An Advanced Diagnostic and Prognostic System for Gas Turbine Generator Sets with Experimental Validation

Clemson University

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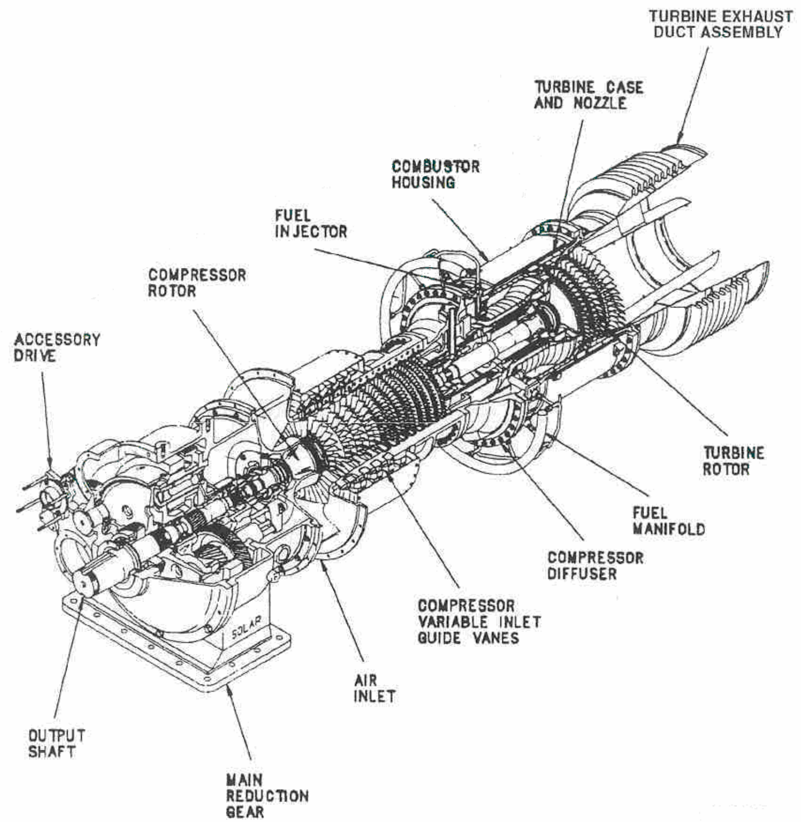
$319,479 Total Contract Value ($319,479 DOE)

Gas Turbine Need

- The Reliability, Availability, and Maintainability (RAM) technical area within High Efficiency Engines and Turbines (HEET) Program encompasses the design of gas turbine health management systems
- The introduction of real-time diagnostic and prognostic capabilities on gas turbines can provide increased reliability, safety, and efficiency
- Opportunity exists to develop and demonstrate advanced health monitoring strategies at Clemson



Solar Turbine Taurus 60 system

Project Objectives

Technical Objectives:

• Develop a real-time system monitoring algorithm capable of detecting and isolating the occurrence of anomalies, as well as predicting future degraded operation for maintenance scheduling

• Numerically and experimentally demonstrate the health monitoring concept

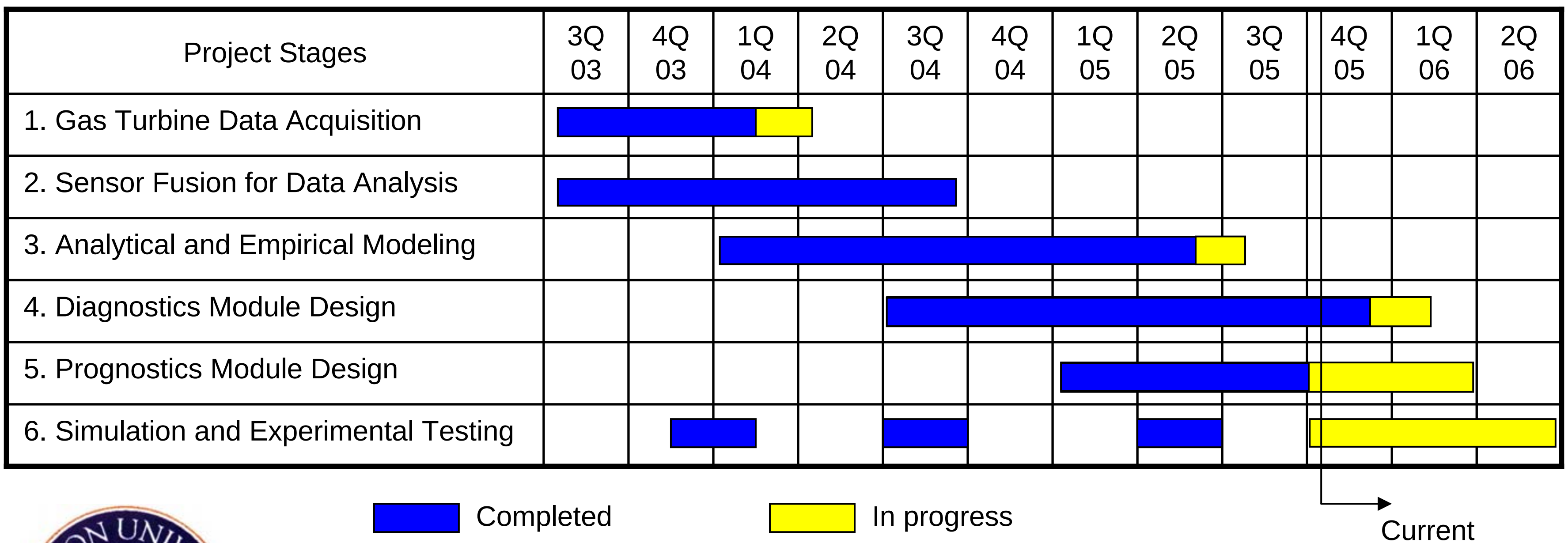
Educational Objective:

• Involvement of undergraduate students through an “Undergraduate Research Award” to promote the program's educational mission

• Preparation of graduate engineering students for employment in the gas turbine industry

Approach

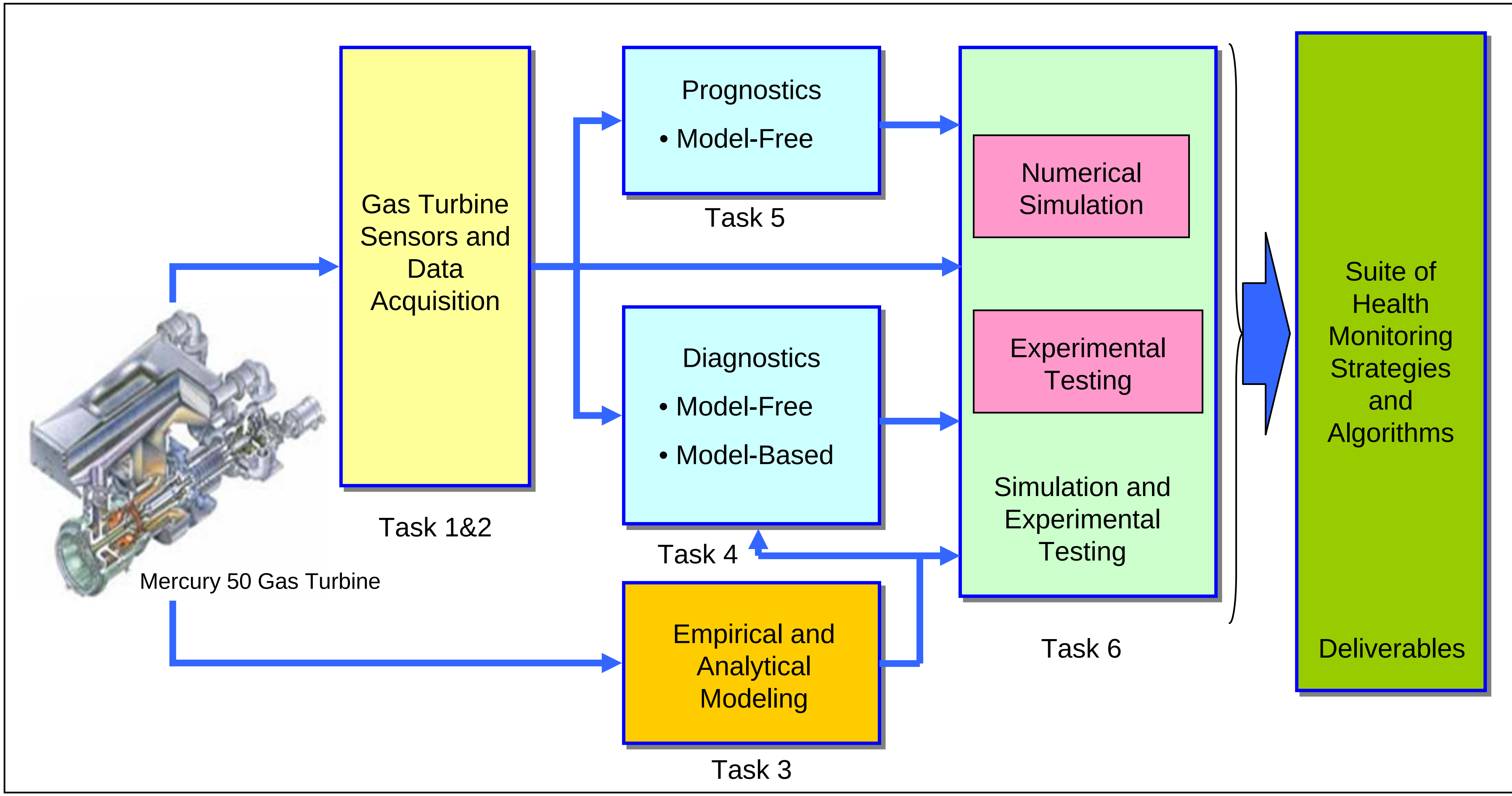
- Open issues to be accomplished by research team in upcoming months
  - Complete real-time data manipulation collaborating with Mathworks on “OPC” software
  - Finish derivation of diagnostic and prognostic software strategies; resolve modeling issues
  - Examine Mercury 50 operation at Clemson University and feasible modifications



Accomplishments

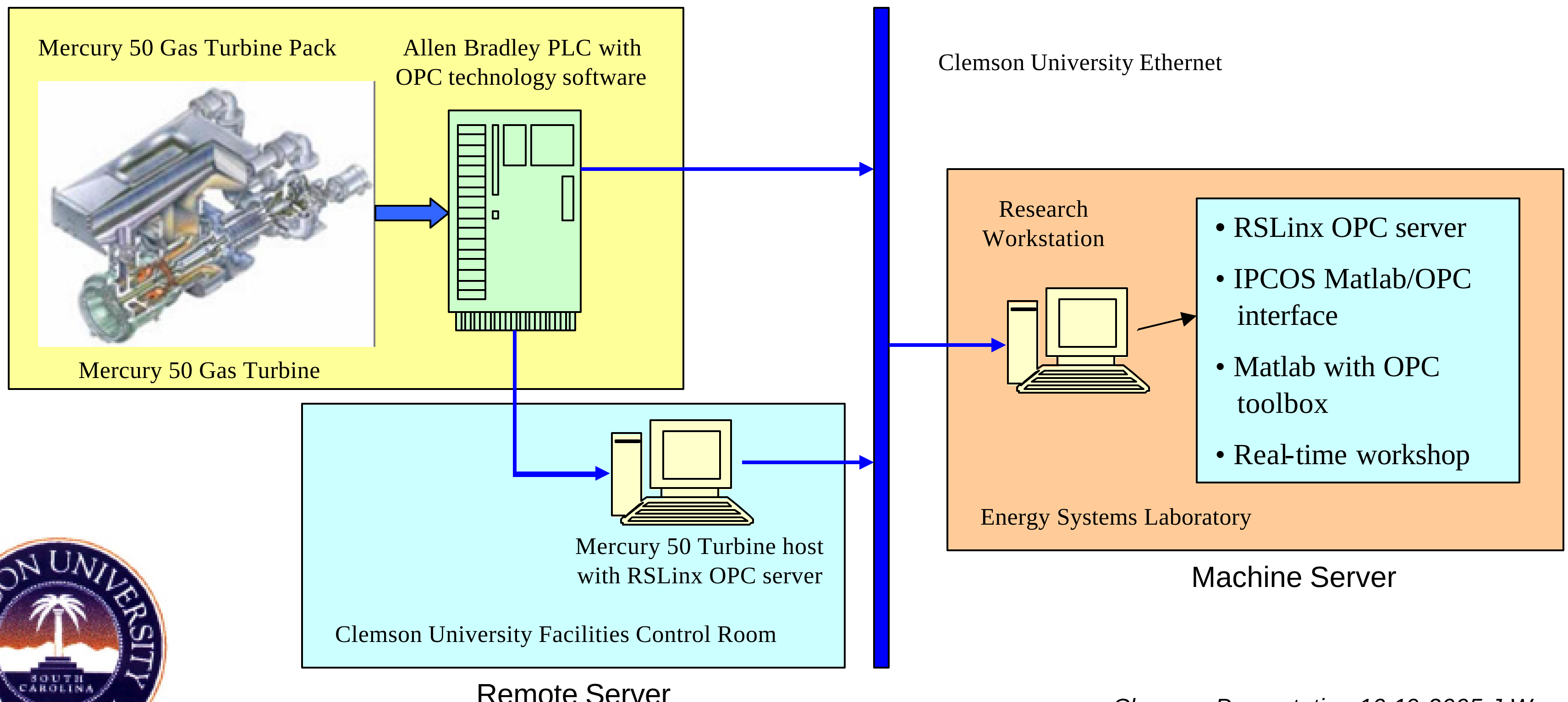
- Achieved a model-free trend checking diagnostic algorithm (12/03)
- Demonstrated real-time data streaming between the Mercury 50 gas turbine and the Energy Systems Laboratory using Matlab OPC Interface (03/04)
- Created a compressor map of the Solar Mercury 50 gas turbine based on actual blade geometry and experimental data (07/04)
- Undergraduate research group member completed HEET Summer Intern Program at Solar Turbines, San Diego, CA (09/04)
- Established a sensory architecture of 28 signals for diagnostics/prognostics (12/04)
- Developed a dynamic (transient) model for the gas turbine (04/05)
- Created an initial methodology for the prognostics module (05/05)
- Verified and validated the dynamic model with limited experimental data (06/05)
- Established initial model-free/model-based diagnostics; ready to validate (10/05)

