Urban Air Mobility: A Control-Centric Approach to Addressing Technical Challenges

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FORCE Seminar (Forum On Robotic and Control Engineering)
May 14, 2021

Outline of Major Topics

- Introduce Urban Air Mobility – new aviation sector
  - Convergence of electric propulsion and vehicle autonomy
  - complexity of operations in the urban environment
  - the unconventional vehicle configurations designed to take advantage of new propulsion technologies, result in numerous challenges that benefit from a control-centric approach
  - Autonomous flight for full economic potential
  - Contingency management – biggest challenge for autonomous flight
    - Atmospheric disturbances – appropriate modeling → direct impact on trajectory precision, energy consumption, decisions on mission execution or modification
  - Noise
- Control centric approach to addressing UAM challenges – brief highlights from our research team
  - Contingency management – how far can machine decision making take us towards vehicle autonomous flight?
  - Baseline control – RSLQR + modified AGI control allocation
  - Fast –replanning + L1 adaptive control
  - Safe and learning control
  - Hierarchical noise abatement
- Summary and future directions

Where are we heading in Aeronautics?

Third Aviation Revolution

- Urban Air Mobility
  - Part of **Anyone, Anywhere, Anytime** Advanced Air Mobility concept
  - Largely enabled by convergence of electric propulsion and vehicle autonomy
  - **Autonomous flight** to fully realize the market potential
  - Operation in complex environment and densely populated areas

Urban Air Mobility – Vehicle Configuration Spectrum

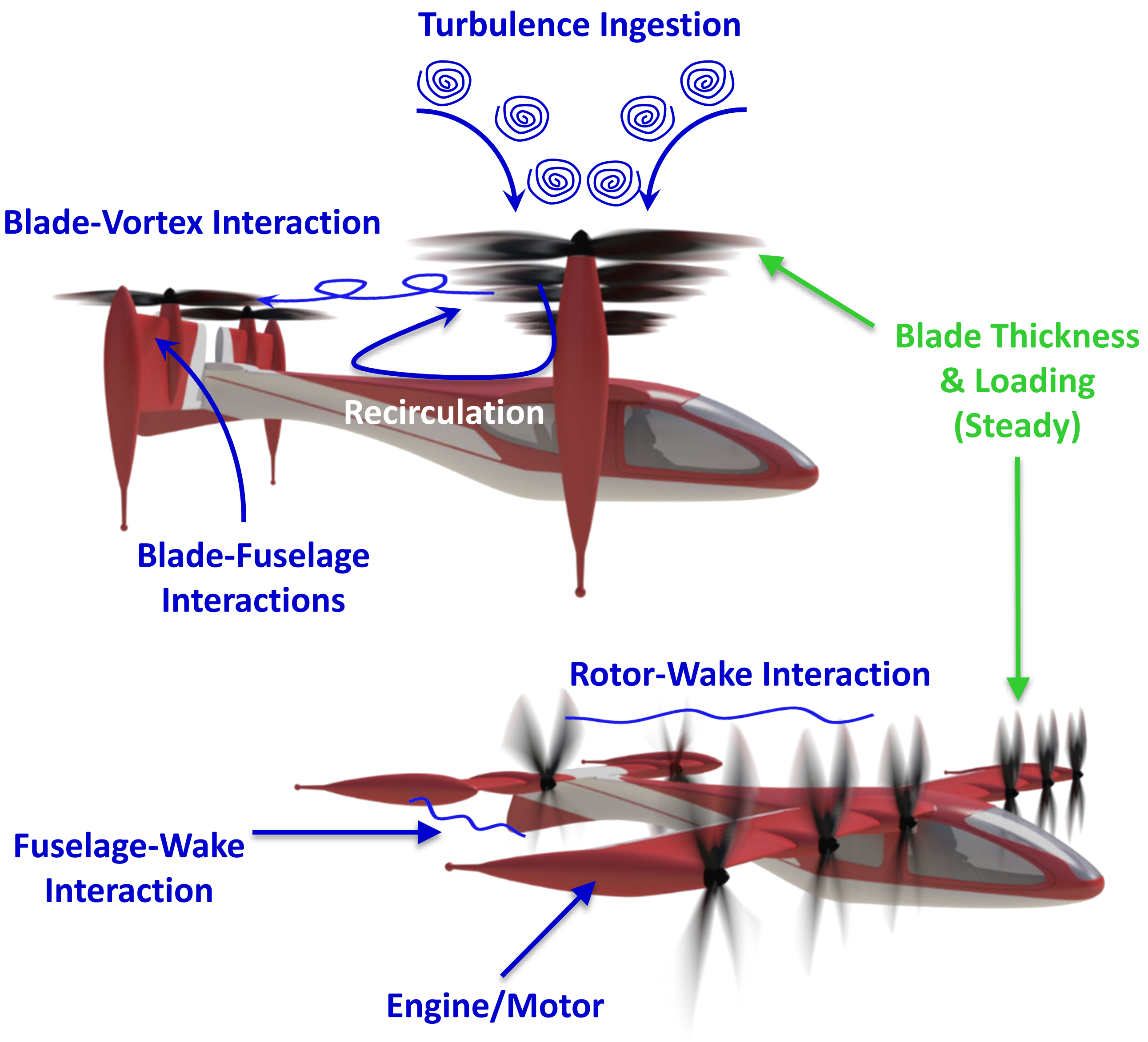
Proliferation of unconventional vehicle configurations

- Rotor-borne flight
- Blended rotor/wing borne flight
  - Tilt-wing
  - Tilt-rotor
  - Lift+cruise
- Ducted Fan
- Challenge in flight dynamics modeling and control, especially for the hybrid vehicles with 3 separate flight phases:
  - Hover (rotor borne)
  - Fixed-wing
  - Transition

Unconventional vehicle configurations designed to take advantage of new propulsion technologies, result in numerous challenges that benefit from a control-centric approach

UAM Vehicle Noise*

- **Expected Characteristics of UAM Vehicles**
  - Multiple propulsors (rotors, propellers, etc.)
  - Close proximities between propulsors and/or airframe
  - Possibly high propulsor blade counts
- **Interactional Noise Mechanisms**
  - Potentially complex noise sources
  - Relative importance different across vehicle configurations
  - Encompass interactions between rotors and airframe and rotors with each other
- **Reflections and Scattering**
  - Acoustic wavelengths may be on par with airframe components
  - Sources may become highly directive



*Slide from N. Zawodny, NASA Acoustics Technical Working Group Meeting, Spring 2020.

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Installed Propellers:

Prop-to-Wing Interactions

- Scattering/shielding of propeller acoustic source (source directivity important)

  )))
- Effects of wing flow field on propeller blade loading may result in modification of resultant propeller source

  ↖
- Propeller wake impinging on aircraft surfaces may effect aerodynamic performance and produce additional noise sources

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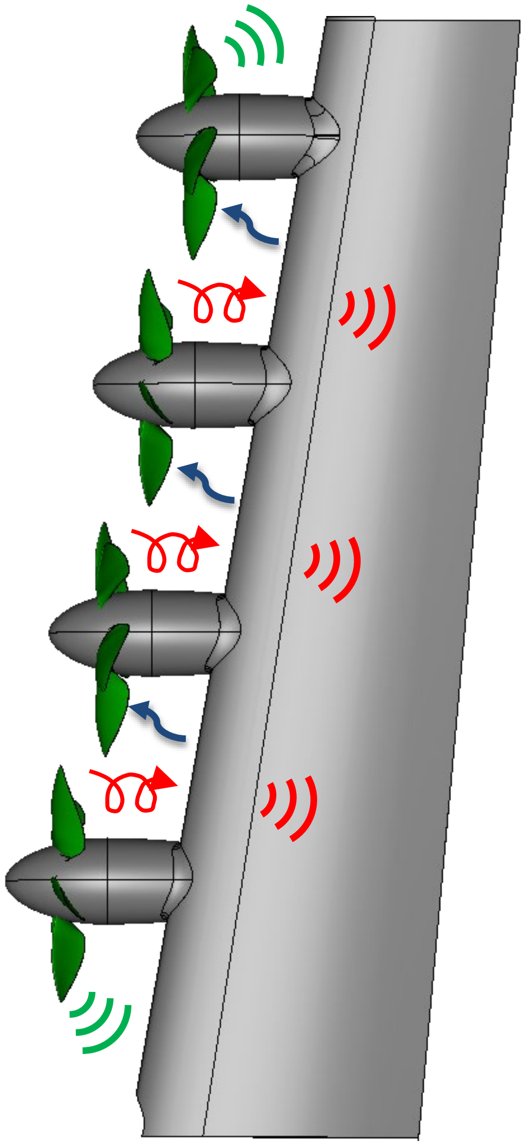

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*Slide from N. Zawodny, NASA Acoustics Technical Working Group Meeting, Spring 2020.

Atmospheric Disturbances and Vehicle Performance

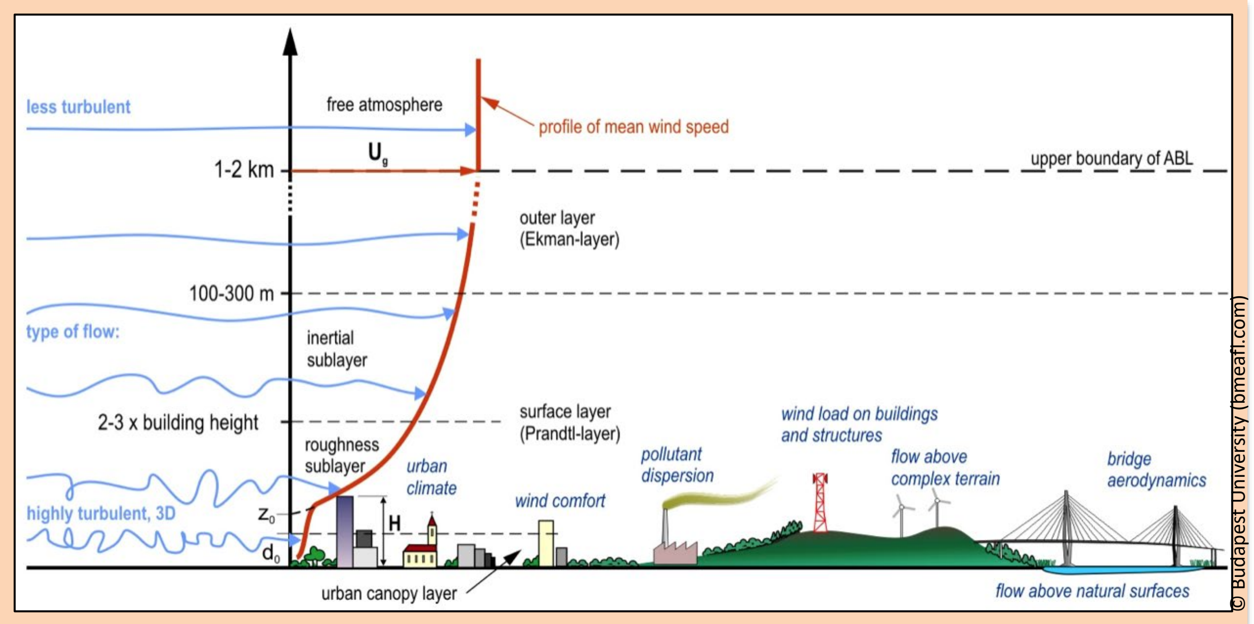
- UAM flight limits the scales in and just above the Atmospheric Boundary Layer (ABL) (< ~1km)
- Urban environments add extra complexity to winds and turbulence
  - Wind channeling
  - Turbulence from buildings

→ Better understanding of low-level and urban micro-weather

- Blended rotary/wing configurations present unique challenges to turbulence modeling

→ Performance characteristics to understand what conditions are hazardous, response to wind and turbulence determine comfort and safety

- Proper representation of atmospheric dynamics/turbulence in vehicle simulations



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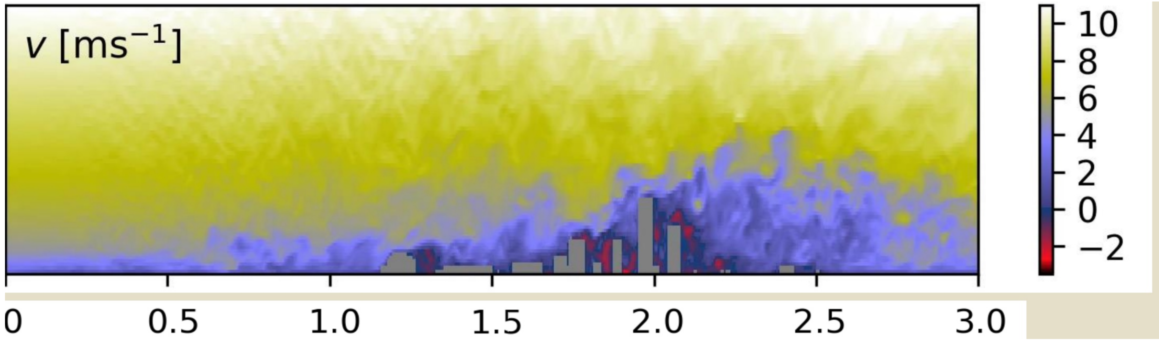


