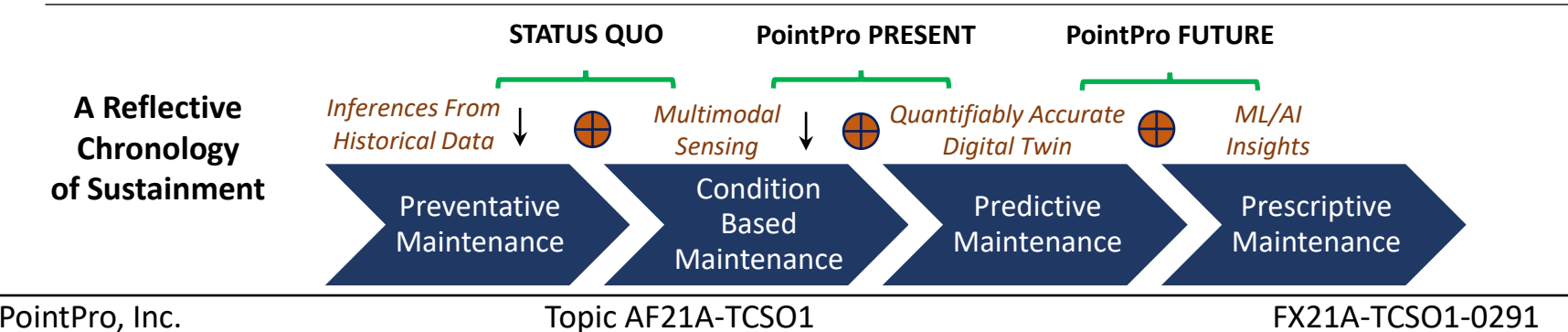


Overall Summary

Trustworthy Sustainment Solutions via a Learning-Assisted Digital Twin

- PointPro, Inc. offers a computational platform that performs adaptive, closed-loop predictive simulations in order to support the Air Force in sustainment operations. PointPro builds on the user’s digital twin physics-based models to deliver forecasts within user defined accuracy.
- Technical Abstract:** 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?
- Project Overview:** A Phase I feasibility study is designed to elicit feedback from SMEs regarding PointPro use for forecasting complex systems. The first intended use case is jet-engine maintenance. This will support existing predictive maintenance needs and accelerate prescriptive maintenance capabilities. Feedback related to specific users, applications, and necessary additions to the software will serve as a workplan for further work.



Technical Merit Summary [1/4]

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: “*enhanced reliability centered maintenance*” [1]
2. Status-quo of uncertainty forecasting is open loop [2]. It cannot deliver actionable, decision-quality analytics within stipulated confidence bounds without manual, expensive simulation tuning, e.g. [3].
3. While physics-based digital twins remain elusive, deep learning tools for system-specific evolutionary models offer early promise, e.g., Koopman autoencoders. [4]

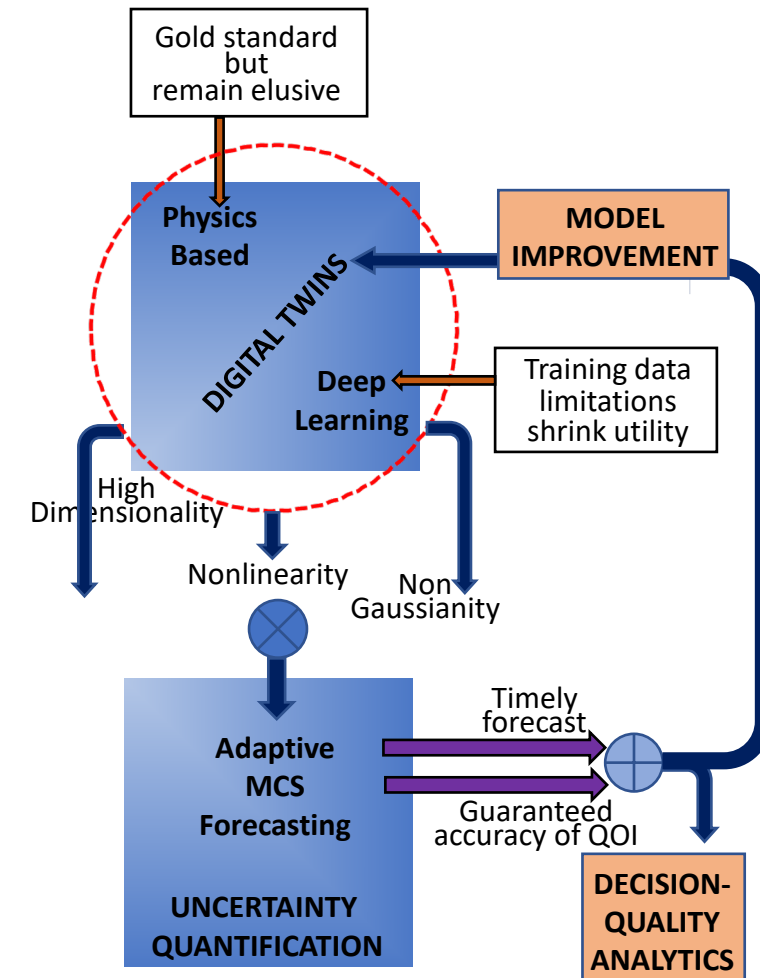
[1] Joint Artificial Intelligence Center (JAIC), “Harnessing AI to Advance Our Security and Prosperity: Summary of the 2018 Department of Defense Artificial Intelligence Strategy,” 2018, [available here](#)

[2] 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

[3] M. D. Hejduk, *Conjunction Assessment Risk Analysis: Collision Avoidance Short Course*, NASA/CNES, September, 2017

