

PHYSICS-INFORMED NEURAL NETWORKS FOR SYNTHETIC AIR DATA ESTIMATION

Álvaro Ribeiro Gomes de Oliveira⁽¹⁾, Roberto Dias Pereira⁽²⁾, Luiz Carlos S. Góes⁽¹⁾

⁽¹⁾Instituto Tecnológico de Aeronáutica

⁽²⁾EMBRAER

Keywords: Physics-Informed Neural Networks, Synthetic Air Data, Uncertainty Quantification, Flight Dynamics, System Identification

Abstract

Air Data Systems (ADS) comprised of airspeed (V), angle of attack (α), and sideslip angle (β) are key inputs to most modern flight control systems. Envelope protection, performance monitoring, and autopilot functions all depend on them. Pitot tubes and mechanical flow-angle probes measure these quantities, but because they are directly exposed to the airflow, they are vulnerable to icing, debris accumulation, and common-mode failures. Synthetic Air Data Systems (SADS) aim at estimating air data from inertial and navigation sensors (IMU and GPS), using a mathematical model of the aircraft aerodynamics as a physical constraint. Many estimation methods have been used as SADS including Extended Kalman Filters paired with linearized aerodynamic models, which marked the first generation of solutions. These approaches work well near the linearization point but degrade when the flight condition moves away from the nominal regime. More recently, data-driven methods based on neural networks have been explored. Such methods gain flexibility, but without structural constraints a neural network may produce physically implausible outputs when extrapolating beyond its training data, and it forgoes the interpretability of a model-based approach. This work proposes a Physics-Informed Neural Network (PINN) framework for synthetic air data estimation capable of simultaneously recovering airspeed (V), angle of attack (α), and angle of sideslip (β), while identifying aerodynamic and control derivatives from flight data. The idea consists of embedding the governing differential equations directly into the training loss so that the network is forced to respect the underlying physics while still benefiting from the representational capacity of deep learning. PINNs have been applied to aerodynamic flow prediction, flight parameter estimation, and aerodynamic coefficient identification. No previous work has reported a complete PINN-based SADS that jointly estimates air data states and aerodynamic parameters, incorporates atmospheric modeling, and provides uncertainty quantification in a single framework. The proposed framework recovers V , α , β and simultaneously identifies aerodynamic coefficients through a composite physics-

informed loss that combines 6-DOF dynamics residuals with a trigonometric consistency constraint linking predicted air data to measured body-frame velocities, with thermodynamic quantities derived from the U.S. Standard Atmosphere 1976. A deep ensemble of models and split conformal prediction provide calibrated prediction intervals. The approach is evaluated on unseen test flights from a 100-flight dataset, and both strengths and limitations are reported. These results establish the PINN framework as a viable architecture for sensor-independent air data estimation, with the physics embedding providing both improved generalization and interpretable coefficient recovery. Identified limitations include the assumption of flight-condition-invariant aerodynamic coefficients and the absence of hard parametric constraints during training.