Intelligent Contingency Management

(what the heck is it and why do I care?)

We have Nominal Autonomous Operations Nailed!!

Aerospace Control and Guidance Systems Committee Meeting #131

10/25/2023

Michael J. Acheson: michael.j.acheson@nasa.gov
Irene M. Gregory: irene.m.gregory@nasa.gov

Off-Nominal Autonomous Operations Major Research Challenge!!

Why Autonomy in Aviation?

- **Autonomy enables** new **ECONOMIC** activity, **DIVERSITY** of missions
- **Autonomy changes** the nature of
  - Transportation system (local/regional), supply chain logistics
    - Regional cargo delivery competing in cost with trucking
  - Maintenance logistics and safety well beyond traditional aerospace
    - Oil platforms, pipelines, power lines, wind turbines, infrastructure inspection and maintenance
  - Agriculture, land management, first responders (e.g., rapid response to inaccessible disaster areas)
- **Long Term** Aviation Autonomy **Impacts**:
  - Enables rapid flexibility and facilitates resilience in local/regional economic activity
  - Reduces costs and environmental impact of automotive/rail infrastructure (e.g., roads, bridges etc.)
  - Alleviate ground transportation congestion and capacity limitations
- **Benefits of Autonomy**:
  - System wide **performance** improvements, maximizes capability for fleet/vehicle operations over human operator
  - Enhances aviation **sustainability**
  - Maintains and enhances **safety** as density of heterogeneous fleet of vehicles and operations increases

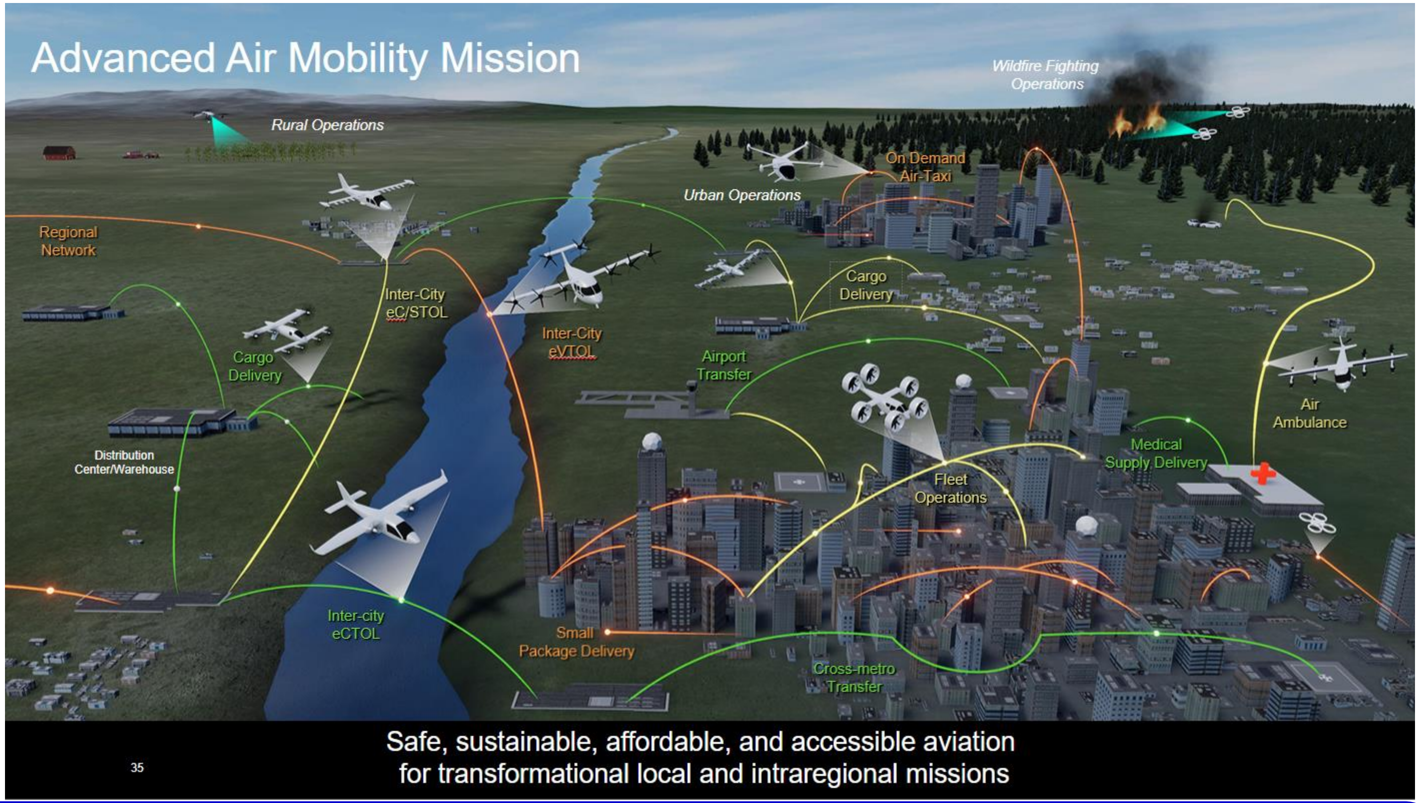
Autonomy is a REQUIRED GAME CHANGER to enable revolution in the aerospace industry

Where are we heading in Aeronautics? – Advanced Air Mobility

Safe, sustainable, affordable, and accessible aviation for transformational local and intraregional missions

Paradigm shift in Aviation

- Anyone, Anywhere, Anytime concept
- On demand air transportation
  - Urban suburban, rural, inter-city
  - Moves people and cargo
- Largely enabled by electrification and automation



Autonomy is REQUIRED to enable paradigm shift

Autonomy must be implemented in a safe, efficient, scalable, certifiable way

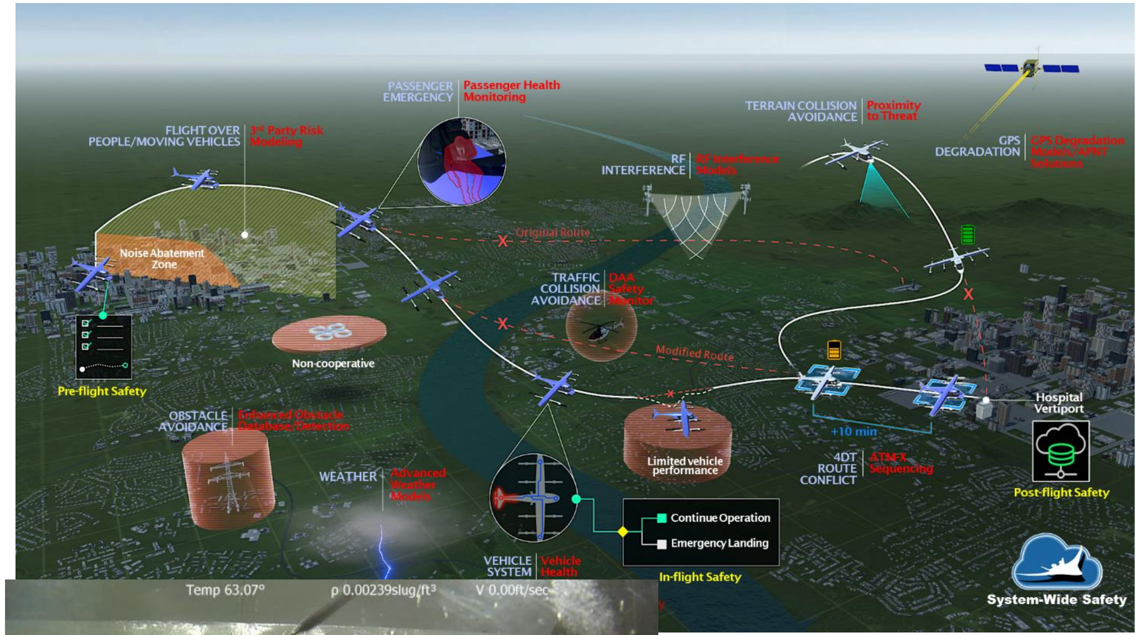
Autonomous Flight - Motivation for Intelligent Contingency Management

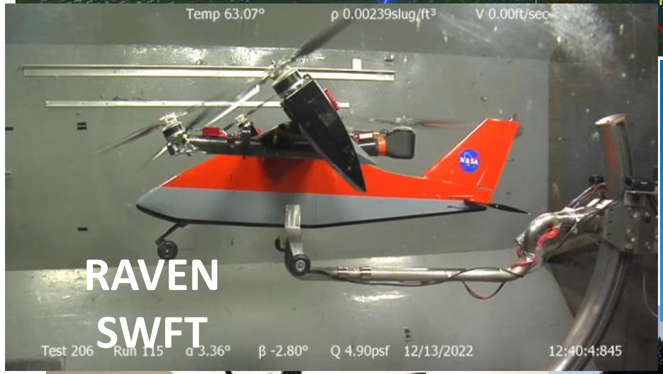
Emerging aviation characteristics:

- **Complexity** of the environment
- Unconventional vehicle configurations with **multi-modal dynamics**
- **Highly nonlinear flight dynamics**

Challenges:

- **Off-nominal events – both common and unforeseen**
- **New technology** – more likely to experience performance degradation/failures
- **Narrow performance margins** – cannot afford conservatism
- **Accurate trajectory following** under system uncertainty and atmospheric disturbances
- **Safe control** while learning elements are engaged





NASA TTT Intelligent Contingency Management

Who are we?

- Subproject under NASA TTT Autonomous Systems
- Small Research Team (~6 Govt, ~2 Contractor)
- Larger "Virtual Team": Other NASA projects who work the same problems…
- Agile Development Team that works ALL aspects of contingency management…

- We are a small team and this is a huge research field!!
- We are active Collaborators with Academia and Industry!