[4] 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

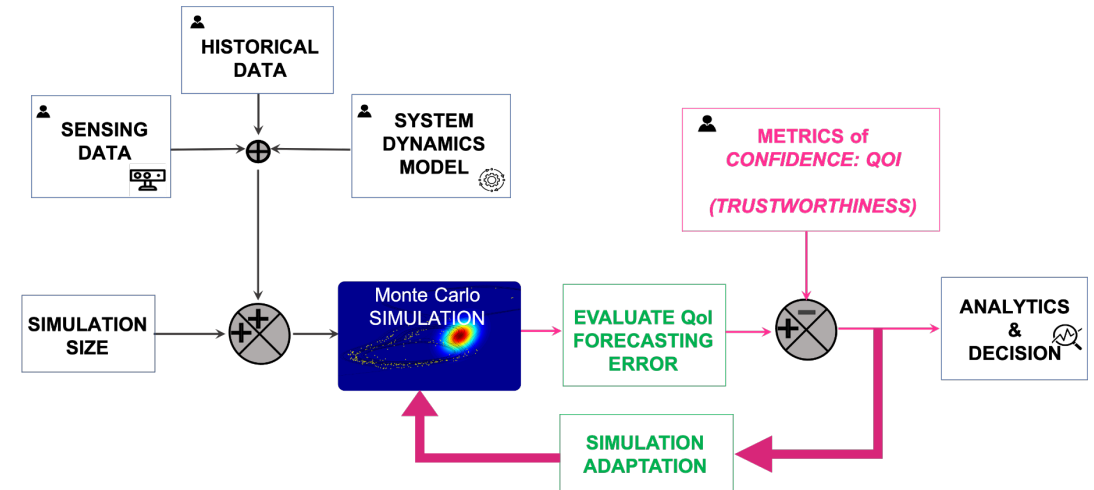
Components of Sustainment



Technical Merit Summary [2/4]

Technical Merit: Key merits of 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:

- [6] 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
- [7] A. VanFossen and M. Kumar, "Parallelized global stochastic optimization for efficient ensemble enhancement within an adaptive Monte Carlo forecasting platform," *Scitech*, 2021
- [8] 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

Past/Current 6.1 Funding:

- A. NSF: CAREER: 2013-18 (Wind Forecasting)
- B. AFOSR: YIP: 2015-19 (Particle Methods)
- C. AFOSR: Remote Sensing: 2020 – 23 (Space Situational Awareness)

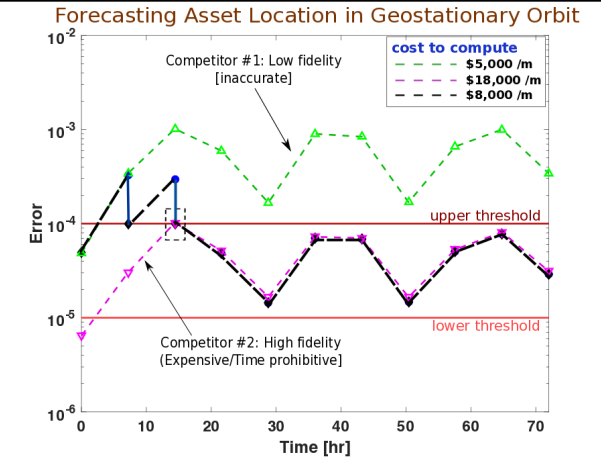
Technical Merit Summary [3/4]

Benchmark Studies

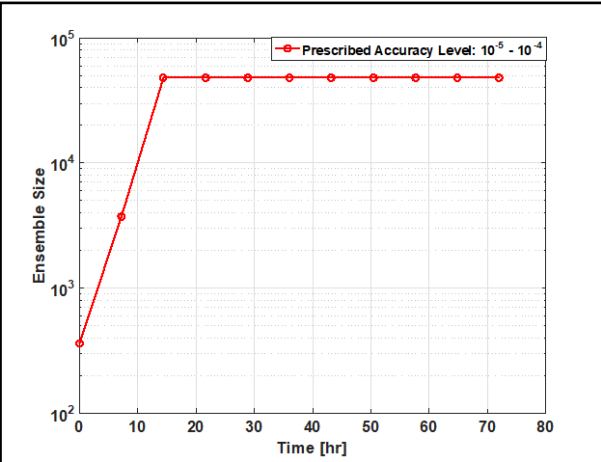


In studies so far, up to 3x productivity gain has been demonstrated. Gains improve with increasing system complexity.

Example 1. Forecasting Asset Location in GEO: QOI = Asset Longitude [9]

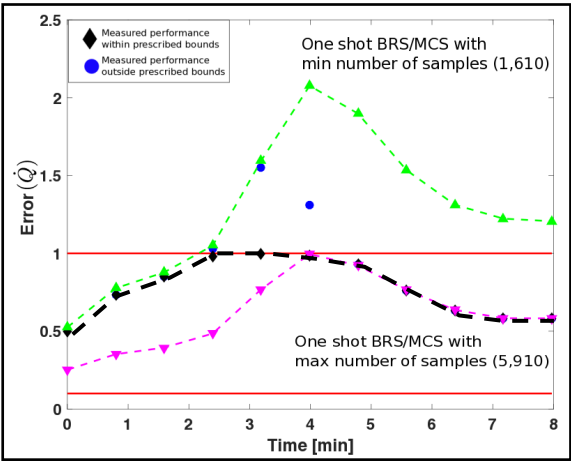


QOI Forecasting Error vis-à-vis User-Defined Bounds

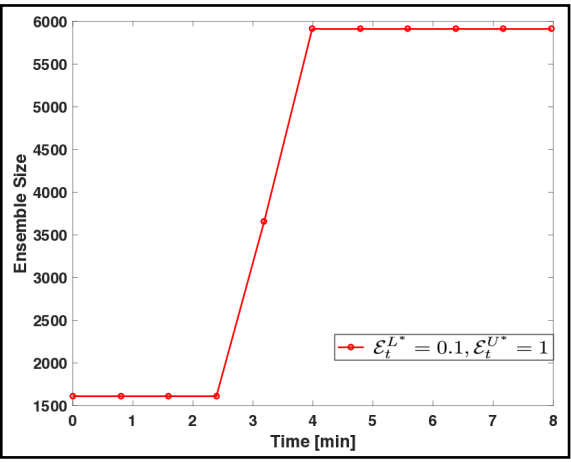


Time History of Simulation Adaptations

Example 2. Martian Entry/Descent/Landing: QOI = Heat Flux [6]



