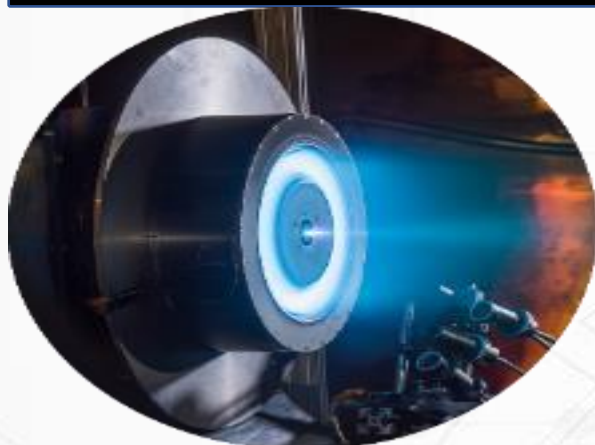


FY21 CIF/IRAD Final Review

November 2-4, 9, & 10, 2021

National Aeronautics and
Space Administration



Title: Towards Real-Time and High-Precision
Trajectory Simulation for EDL Systems

PI Names: Robert Williams (D205)
James Warner (D309)

Team: Luke Morrill (E302), Soumyo Dutta (D205),
Geoffrey Bomarito (D309)

Date: 11/3/21



- **Goal of EDL**: To conceive, design, assess, and optimize vehicle systems for entry, descent, and landing (EDL) at the Earth as well as the other planetary bodies of the solar system
- Primary flight mechanics tool used at Langley is the Program to Optimize Simulated Trajectories II (POST2)
 - Simulates vehicle trajectory given conditions and physical model parameters
 - Utilized across the agency, in industry, and academia
 - Leveraged for many Mars and Lunar missions



- Landing ellipse for current robotic Mars missions are on the order of kilometers (7 x 5 km for Mars 2020)
 - Needs to be decreased to 10's of meters for human-class Mars missions
- Much of the work is done pre-flight to determine best-guess of vehicle trajectory, given uncertainty in environmental, vehicle, and model parameters
- Current state involves using Monte Carlo simulations to propagate uncertainty
 - Depending on desired statistics, can involve thousands or even millions of simulations
 - Can be very time-consuming



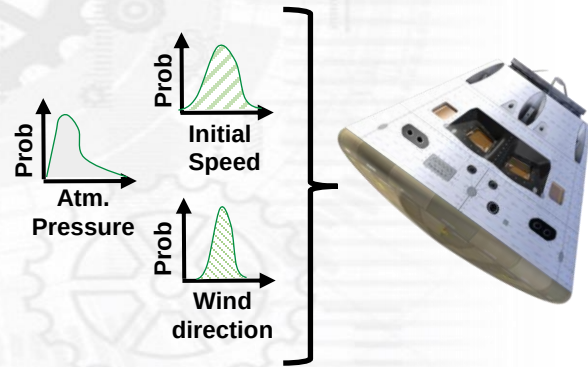
- Number of simulations needed to show, i.e. one-in-a-million chance of failure, can prove to be intractable
- Modern uncertainty propagation techniques may decrease the time needed to reach a solution, while maintaining desired accuracy
- Strategic Technology Investment Plan (STIP) Grand Challenge: 5 – Innovative Concepts for Landing 20mt on Mars
 - Increase EDL simulation capability by utilizing state-of-the-art uncertainty propagation techniques

Technical Challenge: Uncertainty Propagation



Trajectory Simulation

Trajectory simulation
uncertainties



HiFi Model:
POST2

Goal: Predict expected
landing location

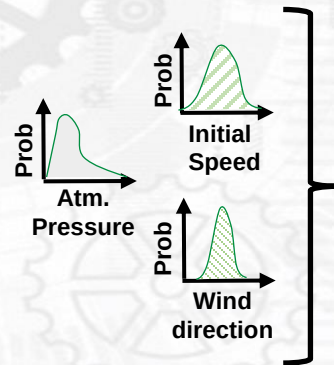


Technical Challenge: Uncertainty Propagation



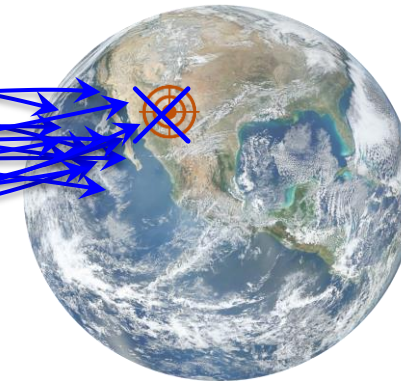
Approach: Monte Carlo Simulation *with High-Fidelity Model*

