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MODEL IDENTIFICATION APPROACH FOR AIRCRAFT FAILURE DETECTION ON TAKE-OFF MANEUVER USING A MOTION-BASED SIMULATOR

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Abstract. *This work presents a model identification approach for aircraft failure detection on take-off maneuver. A motion-based simulator was used to perform experiments of normal and failure flight conditions. Data from normal flights were used to estimate an ARX model based on least-squares method. The failure detection method proposed is based on the comparison of measured output with ARX model output. Data from normal flights and flights with failures are submitted to the failure detection method and performance is measured by precision and recall. Results show precision of 97.9% and recall of 100%.*

Keywords: *aircraft systems, flight simulator, fault detection.*

1. INTRODUCTION

Flight safety has been recognized as a major current priority within the aircraft and aerospace sector (Duarte, *et all*., 2016; Perhinschi, *et all*., 2014). Failure analysis and identification is essential for obtaining safer operational procedures and it helps define and improve maintenance procedures (Duarte, *et all*., 2016).

Air companies have a large amount of data recorded from flight data records (FDRs). This data can be analyzed to extract information about the flight and look for failures and abnormal behavior that may have occurred during flight.

In this context, the project IVHM - Integrated Vehicle Health Monitoring and Human Factor Analysis, to be developed jointly between Brazilian partners (ITA and Konatus) and Swedish partners (SAAB and Linköping University), aims at proposing an automatic solution to distinguish and classify data from normal flights, flights with aircraft system failures, flights with human abnormal behavior, and flights with abnormal behavior caused both by human and aircraft system problems, based on recorded flight data. In order to support the development and verification of detection and identification algorithms, the IVHM project plans to use data from flights performed using the SIVOR flight simulator, combined with different fault injection mechanisms and submitted to provoked pilot abnormal behaviors.

There are several failure detection and identification (FDI) methods that are being used with flight data. The work of Perhinschi, *et all*. (2014) present an integrated scheme for aircraft subsystem failure detection and identification based on the artificial immune system paradigm augmented with artificial neural networks. Zhang, *et all*. (2011) built a fuzzy neural network (FNN) fault diagnosis model based on fuzzy mathematics and the neural network method. Schram, *et all*. (1998) explore the integration of fuzzy logic and parity space methodologies for the detection and identification problem of actuator failures of aircraft. Purvis, *et all*. (2015) applied cluster analysis techniques to design a fault-detection, diagnosis and self-healing model. Mack, *et all*. (2010) developed a model-based adaptive scheme for detecting aircraft actuator failures and aerodynamic damage. These methods use tools as neural networks, fuzzy logic and cluster techniques and are able to capture nonlinearities present in aircraft dynamic and in the relationship between fault states and fault features. However, there is no assurance that they will be able to identify and classify different human factors.

In the context of the IVHM Project, our proposal is to start with a fractionate flight envelope, and to develop specific models adapted to different types of maneuvers. When studying a small section of flight envelope, as a specific maneuver, non-linear behavior can be approximated by linear models. The purpose is to maintain the models used in detection and identification as simple as possible in order to evaluate their capability of classifying also human behavior.

This paper presents the first results obtained with a model identification approach based on data from SIVOR flight simulator. The approach explores dependencies between different measurable signals in order to identify mathematical models that are able to distinguish between normal flights and flights with failures (Isermann, 2011). The models are adjusted using estimation techniques and data from normal flights only. They are then submitted to both normal flights and flights with failures. The results presented in the paper focus on failure detection during take-off maneuver and consider as inputs and outputs only signals that are usually stored on FDRs for offline analysis.

2. METHODOLOGY

2.1 Simulation Environment

The main components of the simulation environment used for the purpose of this paper are described in this section. The SIVOR simulator is a robotic-based flight simulator with 6 degrees of freedom. It is currently being developed by Aeronautics Institute of Technology (ITA) and EMBRAER. The purpose of the project is to develop a flight simulator with a high fidelity environment and flexible so it can be reconfigured to several aircrafts of the same category. A prototype of the final simulator is in operation and it can be seen in Fig. 1.

Figure 1- Prototype of the SIVOR Simulator.

The aircraft model used in the experiment is a public version of the Embraer Phenom 300 and the visual system is rendered by XPlane 10™.