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



Time History of Simulation Adaptations

KEY

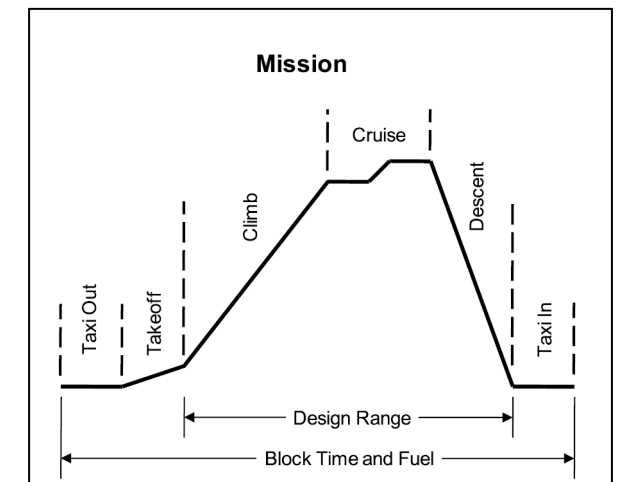
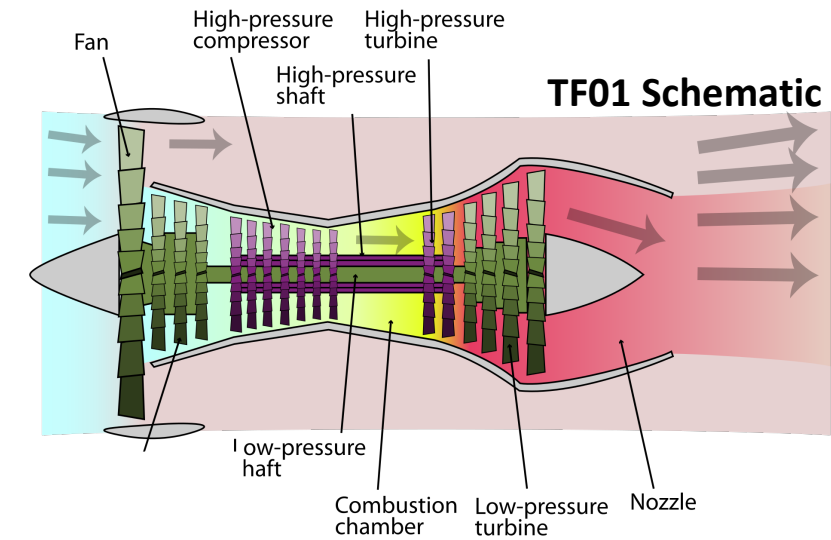
- Low-fidelity (inexpensive, inaccurate)
- High-fidelity (expensive, overkill)
- Adaptive Monte Carlo (meets user specs, minimal time)
- User defined error bounds

[6] 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
[9] 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

Technical Merit Summary [4/4]

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 every 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



Team's Ability to Perform Research Summary

- PI Kumar (Ph.D., Aerospace Engineering) has 15 years of research experience in uncertainty quantification of complex/data-driven systems. He been awarded over \$3.5M in federal grants for 6.1 research in this area.
- Matthew Bell has participated in all stages of product development and has experience in investment feasibility studies/evaluations for large, complex projects.
- PointPro's primary focus will be executing the feasibility study, quickly.
 - PointPro has recently finished a Phase I TVSF grant to create a user interface. The next step in our development is to get feedback from users to identify the prerequisite features necessary for immediate customer adoption.
- Experienced advisors including Mr. Thoet, retired EVP with Booz Allen Hamilton, where he ran the Decision Analytics practice (1,900 staff and \$400M business).
- Commercialization coaching and resources from Rev1 Ventures through Phase I engagement. Rev1 is a selective startup studio in Columbus, Ohio.



William Thoet
Advisor
(Retired EVP, Booz
Allen Hamilton: 27
Years)



Rev1 Ventures
Advisors
Startup Studio

Commercialization Potential Summary [1/3]

Pathways for PointPro

PointPro is perfectly positioned to bring significant value to customers as more firms adopt digital twin technology. The digital twin market is large and growing as a result of the convergence of enabling technologies including cloud computing, AI/ML, and growth at an increasing rate is projected as further technologies come into wider use, such as IoT and 5G.

- In preliminary conversations with **Dr. Brent Rankin**, Research Engineer in the Combustion Branch of AFRL, the Air Force Life Cycle Management Center (AFLCMC) at Tinker AFB in Oklahoma was identified as a potential user of the PointPro software. The PointPro software would benefit sustainment operations as the organization prioritizes newer technologies for predictive maintenance.

PointPro Customer Type Targets in the non-defense commercial market:

- **Firms with Digital Twin capability** – Firms using digital twins for condition monitoring can use PointPro to create forecasts using their existing physics-based or black box models. Gartner predicted that by 2022, over two-thirds of companies that have implemented IoT will have deployed at least one digital twin. Example customers in the aerospace industry are GE Aviation and Boeing.
- **Simulation Software Firms** – Firms who offer digital twin simulation software could add PointPro to their software enabling their customers to forecast with front-end user specified error control. Potential customers are Ansys, Bentley and Mathworks



PointPro CEO Matthew Bell brings expertise in financial analysis and business case development. He is a leader in corporate strategy and held responsibility for leading large, complex acquisitions and divestiture (M&A) transactions at a Fortune 20 company.



Tech inventor and PointPro CTO Dr. Mrinal Kumar is a respected scholar in the field of uncertainty quantification of complex systems. His research has won several accolades and this tech is set to change the course of the field of uncertainty forecasting.



The PointPro team has able guidance from Mr. Bill Thoet (formerly a senior leader with Booz Allen Hamilton), The Ohio State Technology Commercialization Office and Rev1 Ventures, a selective startup studio in the Central Ohio Region.



GE Aviation



MathWorks®

Commercialization Potential Summary [2/3]

