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APPLICATION OF A HYBRID-AI-PHYSICS BASED ANOMALY DETECTION SYSTEM FOR COMPRESSION EQUIPMENT

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Abstract

A hybrid approach employing neural networks coupled with a physics-based model has been applied for fault detection for common gas turbine types used in Pipeline Compression. This work has been tested against common, data-driven approaches employed within industry for fault detection and shows promising ability to detect faults that would otherwise be missed by current methods. The method has been successfully back tested using multiple compression sites to detect various failures modes (blade failures, combustion system fouling, and efficiency degradation, to name a few). This paper will discuss physical modeling details and requirements, methodology for using neural networks to calibrate the model to site data, and options for modeling and implementation at an enterprise level and live monitoring. Current models have been successfully tested to work within TC Energy's Canada Gas Compression fleet. The modeling techniques and architecture are scalable and easily used for other categories of compression equipment. This approach provides a path for broader physics-based model integration.

Introduction

This work developed a hybrid physics-based model of a gas turbine with the goal of detecting faults and failures for monitoring applications. This hybrid approach trains artificial neural networks to parametric physical models to enable embedding within a centralized enterprise monitoring center environment. This paper is focused on gas turbines; however, the process described is applicable to any physics-based model and the practice is shared to provide examples of integrating high-fidelity models for real time monitoring.

A 3-phase process was employed as shown in Figure 1. In Phase I, the team created a physics basedmodel representation of a reference gas turbine using the Numerical Propulsion System Simulation (NPSS) software. This process requires personnel with model creation expertise; however, the model setup is performed in such a way that only one reference model needs to be created for each unit variant. In other words, the first phase is a one-time investment for each unit variant.

Once the reference model has been created in Phase I, Phase II performs two steps. First, an artificial neural network is created from the NPSS reference model. This is done for two reasons. First, NPSS executes relatively quickly, but still takes some time to process data. For example, a year's worth of process data at 5-minute intervals is roughly 80,000 data points. Evaluating each of the 80,000 points within NPSS as a batch run takes approximately 10 hours to execute on modern desktop PC hardware. Evaluating the same 80,000 points using a neural network regression model is almost instantaneous. This incredible speed-up in execution time enables additional parametric studies and sensitivities to be performed near real-time that would be difficult using the physics based model directly. Portability is the second reason to use an artificial neural network. The regression essentially learns the physics from the underlying physical model and enables a substitution of the neural network anywhere the NPSS physical model would traditionally be used. Furthermore, the neutral network is represented as a series of closed-form equations which can be implemented into any software package capable of using custom functions including Excel, PI Asset Framework, or almost any commonly used monitoring and diagnostic (M&D) package with custom calculation engines.

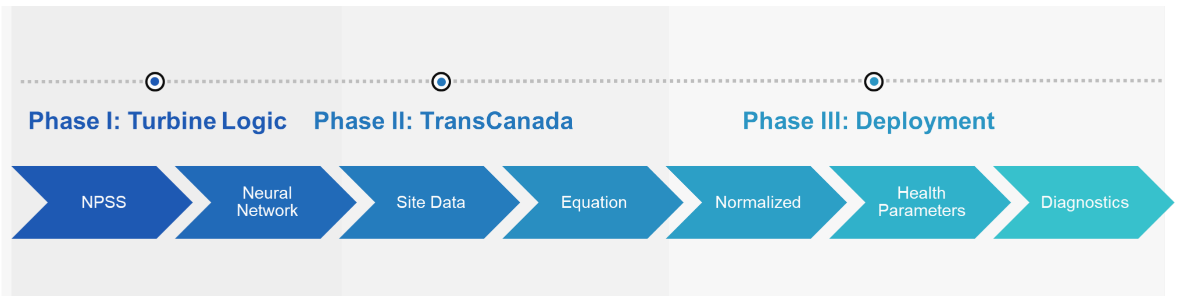

FIGURE 1: PHYSICAL MODEL CREATION PHASES

Once the neural network representation is created the model can be executed to compare predictions to measured site process data. Calibration to site can also be performed in this step. Calibration is the process of changing model settings to match site specific performance data. For example, the stage 1 gas generator turbine nozzle area has a large influence on performance and will vary site to site. It is not known in real time and must be estimated.

Phase III is focused on model use and deployment. Briefly, the calibrated and validated NPSS model can be used in multiple ways including processing of site process data to generate virtual sensors and health parameters, performing sensitivity studies to understand how faults will manifest themselves in measured process data under varying site operational conditions (e.g., outside temperature or load), and prediction of gas generator performance in the future based on the known state and degradation rates.