Courtesy of L. Cornman, National Center for Atmospheric Research

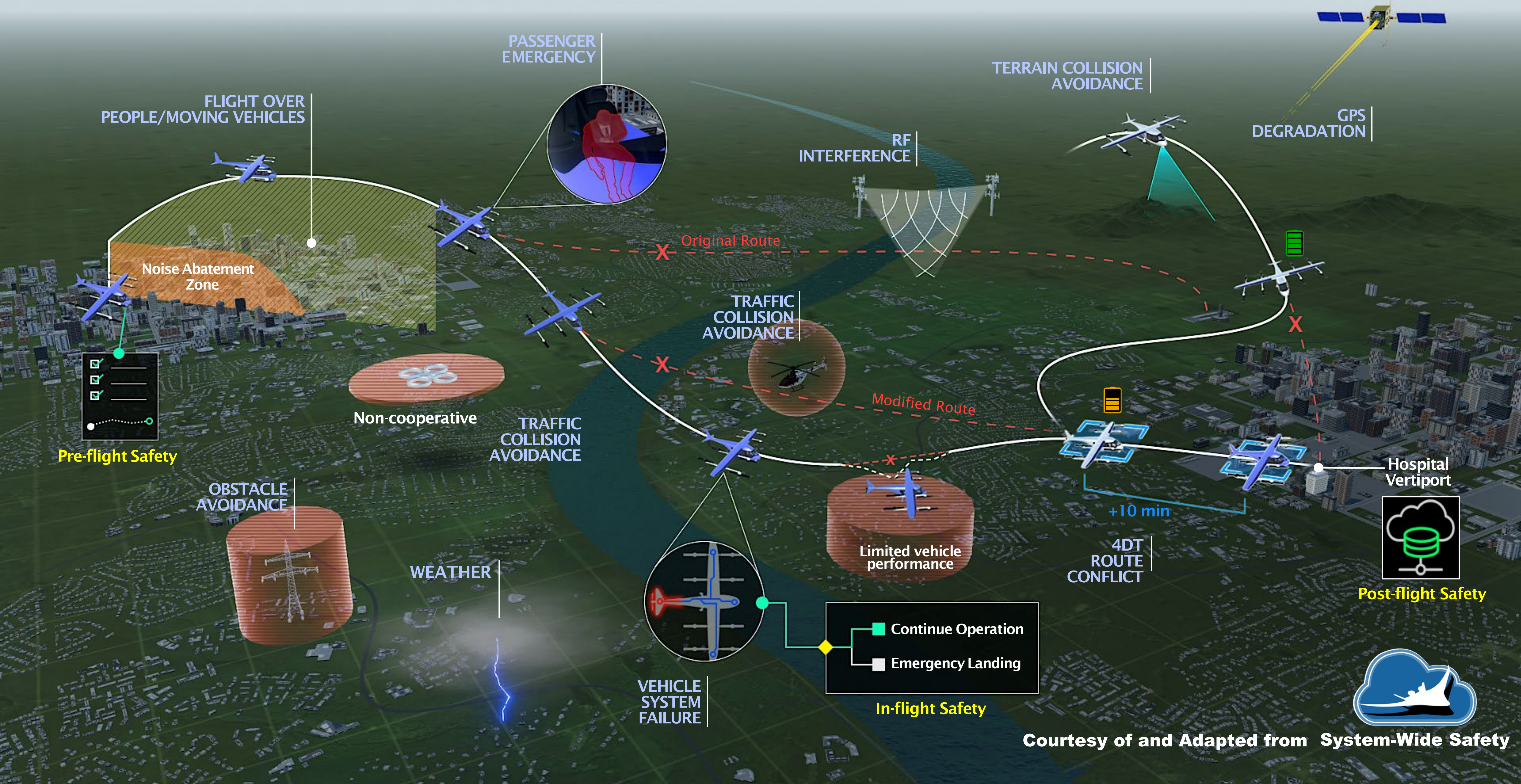
Flight Dynamics Modeling of Sufficient Fidelity

- In an Urban Air Mobility, aircraft may embrace many features from both aircraft and rotorcraft. These designs present greater complexity, aerodynamic nonlinearity, and a large number of interacting factors, compared to conventional aircraft.
- Conventional experimental methods, in particular one-factor-at-a-time testing, fail to capture the complexity and numerous interactions, often resulting in costly studies in terms of time/resources and may still produce models with deficient information.
- Low fidelity models miss major factors influencing vehicle behavior → typically arise in transition regime and from wing propulsor interactions

Control–centric Approach to Urban Air Mobility

Goal: Autonomous Vehicles in complex urban environment

Complexity of Operational Environment

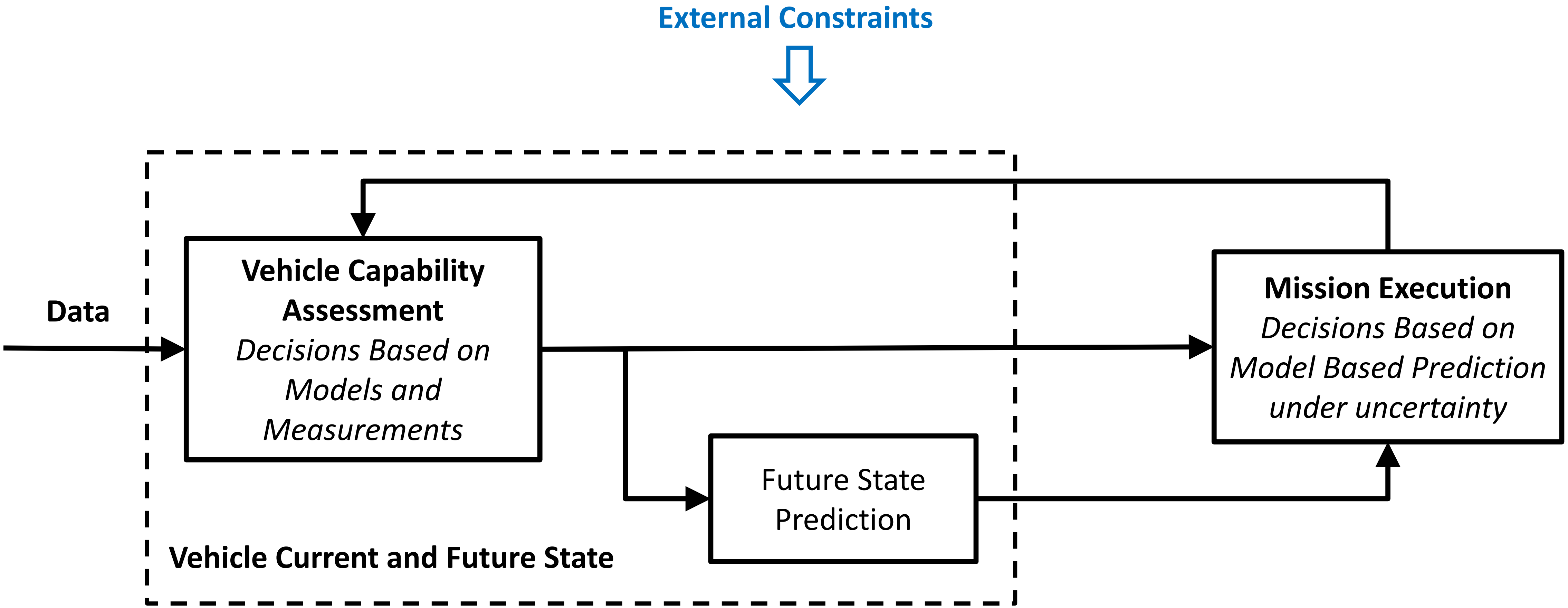


Courtesy of and Adapted from System-Wide Safety

UAM Mission Under Study

- Vehicle mission: Safely fly from pt. A to pt. B following a nominal trajectory
- Environmental and operational constraints:
  - Under all vehicle-allowable weather conditions
  - In a high-density airspace and complex urban environment
- React appropriately to off-nominal situations and contingencies without direct human control
- Currently contingency management is a highly prescribed, rule-based approach
- We are interested in exploring intelligent contingency management that can appropriately handle unanticipated situations

Intelligent Contingency Management – Architecture*



High level architecture

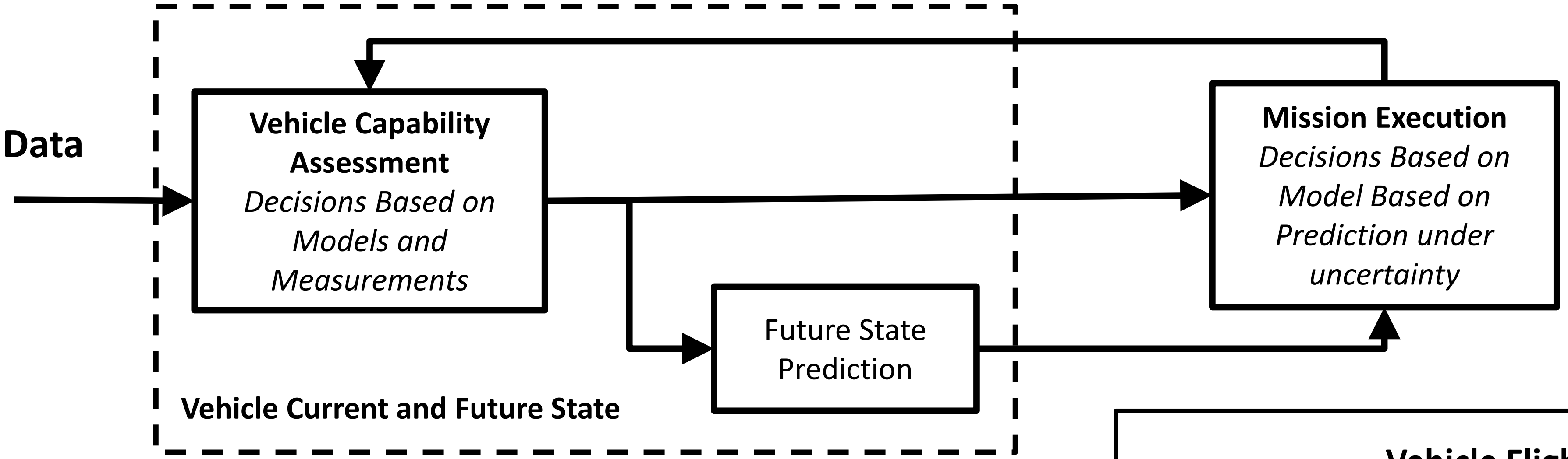
* I. M. Gregory *et al.*, “Intelligent contingency management for urban air mobility,” in *AIAA Scitech 2021 Forum*, 2021.

