Acoustically-aware motion planning with nonlinear stochastic MPC*

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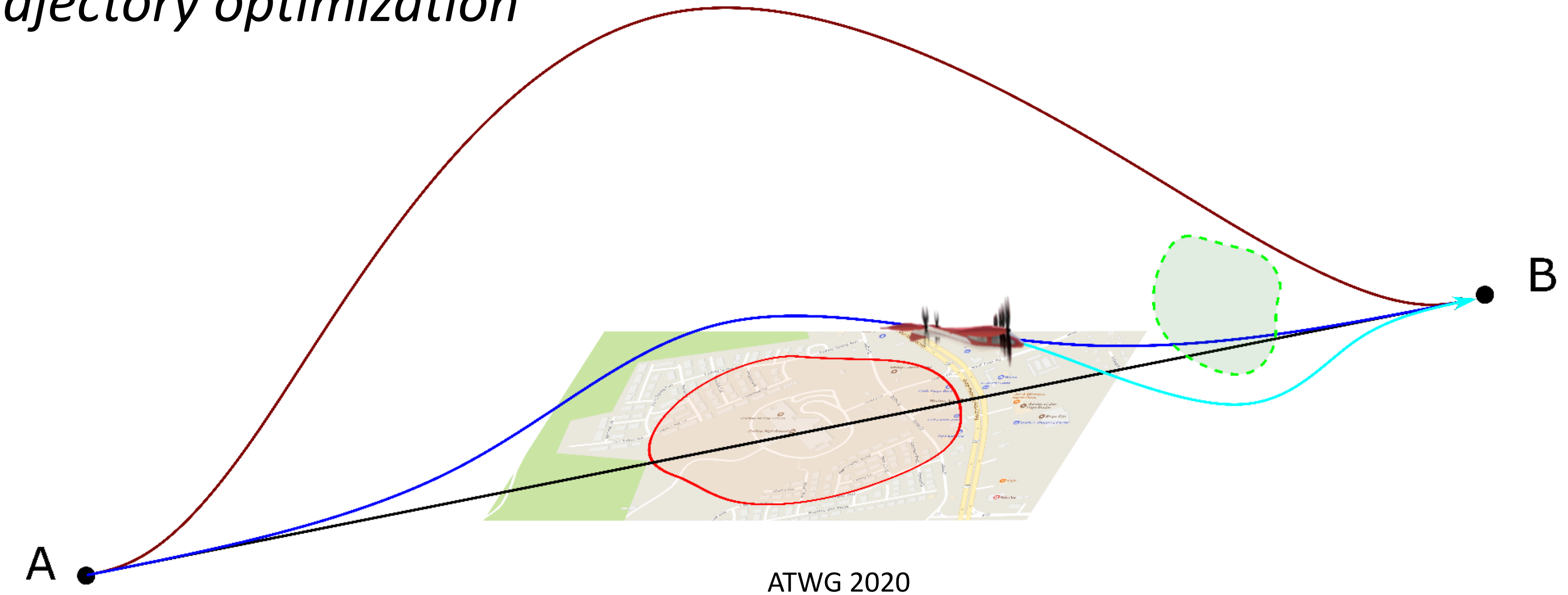
*KA Ackerman and IM Gregory, "A Model Predictive Control Approach for In-Flight Acoustic Constraint Compliance," AIAA SciTech Forum, Jan 2021.

Motivation

- Noise management is one of the major barriers to Urban Air Mobility (UAM)Model Predictive Path Integral control (MPPI) for trajectory planning
- Approaches to noise mitigation (non-exhaustive)
  - Vehicle configuration
  - Directivity control via propeller phase synchronization
  - *Trajectory optimization*



Objective

- Create framework for trajectory generation integrating location-based acoustic metrics and vehicle performance limitations
  - Mission-relevant constraints
    - Mission duration, airspace restrictions, …
  - Vehicle dynamic constraints
    - Aircraft structural limitations, min/max airspeed, …
  - Vehicle separation/obstacle avoidance
  - Acoustic constraints at a number of discrete observer locations

Prior Work

- Full trajectory optimization with polynomial parameterization
  - Simplified vehicle dynamics, acoustic source model, and propagation model
  - Bézier polynomial representation of spatial path and parametric speed
    - Computationally efficient algorithms
    - No discretization of trajectory or constraint functions
    - Constraints can be satisfied to arbitrary precision
  - Efficient for trajectory generation with low-fidelity models
  - Non-smooth nonlinear optimization problem
  - Requires differential flatness of dynamics and constraints
  - Cannot utilize mid- to high-fidelity acoustic source/propagation models

Approach

- Nonlinear stochastic model predictive control for finite horizon trajectory optimization
  - Arbitrarily complex dynamics and state cost function
  - Optimal control approximated via importance sampling
  - Computationally efficient through massive GPU parallelization
  - No differentiation of cost or constraint functions required
    - Due to sampling in place of, e.g., gradient descent
  - “Soft” constraint enforcement through cost function
  - Computed trajectory is suboptimal

Vehicle Dynamics

- 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
  - Dynamics:

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

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

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

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

$$\begin{bmatrix} T & \alpha & p_s \end{bmatrix}^{\mathsf{T}} = \boldsymbol{u}$$

*Adapted from J Hauser, R Hindman, “Aggressive Flight Maneuvers,” IEEE Conference on Decision and Control, 1997.

