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Effects of the Wind Field on the Synthetic Measurement of the Aerodynamic Angles of an Aerial Vehicle

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Abstract—The estimation of the angle of attack and sideslip angle is of fundamental importance for the situational awareness of an aerial vehicle. Historically, several accidents occurred due to failures of the traditional protruding probes applied to measure these two angles. The MIDAS project aims to design and develop a certifiable Air Data System capable of providing the entire set of Air Data, integrating a synthetic estimation of the aerodynamic angles. All operating conditions shall be taken into account, even those related to atmospheric phenomena. The wind effects (both steady and unsteady) represent a very challenging topic when design a synthetic sensor because of its intrinsic nature. In fact, the airflow surrounding the AC can be affected by several phenomena with a very wide range of characteristics (e.g. speed and direction range) that can be hardly simulated during the design stage. It is clear that the atmosphere condition (both steady and unsteady) can affect this particular kind of sensor, and it must be analysed the error in the presence of the wind. The paper shows the estimation error due to the steady wind field and correction to be applied to previous synthetic sensors design in order to be reliable both in still air and in presence of the wind.

Index Terms—synthetic sensor, neural network, flight safety, wind field, AOA vane, observers

GLOSSARY

AC	Aircraft
ADAHRS	Air Data, Attitude and Heading Reference System
ADM	Air Data Module
ADS	Air Data System
AOA	Angle of Attack
AOS	Angle of Sideslip
CS	Certification Specifications
FBW	Fly-by-Wire
FCS	Flight Control System
GNSS	Global Navigation Satellite System

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MIDAS	Modular and Integrated Digital Probe for SAT Aircraft Air Data System
MLP	Multilayer Perceptron
NED	North-East-Down
NN	Neural Network
PAI	Piaggio Aero Industries S.p.A.
PDF	Probability Density Function
SAT	Small Aircraft Transportation
TAT	Total Air Temperature
TS	Training Set
VS	Virtual Sensor

I. INTRODUCTION

During flight, the measurement of the Air Data set is crucial. Basically, there are 2 main reasons. First of all, the forces and moments acting on the aircraft are generated depending on the reciprocal relationship between the aircraft itself and the control volume where the aircraft is flying. Second, Air Data are used as basis to understand the flight condition. For instance, the barometric altitude or the various airspeed definitions. The system applied to measure the air data is composed by a set of external and, generally, protruding probes. Each of them has different requirements in terms of position and power supply and a triplex redundancy is a standard in commercial aviation to deal with the level of criticality of the system.

During the last decades, technology and regulations brought to the significant reduction of the aircraft incidents due to technical reasons. However, the safety of flight still remains an important topic and recent tragedies demonstrate how the physical probes can suffer from the exposure to the external agents. Although the standard was to connect probes and vanes to ADM (Air Data Module) pneumatically, each one connected in turn to the FCS (Flight Control System), this

solution has several drawbacks. More recently, digital solutions have been applied to the ADS (Air Data System) to ease the integration with the modern digital avionics. FBW (Fly-by-Wire) paradigm and more electrical aircraft hence drive a technological transition to achieve the goals defined by the European Community, EC, within the FlightPath 2050 [1]. Moreover, many large AC (Aircraft) are equipped with integrated probes which embed transducers within the probe (or vane) itself [2].

In this framework, the MIDAS (Modular and Integrated Digital Probe for SAT Aircraft Air Data System) project is funded under Clean Sky 2 to design a modular and integrated digital air data system for the SAT (Small Aircraft Transportation) segment. This innovative system provides the entire set of air data, including AOA (Angle of Attack) and AOS (Angle of Sideslip), with a limited number of 2 protruding probes, thanks to the implementation of synthetic sensors. This paper concentrates on the measurement of the aerodynamic angles AOA (or α) and AOS (or β). Several research groups proposed solutions to the problem of the estimation of the aerodynamic angles. Some of them are based on explicit mathematical models [3]–[5] that can be based on Kalman Filters [6], [7] whereas others are based on machine learning techniques [8]–[17]. The MIDAS is equipped with a synthetic sensor based on the Smart-ADAHRS patent [10], based on a NN (Neural Network) estimator.

