



**HAL**  
open science

## **A Neural Double Observer Scheme Based on LSTMs for Air Data Fault Detection and Isolation**

Lucas Lima Lopes, Louise Travé-Massuyès, Carine Jauberthie, Guillaume Alcalay

► **To cite this version:**

Lucas Lima Lopes, Louise Travé-Massuyès, Carine Jauberthie, Guillaume Alcalay. A Neural Double Observer Scheme Based on LSTMs for Air Data Fault Detection and Isolation. 64th IEEE Conference on Decision and Control (CDC 2025), Dec 2025, Rio de Janeiro, Brazil. <hal-05367353>

**HAL Id: hal-05367353**

**<https://hal.science/hal-05367353v1>**

Submitted on 15 Nov 2025

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



HAL Authorization

# A Neural Double Observer Scheme Based on LSTMs for Air Data Fault Detection and Isolation

L. Lima Lopes, L. Travé-Massuyès, C. Jaubertie, G. Alcalay.

**Abstract**—There is an increasing interest in developing algorithmic fault detection and isolation (FDI) of aircraft air data sensors without relying on the existing hardware redundancy. This is a complex problem, as the available state equations have non-observable states in the event of a complete loss of all redundant sensors that measure a flight variable. Furthermore, FDI approaches commonly require surrogate models and the analytical relations they use are strongly subject to external disturbances. Trying to tackle these difficulties, we introduce the Neural Double Observer Scheme based on Long Short Term Memory units (LSTMs), a new estimation framework for FDI that allows for fault isolation in systems with intense coupling of physical equations. This framework is inspired by classic observer schemes for FDI and powered by LSTMs units. Evaluated on real flight data from an Airbus aircraft, it demonstrated promising performance compared to previously used model-driven methods.

## I. INTRODUCTION

Modern airplanes are constantly being equipped with more advanced capabilities and functions for increased safety and to assist pilots with the many operational tasks in a progressively more complex environment. These functionalities are enabled by a variety of systems, in special the air data system (ADS), comprising sensors that provide a series of anemometric and clinometric observations to the flight computers. As a critical system, various forms of fault tolerance exist to prevent and recover from ADS sensor and computer faults. Hardware redundancy, using sensors of dissimilar technologies, is the most important pillar of ADS sensors fault tolerance, and the majority voting logic is the most commonly used consolidation method of the measurements of redundant sensors [1].

Although this architecture has been proved reliable throughout the history of aviation, some systems failures can: "under some extremely unlikely combination of factors and / or circumstances (...) lead to simultaneous and potentially consistent multiple erroneous measurements" [2], at the limit of current architectures capabilities. Simultaneous faults are multiple faults happening at the same time on multiple

This work was carried out as part of a CIFRE PhD project in collaboration between the LAAS-CNRS laboratory and AIRBUS. Our work has benefited from the AI Interdisciplinary Institute funded by the France 2030 program under the Grant agreements n°ANR-19-PI3A-0004 and n°ANR-23-IACL-0002.

L. Lima Lopes is with Airbus Operations S.A.S and with LAAS-CNRS, Toulouse, France [lucas-gabriel.lima-lobes@airbus.com](mailto:lucas-gabriel.lima-lobes@airbus.com)

L. Travé-Massuyès is with LAAS-CNRS, University of Toulouse, CNRS, Toulouse, France. [louise@laas.fr](mailto:louise@laas.fr)

C. Jaubertie is with LAAS-CNRS, University of Toulouse, France [cjaubert@laas.fr](mailto:cjaubert@laas.fr)

G. Alcalay is with Airbus Operations S.A.S, Toulouse, France. [guillaume.alcalay@airbus.com](mailto:guillaume.alcalay@airbus.com)

redundant sensors that measure the same flight variable. They are qualified as coherent when they manifest in the same way. Although extremely rare, some known potential causes of simultaneous and coherent faults are icing [3], lightning strikes [4], structural damage [5] and maintenance errors.

The development of more robust ADS sensors FDI architectures without the reliance on costly and weight adding hardware redundancy is therefore an opportunity to address these situations, while reducing pilot workload, preventing loss of flight protections and autopilot. These interests have motivated a series of recent studies and new techniques, building upon the current extensive safety barriers.

Many of these studies propose model-driven approaches that rely on a kinematic or dynamic model of the ADS to perform fault detection and isolation. Its simplest form is the use of analytical redundancy relations [6] and derived techniques [7]. The equations that associate variables sourced from the Air Data System, the Global Positioning System (GPS) and the Inertial Reference System (IRS) are, however, highly non-linear. Furthermore, two important external disturbances must be considered: wind variations and deviations between the standard atmosphere model and reality. Thus, to account for that, many authors propose observers based on Kalman Filter variations, such as the Extended Kalman Filter [8], [9], [10], [11], [12] and the Unscented Kalman Filter [13], [14]. Other observer-based model-driven techniques such as the use of Unknown Input Observers [15] [16] are also present in the literature.