What do we do?

- Aero-propulsive Modeling (novel configs)
- Adaptive, Robust, Unified control of transition vehicles
- Benchmark Problems
- Control Allocation
- Flight Envelope Prediction (ML)
- Guidance and Trajectory planning: collision avoidance, VFR traffic pattern entry, etc.
- Intelligent Contingency Cognitive Architecture (AI, explainable AI, ML, deterministic, probabilistic…)
- Simulation development

Autonomous Systems ⟺ Humans Are Really Good ICM!

Aka.. Fun with Sea Stories…

- We have Nominal Autonomy Nailed!
- Off Nominal is Biggest Research Challenge!!!!

Cascading Systems Failure + Environment + Perception

- Generator Failure on Cat Shot
- Cascades to Multiple Systems
- No Visible Horizon….

Information Correlation: I'M ON FIRE!!! wait.. am I?

- Large fireball on takeoff rotation!
- System configuration incorrect for phase of flight (switchology…)

Systems Failure + Environment + Human Autonomy Teaming

- 1 of 2 AoA Probes Stuck
- F/A-18 Night Cat Shot

Insidious Systems Fault + Perception = Prevention

- 1 of 2 wing sweep motors fails prior to takeoff
- Systems knowledge + Perception prevents major failure

System of Systems + Environment + Perception

- Night Case III Landings..
- Stack…reporting…approach
- Wait why is that Hornet landing on the bow?

(Autonomous) Intelligent Contingency Management

Human (ICM):

- **Aviate**
- **Navigate**
- **Communicate**

Autonomous (ICM):

- Robust & Adaptive Control
- Safety (Certificates) & Learning Control
- Failure ID & Flt Envelope Estimation
- Collision Avoidance & Pattern Entry
- Perception & Environment…
- ML training & off training guarantees

- Planners: Long, Short, Contingency (Spectrum)
- Perception & Environment
- Recognize Contingency /Failures and Replan..
- Multi-path and Optimizations…

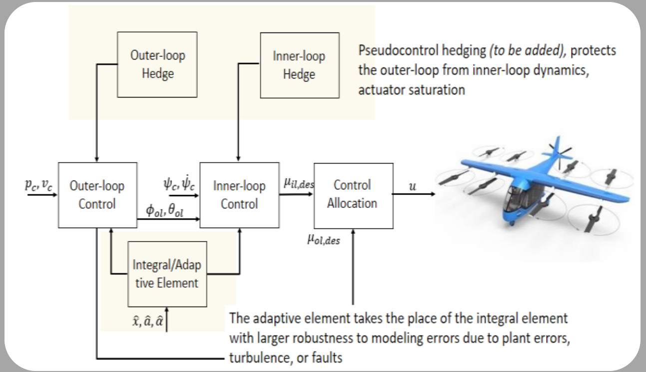
- Algorithm to algorithm (asynchronous, timescales)
- Aircraft system to system
- External aircraft (datalink, voice?)
- System of system communications
- Sift out Faulty Information…

Aviate:

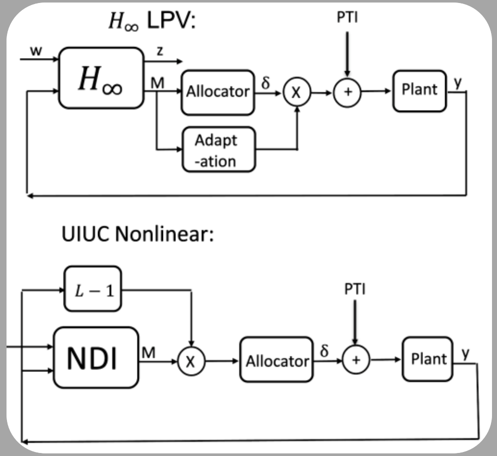
Autonomous Flight – Integrated Algorithms

Controllers

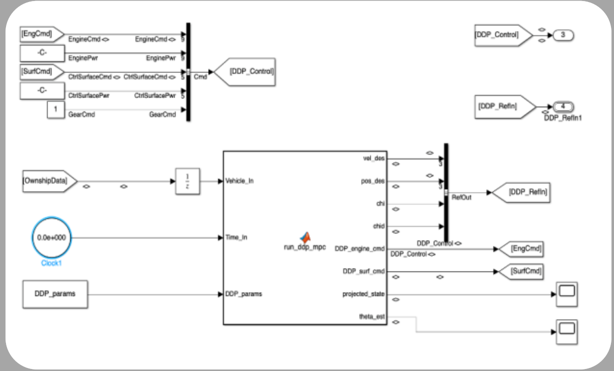
Inner/Outer Loop NDI Adaptive

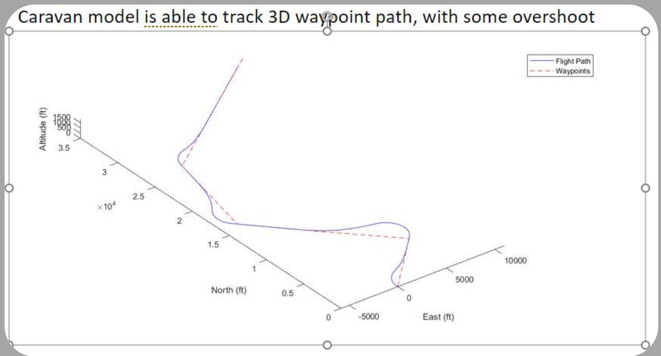


Linear Parameter Varying

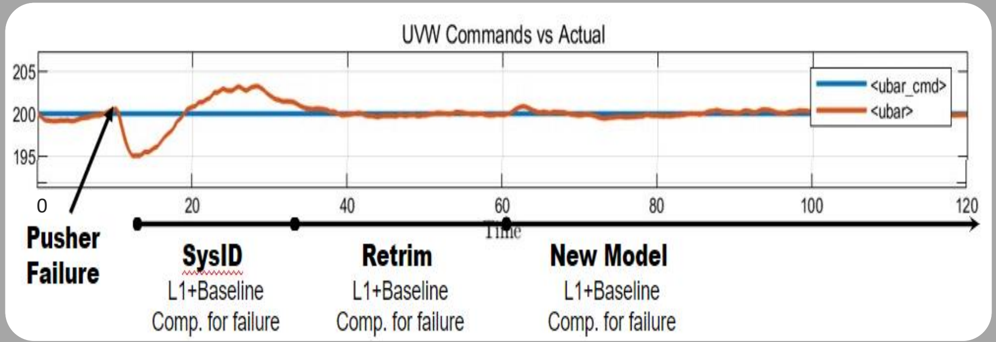


DDP / PDDP





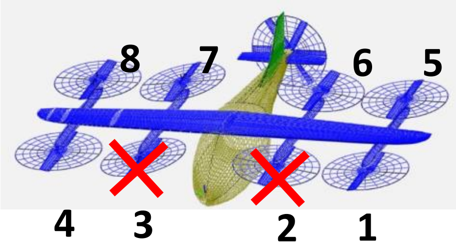
Traffic Controller (Caravan)



L1 Adaptive Learning

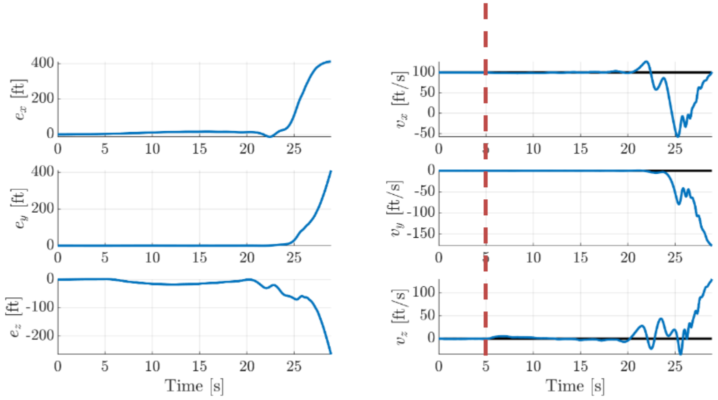
- **Fail-operational stability**
  - If physically capable, must maintain flight, graceful degradation to end mission
- During cruise – **rotors 2 & 3 fail -** vehicle loses half of the rotors that compensate for the longitudinal oscillatory modes, leading to **unstable** performance at this speed
- Without L1 adaptive control, the aircraft is **unstable**
- With **L1,** the aircraft is **stable - ** can run system identification algorithms to correctly identify failed propellers

- **Stable aircraft -** apply learning methods to determine new dynamics, adjust control strategy, path-planning, mission objectives accordingly