As a result of the physical relationship between the wind field and the aerodynamic angles, most of the estimation algorithms for AOA/AOS are intrinsically affected by the wind. Although some of them implements a model of the wind field to improve the estimation accuracy, unfortunately the direct measurement of the wind speed is usually unavailable. Hence, the analysis of the wind effects on the final error uncertainty of the system should be a part of the design flow of every synthetic sensor for air data. This paper shows an empirical analysis of the effect of a steady wind on the synthetic sensor showed in [18]–[21]. Sec. II describes the MIDAS synthetic estimator and the method followed in this paper is described in Sec. III. The results have been reported in Sec. IV and discussed in Sec. V.

II. STRUCTURE OF THE MIDAS SYNTHETIC ESTIMATION

The MIDAS ADS is shown in Fig. 1 and the current configuration is shown in Fig. 2. It consists of two protruding probes for pressures and temperature and a synthetic (or virtual) sensor. The external probes are a Pitot-Static probe and a TAT (Total Air Temperature) probe. The synthetic sensor allows to complete the so-called air triplet with the evaluation of AOA and AOS.

The synthetic sensor is based on the Smart-ADAHRS (Air Data, Attitude and Heading Reference System) algorithm. It is based on the correction of an initial estimation of the angle $\hat{\alpha}$ (respectively $\hat{\beta}$), calculated on the basis of classical flight mechanics equations. The correction, $\Delta\alpha$ (respectively $\Delta\beta$) is evaluated by a NN properly trained to conduct a sort of calibration of the initial evaluation. The architecture selected is

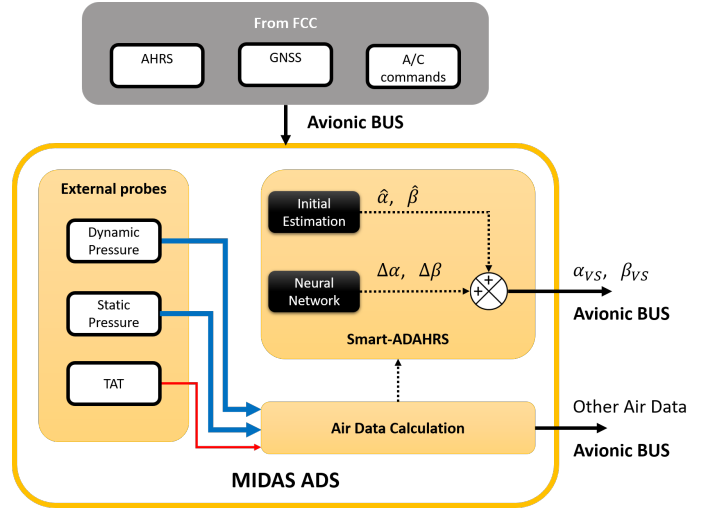


Fig. 1. High-level schematic of the MIDAS ADS.

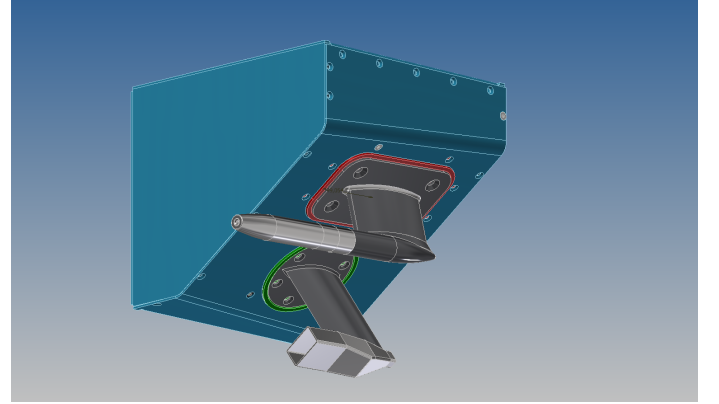


Fig. 2. External view of the MIDAS ADS. Courtesy of SELT A&D [22]

a fully-connected feed-forward MLP (Multilayer Perceptron) corresponding to the map in Eq. 1.

