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IDENTIFICATION OF AERODYNAMIC COEFFICIENTS OF A FLEXIBLE FIXED-WING AIRCRAFT USING DEEP LEARNING

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Abstract. *This work proposes the analyses of the capacity of two deep learning models (Feedforward Neural Network and Long Short Termal Neural Network), neural networks with multiple hidden layers, to identify the parameters of a flexible fixed-wing aircraft, with data obtained in-flight. Thus, the objective is to compare the results obtained between these two different methods of Neural Network. Some alternatives have been proposed with the objective of taking advantage of the generalization power of models obtained with neural networks, while preserving the ability to identify the physical parameters of the analyzed system.*

Keywords: *artificial neural networks, flexible wing aircraft, parameter estimation, system identification.*

1. INTRODUCTION

System identification is a process of building mathematical models of dynamic systems from observed data and has become increasingly popular due to their ability to learn complex relationships from input-output data. This task is crucial for many applications, including control systems, robotics, financial markets and, to this work, in aerospace. The identification of aircraft parameters consists of estimating the values of physical parameters that govern the behavior of an aircraft. This information is essential for designing and testing aircraft control systems and for improving the accuracy of flight simulators. An increasingly adopted approach in system identification is the use neural networks, due to their ability to learn complex relationships from input-output data.

However, there are still many challenges that need to be addressed to improve the accuracy and reliability of neural network-based system identification methods. Other important question in adopting neural network in this area is its black-box description of the modeled system. Classical methods of system identification are based on paradigms from statistics, where they strongly rely on prediction error methods altogether with an ordinary differential equation that describes the system behavior, and the identification process consist of defining the constants for a given reference model. On the other side, neural networks typically are a set of multiple interconnected layers, where each node calculates a weighted sum of its inputs, followed by a non-linear activation function, which do not preserve any relation with real world system. In addition to it, when aircraft is flexible, more degrees of freedom are involved and more complex is the identification process. Majeed *et al.* (2012) states that “the drawback of the neural model is that a large amount of data is required to train the network”. It means that more data is needed to train a neural network (data-driven parameter estimation) than to perform identification using model-based parameter estimation.

Many studies of aircraft system identification using Artificial Neural Networks were made (considering the aircraft as a Rigid-Body), as shown in Curvo (2001), Fethalla (2019), Newton (2020) and Bodin (2020). Newton (2020) highlights that many linear models are used to model aircraft flight dynamics at linear region. However, it is difficult to perform identification of the non-linear regions. In addition to it, the model must be fixed beforehand. With the use of Neural Networks, there is no need to establish a model beforehand, to perform complex modeling of the non-linear region, etc.

Newton (2020) performed a study to check which structure of Neural Network is more suitable for Parameter estimation (for a rigid-body aircraft identification): a feedforward network which is then closed in feedback for simulation, or a recurrent network for explicit time series prediction. While the feedforward network has been favored in literature due to faster training times, the results presented here that despite an almost 2-fold increase in training computation time, the RNN compensates for this with an over 2-fold increase in modeling accuracy.

A study of Identification of a Flexible Aircraft using Feedforward Neural Network (FFNN) was made at Raisinghani and Ghosh (2000). At Raisinghani and Ghosh (2000), a model of a flexible aircraft using flexibility models similar to what is given at Waszak and Schmidt (1988) was used to generate the data to be identified by the Artificial Neural Network (ANN). Subsequently, it was used a model for estimating parameters using the Delta and the Zero methods, proposed by Raisinghani *et al.* (1998). At the present work, the data used to be identified was taken from aircraft with flexible wing and the results will be compared with the real response of the aircraft, using two types of architectures, an FFNN and a Long Short Therm Memory (LSTM).

2. THEORETICAL FOUNDATION

The ANN is an abstract model, initially inspired by neurobiology, that is capable of generalization of input-output mapping, which evolved over the time (Haykin, 2008; Kriegeskorte and Golan, 2019) to accommodate several kinds of requirements. Haykin (2008) states that an ANN is composed by simple processing units arranged in a massively parallel architecture, where each unit is interconnected with many others and each of this synaptic connection stores weights based on the learning process. After the training process the ANN is capable of “storing experimental knowledge and making it available for use".