Customer Discovery

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

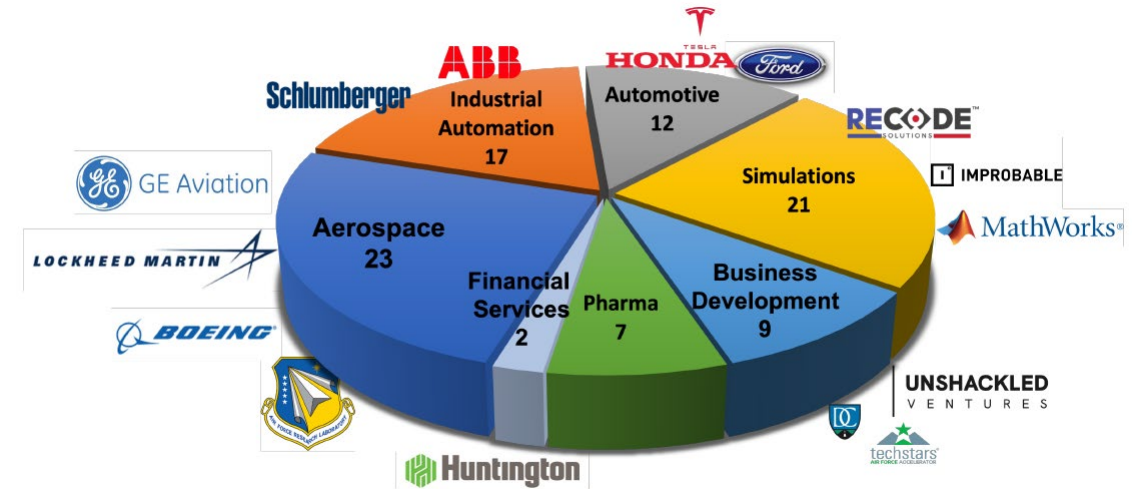
Key Findings

- 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 (Dr. Michael Meade) 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

Commercialization Potential Summary [3/3]

Market Potential

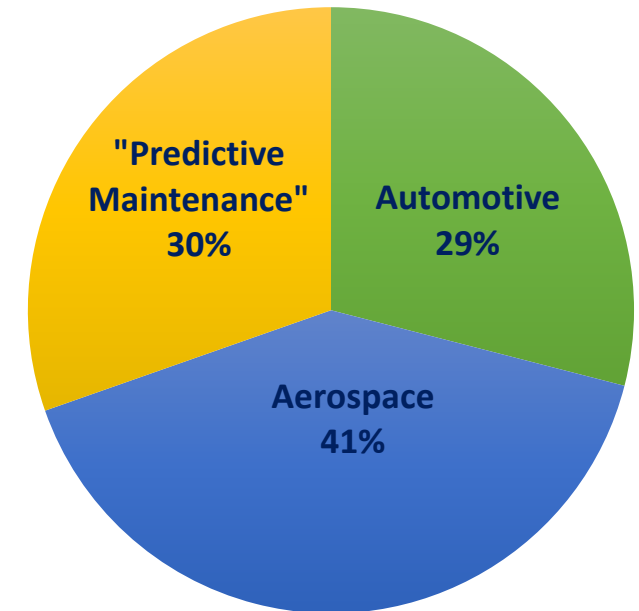
Market Opportunity: Commercial

- The *Prognostics* commercial market is highly fragmented, market size and growth rate depends strongly on segment
- Chart on right shows **growth** share in commercial aerospace, automotive and “predictive maintenance” (mainly manufacturing and energy) serviceable obtainable markets (SOM) [11-13]
- Combined projected dollar **growth** shown: **\$26B**. Average CAGR for segments on this chart: **45%**

Market Opportunity: DoD

- The Joint Artificial Intelligence Center (JAIC) identifies predictive maintenance, automated diagnostics, and condition-based planning as one of the strategic focus areas across the DoD [1]
- Sustainment of USAF high value assets (fighters, bombers, tankers, and other advanced manned/unmanned platforms) is migrating from predetermined schedules to first Condition-Based Monitoring (CBM) [e.g. C-5, B-1] and then, Enhanced Reliability Centered Maintenance (ERCM) [e.g. F-15, F-16, B-52, RC-135, RQ-4 and MQ-9] [14]
- Operations and maintenance accounts for over a third of DoD discretionary spending (**\$254B out of \$695B for 2021**) [15]

Prognostics Growth Share (Non-DoD) 2020 - 2025



[1] Joint Artificial Intelligence Center (JAIC), “Harnessing AI to Advance Our Security and Prosperity: Summary of the 2018 Department of Defense Artificial Intelligence Strategy,” 2018, [LINK](#)

[11] Research And Markets, “Aerospace & Life Sciences Testing, Inspection, and Certification Market - Global Opportunity Analysis and Industry Forecast to 2025”, June 2019. [LINK](#)

[12] Market Reports World, “Automotive Prognostics Market By Application, End-users And Geography - Global Forecast And Analysis 2019-2023”, June 2019. [LINK](#)

[13] Markets and Markets, “Predictive Maintenance Market by Component (Solutions and Services), Deployment Mode, Organization Size, Vertical (Government and Defense, Manufacturing, Energy and Utilities, Transportation and Logistics), and Region - Global Forecast to 2025”, June 2020. [LINK](#)

[14] Defense Daily Article “Air Force to Add 12 Weapons Systems for AI/ML Informed Predictive Maintenance This Year,” 07/09/2020, [LINK](#) (retrieved 11/29/2020).

[15] Swagel, P. L., “Long-Term Implications of the 2021 Future Years Defense Program,” Publication of the Congressional Budget Office, September 2020 [LINK](#)

Significance of Problem/Opportunity [1/4]

Use Case 1/2: 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 [16]

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 [17]
- Similar solutions (Sensing Data + ML/AI insights) have been applied for "enhanced reliability centered maintenance" (ERCM), e.g. [16]. Neither CBM, nor ERCM involves digital twin evolutionary simulations to forecast critical events that foreshadow engine failure

PW F100. Image Credit: Sue Sapp/USAF

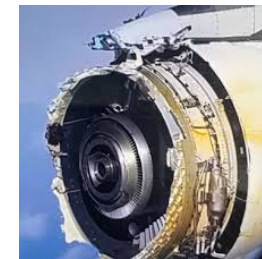
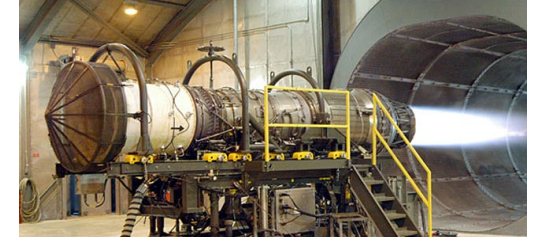
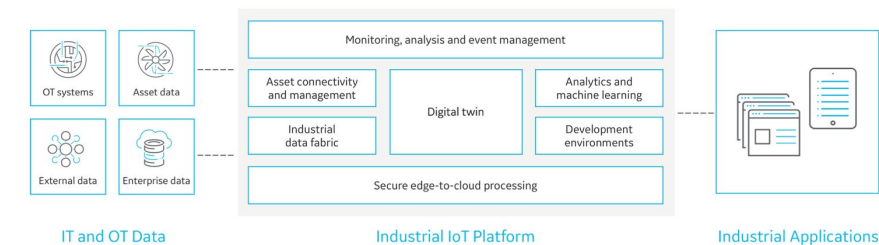