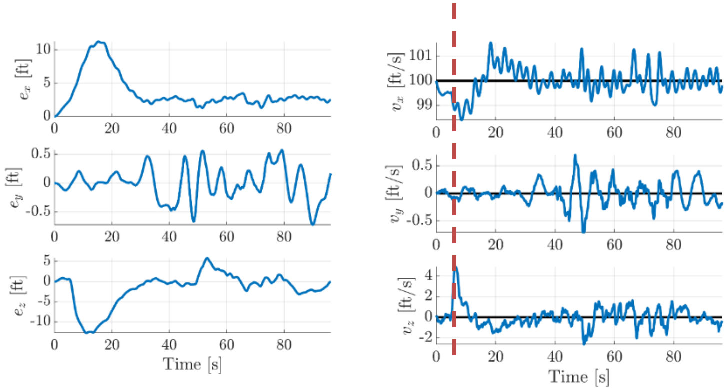
Propeller Failures

L1 AC Off
Unstable



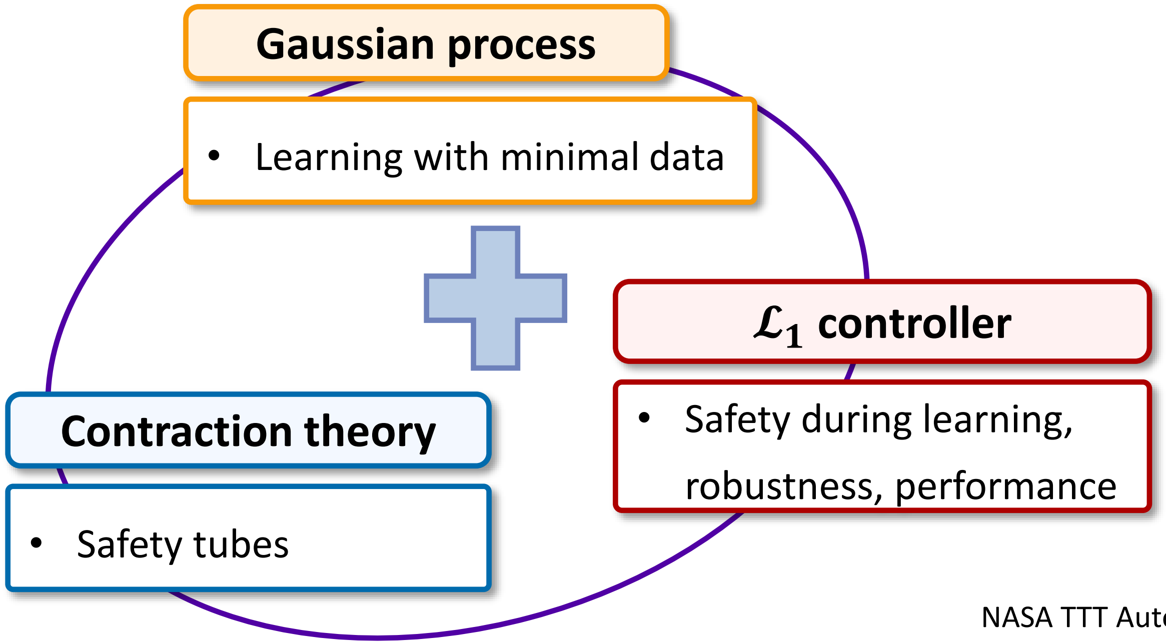
Position error
Velocity Tracking

L1 AC On
Stable

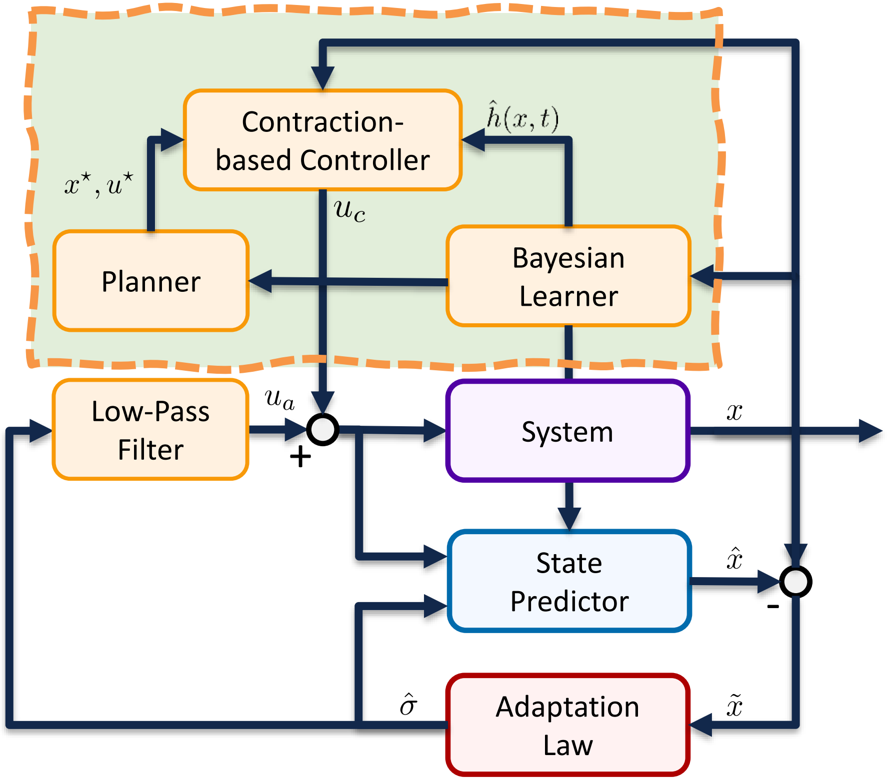


L1 Adaptive Control Architecture for Safe Learning

- **Safety certificates** in the form of tubes from the $\mathcal{CL}_1$- $\mathcal{GP}$ framework which **enables safety during learning**
- Natural framework for learning using $\mathcal{GP}$:
  - **Guaranteed performance** during the learning transients
  - Improved performance of the $\mathcal{L}_1$ adaptive controller, i.e., **smaller tubes**
  - **Improved quality** of the planned trajectory



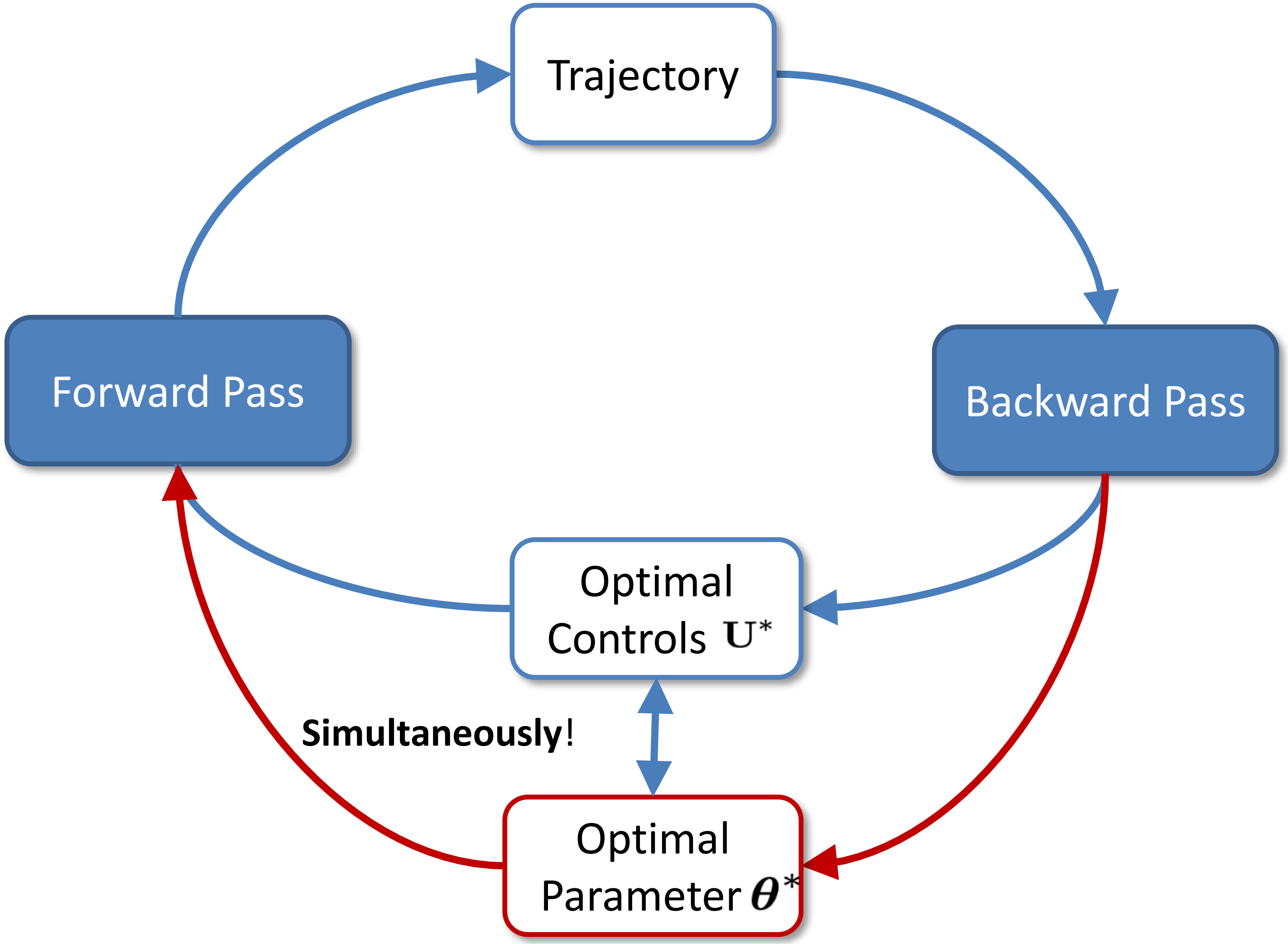
$\mathcal{CL}_1$-$\mathcal{GP}$ Architecture



Gahlawat, Zhao, Patterson, Hovakimyan, Theodorou. $\mathcal{L}_1$-$\mathcal{GP}$: $\mathcal{L}_1$-*Adaptive Control with Bayesian Learning*, L4DC, 2020.