Phase I – Creation of the NPSS Reference Model

Model Description and Validation

The Numerical Propulsion System Simulation (NPSS) provides a framework to build any thermodynamic process model through an object-oriented framework. NPSS stands as an advanced software framework developed for the in-depth modelling, simulation, and analysis of intricate thermodynamic systems, notably in aerospace contexts. Its core strength lies in its modular architecture, enabling users to efficiently integrate and deploy distinct modules tailored for specific simulation tasks, leading to model reusability and operational efficiency. Renowned aerospace entities, including NASA and prominent aerospace corporations, leverage NPSS for its comprehensive propulsion system analysis capabilities. Beyond its primary focus on propulsion, NPSS exhibits a broader applicability, extending to any system governed by fluid dynamics and thermodynamics. A defining feature of NPSS is its open architecture, granting users the autonomy to customize and scale the software to match particularized requirements.[1]

The NPSS framework enables easy matching to any dataset assuming the model has been set up correctly. NPSS does not have any preference or enforced labels for file names or directory structure organization. Calibration of the gas turbine reference model was performed using a TC Energy Turbines engine test report. Data plotted for comparison has been extracted directly from this report. To do the initial calibration and comparison, the NPSS model has been set up to run a heat balance. The shop test visit ran a load sweep at a relatively fixed condition. Plots of major parameters are shown below plotted against corrected power output. In Figure 2, Figure 3, and Figure 4, the red line shows the TC Energy shop test data, and the blue line shows the prediction from the NPSS model using the heat balance setup.

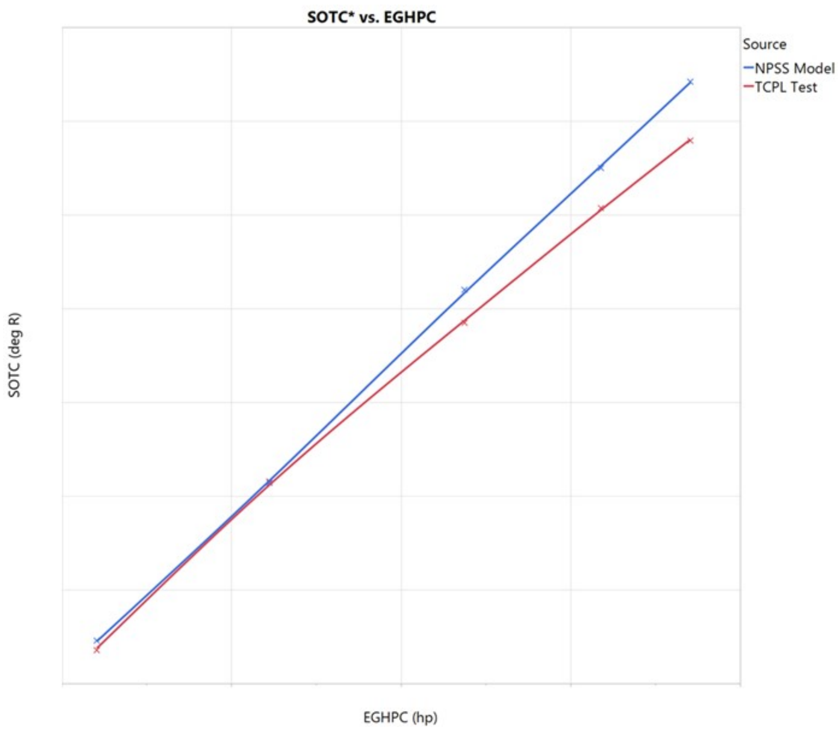

FIGURE 2: COMPARISON BETWEEN NPSS MODEL AND SHOP TEST DATA - STATOR OUTLET TEMPERATURE CORRECTED (STOC) VS. ENGINE GAS HORSEPOWER ISO CORRECTED (EGHPC)

[1] Southwest Research Institute, "Numerical Propulsion System Simulation (NPSS)." swri.org. https://www.swri.org/consortia/numerical-propulsion-system-simulation-npss (accessed Sept. 6, 2023).

