Real-Time Safe and Efficient Navigation in Windy Urban Environments

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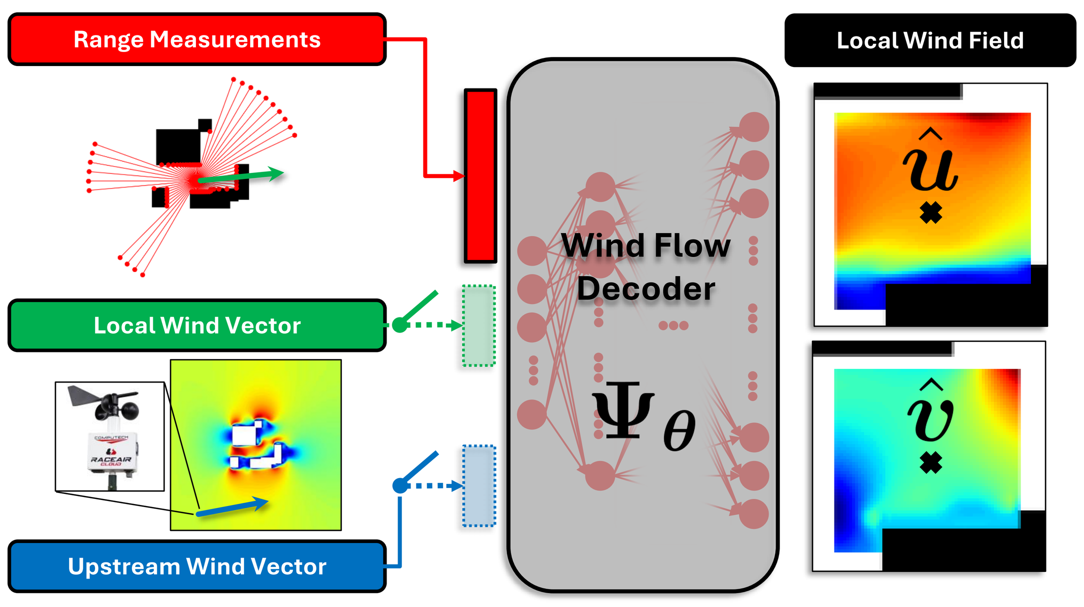
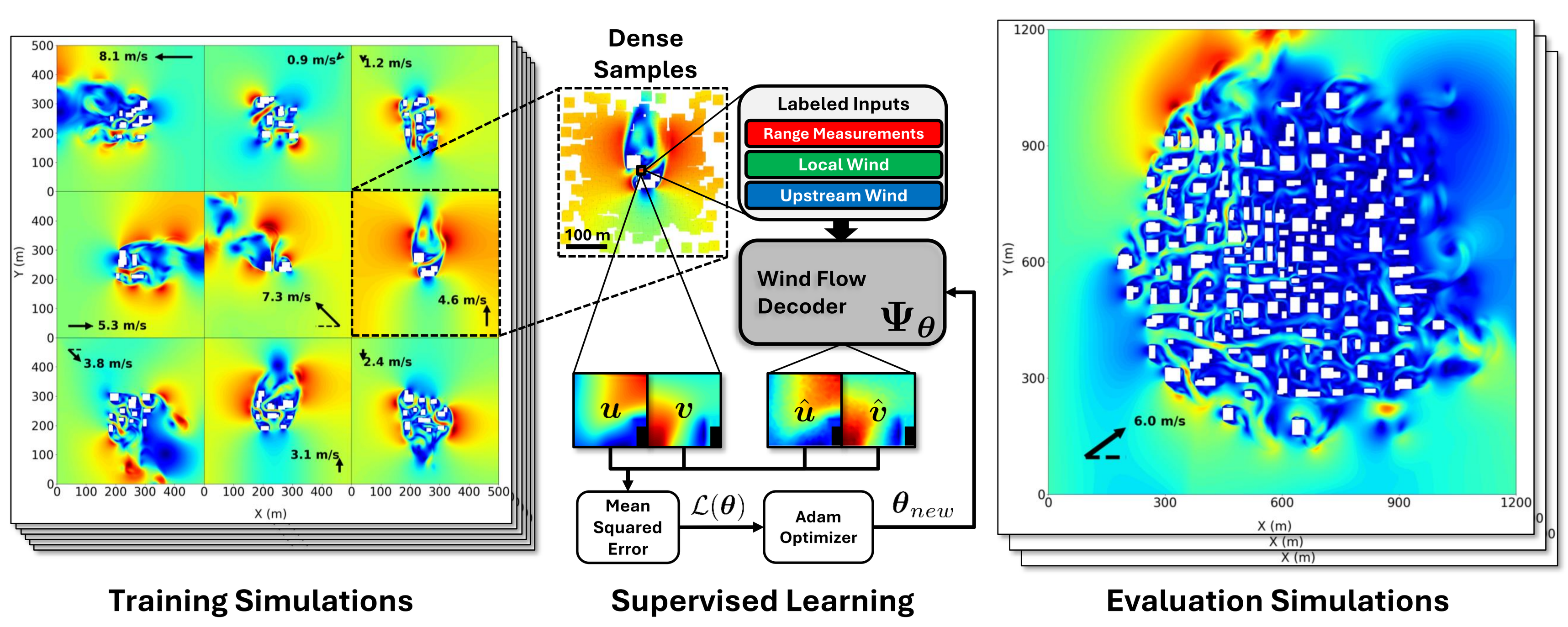
Enabling autonomous aerial robots to "see" complex wind flow fields and adjust flight paths in real time to fly safer and more efficiently in urban environments.