Planner - Parameterized Differential Dynamic Programming*

- Motivation - Multiple operational modes and flight regimes
- Second-order algorithm derived by extending classical optimal control (DDP)
- **Convergence guarantees** independent of initialization
- **Co-optimizes** for controls and parameters simultaneously
- **Generalizes** to multiple tasks, including adaptive MPC and switching time optimization
- Enables time-optimal trajectory planning for multimodal systems, including **eVTOL vehicles**

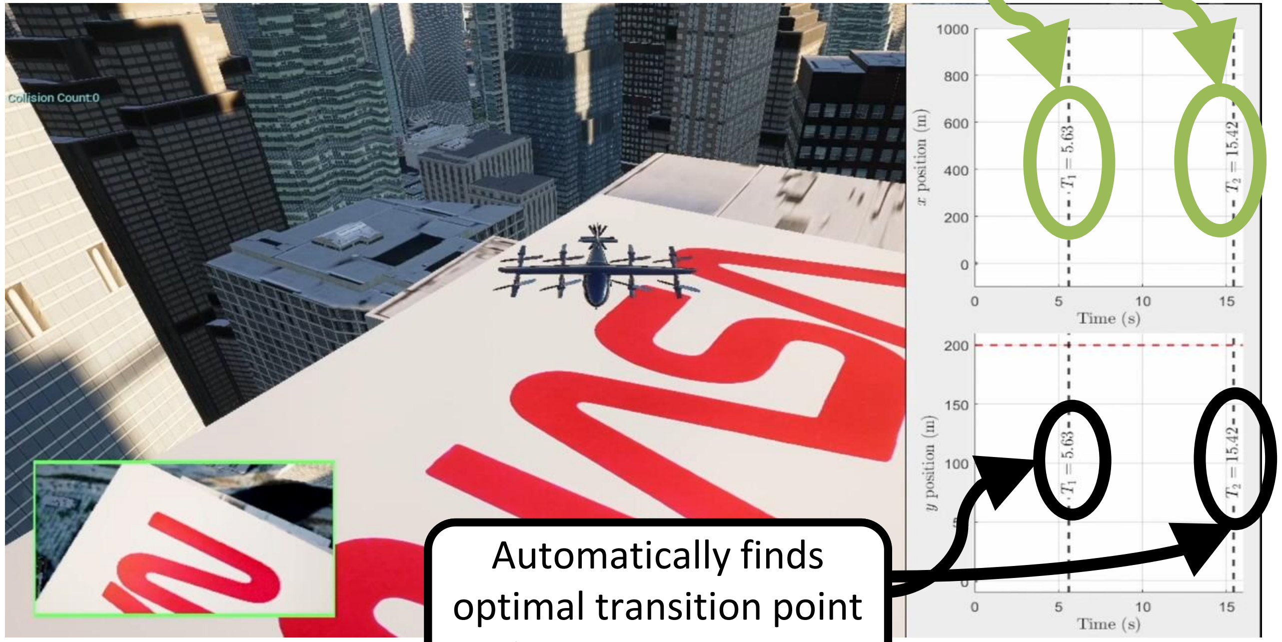


* Oshin, A., Houghton, M., Acheson, M., Gregory, I., and Theodorou, E., "Parameterized Differential Dynamic Programming," *Proceedings of Robotics: Science and Systems*, New York City, NY, USA, 2022. https://doi.org/10.15607/RSS.2022.XVIII.046.

Autonomous Flight Planner - PDDP Applications

Switching Time Optimization

Avoids manual tuning of terminal times!

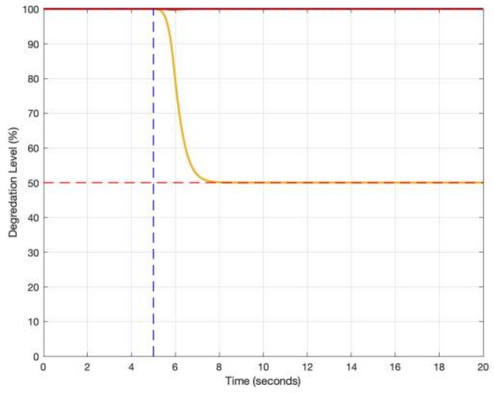


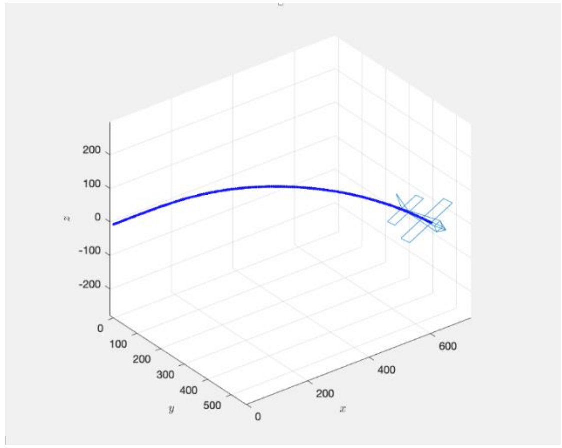
Automatically finds optimal transition point between modes!

Adaptive Model Predictive Control

Moving Horizon Estimation → Maximize likelihood of observed states

Model Predictive Control → Plan future trajectory

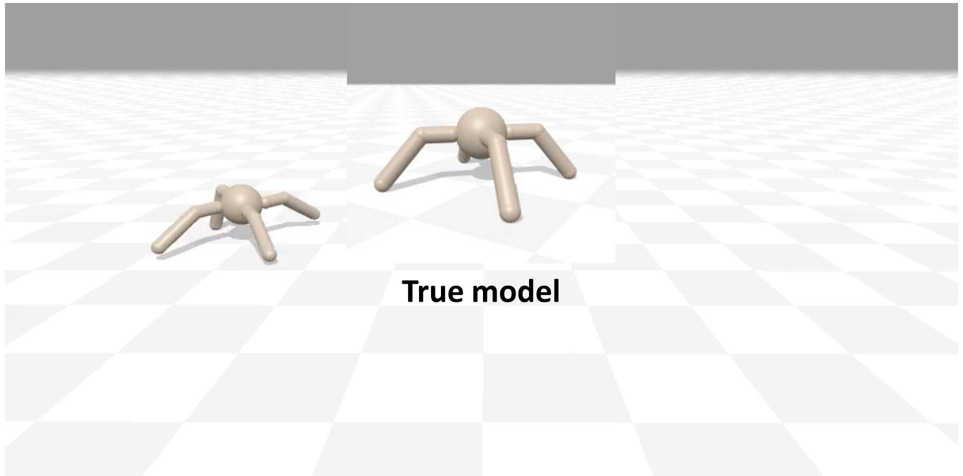




PDDP: Adaptive MPC

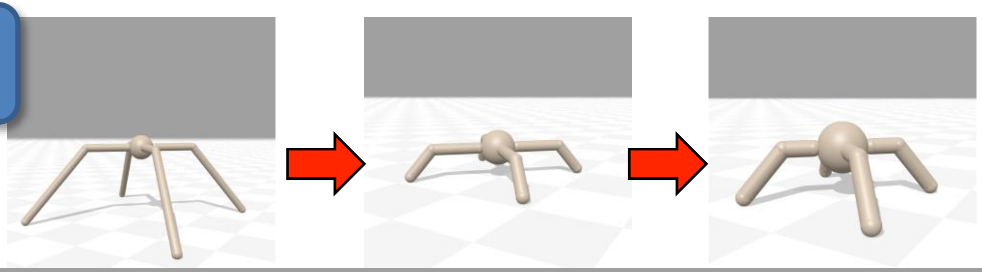
Ant

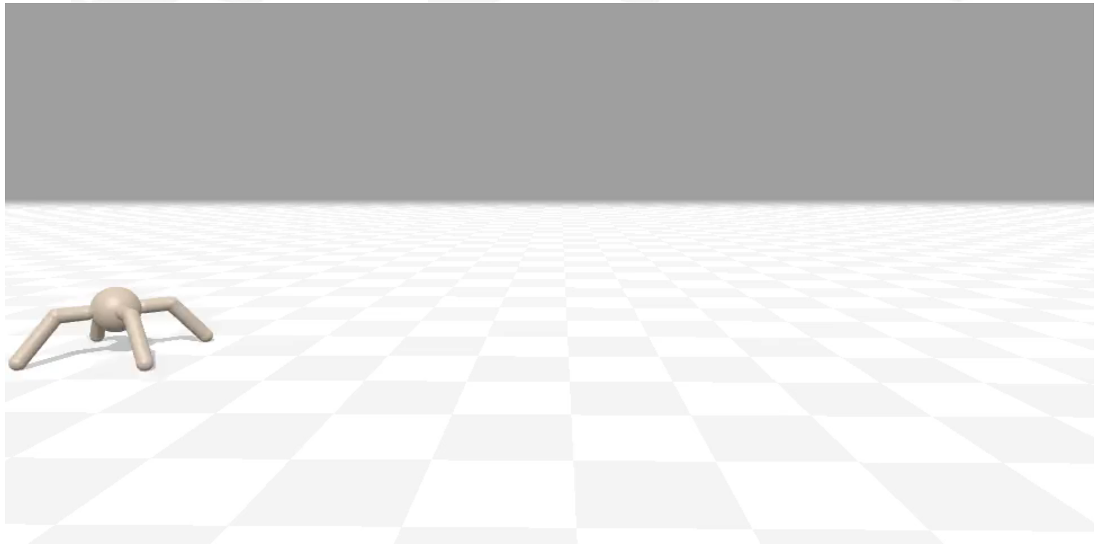
DDP planning on model with incorrect parameters