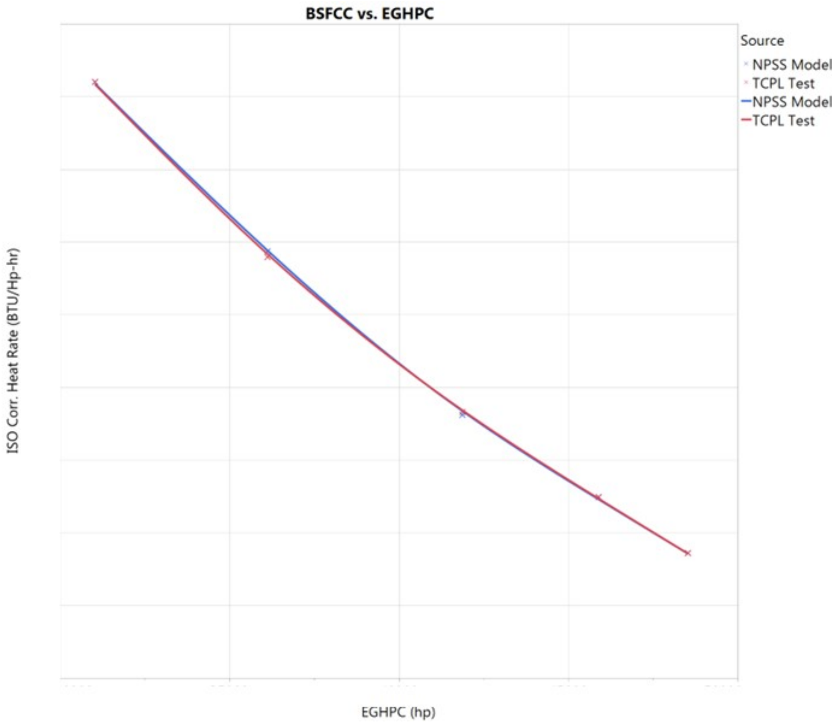

FIGURE 3: COMPARISON BETWEEN NPSS MODEL AND SHOP TEST DATA – ISO CORRECTED HEAT RATE VS. EGHPC

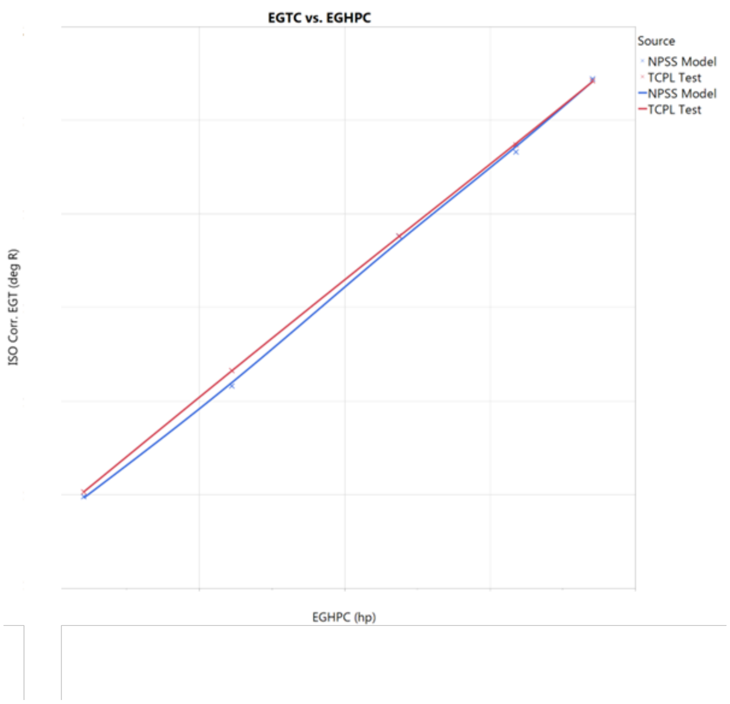

FIGURE 4: COMPARISON BETWEEN NPSS MODEL AND SHOP TEST DATA – ISO CORRECTED EXHAUST GAS TEMPERATURE (EGT) VS. EGHPC

Addition of Health Parameters to Physics-Based Model

Health parameters represent the intrinsic health state of the components within the gas generator. The health parameters can be directly set as inputs or solved for to match existing process data. They represent an unbiased estimate of component health removing effects of ambient conditions, operating load, and the health state of other components within the machine. The health parameter definitions are shown in Table 1.

TABLE 1: HEALTH PARAMETER DEFINITIONS

Health Parameter
Compressor_Health – Indicator of Gas Generator (GG) Compressor Health [0-1]
Burner_DPHealth – Indicator of Burner Pressure Drop [Scalar w.r.t Baseline]
Turbine_effHealth – Indicator of Turbine Efficiency [Scalar w.r.t. Baseline]
Turbine_FlowHealth – Indicator of Turbine Flow Area (Nozzle) [Scalar w.r.t. Baseline]

Artificial Neural Network Creation

After the basic model validation has been performed, the NPSS model is re-executed to create a neural network representation capable of auto-calibration. This neural network creation is performed to make a general representation of the gas turbine that should be adaptable through calibration to any specific unit. This neural network training and regression process should only need to be repeated if the NPSS model is changed due to increases in model fidelity or if a new variant of gas turbine is to be modelled.

The neural network is trained from a design of experiments that is executed through NPSS. The design of experiments executes the reference NPSS model over a range of ambient conditions and health parameters. The inputs and ranges used to generate the design of experiments are shown in Table 2. The ambient condition inputs should be self-explanatory to those familiar with gas turbines; however, the health parameters are unique to this model as explained above.

