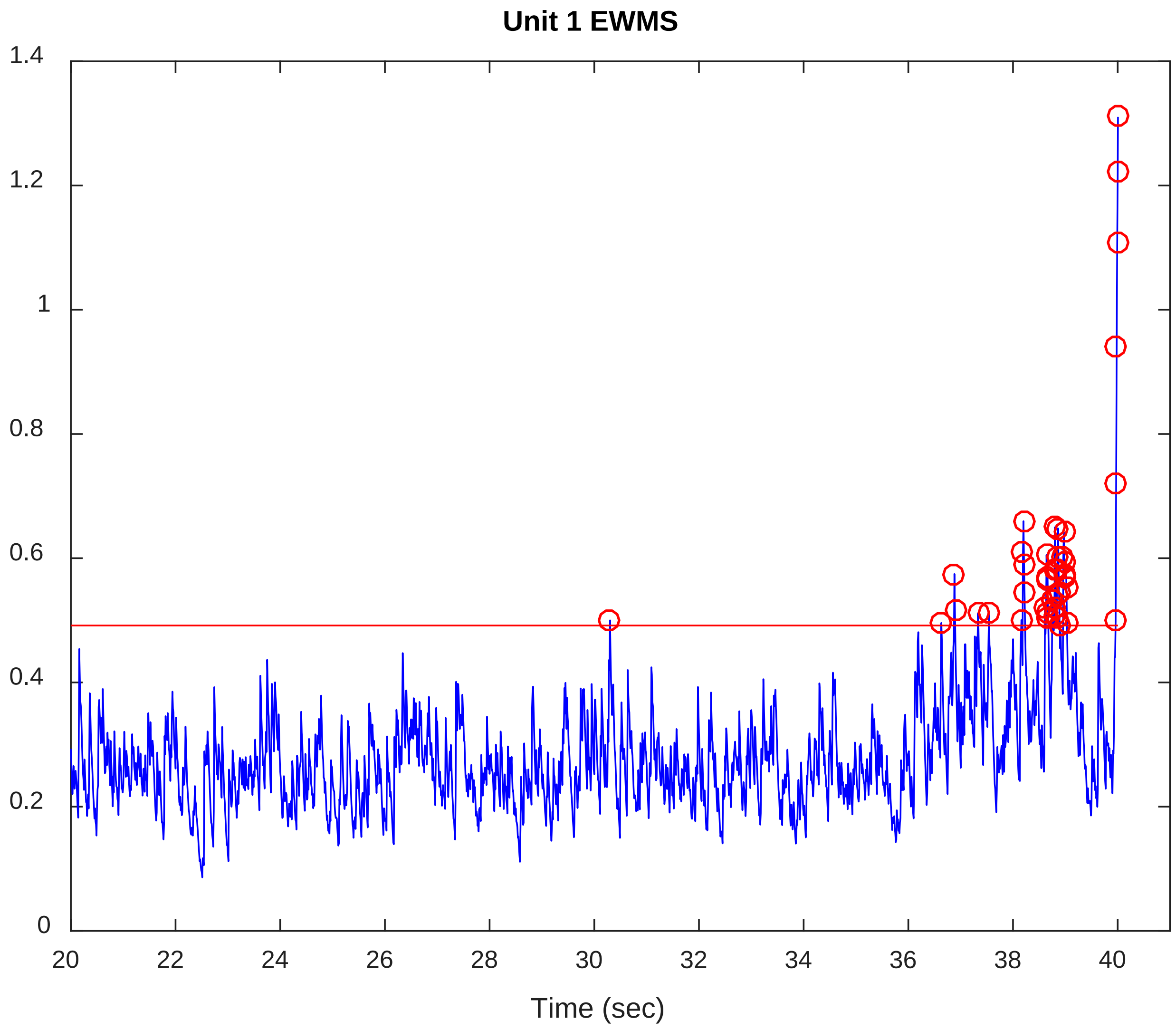


Methodology: Monitor Variance Using EWMS

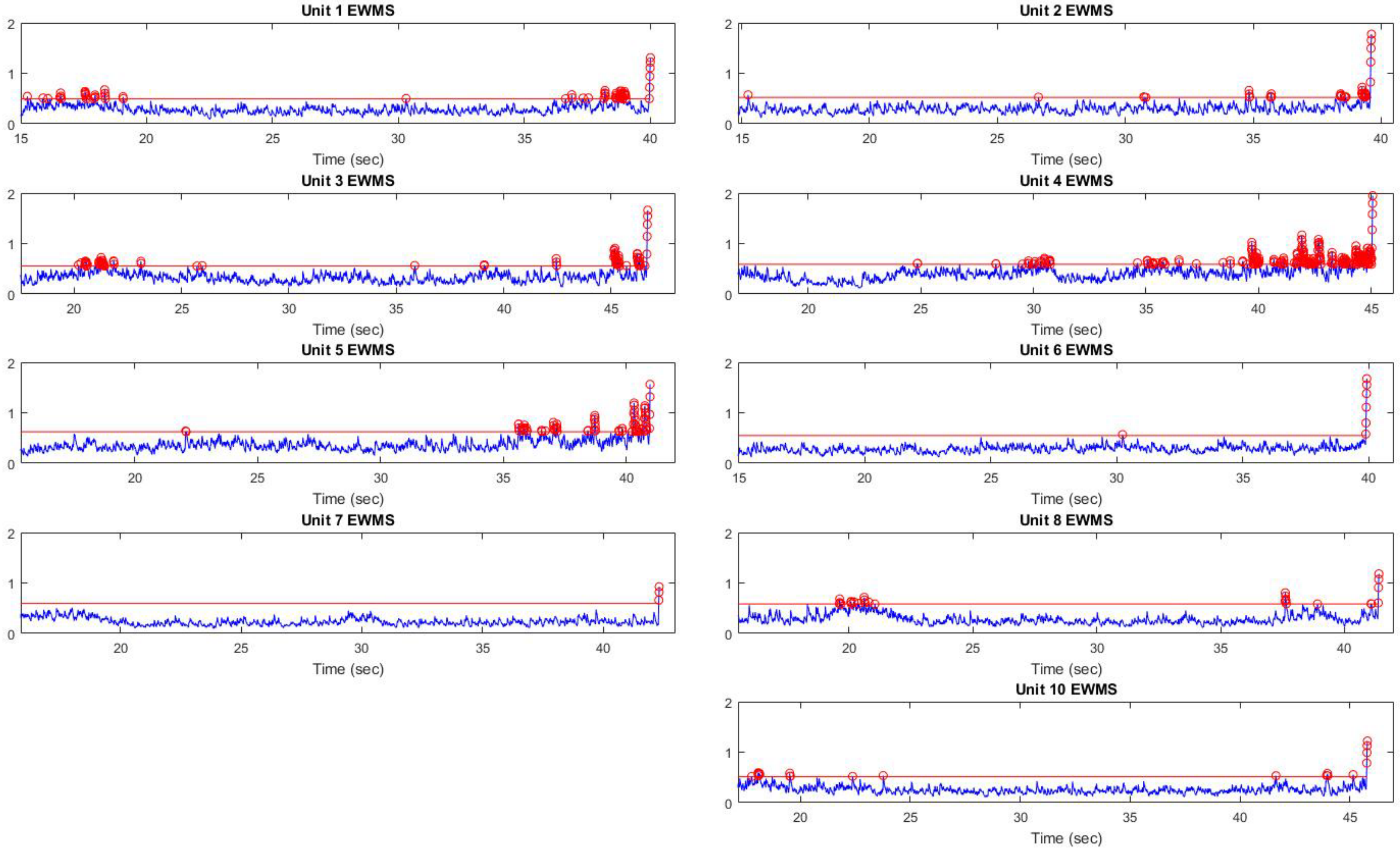
- To monitor the variance of residuals, we use Exponentially Weighted Moving Standard Error (EWMS)

$$S_k = \sqrt{(1-\gamma)S_{k-1}^2 + \gamma \bar{z}_k^2}$$

- Given false alarm rate α, LCL and UCL are determined as $100(\frac{\alpha}{2})$ and $100(1-\frac{\alpha}{2})$ percentiles of S_k from Phase 1