The communication between the aircraft model and SIVOR simulator is performed through LabView™, which implements a washout filter that converts the aircraft dynamics into robot movements.

2.2 Experiment Design

The maneuver performed on the experiment is a take-off run and the experiment procedure is presented in Fig. 2.

The targets during flight are to keep aircraft speed at 150 kts and to keep heading. Throttle command must be minimum only at initial condition and maximum for the entire procedure.

The take-off maneuver is simulated under three conditions: normal (Fig. 3), engine failure (Fig. 4) and flap failure (Fig. 5Figure **5**). The same procedure must be followed on all situations.

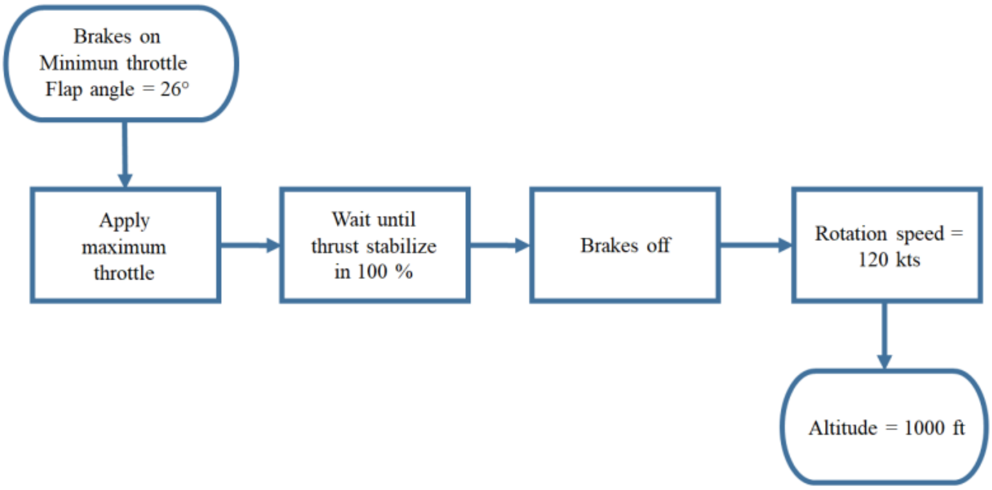

Figure 2 - Experiment procedure.

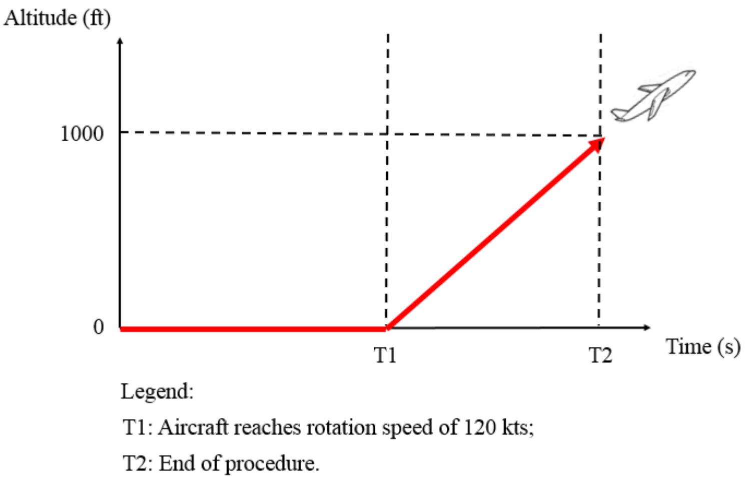

Figure 3 - Take-off maneuver under normal condition.

The engine failure occurs when the aircraft velocity reaches 100 kts: left engine is lost. The flap failure occurs when the aircraft altitude reaches 300 ft: right flap is lost and the left one stays at 26° (flap asymmetry). On both failure situations, the pilot must control the aircraft and follow the procedure.