In real flight operations, the assumptions underlying many model-driven approaches often do not hold, and the surrogate models used for flight coefficients typically lack the precision required for reliable FDI. In the last decade, following the advances on Artificial Intelligence (AI), researchers have tried to address these issues using data-driven approaches. The simplest forms of these methods are trained regressors used as observers, in the form of linear and non-linear regressors [17] [18], multi-layer perceptrons [19], and variations [20]. Supervised classification for anomaly detection are also candidates for the task [21] [22]. AI methods have the potential to implicitly model complex disturbances without relying on a difficult to obtain physical description.

The data-driven FDI methods proposed so far, however, make limited use of the temporal dependencies of the flight variables. Furthermore, evaluating the real performance of any method requires real flight data under the diverse conditions encountered in operation. That is why we propose a novel data-driven FDI method inspired by classical observer schemes [23], which we call the Neural Double Observer

Scheme based on Long-short Term Memory Units (NDOS). This method is motivated by, and applied to, the challenge of air data sensors, yet it is potentially generalizable to any application where state-observer equations are known to exist between sets of monitored and trusted, i.e., assumed fault-free, measurements, even when these equations are non-linear and highly coupled. Its principle is the use of two blocks of multiple parallel memory-capable machine learning models trained in nominal data, i.e., flight points without faults. In this application we use LSTMs for the task. Each LSTM model is built as an observer of a single monitored variable. The block will therefore have as many LSTM models as the number of monitored variables we wish to observe. In the first block, the observers have couplings on the use of monitored variables and provide high-precision estimations, but are globally sensitive to faults in a manner that isolation is not possible with these estimators only. The second block is then a set of decoupled estimators allowing for efficient isolation, despite their lower precision. The complimentary use of the two blocks motivates the name given to the methodology. Additionally, the proposed method ensures continued safe operation even when a sensor fault is detected, as it maintains a robust virtual sensor active.

## II. METHOD DESCRIPTION

Assume a system instrumented by a set of sensors measuring  $N$  variables  $y_i, i \in \mathcal{N} := \{1, \dots, N\}$ , and delivering, at an instant  $t$ ,  $N$  observations vectorized by  $Y^t$ :

$$Y^t = [y_1^t \quad \dots \quad y_N^t]^T. \quad (1)$$

Time is discretized into uniformly spaced sampling instants at which observations or measurements are performed. Given a time window  $\Delta t = [t', t], t' < t$ , of arbitrary fixed length, we introduce the notation:

$$Y^{\Delta t} = \begin{bmatrix} y_1^{t'} & \dots & y_N^{t'} \\ \vdots & \ddots & \vdots \\ y_1^t & \dots & y_N^t \end{bmatrix}^T. \quad (2)$$

Given a set  $\mathcal{V}$  of natural numbers,  $\mathcal{V} \subset \mathcal{N}$ , indexing a subset of the  $N$  observations, we denote by  $Y_{\mathcal{V}}^t$  the subvector of  $Y^t$  containing only the rows with index in  $\mathcal{V}$ , i.e.,

$$Y_{\mathcal{V}}^t = [y_v^t | v \in \mathcal{V}]. \quad (3)$$

This definition can be trivially extended to  $Y_{\mathcal{V}}^{\Delta t}$ .

Let  $\mathcal{T}$  be the subset of indexes corresponding to trusted observations/variables and  $\mathcal{M}$  the subset of indexes corresponding to monitored observations/variables, so that  $\mathcal{T} \cap \mathcal{M} = \emptyset$  and  $\mathcal{T} \cup \mathcal{M} = \mathcal{N}$ . Trusted observations are those provided by sensors that are assumed to be fault-free, while monitored observations are those that are delivered by sensors that may be subject to faults. The justification for the choices of trusted and monitored observations/variables is dependent on the assumptions about the physical system and the sensors.