Intelligent Contingency Management – Major Component Blocks

Vehicle Model
- Model development (RAM-C)

External Constraints (Weather & Other Traffic)

Atmospheric Characterization
- Turbulence models for low altitude



Data

Vehicle Capability Assessment
Decisions Based on Models and Measurements

Future State Prediction

Vehicle Current and Future State

Mission Execution
Decisions Based on Model Based on Prediction under uncertainty

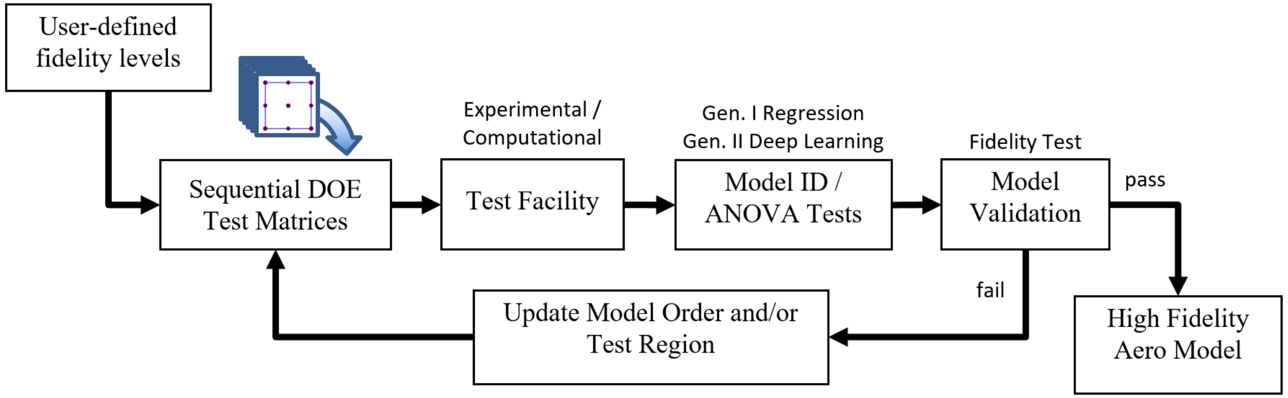
Human Element
- Identification & Formalization of Safe Strategies

Vehicle Safety
- Safe dynamic envelope
- Collision Avoidance

Vehicle Flight
- Trajectory planning
- Unified control – *robust adaptive control with novel allocation*

Rapid Aero Modeling (RAM) Applied to CFD Experiments*

- RAM provides an automated, efficient, statistically rigorous, testing and modeling process.
- RAM improves test and modeling efficiency, in the face of greater complexity, nonlinearity, and large numbers of interacting factors associated with eVTOL vehicles.
- Demonstrated in application to computational experiments for the NASA Lift+Cruise aircraft.
- Full-envelope aerodynamic model identified and integrated into an FD&C simulation.



User-defined fidelity levels

Sequential DOE Test Matrices

Experimental / Computational

Test Facility

Gen. I Regression

Gen. II Deep Learning

Model ID / ANOVA Tests

Fidelity Test

Model Validation

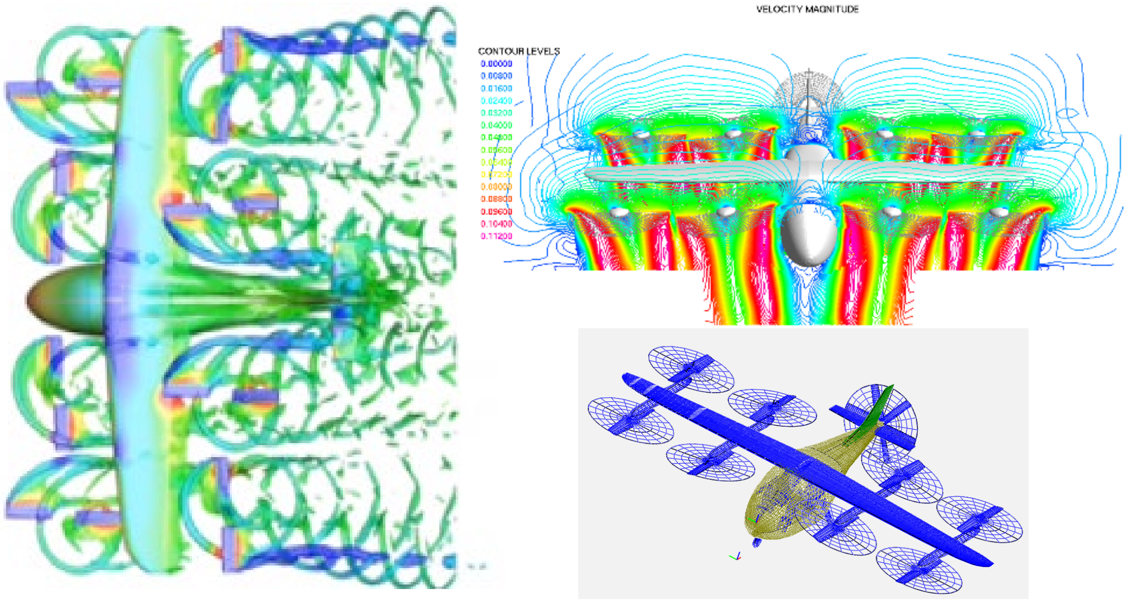
pass

High Fidelity Aero Model

fail

Update Model Order and/or Test Region

RAM process block diagram.

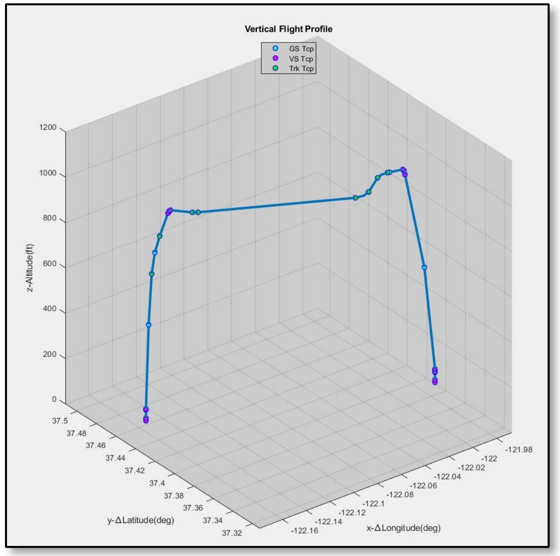


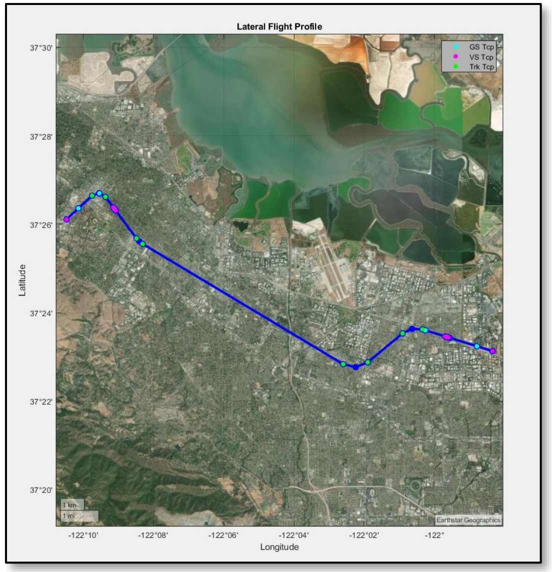
Lift+Cruise computational experiments.

* Murphy, P. C., Buning, P. G., and Simmons, B. M., “Rapid Aero Modeling for Urban Air Mobility Aircraft in Computational Experiments,” *AIAA SciTech 2021 Forum*, January 2021.

Baseline Control Summary

- Control approach enables the aircraft to fly the way it wants to fly
- Control framework is aircraft independent, well-suited for eVTOL
- Automated and simplified pilot commands use identical controls
- Translates to a unified commands across all flight phases (hover, transition, cruise)
- Design controllers separately, but integrate with allocation (without classical effector partition) while achieving overall performance (trajectory tracking etc..)
- Allocation enables desired command to be achieved after effector saturation – get maximum attainable moment while preserving direction

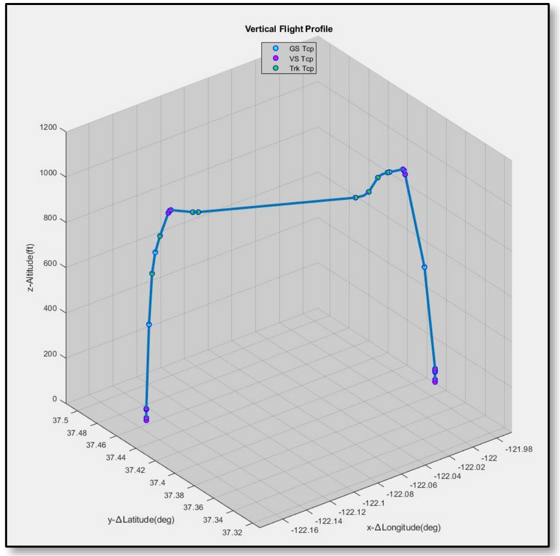


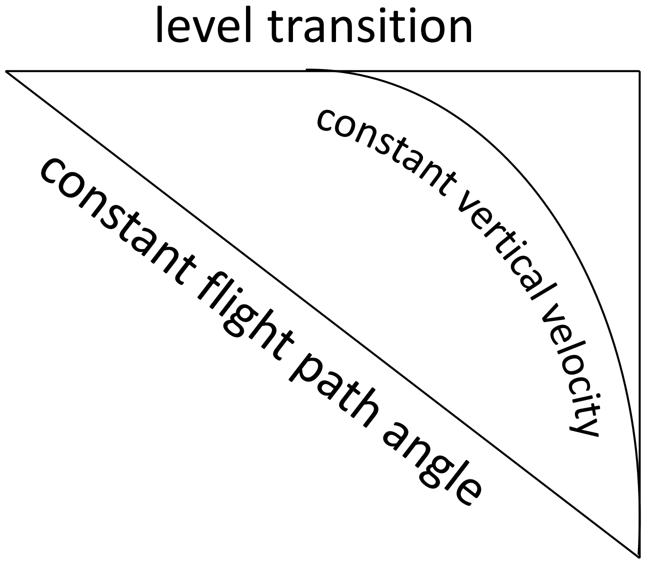


Use of approach for UAM full trajectory tracking complete

Nonunique Solutions in Transition Phase

- Efficient UAM operations require rapid and **precise descend and deceleration** capabilities of VTOL aircraft
- Aircraft in forward flight are designed to be slippery
- Aircraft designs and trajectories need to take into account the broad range of flight conditions a VTOL aircraft may experience
  - Stall/high AoA
  - Control authority
  - Hard limits on capabilities
- Aircraft limitations during descent and decelerate
  - One sided actuation from propulsion
  - Descend and Decelerate in transition
    - Requires the wings to be stalled, AoA goes from 0-90 degrees
    - Typically occurs at velocities
      - low to no thrust from propulsors
      - high pitch angle
      - stalled surface actuators
    - Trimming in this region is problematic





Machine Learning for Vehicle Capability Assessment

- Dynamic vehicle assessment for intelligent contingency management of UAM vehicles [1]
- Loss of control detection using conditional variational autoencoders [2]
- Use of Design of Experiments (DOE) in determining neural network architectures for loss of control detection[3] → initial step in generalizing using DOE to determine NN architecture for any specific aeronautics application

[1] Campbell, N.H., Acheson, M.J., Gregory, I.M., "Dynamic Vehicle Assessment for Intelligent Contingency Management of Urban Air Mobility Vehicles," 2021 AIAA SciTech Forum, January 2021.

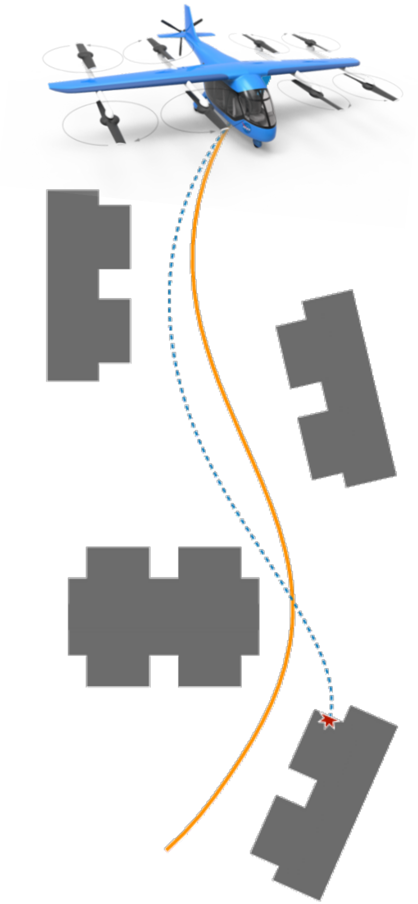
[2] Campbell, N.H., Grauer, J.A., Gregory, I.M., "Loss of Control Detection for Commercial Transports Using Conditional Variational Autoencoders," 2021 AIAA SciTech Forum, January 2021.

[3] Campbell, N.H., Grauer, J.A., Gregory, I.M., "Use of Design of Experiments and Rule-Based Inference in Determining Neural Network Architectures for Loss of Control Detection," 2021 IEEE Aerospace Conference, March 2021.