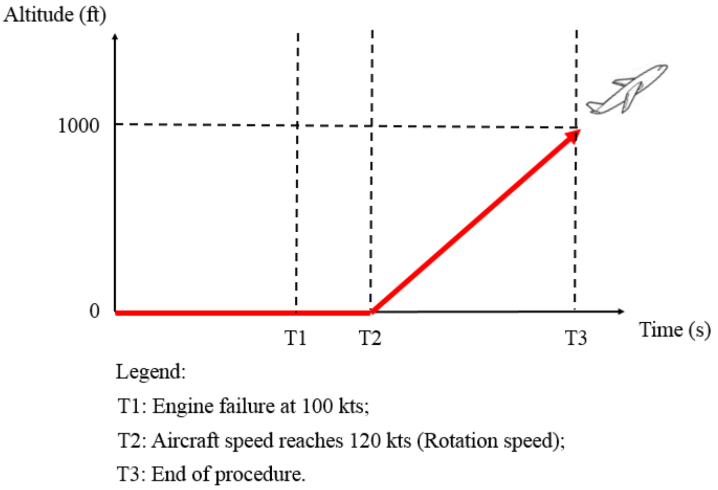

Figure 4 - Take-off maneuver under engine failure condition.

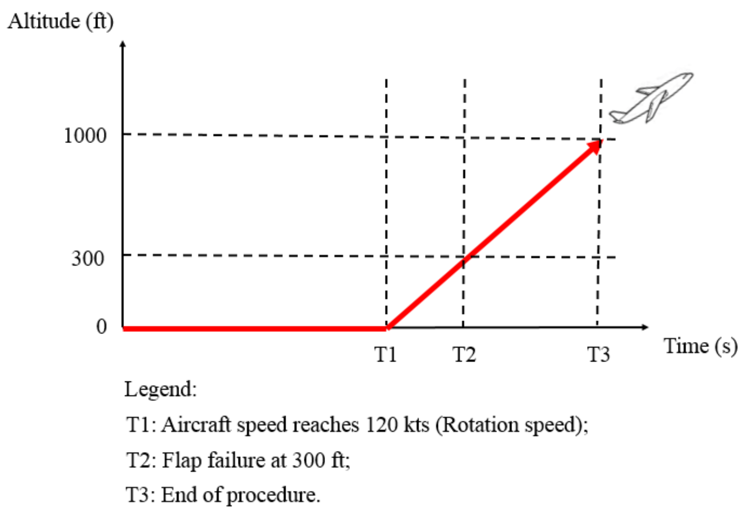

Figure 5 - Take-off maneuver under flap failure condition.

Each maneuver condition is simulated with and without simulator movement. Four experienced pilots were recruited as volunteers in this experimental procedure. Each experiment was repeated 3 times. The experiment sequence was completely randomized for each pilot.

During the experiments, data was recorded from the pilot commands and aircraft behavior.

2.3 Analysis

2.3.1 Dataset

The analysis is based on data recorded from the 72 experiments (3 maneuver conditions, 2 simulator movement conditions, 4 pilots and 3 replicas).

The recorded data was pre-processed in order to perform the data analysis considering the same start and end conditions. Start condition was defined as the moment that throttle is at maximum and brakes are turn off. End condition was defined as the moment airplane altitude reaches 1000 ft.

The dataset was divided in 3 parts: training set, validation set and test set. Both training and validation sets have data only from normal condition experiments (without any aircraft failure). The identification purpose is to describe the normal aircraft behavior for this take-off maneuver. Test set has data from normal and failure condition experiments. The normal condition experiments were randomly divided into 3 groups of 8 experiments, but assuring that all groups have at least one experiment of each pilot.

2.3.2 Identification method

This work intends to describe the aircraft behavior for the normal take-off maneuver using model identification techniques. The proposed system is described by 3 inputs (pilot commands for elevator, aileron and rudder) and 2 outputs (altitude and true airspeed - KTAS).

The chosen identification method is based on a parametric identification of an Autoregressive Exogenous (ARX) model. The work of Chetouani (2008) show that ARX model is representative for the dynamic behavior of a nonlinear process.

ARX model estimates parameters and covariances (parameter uncertainties) using the least-squares method. The ARX model structure is a simple linear difference equation which relates the current output *y(t)* to a finite number of past outputs *y(t-k)* and inputs *u(t-k)*. For a single input and single output (SISO) system, the ARX equation can be written as:

$$y(t) + a_1 y(t-1) + \cdots + a_{na} y(t-na) = b_1 u(t-nk) + \cdots + b_{nb}\, u(t-nb-nk+1) + e(t) \tag{1}$$

where a_{na} and b_{nb} are the unknown model parameters, *na* and *nb* are the orders of the ARX model, *nk* is the time delay between *y(t)* and *u(t)*, *e(t)* refers to the noise supposed to be Gaussian.

