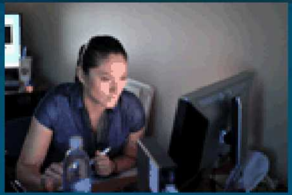
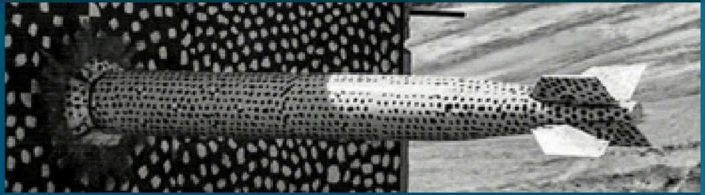
SAND2018-13417PE

Model Fidelity Studies for Rapid Trajectory Optimization





PRESENTED BY

Lisa Gammon Hood

About the Presenter

Lisa Gammon Hood

- ASDL master's student
  - Advisor: Dr. Dimitri Mavris
  - Started January 2017
  - Graduating December 2018
- Year-round graduate student intern with Sandia National Laboratories
  - Technical Advisor: Dr. Julie Parish
  - AE8900 Project is also work for SNL
  - Supporting the Autonomy for Hypersonics program
- Special thanks to Rick Gaffney and Jeff Robinson at NASA for their X-43 expertise

Dr. Dimitri Mavris

Dr. Julie Parish

Motivation

Hypersonic Trajectory Optimization Needs to Be Completed More Rapidly

Current Practice

1. Three degree-of-freedom (3-DOF) model used to create an initial optimized trajectory
2. Refined with 6-DOF, software-in-the-loop simulation
3. Iteration between Monte Carlo simulation and subject matter expert suggestions
   - Constraint violations avoided
   - Robustness increased

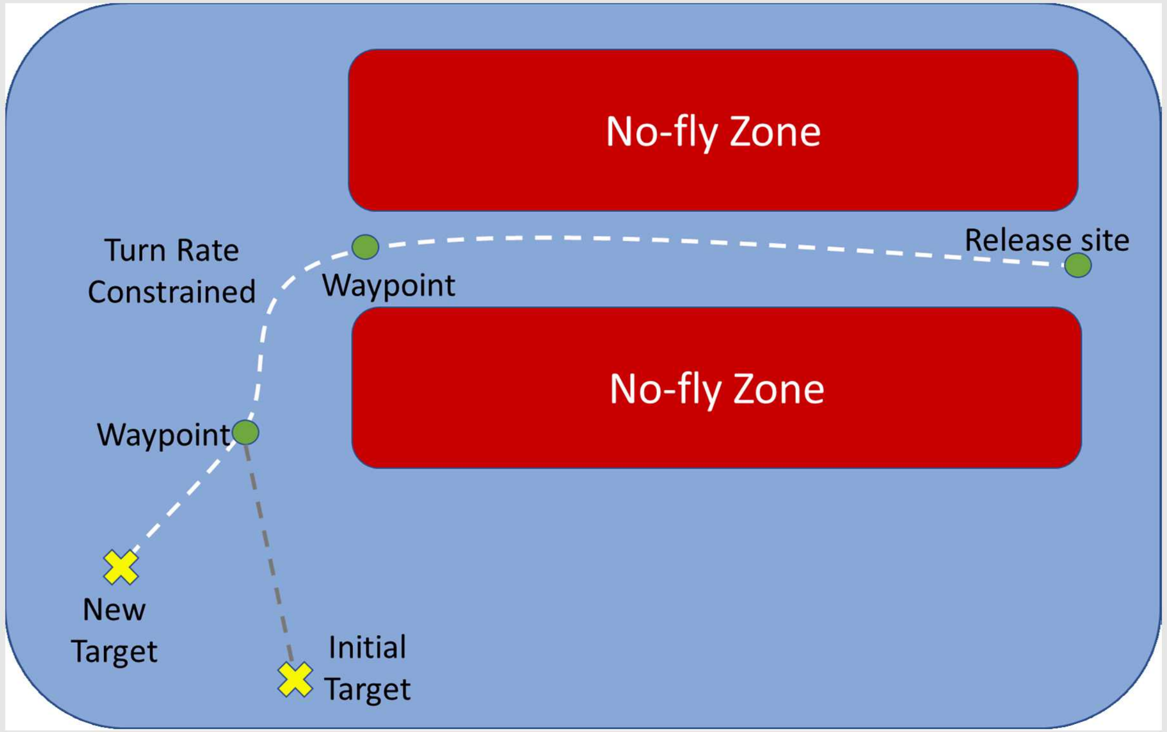
Several months to complete

Desired Operation

1. Only a few minutes to create optimal trajectory to stationary target
2. Moving targets require optimal trajectories generated in flight
3. Rapidly optimized trajectories must still be
   - Feasible
   - Robust

The Many Challenges of Hypersonic Rapid Trajectory Generation (RTG)

- Vehicle Complexity
- Highly non-linear dynamics & aerodynamics
- Heat management
- Constraint Complexity
- No-fly zones, instantaneous impact
- Structures and stability
- Survivability
- Control surface limitations
- Terminal conditions
- Robustness Requirement
- Safety
- Critical missions
- Short Time Window
- Moving targets



Published Research Only Re-Optimizes an Existing Hypersonic Trajectory

Trajectory Optimization for Hypersonic Vehicle After Disturbances[1]

Qazi, Linshu & Elhabian, 2004

- Previously developed nominal trajectory
- 3 types of disturbances: aerodynamic coefficients, specific impulse, inert ass
- Used a pre-trained artificial neural network (ANN) to supply cost function in disturbed state
- Optimized angle of attack profile with sequential quadratic programming (SQP)

Online Re-optimization of Hypersonic Vehicles After Damage or Failure[2]

Allwine, Fisher, Strahler, Lawrence, Oppenheimer & Doman, 2005

- Adjustments to a nominal trajectory for: updated aerodynamics, reduced control authority
- New aerodynamic surrogate models created with real time sensor information

3-D Trajectory Optimization for Lightly Constrained Hypersonic Vehicles[3]

Dong, Chao, Wang, & Yang, 2012

- Start with nominal trajectory
- Bank angles and flight path angles optimized mid-flight to achieve changing down range and cross range targets
- Target errors in the order of 0.2 to 0.3km for 4,000 – 7,000 km flight

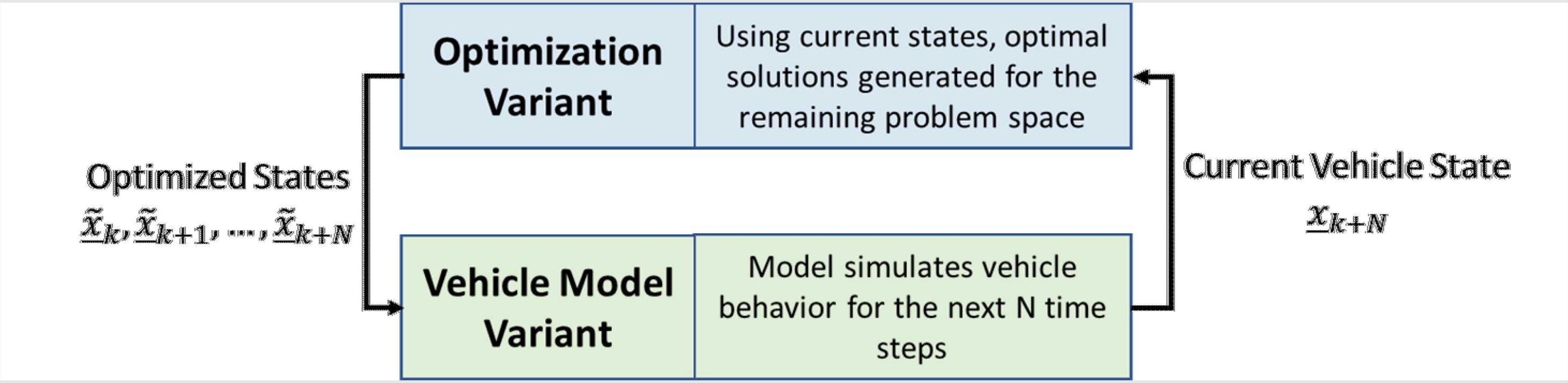
Known target with nominal trajectory provided makes optimization much easier
We want to quickly generate the nominal trajectory for a new mission

Research Questions

Tailored Simulation Fidelity for Rapid Trajectory Optimization

RTG Without a Nominal Trajectory Through Interaction Between Optimizer and Vehicle Model

Introduction
Motivation
Research Questions
Methodology
Results
Conclusion



- What's the lowest fidelity vehicle model we can employ and still produce feasible and robust solutions?
- How does feedback rate between the optimizer and the vehicle model affect the quality of the optimized trajectory?
- Do aerodynamic surrogate models affect computational expense and solution quality?

Methodology

Tailored Simulation Fidelity for Rapid Trajectory Optimization

Pseudospectral Trajectory Optimization Chosen for This Investigation

How PS Optimization Works

1. Starts with a traditional optimal control problem[4]
2. Discretizes at Legendre-Gauss-Lobatto/Radau nodes (shown to produce most accurate approximations, avoiding the Runge phenomenon[5][6])
3. Approximates states and controls with global, orthogonal polynomials (Chebyshev, Lagrange, etc)[7]
   - States and controls of the approximations are constrained to have the exact values at the nodes
   - Derivatives of the interpolating polynomials must exactly equal the problem dynamics at the nodes
4. Optimal Control problem is now a Non-Linear Programming problem and can be solved numerically.[7]

Why PS Optimization ?