TABLE 2: DESIGN OF EXPERIMENTS FOR NPSS NEURAL NETWORK CREATION

Input	*Minimum*	*Maximum*
T1 – GG Inlet Temperature [deg F]	-35	100
P0 – GG Inlet Pressure [psia]	13	15
WAR – GG Inlet Water to Dry Air Ratio [g/kg]	0	0.0219
Fuel LHV – Lower Heating Value [BTU/lbm]	20567	21499
Enthalpy of Fuel – Based on Fuel Composition and Temperature [BTU/lbm]	215	230
N1c – LP GG Compressor Corrected Speed [RPM]	6000	6800
Health Parameters as Described Above	Min	Max

The Compressor Health parameters have been created to tie together shifts in compressor flow, efficiency, and pressure ratio that accompany degradation. This reduces the number of independent variables and increases model accuracy when used for fault detection. The parameters were derived by examining performance data from the unit to understand ranges of degradation and the impact on the compressor operating line. The equations set compressor performance as a function of corrected speed and health. A health parameter setting of 1 indicates a healthy compressor. A setting of 0 indicates a fouled or degraded compressor.

Using the ranges from Table 2, a design of experiments is constructed. 1200 space filling points generated from a Latin Hypercube design with an additional 25 edge and center points are executed through NPSS. NPSS does not natively contain ability to run a table of input data, therefore a Python script was developed to execute the design of experiments shown in Table 2. The design of experiments is dimensionalized using the ranges in Table 2, or other ranges as appropriate. The table is then executed, one case at a time, through NPSS and the results are collected. A python script was created to run the DOE (design of experiments) through NPSS.

The neural network structure is shown in Figure 5. There are 12 inputs and 12 outputs. Six of the inputs come from site data (T1, P0, WAR, LHV, Enthalpy, and N1c) and represent the external state and power setting of the gas generator (GG). The other six inputs represent the health parameters which are inputs to NPSS. The outputs are estimated pressures and temperatures throughout the GG along with estimates of total gas fuel flow and BHP of the unit. These calculations can then be used to calculate fault data by comparing the 'calc' estimates vs. site data.

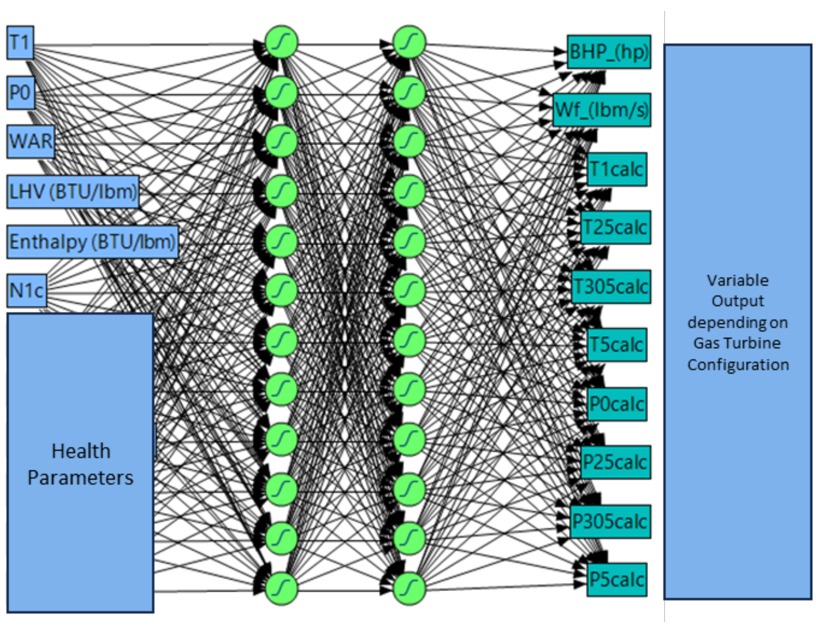

FIGURE 5: NEURAL NETWORK STRUCTURE

Calibrating the neural network to a specific site requires estimating the average health parameters over the site data set extracted from the TC Energy historian. The team evaluated different techniques and determined that for this specific application a filtered Monte Carlo provides the right balance of accuracy, speed, and portability. The calibration and estimation of these parameters is performed at initial model calibration and after any major unit upgrades or repairs. It is possible that calibration may only be required once per unit; however, longer term evaluation across multiple sites will be required to know for sure.

Case Studies

Case Study 1: Blade Damage

Figure 6 shows the calculation of faults for each measurement station using the calibrated neural network (measured minus model prediction). This is a way to normalize the data and identify anomalous operation. This allows easy alignment with the troubleshooting chart in Figure 8. Not all fault signals are shown for clarity of plot, but all were examined. The GG Turbine End Vibration Measurement was also added as it helps with the diagnosis. A clear spike in vibration and exhaust temperature is seen at the end of the period and indicated by the red circle.

