A Review of Fault Diagnosis Techniques Applied to Aircraft Air Data Sensors

Lucas Lima Lopes
Airbus Operations S.A.S, Toulouse, France
LAAS-CNRS, Toulouse, France

Louise Travé-Massuyès
LAAS-CNRS, Université de Toulouse, CNRS, France

Carine Jauberthie
LAAS-CNRS, Université de Toulouse, UPS, France

Guillaume Alcalay
Airbus Operations S.A.S, Toulouse, France

Abstract

Air data sensors provide essential measurements to ensure the availability of autopilot and to maintain aircraft performance, flight envelope protection and optimal aerodynamic surfaces control laws. The importance of these sensors imply the existence of embedded fault tolerance features, mainly represented by hardware redundancy. The latter is prone to fail in case of common fault of multiple sensors, especially if the faults are coherent and simultaneous. Increasing the robustness of fault detection and isolation (FDI) techniques for air data sensors to the aforementioned conditions is essential for the development of more autonomous aircraft, reducing crew workload and guaranteeing flight protections under adverse conditions. This paper reviews recent works on Air Data System (ADS) FDI, assessing proposed model, data and signal-driven approaches. We finally argue in favor of data-driven and hybrid approaches for the development of virtual sensors and semi-supervised anomaly detectors, offering an overview of ways forward.

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1 Introduction

Modern aircraft have steadily been equipped with more and more critical capabilities and functionalities for safe flight and to assist pilots on their tasks in an ever more complex environment. The Flight Control and Management System (FCMS) sustains many of these capabilities. It requires a series of reliable measurements provided by different sensor systems to ensure the availability of autopilot and to maintain aircraft performance, flight envelope protection and optimal aerodynamic surfaces control laws. Alongside important sensor systems such as the Inertial Reference System (IRS) and the Global Positioning System (GPS), the aircraft is equipped with the Air Data System (ADS). The ADS provides the aircraft computers with a series of variables calculated from anemometric and clinometric measurements, arguably the most important parameters for aircraft operation.

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As an essential system, many layers of fault tolerance are applied to prevent and remediate ADS sensor and computer faults. Safety is among the biggest concerns in aeronautics since the earliest aircraft developed, and therefore there is no lack of standard practices and methods for ensuring fault tolerance. In general, these practices involve physical installation segregation, redundancy, dissimilarity, reconfiguration and safety analysis [31].

Hardware redundancy is especially important in the case of ADS sensors fault tolerance and the majority voting logic is widely used for the consolidation of the measurements of the redundant air data sensors. Although they have shown to be reliable numerous times throughout the history of aviation, there are still known cases of coherent and simultaneous faults of two or more sensors of one type that can deceive the voting logic. This has lead the development and on-boarding of new algorithmic solutions for more than two decades, complementing hardware redundancy with analytical redundancy.

Many cases of fault affecting multiple sensors simultaneously and consistently (common mode sensor faults) have been identified: icing is an event that takes place when the flight trajectory crosses a zone at or below freezing temperature with enough humidity. This causes supercooled water droplets to freeze upon contact with the aircraft surfaces [29] and it may block or disturb multiple sensors; lightining strikes might damage and even melt multiple probes [2]; structural damages on the nose radome might disturb airflow around multiple sensors in unpredictable ways [9]; maintenance errors are a common source of issues, the most classic being non-removal of Pitot tube covers, making total pressure measurements to remain stuck in an erroneous value. Although these and other sources of common fault modes have been identified, they do not always provoke the same fault signature. Furthermore, there are still potentially non-identified sources of coherent and simultaneous faults. Therefore generalization is a main concern for FDI on air data sensors.

Previous studies have produced the methods and techniques that ensure the safety required by the aeronautical industry. However, the development of more robust and accurate air data sensor fault diagnosis is an enabler of a more autonomous aircraft, reducing pilot workload and avoiding the loss of automatic protections and auto-pilot. This has renewed the interest in the field of air data sensor fault diagnosis and parameter estimations, resulting in a series of studies and new technologies that expand on the extensive safety barriers already in place. The review presented in this article intends initially to survey the recent studies on the field and present methodologies applied on similar applications that could be exploited in air data diagnosis. In section 4, the current limitations of state-of-the-art and what we consider to be promising lines of research are discussed. Finally, in the conclusion, the most important points discussed and ways forward presented are summarized.

2 Air data sensors

The ADS relies on a series of sensors and processing units. Although dependent on aircraft architecture, these sensors are usually of four types:

- **Static pressure** (P_S) ports: they are visible on the fuselage of the aircraft as round openings. Pressure gauges connected through tubes to the port measure the exterior air static pressure . In the A320 family, three redundant P_S measurements are available.
- **Pitot tubes**: total pressure is an essential concept in fluid dynamics originating in the Bernoulli's equations and is the sum of the fluid static pressure and the dynamic pressure, due to movement of the fluid [6]. The Pitot tube is a classic tool designed to estimate the speed of the air flow by measuring the total pressure. In the A320 family, three redundant P_t measurements are available.

- **Angle-of-attack vanes**: the sensors that measure the aerodynamic angles are usually clinometric vanes that align themselves with the airflow around them, measuring its relative angle to the body axis. A series of positional corrections allow to calculate the angle-of-attack of the airflow around the whole aircraft. Three AoA vanes are present on the A320 family.
- **Total air temperature probes**: measures the total air temperature by decelerating the flow adiabatically in a similar manner to the described Pitot tube. The temperature of the halted air is then measured. A320 family aircraft possess 2 TAT probes.

The measurements from these instruments are used to calculate important flight variables, that are then corrected through the use of exogenous information. The most important resulting output used by flight control and autopilot system or to be displayed to the pilot are indicated air speed, CAS, AoA, β, M, dynamic pressure and baro-corrected altitude/vertical speed.