Technical Results – Research Overview

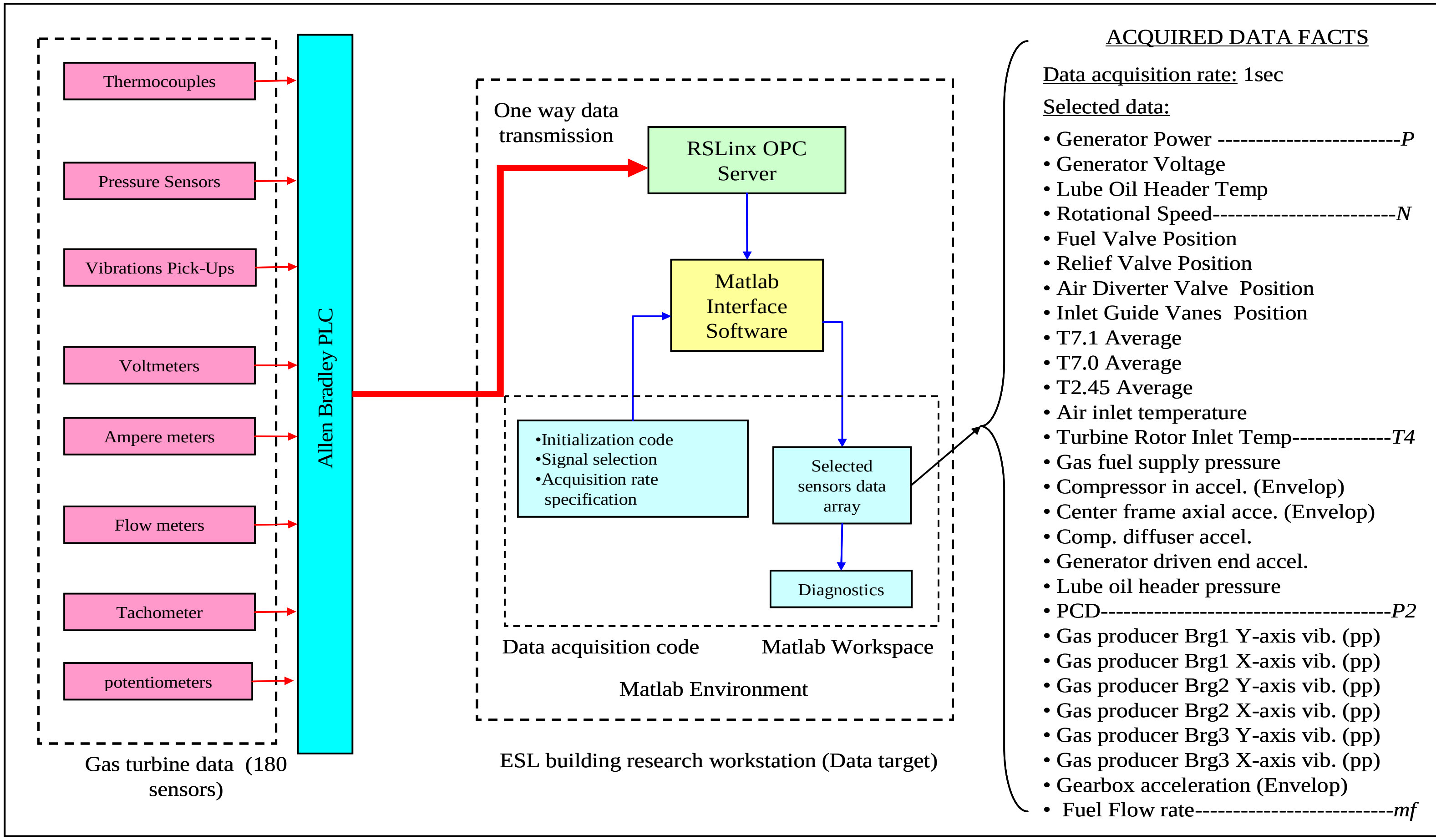


Technical Results – Sensors and Data Acquisition Configuration (Hardware)

- OPC (Ole for Process Control) is a communication technology linking different sensors types through a common software platform (Note: Ole is a city in France)
- Clemson University campus Ethernet connects the turbine and the research workstations
- The research workstations can communicate with two OPC servers; a machine server (installed on the workstation) and a remote server (turbine host computer)

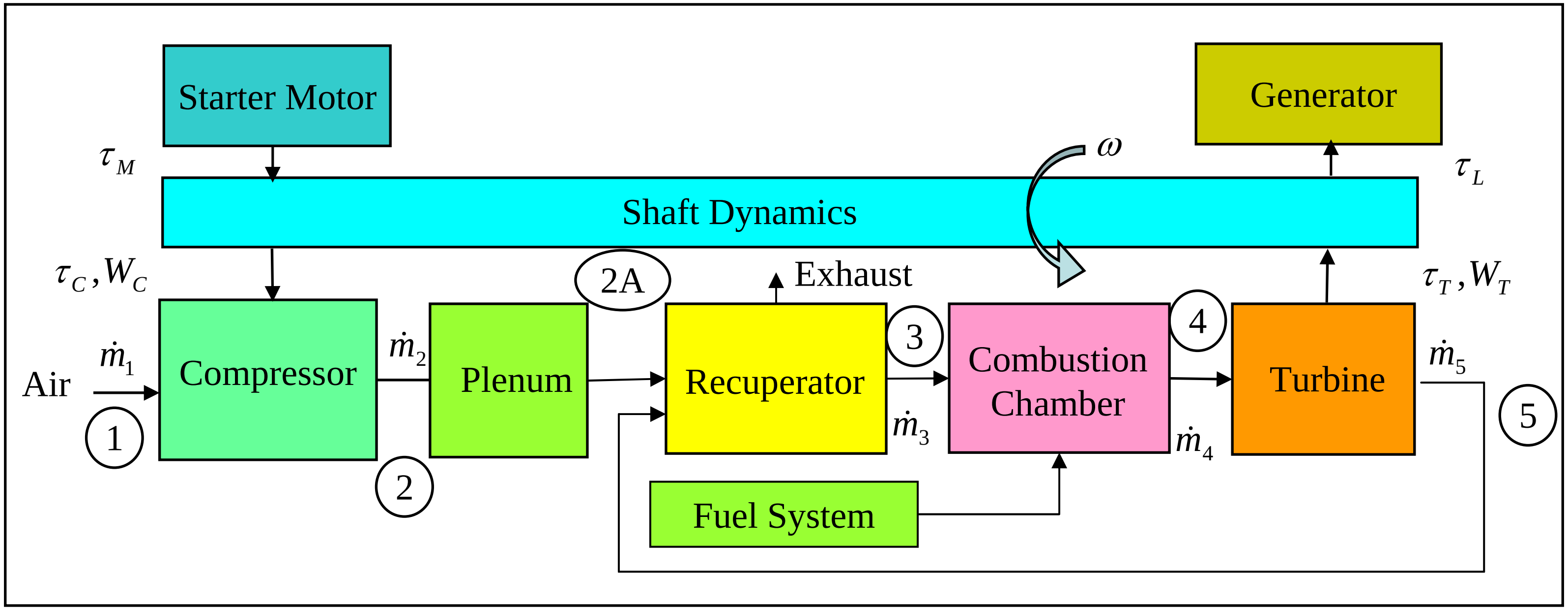


Technical Results – Sensors and Data Acquisition Configuration (Software)



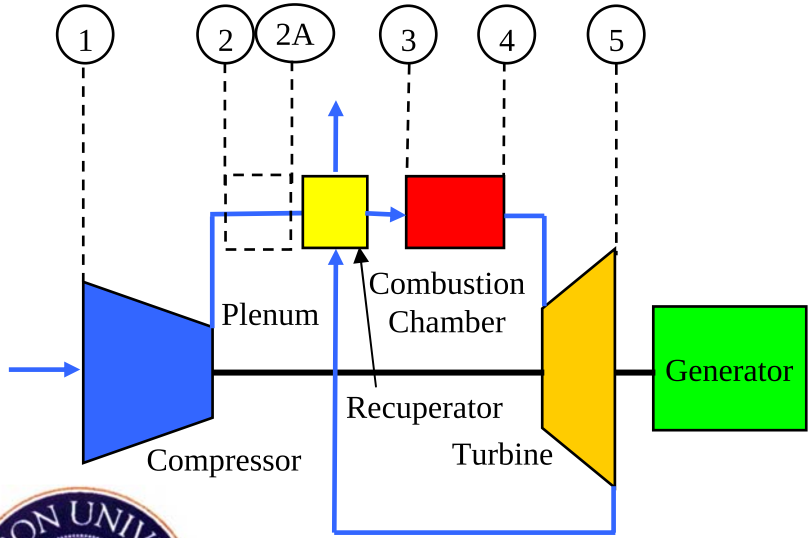
Technical Results - Analytical Gas Turbine Model

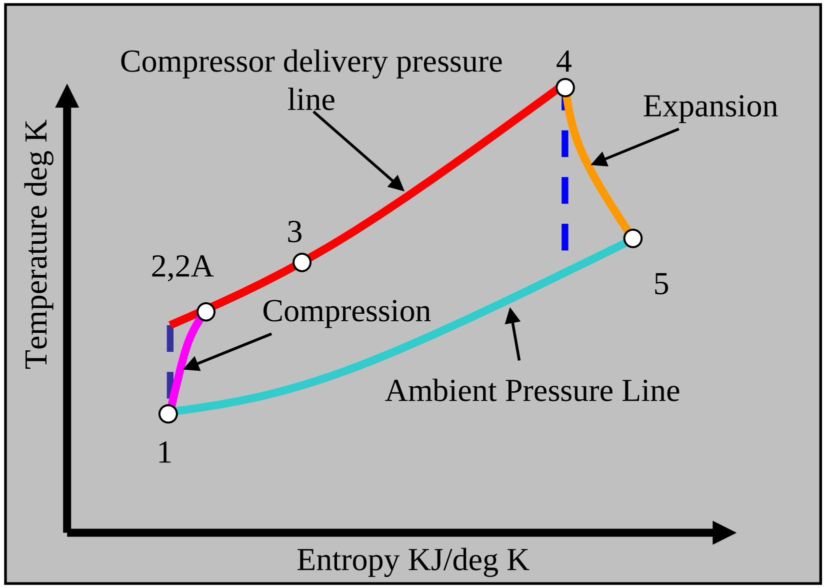
- Analytical/Empirical model estimates normal turbine operation
- Real time model is a sequence of interconnected subsystems which describe the basic components of a stationary gas turbine
- Physical and thermodynamic laws have been used to describe the system dynamics