Vehicle Dynamics

- Aerodynamic model:

$$\boldsymbol{a}_v = \begin{bmatrix} \frac{T}{m}\cos\alpha - \frac{\rho V^2 S}{2m}\left(\sin\alpha\left(C_{N_0} + C_{N_\alpha}\alpha\right) + \cos\alpha\left(C_{A_0} + C_{A_{\alpha^2}}\alpha^2\right)\right) \\ 0 \\ -\frac{T}{m}\sin\alpha - \frac{\rho V^2 S}{2m}\left(\cos\alpha\left(C_{N_0} + C_{N_\alpha}\alpha\right) - \sin\alpha\left(C_{A_0} + C_{A_{\alpha^2}}\alpha^2\right)\right) \end{bmatrix}$$

- Propeller/motor model:

$$T = c_2(J)\omega_p^2 + c_1(J)\omega_p + c_0(J)$$

$$J = \frac{2\pi V \cos\alpha}{\omega_p d_p}$$

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

Acoustic Model

- Optional A-weighting
  - Metric is overall sound pressure level (OASPL)
  - Model fit from computational data from the Propeller Analysis System of the Aircraft Noise Prediction Program (PAS-ANOPP)
  - Based on effective propeller tip Mach number, $M_{\text{eff}} = \dfrac{M_t}{1 + J(1 - M_t)}, \quad M_t = \omega_p d_p / 2c$
  - Optional frequency weighting

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

$$R_A(f) = \frac{12194^2 f^4}{(f^2 + 20.6^2) \left[(f^2 + 107.7^2)(f^2 + 737.9^2) \right]^{1/2} (f^2 + 12194^2)}$$

$$f_k = k f_0 = k \frac{\omega_p N_b}{2\pi}$$

Motion Planning

- Model Predictive Path Integral Control (MPPI)*
  - Stochastic optimization technique used as nonlinear MPC
  - Framework to efficiently solve a finite horizon nonlinear optimal control problem
  - State cost function can be arbitrarily complex
  - Sampling-based optimization leverages GPU for efficient computation
- Description of method:
  - Information theoretic formulation used for this work
  - Sample thousands of control sequences, propagate trajectories in parallel
  - Weight-average sampled controls to compute optimal control sequence
  - Propagate optimal control sequence to obtain nominal trajectory

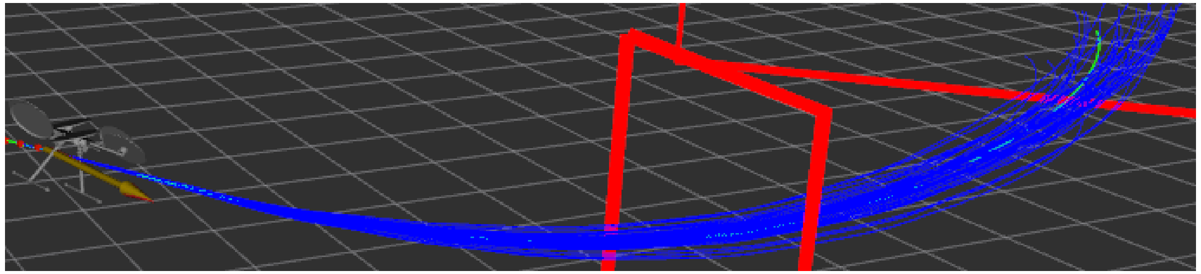


Figure credit: J Pravitra, KA Ackerman, N Hovakimyan, EA Theodorou, "L1-Adaptive MPPI Architecture for Robust and Agile Control of Multirotors," IROS, 2020.

*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.