A more compact way to write the difference equation is using the delay operator (z):

$$A(z)y(t) = B(z)u(t-n_k) + e(t) \tag{2}$$

where:

$$A(z) = 1 + a_1 z^{-1} + \cdots + a_{na} z^{-na} \tag{3}$$

$$B(z) = b_1 + b_2 z^{-1} + \cdots + b_{nb} z^{-nb+1} \tag{4}$$

For a multiple input and multiple output (MIMO) system with *ny* outputs and *nu* inputs, *na*, *nb* and *nk* are matrices: *na* is *ny* x *ny*, *nb* and *nk* are *ny* x *nu*. For the aircraft system with 3 inputs and 2 outputs, *na*, *nb* and *nk* can be written as:

$$na = \begin{bmatrix} na_{11} & na_{12} \\ na_{21} & na_{22} \end{bmatrix} \tag{5}$$

$$nb = \begin{bmatrix} nb_{11} & nb_{12} & nb_{13} \\ nb_{21} & nb_{22} & nb_{23} \end{bmatrix} \tag{6}$$

$$nk = \begin{bmatrix} nk_{11} & nk_{12} & nk_{13} \\ nk_{21} & nk_{22} & nk_{23} \end{bmatrix} \tag{7}$$

2.3.2.1 Model order selection

The selection of the ARX model order (*na* and *nb* elements) must be made in the respect of the parsimony principle: “out of two or more competing models which all explain the data well, the model with the smallest number of independent parameters should be chosen” (Söderstrom and Stoica, 1989).

In this work, *na* and *nb* elements were each varied over the range 1 to 2. For each combination, the optimal values of the model parameters were estimated using the MATLAB™ and the training dataset. Time delay was assumed as one time step. The evaluation criterion was the Akaike’s final prediction error (FPE) (Ljung, 2000).

2.3.2.1 Model validation

Model validation was done by applying validation dataset on the identified model. The evaluation criterion was the Fit Percent. It is calculated by the normalized root mean squared error (NRMSE) and measure how well the response of the model fits the estimation data, expressed as a percentage.

$$Fit\ Percent = 100\left(1 - \frac{\|y-\hat{y}\|}{\|y-\bar{y}\|}\right) \tag{8}$$

where:

y is the validation data output;
$\bar{y}$ is the mean of validation data output;
$\hat{y}$ is the model output;
$\|.\|$ is the 2-norm of a vector.

2.3.3 Failure detection method

The failure detection method proposed is based on model identification of the aircraft normal behavior. Input data from the test dataset is applied in the ARX model and predicted outputs ($\hat{y}$) are compared with measured outputs (y).

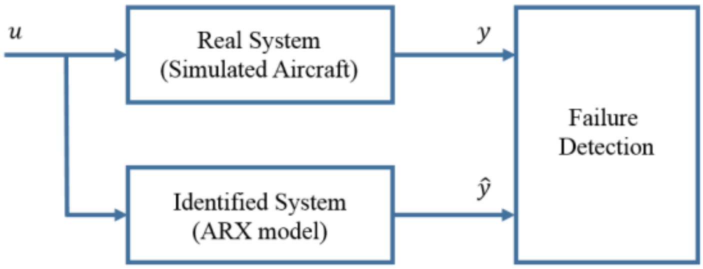

Figure 6 - Failure detection method.

The failure detection algorithm uses the Fit Percent of predicted and measured outputs. The validation dataset is used to define a threshold for the normal condition.

For a normal distribution, about 95% of the data will be within two standard deviations of the mean (Diez, *et all*, 2015). Assuming that the Fit Percent for altitude and KTAS has a normal distribution, threshold values will be adopted as:

$$T_i = \mu_i - 2\sigma_i \tag{9}$$

where:

i is 1 for altitude and 2 for KTAS;
T is the threshold value;
μ is the Fit Percent mean;
σ is the Fit Percent standard deviation.