Physical equations relating the different ADS observations and derivative parameters exist. These are however often dependent on external parameters, some directly measured by IRS, GPS or engine system, some not directly measured, such as wind speed, static air temperature (T_s) and aerodynamic coefficients. Surrogate models often exist for the latter [4], but these are not always reliable. Therefore, the classic FDI approaches of working with analytical redundancy relations derived from minimally structured over determined sets is often hard to apply onboard for ADS diagnostic.

Many of the reviewed approaches propose instead the use of observers to deal with model uncertainties and not measurable inner states for use in diagnostic and variable estimation. The kinematic and dynamic equations relating these variables are however non-linear, as shown in section 3.2, model uncertainties are also often not of zero mean and tend to vary throughout flight. Intense gradient winds and atmospheric turbulence are often not well covered by dynamic models, while integration of IRS and GPS measurements throughout time tend to yield prohibitively large errors for reliable diagnostic in many cases [54].

This comes to illustrate the many challenges of diagnosing faults on air data sensors. Alongside that, diagnostic has to be robust as false-alarms can have very negative impacts, taking pilots attention unnecessarily and triggering unnecessary corrective actions.

3 State-of-the-art ADS sensors fault diagnosis

3.1 Overview

As previously mentioned, the objective of this work is to perform as exhaustively as possible the review of the publicly available research works on ADS FDI. Furthermore, it is our interest to classify and group this work into the generally accepted categories of FDI methods and into logical clusters defined from an utility point of view.

Our first defined classification criterion of the reviewed methods was with respect to its source of analytical knowledge, using the generally accepted separation into model-driven, data-driven and signal-driven techniques [38]. Model-driven methods are those that rely on a physical model of the system of interest, this physical model will provide the analytical redundancy necessary for the fault detection and isolation. Data-driven model extract the system knowledge needed for an analytical redundancy interpretation from historical data on the operation of the system, in this case real flight data or simulated data. Signal-driven methods employ time-domain and frequency-domain tests on the signals of the measurements to detect faults based on expert rules, such as admissible signal saturation and nominal power spectrum.

The second defined classification criterion is made with respect to the type of information output of the methods. We defined two categories: virtual sensors (VS) and non-VS anomaly detectors. Virtual sensor (VS) is a term generally used to a system capable of estimating the value of a variable without directly measuring it, therefore using the measurement of other variables and explicit or implicit analytical relations to estimate the variable of interest. With VSs, FDI is performed by comparing the estimated value against the measured value following a defined comparison logic. Non-VS anomaly detectors is the term used in this paper to designate methods that allow for fault detection and isolation without directly estimating the value of the interest variable. VS will generally provide more information about the fault, allowing for its characterization, and often allow for continued operation through the rejection of the measurement and adoption of the estimation. On the other hand, non-VS anomaly detectors will often not allow for fault characterization and should be combined with additional fault tolerance techniques to allow for continued operation, such as hardware redundancy or live maintenance.

Further classification criteria will be discussed in the dedicated sections of this paper.

More than 40 papers describing novel FDI and variable estimation algorithms and techniques applied to air data sensors were evaluated, a map for reader reference is provided in figure 1. It is observed that the majority of these presented model-based techniques, followed by data-driven techniques. Signal techniques, although globally used as a layer of fault diagnosis in many aircraft system [31], do not have strong presence in the academic research prepared in the last 30 years on the subject. Hybrid methods are a minority as well. 80% of the analyzed papers propose VS architectures, the other part proposing non-VS anomaly detectors.

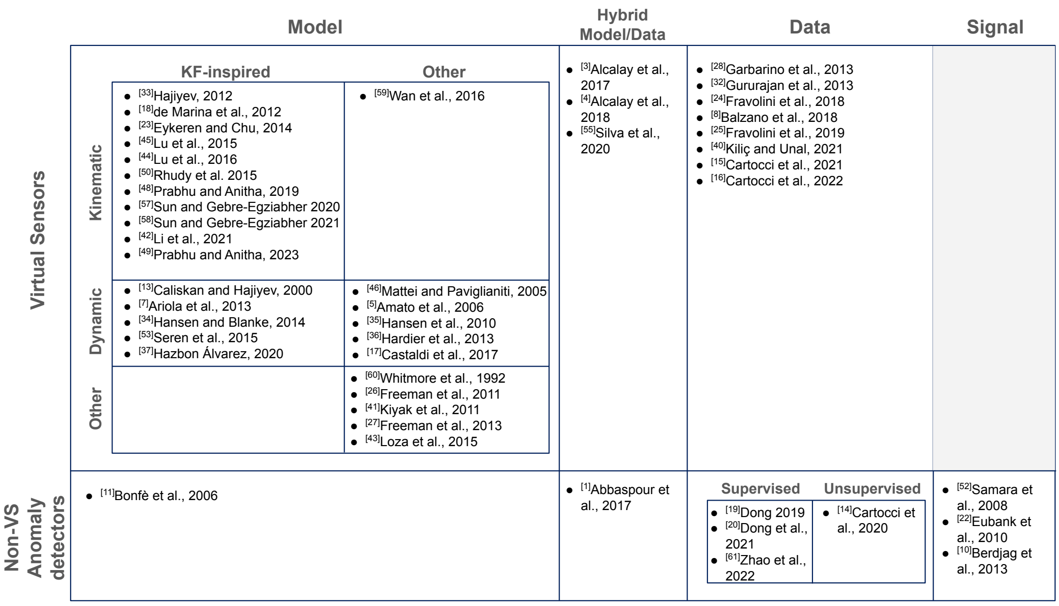

Figure 1 Clustering of different papers reviewed according to the defined classification criteria.

The temporal analysis of the reviewed articles reveal that model-driven approaches have received the highest attention throughout the period analyzed, while data-driven approaches have become popular in the last 6 years, likely motivated by the overall increase in popularity of machine learning and notably deep learning in the same period across domains.

3.2 Model-driven methods

Model-driven approaches rely on a model of the system to perform fault detection and isolation. Different authors impose various restrictions to delimit category. In this paper, this definition is relaxed to include not only parameter estimation and observer approaches, but also classical FDI techniques based on analytical redundancy relations. The idea is to highlight their common dependency on a set of equations that theoretically describe the system.