Technical Results - Analytical Model

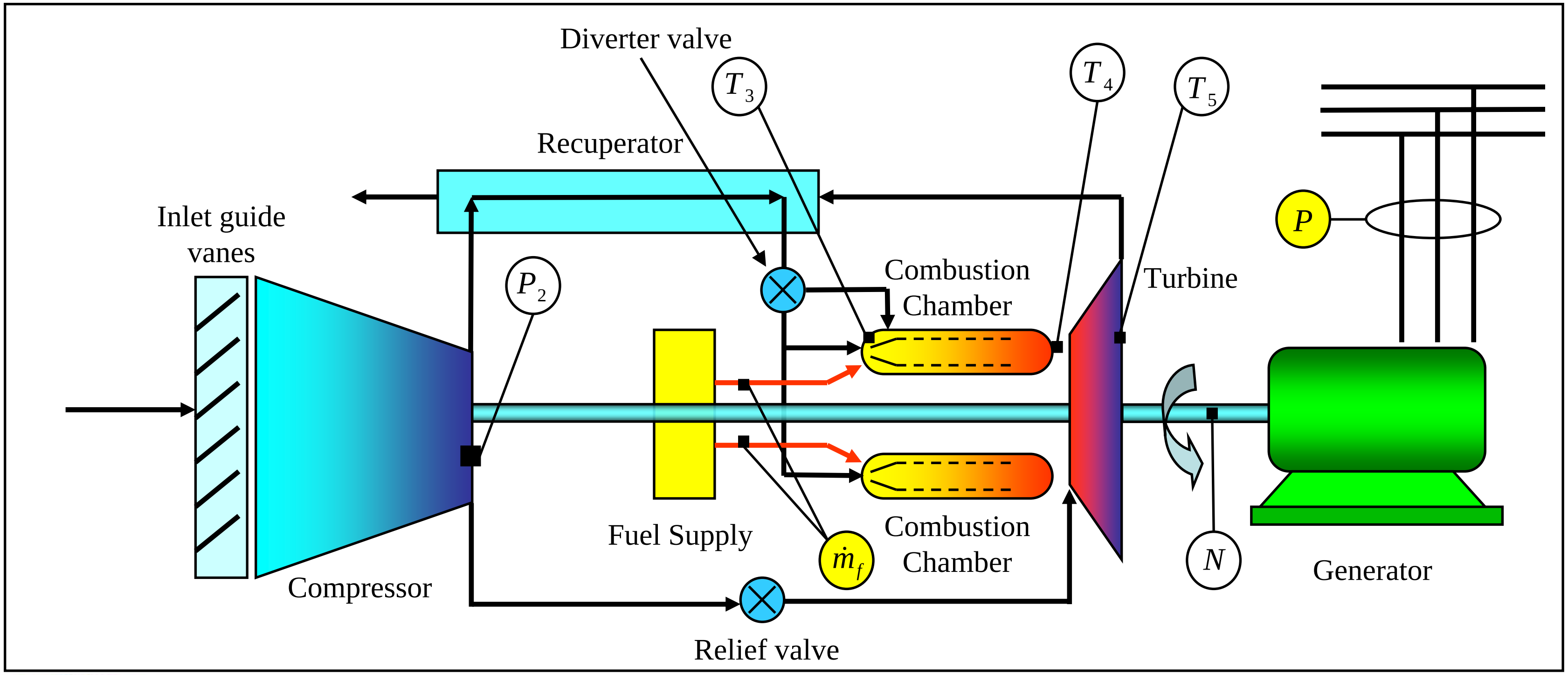
- Thermodynamic analysis of the gas turbine is based on a modified Brayton cycle
  - Compression (Compressor, points 1 to 2,2A)
  - Heat addition (Recuperator, points 2A to 3)
  - Heat addition (Combustion chamber, points 3 to 4)
  - Expansion (Turbine, points 4 to 5)
- Analytical model will incorporate the shaft dynamics and the thermodynamic relations during the turbine's transient operation





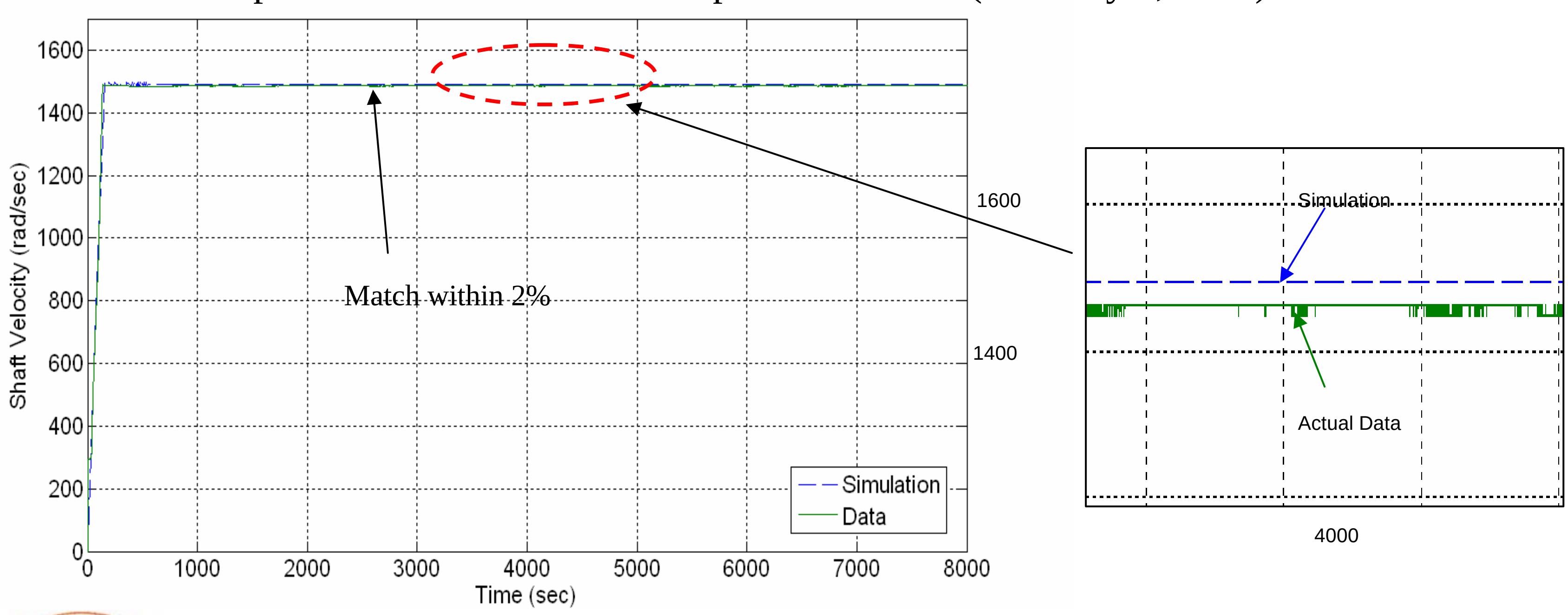
Technical Results - Experimental Model Validation

- Relevant sensor locations in Mercury 50 gas turbine are shown below
- To validate the mathematical model, comparisons between the analytical model and the experimental results from the Mercury 50 gas turbine have been studied



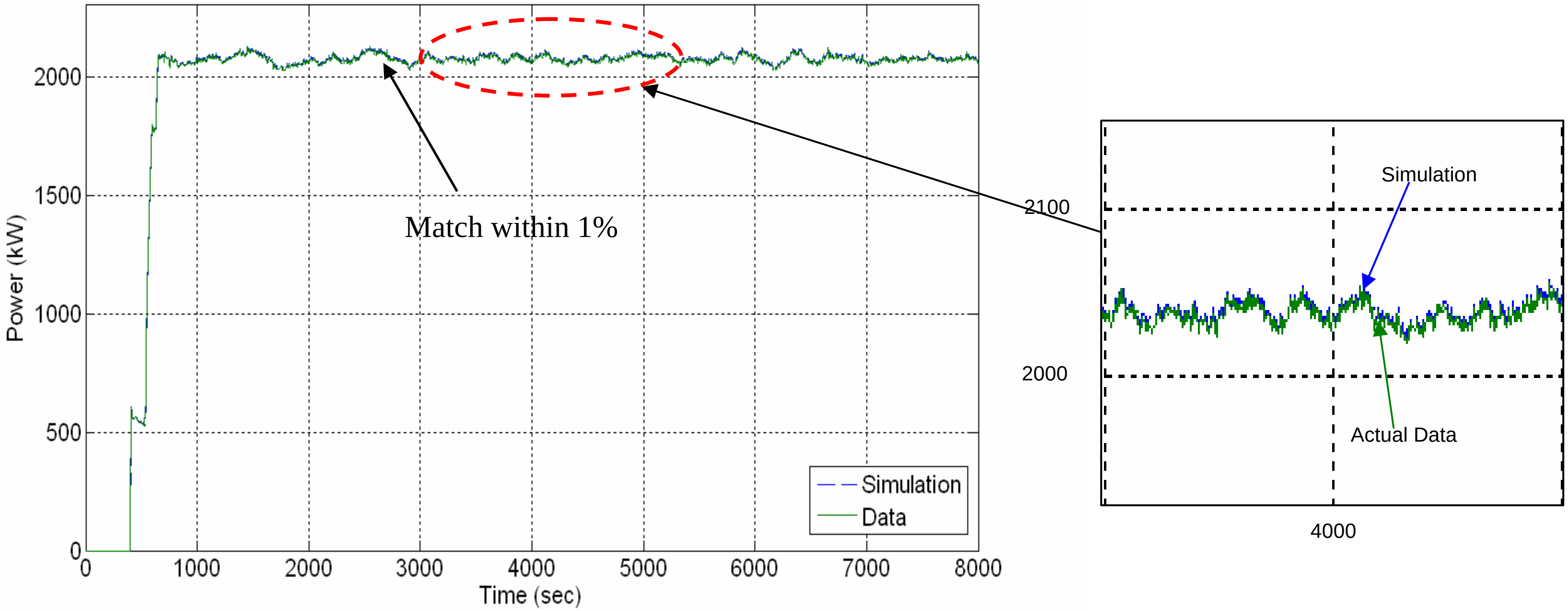
Technical Results - Experimental Model Validation

- Estimated and actual shaft speed comparison
- The overall behavior is well matched with some deviations between 100<t<600 seconds
- Model corresponds to within 2% of the experimental data (Feburary 2, 2005)



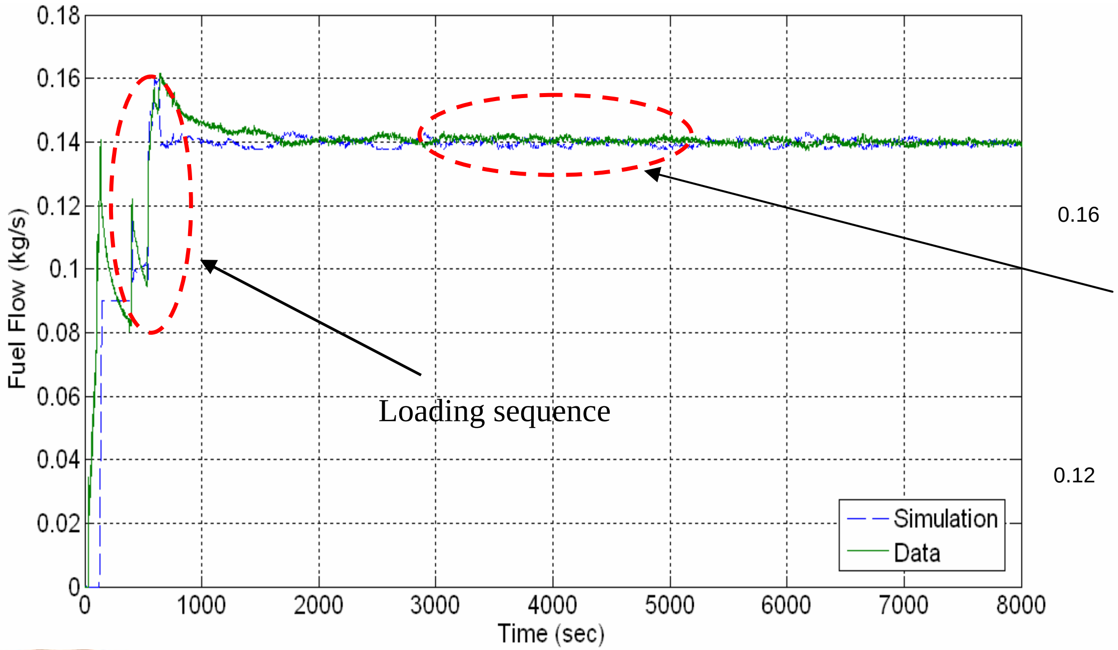
Technical Results – Experimental Model Validation