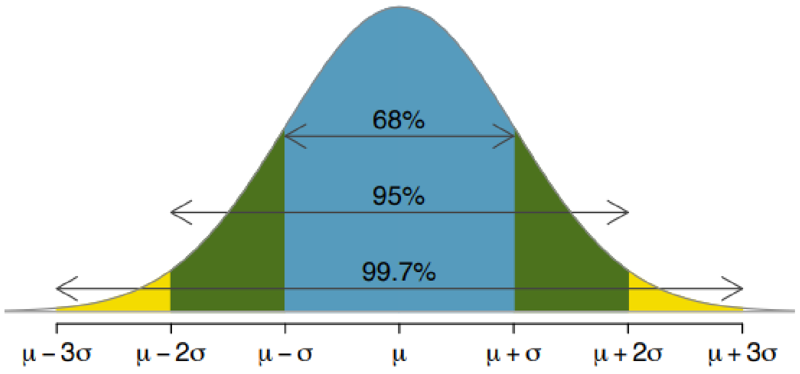

Figure 7 - Probabilities for falling within 1, 2, and 3 standard deviations (Diez, *et all*, 2015).

If the Fit Percent for both altitude and KTAS is above the respective threshold, experiment is classified as a normal condition. If one of the Fit Percent is below the threshold, experiment is classified as a failure condition.

The performance of the proposed failure detection method can be visualized by the confusion matrix (Table 1). The confusion matrix reports the counts of the true positive (TP), true negative (TN), false positive (FP) and false negative (FN) detections (Raschka, 2015).

Table 1 - Confusion matrix.

		Detected Condition	
		Failure	Normal
Real Condition	Failure	TP	FN
	Normal	FP	TN

The metrics proposed in order to evaluate the failure detection method are precision and recall (Raschka, 2015).

$$Precision = \frac{TP}{TP+FP} \tag{10}$$

$$Recall = \frac{TP}{TP+FN} \tag{11}$$

3. RESULTS AND DISCUSSION

3.1 ARX model

The aircraft system with 3 inputs (pilot commands for elevator, aileron and rudder) and 2 outputs (Altitude and KTAS) was identified with an ARX model. Using the FPE evaluation criterion (Ljung, 2000), the order selected for the model is shown below. This structure resulted on the lowest FPE on the training dataset, considering the restriction of values range between 1 and 2.

$$na = \begin{bmatrix} 2 & 2 \\ 2 & 2 \end{bmatrix} \quad (12)$$

$$nb = \begin{bmatrix} 2 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \quad (13)$$

$$nk = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \quad (14)$$

The model identified for the aircraft is represented by Eq. (15-26).

$$A_1^1(z)y_1(t) = -A_2^1(z)y_2(t) + \sum_{i=1}^{3} B_i^1(z)u_i(t) + e_1(t) \quad (15)$$

$$A_1^1(z) = 1 - 1.994\, z^{-1} + 0.9944\, z^{-2} \quad (16)$$

$$A_2^1(z) = 0.01384\, z^{-1} - 0.01386\, z^{-2} \quad (17)$$

$$B_1^1(z) = -0.05842\, z^{-1} + 0.05852\, z^{-2} \quad (18)$$

$$B_2^1(z) = -0.007554\, z^{-1} \quad (19)$$

$$B_3^1(z) = 0.0001738\, z^{-1} \quad (20)$$

$$A_2^2(z)y_2(t) = -A_1^2(z)y_1(t) + \sum_{i=1}^{3} B_i^2(z)u_i(t) + e_2(t) \quad (21)$$

$$A_1^2(z) = 0.0001295\, z^{-1} - 0.0001297\, z^{-2} \quad (22)$$

$$A_2^2(z) = 1 - 1.999\, z^{-1} + 0.9994\, z^{-2} \quad (23)$$

$$B_1^2(z) = -0.00009016\, z^{-1} \quad (24)$$

$$B_2^2(z) = -0.007554\, z^{-1} \quad (25)$$

$$B_3^2(z) = 0.0001738\, z^{-1} \quad (26)$$

where:
y_1 is altitude;
y_2 is KTAS;
u_1 is elevator command;
u_2 is aileron command;
u_3 is rudder command.

Results for model validation by applying validation dataset on the identified model are shown in Table 2.

Table 2 - Model validation results.

Experiment	Fit Percent (%)	
	Altitude	KTAS
1	91.79	84.91
2	93.15	86.68
3	78.02	21.52
4	91.19	85.19
5	90.89	70.08
6	93.96	75.23
7	93.39	66.81
8	90.76	77.95

A comparison of ARX model output and validation data output for the first experiment of the validation dataset is shown in Fig. 8 and Fig. 9Figure **9**.

