Flying Anemometers: From Drone Dynamics to Urban Wind Forecasts

PhD proposal • Department of Aerospace Engineering
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Motivation and objective. Urban wind flows are highly unsteady and spatially heterogeneous: buildings generate turbulent wakes, flow separation, recirculation and intense local gusts. These disturbances challenge safe, energy-efficient drone operations, including urban inspection, delivery, emergency response and rooftop landing. Reliable, high-resolution wind forecasts would also support airborne contaminant-dispersion predictions and the identification of wind-hazard zones. Yet fixed anemometer networks offer limited spatial coverage, while high-fidelity flow simulations are computationally expensive and difficult to update in real time. **Drones offer an alternative solution to this challenge. Their dynamics can be used to estimate local wind without dedicated onboard anemometers.** This PhD will investigate whether shared wind estimates from a cooperating drone team can **train and continuously update a reduced-order latent predictive model of urban wind**, using only sparse drone-derived observations. The resulting forecasts will inform cooperative flight planning and urban-level operation. In turn, drones will be directed towards locations where new measurements are most valuable, **closing the sensing–prediction–control loop**.

Research questions.

RQ1 **Learning from drone observations:** Can a spatially continuous, reduced-order model of urban wind be learned exclusively from sparse, mobile drone-derived measurements and low-fidelity priors, without full-field training data?

RQ2 **Closed-loop swarm control:** Can shared wind forecasts and uncertainty improve cooperative, safe and energy-efficient flight planning while guiding drones towards informative sensing locations?

RQ3 **Operational value:** To what extent can the predicted wind support dynamic wind-hazard/no-go maps, gust-aware rooftop landing and contaminant-dispersion assessment?

RQ4 **Forecasting and generalisation:** Can the reduced-order predictive model generalise under unseen inflow directions, velocities, gusts and incomplete spatial coverage?

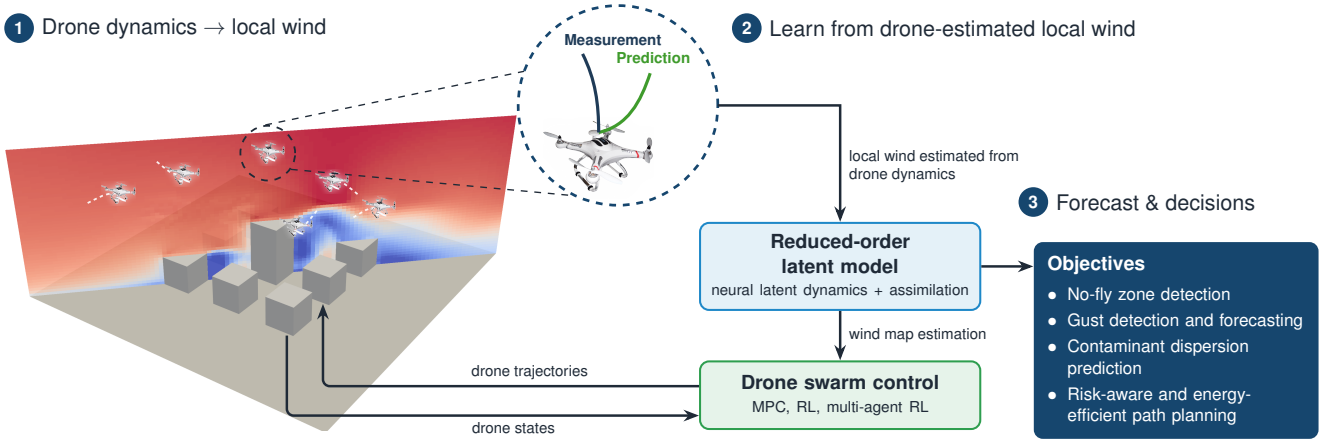


Figure 1: Closed-loop research framework. Drone-derived wind measurements train and update a latent predictive model; its forecasts support cooperative control, sensing and applications.

Methodology. **WP1 – Drone-based wind sensing.** Building on established indirect wind-estimation methods, each drone will combine a calibrated dynamic model with navigation, inertial and actuation data to estimate local wind velocity and its uncertainty [1]. The work will focus on calibration, temporal resolution and measurement reliability, rather than claiming indirect wind sensing itself as a new method. **WP2 – Drone-only latent model learning.** Geolocated, time-stamped wind estimates from repeated flights will train a geometry-aware latent neural operator. The model will learn its reduced representation, spatial reconstruction and temporal evolution directly from irregular observations by predicting withheld measurements and subsequent drone samples [5]. A prior learned from drone-only observation histories will initialise new missions, and arriving measurements will then update the latent state through data assimilation. **WP3 – Wind forecasting and robustness.** The assimilated model will generate short-term, three-dimensional wind forecasts and uncertainty estimates. Prediction skill will be tested for unseen wind speeds and directions, transient gusts, noise, communication gaps and sparse drone coverage. The study will establish where reconstruction is sufficiently observable and where uncertainty or limited measurements make predictions unreliable. **WP4 – Cooperative active sensing and applications.** Shared forecasts will guide multi-agent trajectory planning, balancing information gain, collision avoidance, limited communication, field-of-view constraints, mission progress and energy use. Multi-agent Reinforcement Learning (RL) and Model Predictive Control (MPC) strategies will be investigated for drone dynamic control. The closed loop can be assessed through wind-hazard/no-go mapping, gust-aware landing, risk-aware and energy-efficient routes, and contaminant-dispersion forecasts under prescribed release scenarios.

Positioning, validation and feasibility. Indirect drone wind estimation is an established method [1]; Swarm-based four-dimensional wind field reconstruction has recently been demonstrated in a synthetic turbulent environment, but without addressing temporal forecasting or urban wind flow estimation [2]. Existing urban reduced-order assimilation and sensor-optimisation approaches generally build on CFD-based flow information [3, 4], while recent neural operators offer tools for learning from partial observations [5]. **The PhD novelty lies in developing a reduced-order predictive model of urban wind flows from drone-based wind measurements, enabling wind-aware urban air mobility operations and closing the sensing–estimation–prediction loop through informative trajectory planning.**

[1] Z. Ahmed, M. H. Halefom, C. A. Woolsey, Tutorial review of indirect wind estimation methods using small uncrewed air vehicles, *J. Aerosp. Inf. Syst.* 21(8):667–683, 2024.

[2] A. Tasim, W. Sun, Physics-informed reconstruction of four-dimensional atmospheric wind fields using multi-UAS swarm observations in a synthetic turbulent environment, arXiv:2601.22111, 2026.

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[4] Y. Liang et al., Sensor optimization for urban wind estimation with a cluster-based probabilistic framework, *Phys. Fluids*, 38(4): 045131, 2026.

[5] J. Hou et al., Learning neural operators from partial observations via latent autoregressive modeling, *Proc. AAAI* 40(1):390–398, 2026.