Local Wind Prediction with Deep Learning

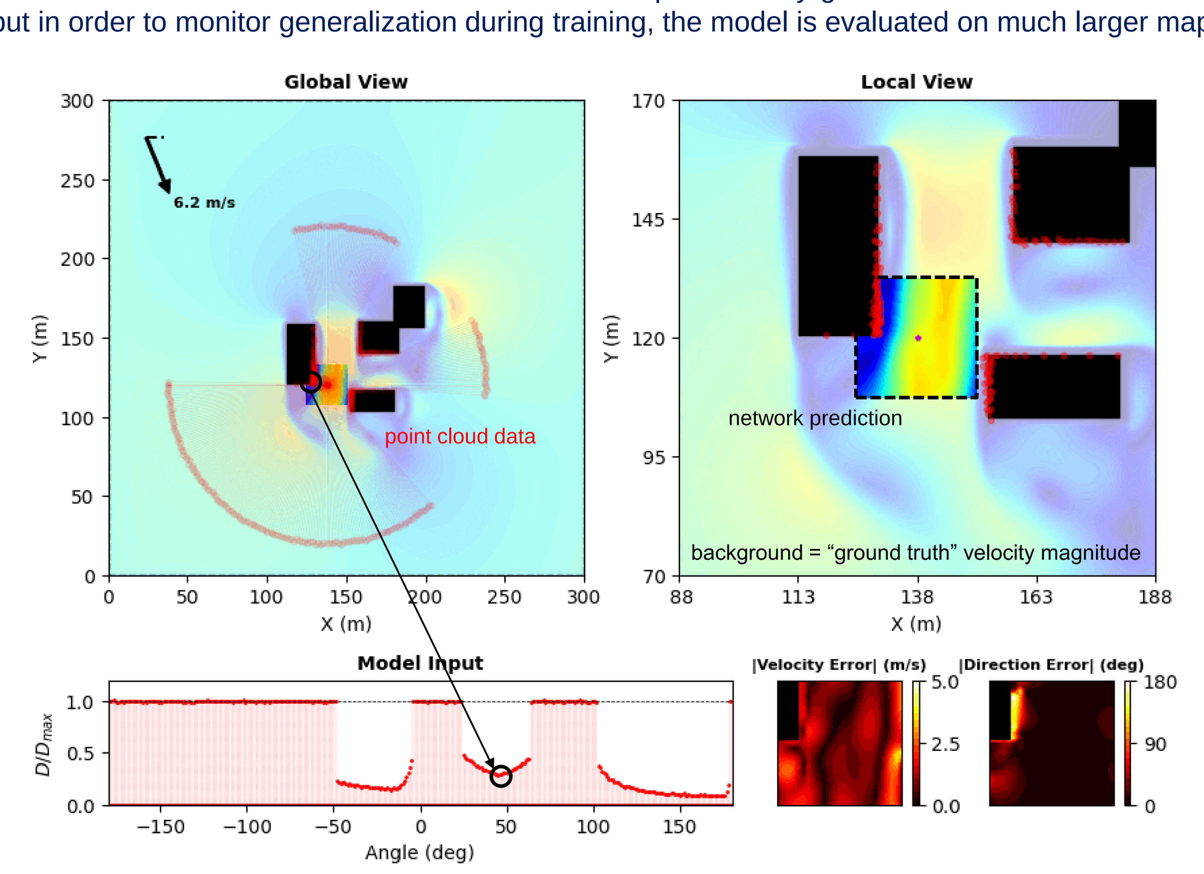
TLDR *Urban winds are complex spatial and temporal fields that pose a critical barrier for autonomous urban aircraft operations. We present a way to predict surrounding wind patterns in real time relying on onboard sensors.*