2.1 Feedforward Neural Network

Feedforward Neural Networks are the simplest type of ANN and has been proven its capability of learning multiple types of patterns in data Haykin (2008); Kriegeskorte and Golan (2019). In the FFNN architecture the information flows in a single direction, from the input layer to the output layer, but they are not able to remember information over time Haykin (2008). Figure 1 is a generalized schematic diagram of an FFNN with n inputs, l hidden layers and m outputs. The simplest form has only the input layer and the outputs, where the use of hidden layers gained importance in recent years. An ANN with multiple levels of hidden layers (Goodfellow, 2016) can be classified as a Deep Neural Network (DNN). An FFNN is a flexible tool for modeling input-output maps and is well fitted to represent nonlinear models, capable of to adapt to different contexts with a single language, is robust to adverse operating conditions and take advantage of parallel processing to speed up the computing time (Haykin, 2008). An FFNN represents a black box model that has no representative correspondence with real systems, but with enough data for training and a adequate model, can capture the behavior of a variety of systems, like economic, physical, medical diagnostics, computer vision, and many others with a common architecture.

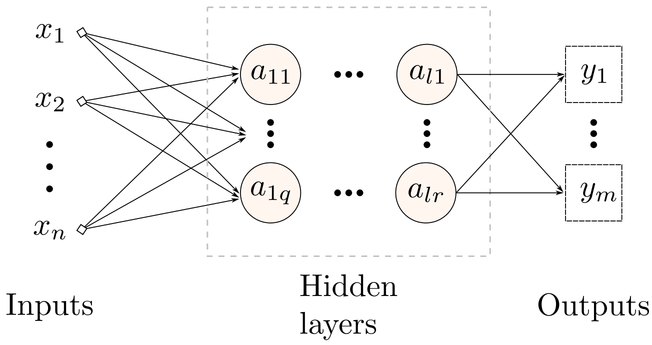

Figure 1. Representation of an FFNN with n inputs, l hidden layers and m outputs.

The inputs of an FFNN represent a set of data that can be formed by data from different sources, they can be a temporal sequence of the same data, a set of pixels of an image or any combination of these and other possibilities. From a set of data, the ANN can be trained to operate as a predictor or a classifier. For a proper training process with sufficient generalizability, a large dataset is usually required. The increase of computational capacity, with specialized hardware and software dedicated to the ANN processing, the number of weights and the size of the FFNN tends to the creation of larger DNNs. The FFNN architecture is capable of approximating any continuous function, specially temporal series, to any desired accuracy as much as it is provided the appropriate number of hidden layers and neurons per layer, if the activation function is continuous and the required amount of data for the training process is available (Hornik *et al.*, 1989).

2.2 Long Short Therm Memory (LSTM) Neural Network

The LSTM (Hochreiter and Schmidhuber, 1997) are modified version of RNNs. The RNNs are a type of ANN with cyclic connections that "enables the RNN to possess the capacity to update the current state based on past states and current input data" (Yu *et al.*, 2019). The LSTM is one of most successful versions of RNNs and a detailed description of LSTM architectures and some variants is available at Yu *et al.* (2019). In RNNs the states of hidden layers are affect not just for current inputs, but also by past states, which gives RNNs the ability to understand the behavior of sequence of data over time (Hochreiter and Schmidhuber, 1997; Kriegeskorte and Golan, 2019; Manaswi, 2018; Yu *et al.*, 2019; Han *et al.*, 2021).

A general representation of LSTM architecture is presented in Figure 2. In this case, the LSTM differs from the FFNN by presenting an internal connection between each consecutive cell (a_i) of the same a layer. This particular configuration allows information from past values to influence the current outputs of an LSTM architecture. This property gives the LSTM architecture the ability to capture the behavior of signals over time.