$$[\Delta\alpha, \Delta\beta]^T = \mathbf{f}_{VS}(\text{TAS}, \hat{\alpha}, n_x, n_y, n_z, \theta, \phi, p, q, r, \delta_e, \delta_a, \delta_r, \delta_{th}, \Delta_{th}, \delta_{hs}) \quad (1)$$

where TAS is the true airspeed, n_x, n_y, n_z are the accelerations measured by the accelerometers respectively in X_B, Y_B and Z_B axes, θ, ϕ are the pitch angle and the roll angle respectively, p, q, r are the body angular rates, $\hat{\alpha}$ is the initial estimation for the AOA, δ_e is the elevator deflection, δ_a is the aileron deflection, δ_r is the rudder deflection, δ_{th} is the throttle command, Δ_{th} is the difference between the torque on the left and right propellers and δ_{hs} is the horizontal stabilizer angle.

The initial estimation of α and β are listed in (3).

$$\hat{\alpha} = \theta - \gamma \quad (2)$$

$$\hat{\beta} = K_\beta \frac{n_y}{q_c} \quad (3)$$

where K_β is a tuning coefficient with an order of magnitude of 1000 kg m^{-2} . The identified feed-forward MLP is composed

by a single hidden layer with 24 neurons which applies a nonlinear activation function to a biased linear combination of the input signals. The correction terms $\Delta\alpha$ and $\Delta\beta$ given by the NN are the biased linear combination of the outputs of the 24 neurons of the hidden layer. For additional details see [20], [23]. The training procedure is the nonconvex optimization process of finding the weights of the MLP in order to minimize an overall metric of the error on the TS (Training Set). The applied heuristic rule is Levenberg-Marquardt. Unfortunately, the function obtained by an MLP is not known a priori and a series of analysis must be conducted to understand the behaviour of the function with points not included in the TS. Besides the consolidated methods of data partitioning, the analysis presented in this paper is one of the tests that the authors suggest. In fact, the wind field can affect the input signals of the NN in two different manners: 1) injection of unforeseen values to the NN that, even perfectly analysed, may respond with unpredictable estimation error; 2) injection of apparently valid values to the NN, leading to higher estimation error.

III. METHOD

The data used for training and test the MIDAS estimator comes from an high-fidelity flight simulator developed by the project leader Piaggio Aerospace. It considers the delays, noises and nonlinearity of the sensors of the AC. A set of manoeuvres has been simulated under the Consortium requirements that identified, based on previous experience, the most important flight conditions necessary to design and test the NN.

From mathematical point of view, AOA/AOS are estimated as the output of a mathematical function obtained by means of a multivariate nonlinear regression. The regression is based on the modification of the set of weights of the NN without the prior definition of a model, where model stands for the basic mathematical function applied for the regression. It is not possible to know if the NN resulted in fitting a straight line, or a parabola or some transcendental function, without a complete study of the function. In this paper, the focus is on the study of the results in case of non-still atmosphere with the VS (Virtual Sensor) trained using data collected in still air. First of all, the VS as obtained in [20] are tested using injected steady wind. Further analysis will be based on gust and sinusoidal wind. The wind vector is considered to be upper bounded by the values prescribed by CS (Certification Specifications)-23 at CS-23.333 [24]. This regulation considers 50 fps (15.24 m s^{-1}) at altitudes between sea level and 20 000 ft (6096 m). Based on this, the VS has been tested under wind condition of 1 m s^{-1} , 5 m s^{-1} and 15.24 m s^{-1} on every direction on the NED (North-East-Down) frame. Moreover, two cases have been added, with the magnitude of the wind vector \mathbf{w} equal to 3.46 m s^{-1} (corresponding to $\mathbf{w} = (2, 2, 2) \text{ m s}^{-1}$) and 15.24 m s^{-1} (about $\mathbf{w} = (8.8, 8.8, 8.8) \text{ m s}^{-1}$). Before testing the performance of the synthetic sensor, the tests that authors have already defined in previous research are conducted (for

example, the hypercube coverage). The performance of the VS are estimated in terms of:

- 1) error PDF (Probability Density Function)
- 2) timeseries analysis

The statistical analysis allows to understand if the VSs are maintained into the specifications required by the project leader PAI (Piaggio Aero Industries S.p.A.). The trend analysis gives detailed information on particular flight conditions that can be beneficial or disadvantageous for the VS performance.