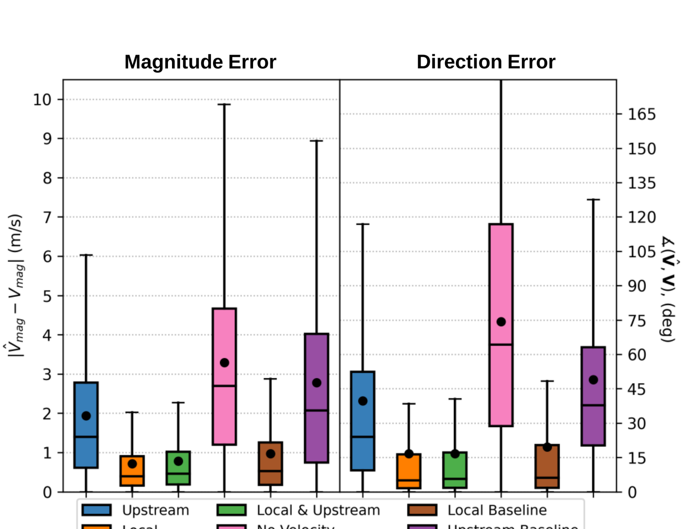
Methodology: LiDAR range measurements are combined with sparse measurements of the wind at the robot's location and/or from an upstream weather station. The output of the neural network are the x/y components of the wind flow *field* centered at the robot's location.



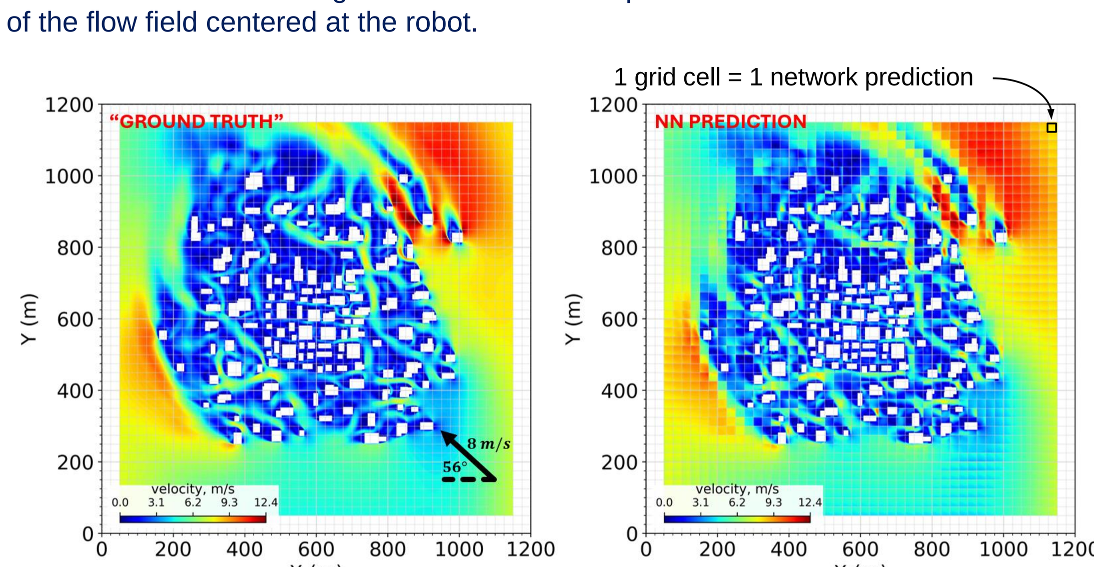
Training Pipeline: The decoder network is trained on thousands of procedurally-generated urban wind flow fields on small maps, but in order to monitor generalization during training, the model is evaluated on much larger maps.



