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Communauté d'universités et établissements de Toulouse

Data Fusion and Data-driven Estimation for Air Data Sensors Fault Diagnosis

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ANITI The PhD Project

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AIRBUS

- Data
- Performance constraints
- Application knowledge

ANITI Université Fédérale Toulouse Midi-Pyrénées

- AI expertise

LAAS CNRS

- Diagnosis expertise
- Research methodology
- Doctoral supervision

Problem definition

Given a dynamic system that at any time can be **subject to a fault affecting one of its sensors**.

Objective: conceive a **data-driven monitoring** algorithm capable of:

- **Detecting** sensor faults**,**
- **isolating** the affected sensor and
- providing **uninterrupted estimation** of the affected measurement.

We are interested on the **sub-class of dynamical systems** evolving according to:

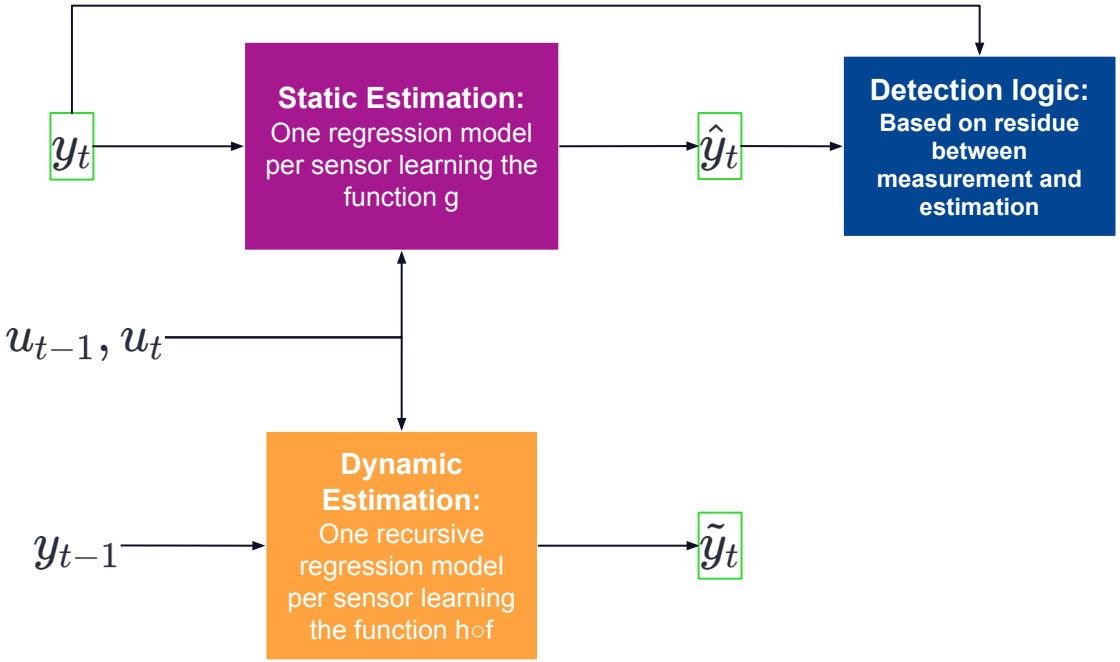
$$\begin{cases} x_t = f(x_{t-1}, u_t) + q_t & \text{(State-transition equation)} \\ y_t = h(x_t, u_t) + r_t & \text{(Observation equation)} \\ g(y_t, u_t) = s_t & \text{(Analytical constraint)} \end{cases}$$

- $x_t \in \mathbb{R}^m, y_t \in \mathbb{R}^n, u_t \in \mathbb{R}^o$ are the state vector, observation vector and input vector respectively
- $q_t \sim \mathcal{N}(0, Q_t), r_t \sim \mathcal{N}(0, R_t), s_t \sim \mathcal{N}(0, S_t)$ are random variables sampled from centered normal distributions representing noise terms.
- f, h, g are non-linear, potentially unknown, functions. The function g represents a constraint associating observations and inputs that is obeyed when all sensors behave nominally, i.e. without fault.