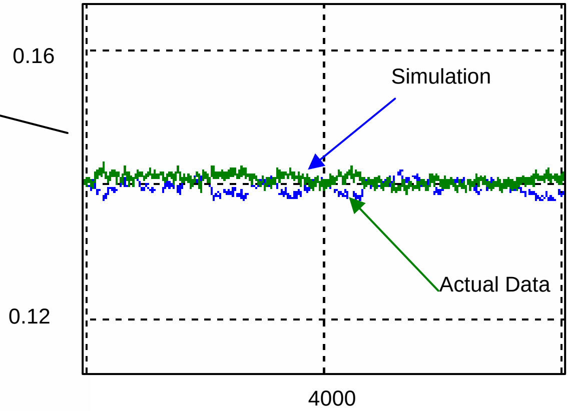
- Estimated and actual power generated comparison
- Sequential loading is started 400 seconds after start up; both steady state and start up phases are well predicted by the mathematical estimates
- Model corresponds to within 1% of the experimental data (Feburary 2, 2005)



Technical Results - Experimental Model Validation

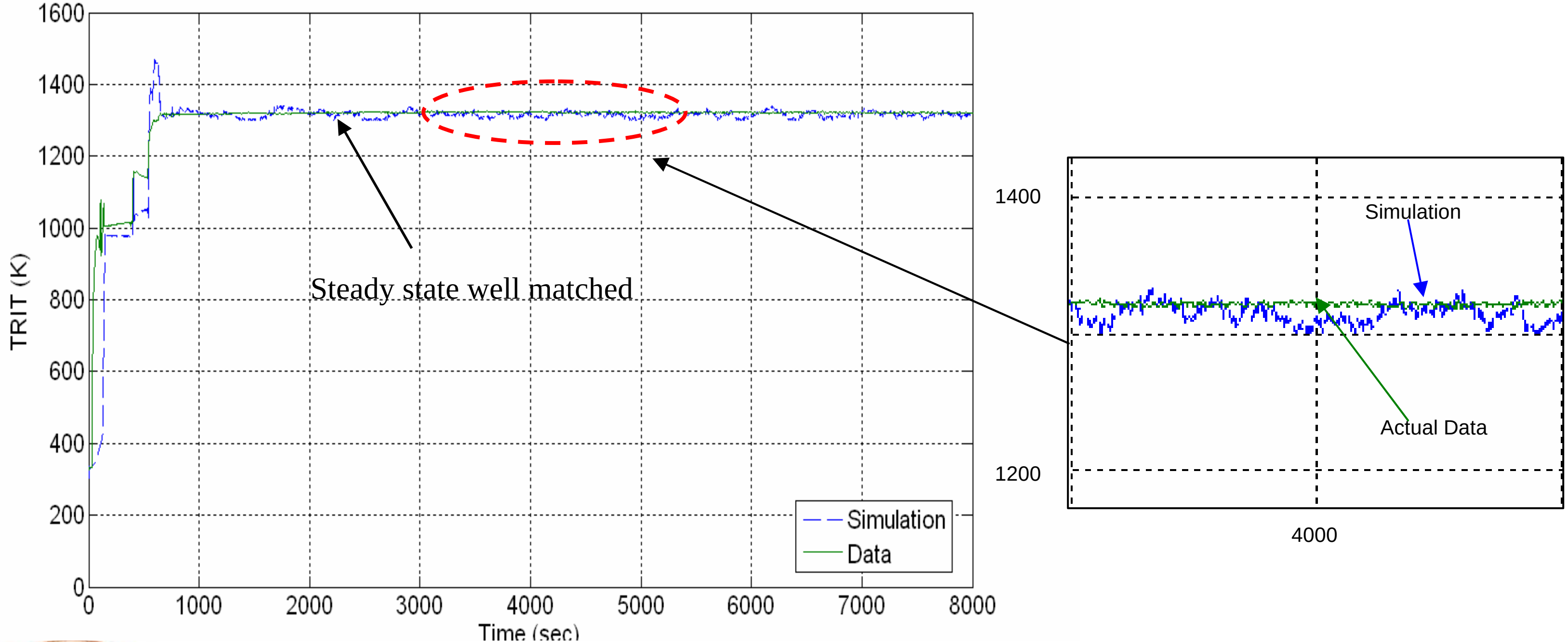
- Estimated and actual fuel flow rate comparison
- A good match is obtained between the experimental data and the estimated fuel flow
- Model corresponds to within 3% of the experimental data at steady state (February 2, 2005); transient stage is under investigation to decrease fuel flow decay after peak





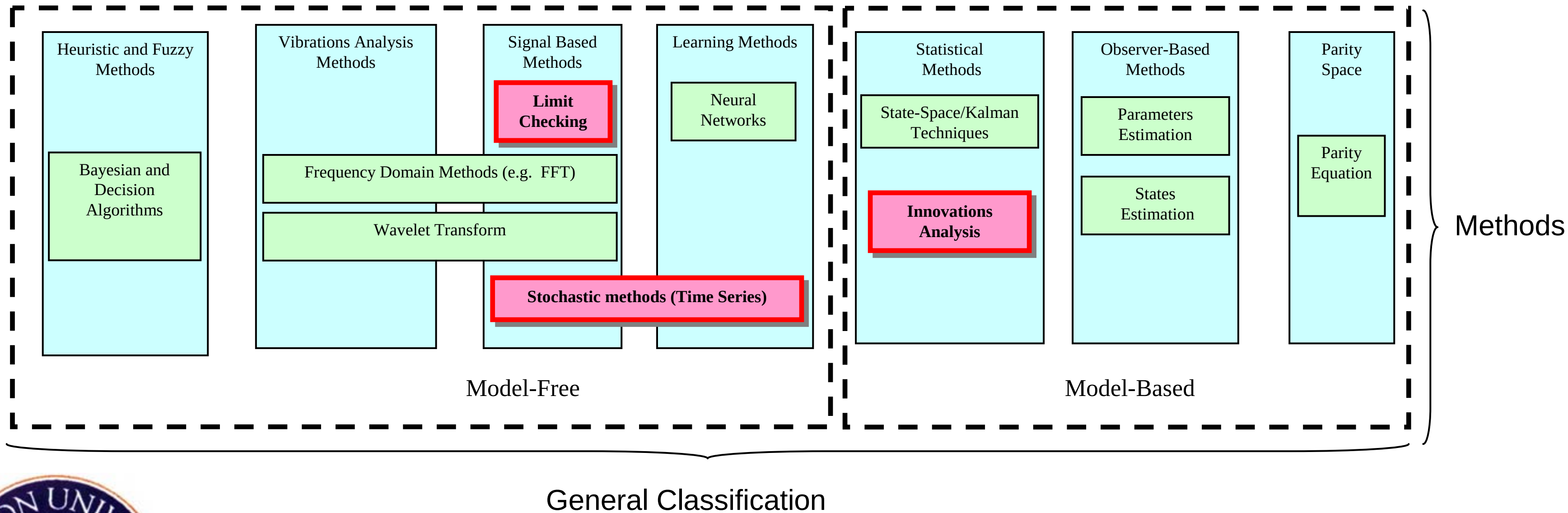
Technical Results – Experimental Model Validation

- Estimated and actual turbine rotor inlet temperature
- Steady state behavior is well matched, start up under investigation
- Model corresponds within 3% of the experimental data during steady state (Feburary 2, 2005)



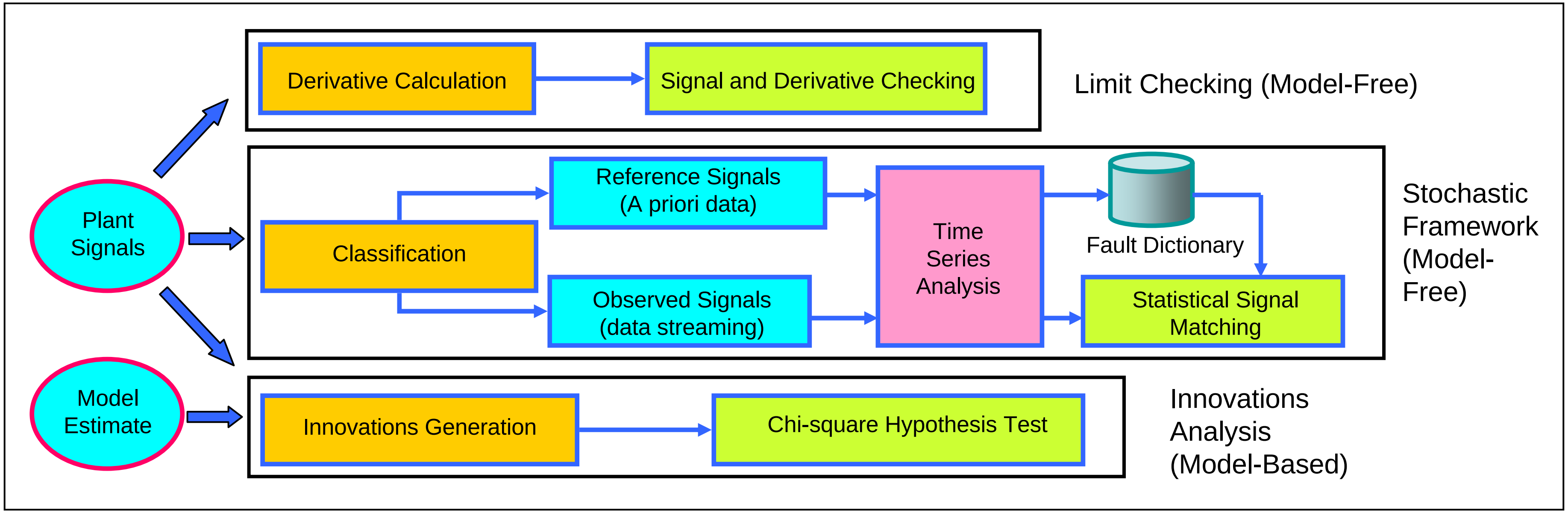
Technical Results – Diagnostics Overview

- Diagnostics detect eminent fault occurrences by analyzing sensory information
- Diagnostic techniques can be generally categorized into model-free and model-based methods
  - In model-free methods, diagnostics are performed by directly analyzing the signals received from the system and compare them to a certain predefined criteria
  - Model-based methods use an analytical or empirical system model to estimate behavior



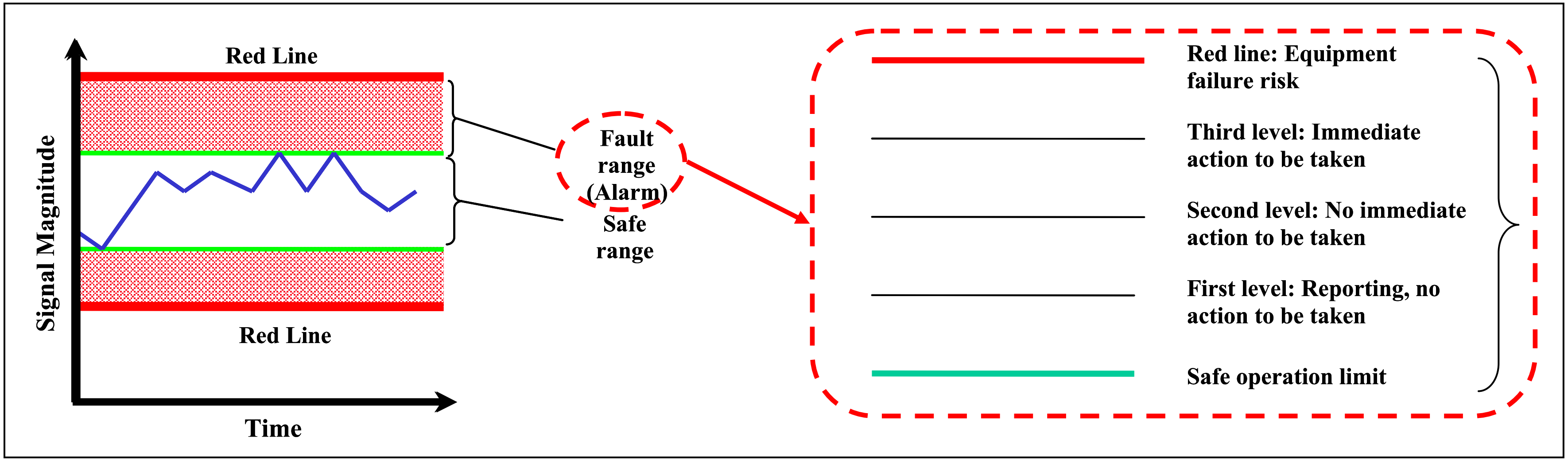
Technical Results – Selected Strategy

- Limit checking is performed for both the signal and its derivative as a preliminary step
- Due to the squared innovations (estimation error), χ^2 , the Chi-square hypothesis test is selected for its robustness in detecting deviations
- A model-free stochastic framework including time series signal modeling, fault dictionary creation, and signal matching techniques is selected for isolation