Trajectory simulation
uncertainties



High-Fidelity Model

Goal: Predict expected
landing location



Each line represents one POST2 simulation
(Typically thousands or millions)

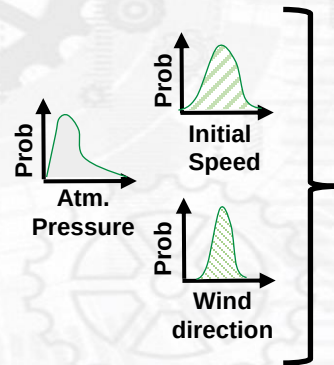
- Produces unbiased estimators; Guaranteed convergence to true expected value
- Computationally inefficient (or intractable) for expensive high-fidelity models

Technical Challenge: Uncertainty Propagation



Approach: Monte Carlo Simulation *with Surrogate Model*

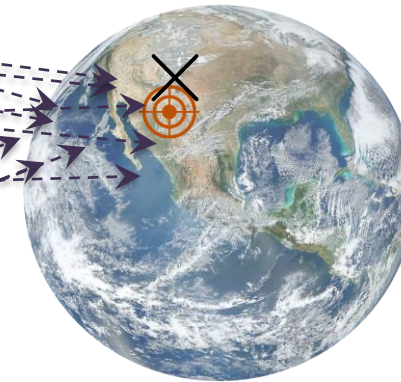
Trajectory simulation
uncertainties



Low-Fidelity Model



Goal: Predict expected
landing location



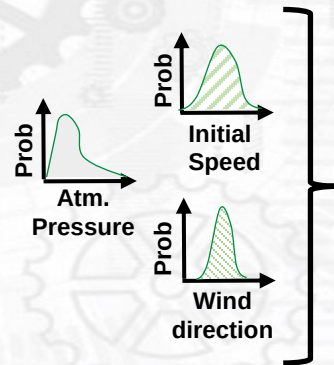
- Computationally efficient (faster run time)
- Produces biased estimators due to model approximation error

Technical Challenge: Uncertainty Propagation



Approach: Multi-Model Monte Carlo Simulation

Trajectory simulation
uncertainties



Low-Fidelity Model

High-Fidelity Model

Goal: Predict expected
landing location



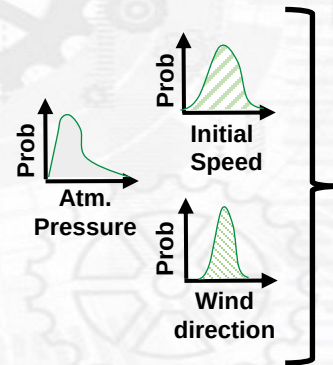
- Computationally efficient
- Produces unbiased estimators; Guaranteed convergence to true expected value

Technical Challenge: Uncertainty Propagation



Approach: Multi-Model Monte Carlo Simulation

Trajectory simulation
uncertainties



Low-Fidelity Models

High-Fidelity Model

Goal: Predict expected
landing location



- These methods generalize to leverage an arbitrary collection of low-fidelity models (analytical, data-driven, coarse discretization, simplified physics, etc.)
 - **Models are beneficial as long as they are correlated with the high-fidelity model & faster to evaluate**
- The key to multi-model Monte Carlo approaches is the optimal allocation of computational resources across available models

[1] Multilevel Monte Carlo (MLMC). Giles, 2008; [2] Multifidelity Monte Carlo (MFMC). Peherstorfer, 2016; [3] Approximate Control Variates (ACV). Gorodetsky, 2020.;