EWMS Control Charts



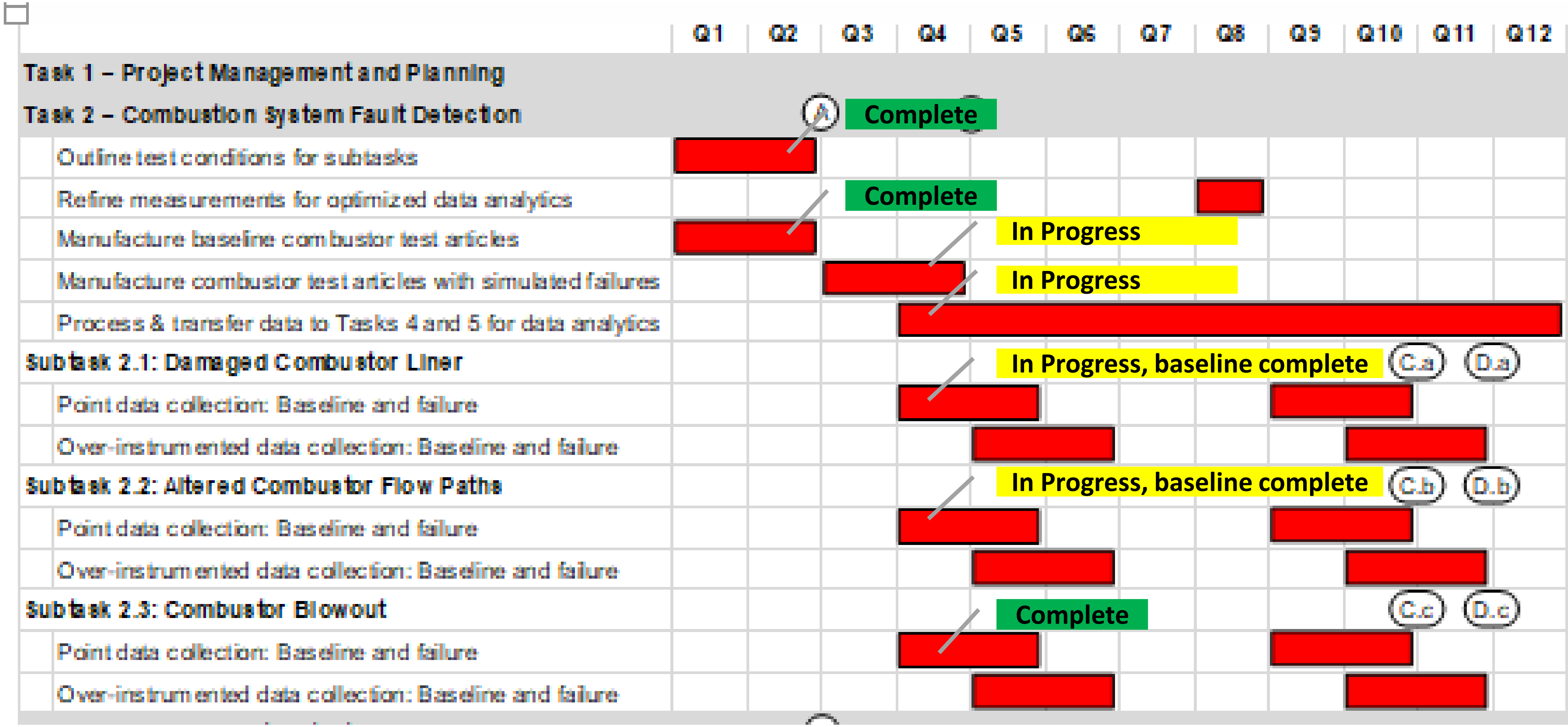
Distribution of Alarms wrt. EQR

Unit #/EQR	[0.40,0.38]	(0.38,0.36]	(0.36,0.34]	(0.32,0.34]	(0.32-0.30]	Total
1	0	24	1	4	39	68
2	1	0	0	37	0	38
3	0	16	21	24	25	86
4	0	0	2	41	181	224
5	0	0	2	0	74	76
6	0	0	0	1	6	7
7	0	0	0	0	3	3
8	0	7	9	7	7	30
10	12	2	0	1	8	23

Review of Research Tasks

- Research Tasks:
  - Project Management and Planning
  - Combustion System Faults and Data. (Experimental)
  - Turbine Faults and Data. (Experimental)
  - Virtual Combustor and Turbine Probes.
  - Big Data Analytics for Gas Turbine Health Monitoring

Timeline


Q1
Q2
Q3
Q4
Q5
Q6
Q7
Q8
Q9
Q10
Q11
Q12
Task 1 – Project Management and Planning
Task 2 – Combustion System Fault Detection
A
Complete
Outline test conditions for subtasks
Refine measurements for optimized data analytics
Complete
Manufacture baseline combustor test articles
In Progress
Manufacture combustor test articles with simulated failures
In Progress
Process & transfer data to Tasks 4 and 5 for data analytics
Subtask 2.1: Damaged Combustor Liner
In Progress, baseline complete
C.a
D.a
Point data collection: Baseline and failure
Over-instrumented data collection: Baseline and failure
Subtask 2.2: Altered Combustor Flow Paths
In Progress, baseline complete
C.b
D.b
Point data collection: Baseline and failure
Over-instrumented data collection: Baseline and failure
Subtask 2.3: Combustor Blowout
Complete
C.c
D.c
Point data collection: Baseline and failure
Over-instrumented data collection: Baseline and failure