In Action: At a given instant, the model takes flattened range measurements and produces a prediction of the flow field centered at the robot.



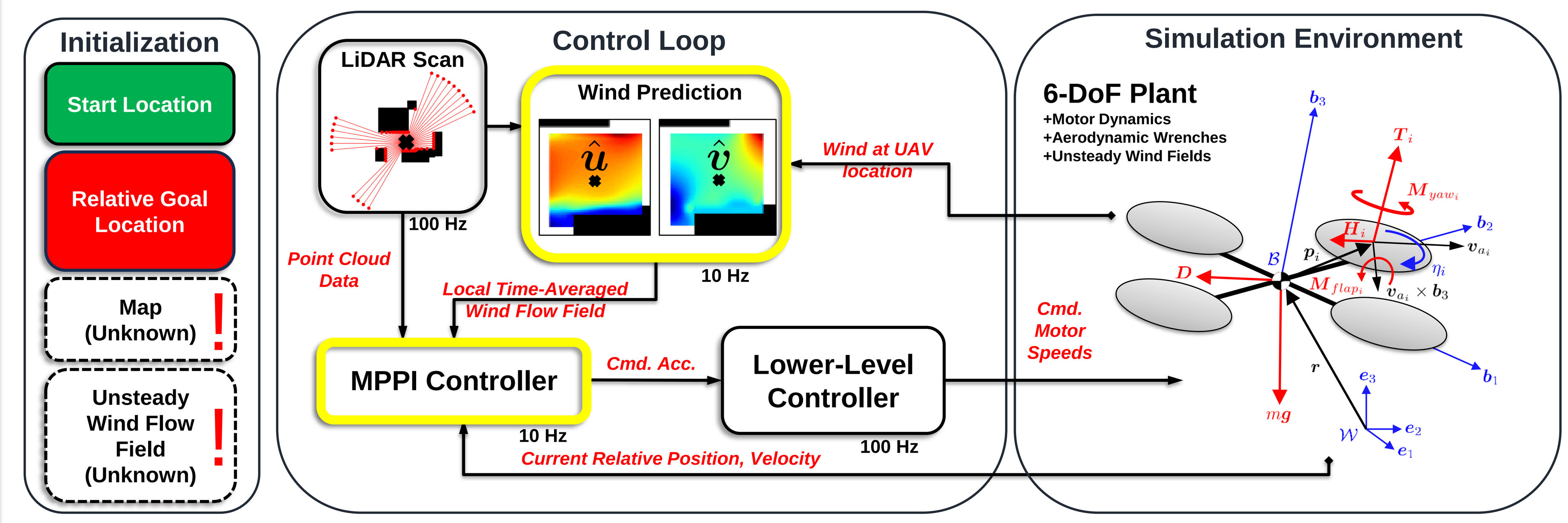
Ablation Study: Local in-situ velocity measurements are critical for accurate prediction.



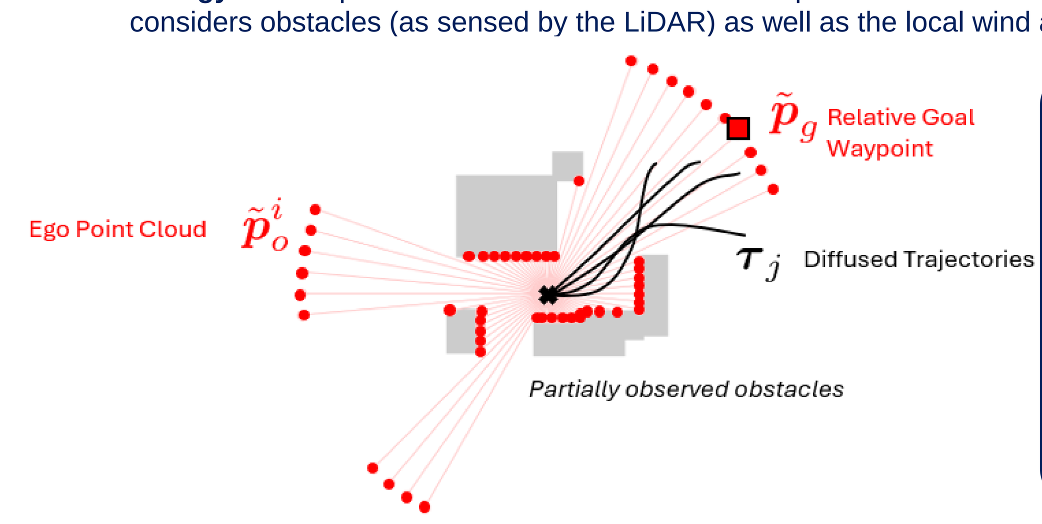
Global Reconstruction: Large persistent flow features (e.g. "urban rivers") can be recovered by flying the UAV around an environment.