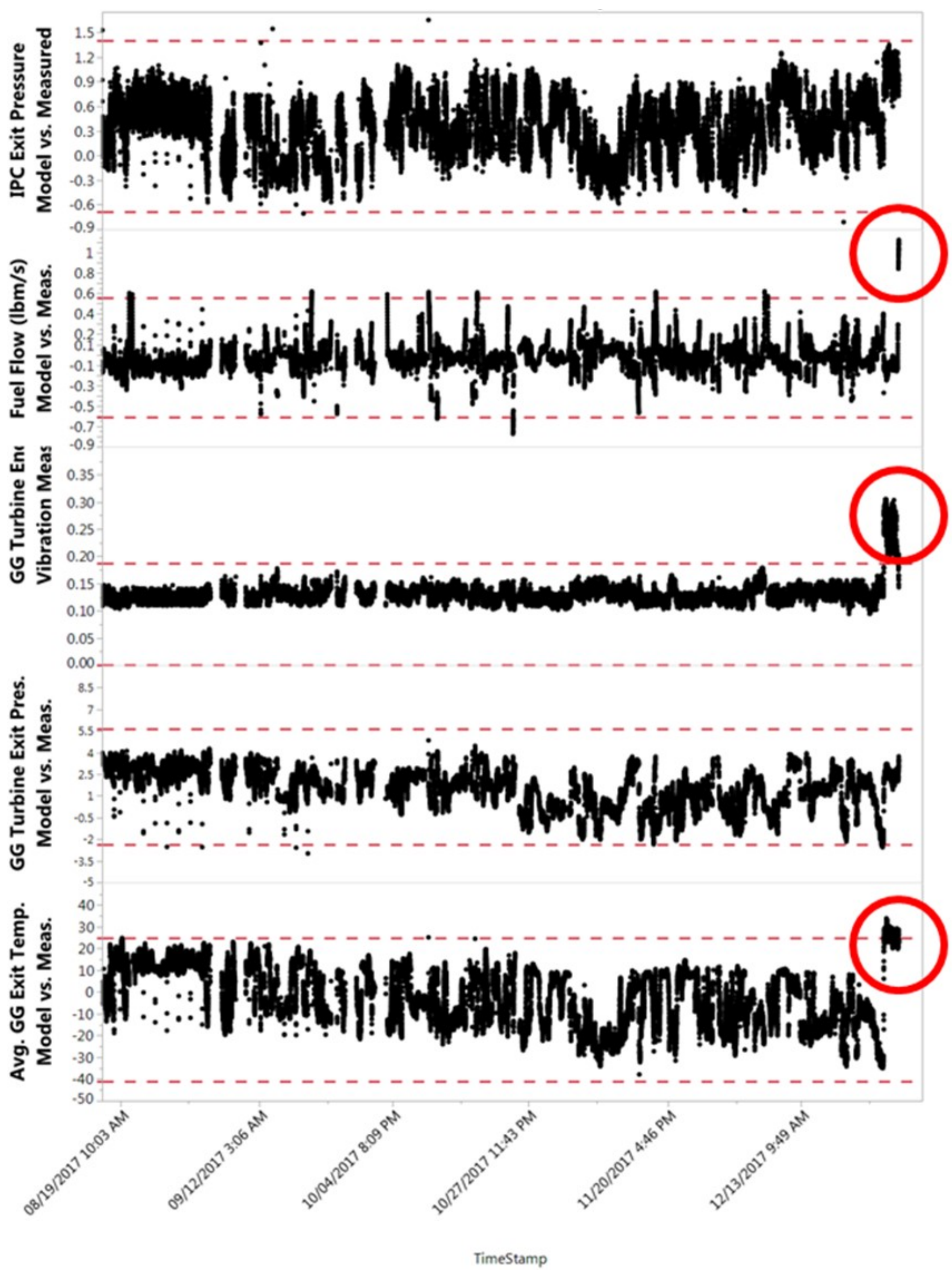

FIGURE 6: SITE B FAULT SIGNALS (MEASURED - NN PREDICTION)

The exhaust temperature spreads are shown in Figure 7. The light black area represents normal operation. The darker black area shows spreads two days prior to the failure event. This alone may not have been sufficient for unit shutdown, but may have prompted additional monitoring. The red dots show post failure spreads. Individual thermocouples were not trended, but if a shift in typical operation occurs they may be used to identify the location of the fault circumferentially within the turbine or combustion system.