High-performance Safe Autonomy

Safety and Performance of Autonomous Systems require:

- High performance, real time trajectory planning (robust to dynamics uncertainties)
- Controller execution of planned trajectory: robust to dynamics uncertainties and disturbances with safety guarantees



Unified Control Approach Incorporating Generalized Control Allocation*

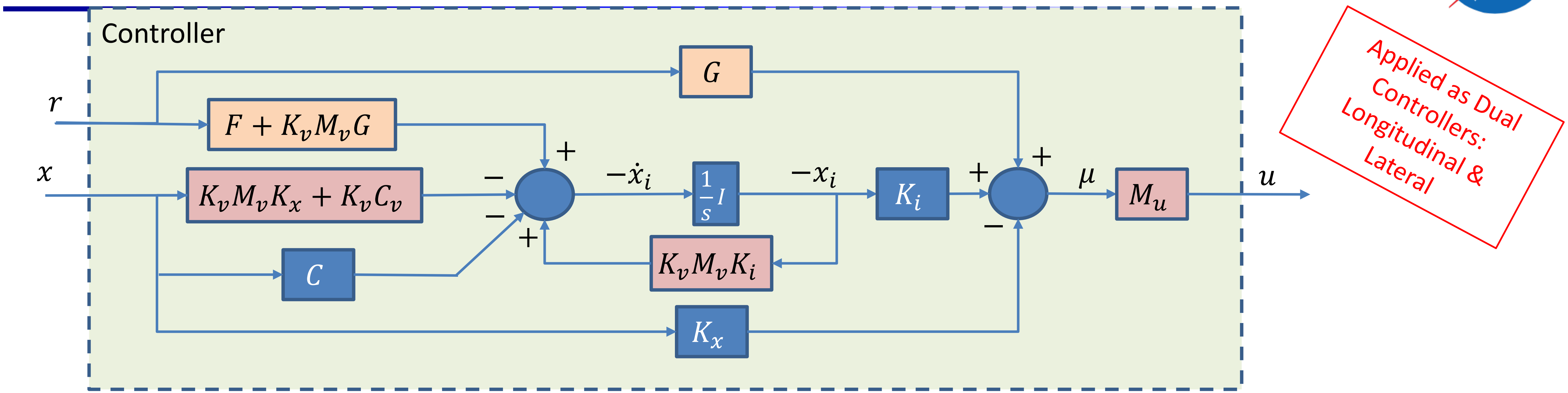
Control approach enables the aircraft to fly the way it wants to fly

Translates to a unified set of commands across all flight phases (hover, transition, cruise)

- Uniform Control Structure
  - Optimal Control (Linearized Gain Schedule)
  - Separation into Controller Performance Design & Control Allocation
- Present Longitudinal Controller and Performance Example
- Control Allocation
  - Legacy Affine Generalized Inverse (AGI) & Research Improvements to AGI
  - Longitudinal Performance Comparisons (Baseline & AGI allocators)

* M.J. Acheson, J. W. Cook, and I. M. Gregory, “Examination of Unified Control Approaches Incorporating Generalized Control Allocation,” in *AIAA Scitech 2021 Forum*, 2021.

General Uniform Control Structure: Optimal Control & Control Allocation



Applied as Dual Controllers: Longitudinal & Lateral

- Provides a uniform approach to control design throughout the entire flight envelope
- Uses established robust control design techniques (RSLQR and gain scheduling)
- Lends itself to MIMO system stability and robustness analysis techniques
- Handles redundant control effectors in an intuitive way
- Control allocation handles effector saturation and limited flight envelope protection
- Augmented with L1 adaptive control (not shown)

Longitudinal Frame

Heading frame dynamics in steady non-turning flight ($\dot{\psi} = 0$)

$$\begin{bmatrix} \dot{\bar{u}} \\ \dot{\bar{w}} \\ \dot{q} \\ \dot{\theta} \end{bmatrix} = \begin{pmatrix} \frac{1}{m}\bar{X}(x,u) \\ g + \frac{1}{m}\bar{Z}(x,u) \\ \frac{1}{J_y}M(x,u) \\ q \end{pmatrix}$$

$$x = [\bar{u} \quad \bar{w} \quad q \quad \theta]^T,$$
$$u = [\boldsymbol{\omega_r} \quad \omega_p \quad \delta_e \quad \delta_f]^{\mathrm{T}}$$

Reference Commands

$$r = [\bar{u}_{des} \quad \bar{w}_{des}]$$

Performance Design System

$$\dot{\bar{x}} = \bar{A}\bar{x} + \mu$$
$$y = \bar{x}$$

Performance Design States and Inputs

$$\bar{x} = \begin{bmatrix} \bar{u} \\ \bar{w} \\ q \end{bmatrix}, \qquad \mu = \begin{bmatrix} \bar{a}_x \\ \bar{a}_z \\ \alpha_q \end{bmatrix}$$

Performance Design Parameters

$$\bar{A} = \begin{bmatrix} \frac{1}{m}\bar{X}_{\bar{u}} & \frac{1}{m}\bar{X}_{\bar{w}} & \frac{1}{m}\bar{X}_q \\ \frac{1}{m}\bar{Z}_{\bar{u}} & \frac{1}{m}\bar{Z}_{\bar{w}} & \frac{1}{m}\bar{Z}_q \\ \frac{1}{J_y}M_{\bar{u}} & \frac{1}{J_y}M_{\bar{w}} & \frac{1}{J_y}M_q \end{bmatrix}$$

$$Q = diag([q_{\bar{u}} \quad q_{\bar{w}} \quad q_q \quad 0 \quad 0 \quad 0])$$
$$R = diag([r_{\bar{a}_x} \quad r_{\bar{a}_z} \quad r_{\alpha_q}])$$

Control Allocation

$$\min_{(u(t),v(t))} \quad [u^T \quad v]\, W \begin{bmatrix} u \\ v \end{bmatrix}$$
$$\text{subject to} \qquad \mu = \bar{B}\begin{bmatrix} u \\ v \end{bmatrix}$$

Physical and virtual control inputs

$$u = \begin{bmatrix} \omega_r \\ \omega_p \\ \delta_e \\ \delta_f \end{bmatrix}, \qquad v = \theta$$

Control allocation Parameters

$$\bar{B} = \left[\begin{array}{cccc|c} \frac{1}{m}\bar{X}_{\boldsymbol{\omega_r}} & \frac{1}{m}\bar{X}_{\omega_p} & \frac{1}{m}\bar{X}_{\delta_e} & \frac{1}{m}\bar{X}_{\delta_f} & \frac{1}{m}\bar{X}_{\theta} \\ \frac{1}{m}\bar{Z}_{\boldsymbol{\omega_r}} & \frac{1}{m}\bar{Z}_{\omega_p} & \frac{1}{m}\bar{Z}_{\delta_e} & \frac{1}{m}\bar{Z}_{\delta_f} & \frac{1}{m}\bar{Z}_{\theta} \\ \frac{1}{J_y}M_{\boldsymbol{\omega_r}} & \frac{1}{J_y}M_{\omega_p} & \frac{1}{J_y}M_{\delta_e} & \frac{1}{J_y}M_{\delta_f} & \frac{1}{m}M_{\theta} \end{array}\right]$$

$$W = diag(\left[w_{\boldsymbol{\omega_r}} \quad w_{\omega_p} \quad w_{\delta_e} \quad w_{\delta_f} \,\middle|\, w_{\theta}\right])$$

$$M = W^{-1}\bar{B}^T\left(\bar{B}W^{-1}\bar{B}^T\right)^{-1}$$

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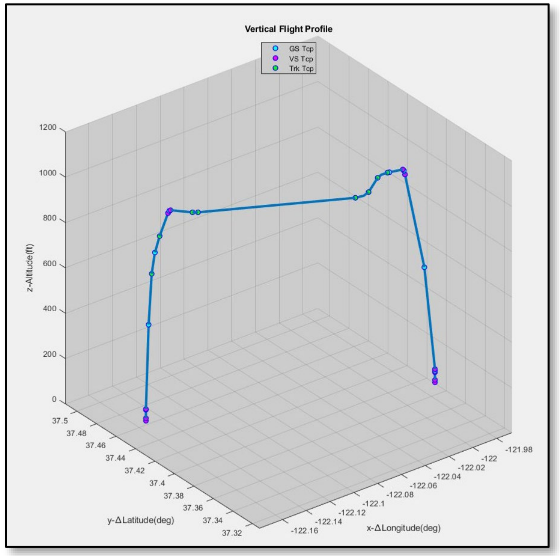
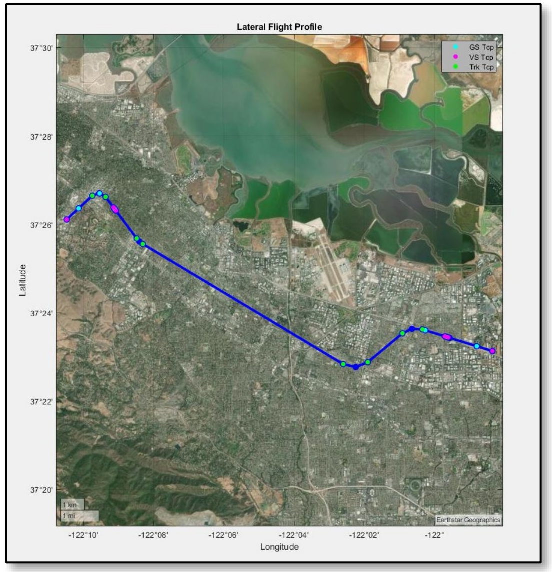
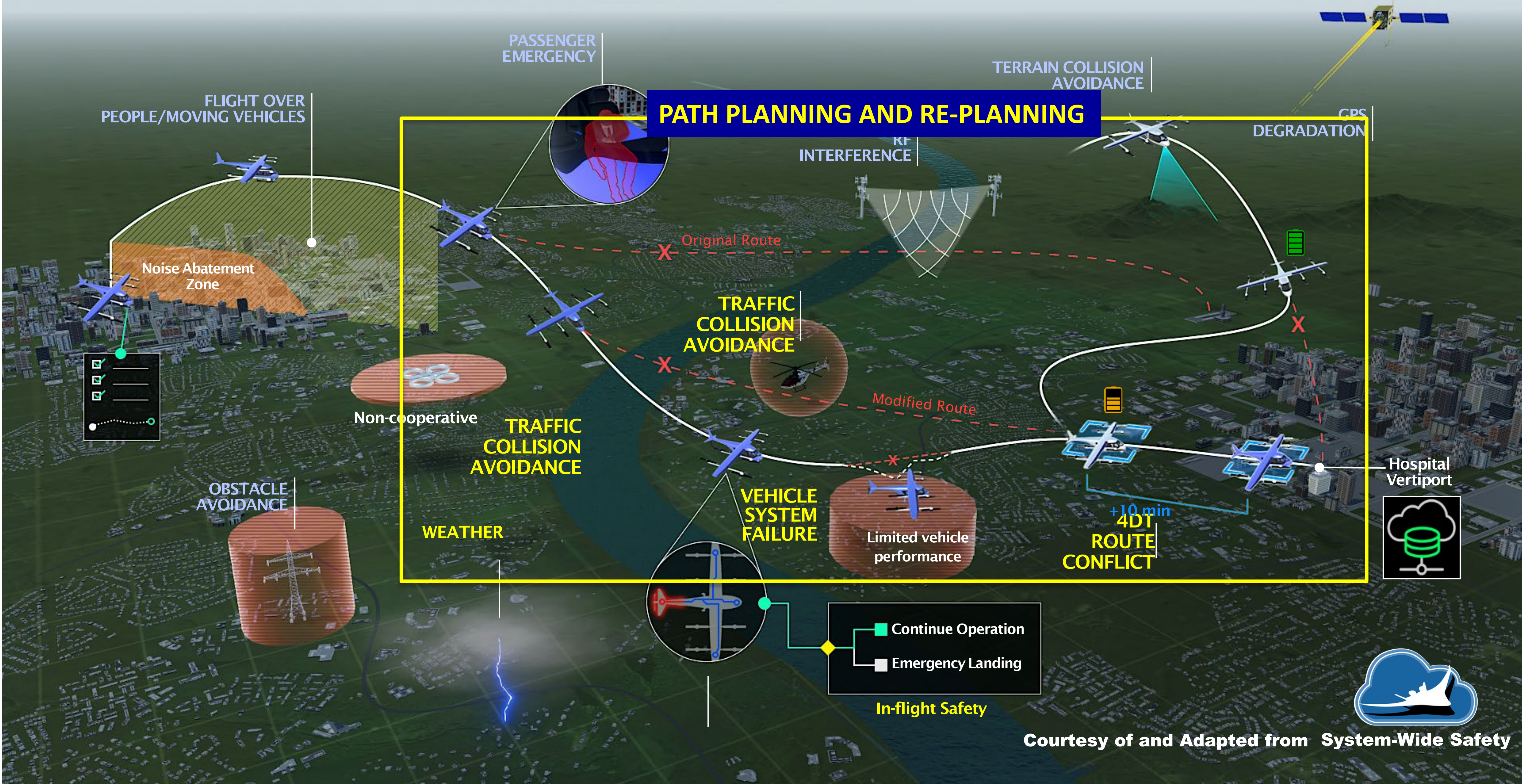