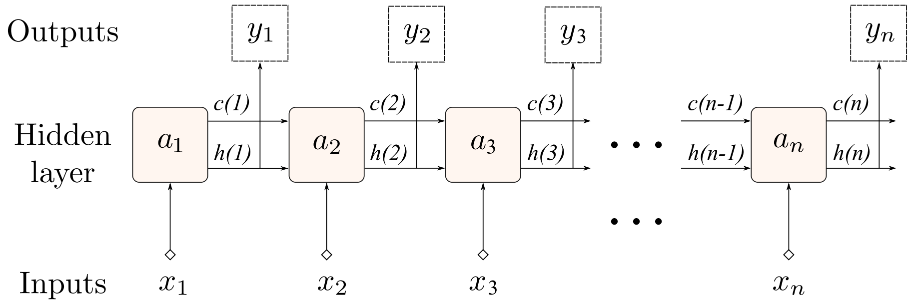

Figure 2. Representation of an LSTM with n past inputs.

The construction of an ANN with the LSTM architecture is not restricted to a single layer, as shown in Figure 2. The composition of an ANN with LSTM with multiple layers can contain other LSTM, FFNN and other architectures layers, by connecting each output y_i to the next layer, according with its requirements. The important fact with the LSTM layer is that in addition to the notion of hidden layer (depth of the network), it also contains the notion of time (or spatial) with the inputs, where x_n represents the current input, and the inputs x_{n-i} represent values from previous inputs. The horizontal connection implies that past data to continue propagating through the network for long periods after its occurrence and continues to influence the future behavior of the outputs. With adequate training, this effect increases the possibilities of using this architecture for prediction capacity for time series (among other types of data).

3. MATERIALS AND METHODS

This section details the construction of the experimental apparatus configuration, which consists of the structural characteristics of the EOLO fixed and flexible wing aircraft, as well as the implementation procedures of the Neural Networks (FFNN and LSTM) used to identify the aerodynamic coefficients.

3.1 Aircraft Description

The EOLO Aircraft is an aircraft manufactured by FT Sistemas in 2018 (Figure 3). Its preliminary rigid aerodynamic coefficients were calculated at Zuñiga (2019), using Vortex-Lattice method and the aeroelastic modes were identified by Zuñiga (2019) using GVT tests to feed Waszak formulation (Waszak and Schmidt, 1988).


Figure 3. EOLO aircraft with flexible wings. Reference: Machado (2019).

The EOLO aircraft has the wing and weight data given at Table 1.

3.1.1 Aircraft Instrumentation

The data acquisition system reads and store measurement data in a sampling rate of 100Hz (NI myRIO data acquisition system). All the sensors and transducers are connected to this data acquisition system. The aircraft instrumented using an Inertial Measurement Unit (IMU) to measure linear accelerations (A_x, A_y, A_z) and angular position (ϕ, θ, ψ) and

Table 1. EOLO wing and weight data. Reference: Machado (2019).

Properties	Value
Wing Span [m]	4
Wing Mean aerodynamic chord [m]	0.2311
Wing Planform Área [m²]	0.8460
Wing Aspect Ratio [-]	18.91
Wing Airfoil	Selig S2091
Weight [kg]	8.87
Ixx inertia [kg.m²]	2.53
Iyy inertia [kg.m²]	1.60
Izz inertia [kg.m²]	3.96

velocities (p, q, r) at three body-system axis (AHRS-400CC-200 from the manufacturer Crossbow). One anemometer sensor for measuring atmospheric pressure, temperature and air direction (Angle of Attack and Angle of Sideslip) was installed into the aircraft (air data boom). In addition to it, accelerometers and strain gauges were installed at the wing, as shown at Figure 4.

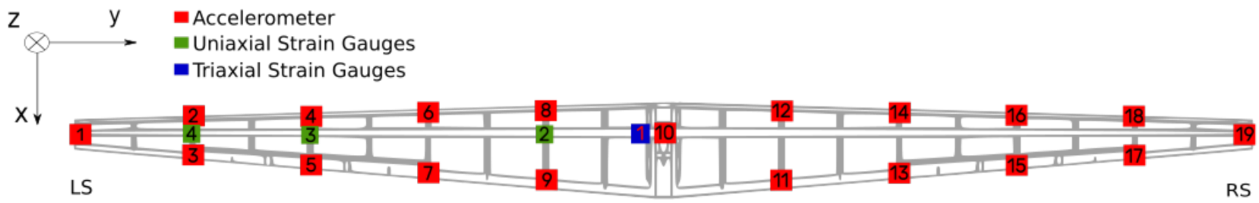

Figure 4. Accelerometers and Strain gage at EOLO aircraft wing. Reference: Zuñiga (2019).