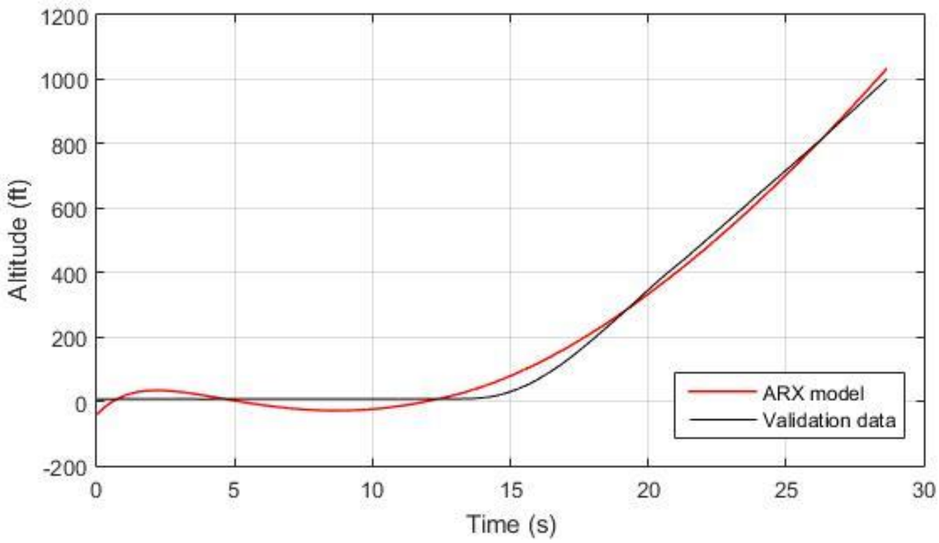

Figure 8 - Comparison of ARX model and validation data for altitude.

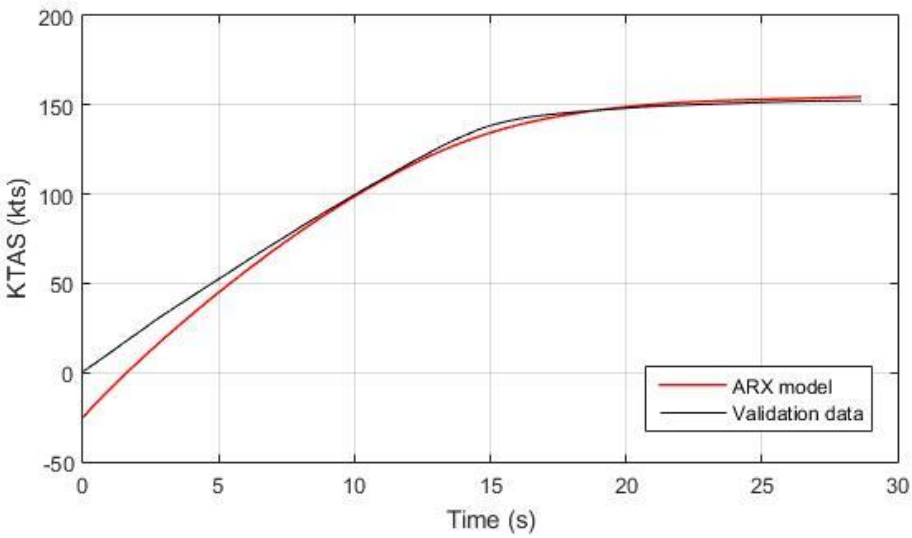

Figure 9 - Comparison of ARX model and validation data for KTAS.

The ARX model identified was able to capture the aircraft normal behavior. Model validation results show high Fit Percent for altitude and KTAS in 7 of the 8 experiments analyzed. Experiment 3 was not represented by the ARX model. Figure 10 shows validation set output data and it can be seen that all experiments are similar except experiment 3. The major difference is in KTAS behavior, when the aircraft reaches 150 kts it starts to lose velocity, but it should have been kept constant at 150 kts. This suggests that the experimental procedure was not followed properly for experiment 3.