The second classification criteria presented previously was the separation between VS and non-VS anomaly detectors. The model based approaches are almost always VS approaches, performing detection by comparing the difference between observation and estimation, the so called residue.

The next classification criteria chosen was the physical model used by the proponents. Two main models were used, the aircraft flight kinetic model and the flight dynamics model.

- **Kinematic model**: a kinematic model is by definition a physical model of the system that concerns itself with movement with no regard to its cause, therefore not taking the forces involved into consideration. In the context of aircraft movement and air data sensors, this means a system of equations that associate airspeeds in the body-axis (u, v, w) , angle of attack (α), sideslip angle (β) and attitude angles (ϕ, θ, ψ) to ground speed (V_x, V_y, V_z), attitude angular rates around the body axis (p, q, r), accelerations (a_x, a_y, a_z), wind speeds (w_x, w_y, w_z) and true air speed (TAS). The exact equations used throughout the analysed papers vary according to objective and system specificity, but they derive from the model below with vectors on the body-frame system of coordinates.

$$\begin{cases} x = [u, v, w, \phi, \theta, \psi]^T \,, \\ z = [a_x, a_y, a_z, p, q, r]^T \,, \\ y = [TAS, \alpha, \beta, V_{xGPS}, V_{yGPS}, V_{zGPS}]^T \end{cases} \tag{1}$$

With state-transition equations given by:

$$\begin{cases} \begin{bmatrix} \dot{u} \\ \dot{v} \\ \dot{w} \end{bmatrix} = \begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix} - \begin{bmatrix} 0 & w & -v \\ -w & 0 & u \\ w & -u & 0 \end{bmatrix} \begin{bmatrix} p \\ q \\ r \end{bmatrix} - \begin{bmatrix} \dot{w_x} \\ \dot{w_y} \\ \dot{w_z} \end{bmatrix} \\ \begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} 1 & s_\phi t_\theta & c_\phi t_\theta \\ 0 & c_\phi & s_\phi \\ 0 & s_\phi c_\theta^{-1} & c_\phi c_\theta^{-1} \end{bmatrix} \begin{bmatrix} p \\ q \\ r \end{bmatrix} \end{cases} \tag{2}$$

And observation equations given by:

$$\begin{cases} TAS = \sqrt{u^2 + v^2 + w^2}, \\ \alpha = arcsin(w/u), \\ \beta = arcsin(v/u), \\ \begin{bmatrix} V_x \\ V_y \\ V_z \end{bmatrix} = DCM(\phi, \theta, \psi)^{-1} \left(\begin{bmatrix} u \\ v \\ w \end{bmatrix} + \begin{bmatrix} w_x \\ w_y \\ w_z \end{bmatrix} \right). \end{cases} \tag{3}$$

The kinematic model presents the advantage of simplicity. Acceleration and angular rates in the body frame of reference are given by the inertial reference system, while ground speeds are provided by GPS. No model of forces is required, therefore no aerodynamic equations are necessary. This simplicity is likely the reason why this is the most used modeling in the papers reviewed. The ADS-derived observations monitored by this modeling are TAS, AoA and β. The immediate issue from using this approach is that a fault in the static pressure cannot be easily differentiated from a fault in the total pressure, as they are not individually monitored. Instead, a fault in any of these variables would affect the TAS observation. Most works that chose this approach had as main concern the diagnostic of fault in airspeed measurements as whole, instead of conceiving an individual monitoring of static and total pressure.

- **Dynamic model**: The flight dynamics model, on the other hand, concerns itself with the causes of the movement, therefore calculating the aerodynamic forces. As there are many different forms of adding force equations to the kinematic model in order to allow observability of P_s, P_t and TAT, a framework model will not be derived here as done with the kinematic model, but only descriptive explanation. Considering flight in subsonic compressible regime, the TAS can be associated to M and to T_s by $TAS = M \times c = \sqrt{\gamma R T_s}$ Where c is the speed of sound through air, R the atmospheric air individual gas constant and γ the heat capacity ratio. M on the other hand can be associated to P_s, P_t, T_s, T_t through the energy equation, one of its forms presented below:

$$\frac{P_t}{P_s} = \frac{T_t}{T_s}^{\gamma/(\gamma-1)} = \left(1 + \frac{\gamma - 1}{2} M^2\right)^{\gamma/(\gamma-1)} \tag{4}$$

Additional aerodynamic forces equations allow for the calculation of the dynamic pressure $P_d = P_t - P_s$, one these being the lift L equation $L = P_d S C_L$. Where S is the aerodynamic surface of the airplane and C_L the lift coefficient.
With the kinematic equations providing acceleration, with the knowledge of the aircraft mass and using the aerodynamic forces equations, the dynamic pressure and consequently with the energy equations static pressure and total pressure become observable. A requirement for that is to have a state transition equation for the static temperature, or an equation that allows its observation from the internal states, this can be accomplished by the use of an stand atmospheric model or through the use of a propulsion model, which will not be discussed here.
The dynamic model enables observability of total pressure, static pressure and total temperature sensors, but comes with added complexity. Surrogate models for aircraft aerodynamic coefficients are needed, as these vary with control surfaces configurations, incidence angles and flight regime. Modeling static temperature with a standard atmospheric model comes with significant imprecision, while using a propulsion model requires detailed engine performance knowledge. Reaching the expected accuracy may then require the estimation of modeling biases leading to a complex management of the model observability. This is likely the main reason why the use of dynamic equations is less popular in the reviewed papers.

The next classification criteria of the model-driven methods was with respect to the approach used for FDI.

The simplest form of model-driven FDI is through the use of analytical redundancy relations (ARR). An ARR can be obtained from a structurally overdetermined set of equations that include the system internal states and observations as variables. These can be obtained, for example, through the use of parity equations. This method is simple and reliable, but does not deal well with evolving systems, external disturbances and notably model uncertainty. [47]

A second form of model-based diagnosis is through the use of estimators. By estimating the model parameters, and thus the physical parameters, through the use of the observations, inputs and the model, one can observe the changes on these estimated parameters to declare or not a fault. Notable techniques include recursive least squares estimation, the Hagglund method, and the Favier and Arruda method [47]. Estimators are another simple approach, but ignore any temporal evolution of the system states if they are available.