Motion Planning

- Implementation*
  - Discrete-time dynamics $\boldsymbol{z}_{t+1} = \boldsymbol{f}(\boldsymbol{z}_t, \boldsymbol{\nu}_t), \ \boldsymbol{\nu}_t \sim \mathcal{N}(\boldsymbol{u}_t, \boldsymbol{\Sigma})$
  - Cost functional

$$\boldsymbol{J}(\boldsymbol{U}) = \mathbb{E}\left[\phi(\boldsymbol{z}_{t+T}) + \sum_{k=t}^{t+T-1} q(\boldsymbol{z}_k) + \lambda \boldsymbol{u}_k^\top \boldsymbol{\Sigma}^{-1}(\boldsymbol{\nu}_k - \boldsymbol{u}_k)\right]$$

  - State cost and control weight for each control sequence

$$S(\boldsymbol{V}_t^i) = \phi(\boldsymbol{z}_{t+T}^i) + \sum_{k=t}^{t+T-1} q(\boldsymbol{z}_k)$$

$$w(\boldsymbol{V}_t^i) = \exp\left[-\frac{1}{\lambda}\left(S(\boldsymbol{V}_t^i) - \sum_{k=t}^{t+T-1} \boldsymbol{u}_t' T \boldsymbol{\Sigma}^{-1} \boldsymbol{\nu}_k^i - \beta\right)\right]$$

  - Approximate optimal control

$$\boldsymbol{u}_t^* \approx \boldsymbol{u}_t = \boldsymbol{u}_t' + \frac{1}{\sum_{i=1}^{N_s} w(\boldsymbol{V}_t^i)} \sum_{i=1}^{N_s} w(\boldsymbol{V}_t^i)(\boldsymbol{\nu}_t^i - \boldsymbol{u}_t^i),$$

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

Motion Planning – Application

- Dynamics $\boldsymbol{z}_t = \begin{bmatrix}\boldsymbol{x}_t & \boldsymbol{v}_t & \boldsymbol{q}_t & T_t & \alpha_t\end{bmatrix}^\mathsf{T}$

$$\boldsymbol{z}_{t+1} = \boldsymbol{z}_t + \begin{bmatrix}\boldsymbol{v}_t & \boldsymbol{g} + \boldsymbol{R}\boldsymbol{a}_{v,t} & \frac{1}{2}\boldsymbol{q}_t \otimes \begin{bmatrix}0 \\ \boldsymbol{\omega}_{v,t}\end{bmatrix} & \dot{T} & \dot{\alpha}\end{bmatrix}^\mathsf{T} \Delta t$$

- Sampled controls $\boldsymbol{\nu}_t = \begin{bmatrix}\dot{T}_t & \dot{\alpha}_t & p_{s,t}\end{bmatrix}^\mathsf{T}$

- Running cost – Track spatial path at constant speed while maintaining noise at observers below threshold

$$q(\boldsymbol{z}_t) = \frac{1}{N_s}(\boldsymbol{\xi}_k - \boldsymbol{\xi}_d)^\mathsf{T}\boldsymbol{Q}_2(\boldsymbol{\xi}_k - \boldsymbol{\xi}_d) + \|\max\{\boldsymbol{0}, \boldsymbol{Q}_1(\boldsymbol{\xi}_k - \boldsymbol{\xi}_d)\}\|_1$$

$$\boldsymbol{\xi} = \begin{bmatrix}\boldsymbol{x}_i^\mathsf{T} & V & \boldsymbol{OASPL}^\mathsf{T}\end{bmatrix}^\mathsf{T}$$

$$\boldsymbol{Q}_2 = \mathrm{diag}\left(\begin{bmatrix}0 & 100 & 100 & 10e3 & 0\end{bmatrix}\right)$$