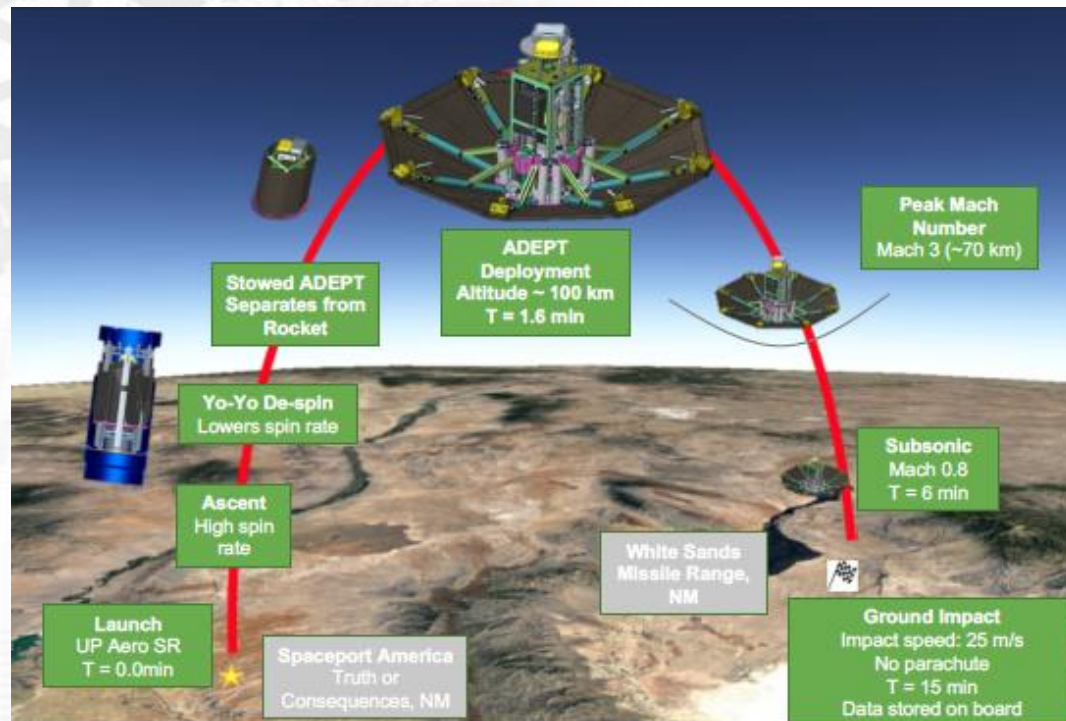
- **Goal:** deliver a rapid, high-precision trajectory simulation framework for EDL
- **Approach:** adopt & extend state-of-the-art multi-model UQ methods to fuse predictions from a well-established, high-fidelity EDL code (POST2) with estimates from low-fidelity models
 - Generate suite of possible low-fidelity models:
 - POST2 simulations simplified physics; data-driven machine learning models; etc.
 - Package & release general-purpose multi-model UQ software for broader NASA use
 - Define benchmark trajectory simulation problem to quantify speed/precision gains from proposed approach with existing approaches
- **Deliverables:**
 - Fast, precise trajectory simulation framework with quantified improvement vs. SOA
 - General-purpose NASA UQ software
 - Publications:
 - Conference/Journal paper(s) on theory, application

Benchmark Problem*



Analysis of the Adaptable Deployable Entry & Placement Technology (ADEPT) Sounding Rocket 1 (SR-1) test flight

ADEPT SR-1 Test Flight Schematic



Trajectory Qols Considered

Abbreviation	Description
lat-td	Geodetic latitude at touchdown
long-td	Longitude at touchdown
rollrt-80km	Roll rate at 80km geodetic altitude
rollrt-60km	Roll rate at 60km geodetic altitude
alt-apo	Apoapsis altitude
alt-mach1	Altitude at Mach 1
alt-deploy	ADEPT deploy altitude
time-td	Touchdown time
vel-term	Terminal velocity
accel-max	Max acceleration (Earth g's)
aoa-2km	Total angle of attack at 2km geodetic altitude
aoa-10km	Total angle of attack at 10km geodetic altitude
aoa-35km	Total angle of attack at 35km geodetic altitude
aoa-60km	Total angle of attack at 60km geodetic altitude
aoa-80km	Total angle of attack at 80km geodetic altitude

- POST2 was used to model the flight trajectory
- The accuracy of multi-model MC QoI estimates was quantified versus both high- and low-fidelity MC

