

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

Project Kickoff Meeting
October 26, 2017

PIs: Nagi Gabraeel¹, Tim Lieuwen², Kamran Paynabar¹, Reid Berdanier³, Karen Thole³
PO: Omer Bakshi

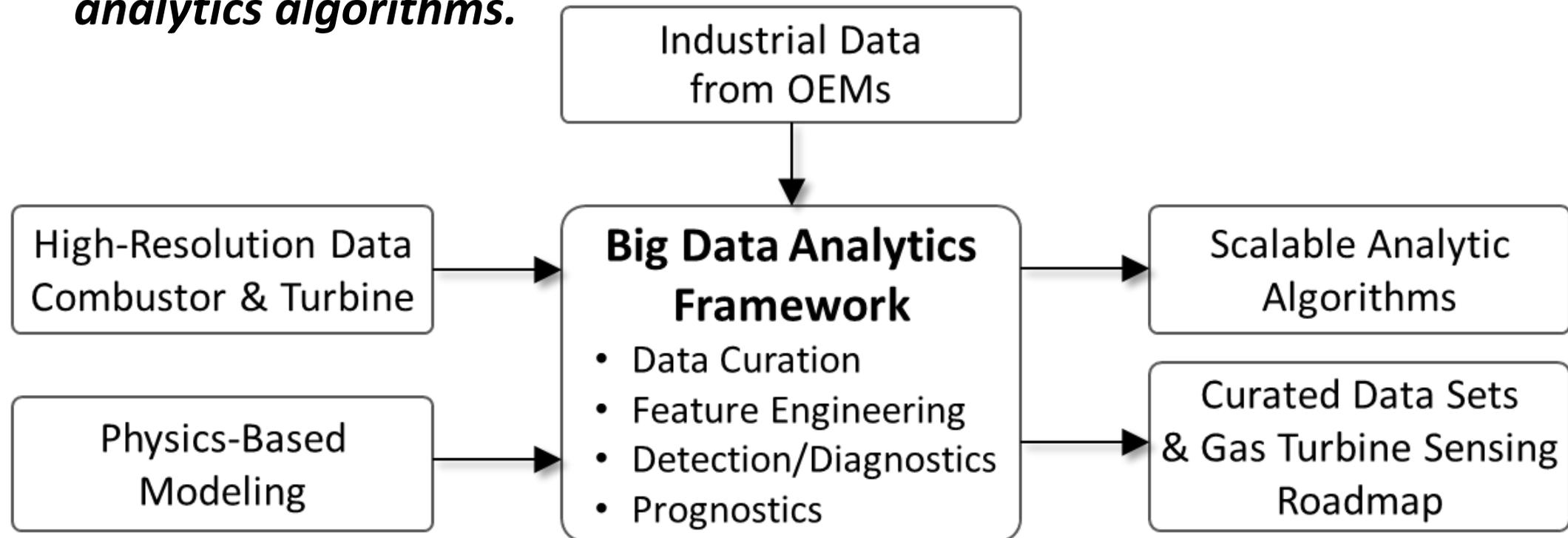
¹School of Industrial and Systems Engineering, Georgia Tech

²School of Aerospace Engineering, Georgia Tech

³Department of Mechanical and Nuclear Engineering, Penn State

- Gas turbines and combined-cycle plants are equipped with hundreds to thousands of sensors.
- Data generated by the sensors are used for monitor turbine performance or physical degradation.
- Large volume of data generated by these sensors and conventional data analytic tools are no longer effective.
- **Big Data Analytics** holds enormous potential for improving the reliable operation of power generating gas turbines and combined cycle plants.

- 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.*



- Develop a Big Data Analytics platform for critical gas turbine components using a systematic **experimental design** that aims to generate data-driven fault signatures using industry-class turbine test rigs.
- Interdisciplinary team of PIs:
 - Reid Berdanier: Penn State
 - Nagi Gabraeel: Georgia Tech
 - Tim Lieuwen: Georgia Tech
 - Kamran Paynabar: Georgia Tech
 - Karen Thole: Penn State

- **The project is organized into five tasks:**
 - Task 1: Project Management and Planning.
 - Task 2: Combustion System Fault Detection. (Experimental)
 - Task 3: Turbine Fault Detection. (Experimental)
 - Task 4: Virtual Combustor/Turbine Probes. (Analytical)
 - Task 5: Big Data Analytics for Gas Turbine Health Monitoring. (Analytical)

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 initiate as
 - 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: Lean Blowout

- 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 a 138 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.

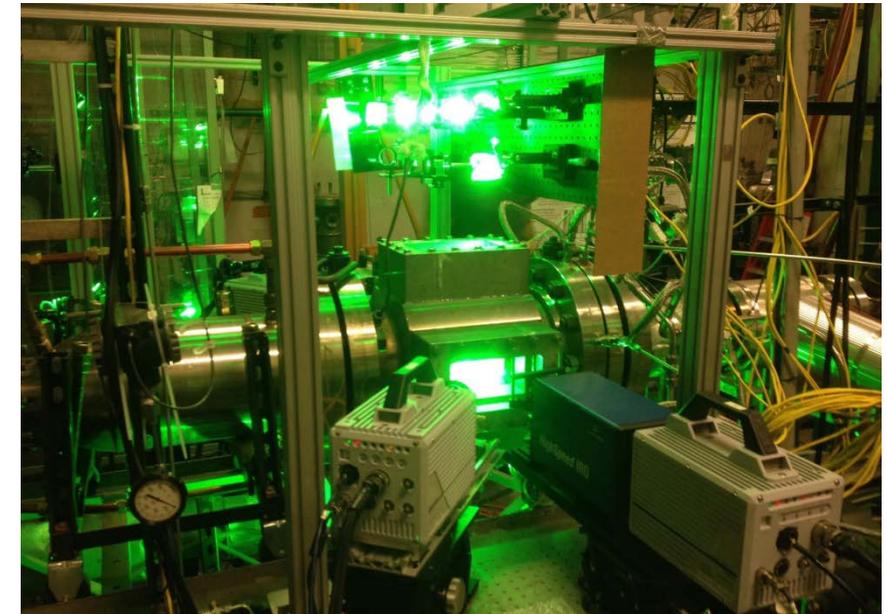
Indications are that six combustion turbine (CT) generators within the Region that were operating in a lean-burn mode (used for reducing emissions) tripped offline as result of a phenomenon known as "turbine combustor lean blowout." As the CT generators accelerated in response to the frequency excursion, 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.

