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Focus	Better, Faster, With Less: Accelerating Drone Design Process for Challenging Environments
Design Process	The work targets the aerodynamic analysis and verification stage of drone design for challenging environments, where design decisions and simulation results need to iterate rapidly for control and optimisation purposes. The Mars drone case study was used to test whether machine learning accelerated surrogate aerodynamic model could be brought earlier into the design loop, before expensive physical prototyping. CFD will have been used for data collection and validation.
Tools Used	High-fidelity CFD simulations for training data generation; a custom geometry-aware and time-aware machine-learning surrogate model; data preparation and post-processing workflows for velocity, pressure, lift, and drag histories; and presentation outputs prepared for the Digital Design Network+ research challenge. Platform test will be carried out for future study.
Links	Will be released after we publish.

Executive Summary

This case study explored how machine learning can accelerate simulation-led drone design for challenging environments. Using the Mars helicopter as a representative system, the work focused on replacing repeated high-cost CFD runs with a machine learning (ML) surrogate model that can predict unsteady flow behaviour, pressure fields, and aerodynamic performance much more quickly.

A training dataset was generated from CFD across different geometries, operating conditions, and time steps. The resulting geometry-aware, time-aware model demonstrated strong learning convergence and produced useful predictions for velocity, pressure, and lift/drag trends, including across different angles of attack. The outcome is a workflow that can support earlier design iteration and virtual verification, real-time control and optimisation.

Problem

Drone design in challenging environments is slow because design and simulation are tightly coupled, yet the simulation step is expensive and manual. Engineers often spend significant time iterating between geometry changes and CFD runs, while formal verification activities are delayed until late-stage prototypes are available. For Mars-relevant systems, the aerodynamic regime is especially demanding, so the cost of exploration rises further. The design problem addressed here was how to preserve CFD-level insight while reducing turnaround time enough to support fast iteration and earlier virtual verification.

Digital Design Solution

The solution was an ML-accelerated fast-simulation workflow trained on CFD data. First, a structured training dataset was prepared from CFD cases spanning relevant geometries, flow conditions, and angles of attack. The surrogate model was then designed to be geometry-aware and time-aware, enabling it to predict future flow fields from a reference input frame and a set of conditional parameters. The results show convergence in both training and validation loss, qualitative agreement between predicted and ground-truth velocity/pressure fields, generalisation across various angle of attacks, and extension to different geometries with time-evolving lift and drag traces. In effect, the approach turns high-fidelity simulation data into a reusable digital design asset rather than a one-off analysis.

How it makes Digital Design Better, Faster and/or With Less

The main benefits are speed and cost. Once trained, the model produces flow-field and performance predictions far faster than running a fresh CFD simulation for each iteration. This enables more design options to be screened at the concept stage, shortens the loop between geometry changes and feedback, and supports earlier requirement checking using virtual models.

The approach also improves digital design quality by making simulation evidence more accessible throughout the process, rather than only at isolated milestones. In practical terms, it reduces manual effort, makes better use of existing simulation data, and creates a pathway toward lower-cost exploration of the design space.

Reflections

The work showed that ML surrogates can be genuinely useful for aerodynamic design, but only when the training data and problem formulation are tightly aligned with the intended design questions. Generalisation remains the central challenge: it is not enough to predict well on familiar cases; the model must also be trusted on new geometries, operating points, and time horizons.

This points to the need for uncertainty quantification, physics-aware learning, and clearer integration with optimisation workflows. Beyond the model itself, adoption will depend on reliable data pipelines, interpretable validation criteria, and tools that fit naturally into how engineers already make design decisions. The future-work directions identified in the presentation - uncertainty quantification, PINN-based physical consistency, and geometry optimisation with reinforcement learning are therefore our next steps.

References

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Appendix

[Supporting media available from the presentation materials includes:

- Training and validation loss curves showing rapid convergence at different epochs.
- Predicted vs ground-truth flow fields for velocity and pressure, including absolute-error plots.
- Generalisation examples for different angles of attack, including AoA = 7 -9 degs.
- Geometry-aware and time-aware prediction examples with lift and drag histories.