Wind- and Energy-Aware MPC

TLDR *Urban winds introduce risky and inefficient routes for aircraft. We formulate a receding horizon planner exploiting local wind information to find routes through these complex flow conditions, in real time, that are safe and efficient.*



Methodology: LiDAR point cloud data is fed into the wind prediction module to provide a local wind information. The MPPI controller considers obstacles (as sensed by the LiDAR) as well as the local wind and produces a low-rate thrust vector command.



Model Predictive Path Integral (MPPI) Control

1. Generate many future trajectories using randomly sampled admissible control inputs and an abstracted dynamics model.
2. Score each possible trajectory based on a user-defined cost function.
3. Compute the best next control action that minimizes the user-defined cost function over a horizon.
4. Take one control step, receive new measurements, and repeat steps 1-3.

1. Dynamics Model

$$\mathbf{x}_k := \begin{bmatrix} \tilde{\boldsymbol{p}}_k \\ \boldsymbol{v}_k \end{bmatrix}$$

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \begin{bmatrix} \boldsymbol{v}_k \\ \mathbf{u}_k + \boldsymbol{d}(\boldsymbol{v}_k, \boldsymbol{w}_k) \end{bmatrix} \Delta t$$

3. Control Law

$$\mathbf{u}_k^* = \frac{\sum_{j=0}^{N_\tau} \left(\exp\left(-\frac{1}{\lambda} J(\boldsymbol{\tau}_j)\right) \boldsymbol{u}_{k,j}\right)}{\sum_{j=0}^{N_\tau} \exp\left(-\frac{1}{\lambda} J(\boldsymbol{\tau}_j)\right)}$$

2. Trajectory Scoring Functions

"progress to goal"

$$J_{prog}(\tau) = \sum_{k=0}^{N_k+1} (\tilde{\mathbf{p}}_k - \tilde{\mathbf{p}}_g)^\top (\tilde{\mathbf{p}}_k - \tilde{\mathbf{p}}_g)$$