1. **Exact satisfaction of constraints**[8]
   - Population-based methods enforce dynamics constraints through penalty functions
   - Heavily influenced by weighting of those penalties
2. **Exact satisfaction of the system dynamics**[7]
   - Differential Dynamic Programming uses approximations[9]
3. **Converges, even without a close guess**[8][10]
   - Indirect (variational) and population-based methods need a good guess (a priori knowledge) converge
4. **Converges rapidly**
   - Faster than population-based or direct shooting[4][7]
   - Improved with phases and a sparse solver[11][5]
5. **Trusted software available**[11][5]
   - DIDO
   - GPOPS-II

X-43 Used as Test Vehicle

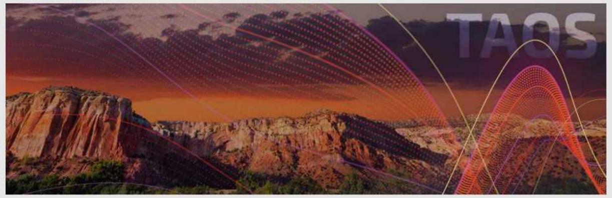
X-43 chosen because

- Hypersonic[12]
- Glide test flight trajectory data available for verify the models[13]

Vehicle Model Fidelity Options

- Simple 3-DOF physics (Vinh[14])
- 3-DOF++
  - Flight angles (α, β, ϕ)commanded directly
  - Constraints on flight angle rates
  - Improved gravity and atmospheric model
  - Control surface deflections approximated with trim table
- 6-DOF – Low Fidelity
  - PID controller commands control surface deflections $(\delta_e, \delta_a, \delta_r)$ to meet optimized flight angles
  - Limits of deflection and deflection rate of control surfaces
- 6-DOF – High Fidelity
  - Dynamic Inversion Adaptive Controller[15][16]
  - Includes control surface slew-rates and other details
  - Current "gold standard"

$$\begin{bmatrix} \dot{x}(t) \\ y(t) \\ z(t) \\ V(t) \\ \gamma(t) \\ \psi(t) \end{bmatrix} = \begin{bmatrix} V\cos\gamma\cos\psi \\ V\cos\gamma\sin\psi \\ -V\sin\gamma \\ \frac{-D}{m} - g\sin\gamma \\ \frac{L\cos\phi - S\sin\phi}{mV} - \frac{g\cos\gamma}{V} \\ \frac{L\sin\phi + S\cos\phi}{mV\cos\gamma} \end{bmatrix}$$

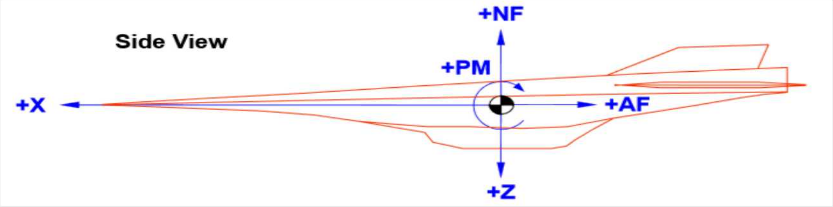


www.sandia.gov/taos

Credit: NASA

Aerodynamic Surrogate Models Created with Aim of Reducing Computational Expense

- X-43 Aero tables provided by NASA
  - Created using wind tunnel tests and CFD[17][18]
  - $C_N, C_A, C_Y, C_l, C_m, C_n, C_{N_{\delta r}}, C_{A_{\delta r}} C_{Y_{\delta r}}, C_{l_{\delta r}}, C_{m_{\delta r}}, C_{n_{\delta r}}, C_{Y_{\delta a}}, C_{l_{\delta a}}, C_{n_{\delta a}}$ as functions of $M, \alpha, \beta, \delta_e, \delta_r, \delta_a$



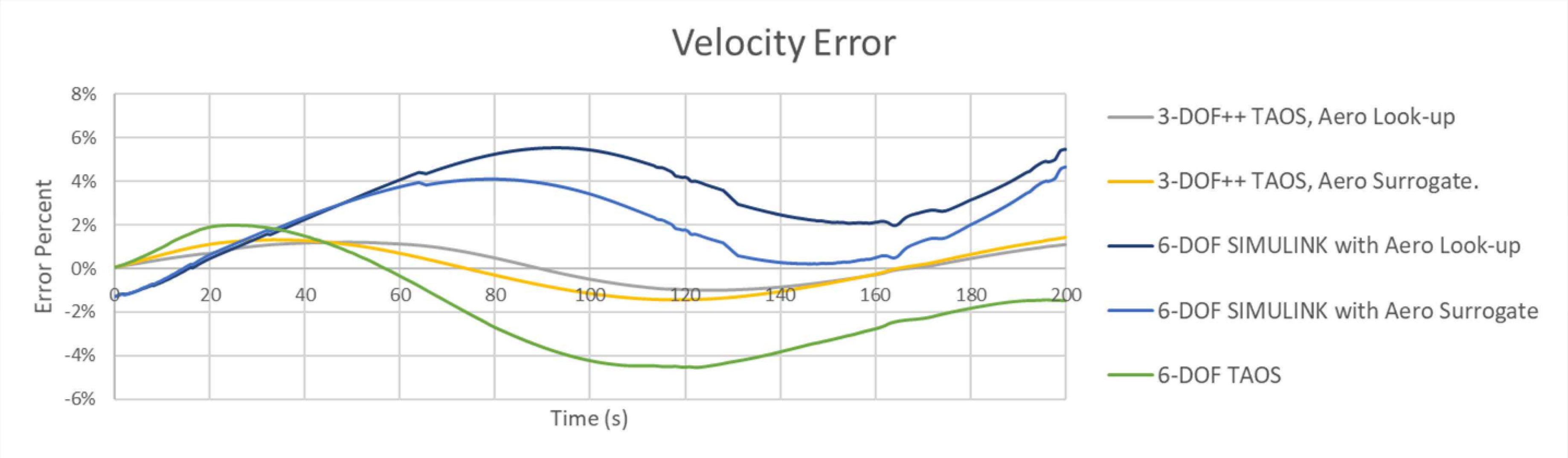
Credit: NASA

- Trajectory simulation tools spend a large portion of their computation time querying the aerodynamic coefficient database and interpolating.
- ASDL has employed surrogate models to reduce computational expense for conceptual design[19][20]
- ASDL has also shown that creating aerodynamic surrogates that are accurate enough to be useful is difficult even with multi-fidelity and adaptive sampling[20][21][22]
- Surrogate models created for X-43 aero
  - 48: 16 for each of 4 Mach regions
  - $0.9532 \leq R^2 \leq 0.99995$
  - Kriging had better correlation than polynomial, artificial neural network, and radial basis functions

DAKOTA
Explore and predict with confidence.
https://dakota.sandia.gov

- Optimizer/model combos tested with and without surrogate models for aerodynamics

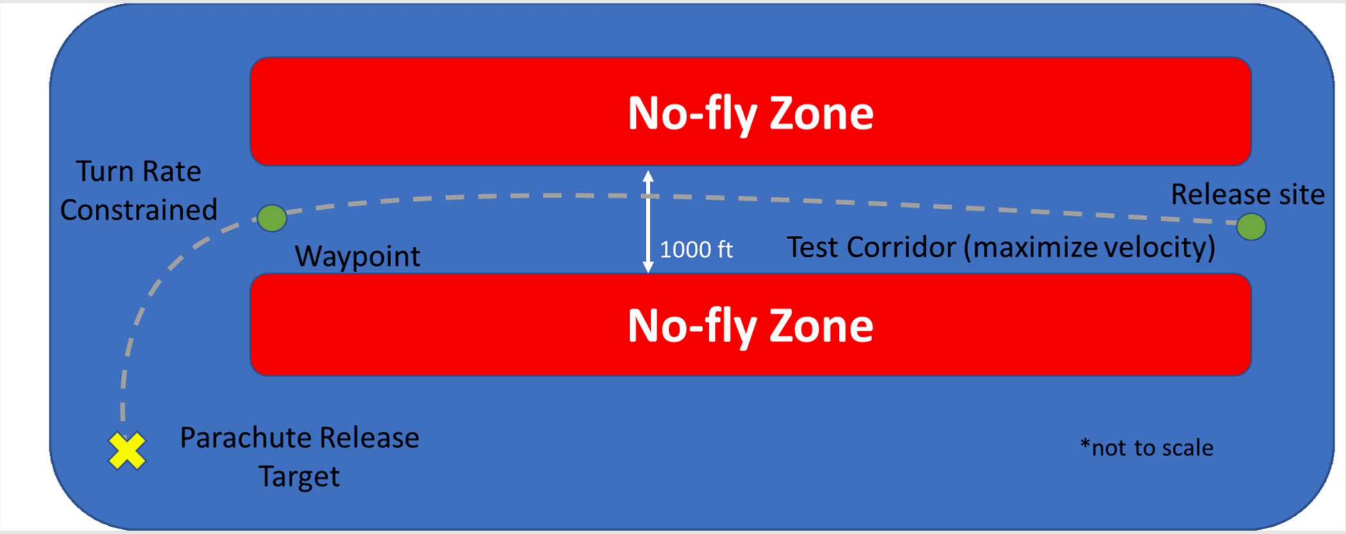
All Models Performed In Family with X-43 Test Flight



Trajectories Optimized for Two Representative Missions

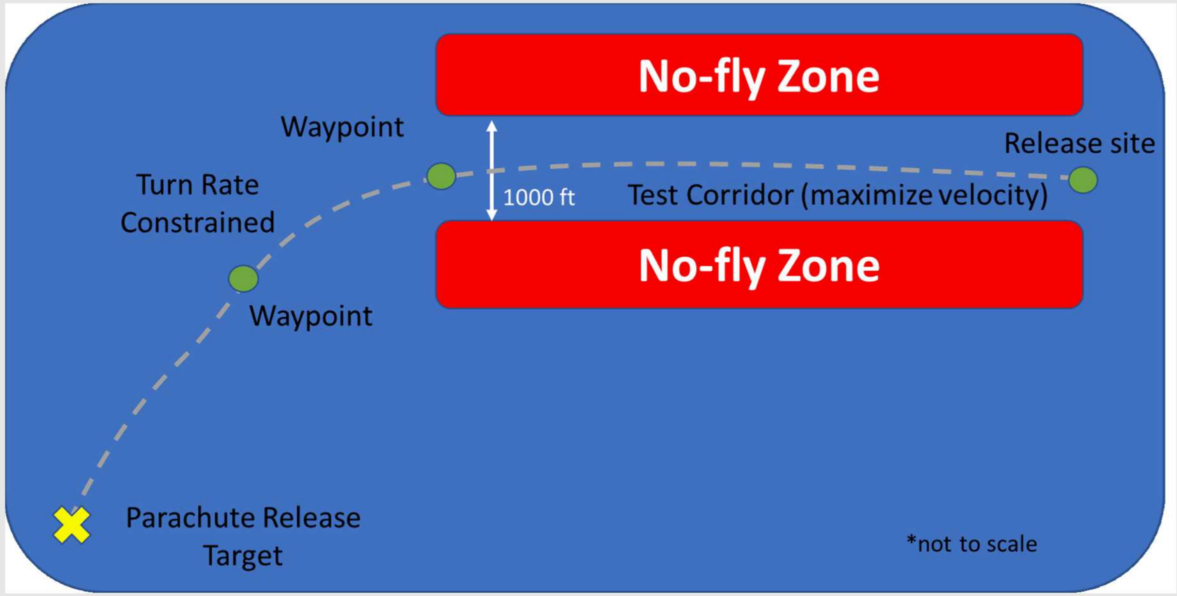
Mission 1

- Long narrow corridor of flight
- Hard turn near the target



Mission 2

- Shorter corridor of flight
- Gentler turn at higher speed
- Straighter flight near target