* Warner et al. *Multi-Model Monte Carlo Estimators for Trajectory Simulation*. 2021 AIAA SciTech Form. January 2021

Benchmark Problem: Trajectory Simulation Models



High-fidelity model:

- POST2 with time step $\Delta t = 10^{-3}$ sec

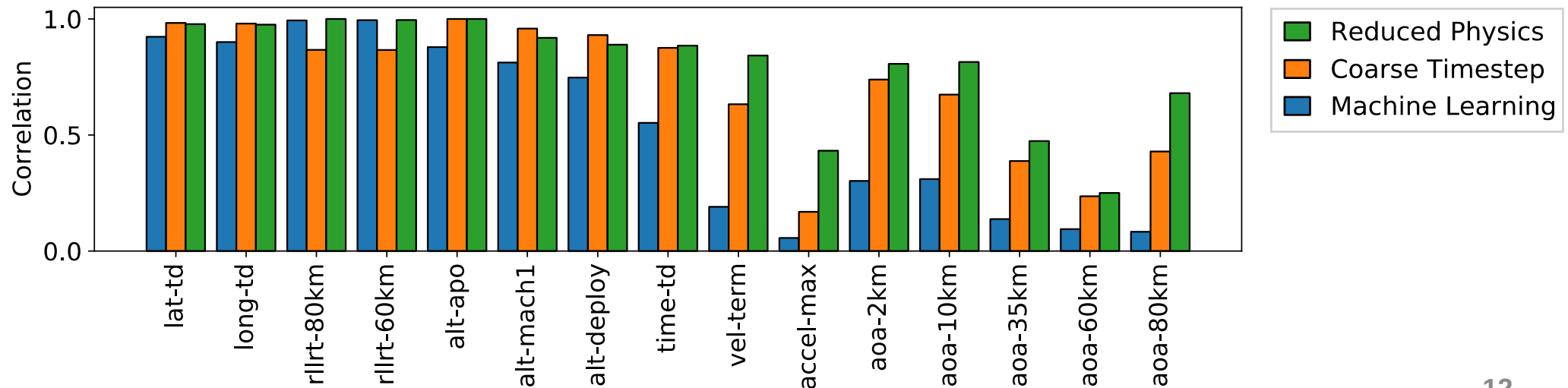
Low-fidelity models:

1. Reduced physics: POST2 with simplified atmosphere model
2. Coarse time step: POST2 with $\Delta t = 10^{-1}$ sec
3. Machine learning: Support vector machine (SVM) regression trained with input/output data from 250 POST2 simulations

Trajectory Simulation Model Run Times

Model	Run Time (sec)	Speedup (X)
High Fidelity	2.2×10^2	1.0×10^0
Reduced Physics	4.7×10^1	4.6×10^0
Coarse Time Step	2.8×10^0	7.8×10^1
Machine Learning	7.0×10^{-4}	3.1×10^5