Combustion Background: Instrumentation

- In-engine instrumentation limited to basic point measurements
 - Single-point pressures, temperatures
 - Harsh conditions prevent instrumentation of some parts of flow path due to reduced probe durability
- Combustor test rigs enable over-instrumentation
 - Optical accessibility admits optical diagnostics
 - Spatio-temporally resolved data even in harsh regions
- Faults associated with altered flow paths/fluid dynamics
 - Directly detectable with over-instrumentation
 - Learn fault fingerprints in single-point data



<https://www.omega.com>

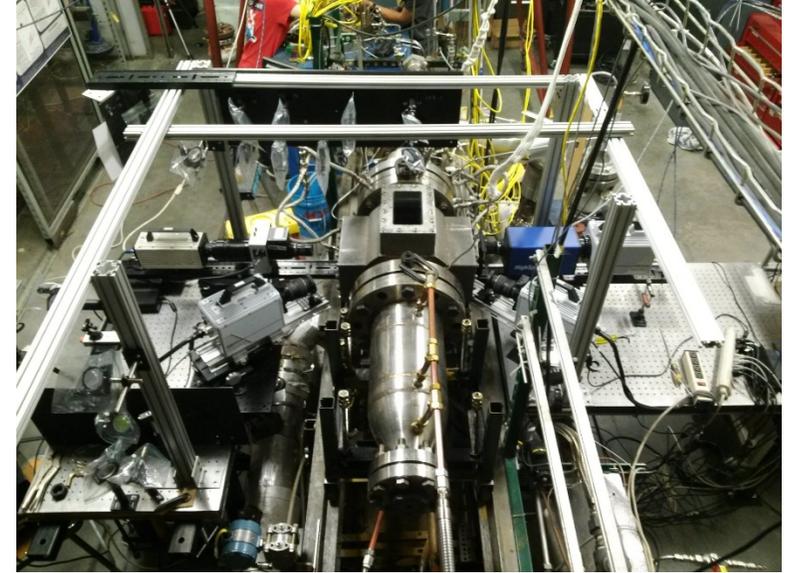


Over-instrumented blowout experiment in optically accessible combustion test rig at Georgia Tech

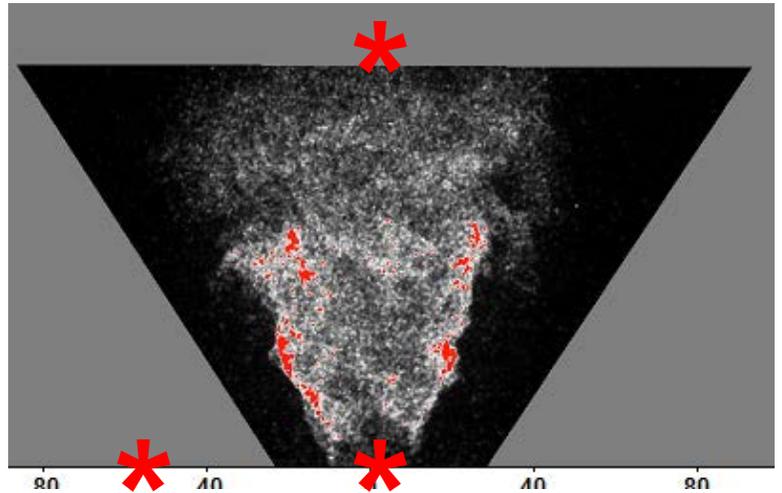
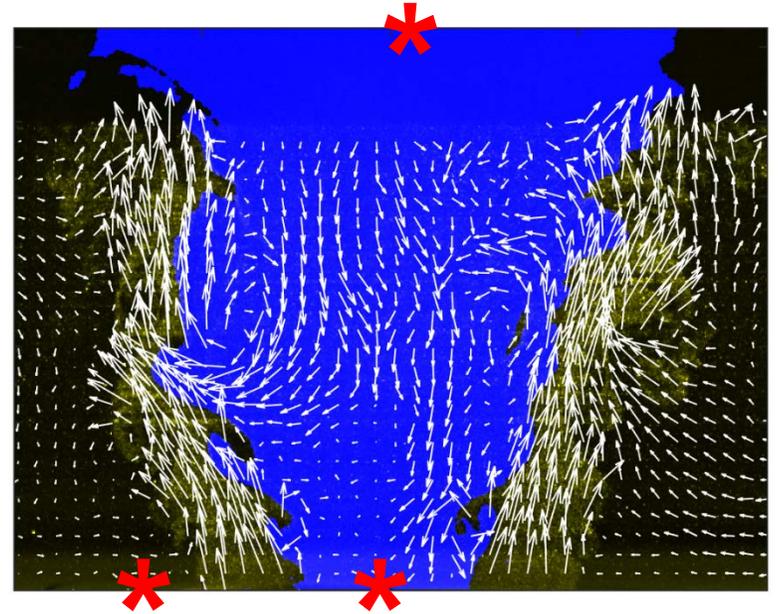
Combustion Goals (Task 2)

