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EFFECT OF MANUFACTURING VARIABILITY ON TURBINE ENGINE PERFORMANCE A PROBABILISTIC STUDY

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While turbine engine Original Equipment Manufacturers (OEMs) accumulated significant experience in the application of probabilistic methods (PM) and uncertainty quantification (UQ) methods to specific technical disciplines and engine components, experience with system-level PM applications has been limited.

To demonstrate the feasibility and benefits of an integrated PM-based system, a numerical case study has been developed around the Honeywell turbine engine application. The case study uses experimental observations of engine performance such as horsepower and fuel flow from a population of engines. Due to manufacturing variability, there are unit-to-unit and supplier-to-supplier variations in compressor blade geometry. Blade inspection data are available for the characterization of these geometric variations, and CFD analysis can be linked to the engine performance model, so that the effect of blade geometry variation on system-level performance characteristics can be quantified. Other elements of the case study included the use of engine performance and blade geometry data to perform Bayesian updating of the model inputs, such as efficiency adders and turbine tip clearances.

A probabilistic engine performance model was developed, system-level sensitivity analysis performed, and the predicted distribution of engine performance metrics was calibrated against the observed distributions. This paper describes the model development approach and key simulation results. The benefits of using PM and UQ methods in the system-level framework are discussed.

This case study was developed under Defense Advanced Research Projects Agency (DARPA) funding which is gratefully acknowledged.

1 INTRODUCTION AND PROBLEM STATEMENT

The application of Probabilistic Methods (PMs) to the design, manufacturing and field management of gas turbine engines spans well over two decades. However, the use of PM in the propulsion gas turbine engine industry has not reached the desired levels, leaving significant unrealized potential and benefits on the table, such as cost and weight savings, reduced testing, improved safety and reliability, and optimized maintenance and logistics. Some of the main factors inhibiting the use of PMs on a broader scale include challenges in defining a clear business case, organizational culture change from deterministic to probabilistic processes, validation of probabilistic predictions, and data availability. DARPA funded PADME program was designed to address some of these issues and to pave the way for a broad system-level application of PMs in accordance with the high-level program objective as defined in [1]: "*PADME will demonstrate the feasibility of implementing probabilistics in system level analysis and design of turbine engines*".

To demonstrate the feasibility and benefits of an integrated PM-based system, Honeywell developed a numerical case study around actual turbine engine application with substantial production and field experience.

Figure 1 shows a high-level view of the integrated engine life cycle process, with the elements of the process conducive to the application of the PMs marked with a letter "P". This consideration has been translated into a specific definition of a case study used as a proof of concept for a system level PM application. A detailed technical approach for several elements of the case study, include prediction of engine performance shift attributed to component suppliers variation, and calibration of performance models using engine test data, is discussed in Section 2.

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Figure 1. This is the control or supervised regime for cyber process.

2 TECHNICAL APPROACH

Figure 2 illustrates the architecture. Raw telemetry from OT networks and IT systems enters via a vendor-neutral ingestion layer and is normalized into a common schema. Feature extraction computes rolling statistics, inter-arrival times, and protocol-specific features. Two complementary detectors operate on the feature stream: a supervised classifier trained on labeled attack data from MITRE ATT&CK for ICS and a semi-supervised anomaly detector trained on benign traffic only, so that novel attacks can still be flagged. Alerts are scored for severity and enriched with asset criticality and recent change context before reaching the analyst queue. Analyst verdicts flow back into the labeling pipeline, closing the loop. Models are versioned and deployed through a standard MLOps pipeline with shadow mode, canary rollout, and automatic rollback on degradation. Every decision is logged with the model version, feature values, and explanation, so that any alert can be reconstructed months later for audit or incident response.

2.1 Literature

Prior work on ICS anomaly detection has been dominated by benchmark datasets such as SWaT, WADI, and Modbus traces from laboratory testbeds. Reported results are strong, but deployment reports from utilities and vendors consistently describe alert fatigue, concept drift, and the absence of labels as the binding constraints. Surveys of the field make the gap between benchmark AUC and operational usefulness explicit. This paper treats those constraints as the main design problem rather than as caveats to a detector that already works.