In our NDOS, we wish to build a set of  $M$  estimators  $\{D_m | m \in \mathcal{M}\}$ , where  $M = \text{card}(\mathcal{M})$  is the cardinality of  $\mathcal{M}$ , so that:

$$D_m(Y_{\mathcal{T} \cup \mathcal{M} \setminus \{m\}}^{\Delta t}) := \hat{y}_m^t. \quad (4)$$

The set  $\mathcal{T} \cup \mathcal{M} \setminus \{m\}$  denotes the set of all variables except the one indexed by  $m$ , as for the notation introduced prior. These estimators should be built such that  $\epsilon_m^t$ , the detection residue between the estimation  $\hat{y}_m^t$  and the observation  $y_m^t$  at time  $t$ , is bounded by a detection threshold  $\delta_m$  if no faults are present:

$$\begin{aligned} \epsilon_m^t &:= |y_m^t - \hat{y}_m^t|, \\ \epsilon_m^t &\leq \delta_m, \forall t, \text{ if no fault.} \end{aligned} \quad (5)$$

The estimators  $D_m, m = \{1, \dots, M\}$ , are often qualified as *virtual sensors* of the corresponding variables. Assume now that the sensor  $S_{y_m}$  measuring  $y_m, i \in \mathcal{M}$ , becomes faulty at time  $t$ , then it is expected that the residue  $\epsilon_m^t$  overshoots the detection threshold if the estimator has enough quality.

Since each estimator  $D_m$  uses all available variables except that being estimated  $y_m$  as information, as per definition in Equation (4), a fault in sensor  $S_{y_m}$  should affect the residual  $\epsilon_m^t$  of  $D_m$  for some  $t$  but it is also likely to affect the estimation of some or all the other estimators, which could cause all the affected residuals to overshoot their respective thresholds. Therefore an overshoot of  $\epsilon_m^t$  implies a fault, but not necessarily a fault in  $S_{y_m}$ . Thus,  $D_m$  estimators given by (4) are only effective for fault detection and we call them *detection estimators*.

To overcome the isolation problem, we build a second set of estimators  $\{I_m | m \in \mathcal{M}\}$ , named *isolation estimators* as opposed to detection estimators, using only the set of trusted variables as input:

$$I_m(Y_{\mathcal{T}}^{\Delta t}) := \tilde{y}_m^t. \quad (6)$$

These new uncoupled isolation estimators are less precise but completely uncoupled, and they can be exploited for isolation as follows.

The normalized isolation residual  $\eta_m^t$  is computed between the estimation  $\tilde{y}_m^t$ , given by (6) and independent of faults in all sensors except  $S_{y_m}$ , and the observation  $y_m^t$ , as follows:

$$\eta_m^t = \tilde{\epsilon}_m^t / \sigma_m^{\Delta t} \quad (7)$$

where,

$$\tilde{\epsilon}_m^t := |y_m^t - \tilde{y}_m^t|, \quad (8)$$

$$\sigma_m^{\Delta t} := \sqrt{\frac{1}{\text{card}(\Delta t)} \sum_{t \in \Delta t} \left( \tilde{\epsilon}_m^t - \frac{1}{\text{card}(\Delta t)} \sum_{\tau \in \Delta t} \tilde{\epsilon}_m^\tau \right)^2}, \quad (9)$$

and  $\sigma_m^{\Delta t}$  is the standard deviation of the raw isolation residual  $|y_m^t - \tilde{y}_m^t|$  during a sliding window of fixed length  $\Delta t$ .

Although the above normalized residuals are not expected to be bounded for detection, they can be used for isolation after a fault is detected. The hypothesis is that the residual

of the isolation residual of a variable measured by a faulty sensor changes in a disproportionately compared to the isolation residuals of the non-faulty variables. Therefore, a fault is detected if any of the residuals of the first block of detection estimators overshoots its respective threshold. Once a fault is detected, the highest normalized residual of the second block of isolation estimators indicates the location of the fault.

Once  $S_{y_m}$  has been identified as the faulty sensor, the estimation  $\hat{y}_m^t$  provided by  $D_m(Y_{\mathcal{T} \cup \mathcal{M} \setminus \{m\}}^{\Delta t})$ , which offers the highest precision, is adopted as the most reliable estimate of  $y_m^t$  and used in place of the sensor's measurement.

Building the estimators  $D_m$  and  $I_m$ ,  $m \in \mathcal{M}$ , using LSTM units serves two purposes. The first is to allow for the trained model to learn the complexities of the observation and state prediction equations without the necessity of knowing the exact form of the equations. The second is to allow it to tune external intermittent disturbances and model imprecision naturally through LSTM memorization and forgetting capabilities. The advantage of this architecture is also its simplicity, as the LSTMs only need to be trained as regression models on real operational data. Each estimator is composed of multiple LSTM layers, originally proposed in [24] and implemented in this work using the *Pytorch* Python library, for which description can be consulted in [25].

The complete NDOS algorithmic schema is given in Algorithm 1.