	Experiment: Hardware Fault <ul style="list-style-type: none">• Baseline experiment with “good” hardware• Experiment with damaged liner• Experiment with swirler	Experiment: Lean blowout <ul style="list-style-type: none">• Baseline experiment at stable operating point• Failure data: operation at blowout limit
Point-Data Same as in-engine data	<ul style="list-style-type: none">• Operating conditions: inlet T, P• Combustion dynamics• Emissions	
Over-instrumented Data In addition to point data Optical diagnostics Spatio-temporal resolution	<ul style="list-style-type: none">• Particle image velocimetry• High-speed chemiluminescence imaging• Focus on flow alteration in vicinity of fault<ul style="list-style-type: none">• Altered mixing• Altered flame configuration	<ul style="list-style-type: none">• Particle image velocimetry• High-speed chemiluminescence imaging• Focus on flow dynamics<ul style="list-style-type: none">• Vortex shedding• Local extinction

- Lean blowout
 - Perform measurements in high pressure test rig
 - Experience operating this rig near/at blowout
 - Experience with detailed diagnostics
- Hardware fault
 - Perform measurements in atmospheric pressure rig
 - Greater degree of optical accessibility to observe minute flow field changes



- Measure detailed physics
 - **Particle image velocimetry**: particularly useful for hardware fault characterization
 - **High speed chemiluminescence**: particularly useful for lean blowout characterization
- Learn to infer these detailed physics from point measurements
 - Inlet pressure
 - Inlet temperature
 - Acoustic pressure
 - Emissions

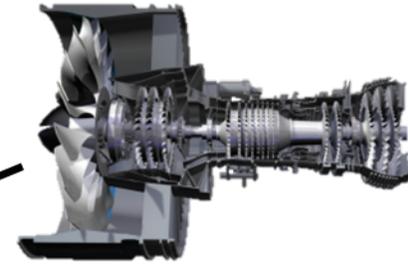
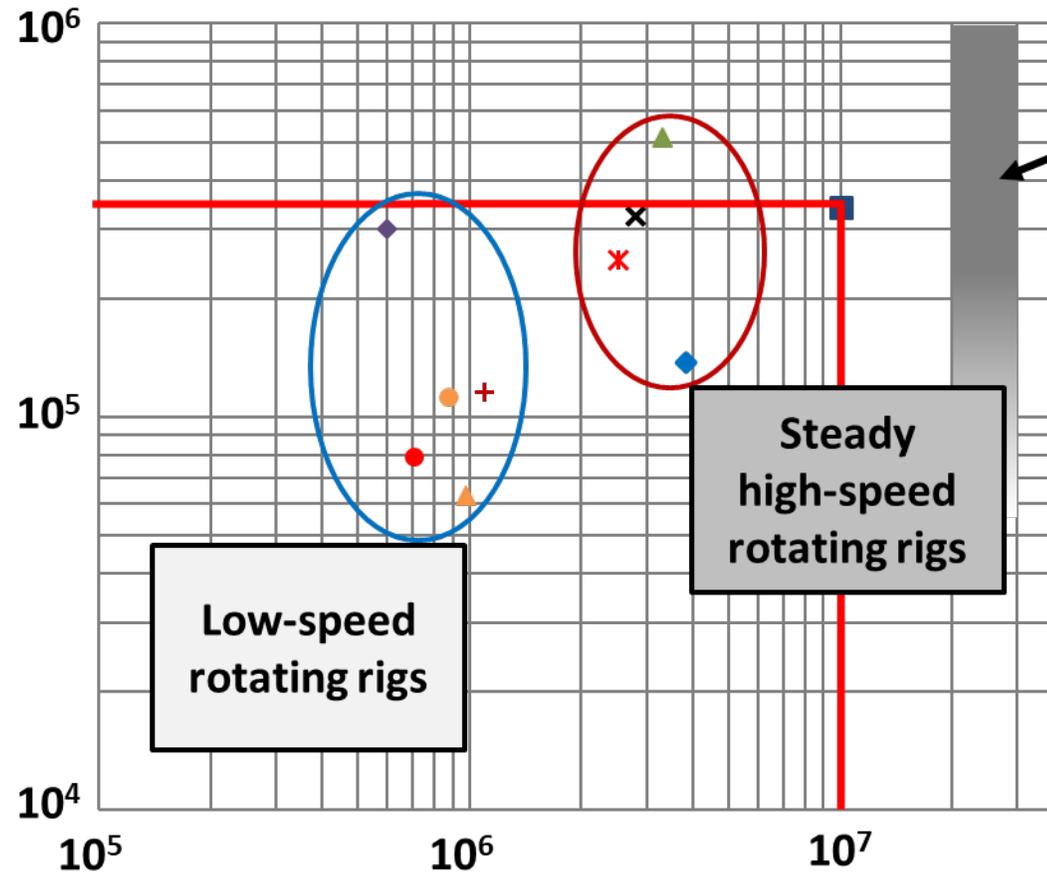


The PSU Steady Thermal Aero Research Turbine (START) Lab was designed to push the envelope of turbine test facilities



