PhD Research Proposal

Title:

AI-Enabled Aircraft Engine Prediction and Fault Detection & Diagnosis (FDD) Framework for Next-Generation Intelligent Aircraft Systems

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1. Introduction

Modern aircraft depend on complex aerodynamic, mechanical, and control subsystems. Ensuring high aerodynamic efficiency and preventing unexpected failures is essential for safety, cost reduction, and mission performance. However, traditional aerodynamic modeling techniques (e.g., CFD) and conventional maintenance strategies (e.g., scheduled or reactive maintenance) face major limitations, including high computational cost and low responsiveness to emerging faults.

With advancements in Artificial Intelligence (AI) and Machine Learning (ML), new opportunities exist to create **intelligent, data-driven, and predictive aeronautical systems** that combine aerodynamic modeling with **Fault Detection and Diagnosis (FDD)** capabilities.

This PhD research proposes a unified **AI-aerodynamics-FDD framework** that predicts aircraft aerodynamic behavior, optimizes performance, and autonomously detects and diagnoses faults in critical subsystems such as control surfaces, actuators, sensors, and aerodynamic components.

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2. Background and Problem Statement

Aircraft faults—such as actuator degradation, sensor drift, control surface jamming, and structural fatigue—can severely affect aerodynamic performance, destabilize flight, and increase fuel consumption.

Current limitations include:

- **CFD models require extensive computation** and cannot support real-time decision-making.
- **Most FDD systems rely on rule-based or threshold-based logic**, which fails under dynamic flight conditions.
- **Aerodynamic models rarely integrate FDD**, although faults significantly influence aerodynamic forces.
- Lack of **robust integration between aerodynamic predictions, flight control, and FDD** using AI/ML.

AI/ML methods can revolutionize this domain by enabling:

- Fast surrogate aerodynamic models
- Autonomous flight control adaptation
- Intelligent FDD for early detection of deviations
- Data-driven decision-making in uncertain conditions

This motivates the need for an end-to-end AI framework that unifies aerodynamics, flight control, and FDD.

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3. Research Objectives

Primary Objective

Develop an integrated **AI-based aerodynamic prediction and FDD framework** enabling intelligent, adaptive, and fault-resilient aircraft systems.

Specific Objectives

1. Develop **ML-based surrogate models** for predicting aerodynamic coefficients and flow fields with high accuracy.
2. Implement **Physics-Informed Neural Networks (PINNs)** to incorporate aerodynamic physics with machine learning.
3. Design a **Reinforcement Learning (RL)–based adaptive flight control system** capable of handling aerodynamic variations and external disturbances.
4. Develop an **AI-powered FDD module** to detect, isolate, and diagnose faults in aircraft subsystems such as control surfaces, actuators, sensors, and structural components.
5. Validate the integrated model using CFD datasets, wind-tunnel data, simulated flight logs, and fault injection experiments.

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4. Research Questions

1. Can ML surrogate models replace or augment high-cost CFD for real-time aerodynamic prediction?
2. How can PINNs improve aerodynamic prediction accuracy while reducing computational burden?

3. How effectively can RL optimize flight control in the presence of faults and uncertainties?
4. Can AI-based FDD accurately detect actuator, sensor, and aerodynamic faults before they become safety-critical?
5. How can aerodynamic predictions and FDD decisions be integrated for fault-resilient flight control?

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5. Literature Review Summary

- **Aerodynamic Prediction:** CNNs and U-Nets show potential for pressure field estimation but lack generalization across flight regimes.
- **PINNs:** Effective for solving simplified Navier–Stokes equations but require validation for high Reynolds number flows.
- **RL in Aerospace:** Used for basic control (e.g., pitch stabilization), but rarely integrated with aerodynamic models or fault scenarios.
- **FDD:** ML-based FDD is well-studied in engines and sensor networks but not deeply combined with aerodynamic behavior modeling.

Key gaps:

- Lack of an integrated AI framework for **aerodynamics + FDD + control**.
- Limited datasets combining aerodynamic behavior with fault states.
- Inadequate use of hybrid physics + data-driven models for FDD.

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6. Proposed Methodology

6.1 Data Collection

- CFD-generated datasets for various aircraft geometries
- Wind-tunnel testing datasets
- Flight simulation data (X-Plane, Simulink Aerospace, JSBSim)
- Sensor-level fault datasets (actuator degradation, sensor noise, bias)
- Synthetic fault injections for FDD validation

6.2 ML-Based Aerodynamic Surrogate Modeling

- Use **CNN/U-Net/Transformer** architectures to predict lift, drag, moment coefficients, and pressure fields.
- Apply **Autoencoders** for reduced-order modeling.
- Embed physics constraints using **PINNs** to respect governing fluid equations.

6.3 Reinforcement Learning for Flight Control

- Develop RL agents (PPO, DDPG, SAC) to optimize:
  - Angle of Attack (AoA)
  - Control surface deflection
  - Energy-efficient trajectories
- Introduce **fault scenarios (stuck actuators, sensor bias)** to train fault-resilient agents.

6.4 FDD Module Development

Types of faults to be analyzed:

- **Actuator faults:** jamming, loss of effectiveness
- **Sensor faults:** bias, noise, drift
- **Control surface faults:** deformation, hinge failure
- **Aerodynamic faults:** icing, surface roughness, flow obstruction

Methods for FDD:

1. **Supervised ML models**
   - Random Forest
   - XGBoost
   - LightGBM
2. **Deep Learning methods**
   - LSTM/GRU for time-series sensor data
   - Autoencoder-based anomaly detection
   - Transformer-based fault classification
3. **Hybrid FDD**

- Integrating aerodynamic surrogate models for fault validation
- Using aerodynamic signatures (e.g., sudden drop in lift)

6.5 Integrated Framework

The proposed system will integrate:

- **Aerodynamics Module** (Predictive)
- **Fault Detection & Diagnosis Module**
- **RL Control Module**
- **Decision-making Unit**

The framework will run in a loop:

1. Predict aerodynamic state
2. Detect and diagnose faults
3. Adjust flight control decisions dynamically

6.6 Validation

- Compare surrogate vs CFD for accuracy metrics
- Inject faults in simulation environments
- Evaluate FDD performance (accuracy, detection time, false alarms)
- Flight tests using small UAV prototypes (if permitted)

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7. Expected Outcomes

1. High-fidelity **AI surrogate aerodynamic models** replacing expensive CFD for real-time estimation.
2. Intelligent **FDD system** capable of detecting faults early with >95% accuracy.
3. Autonomous **RL-based controller** ensuring stable flight even during actuator/sensor failures.
4. A unified **AI-aerodynamics-FDD platform**, publishable in top aerospace journals (AIAA, Elsevier).

5. Practical contributions to UAVs, eVTOLs, hybrid aircraft, and future autonomous aviation systems.

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8. Contribution to Knowledge

This PhD research will:

- Provide one of the first unified frameworks linking **aerodynamics + AI + FDD + control**.
- Reduce computational load for aerodynamic analysis by up to 90%.
- Improve aircraft safety through intelligent, autonomous, real-time fault handling.
- Advance the field of resilient autonomous aviation.

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9. Timeline (4 Years)

Year	Work Plan
Year 1	Literature review, baseline CFD + ML models, initial surrogate modeling
Year 2	PINN development, dataset expansion, surrogate model validation
Year 3	Develop RL control + full FDD module, fault injection experiments
Year 4	System integration, UAV testing, thesis writing, publications