---

**Algorithm 1** FDI at instant  $t$  using the NDOS-LSTM scheme

---

**Input** Observation window  $Y^{\Delta t}$ , a set of monitored variables  $\mathcal{M}$ , trained detection models  $\{D_m | m \in \mathcal{M}\}$ , trained isolation models  $I_m | m \in \mathcal{M}$ , detection thresholds  $\{\delta_m | m \in \mathcal{M}\}$

**Output**  $flag$ , fault location

```

1:  $flag \leftarrow False$  ▷ Initialize flag
2: fault location  $\leftarrow \emptyset$  ▷ Initialize location
3: for  $m$  in  $\mathcal{M}$  do
4:    $\epsilon_m^t \leftarrow |y_m^t - D_m(Y_{\mathcal{T} \cup \mathcal{M} \setminus \{m\}}^{\Delta t})|$ 
5:    $flag \leftarrow \epsilon_m^t \geq \delta_m \vee flag$  ▷ Flag a fault
6:    $\tilde{\epsilon}_m^t \leftarrow |y_m^t - I_m(Y_{\mathcal{T}}^{\Delta t})|$ 
7:   Update rolling std deviation  $\sigma_m^{\Delta t}$ 
8:    $\eta_m^t \leftarrow \tilde{\epsilon}_m^t / \sigma_m^{\Delta t}$ 
9: end for
10: if  $flag$  then
11:   fault location  $\leftarrow \underset{m}{argmax} \{\eta_m^t | m \in \mathcal{M}\}$  ▷ Isolate
      fault
12: end if

```

---

### III. CASE STUDY: AIR DATA SENSORS

This methodology was conceived especially for the case of air data sensors fault detection and isolation. We take only one observation for each variable, as to make it robust for the most demanding fault conditions, that of simultaneous faults of two or all instances of a redundant sensor, these

being potentially coherent. It is important to reiterate that the considered simultaneous faults relate to those happening on multiple sensors measuring the same variable, e.g. all the three sensors of angle-of-attack. In this situation, no more hardware redundancy is available and there is no trivial analytical redundancy that allows for both detection and isolation. That is why, as previously mentioned, this methodology works with one single measurement of each variable at once. In the case of ADR systems, the single measurement is the one consolidated by a prior majority voting system. The case of simultaneous faults of sensors measuring two different variables, for example AOA and PT probes at the same time, is not taken into consideration. That is because it would require triple coherent fault of all AOA and all PT probes at once, which is an extremely unlikely case, even beyond the rarity of a triple simultaneous coherent fault of all sensors of one single variable.

The ADS contains a series of sensors. Although dependent on architecture, four common sensors are generally present:

- **Static pressure ( $P_S$ ) ports:** they appear on the sides of the airplane as round openings. The exterior air static pressure are measured by gauges connected through tubes to openings.
- **Pitot tubes:** total pressure is used alongside the static pressure to calculate the aircraft air speed. The Pitot tubes appear as protuberant tubes close to the nose of the aircraft.
- **Angle-of-attack vanes:** clinometric sensors composed of vanes that align themselves with the airflow around them, measuring its relative angle to the aircraft body axis.
- **Total air temperature probes:** measure the total air temperature using a similar principle to the Pitot tubes.

These instruments produce the observations used to calculate important flight variables necessary for guidance, navigation and control.

For the application of NDOS, We consider the list of available variables in Table I from multiple avionics sources. The observations issued from the ADS are the ones to be monitored by the NDOS. Observations obtained from the GPS, IRS and from the dedicated engine computers are considered *trusted* because they are subject to their own specific monitoring routines. The sensors of these systems can become faulty, but they are not target to this FDI algorithm. Their proper functioning within specified operational performances is taken as a requirement to the application of the NDOS methodology.

The selection of features was made based on the prior knowledge provided by the kinematic equations, by the Mach equations, the standard atmosphere model and lift equation. Referring to the well-known Dulmage-Mendelsohn canonical decomposition [26], these equations do not include an overdetermined part given the available observations. This means that there is no subsystem of equations including redundancies that could be used to generate fault residuals [27]. The ADS hence requires specific FDI architectures.

TABLE I: List of trusted and monitored variables used for training and evaluating the different models. Variables marked as monitored are those analyzed by the NDOS. Trusted variables are those already monitored by other systems, assumed non-faulty only for this specific application.

VARIABLE	NAME	MONITORED
PT	Total pressure	Monitored
TAT	Total temperature	Monitored
AOA	Angle of Attack	Monitored
ZP	Pressure altitude	Monitored
THETA	Pitch angle	Trusted
PHI	Roll angle	Trusted
PSI	Yaw angle	Trusted
VGGPIRS	Horizontal ground speed	Trusted
VZGPIRS	Vertical ground speed	Trusted
VNORTH	North ground speed	Trusted
VEAST	East ground speed	Trusted
VZ	Inertial Vertical Speed	Trusted
NZIIIRS	Z-body load factor	Trusted
NXIIIRS	X-body load factor	Trusted
QIADR	Roll angle rate	Trusted
ZGPIRS	GPS altitude	Trusted
TTRK	True track angle	Trusted
ELEV_POS	Elevator position	Trusted
THS	Trimable horizontal surface position	Trusted
SLAT_POS	Slat position	Trusted
FLAP_POS	Flap position	Trusted
SP	Spoiler position	Trusted
GW	Gross Weight	Trusted
N1	Engine throttle	Trusted
TATENG	Engine TAT	Trusted
PDOT	Roll angular acceleration	Trusted
QDOT	Pitch angular rate	Trusted
RDOT	Yaw angular rate	Trusted