Blade Inlet Reynolds Number,

$$Re_x = \frac{\rho_\infty U_x C_x}{\mu_\infty}$$

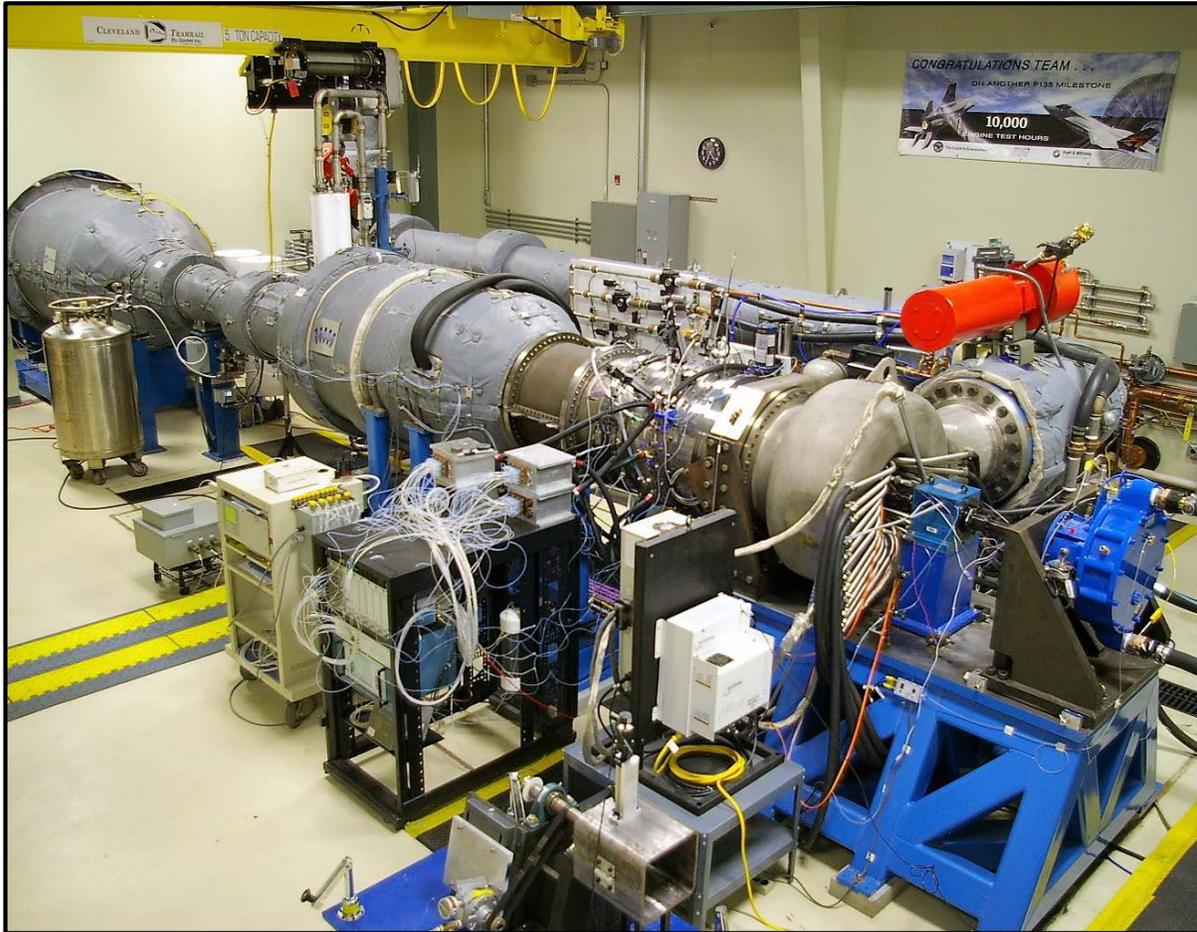


- PSU START
- ▲ GE HGIR
- × Sussex
- ✗ RWTH: Aachen
- ASU 1
- ASU 2
- ▲ Bath
- ◆ Purdue: LSRT
- + ND - ART
- ◆ NASA W6

Rotational Reynolds Number,

$$Re_\phi = \frac{\rho \Omega R^2}{\mu} \Big|_{\text{Hub, Purge}}$$

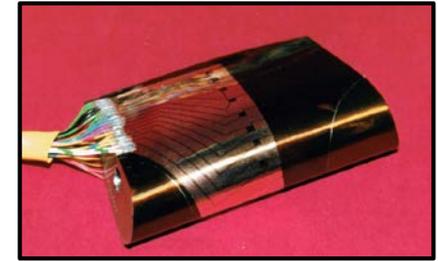
The START Lab leverages four primary research focuses



Study turbine performance with engine-relevant hardware



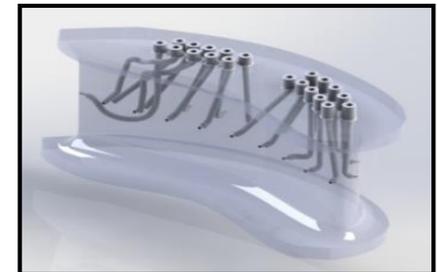
Test bed for instrumentation development



Advance the use of additive manufacturing in turbines

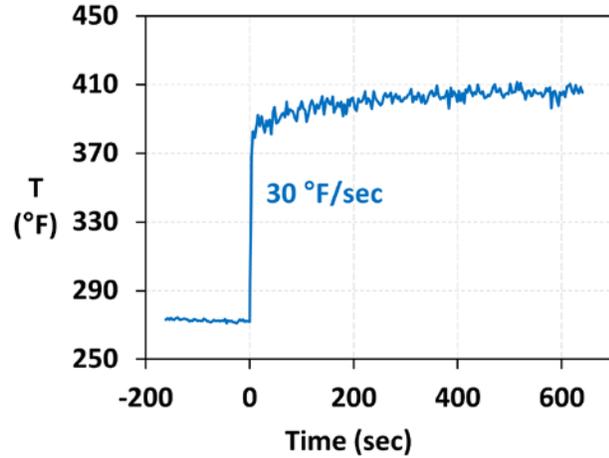


Direct integration of sensors in hardware

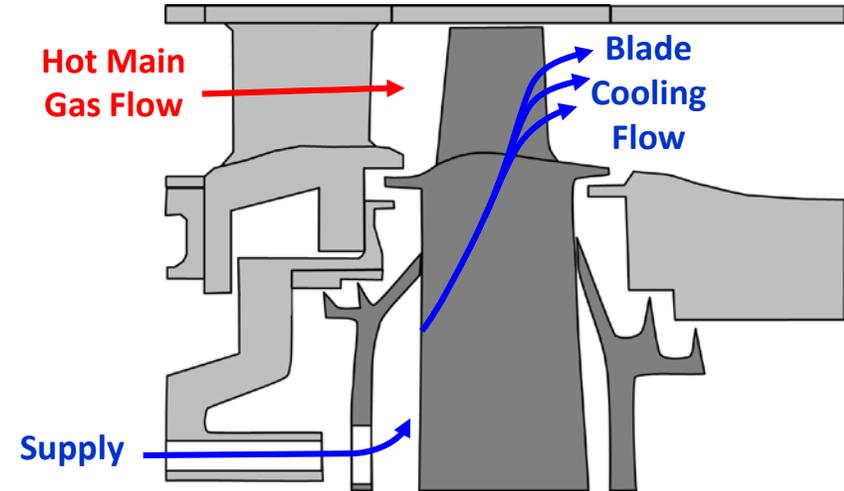


Four turbine faults will be demonstrated for this project (Task 3)