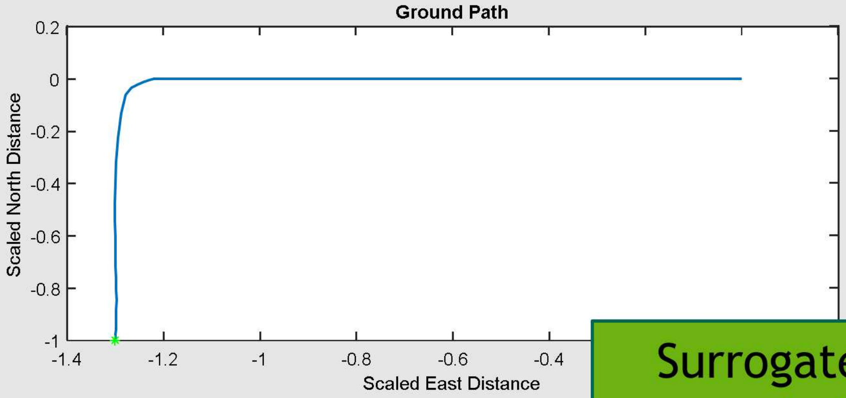


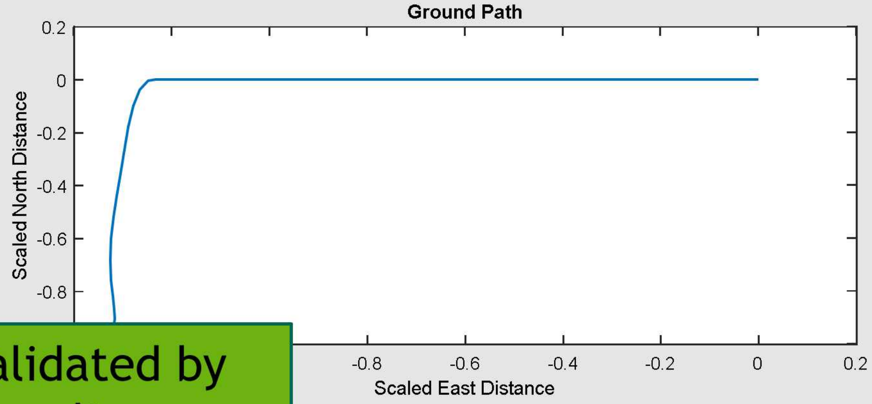
Results

Tailored Simulation Fidelity for Rapid Trajectory Optimization

Optimization with Look-up Tables and Surrogates Produced Similar Trajectories

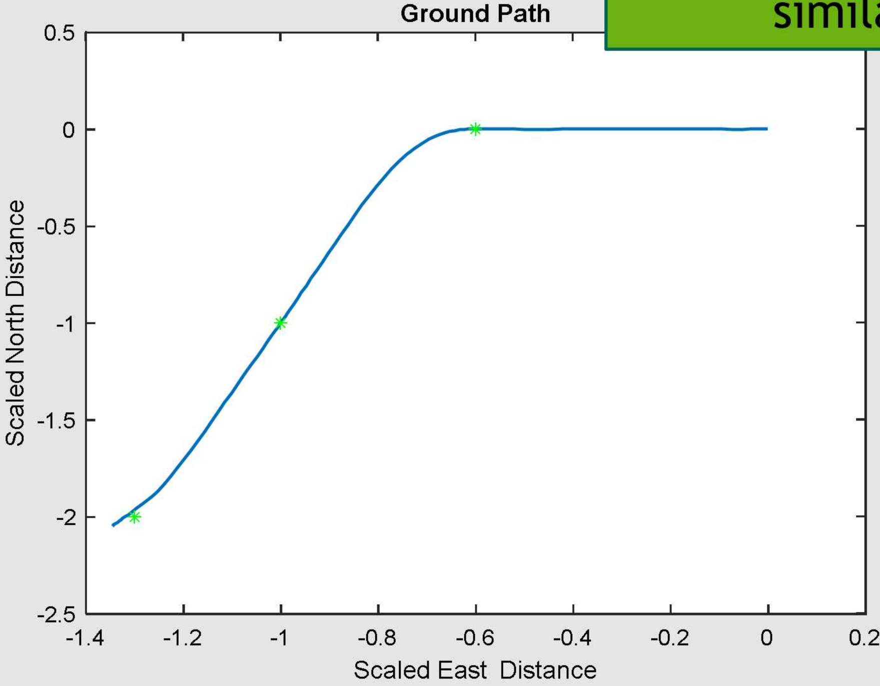
Aero Look-up Tables | **Ground Path** | Aero Surrogates

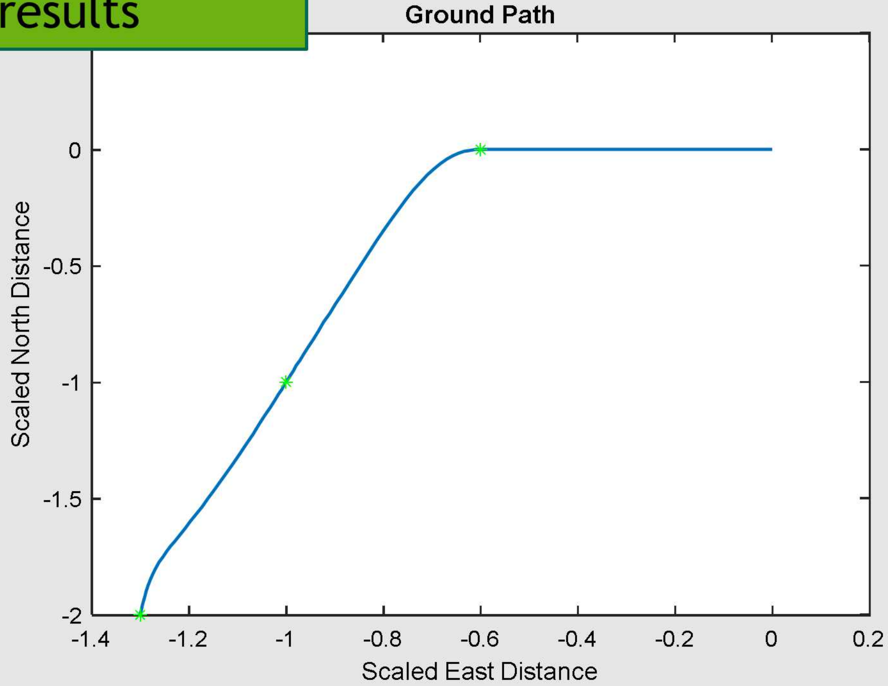




Mission 1

Surrogates validated by similar results



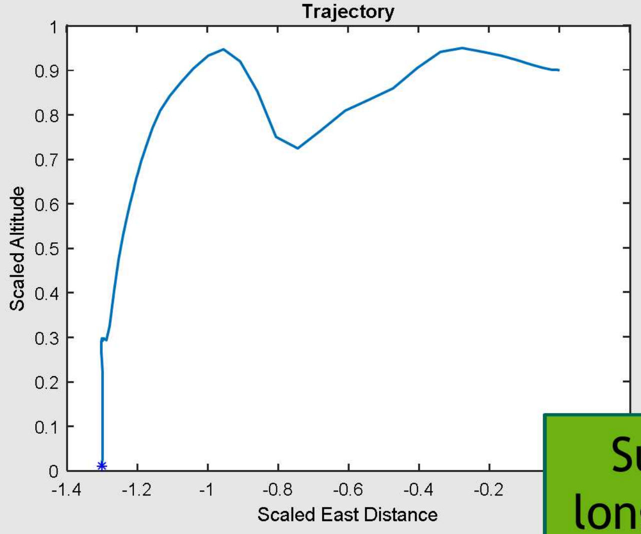


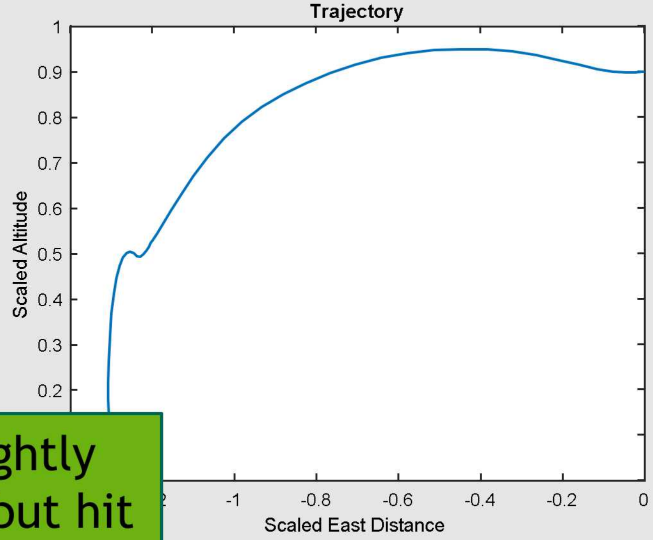
Mission 2

Optimization with Aerodynamic Surrogates Hit Target Exactly, Look-up Table Optimization Did Not

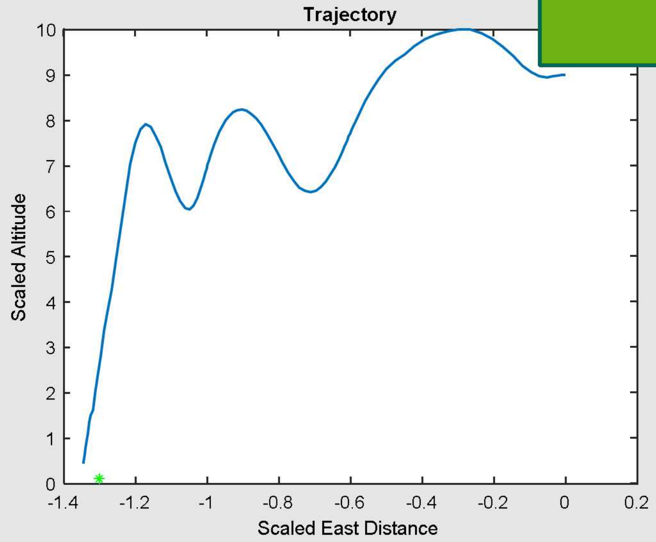
Aero Look-up Tables | **Trajectory** | Aero Surrogates