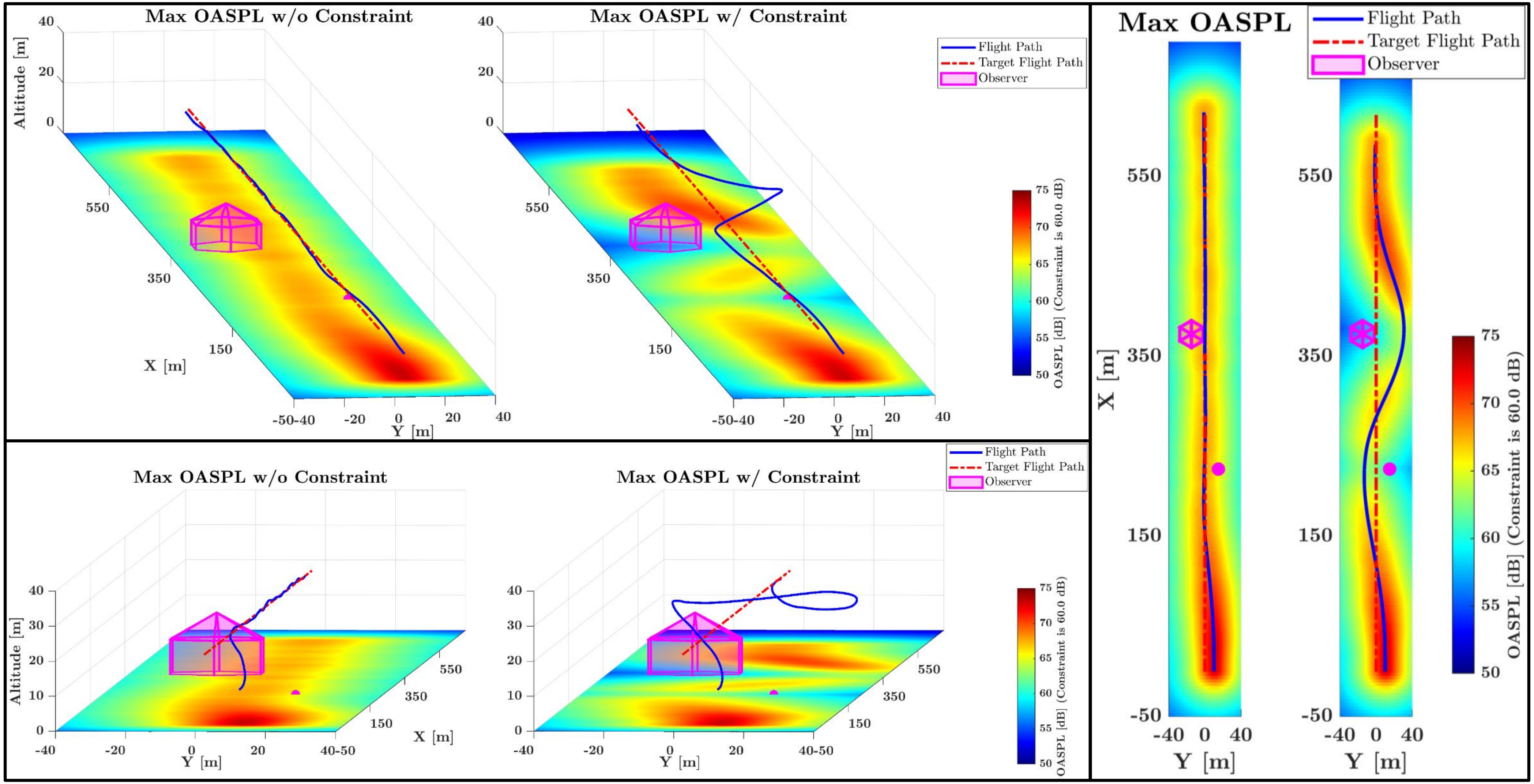
$$\boldsymbol{Q}_1 = \mathrm{diag}\left(\begin{bmatrix}0 & 0 & 0 & 0 & 200e3\end{bmatrix}\right)$$

$$\boldsymbol{\xi}_d = \begin{bmatrix}0 & 10 & -10 & 27.5 & 65\end{bmatrix}^\mathsf{T},$$