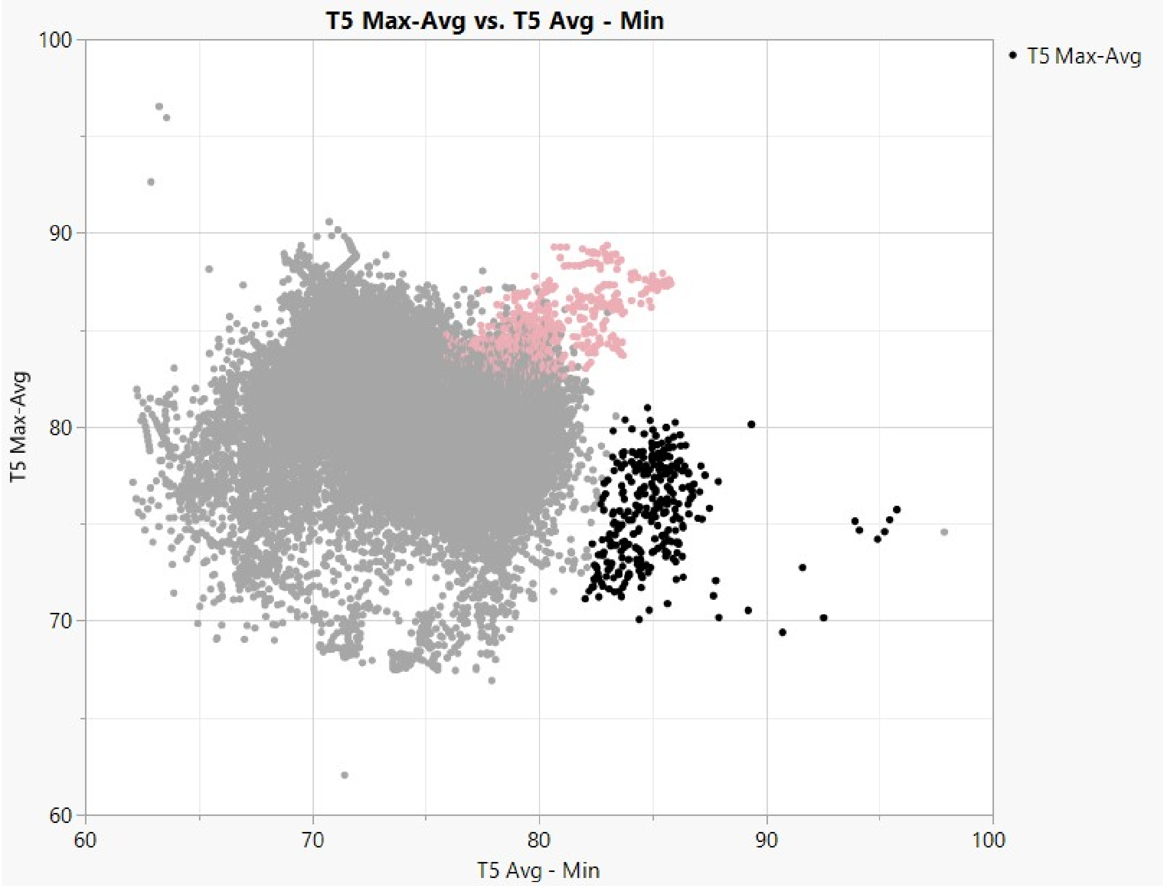

FIGURE 7: SITE B EXHAUST TEMPERATURE SPREADS

Diagnosis

Based on the fault signatures from the model coupled with evaluation of other process data it is concluded that a turbine blade or nozzle failure occurred. The symptoms matched on the troubleshooting chart are shown in Figure 8. The unit continued to run for 2 days after the failure occurred. It appears elevated vibration alone was not sufficient to shut down the unit. Additional information to confirm damage could have prevented additional damage from running the machine post failure.

	Combustion Noise	Vibration	Fuel Pressure		IPC/HPC Pressure Ratio	GG Turbine Pressure Ratio	Bearing Temperatures	Wheel Space Temperature	Exhaust Temperature		Exhaust Temperature Spread	IPC/HPC Efficiency	GG Turbine Efficiency
Direction	Up	Up	Up	Down	Down	Down	Up	Up	Up	Down	Up	Down	Down
Blade Damage		X			X							X	
Filter Clogging					X								
Surge		X					X					X	
Fouling					X							X	
Liner Cracking	X		X	X							X		
Fouling	X		X	X						X	X		
Clogging	X		X						X		X		
Blade Damage		X							X				X
Nozzle Damage		X				X		X	X				X
Fouling								X					X

FIGURE 8: SITE B FINAL DIAGNOSIS

Case Study 2: Turbine Nozzle Damage

Figure 9 shows the calculation of faults for each measurement station using the calibrated artificial neural network (measured minus model prediction). This allows easy alignment with the troubleshooting chart in Figure 11. Not all fault signals are shown for clarity of plot, but all were examined. The GG Turbine End Vibration Measurement was also added as it helps with the diagnosis. There is an excursion in exhaust gas temperature and vibration near the end, marked in red, that then reduces in magnitude. While the vibration returns to normal levels, this is a false indicator of normal performance as the exhaust gas temperature swings lower than expected indicating potential hardware damage.