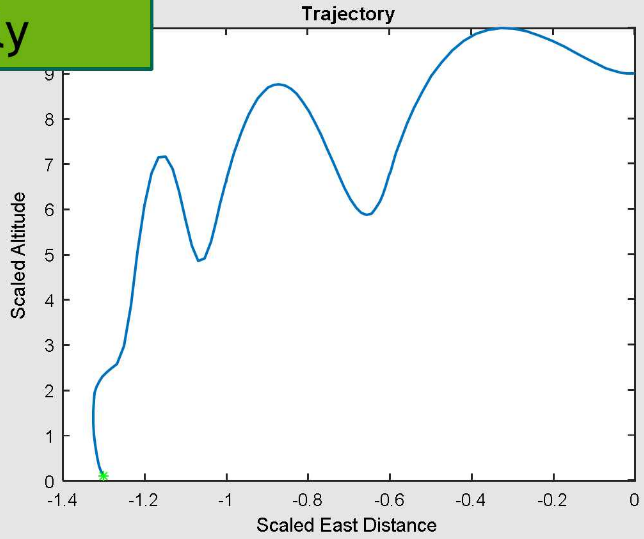
Mission 1





Mission 2





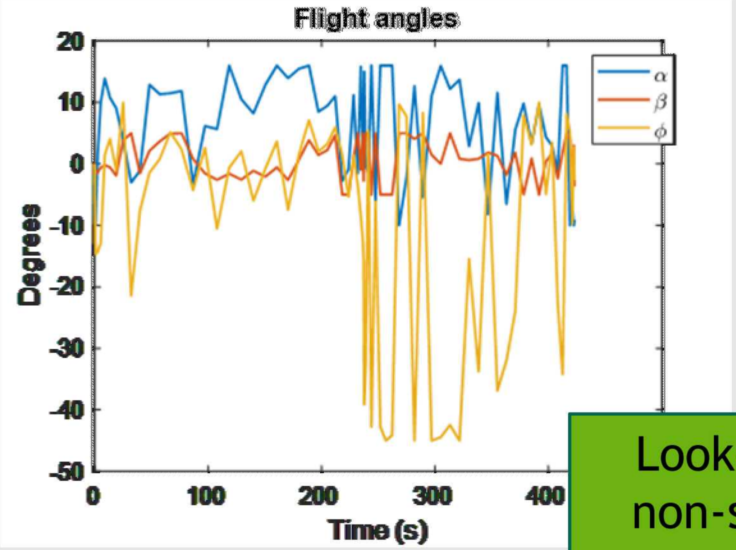
Surrogates took slightly longer to converge, but hit the target exactly

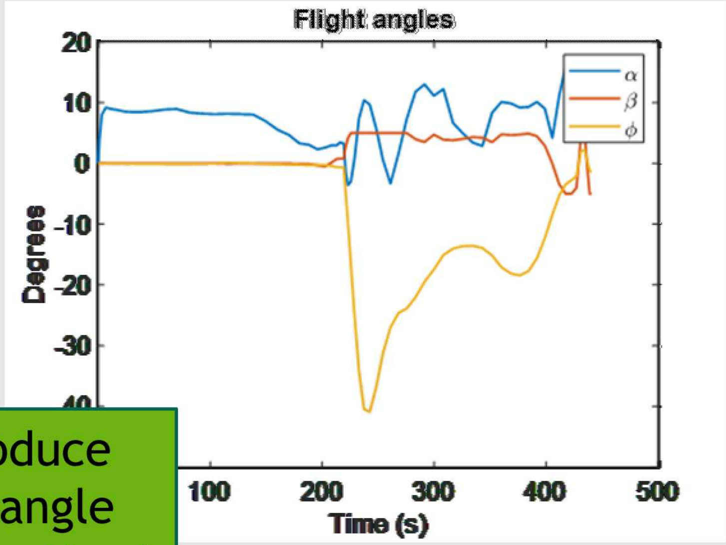
Aerodynamic Surrogates Facilitated Optimizer Convergence

- Introduction
- Motivation
- Research Questions
- Methodology
- **Results**
  - **No Feedback**
  - 3-DOF++
  - 6-DOF
  - Comparison
- Conclusion

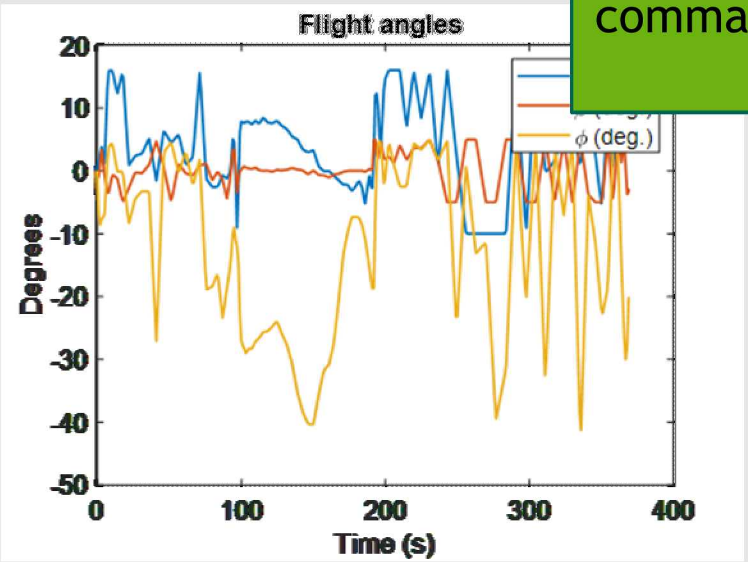
Aero Look-up Tables | **Flight Angles** | Aero Surrogates

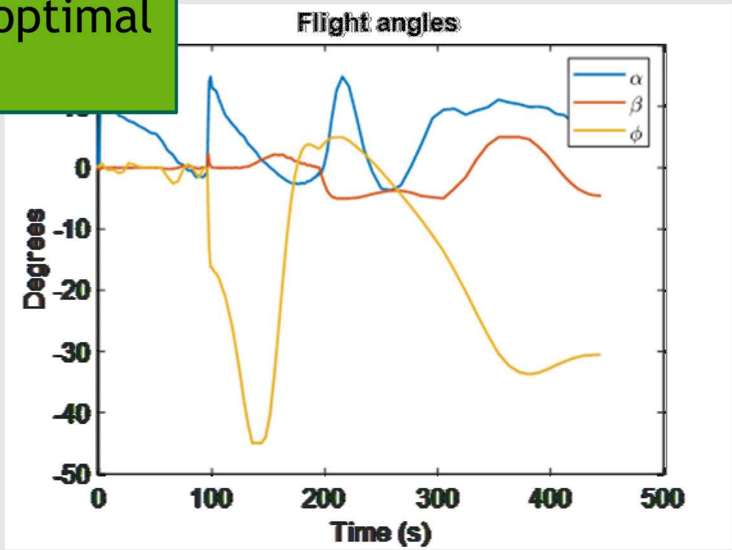
Mission 1





Mission 2





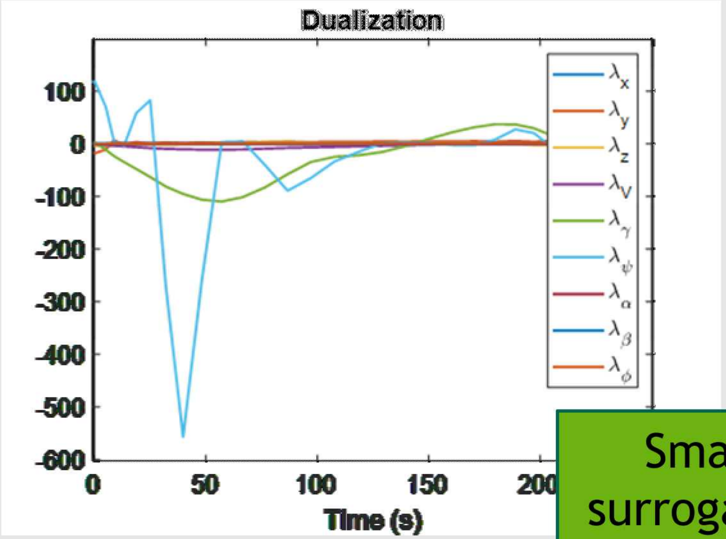
Look-up tables produce non-smooth flight angle commands and sub-optimal solution

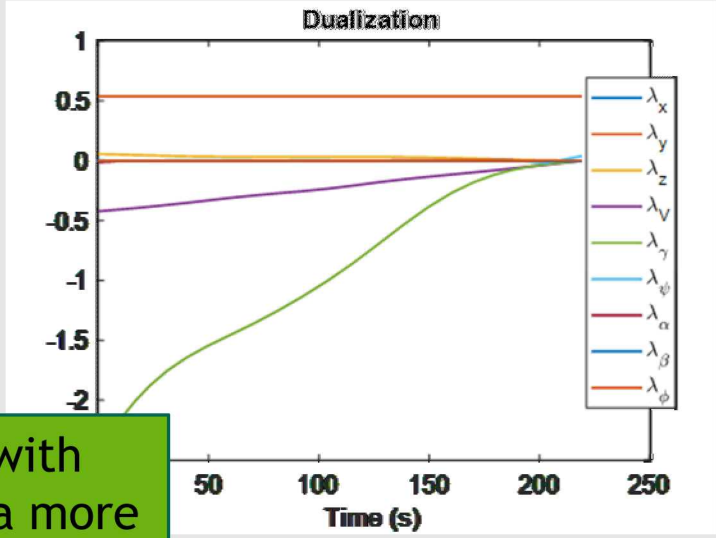
Aerodynamic Surrogates Facilitated Optimizer Convergence

