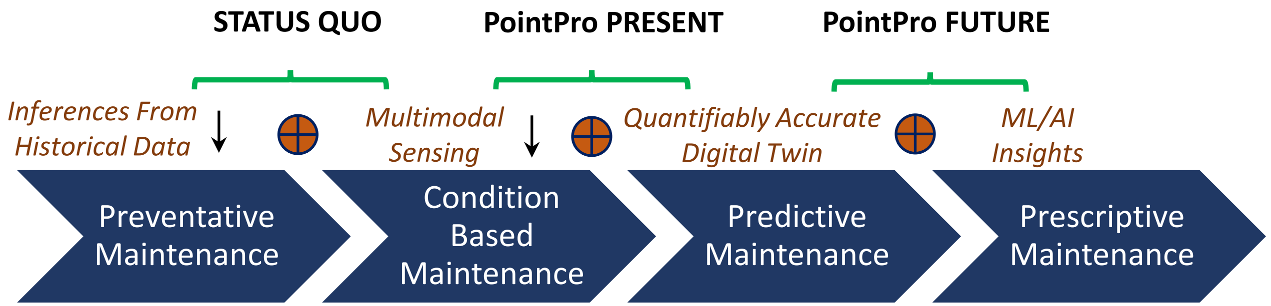
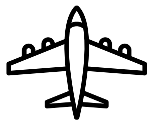
PointPro Overview

- PointPro, Inc. offers a computational platform that performs adaptive, closed-loop predictive simulations to support the firms with predictive and prescriptive maintenance. PointPro builds on the user’s digital twin physics-based models to deliver forecasts within user defined accuracy.
- **Tech Summary:** The future of sustainment is in prescriptive analytics: predicting *what* will fail, *when & how* it will fail, and *what can be done about it?* This demands timely, accurate forecasts of a system’s path to failure. Our software leverages the time-tested robustness and versatility of Monte Carlo simulations in a closed-loop architecture, making it possible to deliver guaranteed accuracy in the forecast of specific quantities of interest. We have in effect answered a long-standing question: to meet a required level of accuracy, how big should the simulation size be?

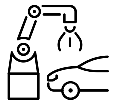
A Reflective Chronology of Sustainment



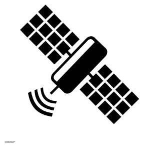
Industries Identified for Entry



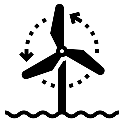
Aerospace Powerplants
- Failure prediction for jet engines
- Airframe health



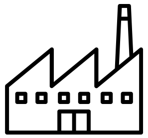
Automotive Health Mgmt.
- Remaining useful life



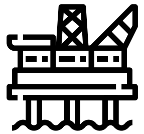
Space Asset Defense
- Station-keeping through predictive situational awareness



Renewable Power
- Health of wind turbines



Manufacturing
- High-value tool failure



Oil & Gas Drilling
- Restricted access equipment failure

Technical Summary

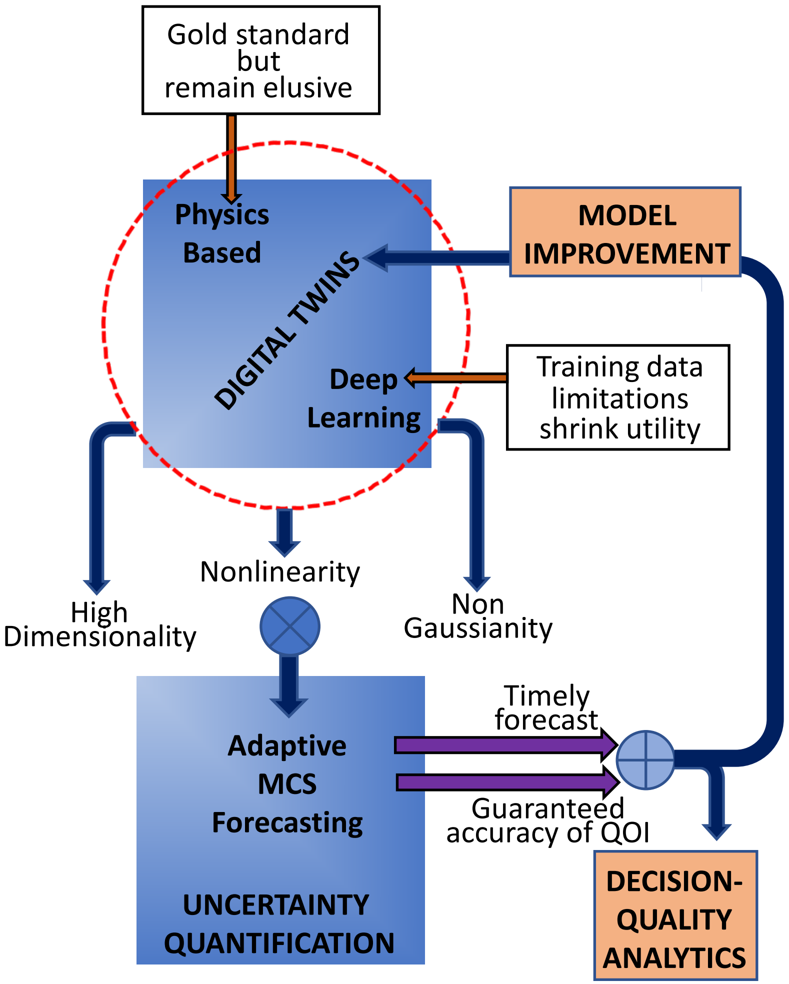
Challenges Addressed: Ability to perform system-specific prescriptive maintenance requires -