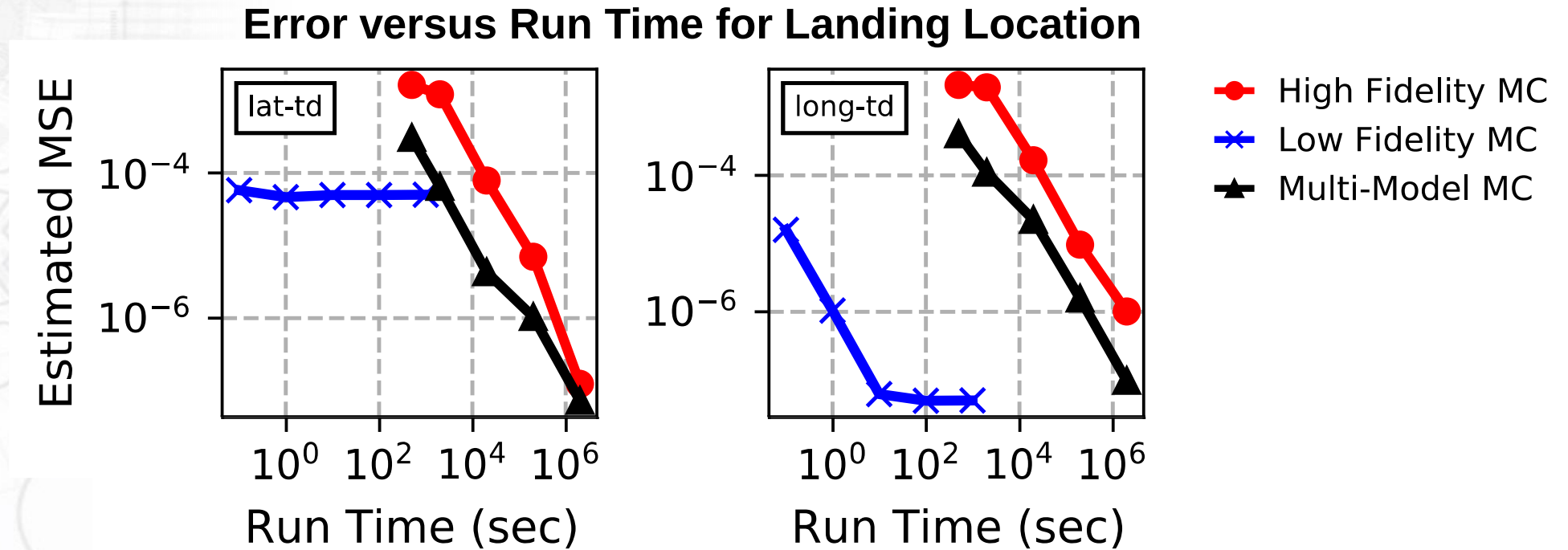
Correlation of low-fidelity models with respect to the high-fidelity model



Benchmark Problem: Estimator Accuracy vs. Run Time



- The error was calculated for high-, low-, and multi-model MC estimators versus a reference solution using high-fidelity MC with 100,000 samples



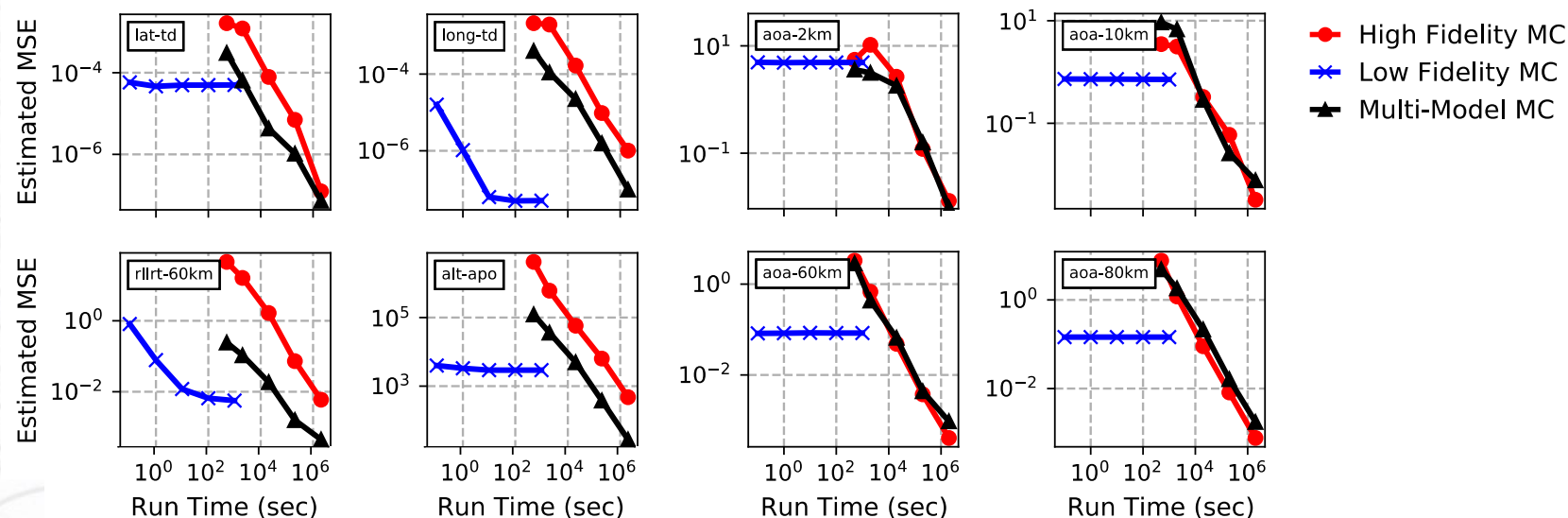
- High fidelity MC requires the most run time for accurate estimators
- Low fidelity MC has irreducible error due to estimator bias
- Multi-model MC is more efficient than high-fidelity MC & is unbiased