Aero Look-up Tables

Costates

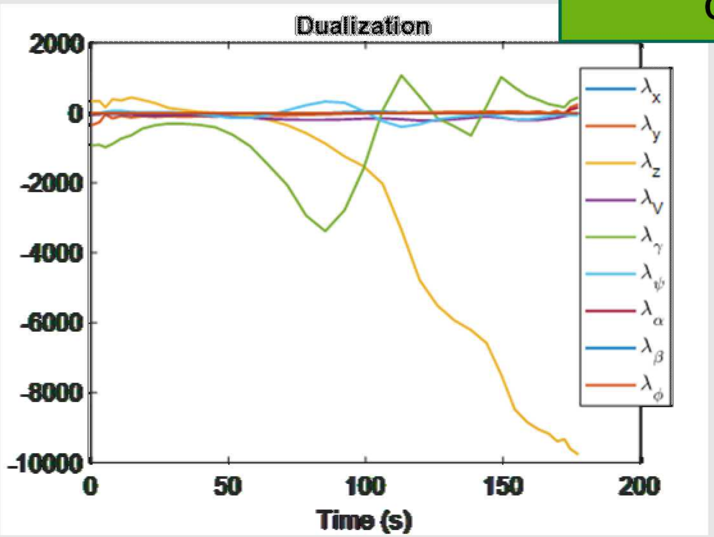
Aero Surrogates

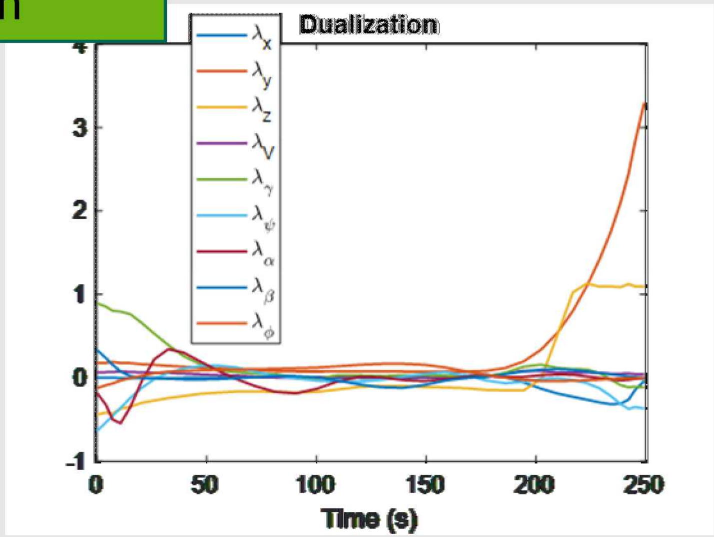




Mission 1 Segment 1

Smaller costates with surrogates indicate a more optimal solution

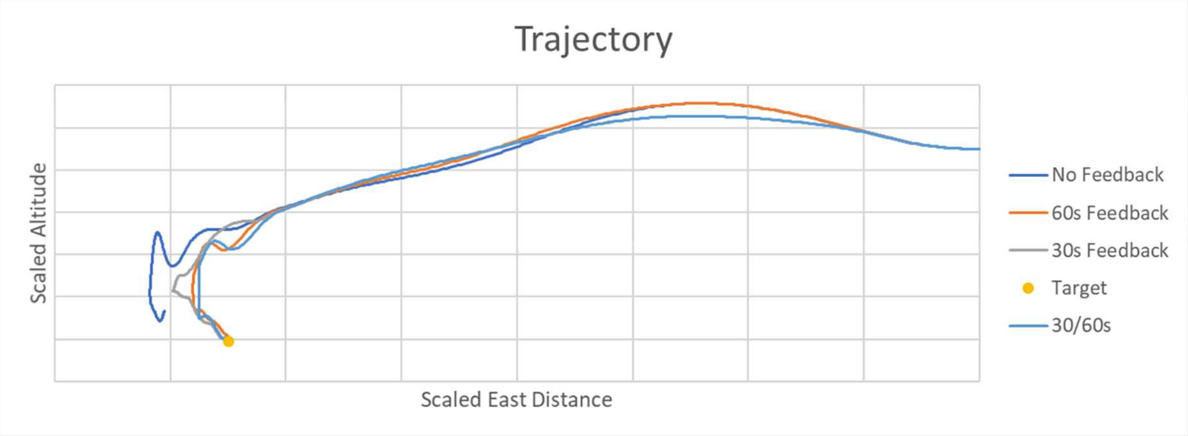


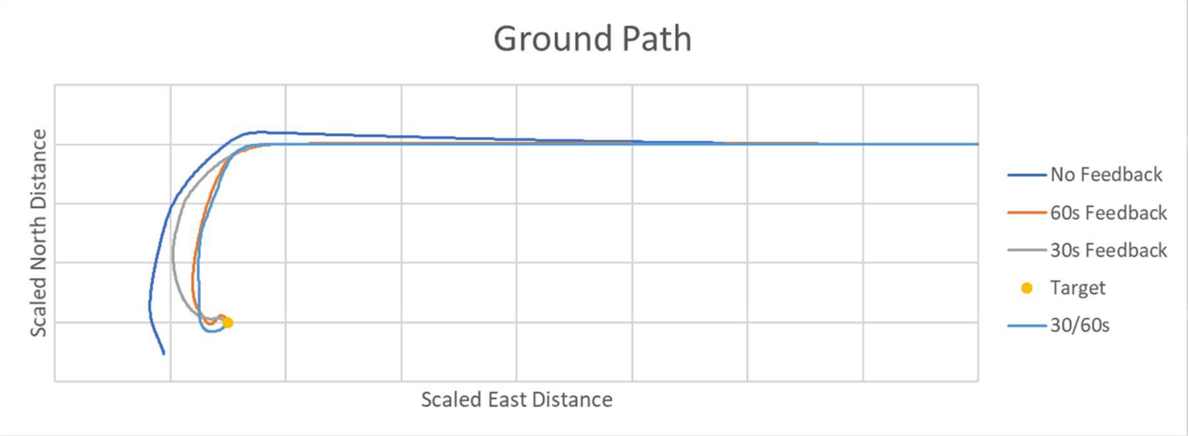


Mission 2 Segment 3

Feedback with Vehicle Simulation Improved Guidance Solution

Mission 1 **Optimizer:** 3-DOF with Surrogates **Vehicle Model:** 3-DOF++ with Tables





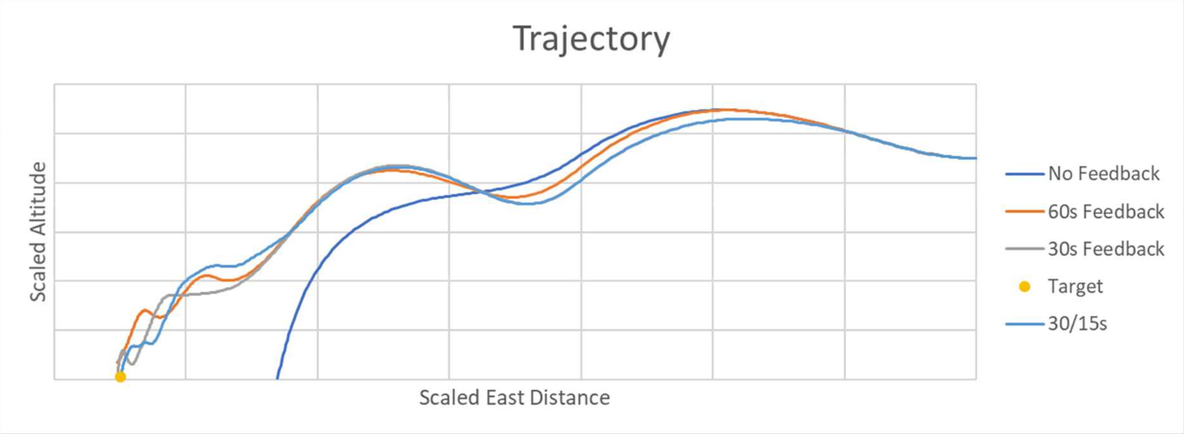
Feedback Period (s)	Target Miss Distance (ft.)	Maximum Constraint Violation (ft.)
None	113778.7	8983.3
60	742.2	705.7
30	2398.1	none
30/60	426.9	none

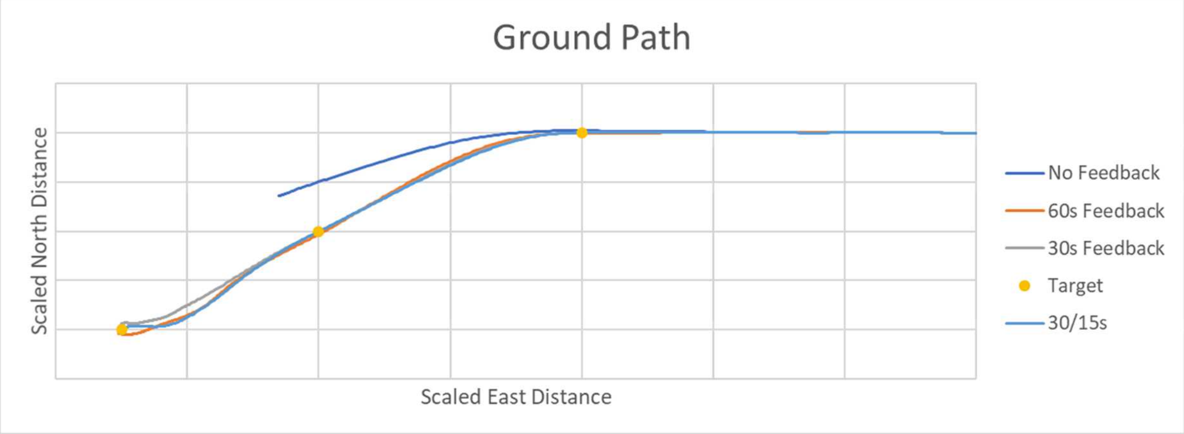
Miss distance reasonable for mission objectives

- A larger feedback period being more accurate suggested that the 3-DOF vehicle model was more maneuverable, especially in difficult transonic region
- Investigated this possibility with Mission 2

Low Model Fidelity Produces Better Solutions Under Simpler Flight Conditions

Mission 2 **Optimizer:** 3-DOF with Surrogates **Vehicle Model:** 3-DOF++ with Tables





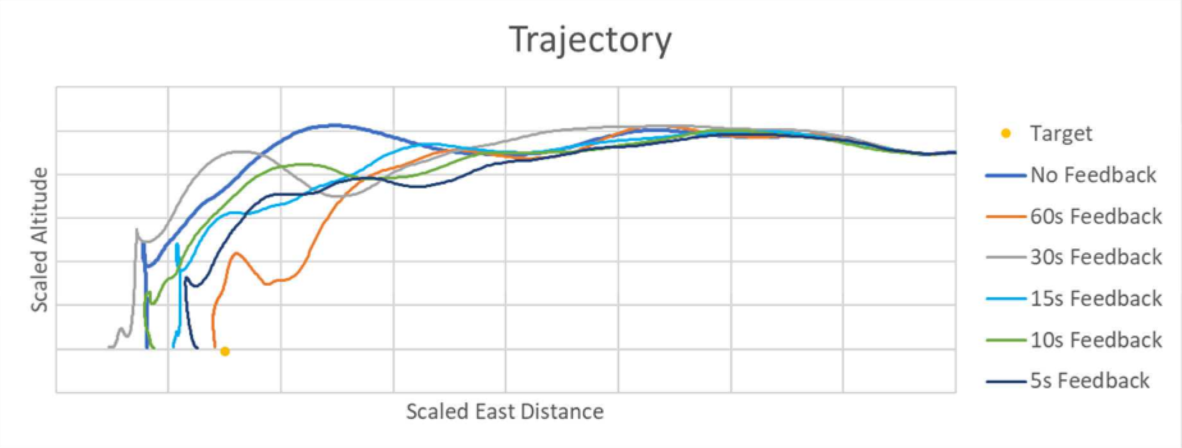
Feedback Period (s)	Final Target Miss Distance (ft.)	Waypoint Miss Distance (ft)	Maximum Constraint Violation (ft.)
None	274947	70459	1626
120s	48473	8209	1626
60s	5696	87	231
30s	3299	399	none
30/15s	308	225	none