Image Credit: NBC News. [LINK](#)

PREDIX



[16] Isobar Federal: Increasing Flight Time With Predictive Engine Maintenance (retrieved 11/29/2020) [LINK](#)

[17] Predix Data Sheet (retrieved 2/12/2021): [LINK](#)

Predix Platform @ GE.com. [LINK](#)

Significance of Problem/Opportunity [2/4]

Use Case 2/2: 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

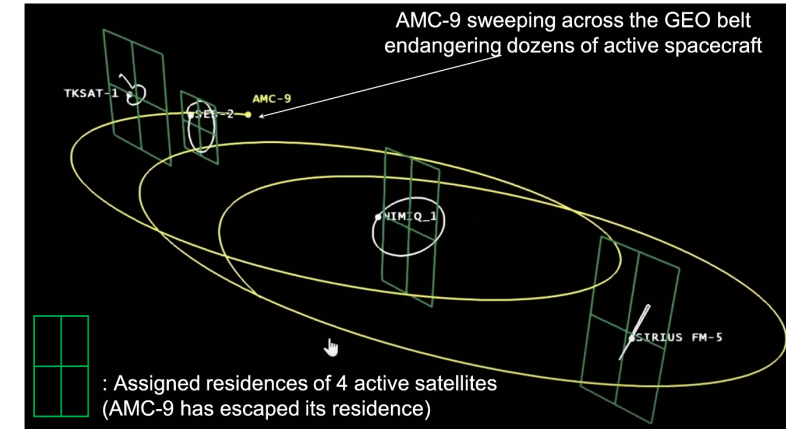
- Space is now a multinational, commercial territory with weak governance
- Simple volumetric analysis suggests 1000+ 3-km conjunction events for the SpaceX constellation per day over the next 10 years (similar issues for other mega-constellations = problems for all)
- To keep our space assets safe from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

Current State of Solution

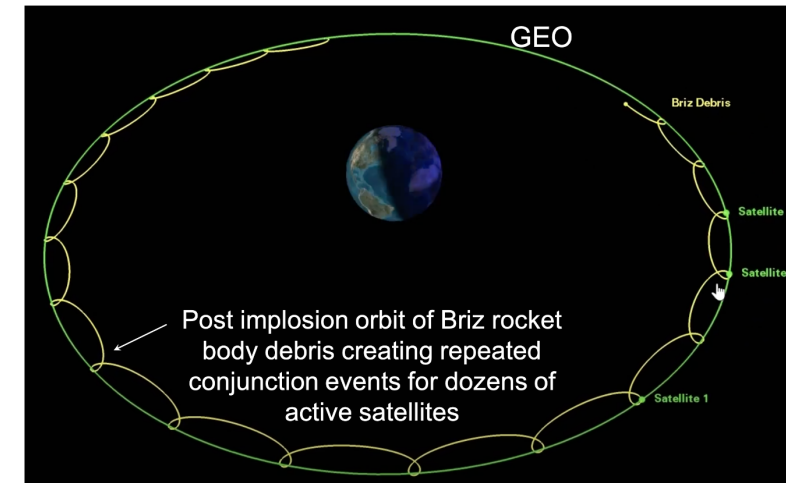
- Many forecasting tools exist, including (standard) Monte Carlo, tensor-methods (e.g. [18]), ML tools (e.g. [19]), but none provide front-end error control and decision-quality forecasts without time consuming (days worth) of manual retrospective tuning.

[18] Balducci et al. Orbit uncertainty propagation and sensitivity analysis with separated representations, Celestial Mech. & Dyn. Astr. 2017

[19] 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

Significance of Problem/Opportunity [3/4]

Competitive Edge

Function

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

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

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.

KOKSMA-HLAWKA INEQUALITY

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

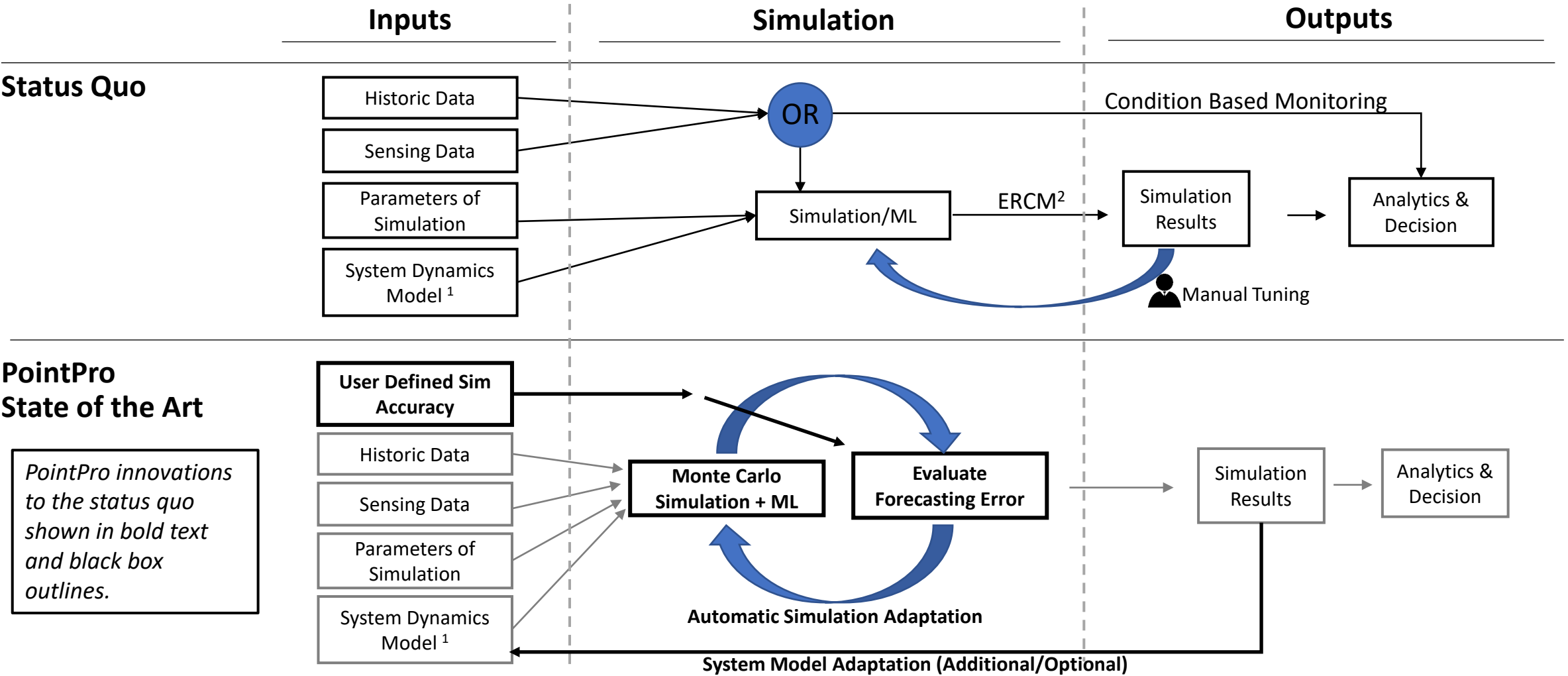
The key to forecasting performance guarantees. Qoi Prediction error is upper upper bounded by the product of dynamic variations (uncontrollable) and initial ensemble discrepancy, which can be optimized to counterbalance dynamic variation