Use of approach for UAM full trajectory tracking complete

Complexity of Operational Environment



Courtesy of and Adapted from System-Wide Safety

Motion Planning

- Model Predictive Path Integral Control (MPPI)*
  - Sample thousands of control sequences, $\boldsymbol{\nu}_t \sim \mathcal{N}(\boldsymbol{u}_t, \boldsymbol{\Sigma})$, propagate trajectories in parallel
  - Exponential cost-weighted averaging to update mean of optimal control distribution, $\boldsymbol{u}_t$
  - Propagate mean optimal control sequence to obtain nominal trajectory

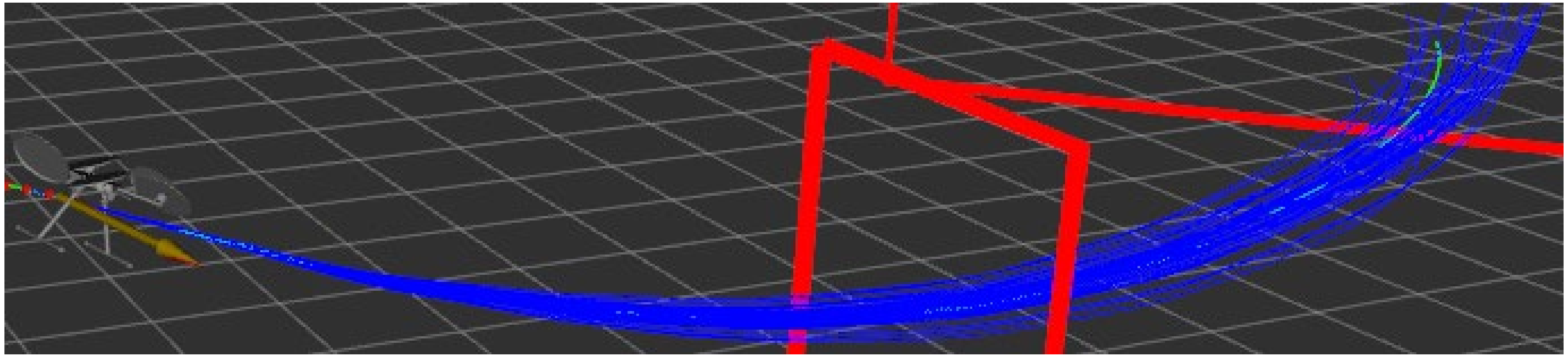


Figure credit: J Pravitra, KA Ackerman, N Hovakimyan, EA Theodorou, "L1-Adaptive MPPI Architecture for Robust and Agile Control of Multirotors," IROS, 2020.

*G Williams, P Drews, B Goldfain, JM Rehg, EA Theodorou, "Information Theoretic Model Predictive Control: Theory and Applications to Autonomous Driving," IEEE Transactions on Robotics, 2018.

Fast and Safe Re-Planning Through $\mathcal{L}_1$- MPPI Control*

- **Fast and robust trajectory planning** is needed for mission success in complex, dynamic and uncertain environments.
- **Model predictive path integral (MPPI) control** generates trajectories and control **on-board** in **real-time**.
- **Robustness** against dynamic uncertainties and disturbances (microclimates) achieved through $\mathcal{L}_1$ **augmentation**.

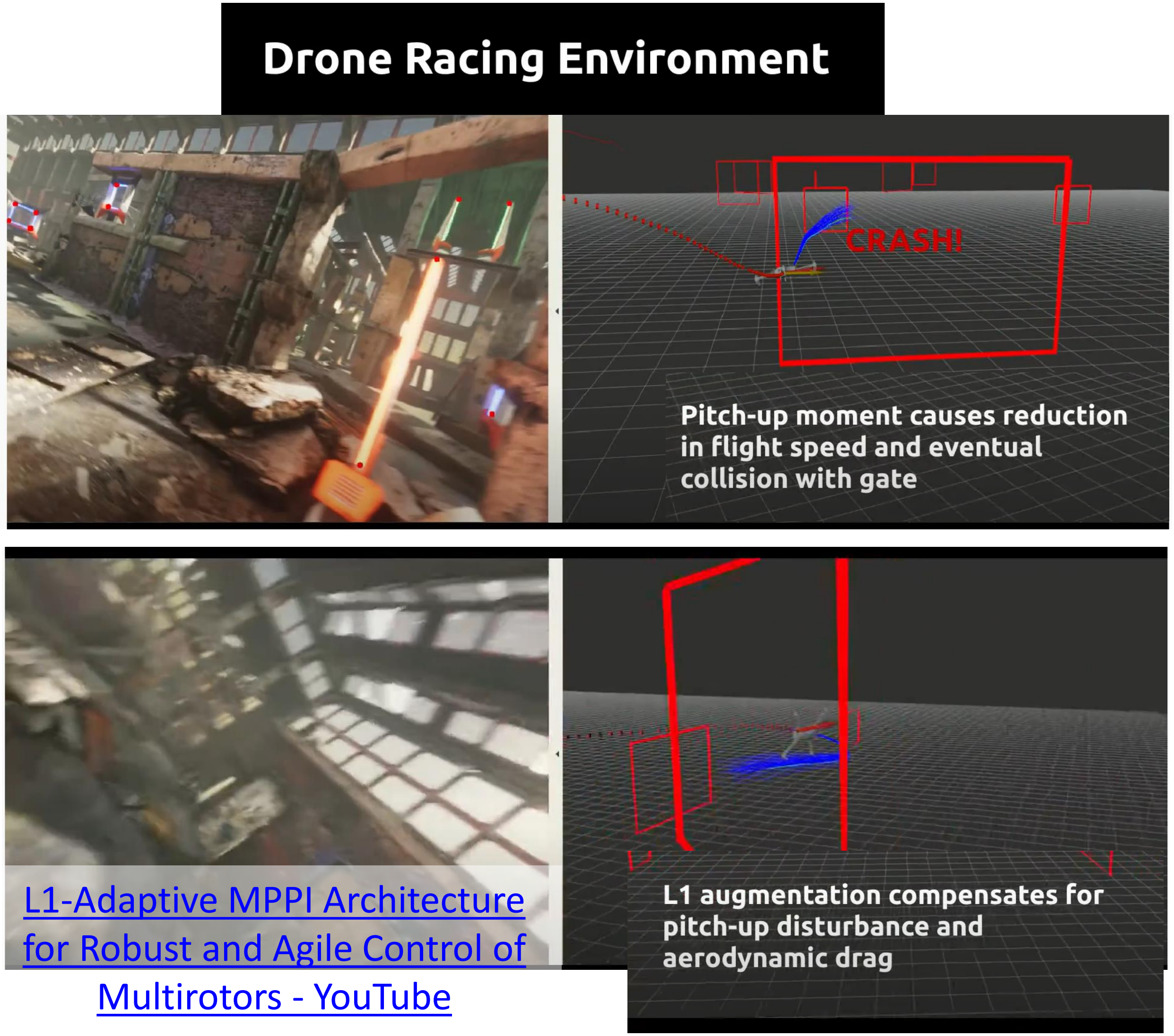
New challenges

- Unpredictable environments
- Obstacle-rich and clustered
- Micro climates
- Nonlinear uncertain dynamics
- High-speed

New requirements

- Fast re-planning
- Safe planning
- Safe learning

with guarantees



Drone Racing Environment

Pitch-up moment causes reduction in flight speed and eventual collision with gate

L1 augmentation compensates for pitch-up disturbance and aerodynamic drag

[L1-Adaptive MPPI Architecture for Robust and Agile Control of Multirotors - YouTube]

Courtesy of Georgia Institute of Technology, University of Illinois Urbana-Champaign

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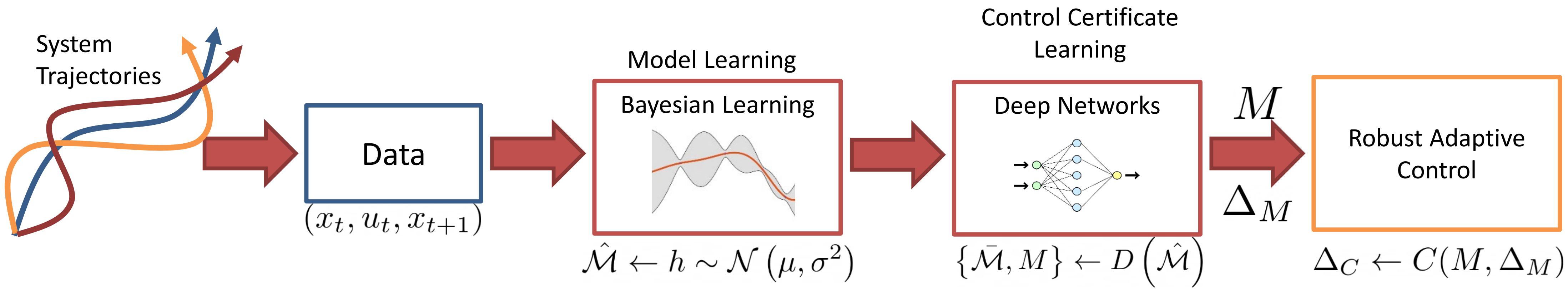
* Pravitra, J., Ackerman, K. A., Cao, C., Hovakimyan, N., and Theodorou, E. A. L1-Adaptive MPPI Architecture for Robust and Agile Control of Multirotors. International Conference on Intelligent Robots and Systems, 2020.

Safe Learning-based Control



System Trajectories

Data

(x_t, u_t, x_{t+1})

Model Learning

Bayesian Learning

$\hat{\mathcal{M}} \leftarrow h \sim \mathcal{N}\left(\mu, \sigma^2\right)$

Control Certificate Learning

Deep Networks

$\{\bar{\mathcal{M}}, M\} \leftarrow D\left(\hat{\mathcal{M}}\right)$

M

Δ_M

Robust Adaptive Control

$\Delta_C \leftarrow C(M, \Delta_M)$

- A **bottom-up** approach
- Foundation based on Control theory: **Safety**
- Build-up based on ML: **Performance**
- Unified in an architecture that decouples safety from learning
- Learning does not affect safety, only performance

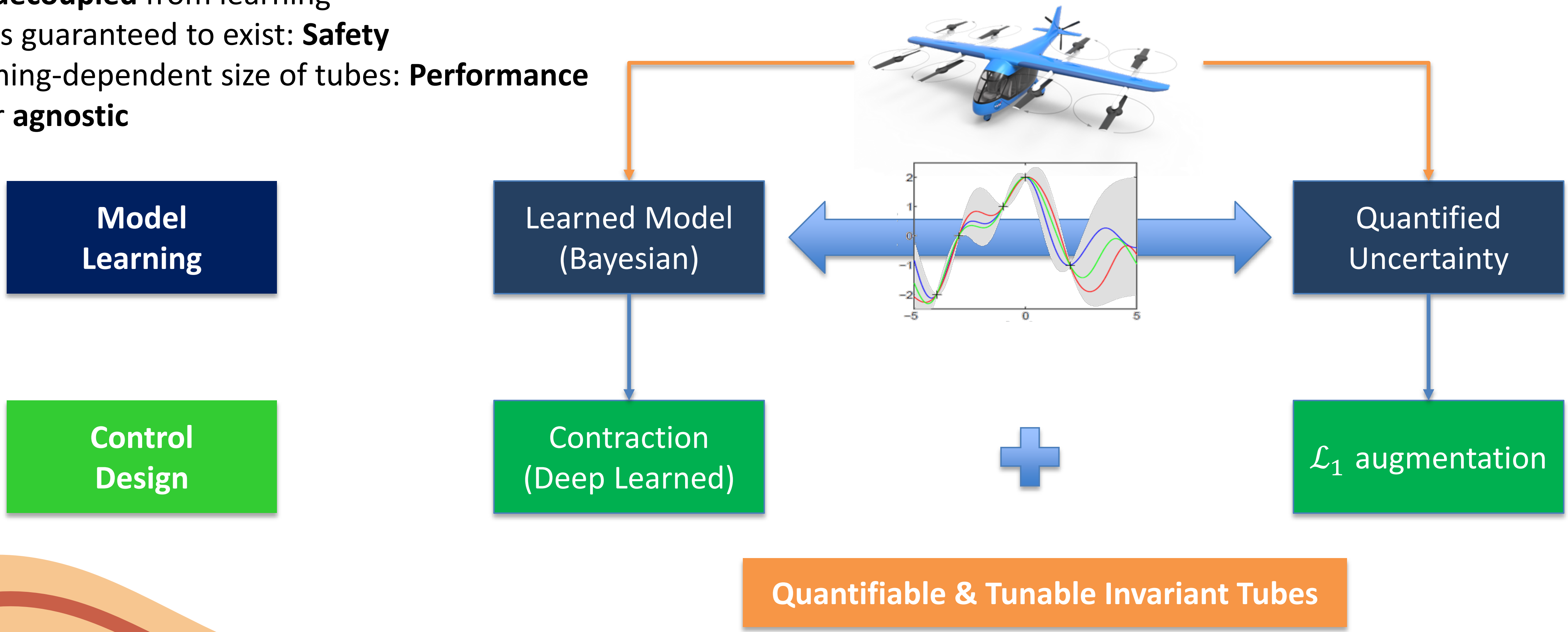
Gahlawat, A., Lakshmanan, A., Song, L., Patterson, A., Wu, Z., Hovakimyan, N., & Theodorou, E. “S2LC: Safe Simultaneous Learning and Control.” *Submitted to* Learning for Dynamics and Control (L4DC) Conference. 2021.