A most popular approach however is the construction of state observers. This approach exploits the knowledge of state-transition equations that provide predictions of the system next state, and of observation equations that associate these states at each instant to the available observations. [56]

In this review, we classify the model-driven approaches in two categories: Kalman filtering (KF) based approaches and non-Kalman filtering based (non-KF) approaches. This classification is motivated simply by the extensive representation of KF based approaches compared to others for ADS variables estimation and FDI.

3.2.1 KF-based approaches

The Kalman filter was initially proposed in [39]. Since then, it has been extensively used to filter noise of observations. The Kalman Filter is a statistical ponderator based in two steps:

- A **prediction step** where the internal states are propagated using a state-transition matrix and an observation matrix
- A **correction step** performed after the calculation of an optimal gain that will weight the contribution of prediction and observation in the final consolidated estimation.

The residues between predictions, observations and estimations can be used for FDI. The original KF formulation was only adapted to systems with linear models of state transition and observation equations and gaussian zero mean noises, which is not adapted for the models of ADS sensors observations described previously. Many derivative forms of the Kalman filter exist to overcome the mentioned limitations and relax the model hypothesis.

The Extended Kalman filter (EKF) is one of these derivative methods, and involves the linearization of the non-linear state-transition and observation equations through the calculation of the respective jacobians around the point of last estimation. In [23], authors apply the EKF on the kinematic model of the aircraft tested on a high fidelity simulator of a twin engine aircraft. The paper also proposes an exhaustive testing of faults with a Monte Carlo approach for fault inserting. The paper however assumes constant wind, a condition not usually seen in reality. [58] and [57] also propose the use of an EKF for the kinematic model, but have a weaker hypothesis on wind conditions, by assuming a first order Gauss-Markov model for wind speed, which supposes wind dynamics are slow, but not constant. More robust to slow wind gradients, but not to turbulence and strong gradients where the lack of a predictive wind model still makes the use of residues for fault diagnosis not robust enough to atmospheric conditions. The paper proposes several forms of FDI using this EKF, including a Receiver Autonomous Integrity Monitoring inspired statistical test for detection. [33] applies EKF to the kinematic model, but proposes an operative method of testing the innovation covariance of the KF, where the defined monitoring statistic is the maximal eigenvalue of the random Wishart matrix. The idea being that determining a confidence domain for testing in real time the KF innovation covariance is harder than determining it through the Tracy-Widom distribution.

[42] proposes a method for FDI on ADS based on EKF on the kinematic model, but considers the time offset between ADS and IRS sensor measurements as a source of possible errors that can trick the detection algorithm. The authors propose an additional observer, with a state-transition matrix defined as the identity matrix, that estimate the time-offset to be used on re-aligning measurements. Since the offset is only observable during maneuver,

their overall air data variables observers adapt during and out of maneuver time. [48] uses a variation of the EKF on the kinematic model of the aircraft, the Exponentially Weighted Adaptive Kalman Filter. This approach calculates the innovation covariance matrix as an exponentially decreasing weighted variance sum of past innovations using a fixed size time window to attenuate external disturbances and is supposed to provide more robust fault detection on turbulence situations. Wind however is modeled as a random walk process, not allowing for assessment of its robustness on strong wind gradients. A work from the same author takes a similar approach in [49], here however an Iterated Optimal Extended Kalman Filter (IOEFK) is used as a tentative to better accommodate the strong non-linearity of the physical model. The EKF works with local linearizations of the model equations, the IOEKF tries to improve the precision of these linearizations by iterating the point around which they are performed by performing the update step of the EKF multiple times.

Another form of dealing with the linear limitations of the KF is by adopting an ensemble strategy. By operating on ensembles of points following a distribution, one does not need to calculate expected values and variances directly. This is the case of the Unscented Kalman Filter (UKF), that uses a collection of sigma points, propagated using the direct non-linear equations of state-transition and observation. [18] uses two UKFs. The first estimates TAS and AoA using thekinematic equations under constant wind assumption and its residues are used for FD. A second UKF estimates the magnitude of the fault when it occurs by estimating the value of an added variable measuring the bias of AoA. The idea behind two filters is to use uncorrected estimations for FD and corrected estimations for fault characterization.

In [45] and [44], authors propose what is essentially an UKF applied to the kinematic model, which they name Robust Three Step Unscented Kalman Filter, for fault detection and isolation. Authors compare the performance of this filter against an Adaptive Fading Unscented Kalman Filter and apply both methods to real flight data. Although not mentioned, it seems wind was considered constant in this work, which is likely why the simple UKF did not perform well. Authors propose a modified version of it they name the Modified Robust Three-Step Unscented Kalman Filter, an UKF that performs a few measurement updates before operation to calibrate the initial states, which performs better. [51] also proposes the UKF applied to an UAV kinematic model, comparing its performance to that of the EKF, where only a slight difference in estimation performance was found in favor of the EKF. Author proposed cumulative sum control charts (CUSUM) and floating limiters for the FD step after obtaining innovations from the filters.