Product/ 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

Significance of Problem/Opportunity [4/4]

Competitive Edge: Innovation over Status-Quo



¹ System dynamic models can be physics based or black box models.

² Enhanced Reliability Centered Maintenance

Phase I Objectives

Overall Goal: Identify feasibility of PointPro technology

Objectives

- 1. Identify users and specific applications
- 2. Identify and document the characteristics in team structure and SME ranked types of problems to first approach with PointPro.
- 3. Identify prerequisite software needs for users to adopt (tools, functions)
- 4. Identify integrations needed (if any) into existing data and analytic systems
- 5. Identify the quantify the value of each use case

Specific Places to Start:

- **AF Life Cycle Management Center**
 - Bombers Directorate: B-1 Digital Twin effort beginning in April 2021
- **PEO Weapons - Munitions**
- **Space Domain Awareness**
 - Directed Energy
 - Space Vehicles
- **NASIC**

Measuring Success for Users

As part of the feasibility study we will measure success to users in two ways:

- 1. Identify and quantify the benefits to users (similar to a cost-benefit analysis). The following categories are illustrative.
 - Direct benefits
 - Value of time saved by maintenance team
 - Decrease in needed maintenance inventory
 - Value of fewer unplanned equipment breakdowns
 - Intangible benefits (to be determined)
- 2. Extent to which existing goals of individuals/teams are aided by PointPro

Related Work (Dual-Use)

Project Title: Adaptive Data-Driven Actionable Intelligence for **Space Situational Awareness**



Research Objective(s):

1. *Decision-quality forecasting for conjunction assessment, with performance guarantees.*
2. *Anomalous behavior detection using sensor data with Koopman operator theory.*

Impact to the Air Force:

- *Deter adversaries, defend against threats.*
- *Pursue resilient space architectures for mission assurance*

Agency, Amount, Duration & Personnel:

AFOSR Grant: \$481,326 for 3 years (single PI): 05/20-04/23

Remote Sensing Program (PM: DR. Michael Yakes)

PI: Dr. Mrinal Kumar, Ohio State University

Related Publications: [8], [17], [20]

Integration with Proposed STTR Grant

1. Opportunity for continued reinforcement of existing IP
2. Strengthen AF ties through summer fellowship programs, target RV and the Space Force

Past conversations with individuals in the AF have produced a list of potential users. The potential users are identified on the Workplan slide under the first “Key Tasks” (Slide 18)

- **Dr. Darrell Lochtefeld** (APEX) identified individuals within PEO Weapons, Space Awareness, and NASIC (#2-4 on the Workplan slide), mentioned the need for integration of prognostics with physics-based models, calling it the “gold standard”
- The asset defense state-of-the-art is based on uncertainty forecasting, but it is open-loop (no explicit error control), leading to low-confidence forecasts (Slide 2 + 11)

[20] VanFossen, A., and Kumar, M., “Determination of Efficient QOI for SSA and Adaptive MC”, 31st AAS/AIAA Space Flight Mechanics Meeting, Jan 31-Feb 04 2021

Relationship with Future Work

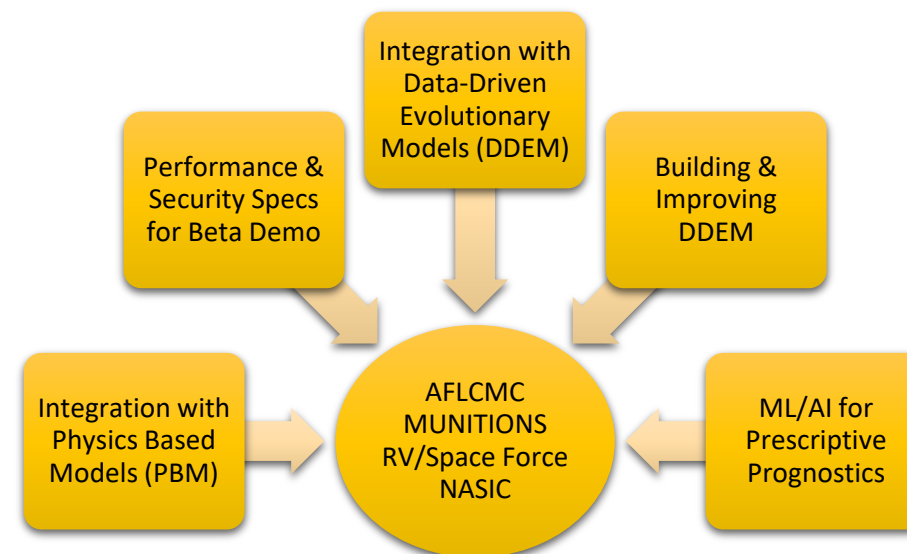
Anticipated Results of a Successful Phase I:

A successful Phase I feasibility study will result in the following deliverables:

- A list of specific USAF users who would benefit from PointPro
- A list of specific starting use cases, with PointPro benefits identified and quantified
- A list of PointPro features or tools needed as prerequisite for customer adoption
- A list of integrations necessary for users to get data into and out of PointPro (i.e., analytic graphics, file formats, database connections, etc.)