Proposed solution: the NDOS

$$\begin{cases} x_t = f(x_{t-1}, u_t) + v_t \\ y_t = h(x_t, u_t) + w_t \\ g(y_t, u_t) = 0 \end{cases}$$

Neural Double Observer Scheme



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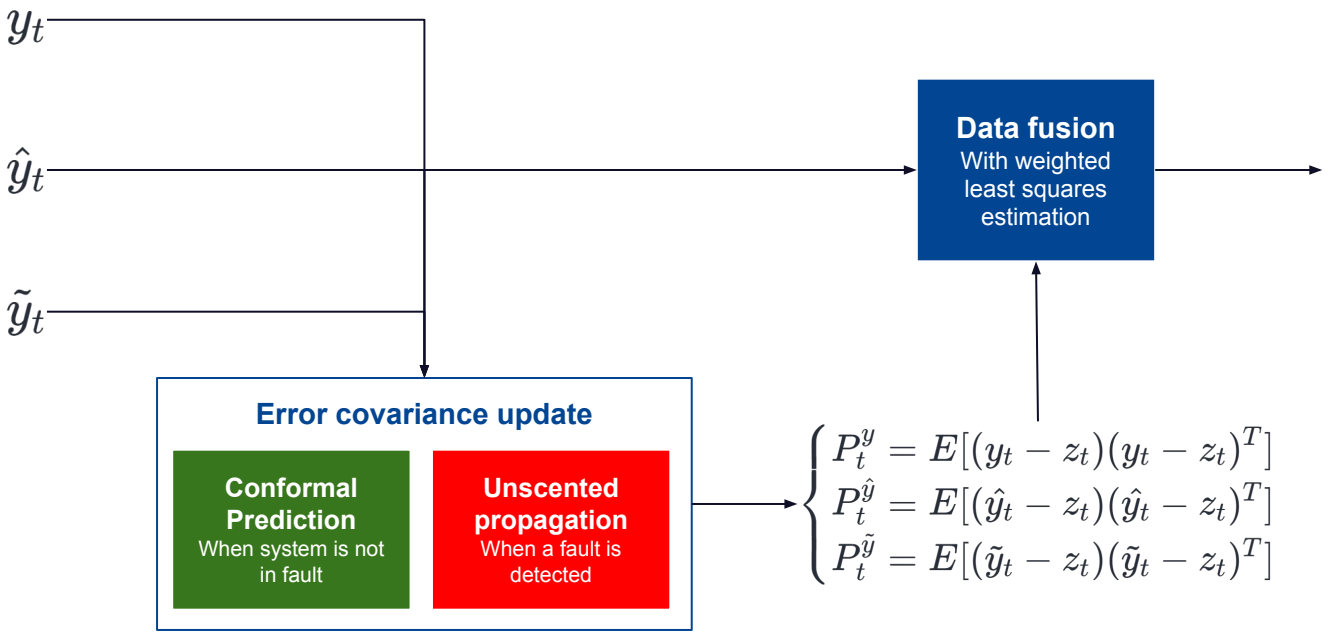
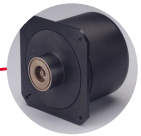


An estimation of the measurements robust to sensor faults

Application case: air data sensors

Angle-of-attack vane (incidence)

Pitot tube (total pressure)



Static pressure port

Application case: air data sensors

Framing into the problem definition

Observations:


AOA


PT


PS

y_t

Inputs:

GPS

IRS

Control surfaces

u_t

Existence of constraint:

$$g(y_t, u_t) := \text{Lift equation}$$

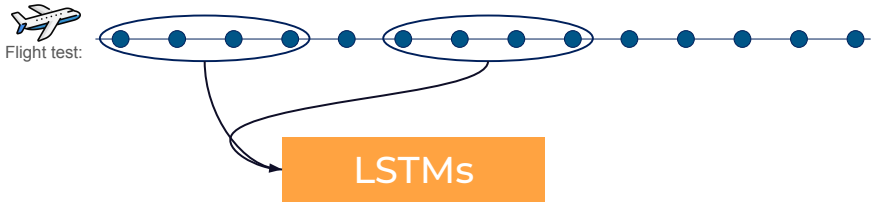
Data and training

Training data: ~100h of flight test data of a commercial single-aisle aircraft

Models and training

Static estimation models: Light GBM fitted on individual flight points

Dynamic estimation models: LSTM units trained on sequences of flight points



Application case: air data sensors

Fault simulation: loss of sensitivity on AOA sensor due to icing

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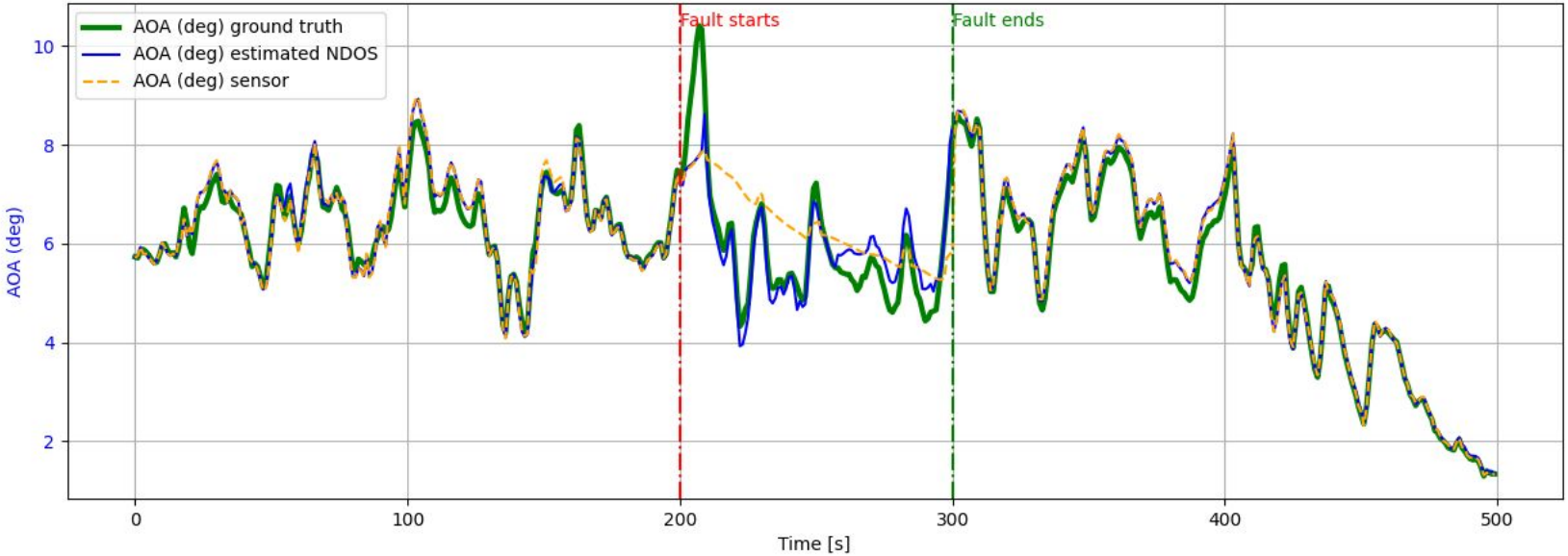

Application case: air data sensors

[1] Lopes, L. Lima, et al. "A Neural Double Observer Scheme Based on LSTMs for Air Data Fault Detection and Isolation." 2025 IEEE 64th Conference on Decision and Control (CDC). IEEE, 2025.

[2] Angelopoulos, Anastasios N., and Stephen Bates. "Conformal prediction: A gentle introduction." Foundations and trends® in machine learning 16.4 (2023): 494-591.

[3] Lopes, L. Lima, et al. "A Neural Double Observer Scheme Based on LSTMs for Air Data Fault Detection and Isolation." 2025 IEEE 64th Conference on Decision and Control (CDC). IEEE, 2025.

[4] S. Julier, J. Uhlmann and H. F. Durrant-Whyte, "A new method for the nonlinear transformation of means and covariances in filters and estimators," in IEEE Transactions on Automatic Control, vol. 45, no. 3, pp. 477-482, March 2000.

Thank you