At the present configuration of the aircraft, only the left wing has strain gauges. The first strain gauge is located near the root of the wing, to capture strain of first bending and torsion modes. The other strain gauges are linear ones to capture information for bending moments.

The accelerometers from IMU (Accel-10) have measurements at x, y, and z directions. The accelerometers at the tip of the wings (Accel-9 and Accel-19) has measurements of acceleration at x and z directions. The rest of accelerometers of the wing has just measurements of acceleration at z direction.

The control surfaces (aileron δ_a, rudder δ_r and elevator δ_e) are equipped with remotely piloted servomotors, and specific circuits for the collection of the actuator position data. These electromechanical equipment have a digital circuit that receives a command signal and a control loop for angular positioning of the servo motor axis.

The propulsion system is a brushless direct current electric motor, which the throttle signal can be taken by measuring the signal received by the engine δ_T.

3.2 Design of the Aerodynamic Coefficients Identification System

3.2.1 Input Data

The inputs of the aircraft are the engine throttle and the primary surface controls (ailerons, elevator and rudder), as follows:

$$U(t) = \begin{bmatrix} \delta_T(t) & \delta_{a_{LH}}(t) & \delta_{a_{RH}}(t) & \delta_r(t) & \delta_e(t) \end{bmatrix}^{\mathrm{T}} \tag{1}$$

Since the Feedforward Neural Network structure needs information from the observation data plus the input data, the input data vector is given as follows. The Air Data System observation data is given by Airspeed (V), Angle of Attack (α) and Angle of Sideslip (β):

$$ADS(t) = \begin{bmatrix} V(t) & H(t) & \alpha(t) & \beta(t) \end{bmatrix}^{\mathrm{T}} \tag{2}$$

The Inertial Reference System observation data is given by the linear accelerations at three body axis (A_x, A_y, A_z), angular position (ϕ, θ, ψ) and velocities (p, q, r):

$$IRS(t) = \begin{bmatrix} A_x(t) & A_y(t) & A_z(t) & \phi(t) & \theta(t) & \psi(t) & p(t) & q(t) & r(t) \end{bmatrix}^{\mathrm{T}} \tag{3}$$

The left wing accelerometers are given by the measurement of acceleration at z direction at all left wing accelerometers plus acceleration at y direction for the accelerometer at wing tip (a_{19}):

$$Acc_{LW}(t) = \begin{bmatrix} a_{11_z}(t) & a_{12_z}(t) & a_{13_z}(t) & a_{14_z}(t) & a_{15_z}(t) & a_{16_z}(t) & a_{17_z}(t) & a_{18_z}(t) & a_{19_y}(t) & a_{19_z}(t) \end{bmatrix}^{\mathrm{T}} \tag{4}$$

The center wing accelerometer is located at the center of the wing and it has measurements at three body axis:

$$Acc_{CW}(t) = \begin{bmatrix} a_{10_x}(t) & a_{10_{y(t)}} & a_{10_z}(t) \end{bmatrix}^{\mathrm{T}} \tag{5}$$

The right wing accelerometers are given by the measurement of acceleration at z direction at all right wing accelerometers plus acceleration at y direction for the accelerometer at wing tip (a_9):

$$Acc_{RW}(t) = \begin{bmatrix} a_{1_z}(t) & a_{2_z}(t) & a_{3_z}(t) & a_{4_z}(t) & a_{5_z}(t) & a_{6_z}(t) & a_{7_z}(t) & a_{8_z}(t) & a_{9_y}(t) & a_{9_z}(t) \end{bmatrix}^{\mathrm{T}} \tag{6}$$