Benchmark Problem: Estimator Accuracy vs. Run Time



- The error was calculated for high-, low-, and multi-model MC estimators versus a reference solution using high-fidelity MC with 100,000 samples

Error versus Run Time for Several Trajectory QoIs

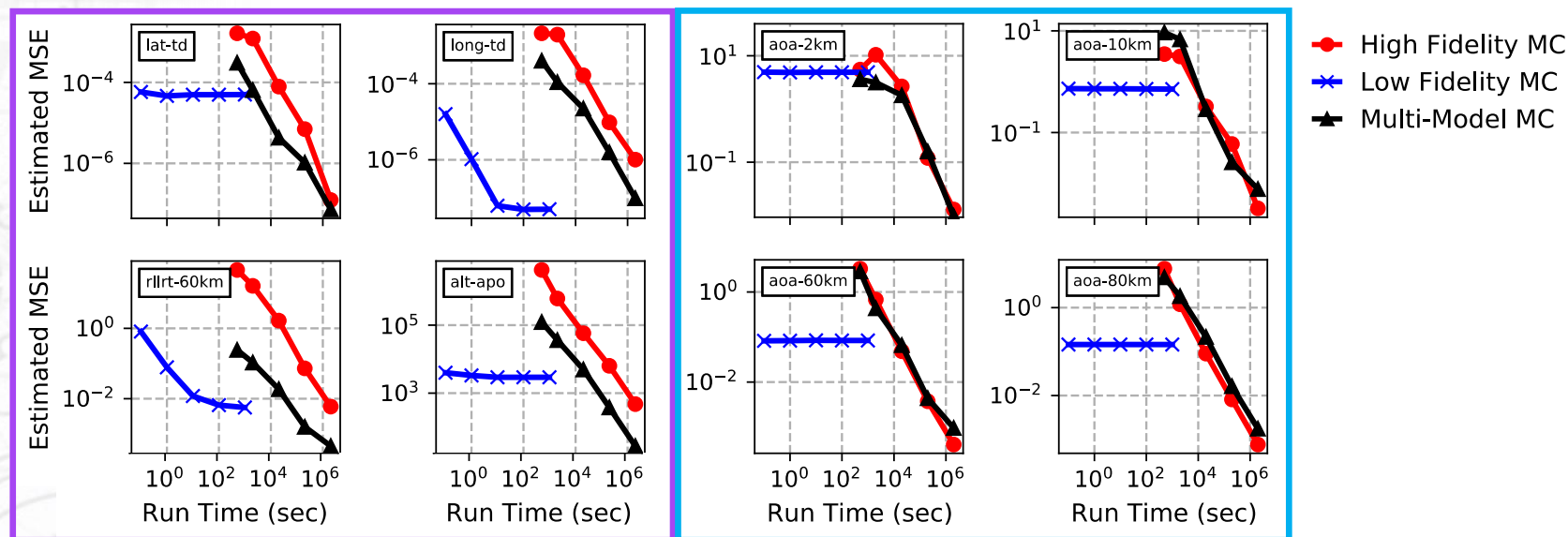


Benchmark Problem: Estimator Accuracy vs. Run Time

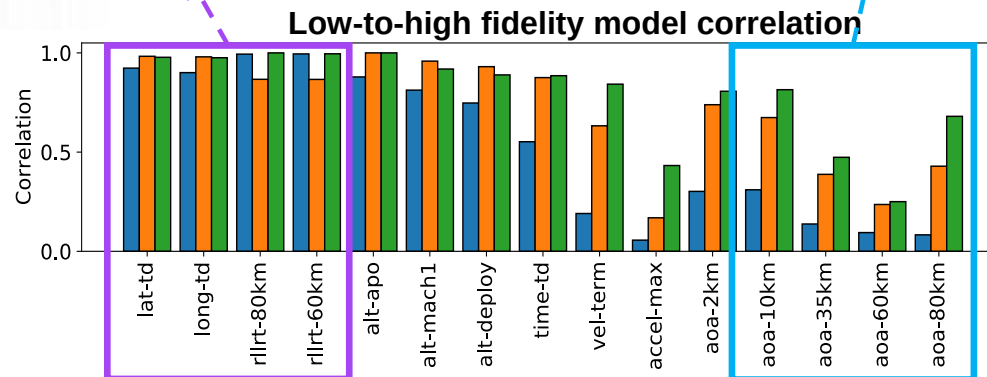


- The error was calculated for high-, low-, and multi-model MC estimators versus a reference solution using high-fidelity MC with 100,000 samples