(1) Inlet temperature transients

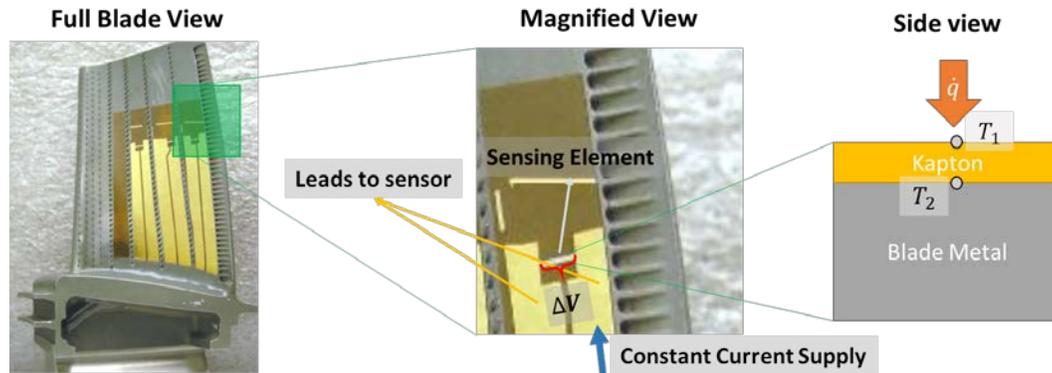


(2) Blade coolant loss

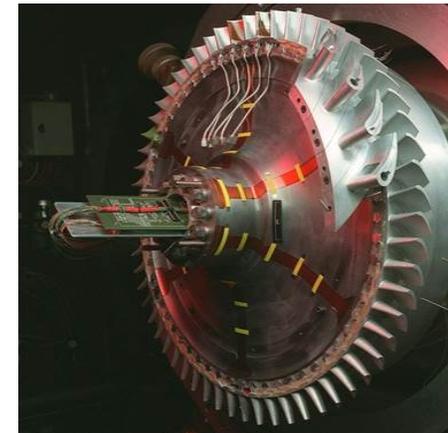


Temporally-resolved:
thin-film heat flux
gages

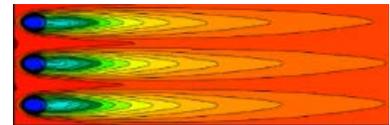
Spatially-resolved:
thermal imaging
(phase-locked)



Anthony et al. 2011

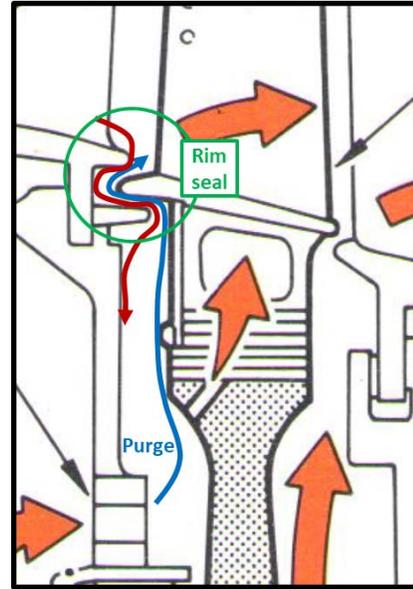
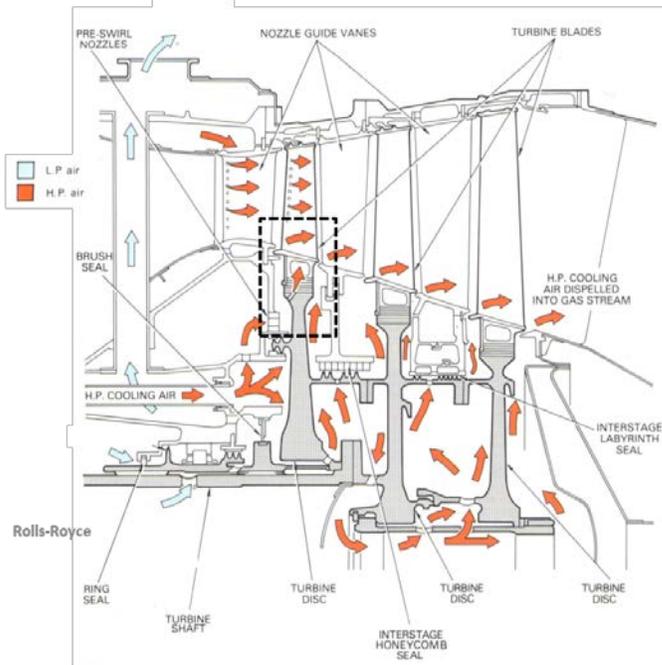


Courtesy of ProXisense



Four turbine faults will be demonstrated for this project

(3) Inter-stage cooling loss

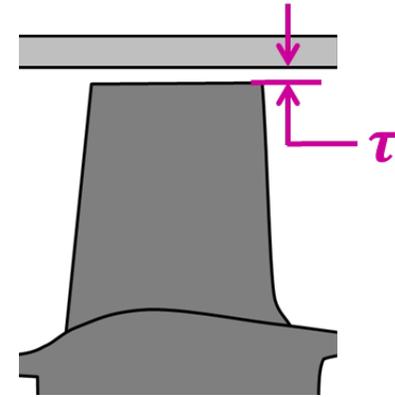


(4) Blade tip clearance

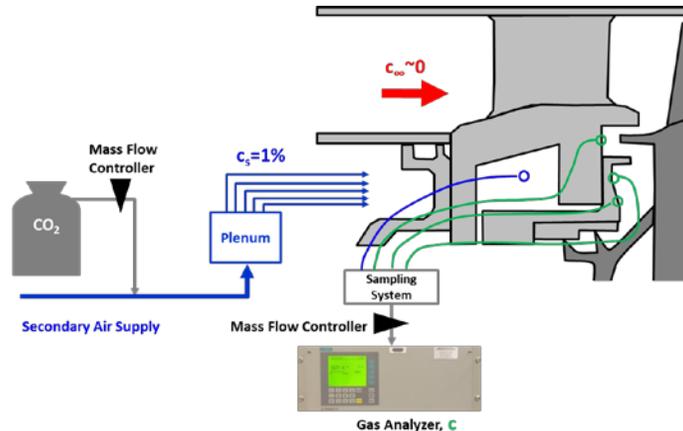
Magnetic bearings enable shaft alignment shifts to create local clearance changes