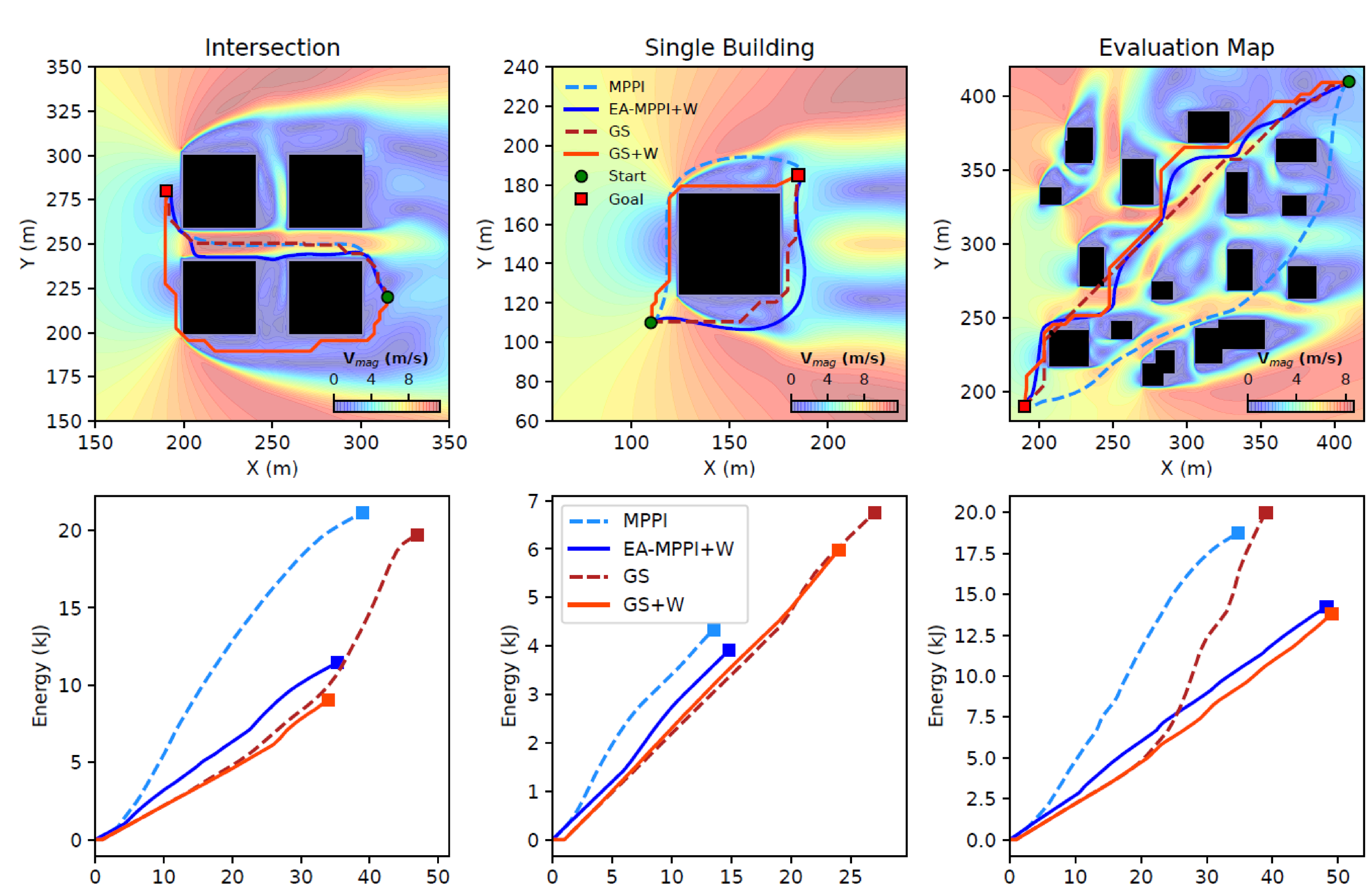
"minimize energy"

$$J_{energy}(\tau) = \sum_{k=0}^{N_k+1} (P(\boldsymbol{v}_k, \boldsymbol{w}_k)\Delta t)$$

$$\boxed{J(\boldsymbol{\tau}) = J_{prog}(\boldsymbol{\tau}) + Q_O J_{obs}(\boldsymbol{\tau}) + Q_E J_{energy}(\boldsymbol{\tau})}$$

"avoid obstacles"

$$J_{obs}(\tau) = \min_{\tilde{\mathbf{p}}_{0:N_k+1}, \tilde{\mathbf{p}}_o^{0:n_r}} \left[\frac{1}{(\tilde{\mathbf{p}}_k - \tilde{\mathbf{p}}_o^i)^\top (\tilde{\mathbf{p}}_k - \tilde{\mathbf{p}}_o^i)}\right]$$