The left wing strain gauges are given by the measurement of one Triaxial Strain Gauges (at the root of left wing) three Uniaxial Strain Gauges (distributed alongside left wing halfspan):

$$Str_{LW}(t) = \begin{bmatrix} \epsilon_{1_x}(t) & \epsilon_{1_y}(t) & \epsilon_{1_z}(t) & \epsilon_{2_y}(t) & \epsilon_{3_y}(t) & \epsilon_{4_y}(t) \end{bmatrix}^{\mathrm{T}} \tag{7}$$

Therefore, the Input data (U_{data}) that will be used for the training of Feedforward Neural Network is given as follows:

$$U_{data}(t) = \begin{bmatrix} U(t) & ADS(t) & IRS(t) & Acc_{LW}(t) & Acc_{CW}(t) & Acc_{RW}(t) & Str_{LW}(t) \end{bmatrix}^{\mathrm{T}} \tag{8}$$

3.2.2 Expected Output Data

Since, at the present article, it is only necessary to predict the rigid-body response of the flexible aircraft, the expected output Z data is given by the following outputs:

$$Z = \begin{bmatrix} ADS(t+1) & IRS(t+1) \end{bmatrix}^{\mathrm{T}} \tag{9}$$

3.2.3 Neural Network Structure

The Neural Network structure was implemented in Python, using Tensorflow framework. The hyperparameters of the structure of the Neural Network were tuned through trial-and-error method, as long as the number of layers and neurons. There is not a recommendation of how to get the best number of layers and/or neurons of a Neural Network to perform the identification of the system. However, the recommendation is to start with low number of layers and low number of neurons and to increase its number until the results are satisfactory. If the number of neurons and/or layers are not enough, the identification will not be good. If the number of neurons and/or layers are excessive, the neural network will identify also the noise of the measurements, leading to a case that is called Overfitting.

The Feedforward Neural Network Structure is given at Table 2.

Table 2. Feedforward Neural Network Structure

Layer	Number of Neurons	Activation Function
Input Layer	75	Leaky ReLU - Alpha = 0.01
Intermediate Layer	150	Leaky ReLU - Alpha = 0.01
Output Layer	13	

The LSTM Neural Network Structure is given at Table 3.

Table 3. LSTM Neural Network Structure

Layer	Number of Neurons	Activation Function
Input Layer	200	Linear - Dropout = 0
Intermediate Layer	200	Linear - Dropout = 0
Output Layer	13	

4. RESULTS

4.1 Feedforward Neural Network training dataset

One sortie of maneuvers were selected to perform the training of the Feedforward Neural Network. These data were taken from different flights than the maneuvers used to check generalization (Output Results). These maneuvers used to train the Feedforward Neural Network were concatenated into a single file.

4.2 Feedforward Neural Network Model Output Results

Other sortie of maneuvers were selected to perform the test of the Feedforward Neural Network (different than the used to train the Neural Network). The inputs used to train the Feedforward Neural Network are given at Figure 5. The Predicted and Expected Outputs of the system used to train the Feedforward Neural Network are given at Figure 6 and Figure 7.

Notice that some variables has some bias. However, these results can be acceptable. Better results can be achieved with LSTM network, as can be seen at next sections.