IV. RESULTS

This section shows some preliminary results of the analysis. Following the methodology described in Section III, the synthetic sensor for AOA has been analysed.

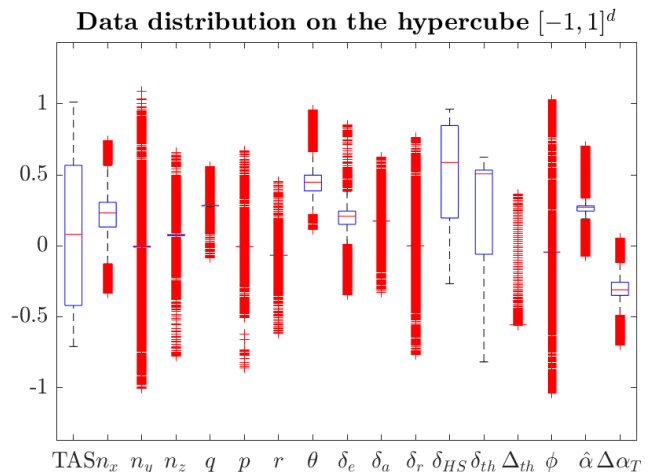


Fig. 3. Distribution of the input and target data on the hypercube of definition of the NN in case of strong Down wind component $w_D = 15.25 \text{ m s}^{-1}$

Fig. 3 shows that the injection of the wind does not affect negatively the inclusion of the test set in the TS. For sake of clarity, it must be recalled that the MLP can represent any function inside the hypercube defined by the TS. However, nothing can be said on the response of the network with input values exceeding the training bounds. When training an MLP for estimation, it is interesting to measure the inclusivity of the TS or, better, if the available remaining data used for testing is included in the hypercube. This is a preliminary analysis and further research should be conducted from this point of view. However, the injection of the steady wind field does not act directly on the input of the NN. In fact, when the AC is flying in a control volume moving with a constant speed with respect to a reference frame on the surface of the Earth, the signals used as input to the MLP do not measure any difference, except for the GNSS (Global Navigation Satellite System). The Down component of the AC ground velocity brings to erroneous evaluation of $\hat{\alpha}$. However, this erroneous value is included in the TS and hence, even if the inclusivity test is passed as can be seen in Fig. 3, it is not sufficient to understand the behaviour of the estimator.

In Fig. 4 it is shown the PDF of the estimation error due to wind injection. As can be seen from Fig. 4 the error mode is still bounded under some degree when the Down component of the wind $w_D < 2 \text{ m s}^{-1}$. In that case, a simple scheduled correction would still be possible. However, when $w_D > 2 \text{ m s}^{-1}$ the error PDF tends to move further on the right and, even worse, to spread.

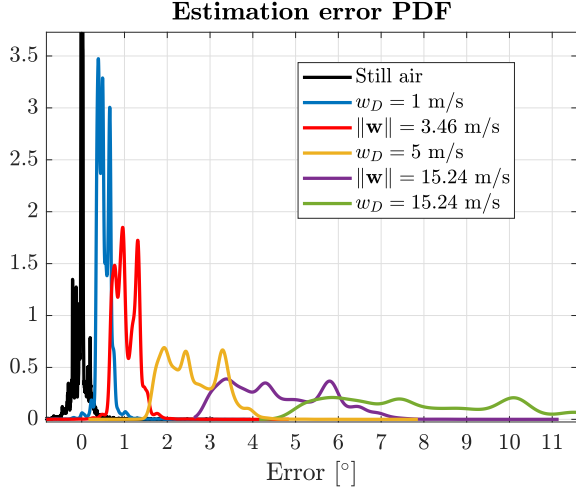


Fig. 4. Wind effects on the estimation error PDF.