Error versus Run Time for Several Trajectory QoIs



Higher correlations yield large accuracy improvement relative to high-fidelity MC



Lower correlations yield accuracy comparable to high-fidelity MC

➤ Better low-fidelity trajectory simulation models are needed

- Demonstration of multi-model Monte Carlo framework on a benchmark trajectory simulation example (ADEPT) & quantified improvements - **completed 11/1/20**
- Publish AIAA SciTech Paper on approach & results - **completed 1/5/21**
- Determine improved low fidelity trajectory simulation models to use in conjunction with framework - **completed 8/1/21**
 - Developed machine learning models with up to 2X higher correlation for roll rate predictions vs. those used in SciTech paper
 - Subject of future work
- Develop capability to predict higher order statistics beyond expected value, variance (e.g., percentiles, probability of failure) – **incomplete**
 - **Issue:** predicting rare events requires significant extensions of multi-model Monte Carlo theory
 - Subject of future work

CIF-IRAD Closeout - Accomplishments & Highlights



- 1) [FY20] Open-source software: *Multi Model Monte Carlo with Python (MXMCPy)*
<https://github.com/nasa/mxmcpy> (April 2020)
- 2) [FY20] NASA TM: *Multi Model Monte Carlo with Python (MXMCPy)*. NASA/TM-2020-220585 (April 2020)
- 3) **[FY21] Journal Paper:** Bomarito, G. F. et al. *On the Optimization of Approximate Control Variates with Parametrically Defined Estimators*. Journal of Computational Physics (In Review, arXiv preprint arXiv:2012.02750).
- 4) **[FY21] Conference Paper / Presentation:** Warner, J. E. et al. *Multi-Model Monte Carlo Estimators for Trajectory Simulation*. 2021 AIAA SciTech Forum. (January 2021)
 - Results showing up to two orders of magnitude improved precision for some quantities of interest
- 5) **[FY21] Conference Presentation:** Bomarito, G. F. et al. *Parametrically-defined Approximate Control Variates*. 2021 SIAM Conference on Computational Science and Engineering (March 2021)
- 6) **[FY21] Conference Presentation:** Bomarito, G. F. et al. *Fast, Unbiased Uncertainty Propagation with Multi-Model Monte Carlo*. DATAWorks 2021. (April 2021)
- 7) **[FY21] Conference Presentation:** Bomarito, G. F. et al. *MXMC: Generalized Multi-Model Monte Carlo Simulation for Uncertainty Propagation*. 16th National Congress on Computational Mechanics. (July 2021)



- **Future work:**

- Developing improved low-fidelity trajectory simulation models
 - 2022 AIAA SciTech: “Improving Multi-Model Trajectory Simulation Estimators using Model Selection and Tuning”
 - Collaboration with Sandia National Labs with support from a NASA HQ Digital Transformation / STMD

- **Future opportunities / Transition:**

- FY22 ESM Project: *Software for Multi-Model Autonomous Real-time Trajectories (SMART) Guidance*
 - **Goal:** develop onboard, real-time powered descent guidance system that uses robust trajectory optimization under uncertainty to achieve precision landing
 - Combines & extends technology developed from this CIF project with “Onboard Autonomous Trajectory Planner (OATP)”

CIF-IRAD Closeout - Funding



- Funding:
 - Proposed (\$30K + 0.3 FTE)
 - Procurement: \$30K for NIFS intern(s)
 - Travel: \$2K for conference travel
 - Status
 - Procurement ((Reduced) \$22.8K spent, \$0.0K remaining):
 - Spring intern was funded through FY20 forward-funding
 - Funding for two summer interns has been obligated
 - Travel (\$0 spent, \$0K remaining):