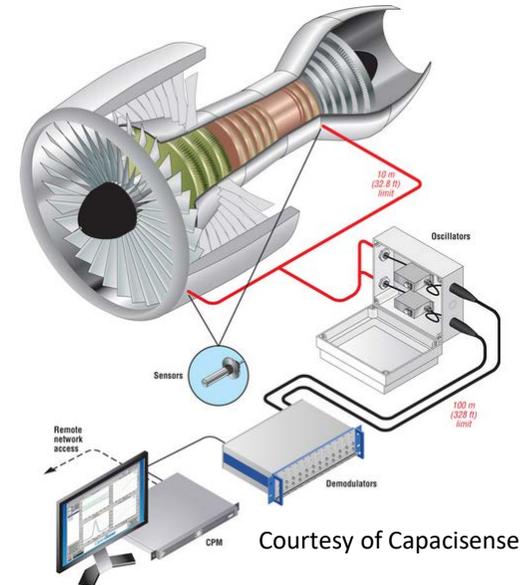
Courtesy of Synchrony



CO₂ tracer gas sampling quantifies sealing effectiveness

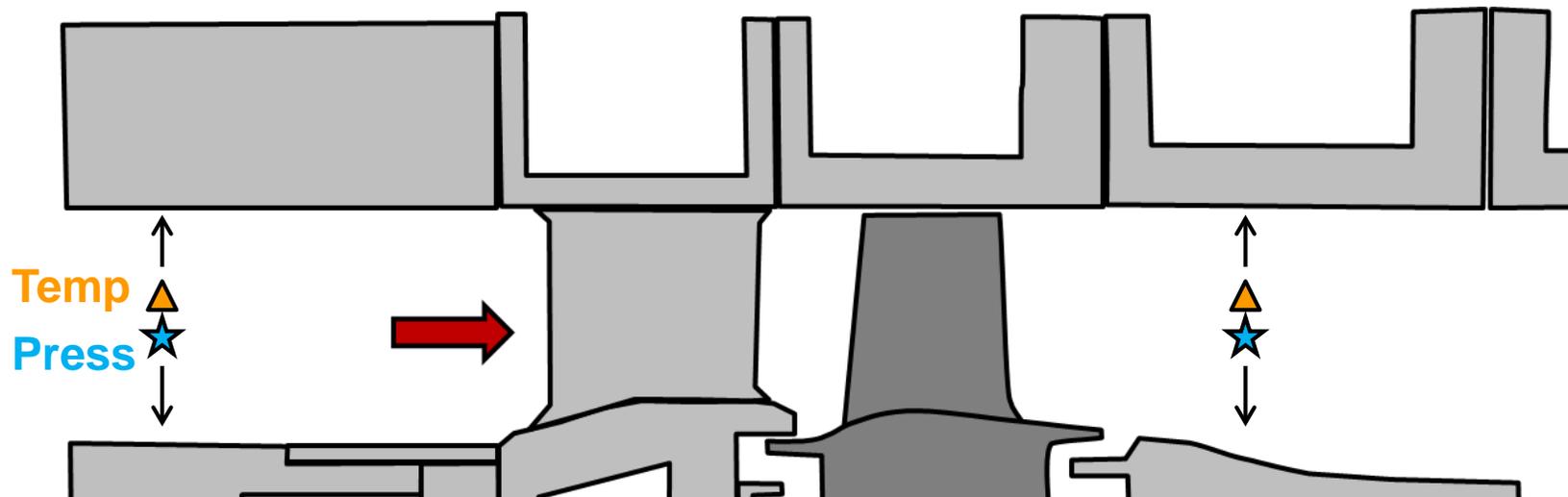
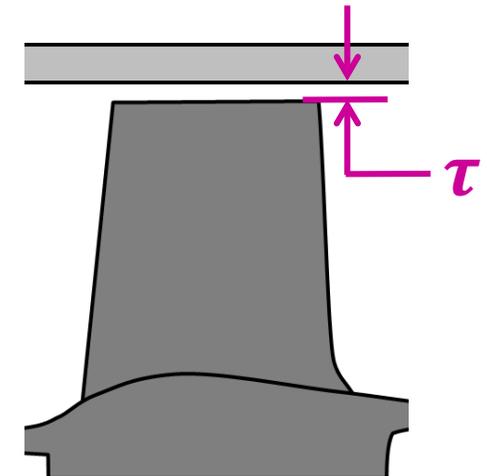
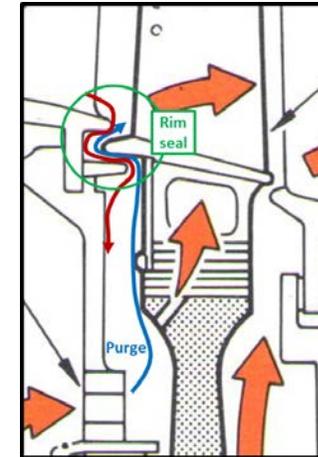
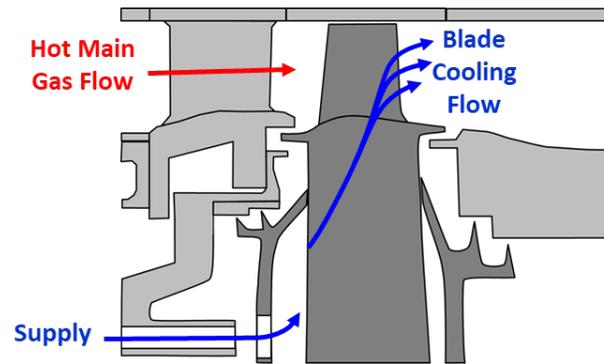
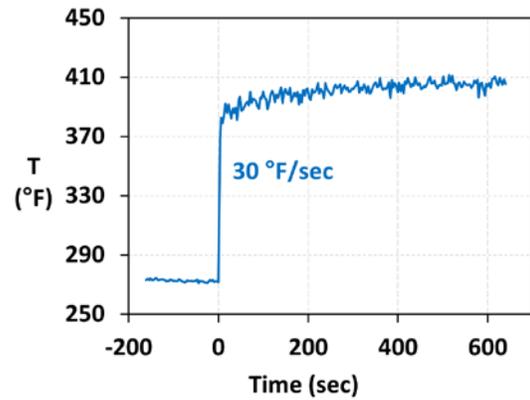