Successful Phase I is the foundation for Phase II:

- The users identified will be the future customers. Relationship with key users will enable quick start
- Use cases and benefits identified will inform workplan
- PointPro necessary features, tools, and integrations will inform the workplan for Phase II



Identifying & Integrating Components for a PointPro PHASE II Sustainment STTR

Work Plan

Workplan goal: Determine technical feasibility of PointPro simulation software for AF users.

Key tasks:

- Outreach to potential end users already identified with introductions via video calls or in person meetings, as appropriate.
 - 1. Air Force Life Cycle Management Center (AFLCMC) at Tinker AFB in Oklahoma
 - 2. PEO Weapons – David Lambert, Chief Scientist, Munitions
 - 3. Space Domain Awareness
 - a. Don Schiffler, Chief Scientist, Directed Energy
 - b. Space Vehicles – Tom Cooley, Chief Scientist, Scott Erwin, Lead: Special Projects
 - 4. NASIC – Duane Harrison, Chief Scientist
 - 5. AFRL – WeaponONE digital twin effort (Craig M Ewing, Senior Scientist for AFRL’s weapons modeling and simulation directorate
 - 6. Lt. Col. Joseph Lay, B-1 Engineering Branch material leader (B1-B Lancer Digital twin starting April 2021. B-1 Program office is part of the Bombers Directorate of the Air Force Lifecycle Management Center
- Identify other AF potential users in conversations with those already identified
- Hold workshops with SMEs – learn current analytics workstream to determine how PointPro fits into existing digital twin process (video calls or in person, as appropriate).

3-Month Schedule

Activity	1	2	3
Contact users identified			
Identify other users			
Workshops			
Report writing			

Key Outputs from Activities

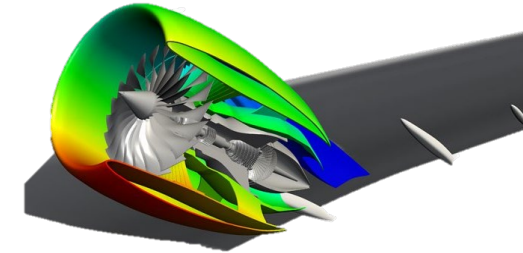
- 1. Identity potential users and applications
- 2. Quantify the potential benefits to each user type (e.g., time saved, newly enabled capabilities, maintenance savings, etc.)
- 3. Determine method for software integrate into current analytics workflow/systems
- 4. List of scalability features needed
- 5. Document model types (physics-based or data driven for PointPro feature prioritization.
- 6. Identify and document software features/capabilities necessary for immediate adoption

Resources: Dr. Kumar and Mr. Bell will perform all activities.

Commercialization Strategy [1/4]

Strategy for Commercializing – Preparation for Launch

- Significant positive from customer research and conversations with firms in industry (e.g., GE Aviation) led to explore commercialization
- While PointPro has a wide variety of applications, our strategy is to first identify a single high-potential industry use case and tailor our software offering to meet it.
- Condition prognostics of jet engines was chosen based on market size, likelihood of customers adoption, and our own domain expertise.
- PointPro is in the final phase of executing a TVSF grant from the Ohio Third Frontier, with an expected completion date of March 2021. The grant funded development of a user interface that will enable product demonstrations to potential customers.
- Receiving industry **subject matter expert (SME) feedback is needed** to identify specific use cases and to inform our next software refinement steps. The workplan steps described on the Workplan slide is our path to gain that feedback to tightly tailor our software to the needs of the end user.
- Following a successful STTR Phase I we will have all the elements needed to tell the value creation story and a path to make software refinements desired by users: user feedback, a workplan of necessary additions for specific AF use cases, and documentation of the economic value created with each use case.



JET ENGINE FAILURE & PROGNOSTICS

Current Product Development

Commercialization Partners



The Ohio State University has invested resources in the commercialization of the PointPro technology through the Corporate Engagement Office.



Rev1 Ventures provides commercialization 1:1 coaching and resources to PointPro. Rev1 is a selective startup studio in Columbus, Ohio.

Commercialization Strategy [2/4]

The nonstandard term “Digital Twin” is used in a variety of ways and in a different contexts making market sizing difficult. Nonetheless, there are many signs pointing toward the continued growth of this market.

The AF is ramping up adoption of Digital twins for predictive maintenance: “All Air Force platforms should be using some form of predictive maintenance by the end of fiscal 2022... The RSO plans to add predictive maintenance for 10-20 platforms per year for the next five years. – AF spokesman Daryl Mayer [21]

A large quickly growing market: “The Digital Twins market is projected to reach US\$ 26B by 2025 with CAGR of 38%.” – Grand View Research [23]

Digital Twin adoption in Manufacturing: “Typically, at the manufacturing plant, the OEE [a measure of operating efficiency] may be 60%. Through the use of digital twins, you can raise that up to maybe 80% and that transfers to real productivity improvement.” – Ansys CTO [22]

Growth of digital twins is occurring in the design, operations, and maintain lifecycle phases: “Of the expanding digital twin market projected to reach \$26 billion by 2025, two-thirds is estimated to focus on assets’ operational phase. About \$5.8 billion is estimated for the design phase, and about \$2 billion for the analysis and maintenance phase.– Ansys CTO [22]

Activity	2020	2021				2022			
	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Company									
Founded Company	■								
Term sheet negotiation			■	■					
Licensing agreement finalized			■	■					
Team Building									
CEO, CTO, Board	■								
Hire: tech talent			■	■	■				
Hire: Marketing/sales						■	■		
Advisory Board expansion							■	■	
Customers									
NSF I-Corps				■	■				
Continued Conversations						■	■	■	■
Identify AF PEO customer			■	■					
First commercial sale						■	■		
First channel customer							■	■	
Product Development									
User interface & data security		■	■	■					
First prototype				■	■				
Data-driven integration						■	■	■	■
Model learning						■	■	■	■
Second use case								■	■
Funding: Grants and VC									
Federal grants (NSF/DoD)		■	■	■		■	■	■	■
Begin VC & Corp. outreach					■	■	■	■	■

PointPro Commercialization Path

[21] <https://www.airforcemag.com/usaf-tripling-data-driven-maintenance-efforts-in-2020/>
[22] <https://www.controlglobal.com/industrynews/2020/af-at-home-23/>
[23] <https://www.grandviewresearch.com/press-release/global-digital-twin-market>

Commercialization Strategy [3/4]

At the completion of STTR Phase II we will have a market-ready software for the AF/DoD and for Industry

- During Phase II our team will begin marketing to the jet-engine prognostics market and creating a pipeline to engage when the software is complete.
- Due to the nature of the simulation, the needs of industry users are likely to be similar to those of AF/DoD users.
- Cash generation will begin at the end of phase II when the software is complete and sales to our pipeline start.