Fig. 5 shows an example of error trend on the time domain for a single flight. The increase of the mean error is clearly correlated with the Down component of the wind. Moreover, it is shown that the flight condition becomes important in terms of estimation error when the w_D increases. It must be stressed that the estimation error does not diverge, even if the plot shown in Fig. 5 seems to suggest a divergence. In fact, the estimation error is already increasing in time also in the nominal trajectory, for reasons related to the regression. The erroneous Down component simply scale the already increasing trend so that it seems to diverge. If the trajectory would be continued in regions of better fitting, the error will return to small values.

V. DISCUSSION

From Sec. IV it is clear that the containment of the test set into the TS is not enough to guarantee the uncertainty obtained during the design process. This means that the variable of input might not be suitable to catch the difference introduced by a constant wind or an unsteady atmosphere. Due to the structure of the synthetic sensor, some hypothesis can be done before starting the tests. In fact, one of the input to the NN is the initial estimation $\hat{\alpha} = \theta - \gamma$ where

$$\gamma = \text{atan} \frac{V_D}{\text{TAS}} \quad (4)$$

Actually, Eq. 4 is valid only under the assumption of still air. In fact, in case of wind there exist 2 different definition of the *flight path angle* γ , one with respect to the local horizontal

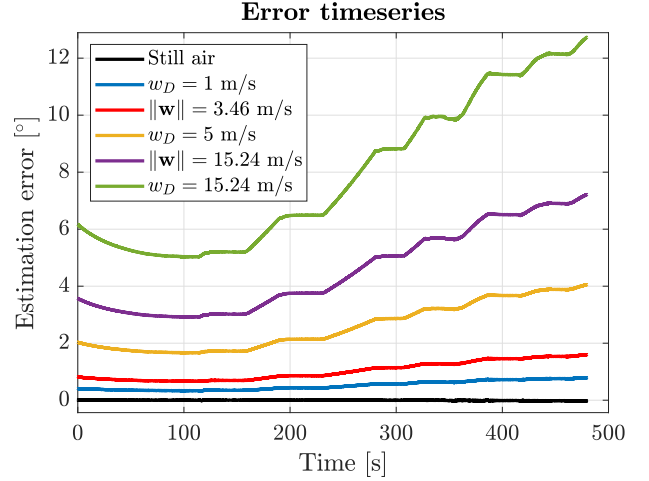


Fig. 5. Example of the wind effects on the estimation error timeseries (Flight # 1).

plane and another one with respect to the local control volume in which the aircraft is flying. Eq. 4 neglects this difference and for this reason is no more valid in case of nonzero wind, even if $\dot{\mathbf{w}} = 0$. This is the main reason of the direct link between w_D and the estimation error. The possible solution that this analysis suggest is to re-design the synthetic sensor without using the $\hat{\alpha}$ as input signal. The main benefit of the initial design is the limited action left to the NN, that is the neural correction is always bounded between few degrees. However, once the design process is well-defined, it is possible to train the NN to cover the entire flight envelope with the same degree of confidence on the results.

Hence, the NN design has been changed from (1) to (5) and the new NN has been trained with the same procedure of the original NN.

$$[\alpha, \beta]^T = \mathbf{f}_{VS}(\text{TAS}, n_x, n_y, n_z, \theta, \phi, p, q, r, \delta_e, \delta_a, \delta_r, \delta_{th}, \Delta_{th}, \delta_{hs}) \quad (5)$$

To compare the performance of the 2 NNs, the same wind field is injected to the new NN obtaining Fig. 6. As it can be seen from the comparison of Fig. 6 with Fig. 4, the modification of the input signals brought significant improvements on the aspect of the sensitivity to the wind field. However, the error PDF widened with a significant impact on the accuracy of the estimator when evaluated on the test set. Fig. 7 compares the error timeseries of the two NNs evaluated on the same flight as Fig. 5. The comparison shows that the performance of the re-trained NN at any wind speed are similar to the performance of the initial NN at $\|\mathbf{w}\| = 15.24 \text{ m s}^{-1}$.