Many authors preferred the kinematic model approach presented above due to its simplicity and reduced model uncertainty. Those who used the dynamic model alternatively had to cope with its complexities in different forms. That is the case of the work of [34], where the aerodynamic lift force is calculated and a model of the engine is used for the calculation of thrust. To circumvent the lack of state-transition equations, the author simplifies the prediction step of the filter to a random walk process, sacrificing the information gained by the time propagation. Fault detection is achieved through a change detection framework through the use of Generalized Likelihood Ratio Tests (GLRT). This approach to dealing with the dynamic model complexity is somewhat similar to that undertaken by [3] and [4] where the state vector chosen is $X = (\overrightarrow{W}, b_{C_L}, \Delta_{ISA}, z_C)$, respectively wind speed vector, bias between lift coefficient from surrogate model and from lift equation, temperature deviation from standard atmosphere model and altitude deviation from standard atmosphere model. The estimation of this state vector allows for the estimation of modeling errors and the analysis of their magnitudes allows for the fault detection. The similarity with the previous work is that no state-transition equations are derived for the state prediction step, instead a constant dynamic is assumed for all these variables, except for b_{C_L} for which a slow first order damping is assumed. [37] also proposes an EKF observer for the dynamic model of the aircraft, where residues are compared to a fixed threshold for fault detection. The interest in the author's approach is the definition of these thresholds as a gain multiplied by the mean residue, setting this gain as a compromise between false alarm rate and sensitivity to faults. [7] proposes the use of an EKF for the dynamic model but with the addition of a bank of integrators, one integrator per residue of each observation, used for fault detection and isolation. [53] proposes the use of an Adaptive Extended Kalman Filter for the observation of ADS variables, tuning the covariance error matrix of observations and state transitions in case of a detected fault. The downside of the proposed approach for larger airplanes is its reliance on a thrust model of the engines, which is not always reliable given the wide range of operation of commercial aircraft.

[13] takes a different perspective on the problem, and is instead concerned on defining the best metrics surrounding KF innovations and residues for optimal FDI on ADS. Four metric are compared, including the trace of the covariance matrix and the generalized variance of the covariance matrix of the innovation sequence, each of the 4 metric present a compromise between robustness to false alarms and sensitivity to faults.

3.2.2 Non KF-based approaches

Despite the majority of papers working with implementations of Extended Kalman Filters and Unscented Kalman Filters, a part of the reviewed works proposed non-KF based alternatives. In this section, these alternatives are presented, those comprise a range of methods from direct analytical redundancy relations to state observers not deriving from the KF.

[60] proposes an analytical redundancy approach to fault detection on a flush AoA probe of an F16 fighter jet. The non-linear model of the sensor is used to generate residues of the individual static pressure ports, and test these residues based on a Chi-square metric for fault detection. The non-linear model is linearized around the last non-failed state to allow the computation of its inverse functions. If fault is detected, a series of statistical tests are performed for isolation: including a reason check and a simple residue magnitude check. This is one example of model-driven approach applied neither to the kinematic nor dynamic models, but to the specific flush probe non-linear model. [17] also works on the direct analytic redundancy relations, by proposing the generation of residues that discriminate the occurrence of different faults so that isolation can be performed with the classical use of a fault sensitivity matrix, using non-linear geometric approach with singular perturbations (SP). SP theory allows for good residue generation on fast and slow dynamic points. Author considers altitude, speed and rate of climb to follow a slow dynamic while angle of attack and pitch rate follow a fast dynamic. [35] proposes another method of FDI on ADS not using observers for a small UAV. In it, residues are generated by using air data measured airspeed and airspeed obtained through the calculation of GPS ground speed (obtained through a KF). The wind speed is assumed to be constant and the airspeed is obtained through the use of an engine thrust model. Residues obtained are found to have colored noise, and filters tuned using flight data are used to bring their means to zero. A generalized likelihood ratio test is performed both on raw signal and whitened signal for FDI. [11] presents an elegant application of redundancy equations by generating residues using the aircraft dynamic model through the use of polynomial residue generators.

[36] proposes an estimator approach for the generation of redundant measurements and residues. FDI is based on the redundancy of aerodynamic coefficients provided by the use of the force and moment equations and the use of surrogate models for these coefficients.

The values of angle of attack and speed are calculated from a least squares optimization procedure. This optimization uses a second order local optimizer to minimize the error between surrogate coefficients and the coefficients coming from the aerodynamic equations. This is an interesting application of model inversion through optimization. However, it relies on the dynamic model, notably on a model for engine thrust, which as mentioned previously might limit its application.

Apart from the KF based observers, the most popular alternative filter used was the H_∞ or *Minmax* filter. In [26] and [27], the author proposes the use of the H_∞ filter for the problem of air data fault diagnosis and estimation applied to the NASA Generic Transport Model (GTM). The scope of the diagnosis is restricted to total pressure and static pressure faults of partial and full blockage. The choice of the H_∞ is interesting as it eliminates the need for strong hypothesis on the noises and disturbances. Another interesting contribution is the implementation of the approach on a closed loop context, where autopilot reference and control commands are used as observations, although authors claim no performance gains were found. [46] applies the H_∞ to the dynamic model of a small commercial aircraft. Here a bank of filters is used to isolate the fault, each bank estimating the observations of one of the two available ADRs.

Unknown Input Observers (UIO) were also present in the evaluated works. That is the case of [41], where an UIO is used to generate residues for threshold analysis for fault detection, with a generalized observer scheme (GOS), where each residue is sensitive to all faults except for one. In [5], authors propose a novel nonlinear observer exploiting UIO theory to guarantee disturbance decoupling with an H_∞ performance level.

Wind disturbances are a major concern for the design of a virtual sensor for ADS. Different approaches were presented previously, including simplifying hypothesis, constant or slow changing wind, or the inclusion of these as state variables. Other authors consider wind disturbances to be bound, using this property for designing observers. This is the case of [59], where the proposition is to perform a moving horizon state estimation using the kinematic model as an optimization problem using Karush-Kuhn-Tucker (KKT) conditions to deal with wind bound constraints, in order to increase the robustness to wind while maintaining sensitivity. [43] also considers the bounded wind hypothesis to estimate the faults based on a non-homogeneous high-order sliding mode observer, in finite time and in the presence of bounded disturbances. The sensor faults are estimated for the class of systems satisfying the structural property of strong observability. A key feature of the proposed solution is concerned by the effect that measurement noise could have on fault reconstruction. The physicial model used was obtained through linearization around a THS trimmed point, which limits however the solution proposed.