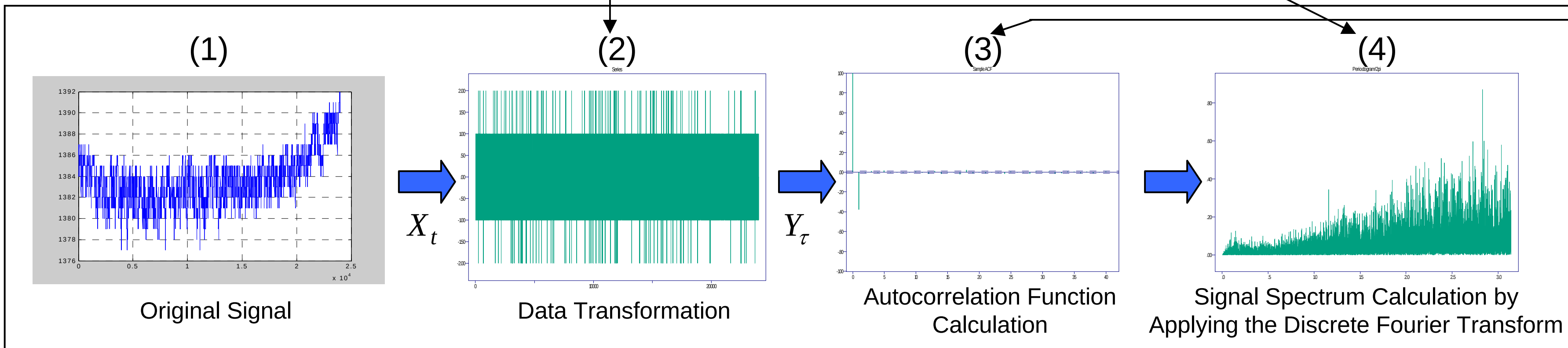
Technical Results – Model-Free Limit Checking Diagnostics

- Accessible parameters signals are compared to a bounded range $Y_{\min} \le Y \le Y_{\max}$
- Levels of alarms are set according to the difference between the safe limit and the signal value $\left|Y - Y_{safe}\right| \ge Y_{alarm}$ to optimize alarm generation
- The signal time derivative $\frac{dY}{dt}$ is measured to predict the behavior of the signal and minimize the chance of generating an alarm for a noisy signal



Technical Results – Time Series Principles

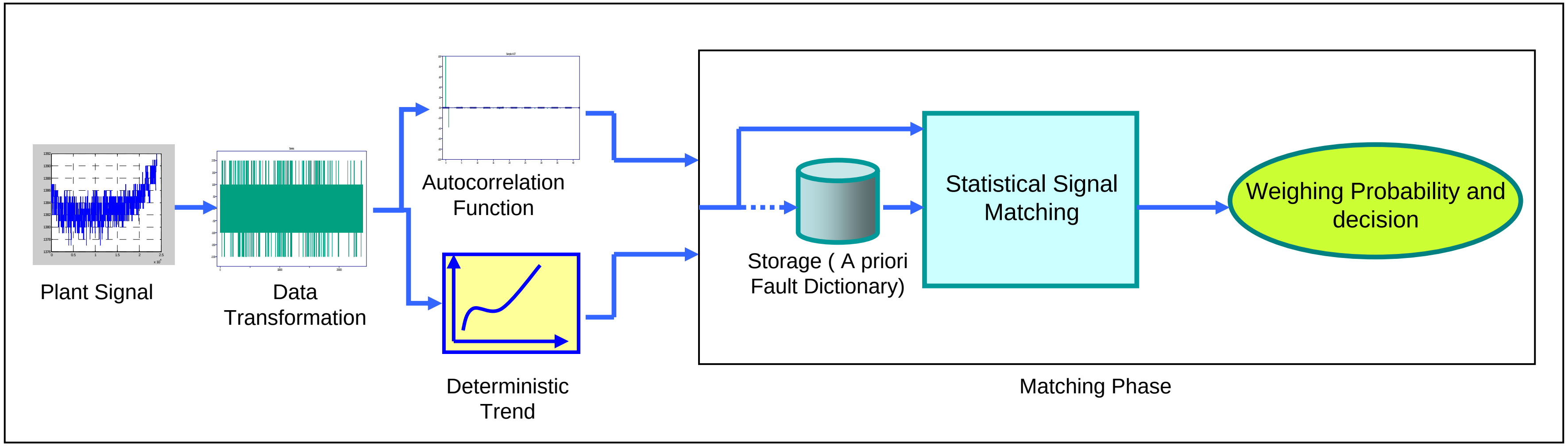
- Time series is a stochastic technique combining both time and frequency domain analysis in a single methodology
- Data transformation **(2)** by examining difference between two data points, $Y_\tau = X_{t+1} - X_t$, is a preliminary step for data exhibiting long memory (slow dynamics)
- A direct indication of the system's impulse response is given by the Autocorrelation Function **(3)** (i.e. Correlation between signal's values at different time intervals, Y_{τ_i} and $Y_{\tau_{i+h}}$)
- The signal spectrum **(4)** transports the analysis to the frequency domain; its relation to the Autocorrelation Function bridges the time and frequency domains



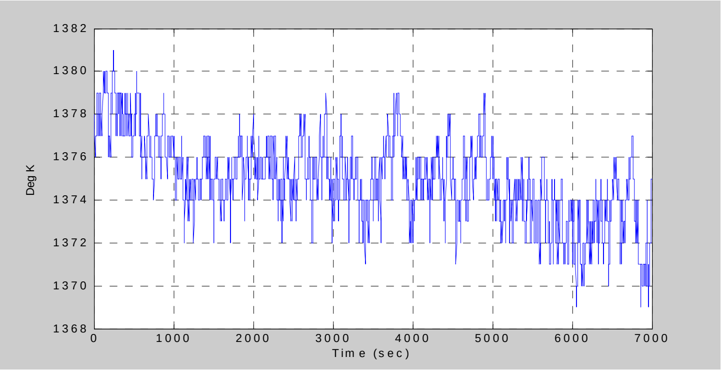
Stages of Time Series Analysis

Technical Results – Model-Free Diagnostics (Matching)

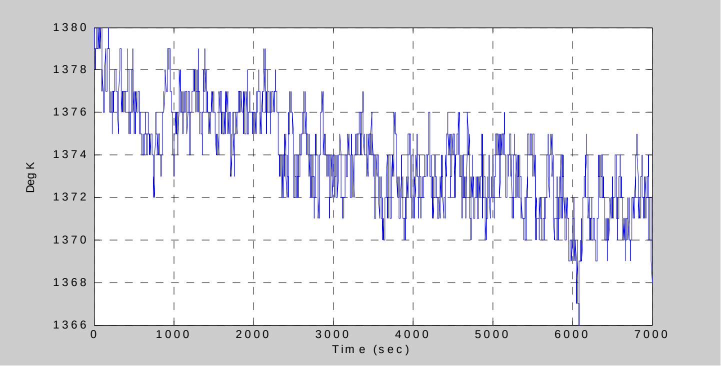
- Transformations are performed to obtain a stationary Autocorrelation Function
- The Autocorrelation Function (dynamic feature) and the Deterministic Trend (static feature) of the plant signal are the signal features used for the matching criteria
- Appropriate statistical matching algorithms will be applied
- Same procedure can be applied to the residuals of gas turbine model and actual signals



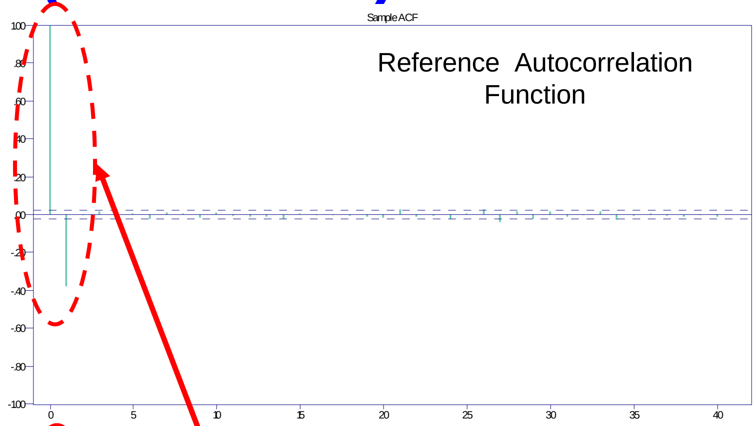
Technical Results – MFD Sample Autocorrelation Matching Results (No Failure)

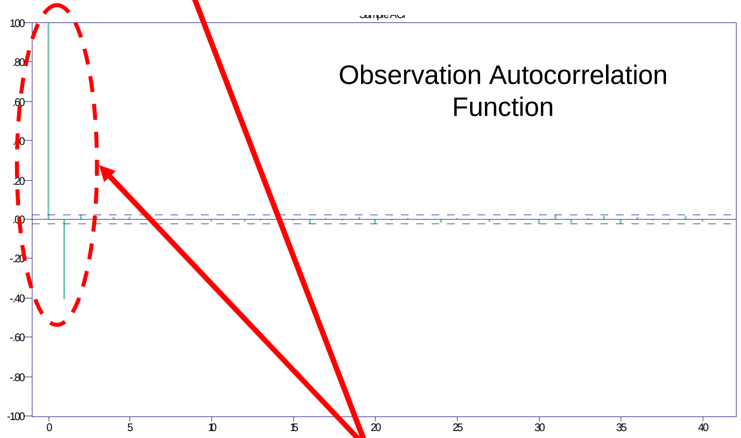


Reference Signal (Healthy "No Failure" A priori data)



Observed Signal (Data Streaming)

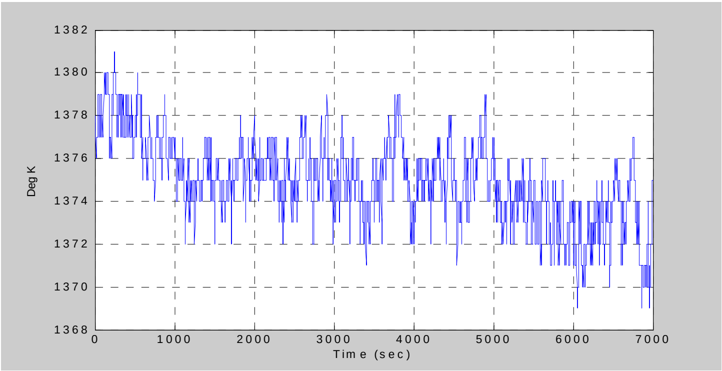




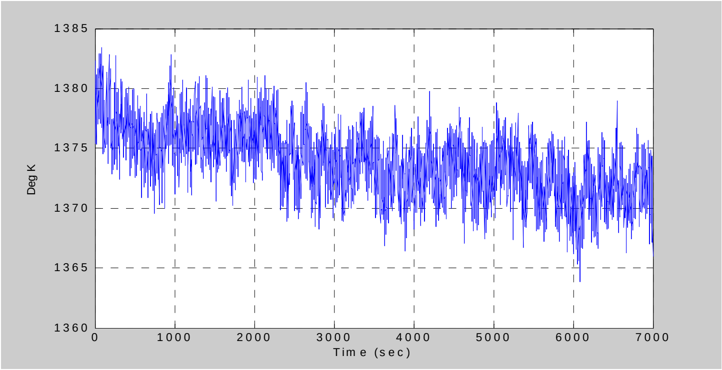
Signal Name	Calculated TRIT
Reference Run	06-14-2005 (No Failure)
Test Run	07-19-2005
Test Method	ACF Matching