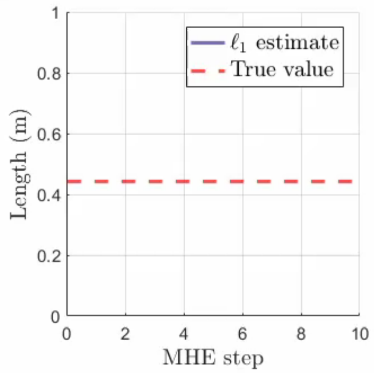
True model

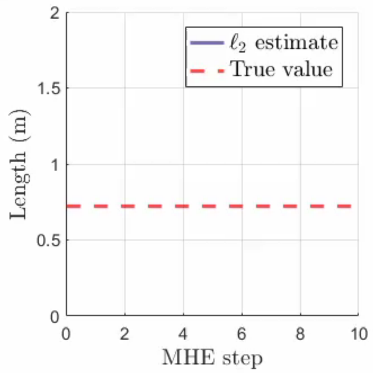
Executing plan on true model: Failure





PDDP with adaptive control: Success



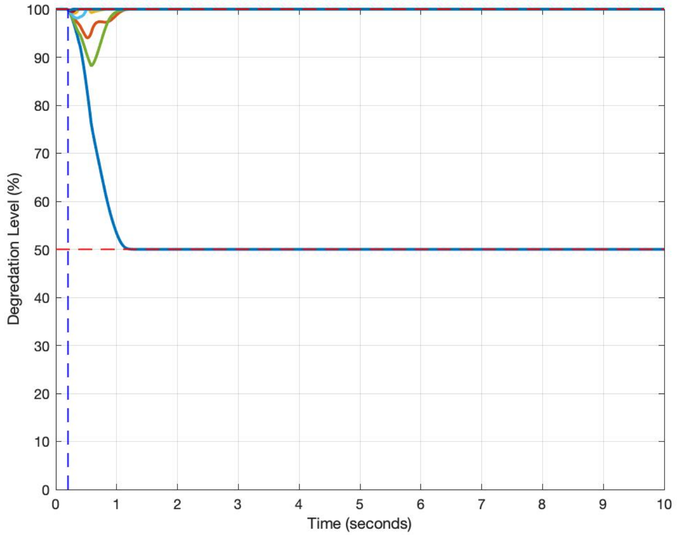


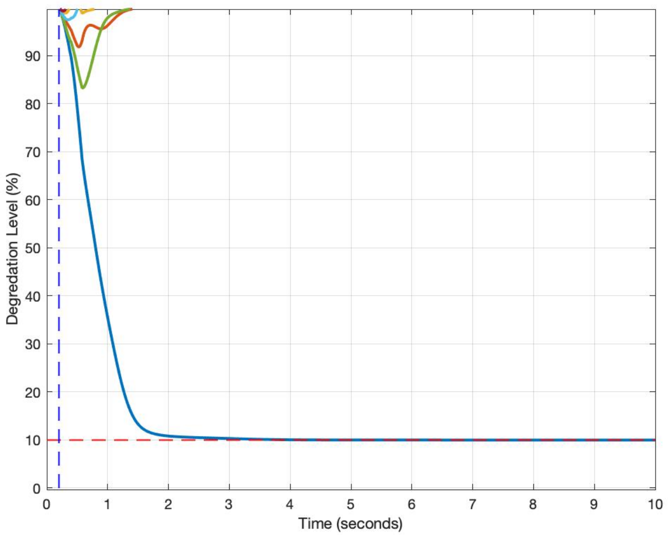
Capability Assessment - Fault Detection: Rotor Failure

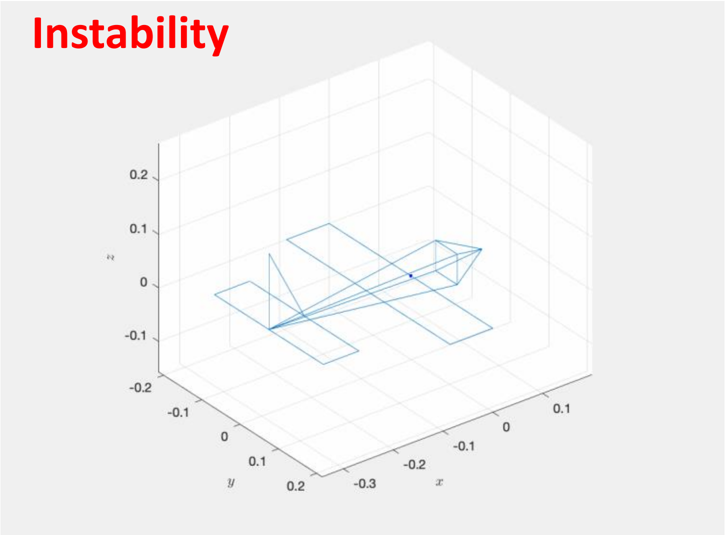
PDDP extends to Fault Detection of vehicle states (rotors and effectors)

<u>Experiment 1: Vertical Takeoff</u>

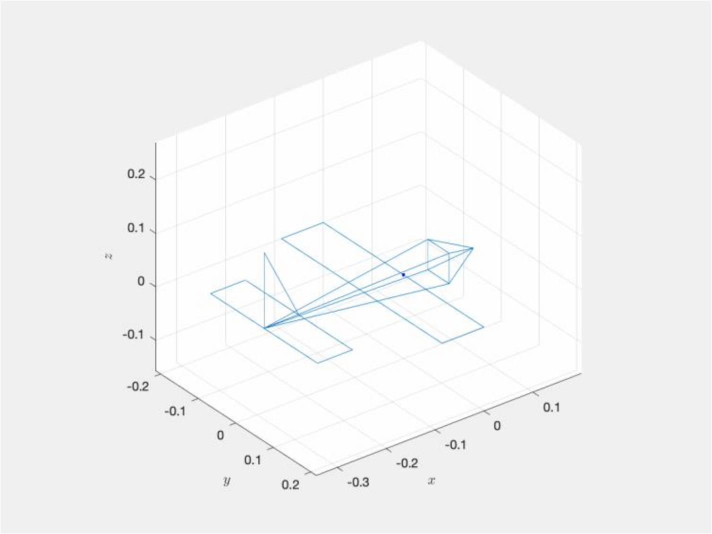
- Begin in hover
- Ascent to 200 ft
- Heavily utilizes rotors in VTOL flight regime
- Early Failure/Degradation



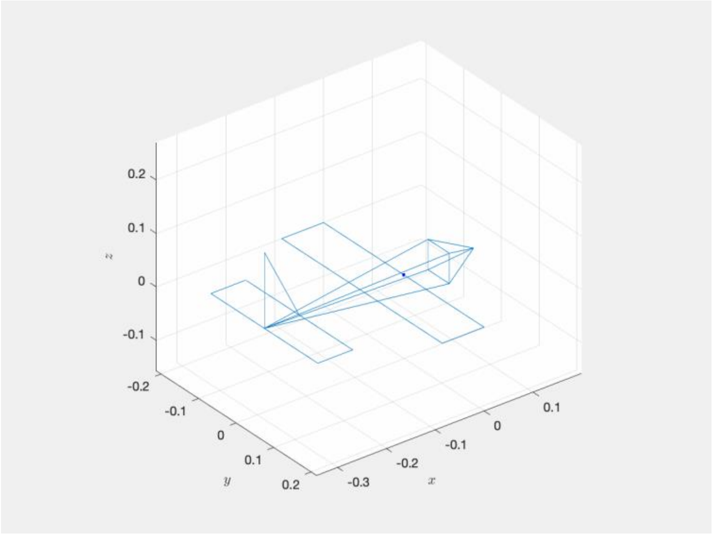




Takeoff Failure Without PDDP



50 % Rotor 1 Degradation



90 % Rotor 1 Degradation

Navigate:

Planner Challenges

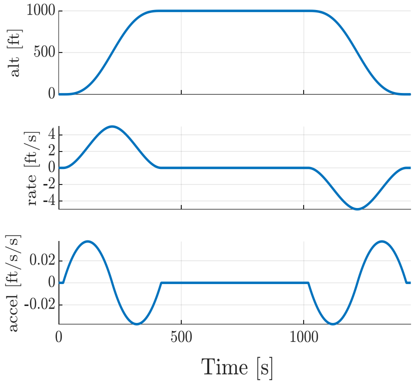
Planner challenges:

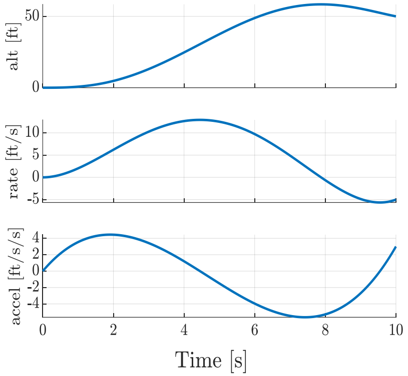
- Principled solutions/guarantees
- Accurate trajectory planning & replanning
- Epistemic uncertainty in model
- Multiple operational modes and flight regimes
- Transferability to different vehicles
- Replanning and collision avoidance for VTOL vehicles with highly nonlinear dynamics are slow and computationally costly

Trajectory Generation Dynamic Complexity Proposed Levels

(Less) < Dynamic Complexity -> (More)

Strategic	**Tactical**	**Full State Dynamic**
Pre-determined velocity and acceleration profiles	Arbitrary derivative profiles	Vehicle specific dynamic behavior