3.3 Data-driven methods

Data-driven methods have become increasingly popular for ADS FDI and for FDI globally as our review has revealed. The main challenge for the application of these techniques are the availability and quality of data. There are usually three sources of ADS data: simulation, flight test and operative flight data. Their use present specific challenges as described in table 1

The presented challenges related to the data use are maybe the main obstacles for the data-driven approaches on ADS FDI, but they are also a blocking point when evaluating and surveying papers, as the performance indicated by authors might often be distant to that achieved by a real application. Most of the data-driven papers reviewed have used simulation data, unless stated otherwise in the text.

Table 1 Description of the three sources of ADS data (simulation, operation and flight test) according to availability, quality, diversity and representativeness of data.

Source	Availability	Quality	Diversity	Representativeness
Simulation	Readily available and allowing the artificial creation of unlimited data	Sampling rates can be set at will, virtually any parameter of interest can be measured.	Depends on simulator complexity, overall many different weather conditions, operation points and maneuvers can be simulated.	Often important deviations from data expected in operation
Operation	Usually not publicly available, but available to airlines and often shared with manufacturers.	Sampling rates are often low, gaps not uncommon. Traceability of maneuvers and flight conditions often poor. Often not all features of interest are recorded.	Diversity of weather conditions, aircraft serial numbers and itineraries. Operation will not reach the extremes of aircraft capabilities and of flight envelope.	The highest possible, as it issues from the final application
Flight test	Industrial secret kept by aircraft manufacturers and not publicly available	High parameter coverage, high sampling rate, thorough annotation of the flight conditions and maneuvers.	Wide range of operation points tested. Aircraft evaluated to the limits of its flight envelope. Multiple allowed and forbidden maneuvers are tested.	Representative data. Limited to a few serial numbers, weather conditions and routes.

Following our defined classification, the existing data approaches are first divided into virtual sensors and non-VS Anomaly Detectors.

3.3.1 Data-driven virtual sensors

VS designs using data-driven methods consist of estimators trained usually on nominal non-faulty data. They are capable of estimating a variable of interest at an instant of time using the other available observations. The observations used might correspond to the current instant only, or can additionally be composed of previous observations along a fixed or variable time window. The previous observations of the variable of interest itself can be used for the estimation. Multiple detection and isolation techniques can be used once the estimations are available, and are usually independent of the estimator.

The simplest form of data-driven VS uses only current observations for estimating the evaluated variable, exploiting implicit relationships between different observations. This is analogous to identifying analytic redundancy relationships using a system model, the difference here being that the system equations are not known and we would like to extract them from system operation data. The advantage of this approach is that many simple machine learning and regression models can be used, feed-forward neural networks (FFNN) of varying architectures, linear and non-linear regressors, regression splines, regression trees, bayesian regression are some examples. The weakness of these methods is that the equation parameters that model the aircraft dynamics are not steady, but instead evolve with fuel consumption and with the changes of aircraft configurations, e.g. high and low lift configurations. If enough diversity of data is available, the simple model should be able to take these as features as well, however the atmospheric disturbance that effect the equations cannot generally be measured, and these simple approaches will suffer from this imprecision.

[28] is one of the earliest works on the use of data-driven methods for ADS FDI. The author uses a simple feed-forward neural network to produce redundant estimations of indicated airspeed using other ADS measurements along with GPS data. The downside is that its real

applicability is very limited, since no consideration was given to wind disturbances. [32] takes a similar approach, estimating airspeed through the use of IRS data, in this case testing two FFNN architectures, a first basic Multi-Layer Perceptron (MLP) and an Extended Minimal Resource Allocating Neural Network. Again no wind corrections were considered. Furthermore as train and validation sets were extracted from data points of the same flights, doubts can arise on its claimed performance.

The work of [8] is also included in this time-less regression approach. Here, a series of neural networks are used to estimate TAS, AoA and β. The main innovation comes on the residue-threshold analysis, where the thresholds are not fixed but are trained using real flight data. The threshold that limits normal operation is therefore dependent on the operating point of the aircraft. [40] proposes another regressor without past observations, but based on Artificial Neural Fuzzification Inference (ANFI) and MLP. The interesting point in the author's approach is that the thresholds for detection were not based on the regressor performance itself, but on the Federal Aviation Agency (FAA) acceptable deltas between captain and first officer displays for the different variables. Features were selected for the regression based on simple Pearson correlation.

Authors also have experimented with simpler regressors, as shown by [15], where linear regression is used to estimate the interest variables the observations of the other sensors and the control inputs. Isolation using residues is done in different forms: the first is by using Mahalanobis distance to compare the residue vector to the fault directions. Another form was by reconstructing the fault vector by finding the minimal fault that best approximates the corresponding residue to the real one, based on the hypothesis that only one fault occurs at a time. Using linear regressions to capture the implicit relations in a non-linear system presents obvious limitations, and the same author proposes an expansion to this work in [16], where non-linear additive regression is used. The author takes advantage of the additive nature of this approach to derive the fault-sensitivity matrix of the observations by local linearization using the first order term of the Taylor expansion of the non-linear terms in function of the states. The author also proposes to take advantage of analytical redundancy through assumed non-faulty variables to produce estimates of the observations through mutivariate adaptative regression splines. The residue is then used to detect a fault.

[24] takes a different and interesting approach, by using interval models to deal with uncertainty on estimation. measurements that fall outside of the interval bounds are considered faults. The non-linear dynamics are estimated by a neural network, while the interval model, linear in nature, explains the dynamic noise and variation.

The next form of data-driven VS can be achieved using the time information provided by the previous observations, this is the data-driven approach analogous to the construction of an observer in a model-driven approach. This approach requires the use of more complex models. The classes of neural networks with memory capabilities, such as Recursive Neural Networks (RNNs), Long-Short Term Memory Units (LSTMs) and Transformers are a few examples. Autoregressive models, e.g. Non Linear Autoregression with Exogeneous Variables (NARX), and time series models that consider exogenous inputs can also be used, such as Autoregressive Integrated Moving Average with Exogenous Inputs (ARIMAX).