- Since the two autocorrelation functions are similar (~100% similarity based on a 95% threshold Limit), the observed signal corresponds to the "No Failure" signal

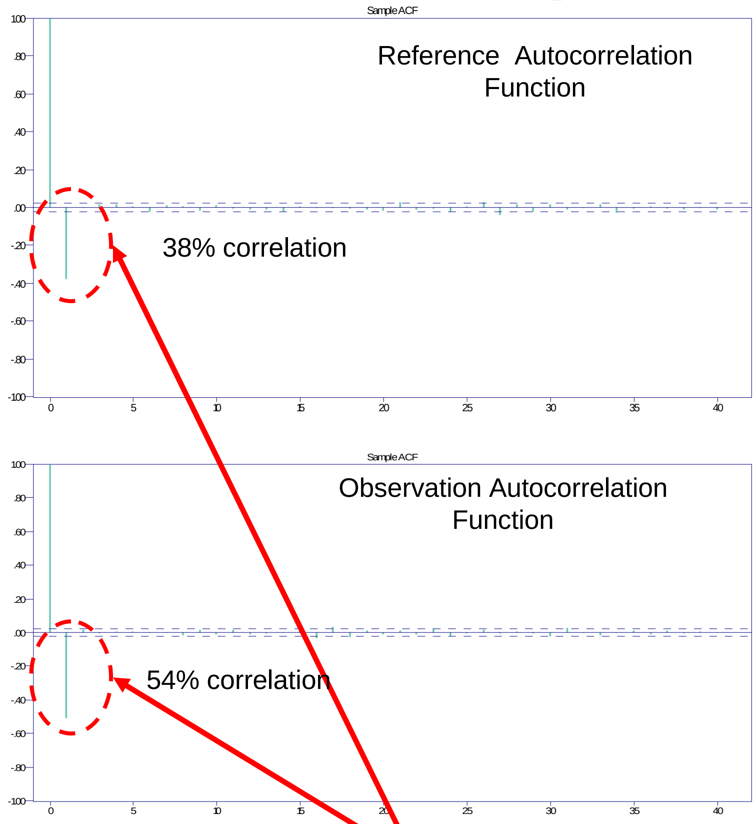
Technical Results – MFD Sample Autocorrelation Matching Results (Excessive Noise Fault)



Reference Signal (Healthy “No Failure” A priori data)



Observed Signal (Data Streaming)



Signal Name	Calculated TRIT
Reference Run	06-14-2005 (No Failure)
Test Run	07-19-2005 +noise(0,2)
Test Method	ACF Matching

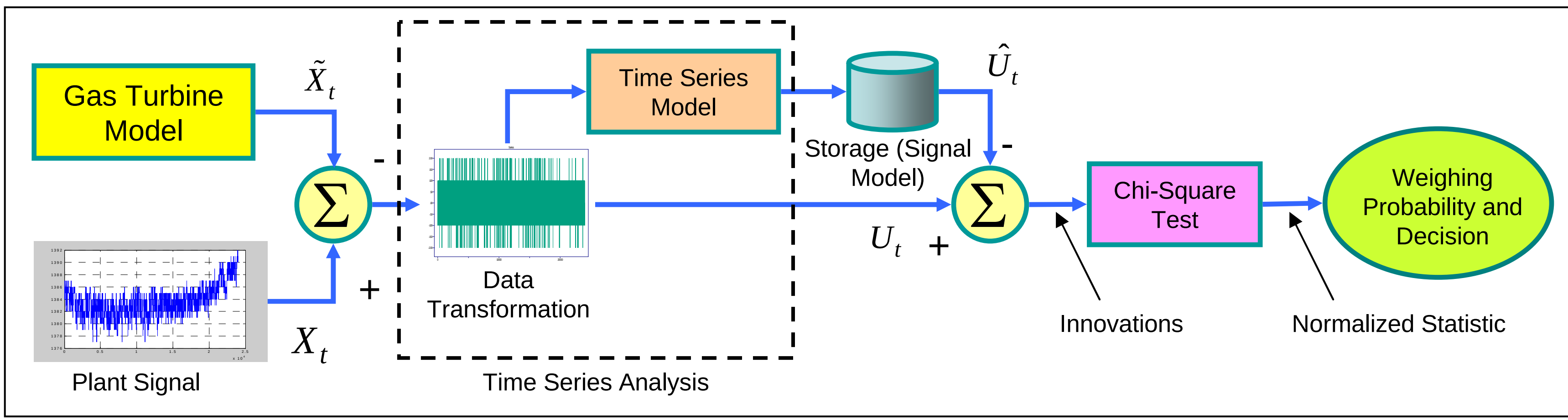
- Since the two autocorrelation functions are not similar (based on a 95% threshold limit), the observed signal does not correspond to the “No-Failure” signal

Technical Results – Model-Based Diagnostics (Innovations)

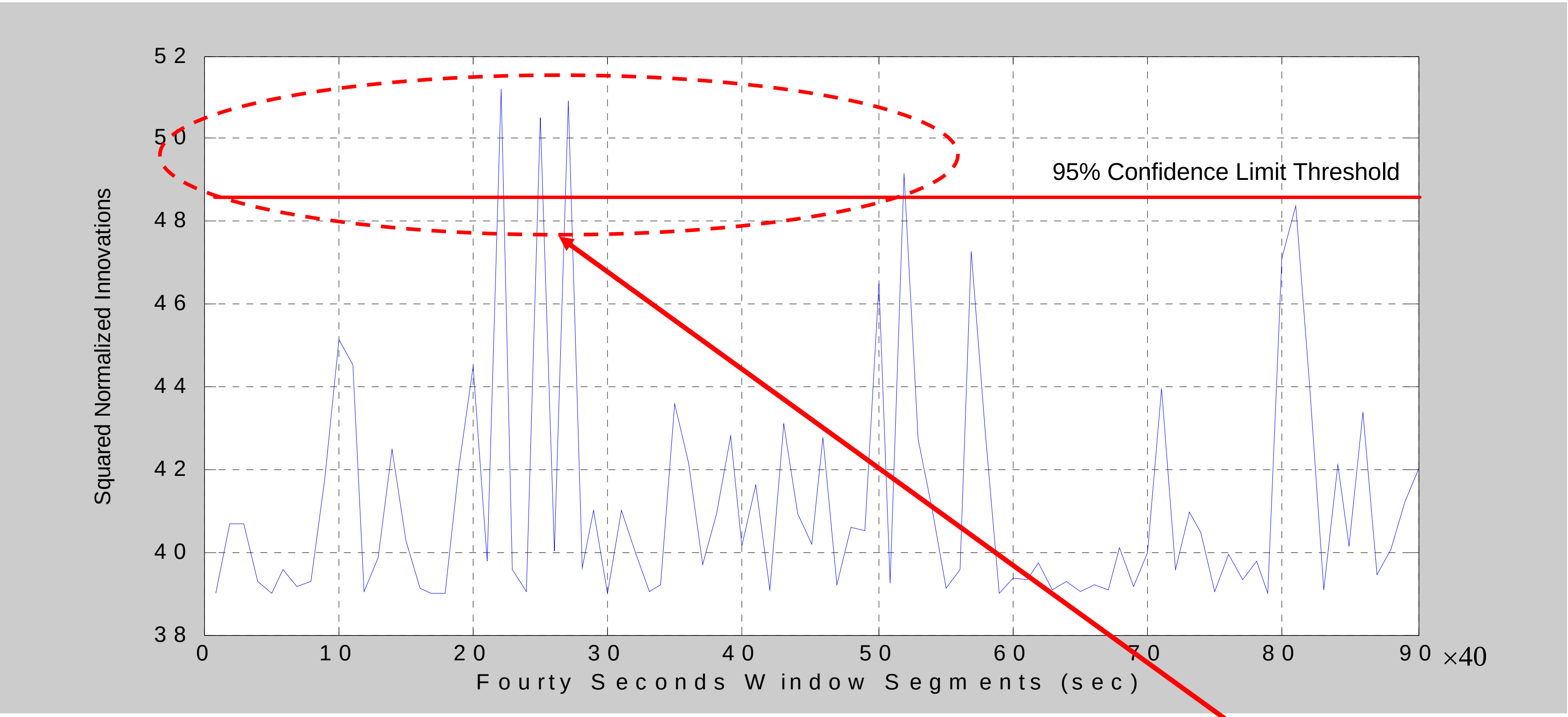
- Under the null hypothesis of “No Failure”, the innovations should be a “white noise” signal
- Sometimes the innovations exhibits an interdependence in spite of the “No Failure” condition. A Time Series model such as

$$\hat{U}_t = \underbrace{a_0 + a_1 t + a_2 t^2 + \dots + a_n t^n}_{\text{Deterministic Trend}} + \underbrace{\phi_1 \hat{U}_{t-1} + \dots + \phi_p \hat{U}_{t-p}}_{\text{Auto Regressive part}} + \underbrace{Z_t}_{\text{White Noise}} + \underbrace{\theta_1 Z_{t-1} + \dots + \theta_q Z_{t-q}}_{\text{Moving Average part}}$$

is introduced to obtain Gaussian independent innovations



Technical Results – MBD Sample Innovations Results (No Failure)

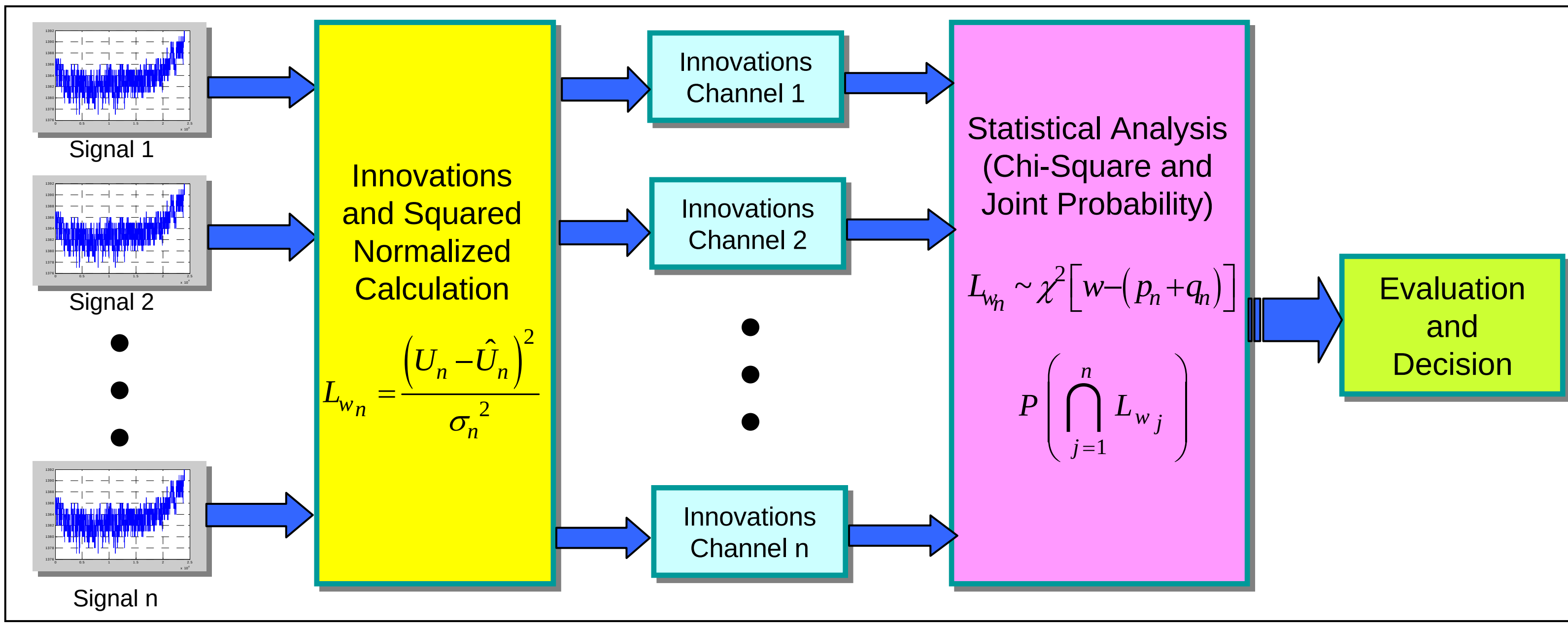


Signal Name	Calculated TRIT
Test Run	06-14-2005 (No Failure)
Time Series Model	ARMA (2,4) [WN variance=1.477]
Test Method	Innovations