Civil Servant	Role	Planned FTE	Outlook FTE
Robert Williams	PI	0.10	0.10
James Warner	co-PI	0.10	0.10
Luke Morrill	co-PI	0.10	0.10

Purchased Item	Planned	Outlook	Obligated
Summer Intern	\$ 11,400	\$ 11,400	\$ 11,400
Summer Intern	\$ 11,400	\$ 11,400	\$ 11,400

Towards Real-Time and High-Precision Trajectory Simulation for EDL Systems

National Aeronautics and
Space Administration



FY21 CIF IRAD Midterm Review

PI: Robert Williams (D205), Co-PI: James Warner (D309), Luke Morrill (E302)

Annual Funding: \$30K + 0.3 FTE

Problem and Impact to NASA

- NASA's aspirations for human class Mars missions are contingent upon significant breakthroughs in entry, descent, and landing (EDL) systems
- An order-of-magnitude increase in payload capability and nearly three-orders-of-magnitude reduction in landing radius over the current state-of-the-art is required
- Predicting a vehicle's landing radius requires simulating a huge number of potential trajectories with time-consuming high-fidelity EDL models to understand the impact of uncertainties in system parameters

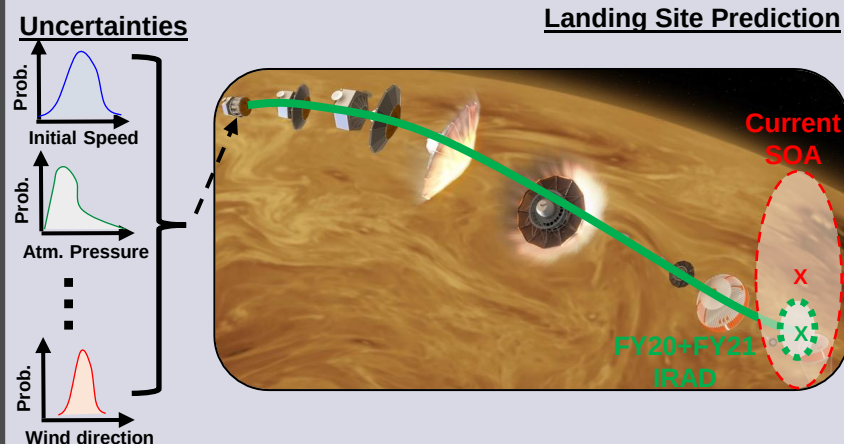
Goal/Objective

- Goal:** advance the current state-of-the-art for EDL technology by delivering a rapid, high-precision trajectory simulation capability that specifically targets the Martian landing radius reduction challenge
- Leverage advanced UQ techniques to make efficient predictions under uncertainty for EDL
- Package and release the adopted UQ methodology as general-purpose software for fast predictions under uncertainty at NASA

Innovation

Adopt cutting-edge multi-fidelity UQ techniques^{1,2} to fuse predictions from a well-established, high-fidelity EDL code³ with estimates from low-fidelity models (e.g., reduced-physics, machine learning)

- Combines the computational efficiency of low-fidelity models along with accuracy guarantees of high-fidelity models
- Substantial improvements in prediction speed and precision are expected over existing approaches that rely **solely** on slow physics-based models **or** biased reduced-order models



- Multi-Model Monte Carlo with Python (MXMCPy)
- Koopman Operator Approach
- Program to Optimize Simulated Trajectories 2 (POST2)

Technical Approach

- Develop in-house software that implements emerging multi-fidelity UQ algorithms
- Continue to develop appropriate interfaces to EDL codes so that trajectory simulation can be integrated with UQ software
- Select benchmark trajectory simulation problems to quantify speed/precision gains from proposed approach with existing approaches

New or Continuing: 1st Year Tier 2 IRAD

Start TRL/End TRL: 3/4

Primary STIP: 5. Innovative Concepts for Landing 20 mt on Mars

Key Milestones/Deliverables

- Preliminary results from a benchmark trajectory simulation problem (e.g., umbrella heatshield reentry) that quantifies the increased precision and computational speedup over the current state-of-the-art approach
- A general and user-friendly UQ software package to be extended to future EDL & broader NASA applications
- A conference/journal publication that details the findings and progress made

Primary Technology area: **TX09.4.5**