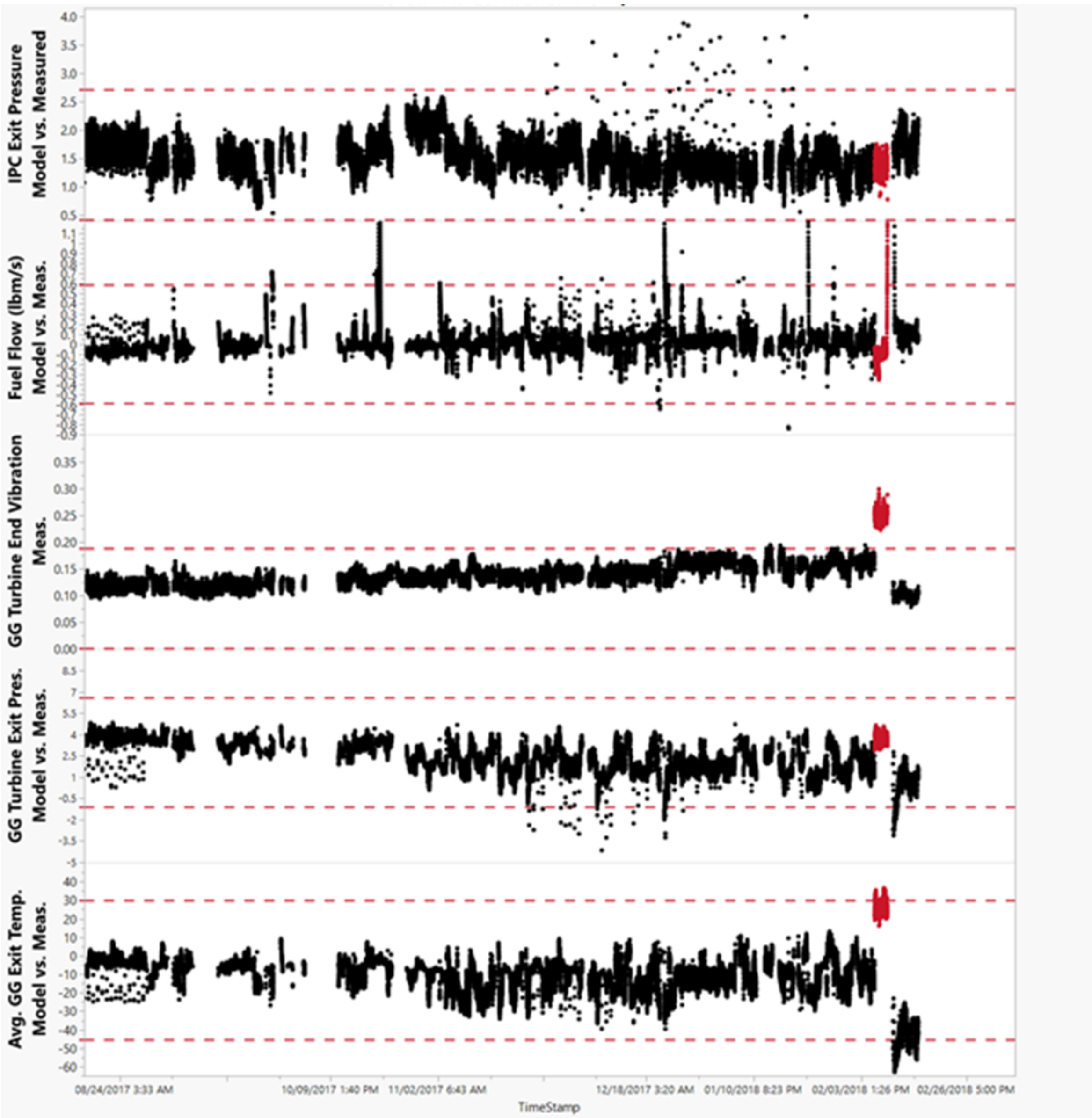

FIGURE 9: SITE A FAULT SIGNALS (MEASURED - NN PREDICTION)

The exhaust temperature spreads are shown in Figure 10. The light black area represents normal operation. The darker black area shows spreads following the high vibration excursion event. Red shows spreads during the high vibration period. This alone may not have been sufficient for unit shutdown, but may have prompted additional monitoring. Post failure shows a large drop in spreads which is atypical for the unit.