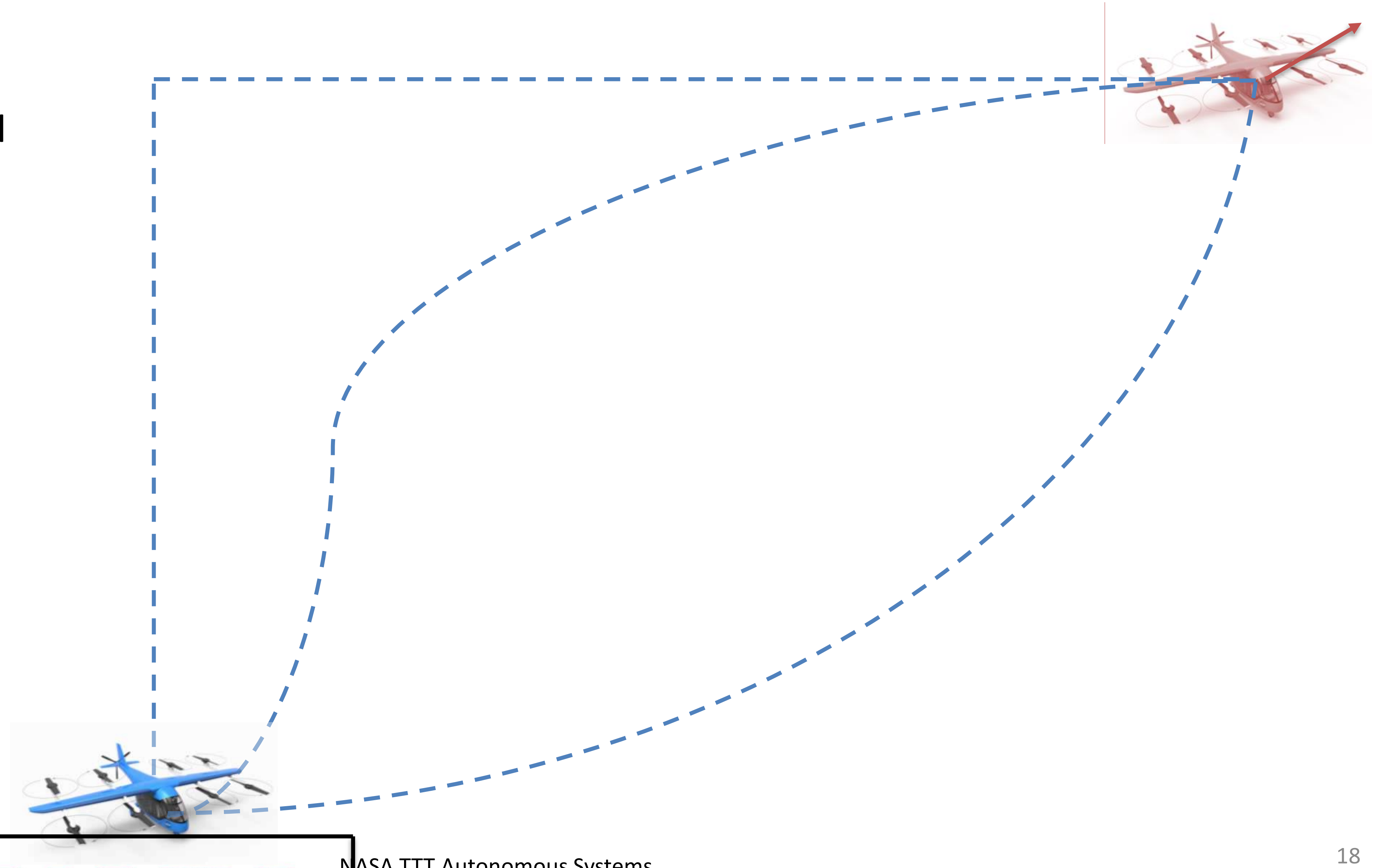
$$
\begin{aligned}
\dot{p} &= \mathbf{v}, \\
\dot{\eta} &= S\omega, \\
\dot{\bar{\mathbf{v}}} &= -\dot{\psi} e_3 \times \bar{\mathbf{v}} + g + m^{-1}\bar{F}\left(\bar{\mathbf{v}}, \omega, \bar{R}, u\right), \\
J\dot{\omega} &= -\omega \times J\omega + \tau\left(\bar{\mathbf{v}}, \omega, \bar{R}, u\right),
\end{aligned}
$$

- All of these levels must be **compatible** – something learned or constructed at one level can be transferred to the others since overall **algorithm spans complexity**
  - Provides freedom to design at highest level and automatically generate something flyable, only need to interact with different levels of detail as needed.

Planner Challenges for eVTOL Vehicles

Two unique challenges:

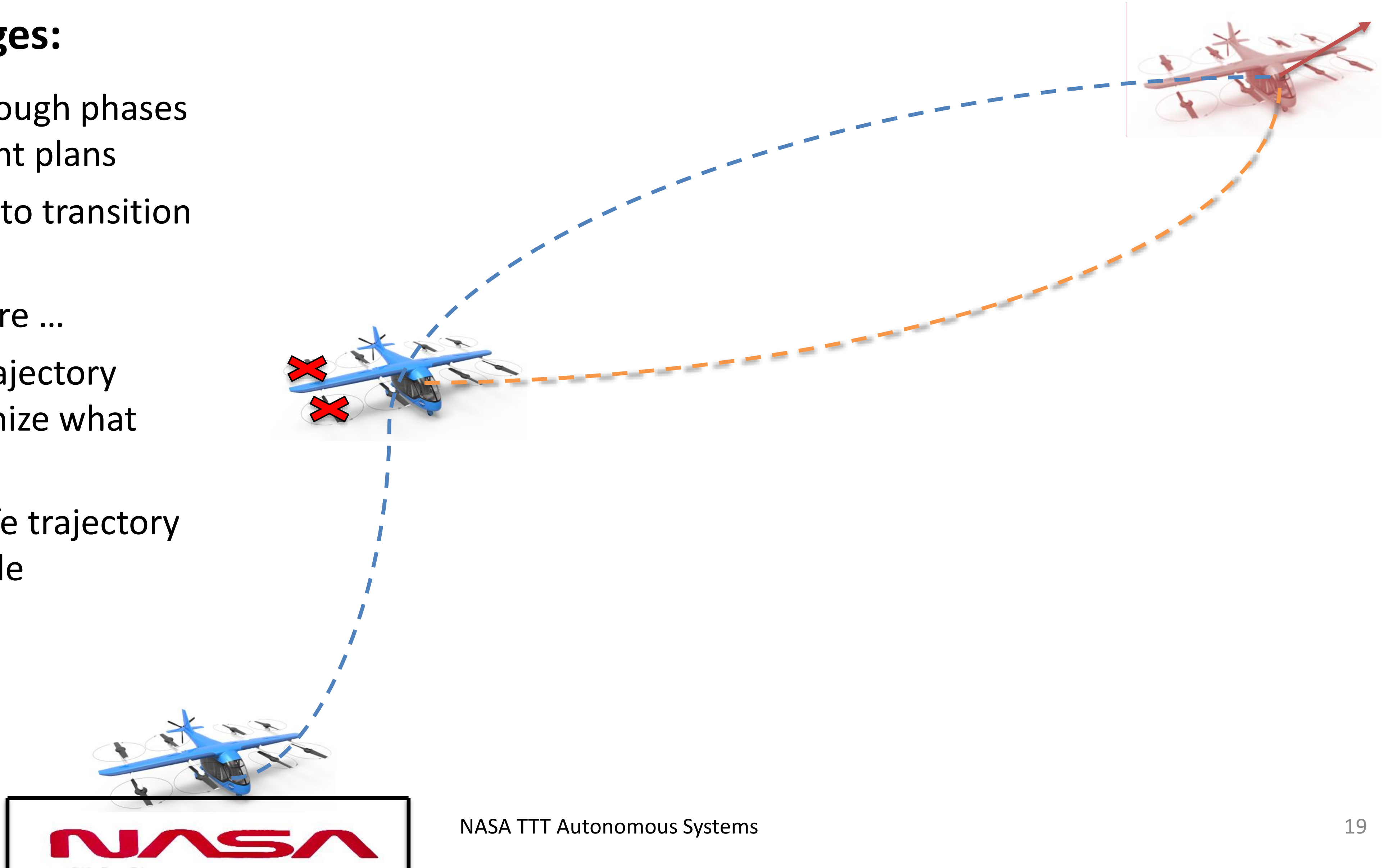
- eVTOL will switch through phases of flight in a typical flight plan
- What is the best way to transition between them?



Planner Challenges for eVTOL Vehicles

Two unique challenges:

- eVTOL will switch through phases of flight in typical flight plans
- What is the best way to transition between them?
- In the event of a failure …
- Are we able to use trajectory information to recognize what failed?
- Can we still plan a safe trajectory with these new vehicle dynamics?