Safe Learning-based Control

Safety **decoupled** from learning

- Tubes guaranteed to exist: **Safety**
- Learning-dependent size of tubes: **Performance**

Planner **agnostic**



Model Learning

Learned Model (Bayesian)

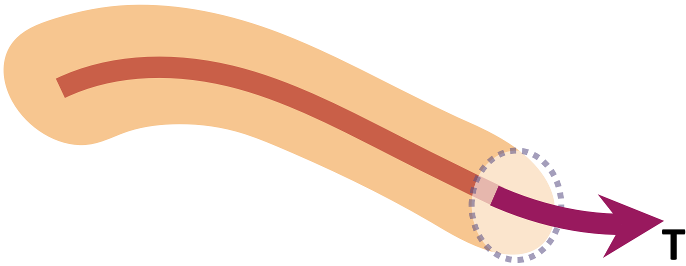
Quantified Uncertainty

Control Design

Contraction (Deep Learned)

$\mathcal{L}_1$ augmentation

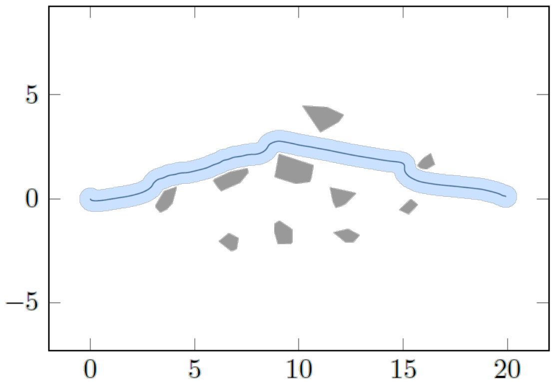
Quantifiable & Tunable Invariant Tubes



Tubes as certificates for safe planning
Tubes **shrink** as learning **improves**

$\mathcal{L}_1$ augmentation allows **tuning** of tubes even under **poor learning**.

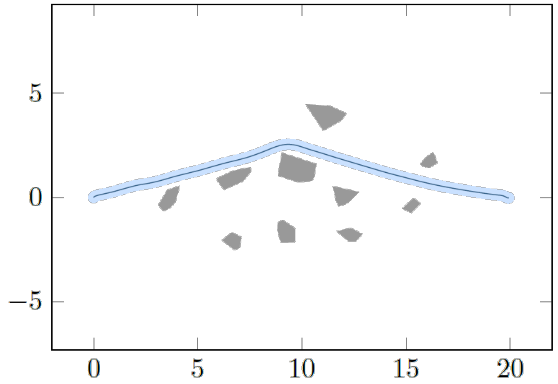
Safe Learning-based Control



(a) Episode 1: $\omega = 90$ rad/s, $\Gamma = 7e10$, $N = 0$.
Traverse time: 27secs.

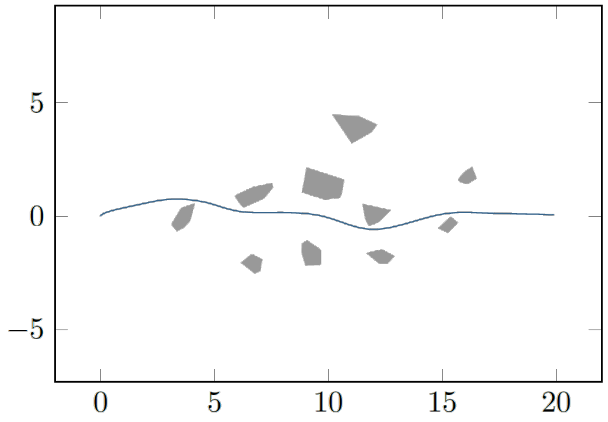
Planar Quadrotor in an obstacle forest

Learning **kicks in** → tube **shrinks** → **better** planning and control



(b) Episode 2: $\omega = 30$ rad/s, $\Gamma = 2e6$, $N = 25$.
Traverse time: 16secs.

Obstacles can be some combination of no-fly zones, static obstacles (buildings)



(c) Episode 3: $\omega = 30$ rad/s, $\Gamma = 2e6$, $N = 100$.
Traverse time: 14secs.

Example of what combination of safe and learning control with a planner can provide in terms of improved performance

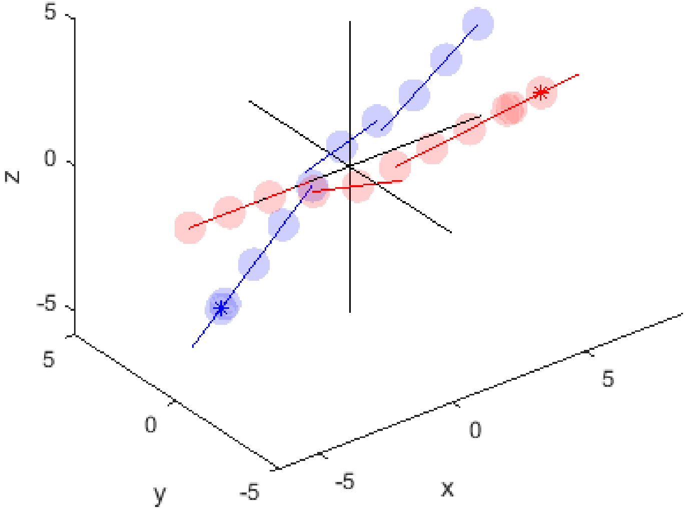
→ culminates in a faster, better performance of navigating a trajectory

→ mission execution and system level implications

Collision Avoidance via Deep Reinforcement Learning

- Approach motivated by learning algorithms used for autonomous navigation through crowds extended to 3D urban air environment
- Challenges are similar
  - Each agent is aware of only a subset of other agent states
  - Need to anticipate interaction patterns
  - Be computationally tractable for real time implementation
- Supervisory training from a known solution provides initial baseline policy
- DRL uses an epsilon-greedy version of baseline policy to explore other options and improve it.
  - Offline learning offloads online computation for real time implementation.

Result of baseline policy



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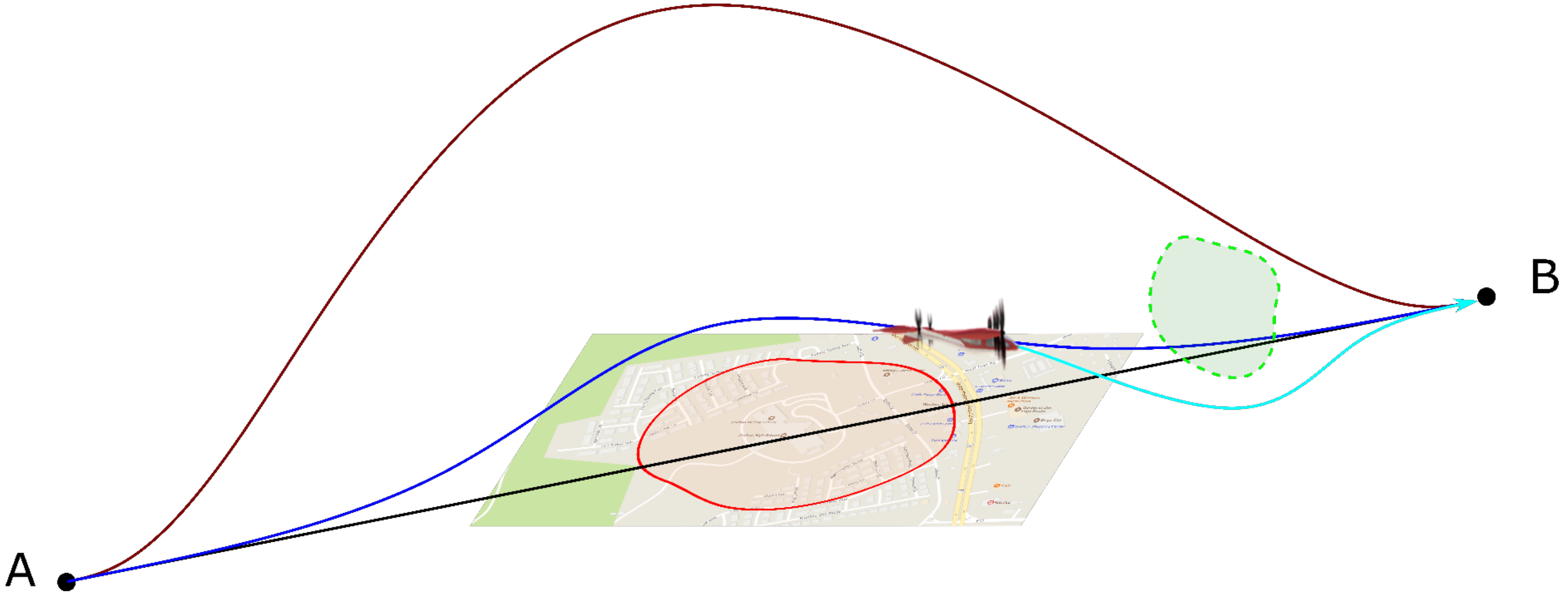
* I. M. Gregory *et al.*, "Intelligent contingency management for urban air mobility," in *AIAA Scitech 2021 Forum*, 2021.

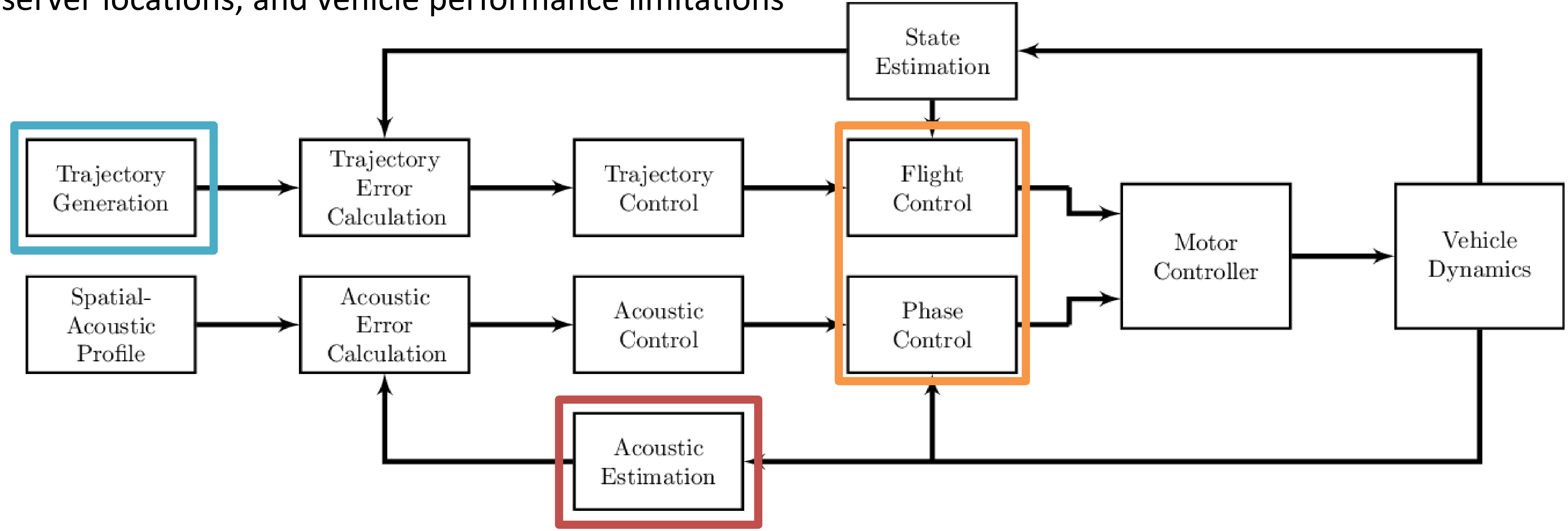
Noise Abatement for UAM

- Noise management is one of the major barriers to Urban Air Mobility
- Approaches to noise mitigation (non-exhaustive)
  - **Trajectory optimization**
  - **Directivity control via propeller phase synchronization**
  - Vehicle configuration
- A Model Predictive Control Approach for In-Flight Acoustic Constraint Compliance
- Trajectory Generation for Distributed Electric Propulsion Vehicles with Propeller Synchronization



Hierarchical Control Framework for Noise Abatement*

Framework for trajectory generation integrating location-based acoustic metrics, at a number of discreet observer locations, and vehicle performance limitations



Vehicle trajectory must be feasible, meeting all the vehicle and mission-relevant constraints.