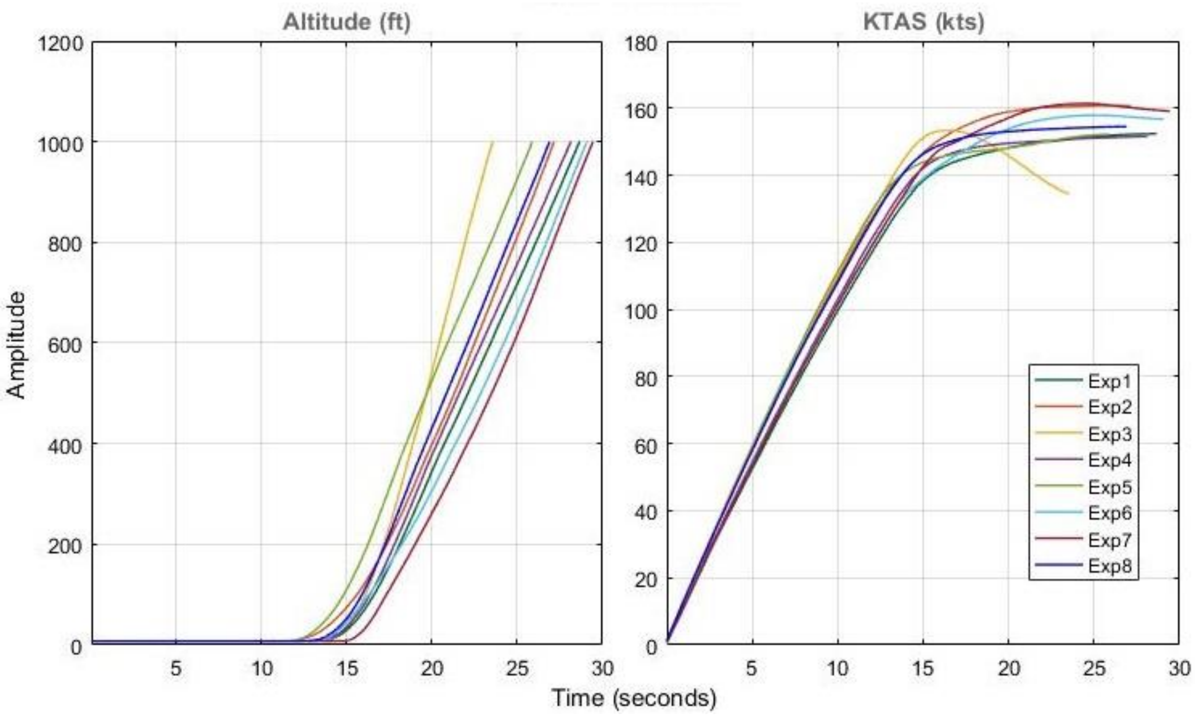

Figure 10 - Validation set output data.

3.2 Failure Detection Method

The Fit Percent threshold values adopted for the failure detection scheme are 89.53 for altitude and 62.41 for KTAS. Fit Percent values from experiment 3 were not used for threshold definition.

The results of the failure detection method are presented in Table 3.

Table 3 - Failure detection method results.

		Detected Condition	
		Failure	Normal
Real Condition	Failure	48	0
	Normal	1	7

Table 3 shows that all failure conditions are correctly detected and only one normal condition experiment is detected as failure condition. This experiment incorrectly detected as failure was performed by the same pilot that experiment 3 from validation set. This stands up the importance of considering human factors when studying failure detection and identification.

The metric results obtained with the failure detection scheme are precision of 97.9% and recall of 100%.

Results show that the proposed failure detection method works for the scenario under consideration. The method is able to detect normal and failure condition for the take-off maneuver.

4. CONCLUSION

This work presented a model identification approach for aircraft failure detection on take-off maneuver. Experiments were performed under normal and failure conditions. The aircraft system was represented by 3 inputs (pilot commands for elevator, aileron and rudder) and 2 outputs (Altitude and KTAS) and it was identified with an ARX model. The ARX model was able to capture the aircraft normal behavior.

The failure detection method proposed uses the Fit Percent to compare measured output with ARX model output. Thresholds were defined to distinguish normal from failure condition. Results show that the proposed failure detection method works for the take-off maneuver scenario.

This work approach allows detecting the occurrence of a failure, but it does not allow to identify or classify them. Future research will focus on developing a failure detection and identification (FDI) method. The goal is to distinguish and classify data from normal flights, flights with aircraft system failures and flights with human abnormal behavior.

5. ACKNOWLEDGMENTS

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