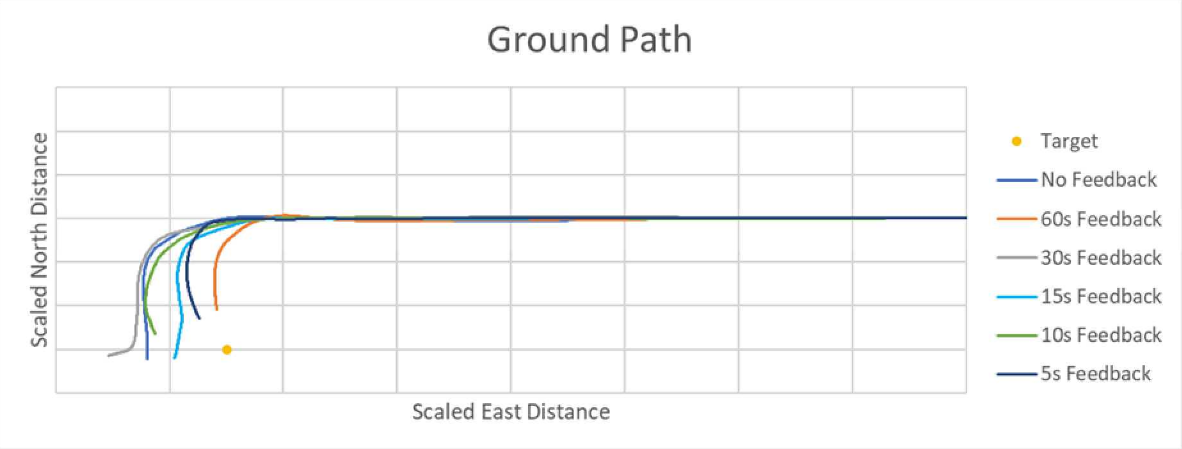
Miss distance even less than with Mission 1

- Most maneuvering done in supersonic, rather than transonic
- Expected improvement with decreased feedback period
- Shows limitations of 3-DOF model for complex mission requirements

Aerodynamic Look-up Tables Insufficient for Pseudospectral Trajectory Optimization with DIDO

Mission 1 **Optimizer:** 3-DOF with Tables **Vehicle Model:** 3-DOF++ with Tables





Feedback Period (s)	Target Miss Distance (ft.)	Maximum Constraint Violation (ft.)
None	139235	2227.7
60	49014	2962.1
30	206884	1182.2
15	81783	427.4
10	126309	264.9
5	60212	117.6

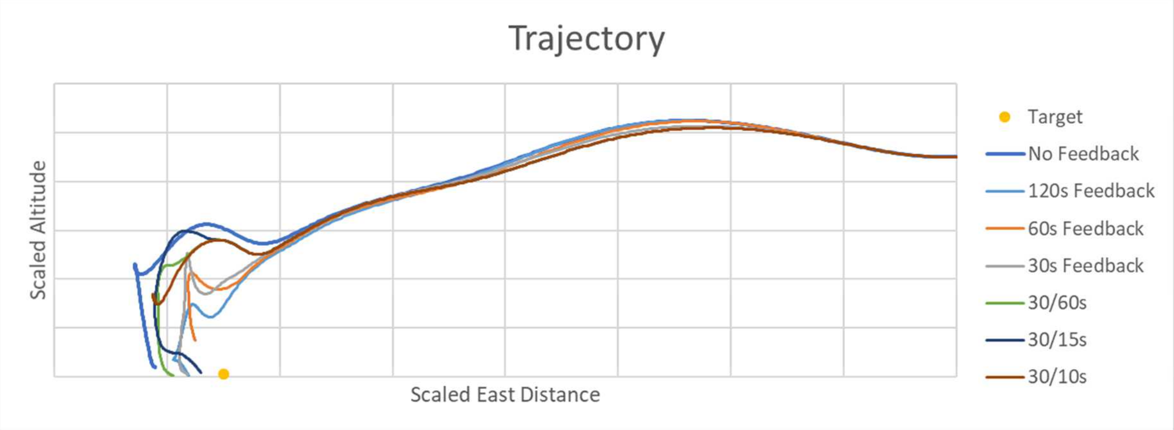
- Even with 5 second feedback period (~3 hours of computation time) couldn't meet constraints
- Best target miss distance was 49,014 ft.

Feedback Period (s)	Optimization Time with Surrogates (s)	Optimization Time with Tables (s)
None	497	208
60	1526	934
30	3171	2010
15	7235	5122

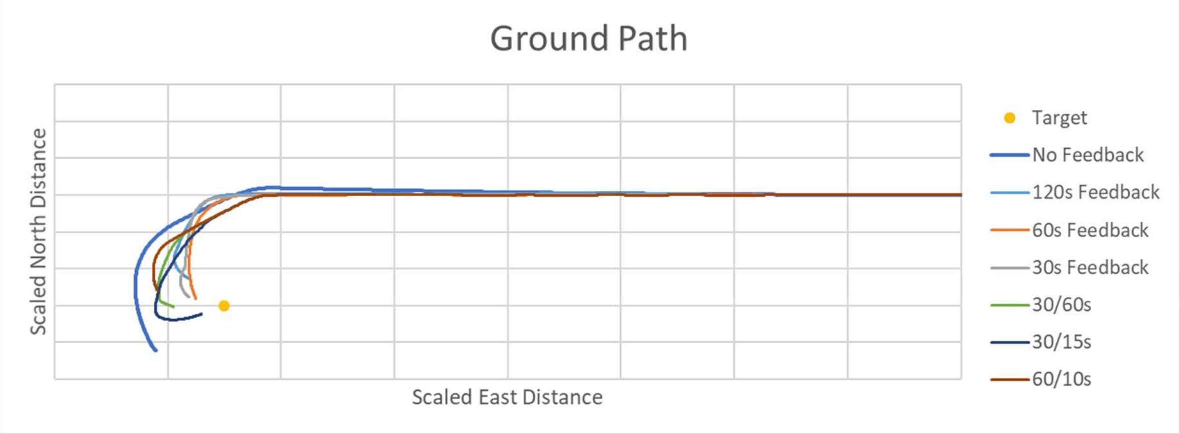
Aerodynamic surrogates allow convergence to solution

3-DOF Vehicle Model Insufficient for Trajectory Optimization Under Complex Flight Conditions

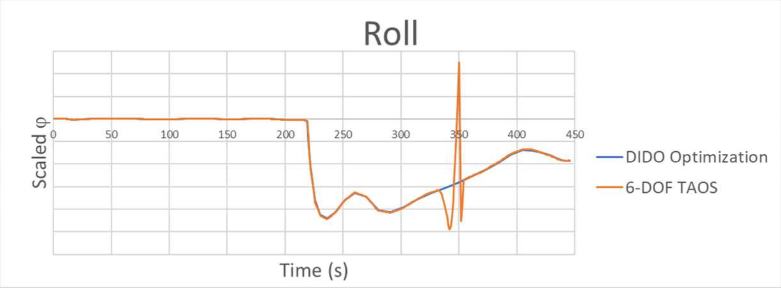
Mission 1 **Optimizer:** 3-DOF with Surrogates **Vehicle Model:** 6-DOF with Tables



Feedback Period (s)	Target Miss Distance (ft.)	Maximum Constraint Violation (ft.)
None	135981	8900
120	117370	2499
60	28389	332
30	61172	none
30/60	89742	none
30/15	32402	none
30/10	120269	none



Roll during transonic maneuver caused vehicle to miss target



3-DOF Vehicle Model Applicable to Simpler Trajectory Optimization and Rapid Mission Space Exploration

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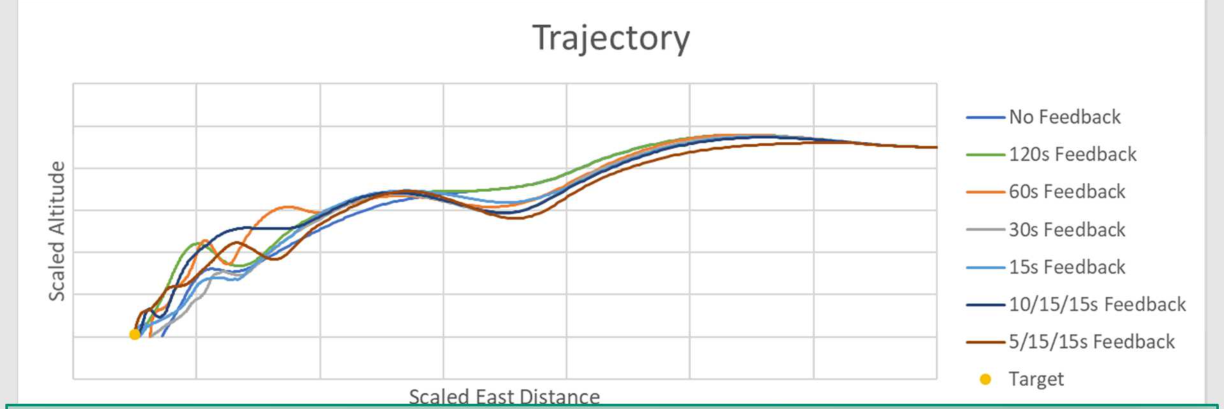
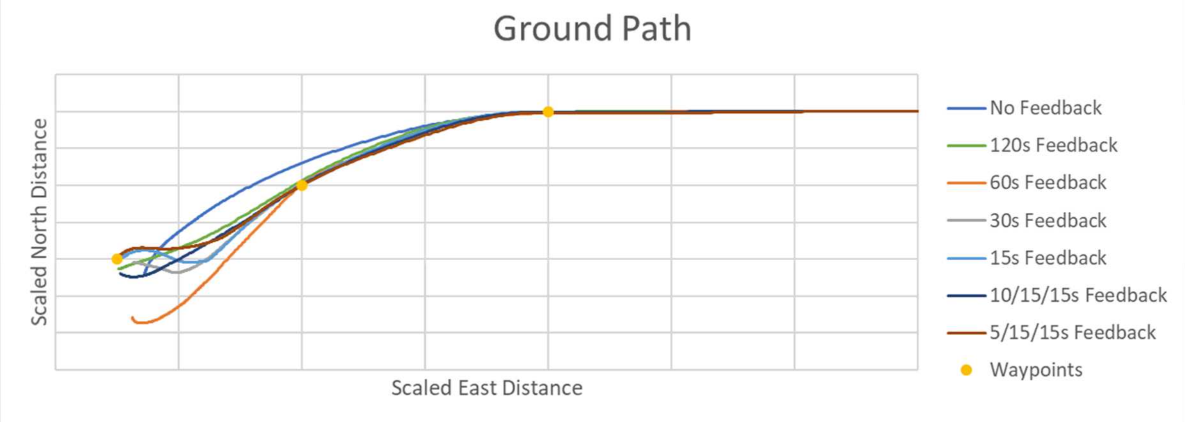
Mission 2 **Optimizer:** 3-DOF with Surrogates **Vehicle Model:** 6-DOF with Tables



Trajectory optimization with a low-fidelity model in feedback with a higher fidelity vehicle simulation has application if the limitations of the vehicle and autopilot are considered



Feedback Period (s)	Final Target Miss Distance (ft.)	Waypoint Miss Distance (ft)	Maximum Constraint Violation (ft.)
None	48665	457	246
120	13864	201	246
60	83031	248	1562
30	27533	1246	288
15	358	18	49
10/15/15	20682	59	12
5/15/15	1179	150	1480

Target miss distance similar to 3-DOF++
Waypoint an order-of-magnitude closer.