Acoustic constraints require acoustic estimation procedure.

Propeller phase control and flight control objectives must be compatible.

*K.A. Ackerman, A.M. Patterson, "Acoustically-Aware Vehicles: Control Driven Noise Reduction for Urban Air Mobility, " Aerospace Control and Guidance Systems Committee Meeting #126 March 25-26, 2021

Vehicle Dynamics & Acoustic Model*

- Fixed-wing distributed propulsion aircraft
  - Can represent tilt-wing or split-propulsion vehicle in forward flight
  - Coordinated flight aircraft model
    - Includes basic aerodynamics model
    - Assumes underlying tracking controller
- Metric is *overall sound pressure level (OASPL)*
  - Model data fit from the Propeller Analysis System of the Aircraft Noise Prediction Program (PAS-ANOPP)
  - Based on effective propeller tip Mach number
  - Optional frequency weighting

$$\dot{\boldsymbol{x}} = \boldsymbol{v}$$

$$\dot{\boldsymbol{v}} = \boldsymbol{g} + \boldsymbol{R}\boldsymbol{a}_v$$

$$\dot{\boldsymbol{q}} = \frac{1}{2}\boldsymbol{q} \otimes \begin{bmatrix} 0 \\ \boldsymbol{\omega}_v \end{bmatrix}$$

Coordinated flight constraint

$$\boldsymbol{\omega}_v = \begin{bmatrix} p_s & -\boldsymbol{e}_3\left(\boldsymbol{a}_v + \boldsymbol{g}\right)/V & \boldsymbol{e}_3\boldsymbol{g}/V \end{bmatrix}^{\mathsf{T}}$$

$$\begin{bmatrix} T & \alpha & p_s \end{bmatrix}^{\mathsf{T}} = \boldsymbol{u} \qquad \boldsymbol{e}_3 = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix}^{\mathsf{T}}$$

Frequency weighting

Number of propellers

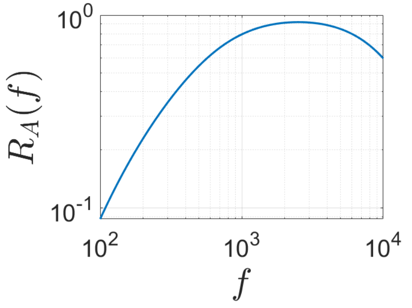
$$OASPL = 10\log_{10}\left(\frac{1}{\hat{p}^2}\sum_{k=0}^{N_f}\left[\hat{p}^2_{\text{rms},k}\left(\frac{M_{\text{eff}}}{\hat{M}_{\text{eff}}}\right)^{\xi_k} R_A(f_k)\right]\left(\frac{\hat{r}}{r}\right)^2 N_p\right)$$

Propeller speed

Distance to observer

$$M_{\text{eff}} = \frac{M_t}{1 + J(1 - M_t)}$$

$$M_t = \omega_p d_p / 2c$$



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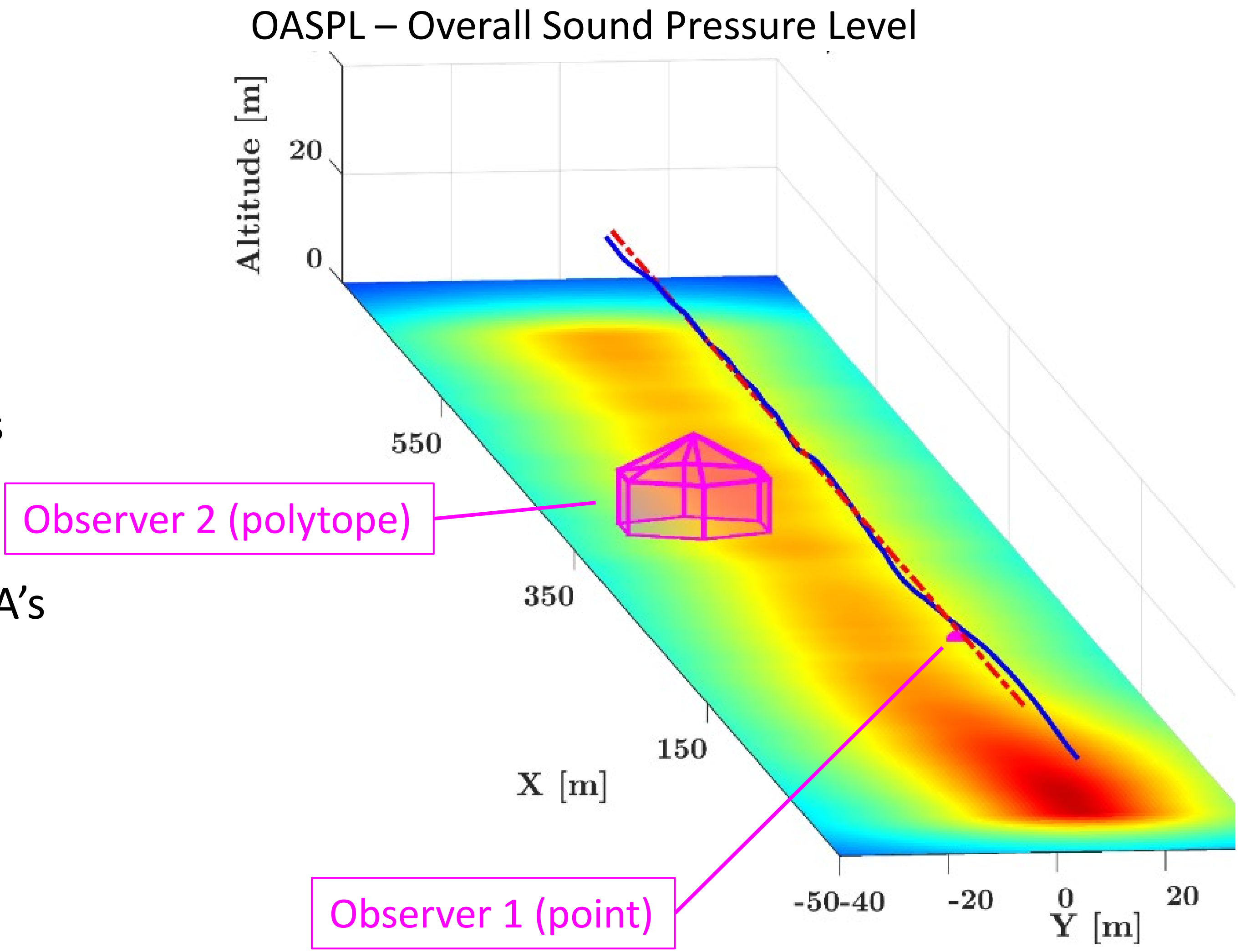
*K.A. Ackerman, I.M. Gregory, E.A. Theodorou, and N. Hovakimyan, "A Model Predictive Control Approach for In-Flight Acoustic Constraint Compliance," AIAA SciTech Forum, Jan 2021.

Motion Planning – Simulation

- Running cost –
  - Track spatial path
  - Constant speed
  - Maintaining noise at observers below threshold

- Acoustic observers defined as polytopes to leverage efficient distance query algorithms

- Parameter values taken from model of NASA's GL-10 aircraft

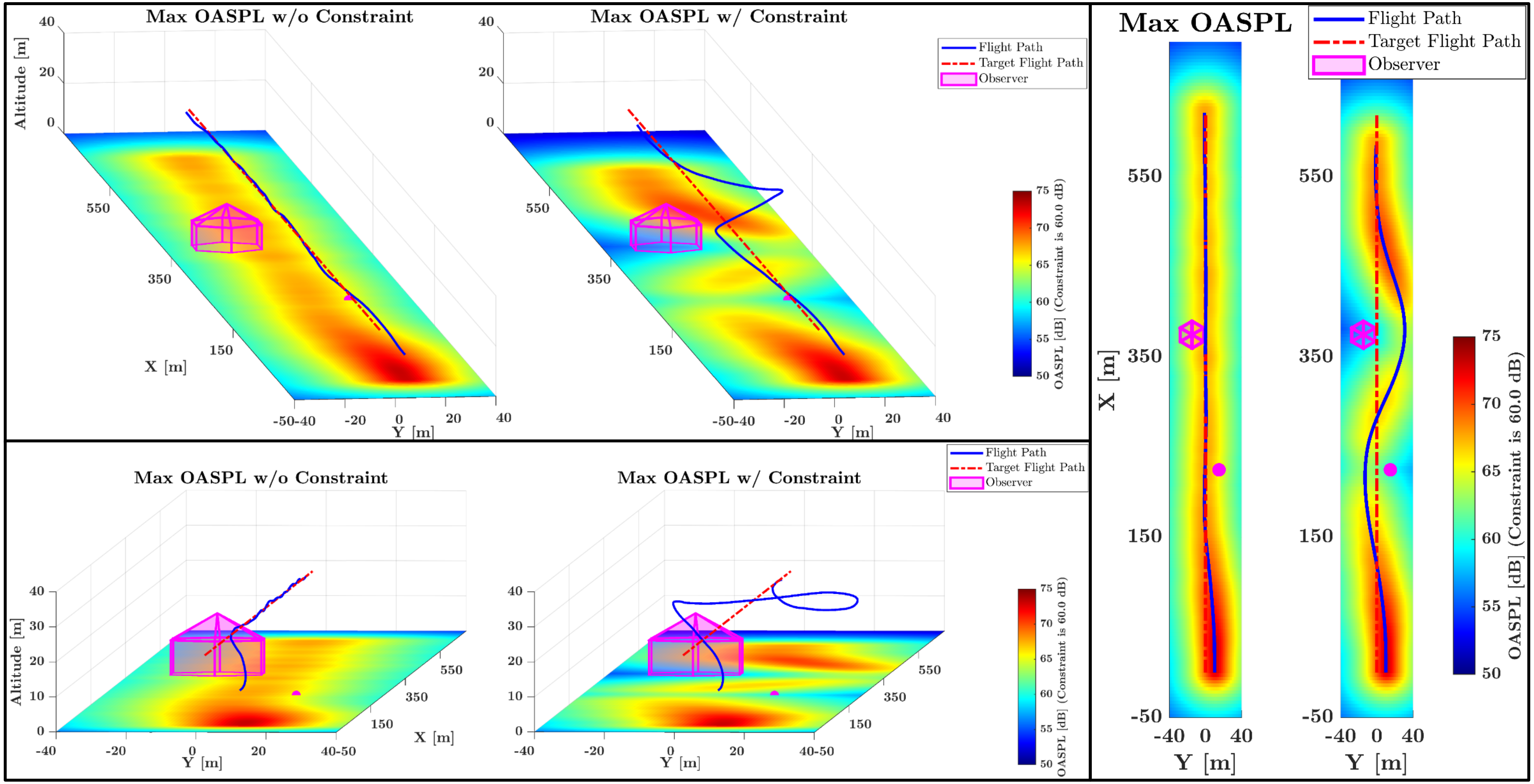

OASPL – Overall Sound Pressure Level

Observer 2 (polytope)

Observer 1 (point)

Simulation Results

- Side-by-side flight path comparison with maximum OASPL footprint



Trajectory Generation for Distributed Electric Propulsion Vehicles with Propeller Synchronization*

- Acoustic model includes directional nature of propeller noise.
- Differential flatness-based trajectory generation for propeller phase control
  - Allows phase targets to be chosen **independent** of spatial trajectory
- Trajectory generation can be parameterized for inclusion in trajectory optimization methods