2.2 OT vs IT: Why Not Just Apply Existing Tools

Network intrusion detection systems such as Zeek and Suricata parse industrial protocols and can alert on known signatures and protocol violations. They are mature, fast, and well understood. They also miss anomalies that look like valid traffic but are wrong in context, such as a setpoint change issued by an authorized engineering station at an unusual time. Signature-based tools require a rule for each attack they know about, and they have little to say about novel behavior. Rule-based systems for process data (thresholds on tag values, rate-of-change limits) catch gross failures but require deep domain knowledge to maintain and generate many false positives when operating conditions shift. Supervised machine learning can learn subtle patterns from labeled data, but labels are scarce and biased toward attacks that have been seen before. Unsupervised methods can generalize to novel behavior but produce alerts that operators must trust before they will act on them. Hybrid approaches combine these strengths and are the dominant pattern in deployed systems. This paper follows that pattern and adds a third layer: a human review loop whose decisions feed back into the training pipeline.

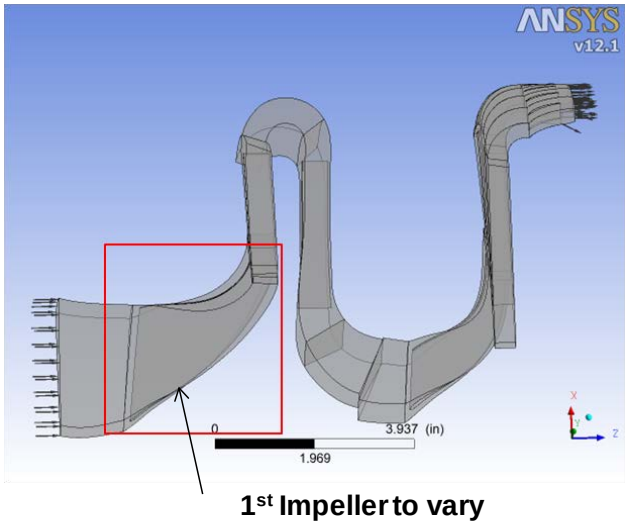
Figure 2. Case study – Supervised predictive system for production control system.

2.3 Supervised Anomaly Detectors

The supervised detector (LightGBM) is fully tunable against labeled data and ranks well when attack classes resemble those seen in training. Its weakness is that it cannot flag what it has never been shown. The unsupervised detector (Isolation Forest) trains only on benign traffic and flags deviations from learned normal behavior. It can surface novel attacks but produces more false positives and requires careful threshold tuning. Neither model is sufficient on its own. Ensemble scoring combines both outputs and lets the operator see which model fired and why.

2.4 Human Review and Feedback

Every alert is scored for severity and enriched with asset criticality and recent change context before it reaches an analyst. Analysts can mark alerts as true positive, false positive, or benign-but-unusual, and their verdicts are stored with the original feature vector and explanation. Weekly retraining jobs consume this feedback to adjust thresholds and update the training set. Models are versioned and deployed through a standard MLOps pipeline with shadow mode, canary rollout, and automatic rollback on degradation. Every decision is logged with the model version, feature values, and explanation, so that any alert can be reconstructed months later for audit or incident response.



1st Impeller to vary

Figure 3. CFX model of compressor.

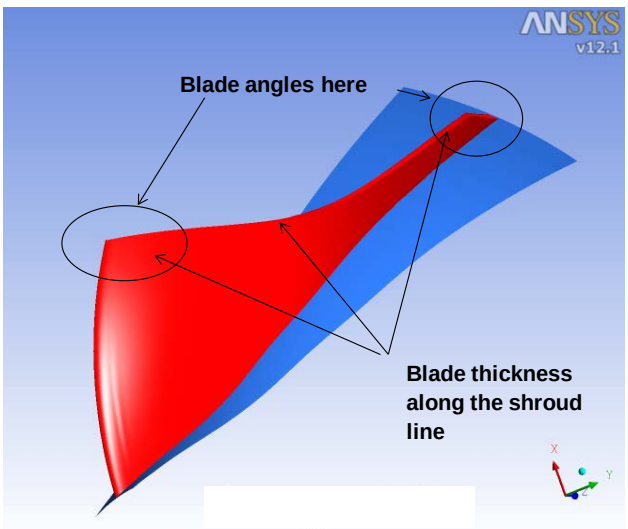


Figure 4. Geometric parameters of first-stage impeller to be varied.