Select Planners:

- Differential Dynamic Programming (DDP)
- Parameterized Differential Dynamic Programming (PDDP)
- Time-Varying (PDDP)
- DDP with Mixed Boundary Conditions
- Multi-shooting DDP
- Optimal Reciprocal Collision Avoidance (ORCA)
- Piece-wise Bernstein Polynomials (Bezier Curves)
- Traffic Pattern Entry (VMC)
- …

Piecewise Bernstein Polynomial (BP) Curves:

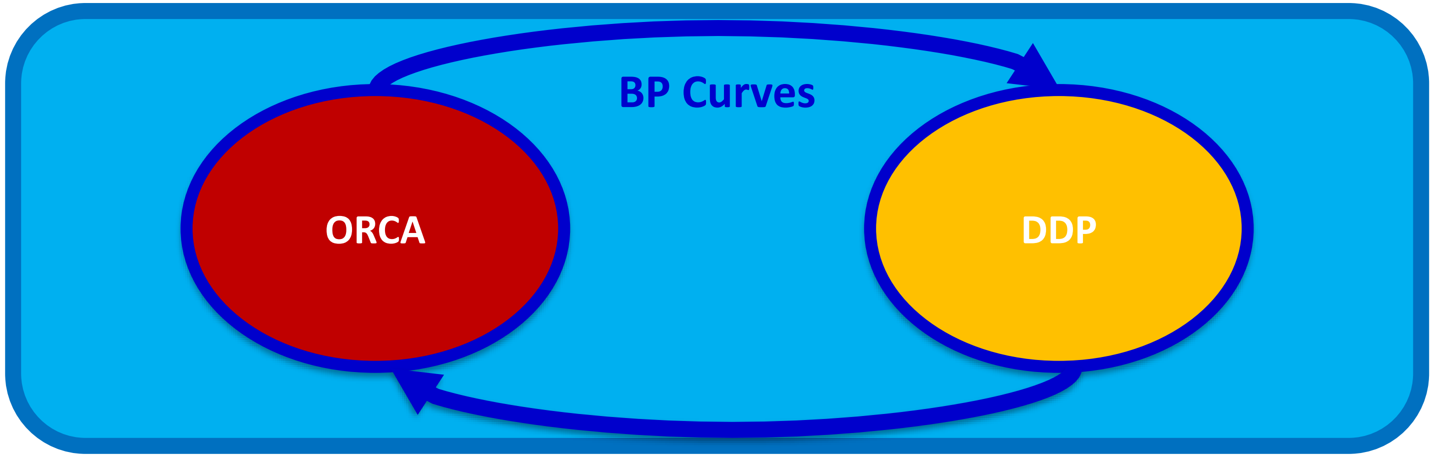
- *Advantages*: Fast and compact trajectory representation, smooth derivatives (position, velocity & acceleration)
- *Disadvantages*: one piece-wise segment cannot represent all curves exactly (e.g., circular arcs)

Optimal Reciprocal Collision Avoidance (ORCA):

- *Advantages*: fast computation for large number of cooperative/non-cooperative with separation assurances
- *Disadvantages*: no assurance of dynamic feasibility

Differential Dynamic Programming (DDP):

- *Advantages*: fast computation of dynamically feasible optimal trajectories
- *Disadvantages*: Degraded computation speed for incorporation of state constraints (e.g., obstacles)



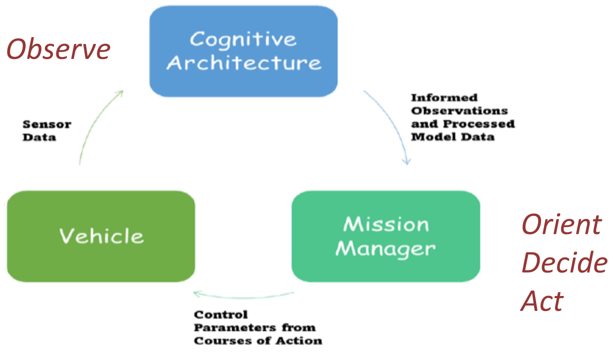
Combine to get best of each algorithm!

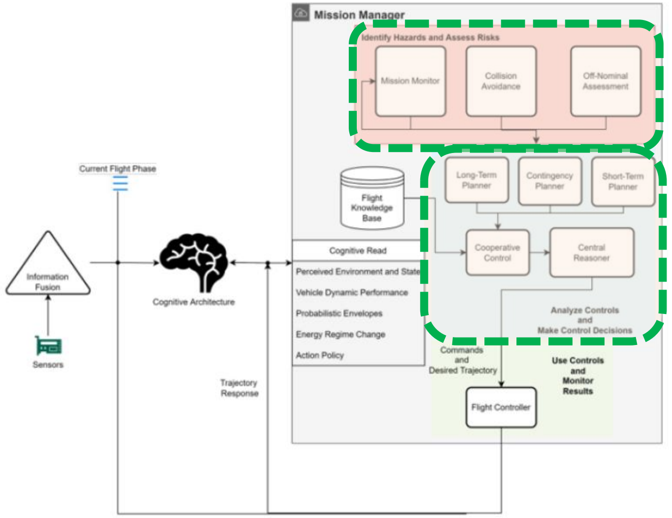
*M.D. Houghton, *et.al.*, "Combined Bernstein Polynomial, Optimal Reciprocal Collision Avoidance, Differential Dynamic Programming for Trajectory Replanning and Collision Avoidance for UAM Vehicles" AIAA SciTech Forum, 2023.

Communicate:

Cognitive Architecture and Mission Manager

- Cognitive Architecture & Mission Manager
  - Established coordination of components for **Identify Hazards and Risks** modules
  - Establish base case decision-making for components of **Analyze Controls and Make Control Decisions**
  - Individual tools integrated within Cognitive Architecture
- Explainable AI (XAI)
  - Use physics-based quantities to provide basis for decisions made by cognitive mission manager
  - Apply ML classification to discriminate between flight phases and vehicle dynamics to identify key contributors

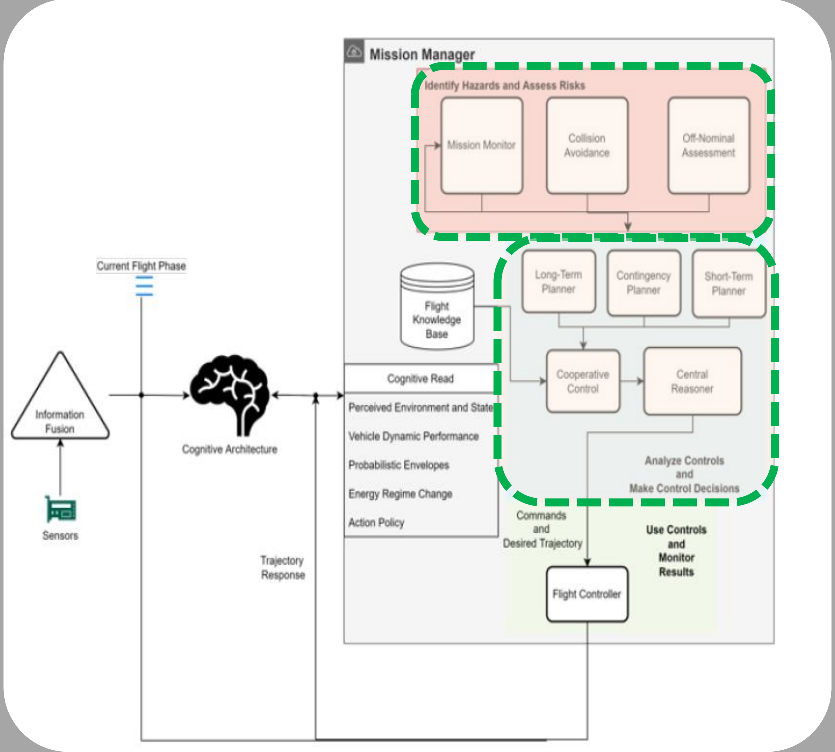




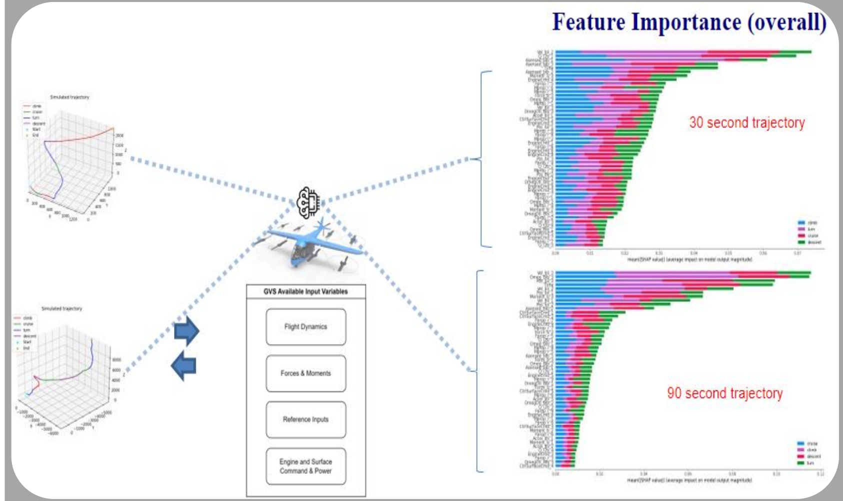
Autonomous Flight – Integrated Algorithms

MM-XAI

AI Cognitive Architecture for Mission Management



Governing Infrastructure



Vehicle Capability Assessment

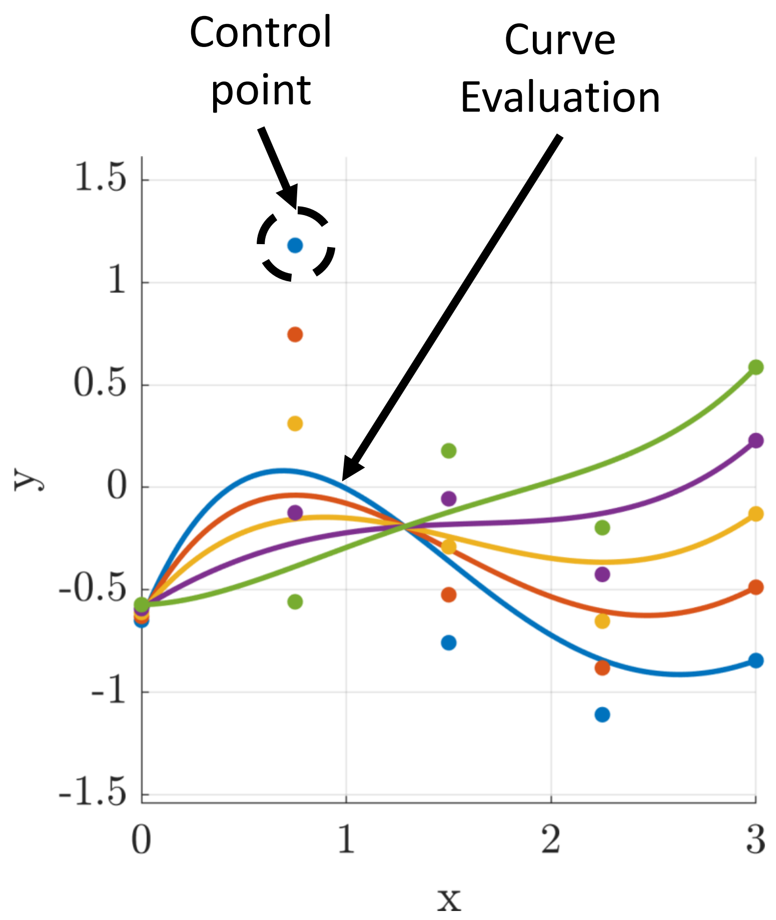
Bernstein Polynomials

Basics

- Polynomial curves using Bernstein basis (rather than monomial basis)
- Polynomial coefficients become control points