- All solutions match closely until difficult transonic region
- Potential application to rapid mission space exploration:
  - Low fidelity models to quickly optimize a large range of mission trajectories
  - Feasibility checked by higher fidelity simulation

Aerodynamic Look-up Tables Insufficient to Optimize in Feedback with a 6-DOF Vehicle Simulation

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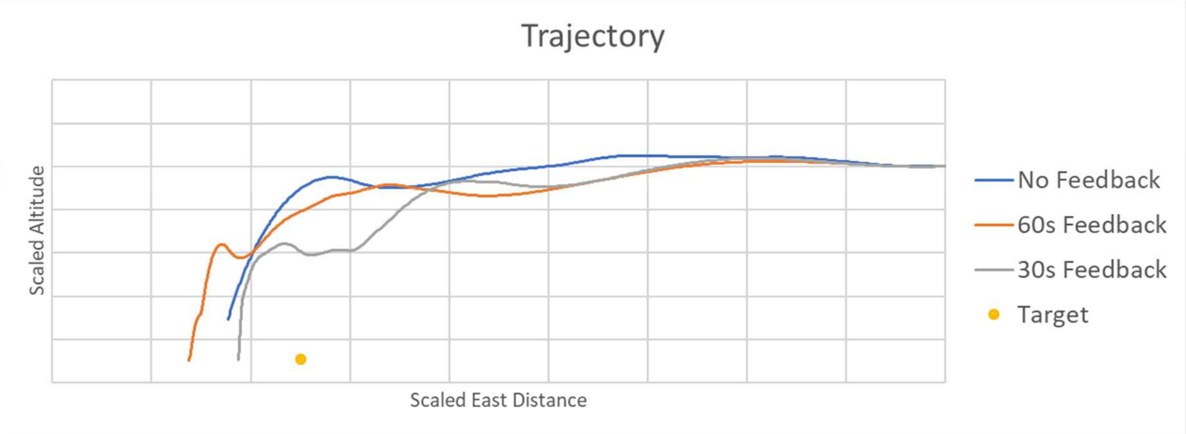
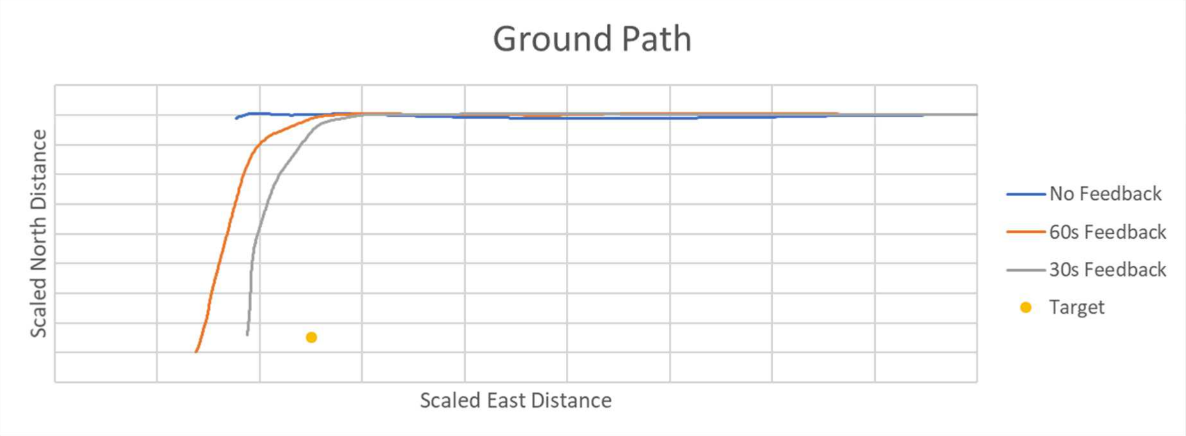
Mission 1 **Optimizer:** 3-DOF with Tables **Vehicle Model:** 6-DOF with Tables



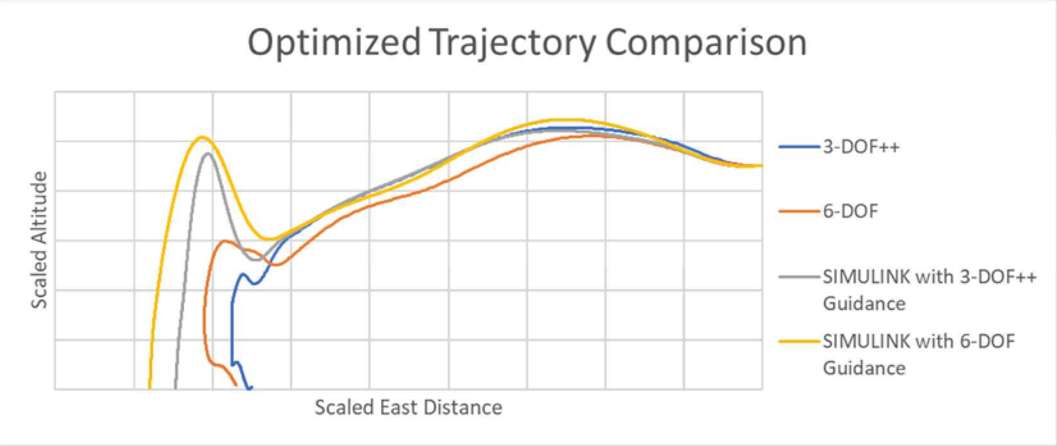


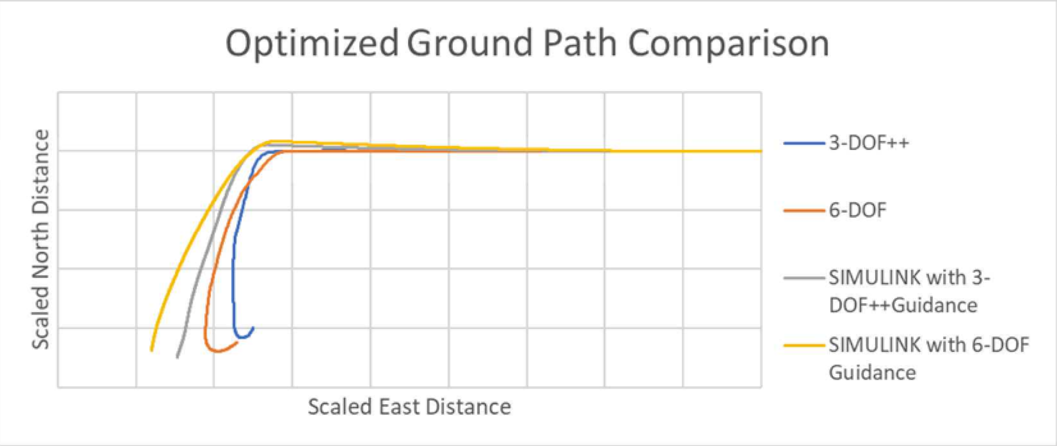
Feedback Period (s)	Target Miss Distance (ft.)	Maximum Constraint Violation (ft.)
None	1395972	2710
60	224637	658
30	124392	315

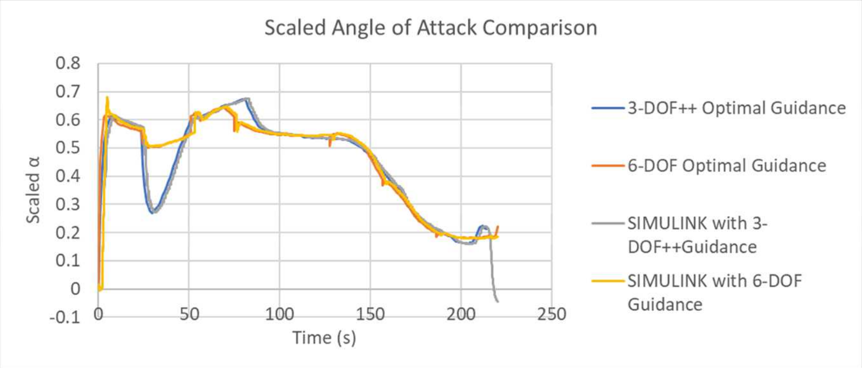
Aerodynamic surrogate models show efficacy as an enabler of pseudospectral trajectory optimization for hypersonic vehicles

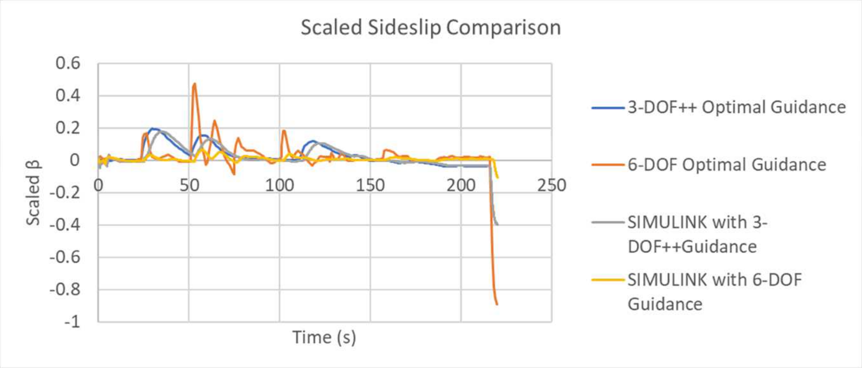
Optimized Trajectories Using Different Model Fidelities Compared Through Flight in Highest Fidelity Simulation