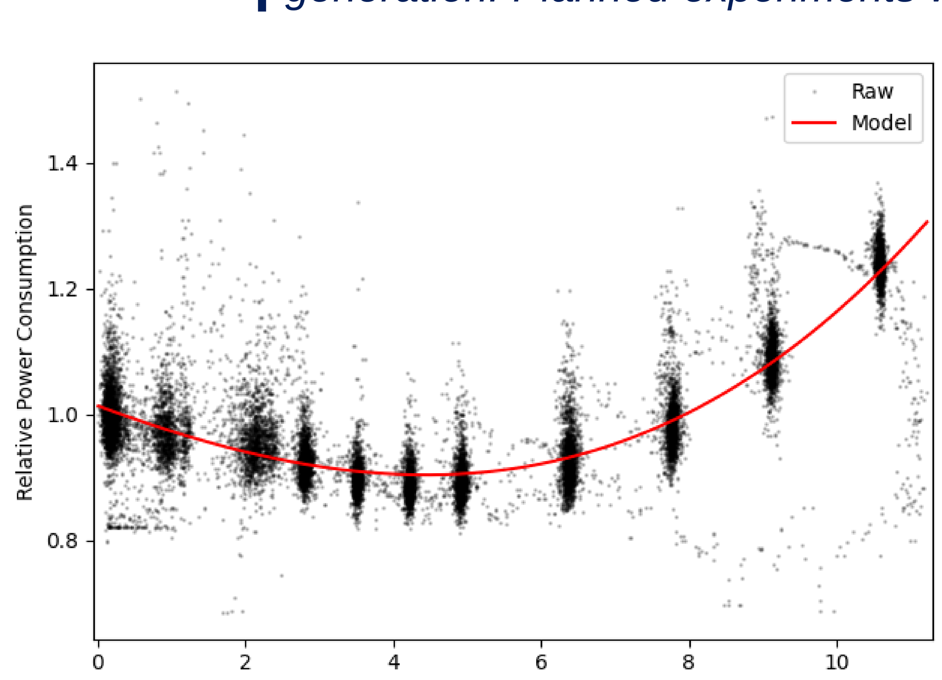


Case Studies: The local wind-aware planner produces paths remarkably similar to globally optimal solutions[1] despite solving in real time. Energy-aware planners adjust not only the path but also the flight speed to minimize energy.

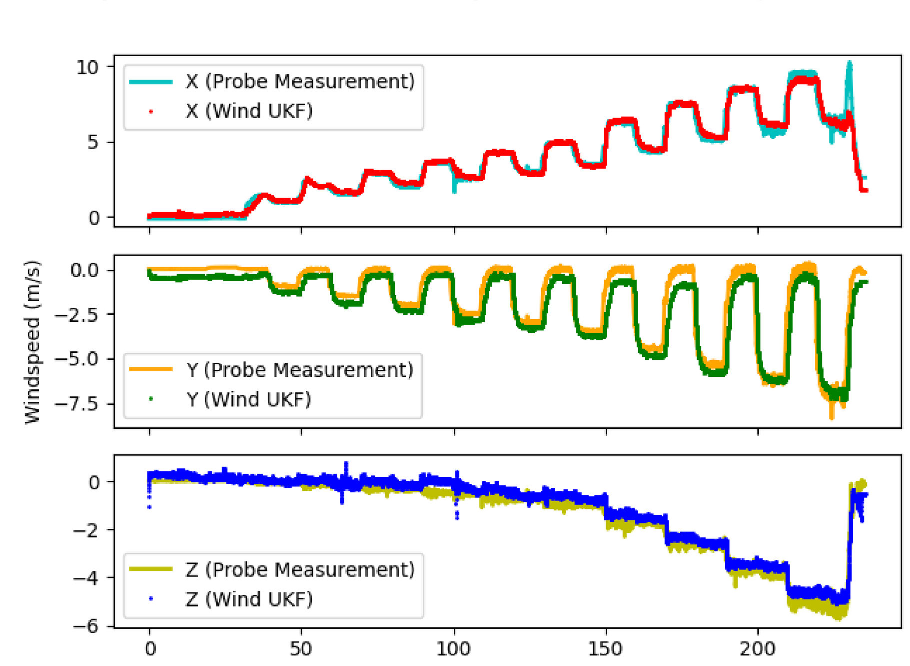
J. Ware and N. Roy, "An analysis of wind field estimation and exploitation for quadrotor flight in the urban canopy layer," 2016 IEEE International Conference on Robotics and Automation (ICRA), Stockholm, Sweden, 2016, pp. 1507-1514, doi: 10.1109/ICRA.2016.7487287.