Benefits of Bernstein Form

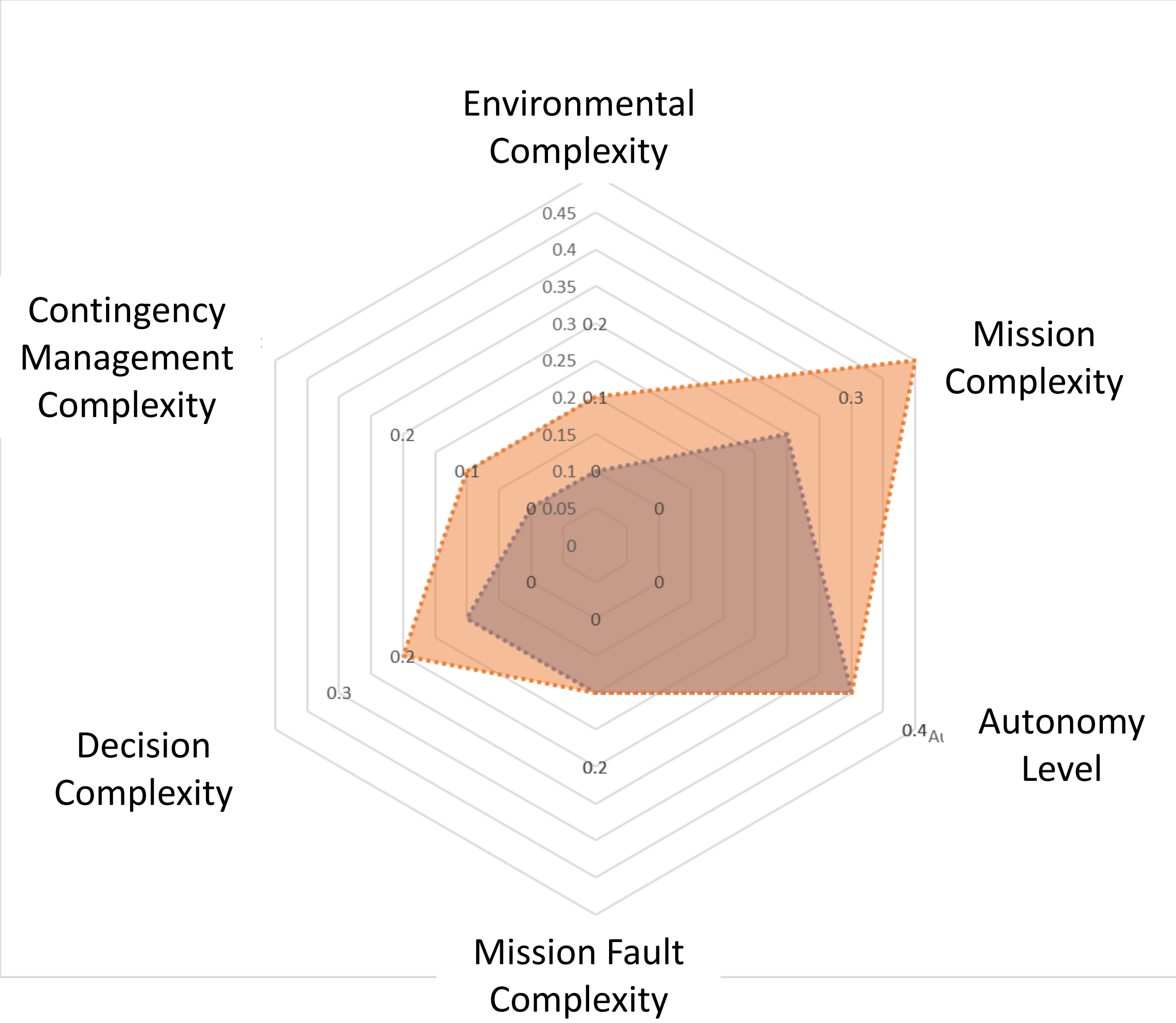
- Control points have physical interpretation
  - Curve connected to end points
  - Curve contained inside control points
- Fast collision and constraint checking algorithms
  - Dynamic feasibility checks
- Differentiation yields Bernstein curve



Bernstein Polynomial control points and evaluations.

Autonomous Flight – Measure of Progress Framework

- Complexity of environment
  - Structured/unstructured, static/dynamic, known/unknown
- Complexity of Mission
  - Simple/complex flight plan, normal/off-nominal operations, recoverable/unrecoverable failure (in current mission sense)
- Complexity (level) of Autonomy
  - No automation to full autonomy; 1-5 similar to SAE
- Complexity of decision
  - Immediate system to mission level
- Mission fault complexity
  - External/internal, correctable/uncorrectable
- Complexity of contingency management
  - Evaluates the potential hazards and consequences of the vehicle in case of a failure or emergency
  - Contingency risk assessment - level of risk posed by a specific contingency action



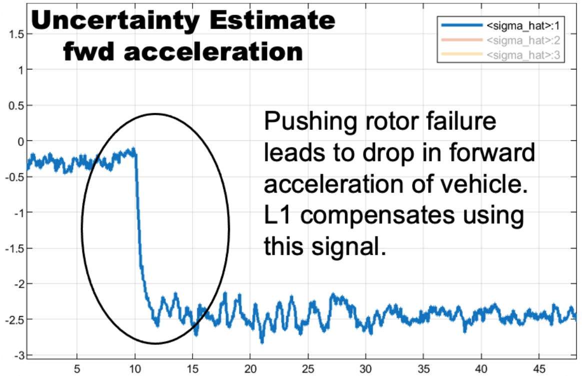
Benchmark III

Sys ID

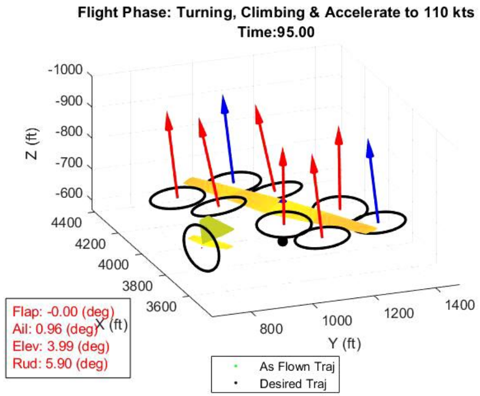
L1 Learning

PDDP

L1

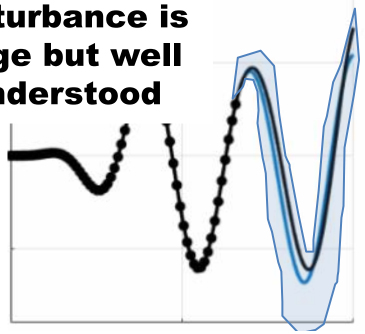


L1 AC Triggers Sys ID

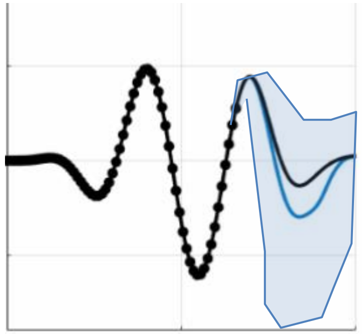


Adaptive L1 Learning Controller: Planning tradeoffs between known & unknown disturbance regions. Conservatism of algorithms

Disturbance is large but well understood



Disturbance is small but poorly understood



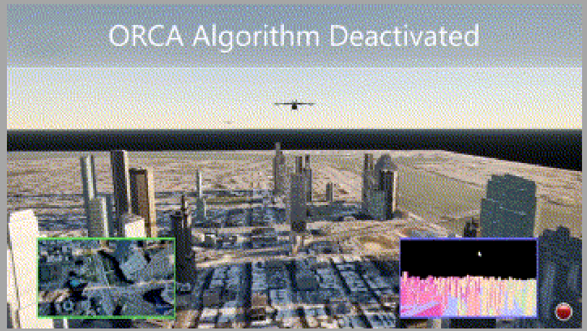
PDDP

Parameter Estimation:

Ant Simulation

Mission Management - XAI

Explainable AI – Based on physical variables



COBRA-DDP

Combines 3 algorithms – real-time, dynamically feasible collision avoidance w guaranteed separation

Hover => Departure => Cruise => Land [Turbulence, L1+Baseline Control, Propulsor & Surface Aileron Degradation, Triggered Sys Id, 2 Moving & 1 Stationary Obstacle]

Collaboration Tool:

Generic Urban Air Mobility (GUAM)

Open-Source Matlab/Simulink simulation

Questions?

Contact Information:

Irene.M.Gregory@nasa.gov

Michael.J.Acheson@nasa.gov