The LSTMs  $\{D_m|m \in \mathcal{M}\}$  and  $\{I_m|m \in \mathcal{M}\}$  are trained using data from 10 real flights obtained from operational tests of an Airbus aircraft. Tests were performed on 2 additional flight tests not used for training. The neural network architectures and hyperparameter tuning was performed using a grid search K-folds cross validation [28]. Each estimator had one recurrent layer. Table II shows, for each target variable, the size of the hidden state in the recurrent layer trained in the detection and isolation blocks, as well as the dropout used.

TABLE II: Chosen hyperparameters for the different networks of the system. The sampling frequency used was 0.5Hz to reduce the training computing cost for training, sequences had size 5. Learning rate was  $10^{-3}$  with an exponential decay of  $\gamma = 0.9$

Monitored	Function	Hidden size	Dropout (%)
AOA	Detection	50	0.1
AOA	Isolation	70	0.1
PT	Detection	100	0.1
PT	Isolation	50	0.1
ZP	Detection	50	0.1
ZP	Isolation	70	0.5
TAT	Detection	30	0.5
TAT	Isolation	70	0.1

The NDOS architecture for this case study is shown in Fig. 1 in the example of an AOA fault.

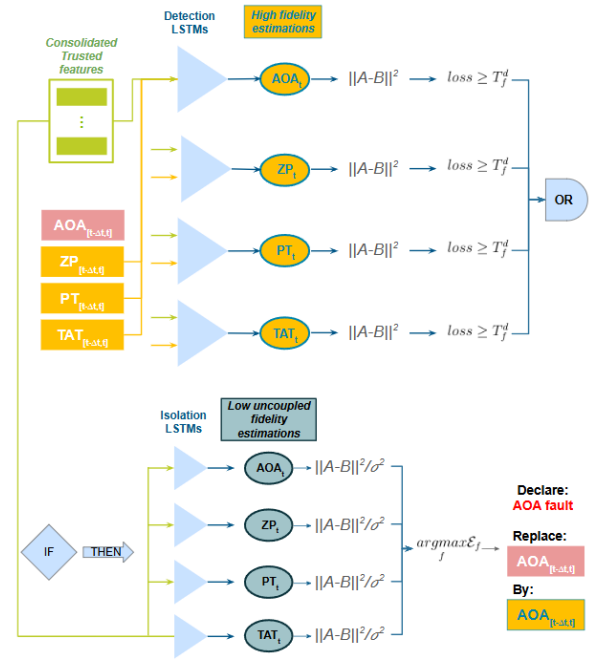


Fig. 1: NDOS-LSTM fault detection and isolation schema exemplified in the case of a consolidated AOA fault (simultaneous sensor fault). Part of the schema is omitted for clarity

## IV. RESULTS

First, we analyze the estimators capability to produce good virtual observations of the monitored variables. The analysis is made using the estimation error normalized by the acceptable error as required by confidential operational constraints, mainly driven by guidance-navigation and control performance. This gives a clear metric that shows immediately if the performance is good or not, while protecting confidentiality industrial constraints imposed.

Second, we analyze the system's global detection and isolation performance. We evaluate this using data from two additional flights from the same aircraft. Sensor faults are artificially injected to the monitored variables during two flight conditions: cruise and take-off/approach, including touch and go maneuvers, i.e., landing and taking-off again without a full stop. The faults are introduced with drift and bias dynamics, where drift means a slow, linear additive error up to a target error and bias means a step additive signal. The severity, i.e. the drift speed and bias magnitude, of the injected fault changes depending on the flight condition, as to simulate the different operational constraints required on each condition. Three metrics are used for the detection and isolation performance: precision, sensitivity (recall) and the F1 score. For detection we consider two classes, *fault* or *no-fault*, while for isolation for each sensor we consider the two classes  $\neg ok(S_{y_i})$  or  $ok(S_{y_i})$ , which indicate a faulty or non faulty sensor  $S_{y_i}$  respectively. In practice, fault isolation is seen as a multiple detection problem for the calculation of the metrics.