Planned Research Activities

- Turbine fault data
- Additional hardware combustor faults (e.g. cracked combustor)
- Virtual probe developments
- Further analytic modeling and developments

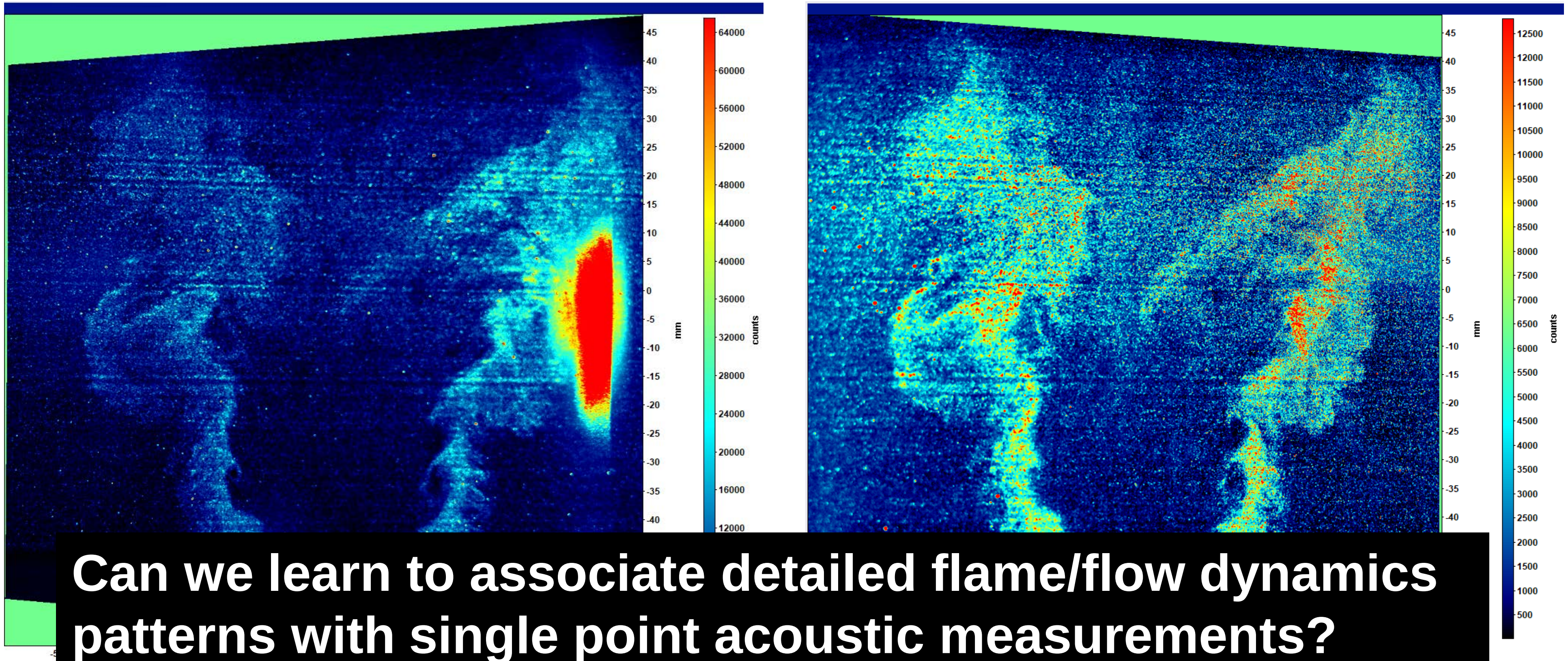
Thank You

Damaged Hardware Measurements

Eroded fuel/air premixer centerbody

Example Results

- Completed preliminary single-point and detailed measurements
- Example: flow visualization



Can we learn to associate detailed flame/flow dynamics patterns with single point acoustic measurements?

Current Work: Seeded Hardware Faults

- Premixing hardware consists of a centerbody and swirler
- These parts commonly degrade
- When these parts degrade due to cracks/melting, they cause
  - Worse emissions
  - Narrowed operability
  - Performance Loss
- Approach: Install damaged parts and assess ability to detect the issue
- Completed work:
  - Baseline measurements complete for healthy hardware
  - Design of eroded centerbody complete