1. **High fidelity system evolution models:** EITHER the user must already have or be willing to invest in developing high-fidelity physics-based models; OR leverage sensor data and deep-learning modeling tools to build a data-driven surrogate.
   Challenge addressed: When physics-based digital twins are available, our tech integrates with them seamlessly. When data-driven digital twins must be used, we offer the means to continuously improve them for the particular purpose of forecasting system failure.
2. **Timely and accurate uncertainty quantification:** need tools that are adapted to *complex* systems and multimodal sensing models.
   Challenge addressed: "complexity" manifests as the triple curses of high-dimensionality, nonlinearity and non-Gaussianity. Together, they detriment the timely estimation of failure probabilities. Our tech tackles these curses head-on.

Scientific Baseline:

1. Predictive maintenance is still retrospective, i.e., not based on system-specific forecasts of failure. It is driven by ML-assisted prediction and condition monitoring
2. Status-quo of uncertainty forecasting is open loop [1]. It cannot deliver actionable, decision-quality analytics within stipulated confidence bounds without manual, expensive simulation tuning, e.g. [2].
3. While physics-based digital twins remain elusive, deep learning tools for system-specific evolutionary models offer early promise, e.g., Koopman autoencoders. [3]

Components of Sustainment

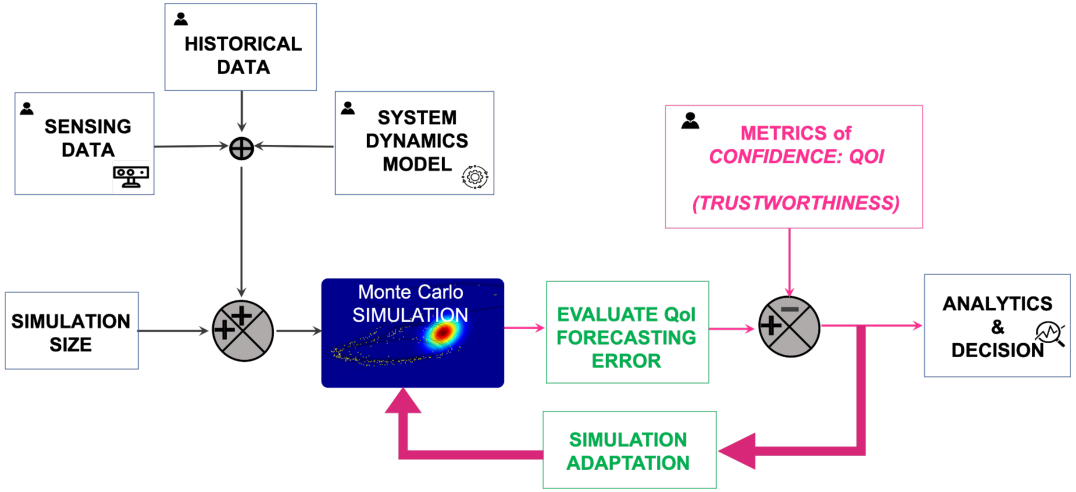


[1] Yang, C. and Kumar, M., "On the effectiveness of Monte Carlo for initial uncertainty forecasting in nonlinear dynamical systems," Automatica, vol. 87, pp. 301-309, 2018
[2] M. D. Hejduk, Conjunction Assessment Risk Analysis: Collision Avoidance Short Course, NASA/CNES, September, 2017
[3] S. L. Brunton, J. L. Proctor, and N. Kutz, "Discovering governing equations from data by sparse identification of nonlinear dynamical systems," Proceedings of the National Academy of Sciences, vol. 113, no. 15, pp. 3932-3937, 2016

Technical Summary

Highlights of the PointPro forecasting software:

1. Adaptive, closed loop architecture eliminates guesswork. It enables front-end error control in the prediction of system-specific quantities of interest (QOI). QOI examples: compressor stage turbine spin rate (jet engine), crack length (component wear), probability of collision in space (space situational awareness)
2. Trust is created when the user sets the level of QOI accuracy appropriate for the application, and it is delivered without further user intervention, e.g., predict compressor stage turbine spin rate within 10 RPM, or predict collision probability within 10^{-8}
3. When forecast error is detected to increase above stipulated bound (top green block), the software implements *optimal* adaptations (bottom green block) to reestablish prediction quality
4. A decision-quality, certifiably actionable forecast is generated in a single-shot, in minimal time
5. The platform integrates equally with physics-based evolutionary models and with data-driven (ML) models; and offers means to improve such models.



CLOSED-LOOP, ADAPTIVE MONTE CARLO SIMULATION PLATFORM

Relevant Literature:
[5] Yang, C. and Kumar, M., “A closed-loop adaptive Monte Carlo framework for uncertainty forecasting in nonlinear dynamic systems,” *AIAA J.G-C-D*, vol. 42, no. 6, pp. 1218-1236, 2019
[6] A. VanFossen and M. Kumar, “Parallelized global stochastic optimization for efficient ensemble enhancement within an adaptive Monte Carlo forecasting platform," Scitech, 2021
[7] I. Nayak, M. Kumar, and F. L. Teixeira, “Reduced-order analysis and prediction of kinetic plasma behavior using dynamic mode decomposition," *J. of Comp. Physics*, 2021, arXiv

Competitive Edge

Function

Generate trustworthy (timely + accurate) predictive analytics through adaptive, closed-loop simulations of complex processes

KOKSMA-HLAWKA INEQUALITY

$$\underbrace{|\varepsilon_n| = \left|\bar{h} - \tilde{h}_n\right|}_{\text{ERROR IN QOI PREDICTION}} \leq \underbrace{\mathcal{D}\left(\{\mathbf{x}_0^i\}_{i=1}^n\right)}_{\text{CAN BE OPTIMIZED TO COUNTERBALANCE}} \underbrace{V(S_t)}_{\text{UNPREDICTABLE \& SYSTEM DEPENDENT}}$$

The key to forecasting performance guarantees. QoI Prediction error is upper upper bounded by the product of dynamic variations (uncontrollable) and initial ensemble discrepancy, which can be optimized to counterbalance dynamic variation

Product Description/Features

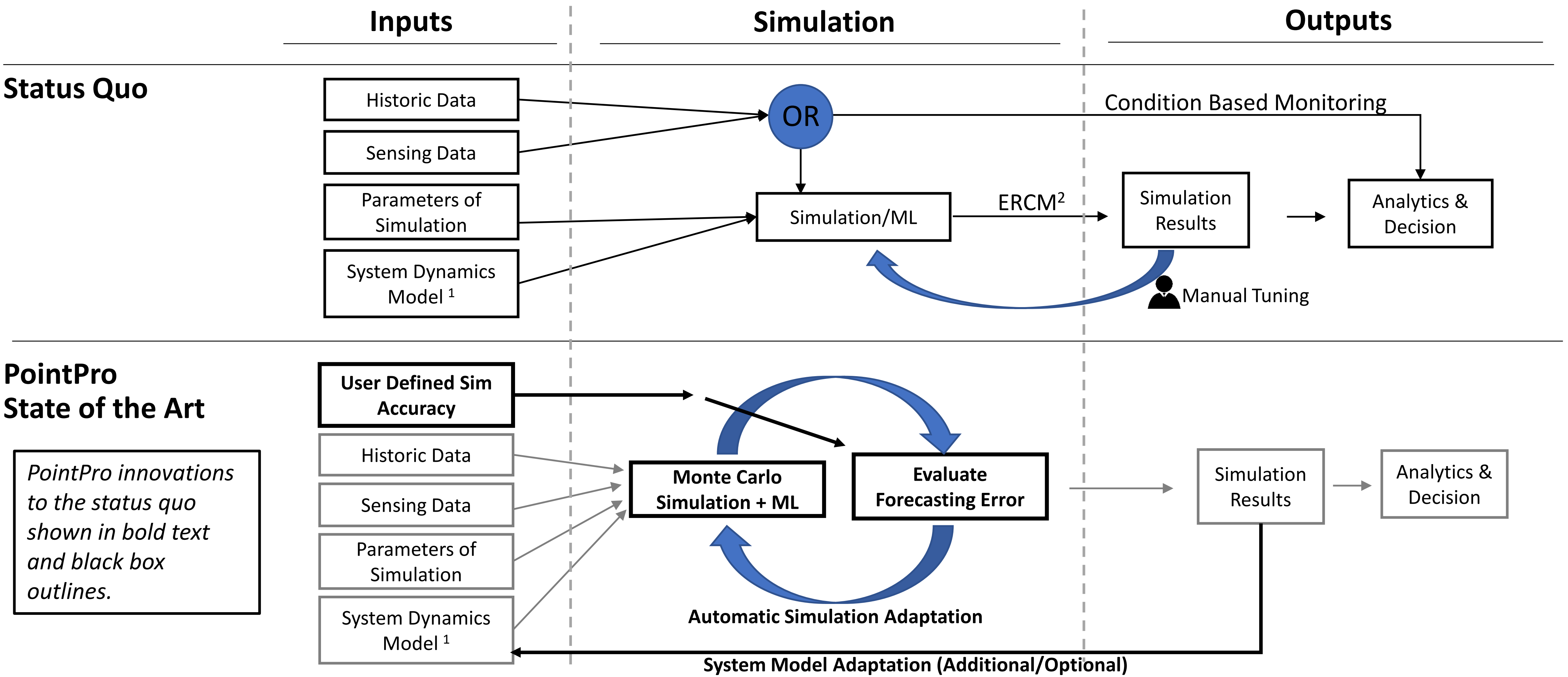
- ***Ensemble Forecasting***: Tried-and-true flexibility & scalability of Monte Carlo simulations
- ***Performance Guarantees***: Decision-quality forecasts by ensuring prediction of user-defined *quantities of interest* within commanded accuracy bounds
- ***Minimal Time Forecasting***: Smallest sized simulation to achieve stipulated accuracy bounds
- ***Integration with Physics***: Seamlessly integrate with complex physics dynamic models
- ***Integration with Black/Gray-Box Dynamics***: Of special interest is Koopman-based autoencoders when physics-based models are impractical or not available
- ***Model Improvement***: On account of forecasting performance guarantees, we can build and improve data-driven dynamic models through optimization of model uncertainty