From these observations, it seems that the availability of a Down component of the AC velocity with respect to the surrounding air would be the better choice. Unfortunately, this measurement is generally not available on board. On the other hand, it must be noticed that both NNs have been trained on

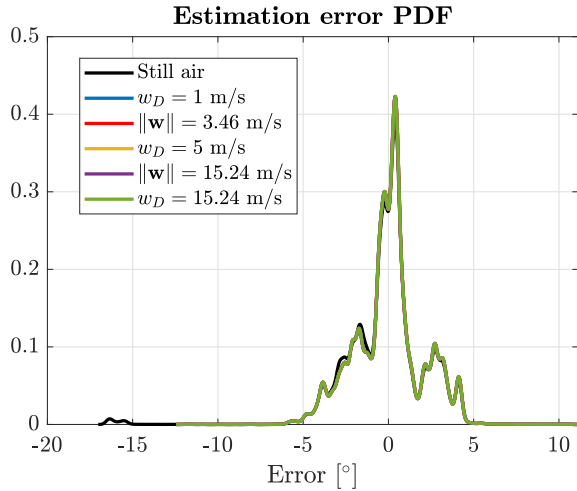


Fig. 6. Wind effects for the re-trained NN on the estimation error PDF.

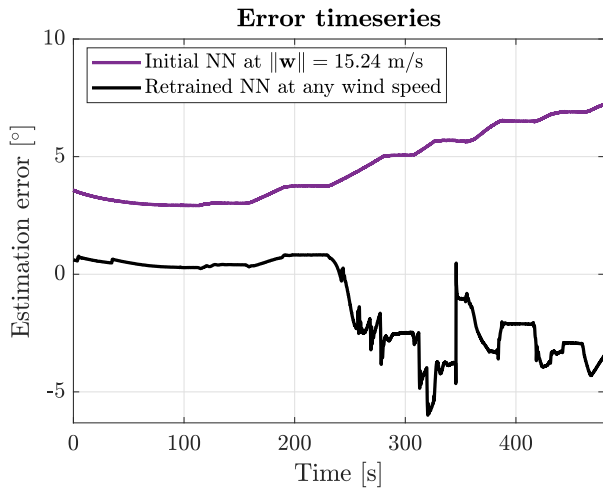


Fig. 7. Comparison of the error timeseries obtained with initial and retrained NN (Flight # 1).

the same training set. Although the application of the same data-set for training allowed to compare the two nonlinear functions at the same conditions, it is highly recommended to try a different partition of the data set for training and test. This aspect goes beyond the scope of the current work and further research will focus also on this aspect. Once the NN defined in (1) has been discarded, a complete and detailed re-design of the NN will be conducted.

VI. CONCLUSIONS

The MIDAS project is funded under CleanSky 2 to design and develop a modular, fully integrated and digital probe capable of providing the entire set of Air Data. The outcome of the project will be a probe certifiable for DO-254 and DO-178 and it will provide the first case of certifiable synthetic sensor. Although there is a large volume of published studies on the design of a synthetic sensor for aerodynamic angle,

much of the current literature focuses on the demonstration of the general validity of the solution. In fact, the design process of this kind of estimator is still in definition. To allow the implementation of a VS into a certifiable probe, a long series of test and procedures must be defined, in order to ensure reliability and repeatability of the results. One of the proposed test is the analysis of the effects of the wind on the final uncertainty and a defect coming from the utilization of an initial estimation based on the GNSS measurement has been highlighted in this study. Moreover, it is shown that this problem cannot be detected by the inclusivity test. Actually, the increase of the estimation error comes from the erroneous implementation of the definition of γ . This paper shows some preliminary results on this topic and it suggests a solution to the arose problem. The results shows that a steady wind with speed higher than 2 m s^{-1} injects a steep rise on the estimation error. The modification of the NN input vector removing the initial AOA estimation gives evidence of a possible solution to the problem. Unfortunately, the error of the estimator on the test set increased of several degrees. Further research will be conducted on unsteady atmosphere, with the simulation of gust and/or turbulence.

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