2.2.2 Engine Performance Input for the Probabilistic Program

One of the analytical modules used for this system-level probabilistic study is an engine performance model. It is represented by Honeywell's proprietary software code FAST (**F**ast **A**ccurate **S**imulation of **T**urbine engines), an analytical tool that uses thermodynamic principles to predict overall engine performance. The performance model was configured to accept (as random inputs) the compressor mass flow, pressure ratio and efficiency scalars. These inputs are derived from the outputs of the compressor CFD runs. Other random input variables accepted by the model include turbine tip clearance and turbine nozzle flow area scalars that have been defined based on expert estimates (see Figure 6). The model was customized to be run from the NESSUS code, and it outputs compressor and turbine component parameters like airflows, pressure ratios, temperatures and component efficiencies in addition to overall engine shaft horse power (SHP), fuel flow and specific fuel consumption (SFC). The cycle output parameters like compressor and turbine temperatures are used as inputs into Blade Lifing module which is based on the blade life prediction algorithms provided by the Turbines department and are discussed in the next section.

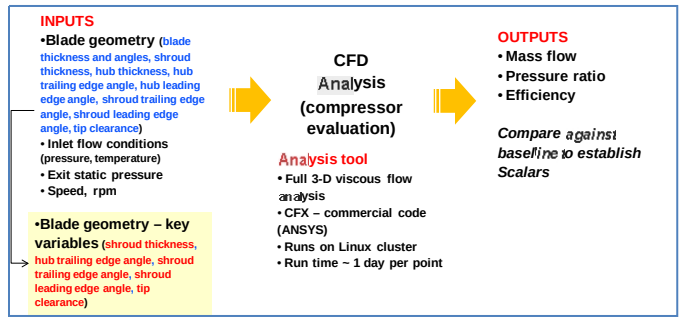


Figure 5. Schematics of the CFD model's key inputs and outputs.

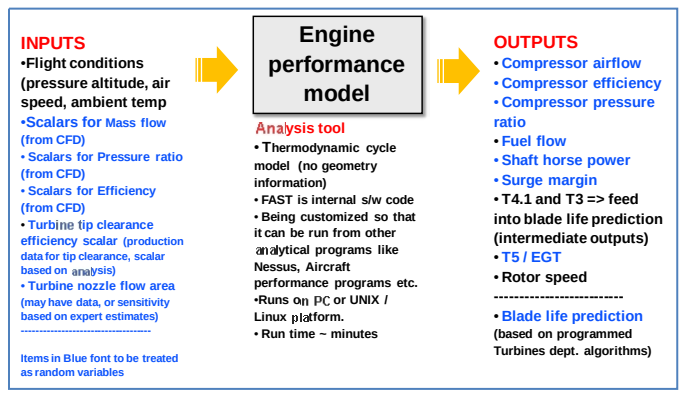


Figure 6. Schematics of performance model's key inputs and outputs.

2.3 Effect of Supplier-to-Supplier Variation

Figure 7 presents the historical performance trend data (SHP margin) acquired in the test cell during the turbine engine acceptance tests. The trend shows a shift in the average engine performance by a few percentage points. It was noted that this shift occurred at about the same time that a change was made in compressor module suppliers, from the original supplier (identified as Supplier #1) to a new supplier (identified as Supplier #2). It should be noted that both suppliers produce components to the same drawing requirements, and thus, the difference in components can be attributed to the difference in supplier process capabilities *within the allowable range of drawing tolerances.*

This performance shift was identified as one of the elements of a case study for using the probabilistic program to study/identify/predict the major random variability drivers causing the noted shift in engine performance.

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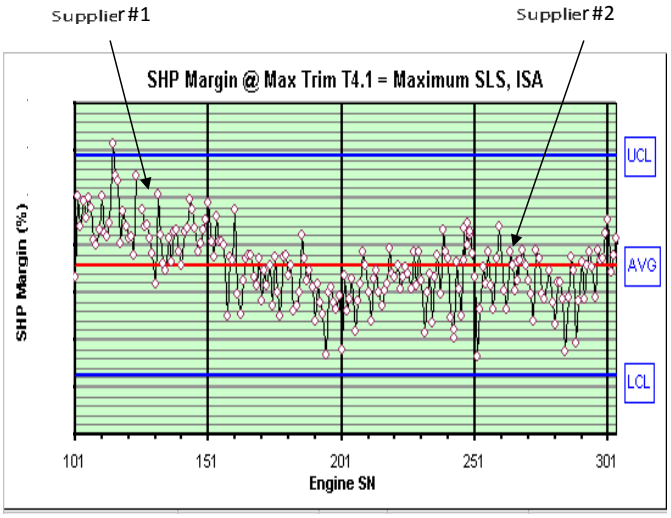

Figure 7. SHP historical engine performance trend data.