Product/ Company	Front-error QoI Error Control	Prescriptive Analytics (when & what to repair)	Minimum Time to Decision ("IN-TIME")	Work with Data-Driven Models	Can Improve Data-Driven Models?
Our Technology	✓	✓	✓	✓	✓
PREDIX (GE) [Status-Quo]	×	×	×	✓	×
SmartUQ	×	✓	×	✓	×
Ascentia [Collins]	×	×	×	✓	✓
ARULE [Ridgetop]	×	×	×	✓	✓
Cassantec [ABB]	×	×	×	✓	✓

PointPro Competitive Edge: Combining adaptive simulation with physics-based models (when available), and machine learning tools when not, to achieve reliable prognostics

We aim to overhaul and ultimately displace inefficient and expensive practice of preventative maintenance and replace it with prescriptive intelligence that enables confident decision-making, as well as optimized maintenance inventory and supply chain.

Competitive Edge: Innovation over Status-Quo

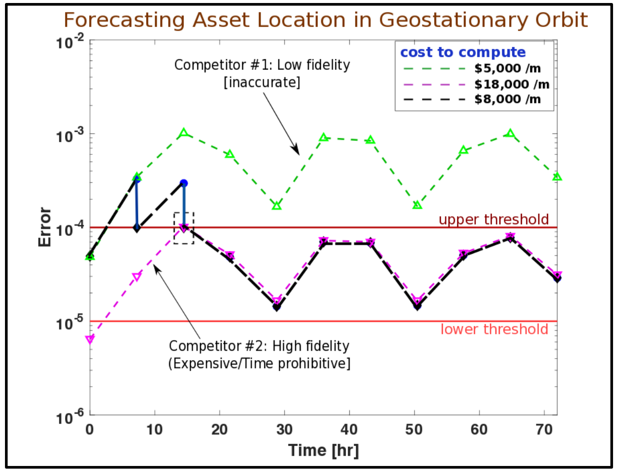


[1] System dynamic models can be physics based or black box models.
[2] Enhanced Reliability Centered Maintenance

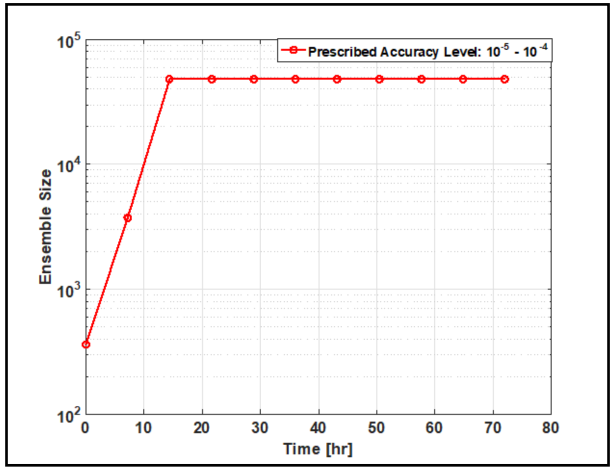
Benchmark Studies

In studies so far, up to 3x productivity gain has been demonstrated. Gains improve with increasing system complexity.