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

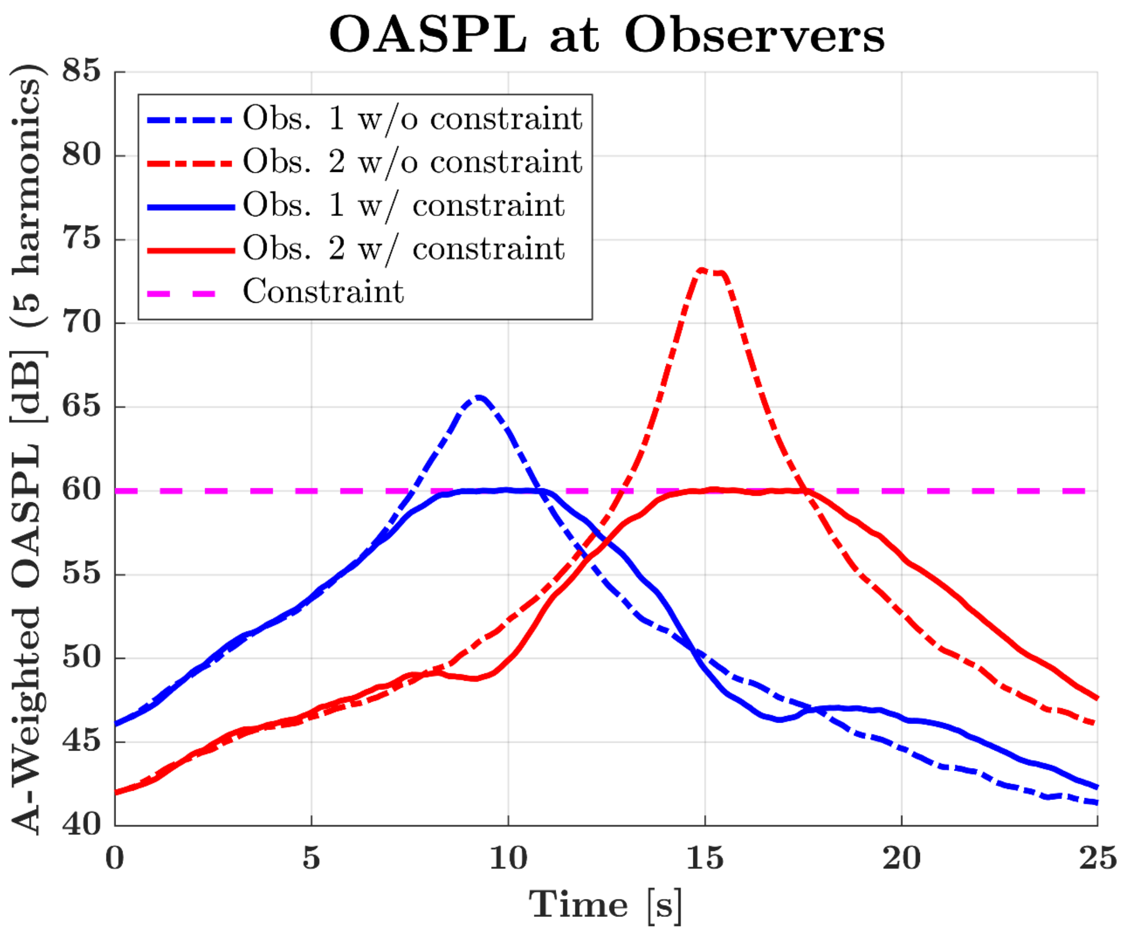
Simulation Results

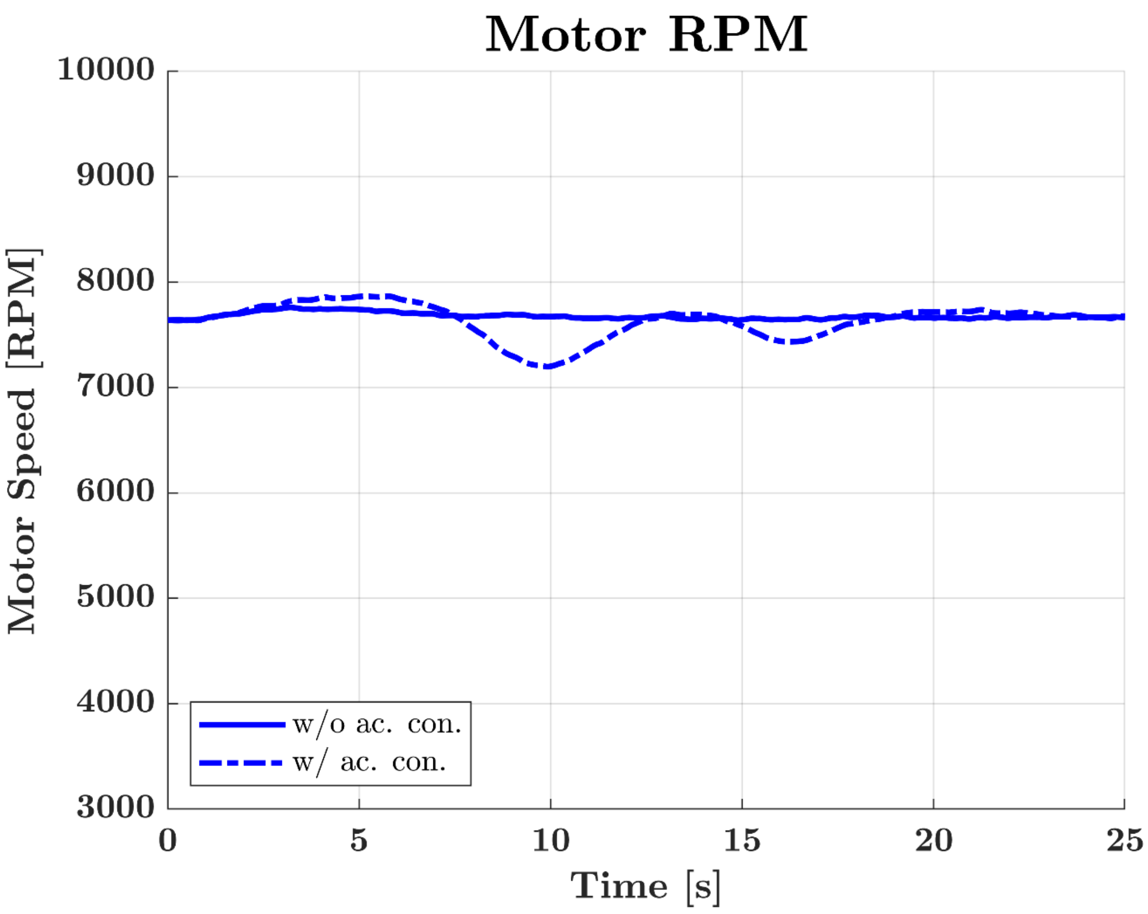
- Side-by-side flight path comparison with acoustic footprint