- Since the threshold violation is less than 5% (actually 4.4%) with a maximum duration of 40 seconds (window length), a test which requires multiple failure windows fails to reject the white noise hypothesis results in a “No Failure” condition

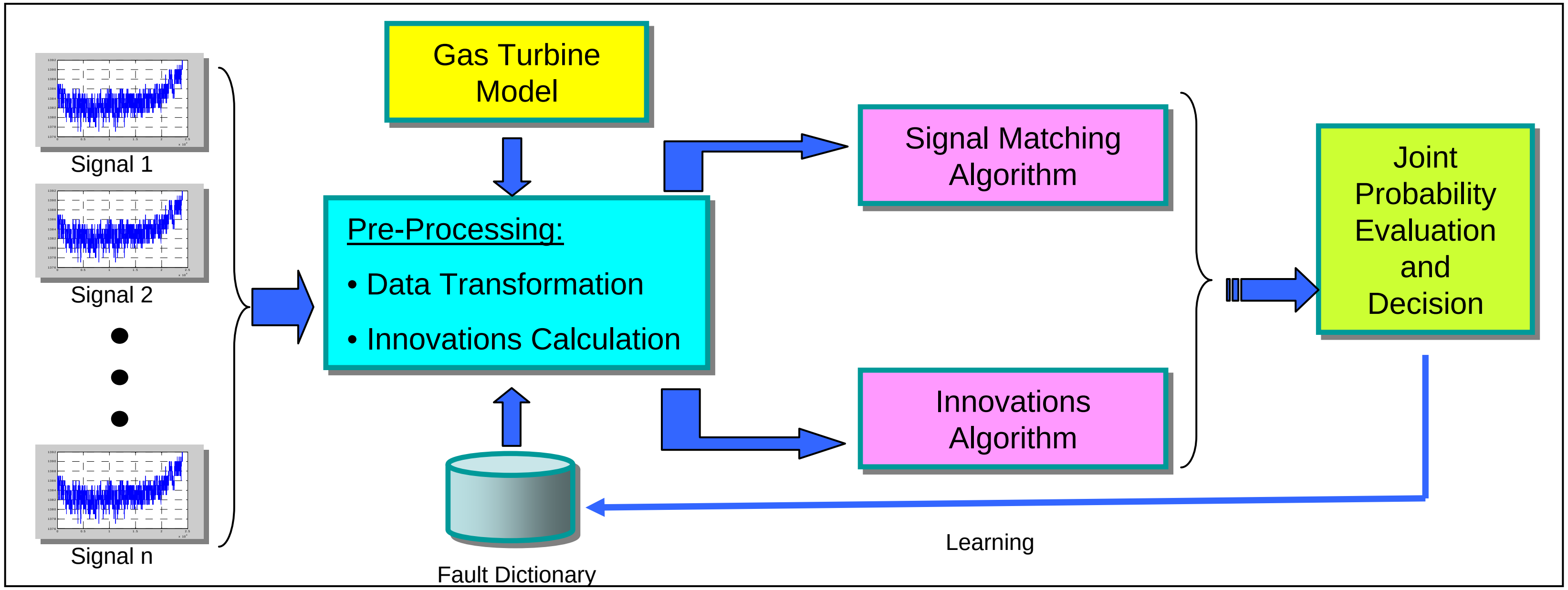
Technical Results – Implementation of MBD Fault Detection

- The innovations calculation is implemented in real-time to investigate the existence of a deviation from normal operation
- Statistical analysis includes the Chi-Square test for each channel and a joint probability calculation
- Limit checking is applied in parallel fashion to the illustrated architecture



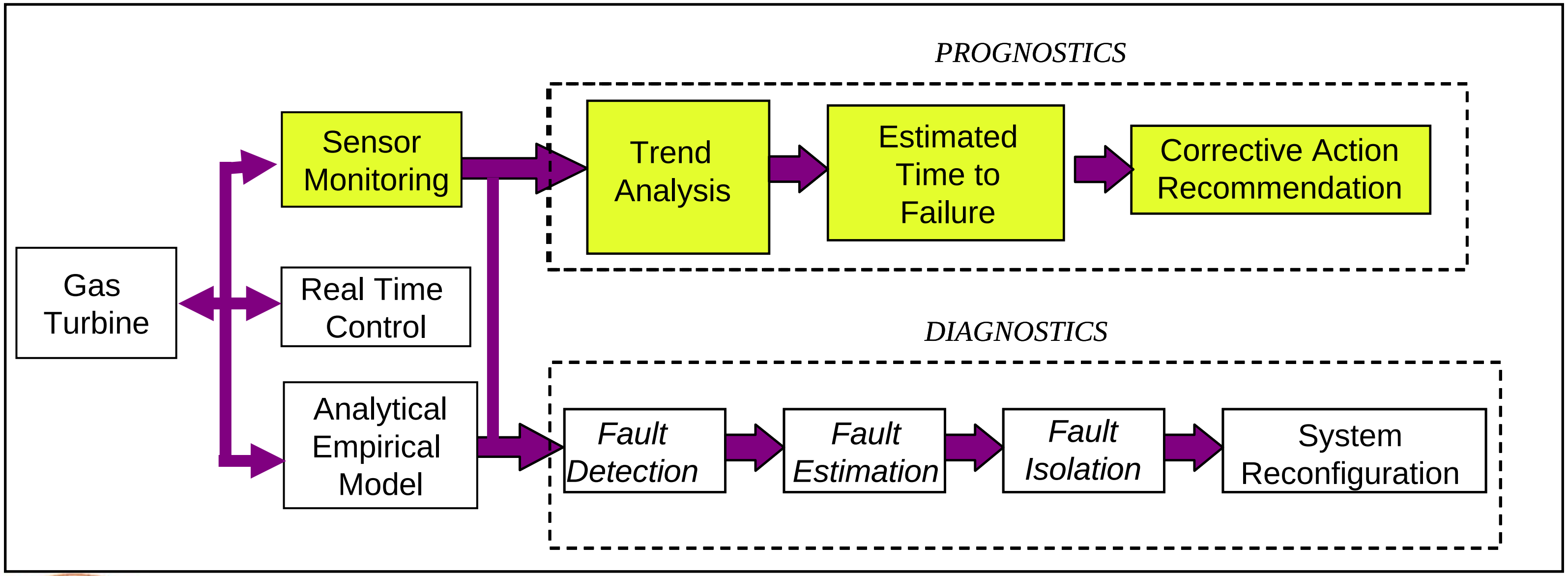
Technical Results – Implementation of Model-Free and Model-Based Isolation

- Upon detection, a detailed analysis is implemented incorporating model-free and model-based isolation methods
- Isolation is achieved by referring to the Fault Dictionary instead of the "No Failure" reference
- Newly defined fault may be added to the Fault Dictionary (i.e. Learning Feature)



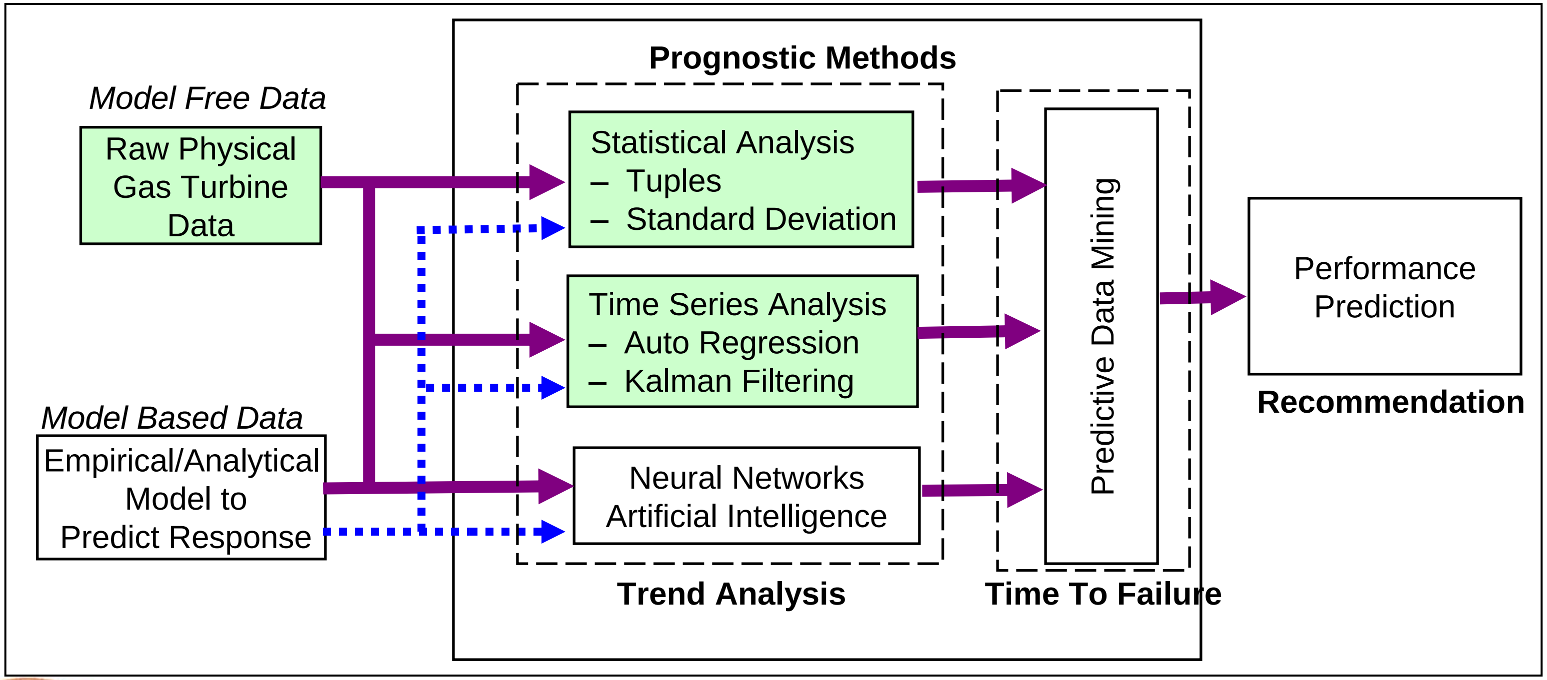
Technical Results – Prognostic Overview

- Prognostic is the study of methods to predict the future values of a signal, variable,….
- In dynamic systems, performance prediction is based on the overall trends of the observed data
- Prognostic strategies can operate in a parallel manner to the diagnostics and utilize the same available sensory information