### A. Estimation quality

Table III shows the mean residual and its standard deviation, normalized by the acceptable estimation errors on each flight condition for the considered monitored variables of our case study, i.e. AOA, ZP, PT, and TAT. The flight conditions being low and high speed as indicated by the Mach number. Assuming a gaussian error distribution, the value  $\mu + 3\sigma$  can be used as an approximation of the 99.7% percentile. Since the residuals are normalized by the acceptable error, a good estimation performance should yield  $\mu + 3\sigma \leq 1$ , i.e. a great majority of points estimated at the highest quality. The table shows that the estimations for all variables are as required, except for *PT*, with only slightly increased error 102% and 107% at the extremes of the distribution.

TABLE III: NDOS estimation performance. Values in the table are the mean and variance of the error between estimation and measurement as a percentage of the acceptable error.

Variable	Mach $\leq 0.5$		Mach $> 0.5$	
	$\mu, \sigma$	$\mu + 3\sigma$	$\mu, \sigma$	$\mu + 3\sigma$
<b>AOA</b>	19%, 15%	64%	20%, 10%	50%
<b>ZP</b>	21%, 17%	72%	25%, 16%	73%
<b>PT</b>	33%, 23%	02%	39%, 22%	107%
<b>TAT</b>	12%, 11%	47%	17%, 11%	50%

### B. Detection and Isolation performance

For this application, the conceived system should add robustness without creating new weaknesses. It means that low recall in detection can be accepted whereas precision must stay high. Indeed, false positive detection flags or erroneous isolation are not tolerable, as they could potentially alarm systems and pilot needlessly. In practice, since the proposed FDI system is intended as an additive layer to other safety measures, even false alarms should not cause the aforementioned negative impacts. The above considerations serve as the threshold tuning philosophy. The thresholds are thus chosen so that they favor 100% precision in the train set even if at the cost of reduced recall<sup>1</sup>. In the test set, the consequent detection and isolation results obtained can be seen in table IV for low speed operation ( $Mach \leq 0.5$ ) and for high speed operation ( $Mach > 0.5$ ). Results are presented separately since constraints defined for low and high speed operation of the aircraft are not the same.

It can be seen from Table IV that the F1 scores are above 0.9 for most tasks, indicating a very good performance. The *AOA* low speed isolation task has a 0.82 isolation score, which is a good but not excellent performance. The high speed *TAT* isolation score is the lowest at 0.76, being the one that requires the most improvement. This poor score is caused by a lack of sensitivity of the detection models in some flight points for the *TAT* estimation. It must be reinforced however that the total air temperature probes are

<sup>1</sup>It should be noted that evaluating with the F1-score alone is not an option as it does not allow independent control of precision.

TABLE IV: NDOS detection and isolation performance presented separately for low and high speed. The detection row shows the binary classification scores for classes *fault* or *no fault*. The variable rows show the binary classification scores for classes  $\neg ok(S_y)$  or  $ok(S_y)$  for  $y \in \{AOA, ZP, PT, PS\}$ .

Low speed results Mach $\leq 0.5$			
Variable	Precision	Sensitivity	F1 Score
<b>AOA</b>	0.79	0.85	0.82
<b>ZP</b>	1.0	0.94	0.97
<b>PT</b>	1.0	0.87	0.93
<b>TAT</b>	1.0	0.85	0.92
<b>Detection</b>	1.0	0.93	0.97
High speed results Mach $> 0.5$			
Variable	Precision	Sensitivity	F1 Score
<b>AOA</b>	1.0	1.0	1.0
<b>ZP</b>	1.0	1.0	1.0
<b>PT</b>	1.0	0.8	0.88
<b>TAT</b>	1.0	0.61	0.76
<b>Detection</b>	1.0	0.85	0.92

the less critical sensors in the system on current aircraft architectures.

Further insight is given by the low and high speed confusion matrix of Fig. 2, which shows that the low false alarm rate enforced on training data is retained on the tested operation of the system on both low and high speeds. This is indicated by the first row of both matrices, where all entries are practically zero, except for the main diagonal. The low speed results show a more equal performance of isolation for each fault but a higher confusion on fault isolation when fault is flagged. Notably, the *AOA* column is polluted, which means the system has a slight tendency to sometimes flag other faults as an *AOA* fault, with a limited low speed precision of 79%. The high speed matrix shows very good results for *AOA* and *ZP* isolation but a high false negative rate for the total temperature observation. Positive, however, is the fact that for high speeds no isolation confusion exists when a fault is flagged, as indicated by the purely diagonal matrix when the no flag row and column are excluded.