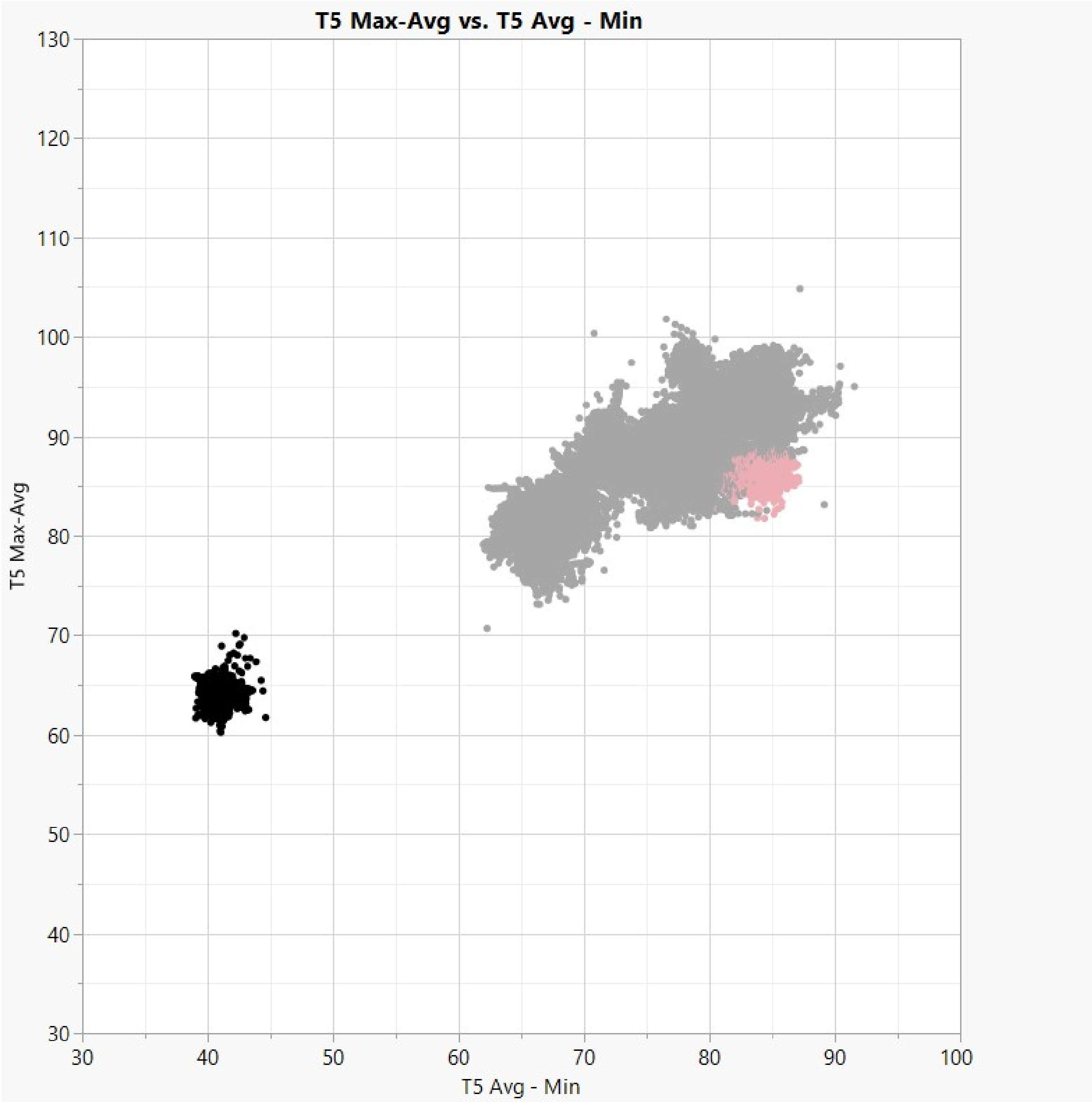

FIGURE 10: SITE A EXHAUST TEMPERATURE SPREADS

Diagnosis

Based on the fault signatures from the model coupled with evaluation of other process data it is concluded that a combustor or turbine nozzle failure may have occurred. The symptoms matched on the troubleshooting chart are shown in Figure 11. The unit continued to run for 2 days after the failure occurred. It appears elevated vibration alone was not sufficient to shut down the unit. Additional information to confirm damage could have prevented additional damage from running the machine post failure. The machine was run for more than five days following the signs of hardware distress which could have caused additional damage.

		Combustion Noise	Vibration	Fuel Pressure		IPC/HPC Pressure Ratio	GG Turbine Pressure Ratio	Bearing Temperatures	Wheel Space Temperature	Exhaust Temperature		Exhaust Temperature Spread	IPC/HPC Efficiency	GG Turbine Efficiency
	Direction	Up	Up	Up	Down	Down	Down	Up	Up	Up	Down	Up	Down	Down
Compressor	Blade Damage		X			X							X	
	Filter Clogging					X								
	Surge		X					X					X	
	Fouling					X							X	
Combustor	Liner Cracking	X		X	X							X		
	Fouling	X		X	X						X	X		
	Clogging	X		X						X		X		
Turbine	Blade Damage		X							X				X
	Nozzle Damage		X				X		X	X				X
	Fouling								X					X

FIGURE 11: SITE A FINAL DIAGNOSIS

Conclusions

A condition monitoring approach using neural networks to implement a physics-based gas turbine model has been developed to the end of the proof-of-concept phase. It has been successfully demonstrated to show how it can supplement monitoring of ‘raw’ historian data to identify potential hardware damage through changes in thermodynamic performance of the gas turbine. In two cases the developed approach is capable of identifying anomalous behavior which corresponds to known part failures. The process of creating a neural network for any physics-based model can be adapted to any system for real time monitoring.