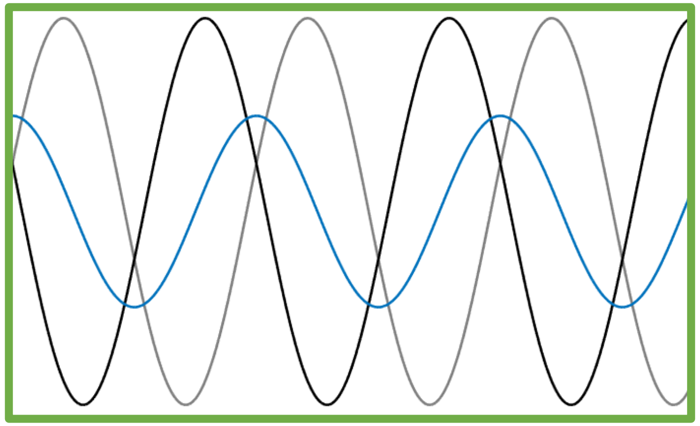
*A Patterson, KA Ackerman, N Hovakimyan, IM Gregory, "Trajectory Generation for Distributed Electric Propulsion Vehicles with Propeller Synchronization," AIAA SciTech Forum, Jan 2021

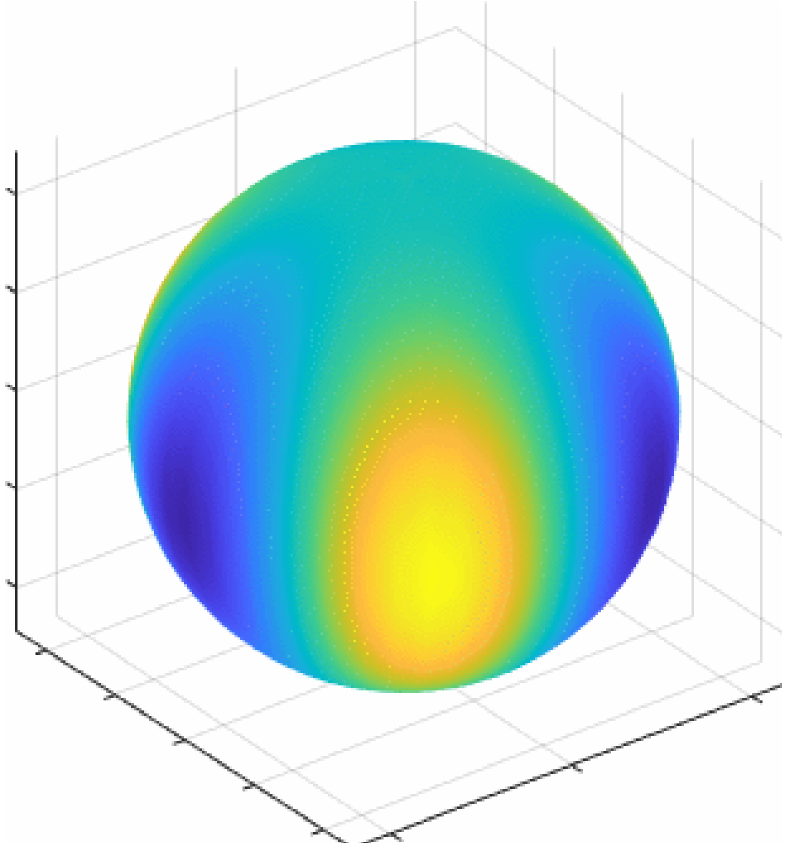
Acoustic Model

Three-part model for tonal acoustic pressure at kth observer:

$$p_k(t) = \sum_{n=1}^{N} \beta_n(t) \mathcal{S}_n(\Theta, \omega_n, v_n, \alpha_n) \boxed{\sin(\omega_n(t-\tau)+\theta_n)}$$

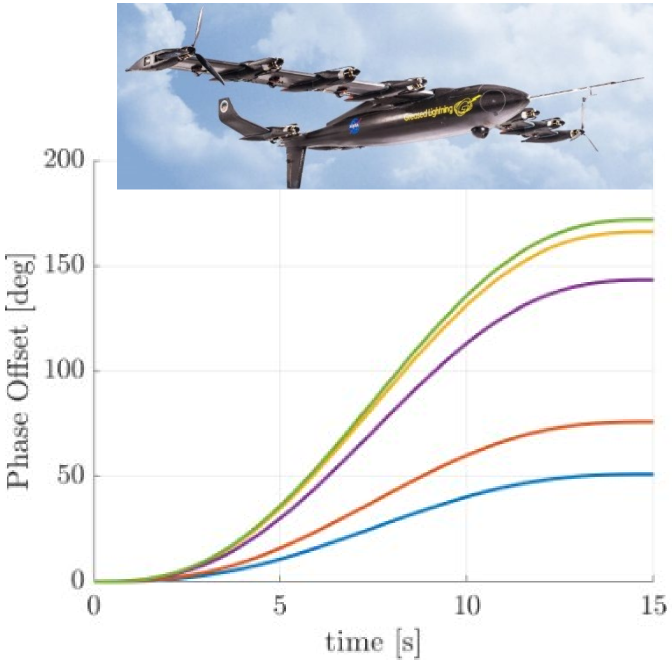
Phase shifted sine waves representing the rotation of the propeller blades in time.



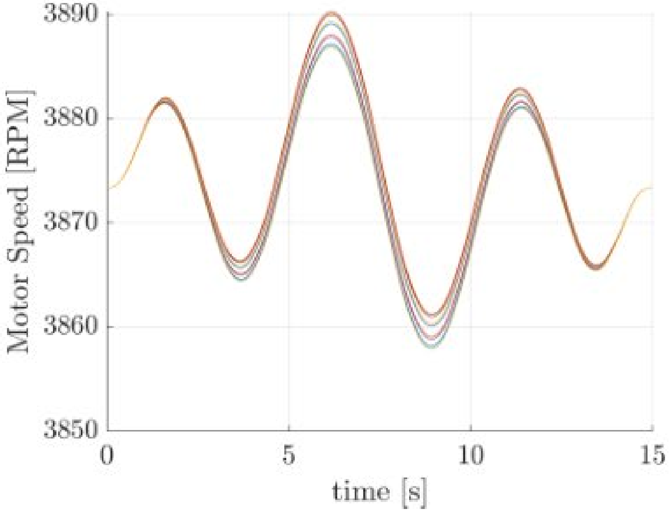


Resulting Trajectories

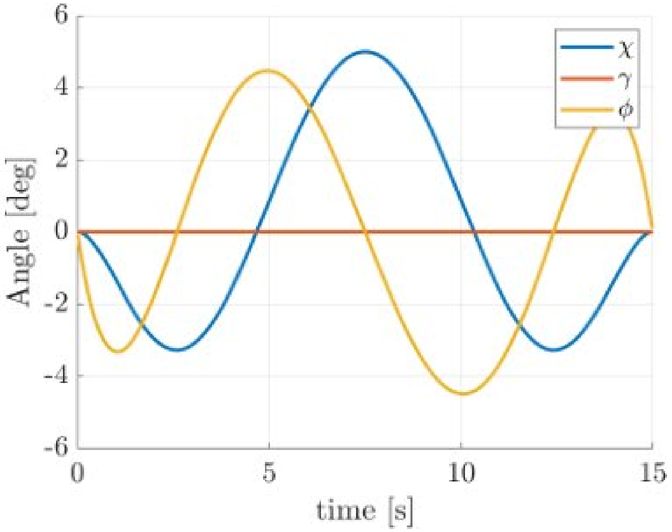
Scenario: Vehicle with must follow fixed spatial trajectory, while adjusting propeller phase angles.



Propeller phase angles between each pair of propellers.

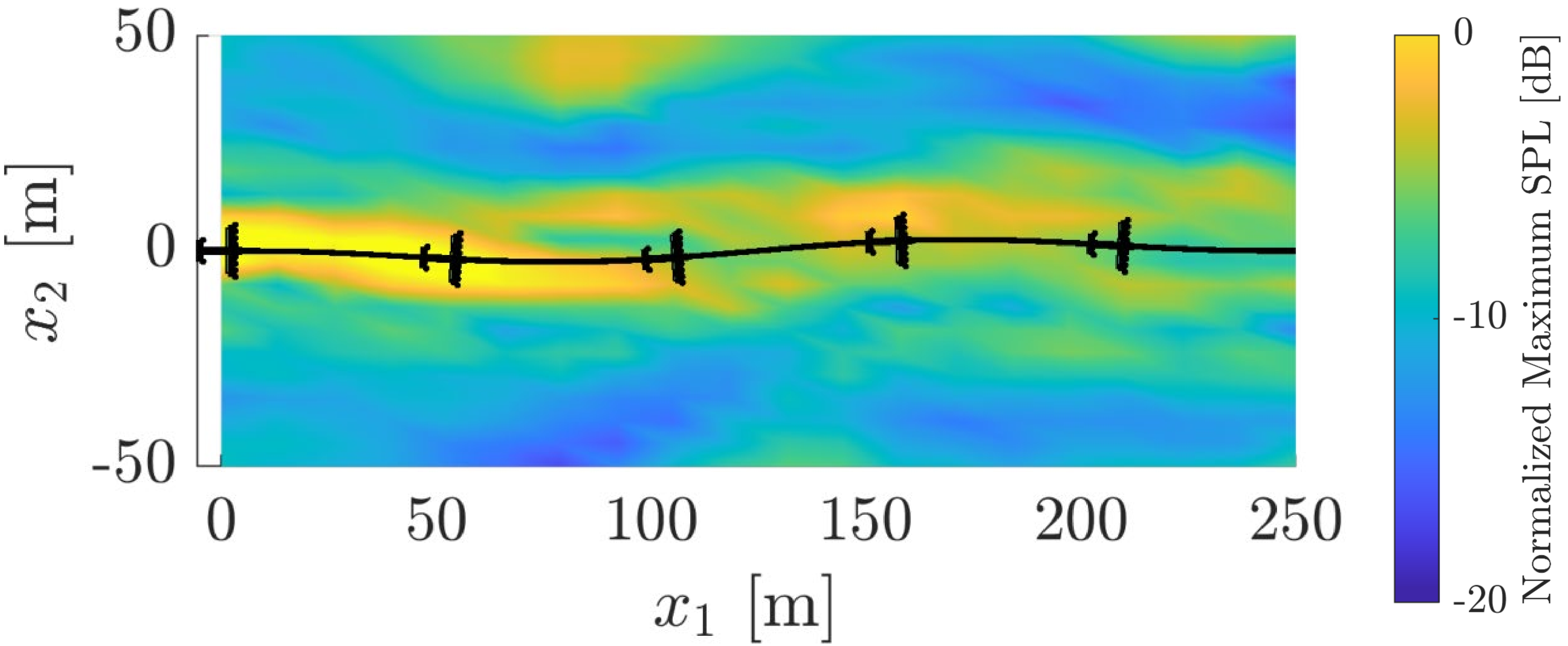


Vehicle propeller speeds, changing to meet both thrust and phase requirements.



Vehicle orientation over time, changing to meet spatial constraints.

Resulting Acoustic Performance



Acoustic performance for the phase transition scenario. The colors show the maximum sound pressure level (SPL) heard over the full duration of the flight.

Future Directions

- Higher fidelity acoustic models
    - Source hemisphere database
- Additional vehicle dynamics and low-level controller design
- Flight testing
    - Targeting single tilt-wing design under development at NASA Langley Research Center
- Integrate phase control into optimization framework

Summary and Future Directions

- Urban Air Mobility for the masses is a major component of user-driven, immediate and flexible air travel
- Autonomous flight for full market potential
- Biggest challenge for autonomous flight is contingency management, i.e. making decisions with incomplete information to respond to off-nominal events, both common and unforeseen
- Intelligent contingency management (ICM) and its control-centric approach is one of the enabling technologies
- Basic premise of vehicle ICM:
  - Vehicle aware of its internal state and external environment at all times
  - Ascertains its capability
  - Makes decisions about mission completion or modification
  - Robustification of decision making through multiple approaches and architectural framework
  - Layered approach to allow mature technologies to be incorporated into early phases of UAM
- Open questions we are trying to address
  - ☐ How can machine agents handle unforeseen contingency events?
  - ☐ How can machines intelligently make decisions in the presence of uncertain, unreliable, and incomplete information?
  - ☐ How can we assure learning ICM algorithms?

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This work has been supported by

NASA Transformative Tools and Technologies Revolutionary Air Mobility Project

NASA Revolutionary Vertical Lift Technologies Project

NASA Airspace Traffic Management Exploration Project

Thank you

QUESTIONS?

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