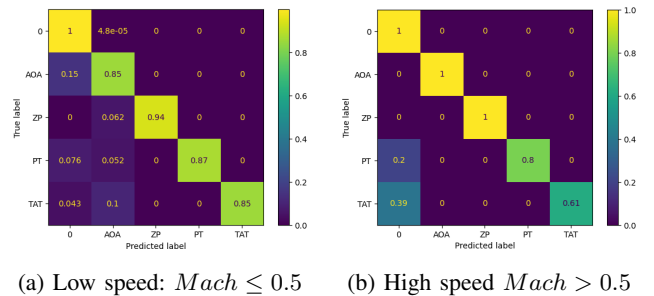


Fig. 2: Confusion matrix obtained for the task of detection and isolation for simulation in low speed 2a and high speed 2b. On vertical axis is the true label, the flag given by the system is present on the horizontal axis. Label '0' represents *no fault*. Values are given as ratios, 1 being equivalent to 100%.

## V. CONCLUSIONS

In [29], the authors have reviewed the ADS fault diagnosis landscape and argued in favor of further development of data-driven FDI methods applied to air data sensors. The Neural Double Observer Scheme based on LSTMs is one product of this research. Although the method is born as an answer to a specific application, we believe that the general framework given can be adapted to similar systems. It is a simple method, which is a desirable characteristic in safety critical applications. The models used were trained and tested on real flight test data, with flight points in several possible conditions and aircraft control surfaces configurations. The system has proven to be robust to false alarms, and showed a good performance given the challenging environment in which it was evaluated. It must be noted that the certification of systems based on artificial intelligence is still a difficult endeavor in aeronautics, due to the intrinsic challenge of explainability and interpretability. This imposes a challenge on short-term industrial applications, although significant advances are currently being made on this regard [30][31]. Another point of attention is the computational load of the algorithm on aircraft computers: considering  $n$  the hidden size of the LSTMs, the forward pass has a  $O(n^2)$  complexity. This can be calculated from [25]. This means that each LSTM network performs tens of thousands of multiplications. The proposed methodology anticipates future computer generations and is not meant for present-day calculators.