Example 1. Forecasting Asset Location in GEO: QOI = Asset Longitude [8]



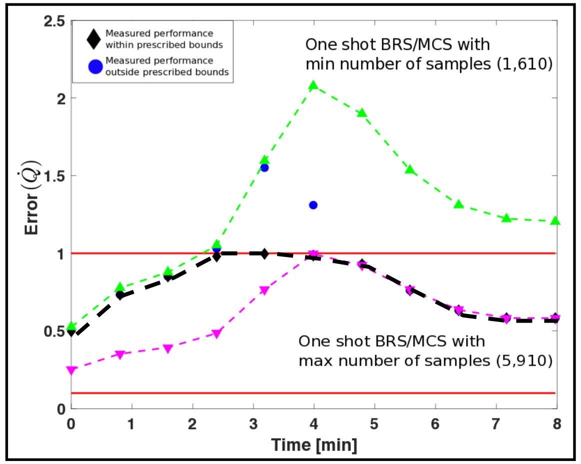
QOI Forecasting Error vis-à-vis User-Defined Bounds



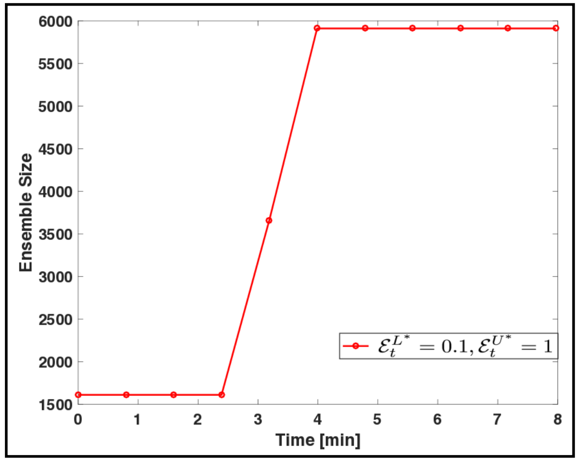
Time History of Simulation Adaptations

KEY
- Low-fidelity (inexpensive, inaccurate)
- High-fidelity (expensive, overkill)
- Adaptive Monte Carlo (meets user specs, minimal time)
- User defined error bounds

Example 2. Martian Entry/Descent/Landing: QOI = Heat Flux [5]



QOI Forecasting Error vis-à-vis User-Defined Bounds



Time History of Simulation Adaptations

[5] RIGHT: Yang, C. and Kumar, M., “A closed-loop adaptive Monte Carlo framework for uncertainty forecasting in nonlinear dynamic systems,” *AIAA J Guidance Control & Dynamics*, vol. 42, no. 6, pp. 1218-1236, 2019

[8] LEFT: Yang, C. and Kumar, M., “An adaptive Monte Carlo method for uncertainty forecasting in perturbed two-body dynamics," *Acta Astronautica: Special Issue on Space Situation Awareness*, vol. 155, pp. 369-378 2019

Current Product Development: Jet Engine Prognostics

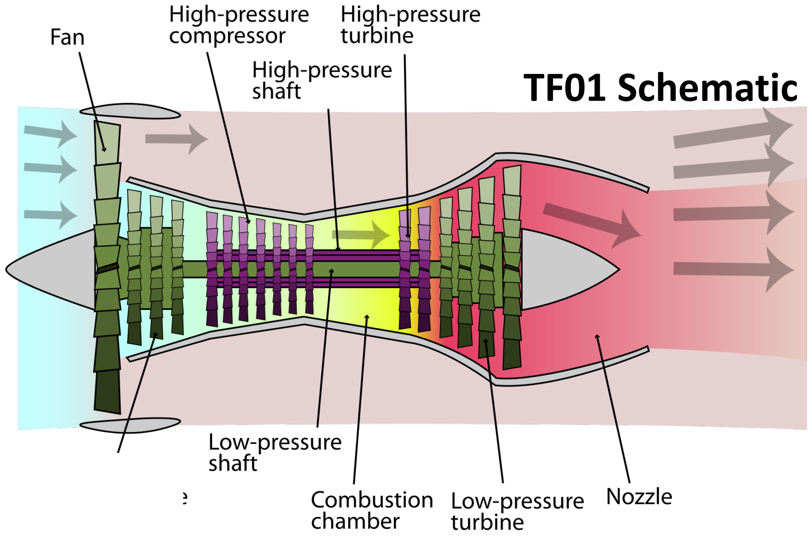
- Jet Engine Prognostics Use Case is under development
  Funding: Tech Validation & Startup Fund (Ohio Third Frontier Incubator): Accelerator Grant