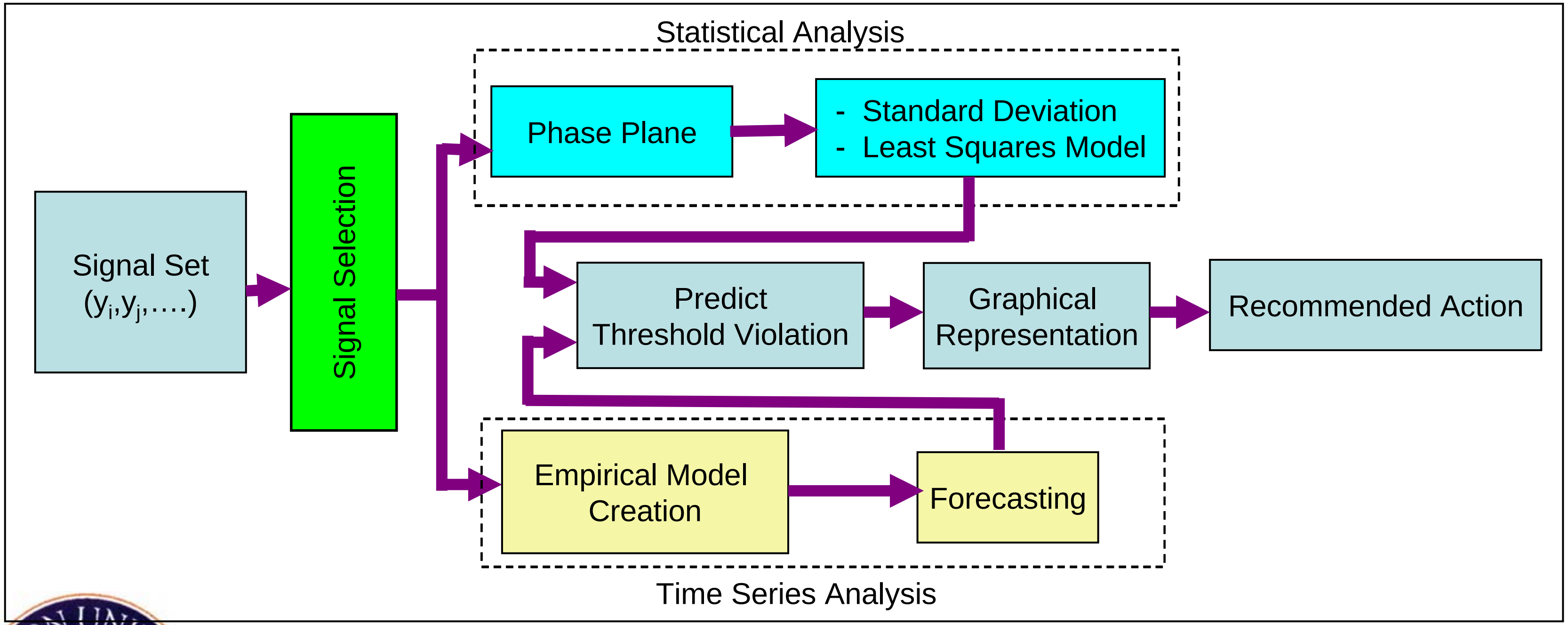
Technical Results – Select Prognostic Methods

- Model free methods do not rely on a physical model but rather directly examine signals
  - Statistical models use input/output data to analyze trends; requires a data base
  - Time Series analysis may use auto regression and Kalman prediction techniques
- Analytical/Empirical models may be use to predict response



Technical Results – Model Free Prognostic Methods

- Selection and evaluation of plant signals either individually and/or in various combinations
- Two proposed prognostic strategies for stationary gas turbines
  - *Statistical Analysis* using standard deviation and a least squares method with a graphical representation for display purposes
  - *Time Series* with empirical models created based on past operating history; used to predict future plant behavior

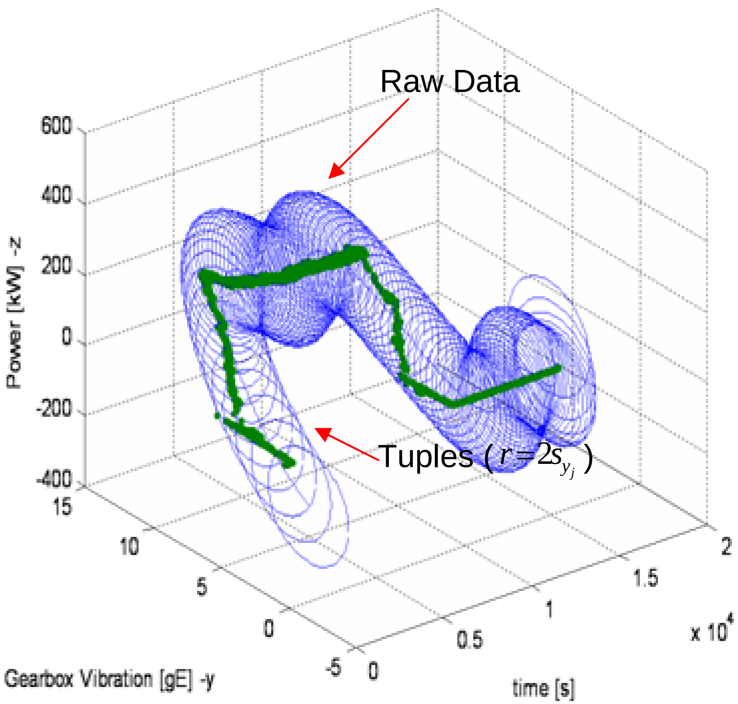


Technical Results – Model Free Statistical Analysis Prognostic Method

- A variety of gas turbine signals are collected and stored at regular time intervals $(t_1, t_2, \ldots t_n)$

$$y_j(t_i) = \begin{bmatrix} y_1(t_1) & y_1(t_2) & \cdots & y_1(t_n) \\ y_2(t_1) & y_2(t_2) & \ldots & y_2(t_n) \\ \vdots & \vdots & \ddots & \vdots \\ y_m(t_1) & y_m(t_2) & \ldots & y_m(t_n) \end{bmatrix}$$

- The standard deviations of the signals are calculated , s_{y_j} (j = 1,…,m)
- The signals dominant trends are obtained using a minimized least squares method, Z_j
- Tuples centered on polynomial trend (using the minimized least square equation) may be drawn with $2s_{y_j}$ as the radius
- A trend may be projected to predict threshold violation in the future time interval



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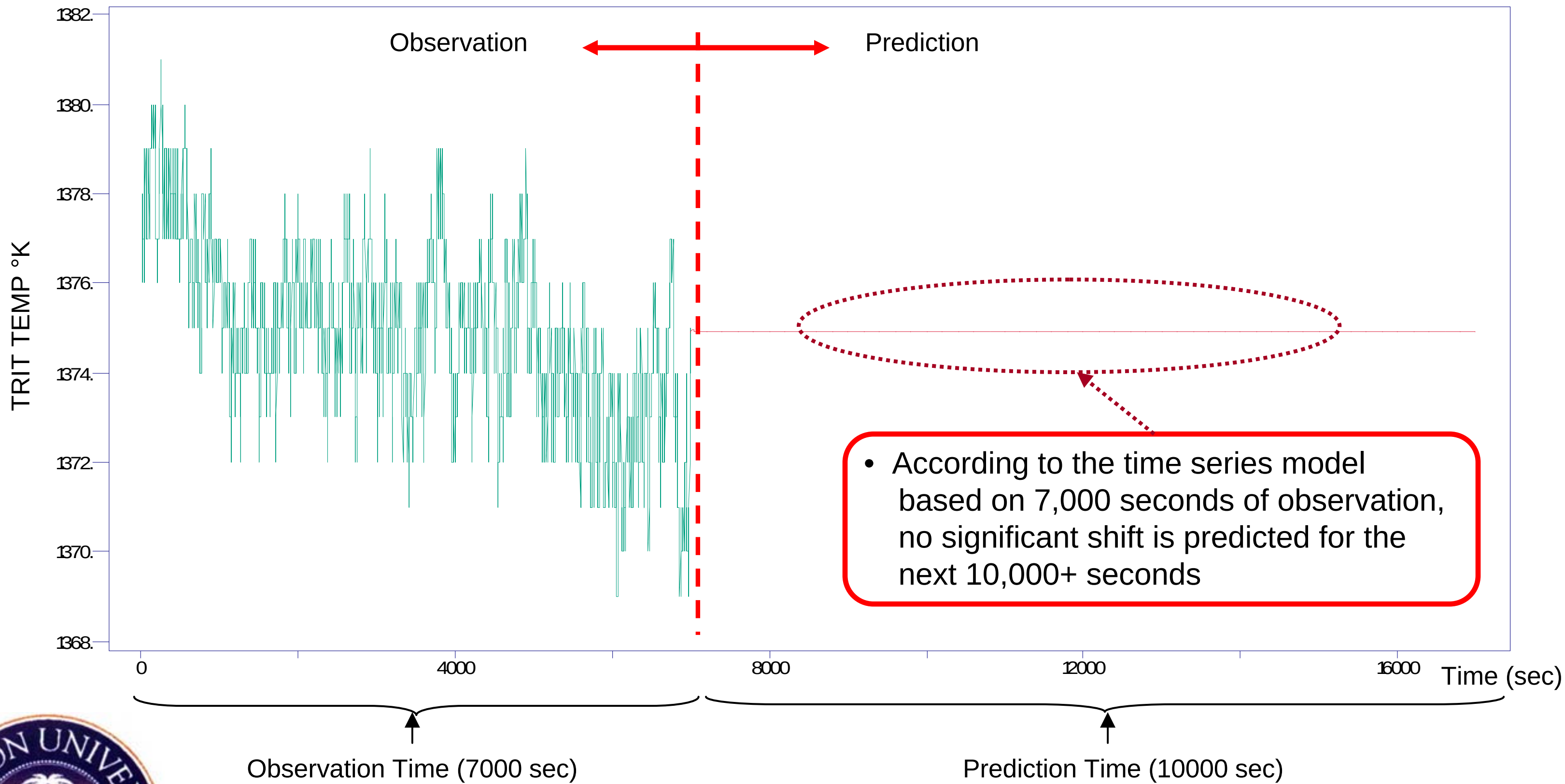
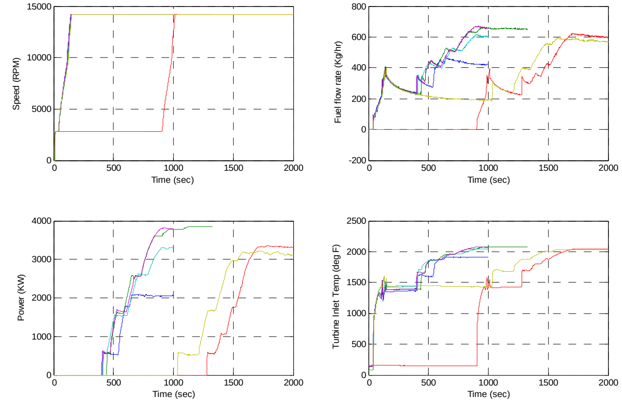
Technical Results – Time Series in Prognostics

- Time series methods can fit parametric models to select signal time histories; these methods are powerful in handling misleading stochastic trends and signal interdependences
- Based on a time series model, a forecast technique can predict the signal's future behavior



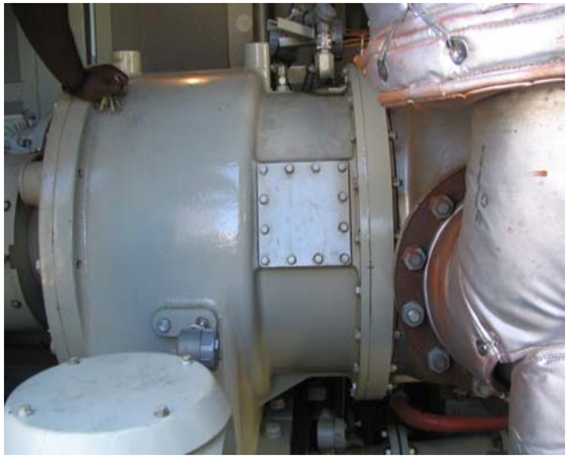
Summary

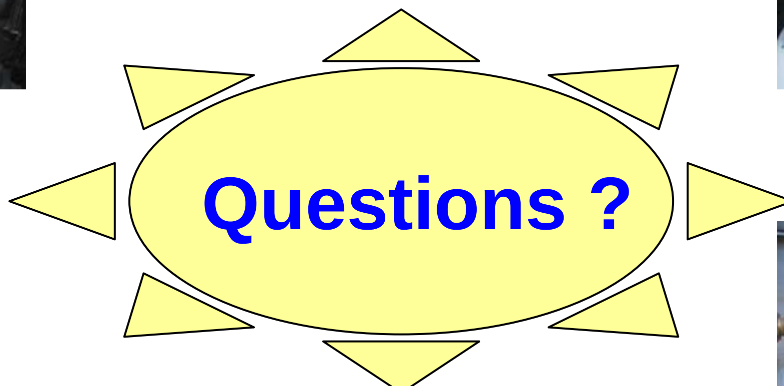
- **Research Achievements**
  - Real time data logging of the Mercury 50 gas turbine was achieved
  - A set of 28 sensors out of 180 sensors has been selected for analysis
  - A generic mathematical model based on a thermodynamic Brayton cycle analysis was developed
  - Model has been initially validated using the acquired turbine data
  - Two diagnostics approaches have been developed for stationary gas turbines
  - Created a statistical framework for prognostics
- **Present Activities**
  - Complete work on diagnostic and prognostic modules
  - Experimentally/numerically implement diagnostic/prognostic algorithms



Assortment of Mercury 50 start-up data


Mercury 50 Combustion Chamber


Mercury 50 Compressor Section




Clemson Mercury 50 Power Pack


Mercury 50 Turbine Section


Two research team members

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