## REFERENCES

- [1] P. Goupil, "AIRBUS state of the art and practices on FDI and FTC in flight control system," *Control Engineering Practice*, vol. 19, no. 6, pp. 524–539, 2011. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0967066110002704>
- [2] EASA, Airbus, and T. Delft, "Enhanced fault detection and diagnosis solutions for air data systems," <https://www.easa.europa.eu/en/downloads/139460/en>, accessed: 2025-03-26.
- [3] R. W. Gent, N. P. Dart, and J. T. Cansdale, "Aircraft icing," *Philosophical Transactions of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences*, vol. 358, no. 1776, pp. 2873–2911, 2000.
- [4] 'AIRBUS', "Lightning strikes," <https://safetyfirst.airbus.com/lightning-strikes/>, accessed: 2024-09-27.
- [5] J. Barthe, "Unreliable speed," [https://safetyfirst.airbus.com/app/themes/mh\\_newsdesk/documents/archives/unreliable-speed.pdf](https://safetyfirst.airbus.com/app/themes/mh_newsdesk/documents/archives/unreliable-speed.pdf), accessed: 2024-09-27.
- [6] S. Whitmore, T. Moes, and C. Leondes, "Failure detection and fault management techniques for flush airdata sensing systems," in *30th Aerospace Sciences Meeting and Exhibit*, 1992, p. 263.
- [7] M. Bonfè, P. Castaldi, W. Geri, and S. Simani, "Fault detection and isolation for on-board sensors of a general aviation aircraft," *International Journal of Adaptive Control and Signal Processing*, vol. 20, 2006.
- [8] L. V. Eykeren and Q. Chu, "Sensor fault detection and isolation for aircraft control systems by kinematic relations," *Control Engineering Practice*, vol. 31, pp. 200–210, 2014.
- [9] K. Sun and D. Gebre-Egziabher, "Air data fault detection and isolation for small UAS using integrity monitoring framework," *Navigation*, vol. 68, no. 3, pp. 577–600, 2021, publisher: Wiley Online Library.
- [10] C. Hajjiyev, "Tracy–Widom distribution based fault detection approach: Application to aircraft sensor/actuator fault detection," *Isa Transactions*, vol. 51, no. 1, pp. 189–197, 2012, publisher: Elsevier.
- [11] Z. Li, Y. Cheng, H. Wang, and H. Wang, "Fault detection approach applied to inertial navigation system/air data system integrated navigation system with time-offset," *IET Radar, Sonar & Navigation*, vol. 15, no. 9, pp. 945–956, 2021, publisher: Wiley Online Library.
- [12] G. Alcalay, C. Seren, G. Hardier, M. Delporte, and P. Goupil, "An adaptive extended kalman filter for monitoring and estimating key aircraft flight parameters," *IFAC-PapersOnLine*, vol. 51, no. 24, pp. 620–627, 2018, number: 24 Publisher: Elsevier.
- [13] P. Lu, L. Van Eykeren, E. Van Kampen, C. De Visser, and Q. Chu, "Adaptive three-step Kalman filter for air data sensor fault detection and diagnosis," *Journal of Guidance, Control, and Dynamics*, vol. 39, no. 3, pp. 590–604, 2016, publisher: American Institute of Aeronautics and Astronautics.
- [14] G. H. de Marina, A. Marcos, and R. Haya, "Angle of Attack and True Airspeed failure sensor detection and recovery based on Unscented Kalman Filters for the ALPHA vehicle," *Ifac Proceedings Volumes*, vol. 45, no. 20, pp. 1197–1202, 2012, publisher: Elsevier.
- [15] F. Amato, C. Cosentino, M. Mattei, and G. Paviglianiti, "A direct/functional redundancy scheme for fault detection and isolation on an aircraft," *Aerospace Science and Technology*, vol. 10, no. 4, pp. 338–345, 2006, publisher: Elsevier.
- [16] E. Kiyak, A. Kahvecioğlu, and F. Caliskan, "Aircraft Sensor and Actuator Fault Detection, Isolation, and Accommodation," *Journal of Aerospace Engineering*, vol. 24, pp. 46–58, 2011.
- [17] N. Cartocci, M. Napolitano, G. Costante, and M. L. Fravolini, "A Comprehensive Case Study of Data-Driven Methods for Robust Aircraft Sensor Fault Isolation," *Sensors (Basel, Switzerland)*, vol. 21, 2021.
- [18] N. Cartocci, M. R. Napolitano, F. Crocetti, G. Costante, P. Valigi, and M. L. Fravolini, "Data-Driven Fault Diagnosis Techniques: Non-Linear Directional Residual vs. Machine-Learning-Based Methods," *Sensors*, vol. 22, no. 7, 2022. [Online]. Available: <https://www.mdpi.com/1424-8220/22/7/2635>
- [19] L. Garbarino, G. Zazzaro, N. Genito, G. Fasano, and D. Accardo, "Neural network based architecture for fault detection and isolation in air data systems," in *2013 IEEE/AIAA 32nd Digital Avionics Systems Conference (DASC)*. IEEE, 2013, pp. 2D4–1.
- [20] U. Kilic and G. Unal, "Aircraft air data system fault detection and reconstruction scheme design," *Aircraft Engineering and Aerospace Technology*, vol. 93, no. 6, pp. 1104–1114, 2021, publisher: Emerald Publishing Limited.
- [21] Y. Dong, J. Wen, Y. Zhang, and J. Ai, "Deep neural networks-based air data sensors fault detection for aircraft," in *2021 33rd Chinese Control and Decision Conference (CCDC)*. IEEE, 2021, pp. 442–447.
- [22] Y. Zhao, H. Zhao, J. Ai, Y. Dong, and others, "Robust data-driven fault detection: An application to aircraft air data sensors," *International Journal of Aerospace Engineering*, vol. 2022, 2022, publisher: Hindawi.
- [23] P. M. Frank, "Fault diagnosis in dynamic systems using analytical and knowledge-based redundancy: A survey and some new results," *automatica*, vol. 26, no. 3, pp. 459–474, 1990.
- [24] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997.
- [25] "Pytorch documentation: Lstm," <https://pytorch.org/docs/stable/generated/torch.nn.LSTM.html>, accessed: 2025-03-25.
- [26] A. L. Dulmage and N. S. Mendelsohn, "Coverings of bipartite graphs," *Canadian Journal of Mathematics*, vol. 10, pp. 517–534, 1958.
- [27] M. Blanke, M. Kinnaert, J. Lunze, M. Staroswiecki *et al.*, "Diagnosis and fault-tolerant control [electronic resource]."
- [28] Y. Jung, "Multiple predicting k-fold cross-validation for model selection," *Journal of nonparametric statistics*, vol. 30, no. 1, pp. 197–215, 2018.
- [29] L. Lima Lopes, L. Travé-Massuyès, C. Jauberthie, and G. Alcalay, "A Review of Fault Diagnosis Techniques Applied to Aircraft Air Data Sensors," in *35th International Conference on Principles of Diagnosis and Resilient Systems (DX 2024)*. Schloss Dagstuhl–Leibniz-Zentrum für Informatik, 2024, pp. 3–1.
- [30] E. U. A. S. A. EASA, "Easa concept paper: First usable guidance for level 1&2 machine learning applications," 2023.
- [31] E. Jenn, A. Albore, F. Mamalet, G. Flandin, C. Gabreau, H. Delseny, A. Gauffriau, H. Bonnin, L. Alecu, J. Pirard *et al.*, "Identifying challenges to the certification of machine learning for safety critical systems," in *European congress on embedded real time systems (ERTS 2020)*, 2020.