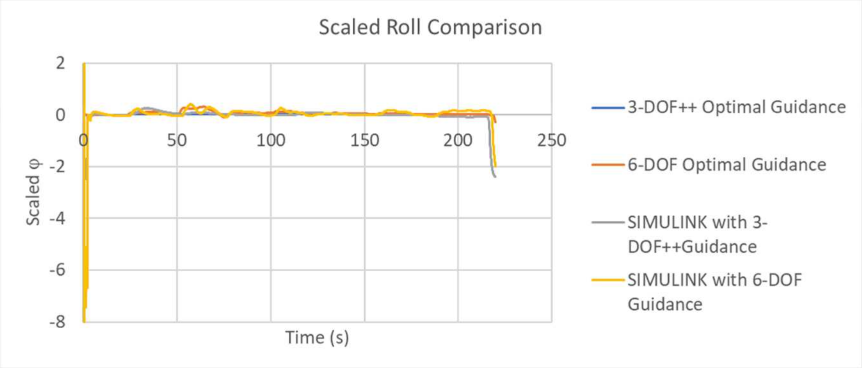
Mission 1









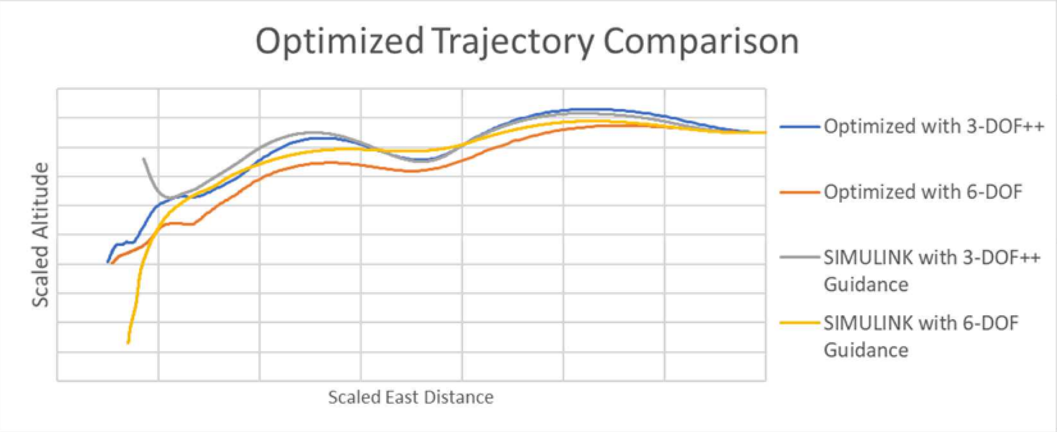


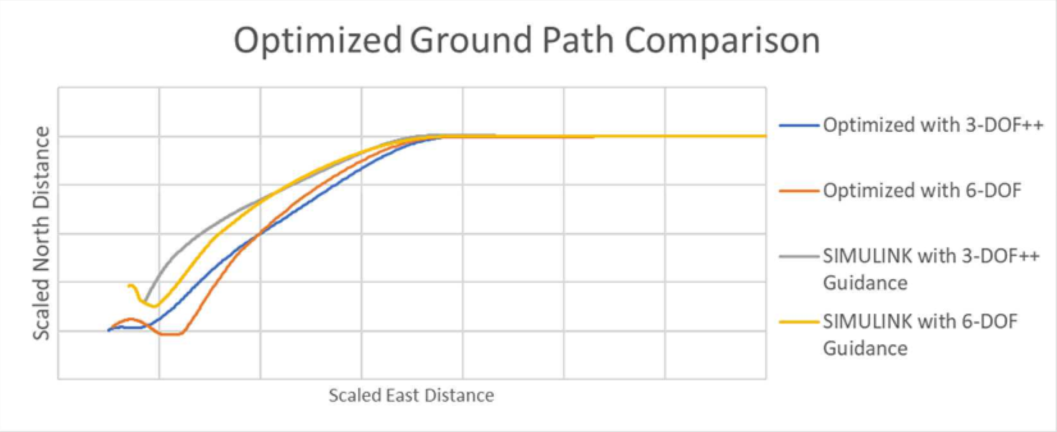
High fidelity models diverge from low-fidelity predictions under stressful flight conditions

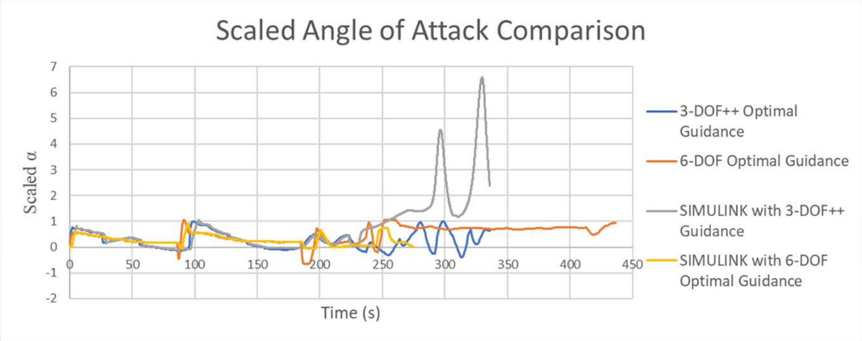
Optimized Trajectories Using Different Model Fidelities Compared Through Flight in Highest Fidelity Simulation

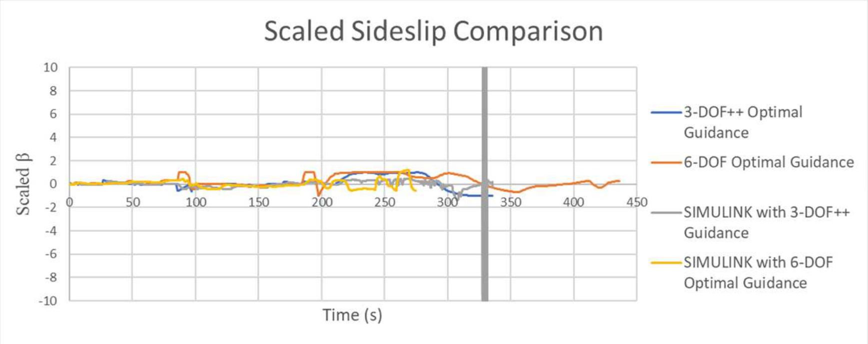
Introduction
Motivation
Research Questions
Methodology
Results
No Feedback
3-DOF++
6-DOF
Comparison
Conclusion

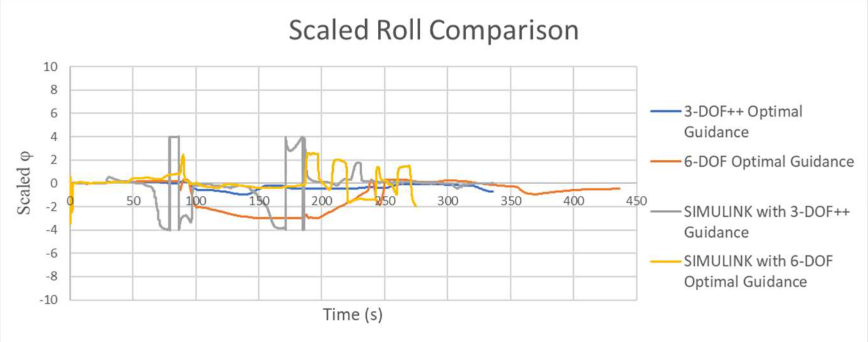
Mission 2











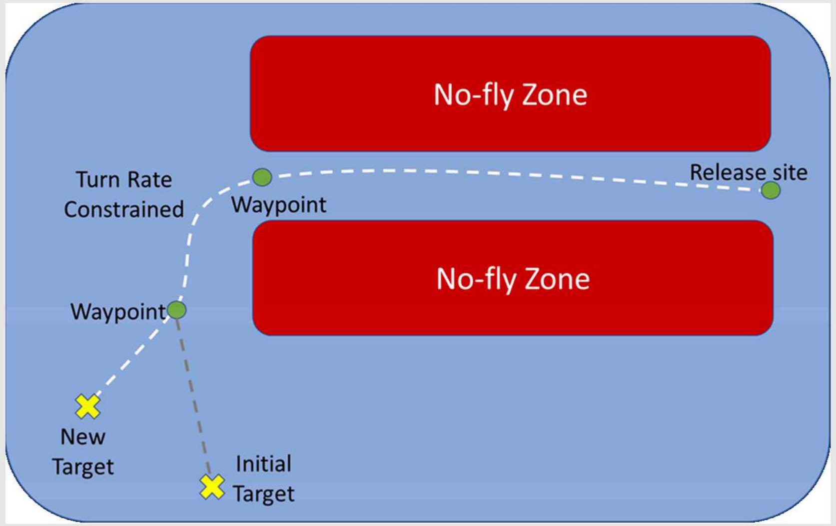
Under benign conditions, model correlation improves

Conclusion

Tailored Simulation Fidelity for Rapid Trajectory Optimization

Some Answers to Posed Research Questions

- Rapid trajectory optimization is needed to utilize hypersonic vehicles subject to complex constraints and stringent safety and robustness requirements.
- Model fidelity studies are a necessary enabler for rapid trajectory optimization
  - Use enough fidelity to ensure feasibility and robustness
  - Use as little fidelity as possible
    - Lessen computation expense
    - Expand operational flexibility
    - Decrease launch timeframe



➢ What's the lowest fidelity vehicle model we can employ and still produce feasible and robust solutions?

Depends on the complexity of the trajectory being optimized

➢ How does feedback period between the optimizer and the vehicle model affect the quality of the optimized trajectory?

More than feedback period is important, but15 – 30 seconds appears sufficient for solution, if a solution is possible at that fidelity

➢ Do aerodynamic surrogate models affect computational expense and solution quality?

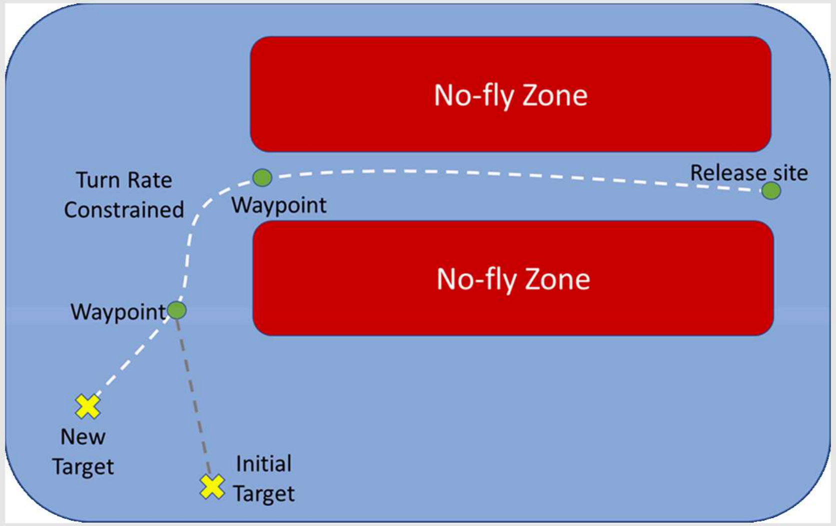
Aerodynamic surrogates are show efficacy for pseudospectral optimization of hypersonic trajectories

Future Work

- What's the lowest fidelity vehicle model we can employ and still produce feasible and robust solutions?

  Can we introduce constraints on the 3-DOF optimization vehicle model to account for more complex missions?

  Can we use a more complex model (3-DOF++) in the optimizer and still achieve rapid convergence?



- How does feedback period between the optimizer and the vehicle model affect the quality of the optimized trajectory?

  Would seeding higher-fidelity feedback loops with the results of lower-fidelity optimization allow for RTG without a nominal trajectory?

- Are there other potential uses for the feedback between optimizer and simulation?

  Can we rapidly define a mission space?

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