Advanced capacitance probe measurement system accurately resolves 0.001-in. clearance changes



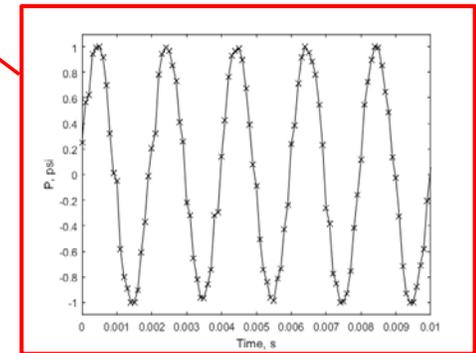
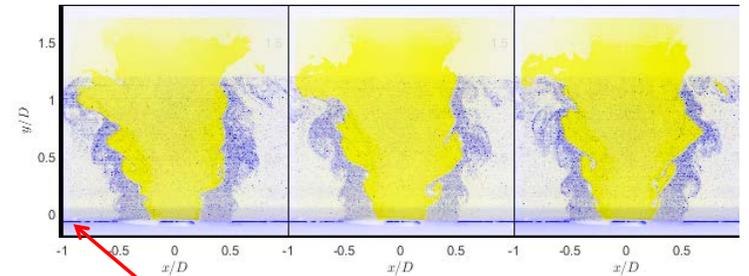
Courtesy of Capacisense

Global and local measurements will be combined to guide optimal sensor placement and assess fault severity



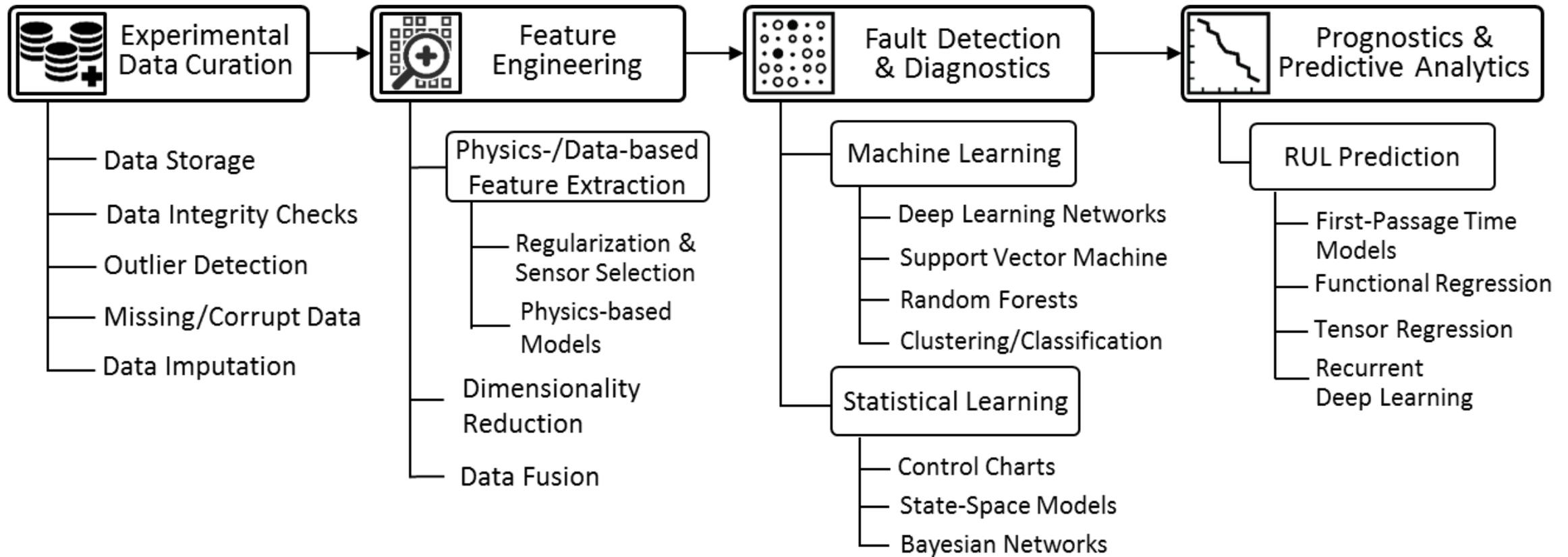
Virtual Sensing Using Machine Learning (Task 4)

- Virtual probes are used to infer measurements of components or phenomena that otherwise cannot be measured directly.
- **Objective:** Develop virtual probes that have been trained to map single point measurements to high-resolution data.
 - Virtual probes are technically software elements where machine learning models have been trained as a mapping functions between input & output.
 - High-resolution experimental data contain very rich information often not captured by single point probes.
 - Machine learning tools suited for high-dimensional e.g. images & fluid flow structures will be used.