Simulation Results

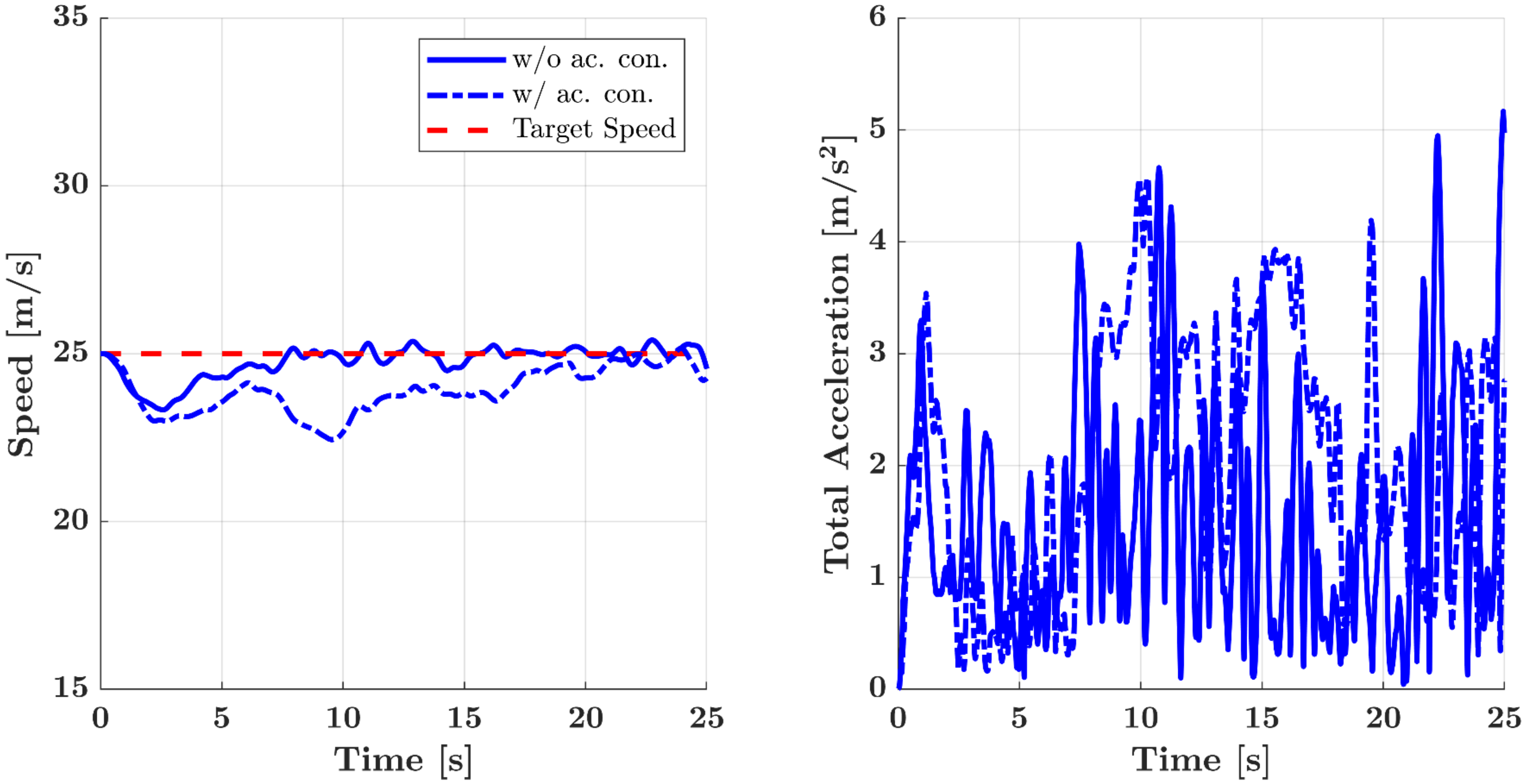
- OASPL at both observers and propeller RPM