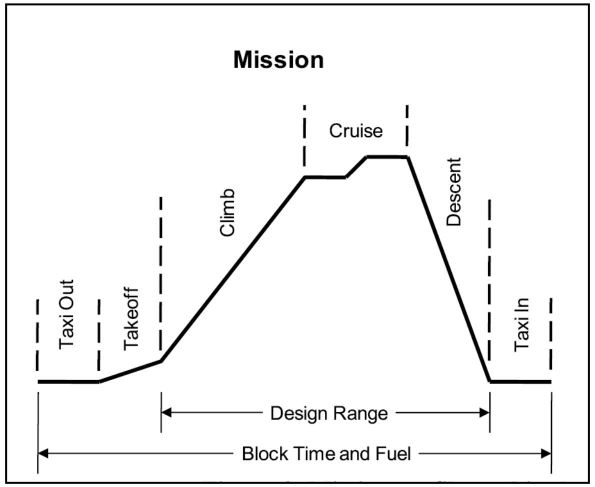
- **NEED:** Current prognostics solutions cannot generate timely and trustworthy forecasts of critical events that foreshadow engine failure. A one-size-fits-all preventative maintenance regimen is followed that causes unnecessary downtime, costing millions of dollars per day. Even more costly is the incidence of surprise breakdowns, especially in-flight breakdowns, which are increasingly commonplace.

- Physics-Based Aerothermodynamic Model: NPSS (Numerical Propulsion System Simulation)
  - Common Development Model (CDM) Turbo Fan 01 (TF01)
  - Close to GE GE9X engines. (Contributed by GE)
  - Integration with software using representative flight profiles, e.g., JFK-LAX cycles
  - QOI per GE guidance: Pressure/Temp at specific stations; HPT/LPT speed, SFC ratio
  - Using “bridging functions” to capture inter-cycle engine degradation demo

- Interactive User Interface:
  - .Net Core 3.1 multi-platform interactive web-interface
  - Web deployment on AWS Elastic Beanstalk
  - Data security protocols

TF01 Schematic





Customer Research

Immersive customer discovery validated our hypothesis that PointPro has potential as a horizontal platform serving numerous industries.

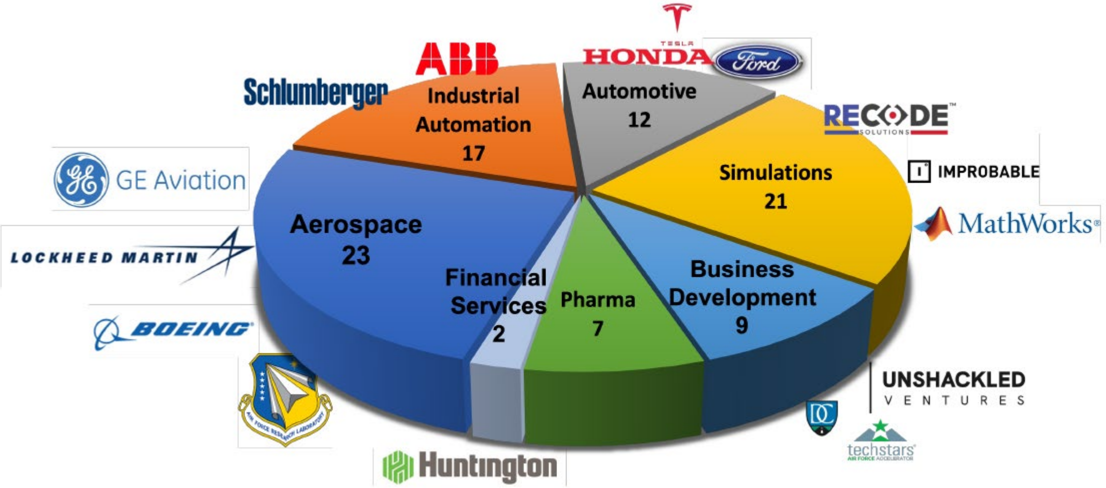
Key Findings

- 66% of interviews found the technology was useful for a broad spectrum of applications. Interviewees emphasized the need for accurate simulations in less time. Dr. Kevin Starr (Global Program Manager of Advanced Services in Oil, Gas & Chemicals at **ABB**) stated that “you are king if your technology’s controllable accuracy can lead to prescriptive analytics”
- Roughly 40% of interviewees advised us to identify the first industry with a high probability of adoption to demonstrate power of PointPro, as a demo with a complex system in one industry would resonate with customers in other industries. The prediction of engine failure in the was identified from viable industries and our own domain expertise.
- About 50% of interviewees emphasized the need to integrate our forecasting platform with data-driven models. PointPro’s ability to *improve* such models was seen favorably.