Big Data Analytics for Gas Turbine Health Monitoring (Task 5)

- Our analytics methodology consists of four key components



Project Schedule and Deliverables

Deliverables	Quarter											
	1	2	3	4	5	6	7	8	9	10	11	12
Task 1 – Project Management and Planning	•											
Revised PMP	•											
Updated PMP			•		•		•		•		•	
Update DMP	•			•				•				•
Task 2 – Combustion System Fault Detection												
Subtask 2.1 – Damaged Combustor Liner			•	•	•	•	•	•	•	•	•	
Subtask 2.2 – Altered Combustor Flow Paths			•	•	•	•	•	•	•	•	•	
Subtask 2.3 – Combustor Blowout			•	•	•	•	•	•	•	•	•	
Task 3 – Turbine Fault Detection												
Subtask 3.1 – Unsteady Turbine Inlet Temps				•	•	•	•	•	•	•	•	
Subtask 3.2 – Blade Coolant Loss	•	•	•	•	•	•	•	•	•	•	•	
Subtask 3.3 – Inter-stage Sealing Loss	•	•	•	•	•	•	•	•	•	•		
Subtask 3.4 – Blade Tip Clearance			•	•	•	•	•	•	•	•	•	
Task 4 – Virtual Combustor and Turbine Probes												
Subtask 4.1 – Virtual Sensing Using Machine Learning			•	•	•	•	•	•	•	•		
Task 5 – Big Data Analytics												
Subtask 5.1 – Data Curation	•	•	•	•	•	•	•					
Subtask 5.2 – Feature Engineering			•	•	•	•	•	•	•	•	•	
Subtask 5.3 – Detection & Diagnostics			•	•	•	•	•	•				
Subtask 5.4 – Prognostics						•	•	•	•	•	•	•
Reporting												
Quarterly Progress Reports	•	•	•	•	•	•	•	•	•	•	•	•
Semi-Annual Reports		•		•		•		•		•		•
Annual Reports				•				•				•
Final Report												•

Risk Management

Deliverables	Risk	Risk Mitigation
Task 2 – Combustion System Fault Detection	<i>Combustor related experimental risks</i>	
Subtask 2.1 – Damaged Combustor Liner	Leakage of hot gases on parts no designed for high temps (M)	Appropriate design of outer combustor cooling
Subtask 2.2 – Altered Combustor Flow Paths	Non-uniform stresses due to altered flame temperatures (L)	Building safety margin into the vessel design
Subtask 2.3 – Combustor Blowout	Large overpressure events following blowouts (M)	Building fuel flow controls that require indications of flame to maintain fuel flow
Task 3 – Turbine Fault Detection	<i>Turbine related experimental risks</i>	
Subtask 3.1 – Unsteady Turbine Inlet Temps	High temperatures of the turbine test rig due to excessive gas input in the combustor upstream (M)	Managed by a series of validated lock-out controls.
Subtask 3.2 – Blade Coolant Loss	Installation and survivability challenges related to thin film heat flux gages (M)	Refinement through a collaborations with partnering engine OEM
Subtask 3.3 – Inter-stage Sealing Loss		
Subtask 3.4 – Blade Tip Clearance	Confounding due to thermal and mechanical interference of flow-path components and blades (L)	Predicted growth of the blades will be less than the planned blade tip clearances
Task 4 – Virtual Combustor and Turbine Probes		
Subtask 4.1 – Virtual Sensing	Model overfitting and underfitting challenges (M)	Statistical regularization and early stopping methods.
Task 5 – Big Data Analytics		
Subtask 5.1 – Data Curation		
Subtask 5.2 – Feature Engineering	Features significantly larger than samples size (L)	Statistical variable selection methods
Subtask 5.3 – Detection & Diagnostics	False alarm due to varying operating modes (M)	Clustering normal operation modes
Subtask 5.4 – Prognostics	Poor accuracy due to poor data quality or limited observations to identify trend (H)	Data imputation and defining soft failure thresholds

Budget Summary and Categories

- Budget Summary

	Federal	Cost Share	Total
Year 1	\$199,999	\$50,024	\$250,023
Year 2	\$199,999	\$50,261	\$250,260
Year 3	\$200,000	\$50,261	\$250,261
Totals	\$599,998	\$150,546	\$750,544

CATEGORY	Budget Period 1	Budget Period 2	Budget Period 3	Total Costs	% of Project
a. Personnel	\$34,919	\$65,965	\$65,966	\$166,850	39.54%
b. Fringe Benefits	\$4,348	\$8,552	\$8,552	\$21,452	39.86%
c. Travel	\$2,000	\$3,000	\$3,000	\$8,000	37.50%
d. Equipment	\$25,000	\$0	\$0	\$25,000	0.00%
e. Supplies	\$17,237	\$4,150	\$2,978	\$24,365	12.22%
f. Contractual					
Sub-recipient	\$99,025	\$84,375	\$84,375	\$267,775	31.51%
Vendor	\$0	\$0	\$0	\$0	0.00%
FFRDC	\$0	\$0	\$0	\$0	0.00%
Total Contractual	\$99,025	\$84,375	\$84,375	\$267,775	31.51%
g. Construction	\$0	\$0	\$0	\$0	0.00%
h. Other Direct Costs	\$19,227	\$37,014	\$38,864	\$95,105	40.86%
Total Direct Costs	\$201,757	\$203,056	\$203,734	\$608,547	33.48%
i. Indirect Charges	\$48,266	\$47,204	\$46,527	\$141,997	32.77%
Total Costs	\$250,023	\$250,260	\$250,261	\$750,544	66.24%

Summary

- Project Officer Proposed project aims to leverage unique datasets from combustor and turbine faults to enable the development of a Big Data Analytics platform for fault Detection, Diagnostics and Prognostics.
- The project consists of five key tasks, one for project management, two for experimental research (combustor and turbine), and two for analytics-related research (virtual sensing and Big Data analytics).
- The team consists of five PIs with extensive experience that thoroughly addresses the needs to execute the research tasks.
- Project timeline is 3 years with total federal funding ~\$600K and ~\$150K in cost share.