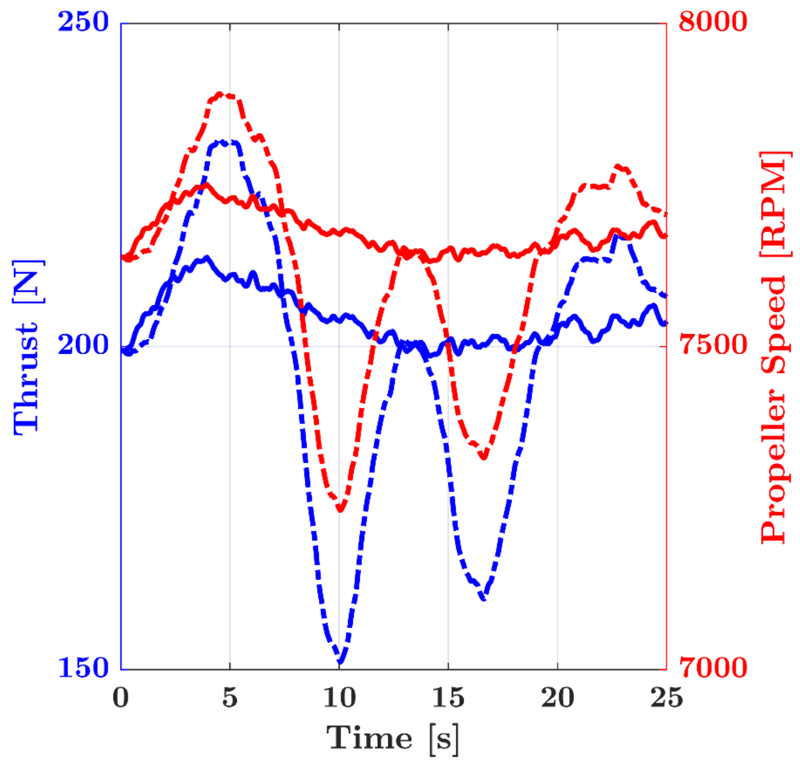
Simulation Results

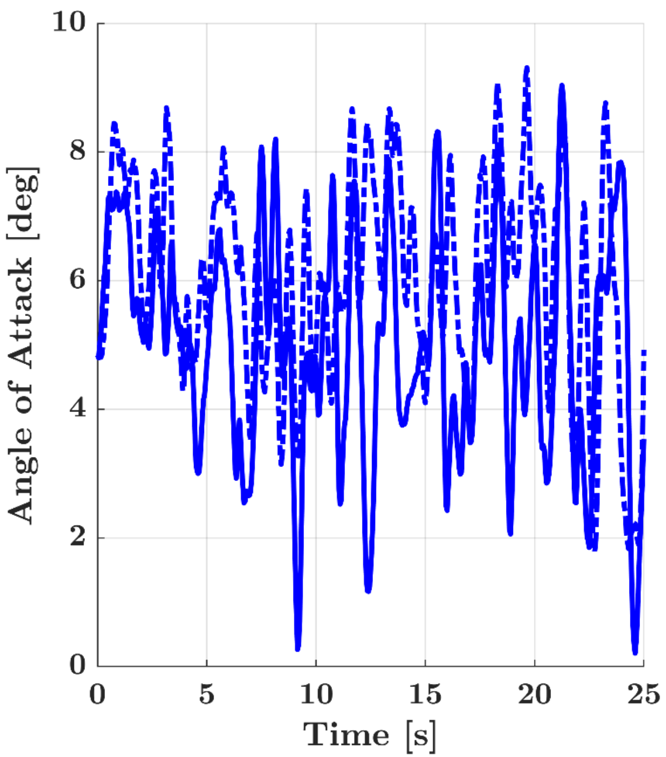
- Speed and total acceleration

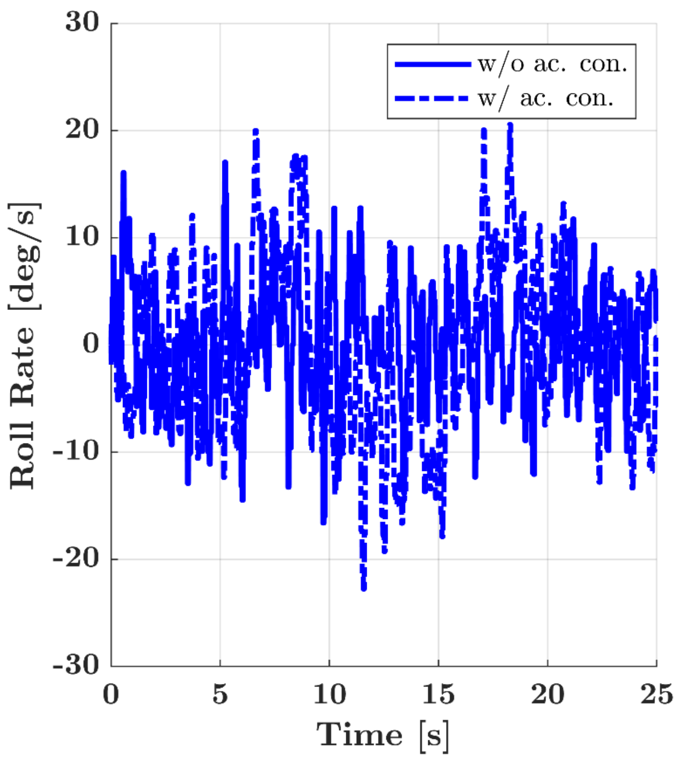


Simulation Results

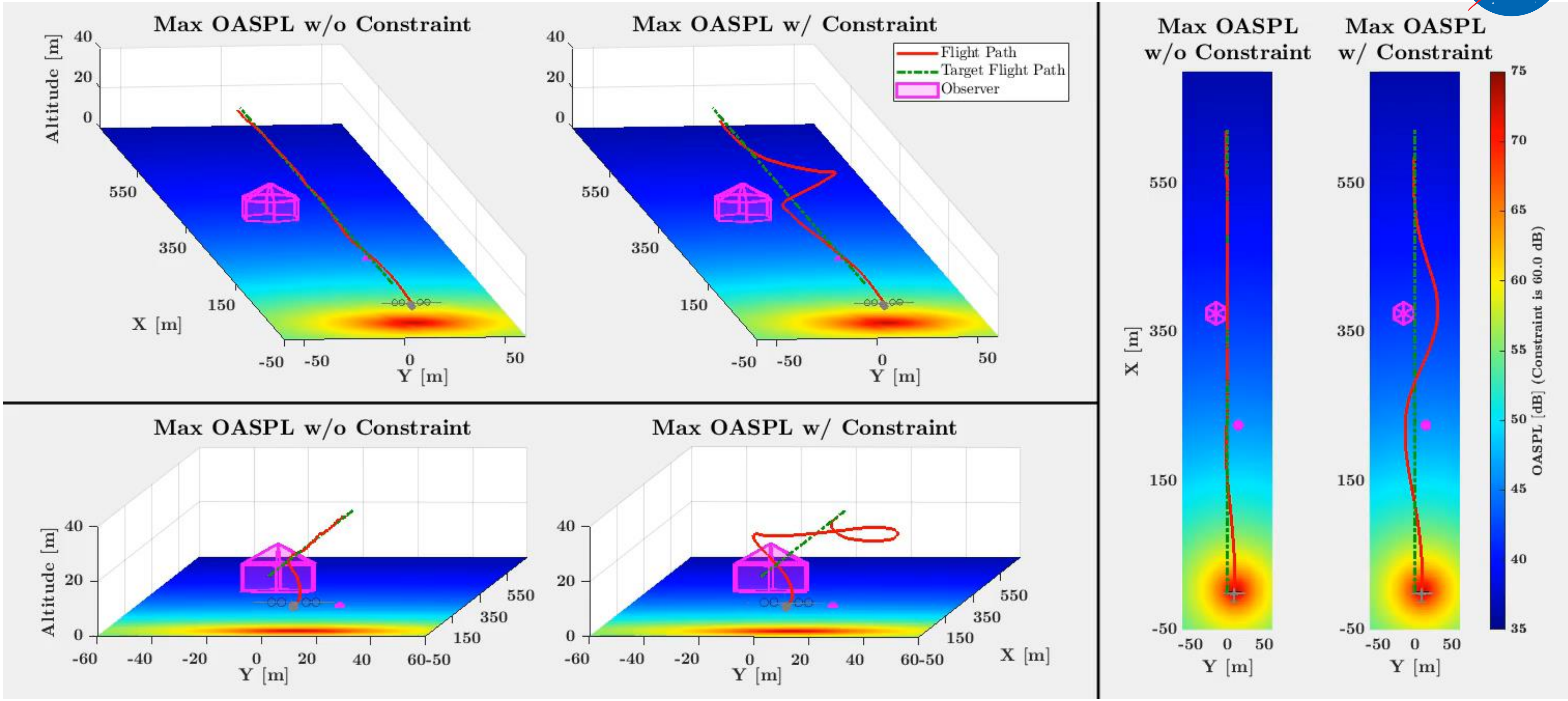
- Control states
  - Variability introduced by probabilistic control sampling
    - Facilitates state space exploration but introduces noise in control channel
    - (Non-causal) filtering of optimal control sequence reduces high frequency content
    - Spectral power concentrated below 1-2 Hz







Simulation Results – Video



*Aircraft is animation only, not to scale or representative

Summary

- Motion planning with nonlinear stochastic MPC
  - Fixed-wing, coordinated-flight aircraft
  - MPPI control law trajectory optimization
- Multiple 3D observers
  - Polytope definition for efficient distance queries
- Multiple-fidelity acoustic model
  - Harmonics and frequency weighting optional
- Simulation results demonstrate ability to modify trajectory in real-time to satisfy acoustic constraints

Future Directions

- Higher fidelity acoustic models
  - Source hemisphere database
- Additional vehicle dynamics and low-level controller design
- Integration with directivity control
  - Propeller phase control under development at University of Illinois at Urbana-Champaign
- Flight testing
  - Targeting single tilt-wing design under development at NASA Langley Research Center

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