Scale

- Contemplated as an industry and application agnostics software, our team has identified the need for high-fidelity simulation in many other use cases.
- The PointPro software is currently focused solely on generating forecasts, though there is a significant opportunity to build wrap around features for users, such as ways manage simulation studies, create workflows, and produce compelling visuals.

Funding

- VC or corporate funding will speed up the process to scale to use cases identified.
- During Phase II we will engage with investors to gain funding to support growth into new markets and software feature expansions.
- There are a variety of both corporates and VC focused on advancing simulation to take advantage of the forecasted continued high growth in these markets, as the supporting technologies become more widespread (e.g., cloud computing, IoT, 5G, and industrial automation).

Industries Identified for Entry



Aerospace Powerplants

- Failure prediction for jet engines
- Airframe health



Automotive Health Mgmt.

- Remaining useful life



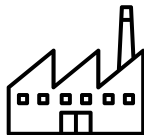
Space Asset Defense

- Station-keeping through predictive situational awareness



Renewable Power

- Health of wind turbines



Manufacturing

- High-value tool failure



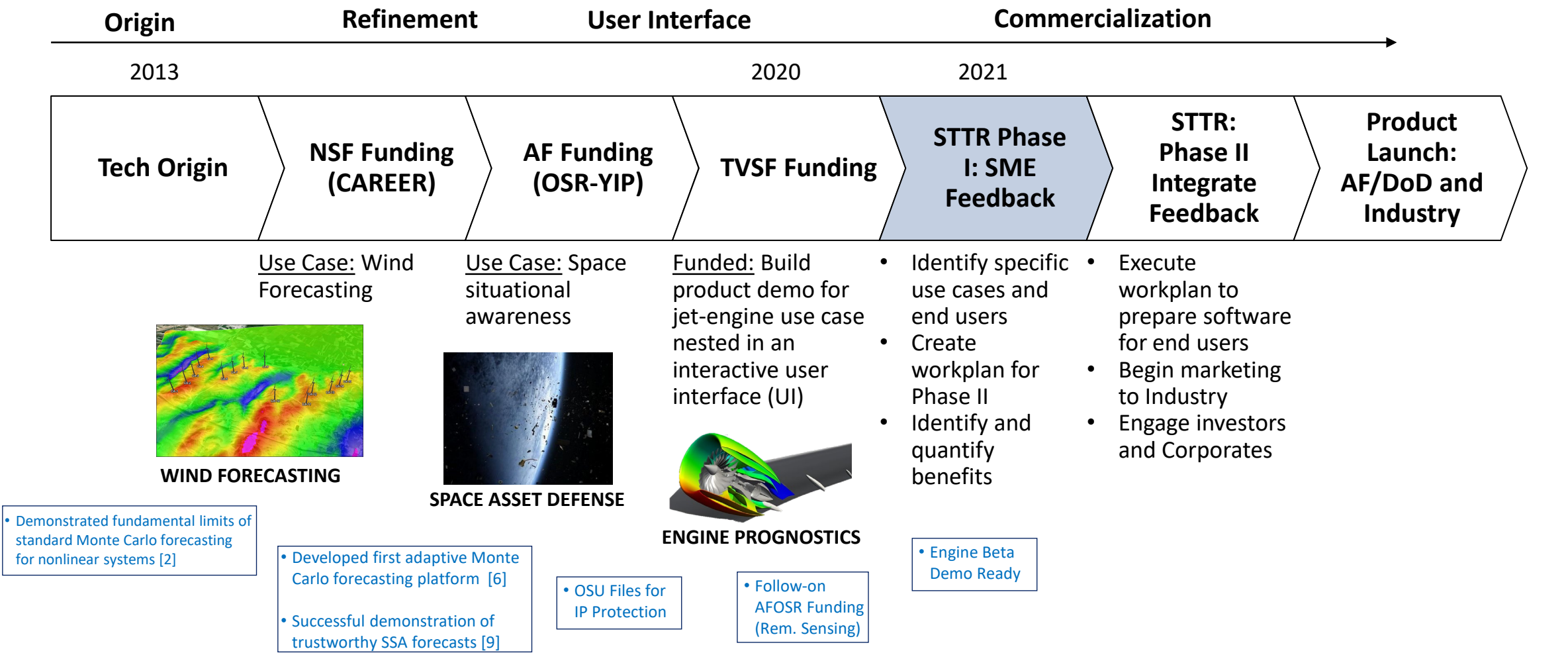
Oil & Gas Drilling

- Restricted access equipment failure

Commercialization Strategy [4/4]

Evolution of PointPro Technology

SME Feedback is the next planned iteration in the commercialization process



Key Personnel



Matthew Bell

Founder
CEO

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



Mrinal Kumar

Inventor/Founder, CTO
Associate Professor at
OSU

Principal Investigator Dr. 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

Prior, Current, or Pending Support of Similar Proposals or Awards

This is the first proposal of its type for the SBC. The information below is for PI Kumar at Ohio State University

Type	Supporting Agency	Amount	Effective & Expiration Dates	% Committed Time	Title of Project
Current	AFOSR [Remote Sensing]	\$481,326	05/2020 – 04/2023	17%	Adaptive Data-Driven Actionable Intelligence for SSA (6.1 Fundamental Research)
Current	Ohio Third Frontier	\$99,942	07/2020-06/2021	2%	Data Security Measures and User-Layer Development for a Prognostics Use Case (Accelerator Grant)
Pending	NSF [PFI]	\$249,999	09/2021-05/2023	7%	Learning Assisted Closed-Loop Forecasting for Trustworthy Prognostics of Complex Systems (Partnerships For Innovation: PFI Program with GE Aviation as Technology Partner)

Registrations

- DUNS: 117734378
- CAGE: 8S8Z0
- SBA SBIR ID: SBC_001882815
- Address: 47 W. 4th Ave, Columbus, Ohio 43201-3212