Scaled Hardware Experiments for Urban Aircraft Operations Research

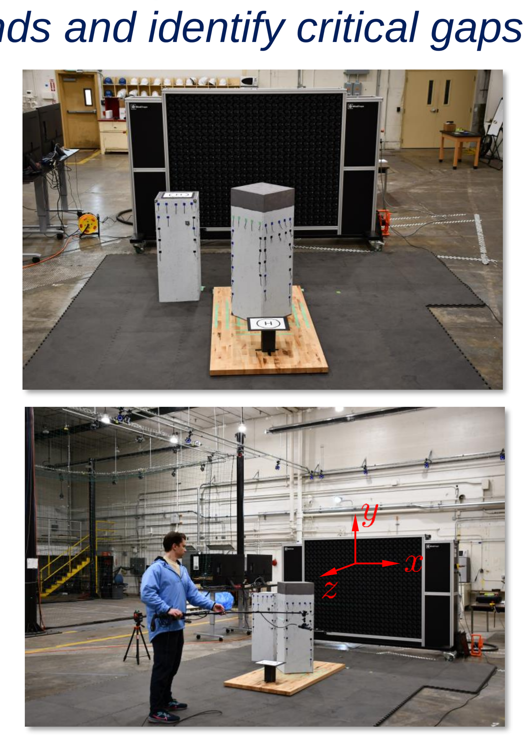
TLDR *We are developing a novel laboratory environment to study autonomous urban aerial operations with a particular emphasis on understanding how wind affects autonomous flight in the urban canopy layer. The facility features a 40x70x14-ft motion capture space with a free flight wind tunnel with 1134 programmable fans for spatio-temporal flow field generation. Planned experiments will attempt to validate concepts above using real world winds and identify critical gaps between simulation and reality.*

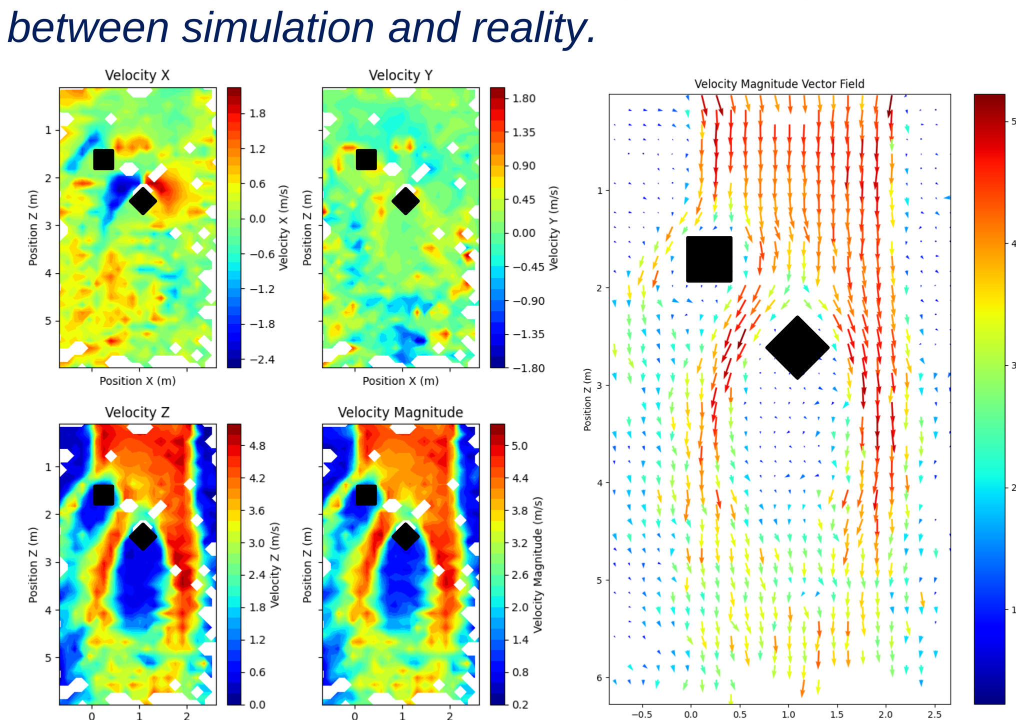


Power Characterization: Constructing a model of steady state power consumption as a function of wind.



Model-Based Wind Estimation: Calibrating and validating indirect wind filters to provide estimates of the wind at the robot's location.





Scaled Urban Winds: Establishing urban winds that can be probed for an accurate "ground truth" to use for fine tuning models, repeatable experiments for statistical significance, and insight into algorithmic behavior in real winds.

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