Study Detail

- Over 100 customers interviews spanning practitioners primarily in 3 key industries: aerospace, simulations, and industrial automation
- Discovery funded by the Ohio Department of Higher Education - 2019 Engineering cohort of I-Corps@Ohio. This program is modeled after the NSF I-Corps program.

Cross Section of Customer Discovery Interviewees



Market Conversation Highlight: GE Aviation

- High Pressure Turbine Airfoils Team, GE9X
- Team Leader provides us technical guidance and evaluation notes
- Supported our successful TVSF Phase I Accelerator Grant (Ohio Third Frontier)
- Supported our NSF product development proposal as tech partner

Use Case 1: Jet Engine Prognostics

Problem

- Will this engine fail over the next month? Focus on particular engine, not a generic engine of a certain type
- Should this engine be taken off the airframe for maintenance?

Significance/Opportunity

- Scheduled maintenance causes wasteful downtime, and may not address urgent failure factors
- Surprise/unforeseen breakdowns are even more expensive and increasingly commonplace
- Example: In 2017, 150 J85 engines were repaired, reinstalled on aircraft and within 2 flying hours, they had to be removed from the aircraft to be repaired again [9]

Current State of Solution

- Bulk of maintenance schedules continue to be preventative based on statistical analysis of historical data
- Condition based monitoring (CBM) defers maintenance decisions to inspection of sensing data. Predictive elements include ML/AI insights that extrapolate combined CBM and historical data, e.g., Predix platform at GE [10]
- Similar solutions (Sensing Data + ML/AI insights) have been applied for ”enhanced reliability centered maintenance” (ERCM), e.g. [9]. Neither CBM, nor ERCM involves digital twin evolutionary simulations to forecast critical events that foreshadow engine failure

PW F100. Image Credit: Sue Sapp/USAF

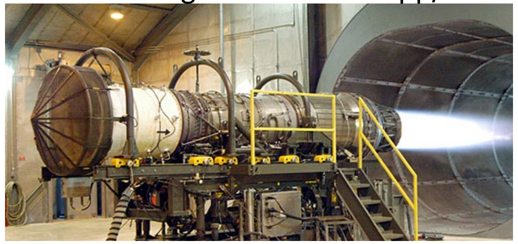
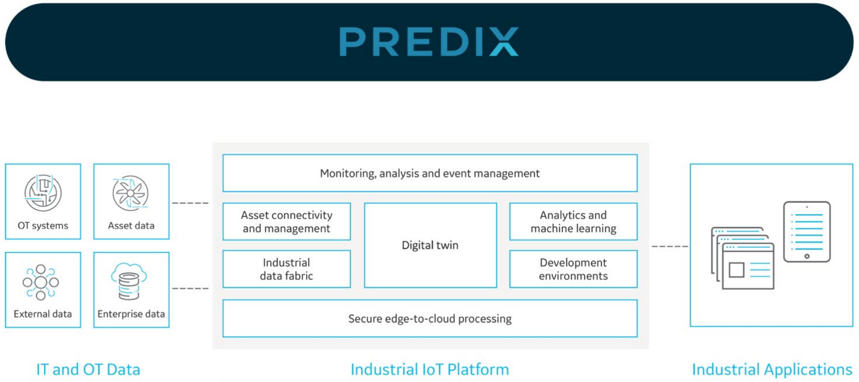


Image Credit: NBC News. LINK



Predix Platform @ GE.com. LINK

[9] Isobar Federal: Increasing Flight Time With Predictive Engine Maintenance (retrieved 11/29/2020) LINK
[10] Predix Data Sheet (retrieved 2/12/2021): LINK

Use Case 2: Space Situational Awareness

Problem

- What is **probability of collision** associated with conjunction events between a given space asset and a passive, active or rogue space object?