This has been the least used approach for data-driven VS design in ADS as observed in this review. [25] tests a series of adaptative regression algorithms for the estimation of TAS and subsequent FDI. The non-adaptative models are the classic implementations of NARX and of the Linear Finite-Impulse Response Model, while their adaptative versions add a term that tends to converge the estimated value to the measured value, analogous to an update step for a KF. The author finds that the adaptative versions of these algorithms performed better and claims that method can detect faults on TAS of as little as 0.7 m/s while being robust to false alarms.

3.3.2 Data-driven non-VS anomaly detectors

Anomaly detection in the context of data analysis is the identification and isolation of items, events or data points that are rare, or that deviate from the trends observed for the majority of the data or, the definition that is more important in our context, that do not follow what is considered as the normal behavior. In the context of ADS FDI, nominal behavior can be seen as sensors measuring their respective values within expected levels of precision, defined often by the sensor uncertainty informed by the manufacturer or by the needs of autoflight, flight control, navigation and guidance. Three types of training for non-VS anomaly detectors are differentiated: supervised, semi-supervised and unsupervised.

Supervised trained non-VS anomaly detectors use training data that is labeled with fault or no-fault. The fault label can be further characterized by the type or class of fault, in which case a classification is performed for a multiclass anomaly detection. This will often be the case with simulated data, where faults are ingested artificially and precise labeling is possible.

[20] and [61] frame the FDI problem similarly as a supervised classification, performed by a Deep Neural Network (DNN) with convolutional layers and LSTM units. 2 dimensional inputs are used, a dimension for the different features and one for the different flight data points in a fixed size time window. The convolutional layers and LSTMs units are used to capture the patterns, such as drift, present in the data that can reveal a fault. A dictionary of 5 types of fault is created labeled from 1-5, while the label 0 is given to nominal flight points. An interesting approach, but limited by the need of defining a dictionary of faults in advance. [19] also chooses to use a supervised trained DNN approach, but focused on the cases of icing detection, an interesting advance is the use of transfer learning techniques to adapt the trained model to the similar task of icing detection on actuators.

Semi-supervised trained non-VS anomaly detectors have a partially labeled data. In the case of ADS FDI, this means having a collection of data points known to be nominal, but no faulty data points. This type of models is often suitable for training using real flight test data. The quality control of flight tests ensure the data is nominal, but no faulty data is usually available for training. Notable exceptions exist, namely when a flight test is performed to test aircraft robustness to a specific type of fault or when faults are artificially inserted into the nominal flight test data after its execution. The former produces only limited cases of fault data while the latter cannot guarantee that the inserted faults represent well the true faulty behavior mid-flight, hindering the use of supervised approaches efficiently. This approach has been largely ignored for ADS FDI to this moment, and is a probable pathway for future works. One reason for this being the use of simulated data by most of the papers reviewed, which is more prone to the training of supervised methods. Readers can refer to [50] for example, where autoencoders are used for FDI of electric motors. Autoencoders are a class of semi-supervised anomaly detectors. They are trained to reduce the number of dimensions of nominal data through encoding, bringing data to a latent representation but retaining a maximum of information. This retaining allows a subsequent decoding of this latent representation back to the normal representation with minimal errors. Ideally, an autoencoder trained in this manner would have low performance when encoding and decoding anomalous or faulty data, as the implicit relations between the dimensions that allow for the retaining of information when bringing data to a latent representation would not be respected. This difference of performance allows for fault detection and isolation.

Unsupervised training is the most challenging form of producing an anomaly detector, and also the most classic. Data is not labeled, and algorithms will try to separate the observations into groups, often referred as clusters, following underlying data patterns. Some interpretation is usually needed for understanding which cluster correspond to normal data and which to do not. This is a less seen paradigma for ADS FDI, but can be the case when training is performed with aircraft operation flight data, where no nominal behavior is assumed.

Principal Components Analysis can be used for unsupervised anomaly detection, and is proposed by [14] for dimensionality-reduction of flight data. Metrics of distance are used inside the principal components space to define if a fault exists or not with a drift diffusion model to avoid fluctuations.

3.4 Signal-driven methods

Mainly signal-driven approaches for fault detection were not featured extensively in recent research ADS FDI, which is partly due to how consolidated these methods are, and the fact that they are already extensively used in aircraft as health checks.

[52] proposes a statistical method capable of independently monitoring a single sensor, without relying on additional redundancy or other variables. It involves cleaning the signal of nonstationary components, whitening via a proposed pooled autoregressive modeling, statistical decision making, and an electronic spike/glitch removal logic.

In [22], authors propose a diagnostic for an UAV seaplane with history of Pitot faults due to blockage with water. They privilege time-domain analysis to frequency-domain as they claim that the common classes of air-data sensors do not generally have a strong frequency component. The detection strategy is based on the analysis of multiple features extracted from sensor signal. The features verified are signal saturation, signal variance peak change rate, signal variance deviation threshold. The thresholds used to characterize a fault through the calcualted features are extracted from data. Fault is declared by a weighted average of the probabilities of fault given by each of the three signal tests, with higher weight for saturation.

[10] proposes a physical redundancy based FDI approach that borrows from data-driven and signal-driven methods. The work is focused on improving diagnosis when three redundant sources are available and allow for oscillatory fault detection and isolation when only two sources are available. The author proposes a fuzzy consolidation of the sources measurements when the three are available, allowing for a continuous transition for a valid consolidated measurement when one of them is to be rejected. Oscillatory fault detection is performed through the use of a Kalman filter to isolate the oscillatory component of the signal, transforming it into a step-like signal for residue-threshold comparison.

3.5 Hybrid methods

Hybrid methods are those that rely on a combination of partial/complete modeling knowledge of the system and data regarding its operation. Four common applications of hybridization are highlighted:

- **Data for compensation of non-modeled effects**: data-driven approaches used in series with model-driven approaches to capture effects not covered by the available model.
- **Model derivation**: when a physical model of the system is unknown, data-driven methods can be used for their derivation. One example is the use of symbolic regression to extract equations linking system variables.
- **Noise handling**: when the model uncertainty or the observation noises covariance matrix are unknown, or change with time/external variables, data-driven methods can be used to provide a noise estimate for the model-driven approach.