2.4 Turbine Blade and Nozzle Life Assessment

Turbine blade/nozzle life is governed by blade/nozzle metal temperature, blade stress level, and mission profile. For this program, the mission profile was considered constant. Blade stress levels vary as a function of casting variation, which is small. Since the engine operates as a constant speed engine, there is no speed variation that would impact blade stress levels.

Blade/nozzle metal temperatures are driven by flowpath gas temperatures as shown in Figure 8: turbine rotor inlet temperature (T4.1), turbine exit temperature (T5) and compressor discharge temperature (T3). These values are outputs from the thermodynamic (engine performance) FAST model.

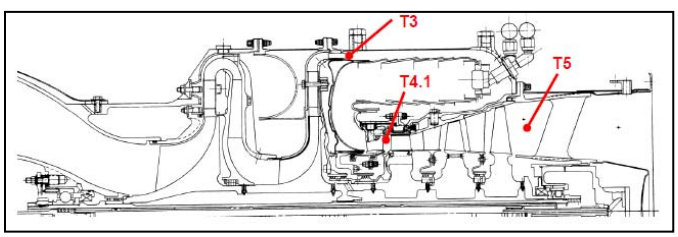

Figure 8. Engine compressor and turbine flow path temperatures.

As shown in Figure 9, T4.1, T5 and T3 variation due to variation in compressor geometry, turbine nozzle flow area, and turbine tip clearance was assessed analytically utilizing the thermodynamic FAST1D engine model. Algorithms were developed and coded into the FAST1D model, which related blade and nozzle metal temperatures to T4.1, T5 and T3. Algorithms were provided to determine normalized blade and nozzle life (stress-rupture and oxidation) as a function of the calculated metal temperatures.

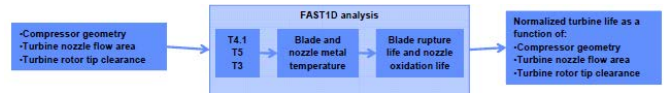

Figure 9. Turbine/engine lifing model.

3 CASE STUDY ANALYSIS AND RESULTS

3.1 Definition of Inputs

The input variables under consideration for this study include the geometry inputs to the CFD analysis, as well as the turbine efficiency, nozzle flow area, and tip clearance inputs to the Engine Performance Model as discussed in Section 2.2. All of these input variables are known to be random variables that exhibit unit-to-unit variation. For the purpose of these probabilistic studies, the inputs are broken into two categories. The first category is those inputs for which test data are available. This category will include CFD geometry inputs. The second category is those inputs for which only bounds are available. These bounds are based on drawing tolerances, expert judgment, or historical data. The inputs in this category include the turbine efficiency, nozzle flow area, and tip clearances. The PDFs for these inputs were initially defined based on given ranges and later updated during the model calibration phase of the study.

3.2 Data-Based Inputs: CFD Geometry

The three CFD geometry input variables that were considered are described in Table 1. These inputs were characterized based on inspection results from 31 units.

Table 1. CFD Geometry Inputs

Variable	Description
THK	Shroud Blade Thickness
LEA	Leading Edge Angle
TEA	Trailing Edge Angle

Normal probability plots for each of the three inputs are shown in Figure 10. The data for LEA and TEA do not show strong deviations from normality. Given the limited amount of data, the normal distribution is a reasonable default choice. The variable THK shows a significant deviation from normality, particularly in the lower tail. A lognormal probability distribution was found to provide a better fit for this variable, as demonstrated in the lognormal probability plot of Figure 11.

Having selected probability distribution model forms for the CFD geometry inputs, the necessary parameters were then identified using the maximum likelihood estimation. The probability distribution models and parameters are described in Table 2. Parameters in Table 2 are based on measured values, and represent deviation from design intent.

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