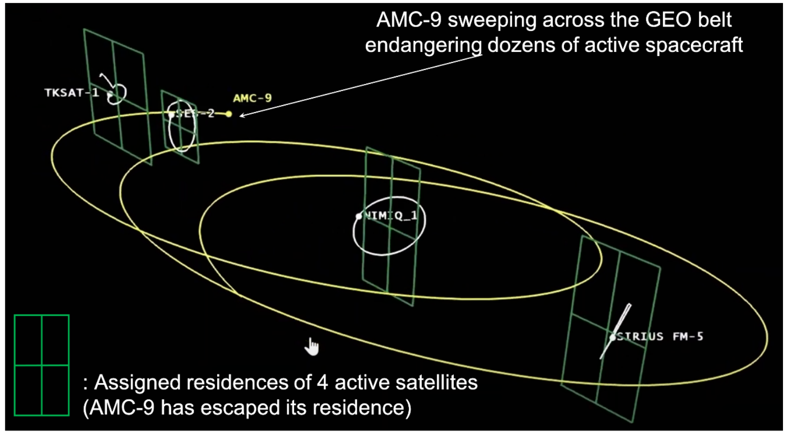
Significance/Opportunity

- Space is now a multinational, commercial territory with weak governance
- Simple volumetric analysis suggests 1000+ 3-km conjunction events for the SpaceX constellation per day over the next 10 years (similar issues for other mega-constellations = problems for all)
- To keep our space assets safe from active and passive threats, trustworthy, actionable simulations are necessary. Here is a scenario in which lack of decision-quality sims is disastrous:
  - i. Orbital simulations predict high collision probability between a satellite and cataloged debris item;
  - ii. Satellite operator decides to change orbit based on threat forecast;
  - iii. However, the forecasting platform did not have appropriate error control mechanisms to accurately characterize the level of risk posed to the satellite in time;
  - iv. The orbit change consumed fuel, and possibly, put satellite on collision course with said debris.
  - v. The actual collision risk to satellite in its original orbit was not high enough to warrant an orbit change.

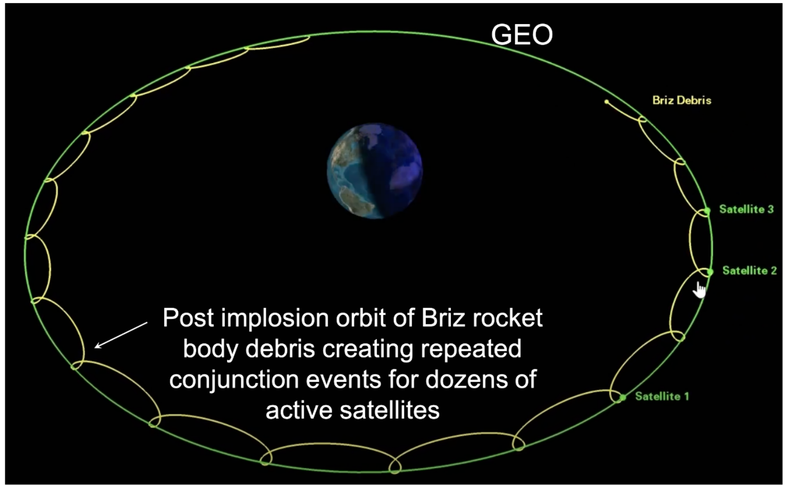
Current State of Solution

- Many forecasting tools exist, including (standard) Monte Carlo, tensor-methods (e.g. [11]), ML tools (e.g. [12]), but none provide front-end error control and decision-quality forecasts without time consuming (days worth) of manual retrospective tuning.

[11] Balducci et al. Orbit uncertainty propagation and sensitivity analysis with separated representations, Celestial Mech. & Dyn. Astr. 2017
[12] H. Peng et al., Machine Learning Approach to Improve Satellite Orbit Prediction Accuracy Using Publicly Available Data, J. Astron Sciences, 2019



AMC-9 anomalous thrusting vent: June 2017. Image Credit: AGI



Russian Briz debris cloud hopping across GEO: Jan 2016
Image Credit: AGI

Team

Matthew Bell
Founder
CEO

Mrinal Kumar
Inventor/Founder, CTO
Associate Professor at OSU

Matthew Bell brings expertise in leading large projects in complex organizations combined with experience in all stages of product development and commercialization.

- Founded Venore, a consultancy supporting organizations as they build and grow their analytic capabilities through designing and implementing data strategies
- Experience in all stages of bringing several new products to market as member of a commercialization team at Fortune 20 company
- Led all aspects of complex acquisition and divestiture transactions including valuation, structuring, diligence, and negotiations at Fortune 20 company

Dr. Mrinal Kumar is a recognized leader in the domain of uncertainty quantification in complex nonlinear dynamic systems.

- Associate Professor of Mechanical and Aerospace Engineering at The Ohio State University
- Associate Fellow of the American Institute of Aeronautics and Astronautics (AIAA)
- Director of the Laboratory for Autonomy in Data-Driven & Complex Systems, 7 completed Ph.D. dissertations to date
- Acquired federal grants totaling over $3.5M to support fundamental research, including NSF CAREER, AF-YIP