- **Adaptive threshold calculation** data-driven methods are trained to adapt the threshold for fault detection over the residues dynamically, when these change over time or by external action. This is done to improve sensitivity and to increase robustness to false alarms.

[55] adopts both the model derivation approach for the data/model hybridization and the adaptive threshold calculation. In the work, a Kalman Filter is used as observer, the model however is not explicitly provided but rather derived from flight test time-series data by means of dynamic mode decomposition (DMD). The threshold for fault detection on residue is decided through the use of a decision tree, trained on labeled faulty/non-faulty data. [4] uses a surrogate model for the lift coefficient trained as basic multi-layer perceptron to account for the unknown modeling, necessary for the implementation of the EKF. [1] proposes on the other hand a combination of EKF with a neural network to perform fault estimation, having its weights adapted online during aircraft operation.

4 Limitations of SoA and ways forward

Excellent works have been produced on the topic of ADS fault detection and isolation. The main problems tackled when applying FDI methods to ADS are the following:
- The underlying models are non-linear by nature,
- Sensors are exposed to external disturbances due to wind gradients and other phenomena, system and environment changing conditions, causing modeling uncertainties, especially when working with aerodynamic forces,
- A variety of types and modes of faults exist, some modes being discovered only after being observed in operation,
- FDI must be performed online on aeronautical-graded computers, with limited computational and parallelization power,
- FDI methods are required to have a high robustness to false alarms as aviation is a safety critical domain.

Signal approaches are useful on their simplicity and reliability to detect deviations from normal behaviour, and are currently used in airplanes not only for ADS FDI but for fault detection in actuators and other systems. Despite their usefulness, they often do not provide enough sensitivity to faults and they should not be used as the sole means for analytical redundancy.

Model-driven approaches can provide the required additional sensitivity and are a way to obtain virtual measurements of faulty variables allowing continued operation. Drawbacks exist however: the non-linear models demand adaptations of the observers used, which increases imprecision, notably seen in case of local linearization, such as with the Extended Kalman Filter and mitigated to some extent with ensemble strategies, such as used by the Unscented Kalman Filter and the Ensemble Kalman Filter. Another drawback is the lack of reliable modeling of the systems. This is most noticeable when methods are transported from the realm of simulation to the realm of real flight: dynamic models suffer from important deviations on the aerodynamic coefficients and on the engine behavior. Models are required to be adaptive or often simplified and some equations discarded. Kinematic and dynamic models suffer with the unknown wind variations, which was dealt with by authors in multiple ways, from bounded optimizations to simplification hypothesis, with varying degrees of robustness to real operation.

We believe data-driven approaches and hybrid approaches have the power to overcome some of these difficulties, exhibiting enough complexity so that they can be trained to detect small deviations but at the same time enough flexibility as to adapt to different flight operation points with the necessary robustness, provided that the data presented for training has enough quality and diversity. Most notably, we believe semi-supervised approaches should be explored. As air data sensors are exposed, faults can have many different causes and present themselves in non predicted forms. This is why we believe practical implementations of supervised methods might suffer from the lack of generality, as labeled faulty data will hardly be representative enough in simulated or real data.

Both data-driven virtual sensors and semi-supervised anomaly detectors exploit nominal data, available with great diversity nowadays from simulated and real flight test campaigns. The former can work as a self-contained system, providing estimations and FDI. The latter, can be combined with model based observers or estimators to provide the estimations in case no trusted measurements are available. Possibilities for implementing data-driven VS are the use of NN ,RNNs, LSTMs and CNNs trained on nominal data to provide estimations. Training can be further improved through the use of data assimilation frameworks [12]. As for semi-supervised anomaly detectors: PCA, correlation analysis and autoencoders are simple but effective choices. These consolidated technologies are the starting points for the research of the authors of this paper.

One of the main historical challenges concerning the use of data-driven methods in aeronautical applications has been the certification. The current trend is for this issue to be mitigated due to the evolution of regulations around the world. The European Union Aviation Safety Agency (EASA) has recently issued a concept paper with guidance for future aeronautical machine learning applications indicating four building blocks for the framework of a *trustworthy AI*: AI trustworthiness analysis, AI assurance, human factors for AI and AI safety risk mitigation [21]. This hints to the future progress and wide utilization of more AI based solutions, which further corroborates our recommendation.

Another important challenge to data-driven methods is explainability and interpretability. An explainable AI model is one whose inner workings can be explained in a human comprehensible manner. An interpretable model is one for which the effects on the outputs through the variations of its inputs are known [30]. Interpretability can be attained more often than explainability. Model-driven and signal-driven approaches are explainable and interpretable, which is often not the case for data-driven approaches. Trustworthy AI will require a degree of interpretability and explainability that is yet to be addressed, as virtually none of the papers reviewed tackled the topic.

Another point of improvement for future works concerns the analysis of robustness. As previously mentioned, false alarms are not tolerated on aeronautical applications. This is especially true at certain times, such as take-off and landing, during turbulence or strong gusts of wind. Therefore, an assessment of robustness should include not only the rates of false alarm, but also an analysis of when they are most prevalent.

5 Conclusions

This review paper intends to perform an exhaustive review of publicly available papers on embedded FDI methods of air data sensors. The papers according to different criteria have been grouped, finding that most proposals were model-driven virtual sensors based on KF variations, most notably the Extended Kalman Filter. Furthermore, it was found that data-driven methods have gained popularity in recent years, with a majority of those works focusing on virtual sensors based on non-linear regressions and different types of neural networks.

We present the challenges for ADS FDI, and highlight the trend towards data-driven methods and the availability of data due to extensive flight test campaigns performed throughout the decades and due to more accurate simulations. Due to those, we believe an important way forward to ADS FDI research lies on data-driven methods, in special on non-VS anomaly detector architectures. These have not received enough attention, as observed in the review, but are especially interesting in ADS systems where often double redundancy is available and the bottleneck for the system lies on the selection of one working sensor alongside two faulty sensors. Certification for these types of systems is still a major challenge as they often have low degree of explainability and interpretability.

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