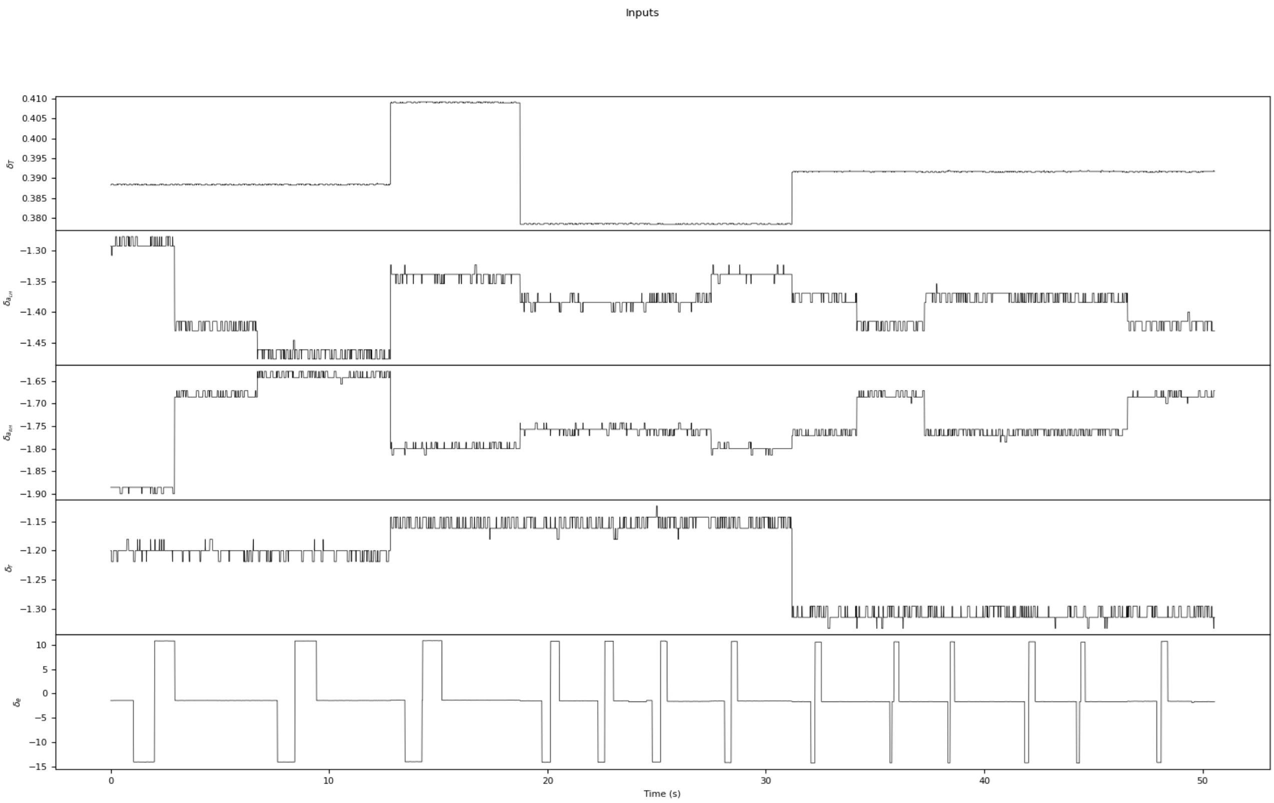

Figure 5. Inputs of the identified maneuvers - Feedforward Neural Network

4.3 LSTM Neural Network training dataset

At the present work, the same sortie of maneuvers were selected to perform the training of the LSTM. Notice that one entire flight was used to train the Neural Network because continuous data must be used to train LSTM neural network. After that, some sortie of maneuvers from other flight were used to check the generalization of LSTM neural network.

The experience shown at training a LSTM neural network is that the amount of dataset has much more impact than the size of the window and the number of neurons. In addition to it, more maneuvers in a single and continuous flight are needed to increase generalization of this Neural Network. Unfortunately, for LSTM network, the combination of two different temporal series concatenated does not generate good results, because LSTM system recognizes the two different temporal series as a single temporal series and then the algorithm diverges.

4.4 LSTM Neural Network Model Output Results

The results of the LSTM Neural Network are given as follows. The inputs used to check the LSTM Neural Network generalization are given at Figure 8. The Predicted and Expected Outputs of the system used to train the Feedforward Neural Network are given at Figure 9 and Figure 10. The maneuvers used to check generalization of LSTM Neural Network were the same used to check generalization of the Feedforward Neural Network.

Notice that the result of the simulation is acceptable. Some treatment at heading ψ values must be made, because the heading angle can vary abruptely between -180° to 180° and it can lead to numerical erros at Neural Network training. Therefore, it must be better to use $sen(\psi)$ values to train the Neural Network because it is a continuous series. Probably, doing this, the results of prediction of (ψ) and yaw rate (r) values will be better.

However, for other outputs, notice that the correlation between predicted and expected outputs are satisfactory.

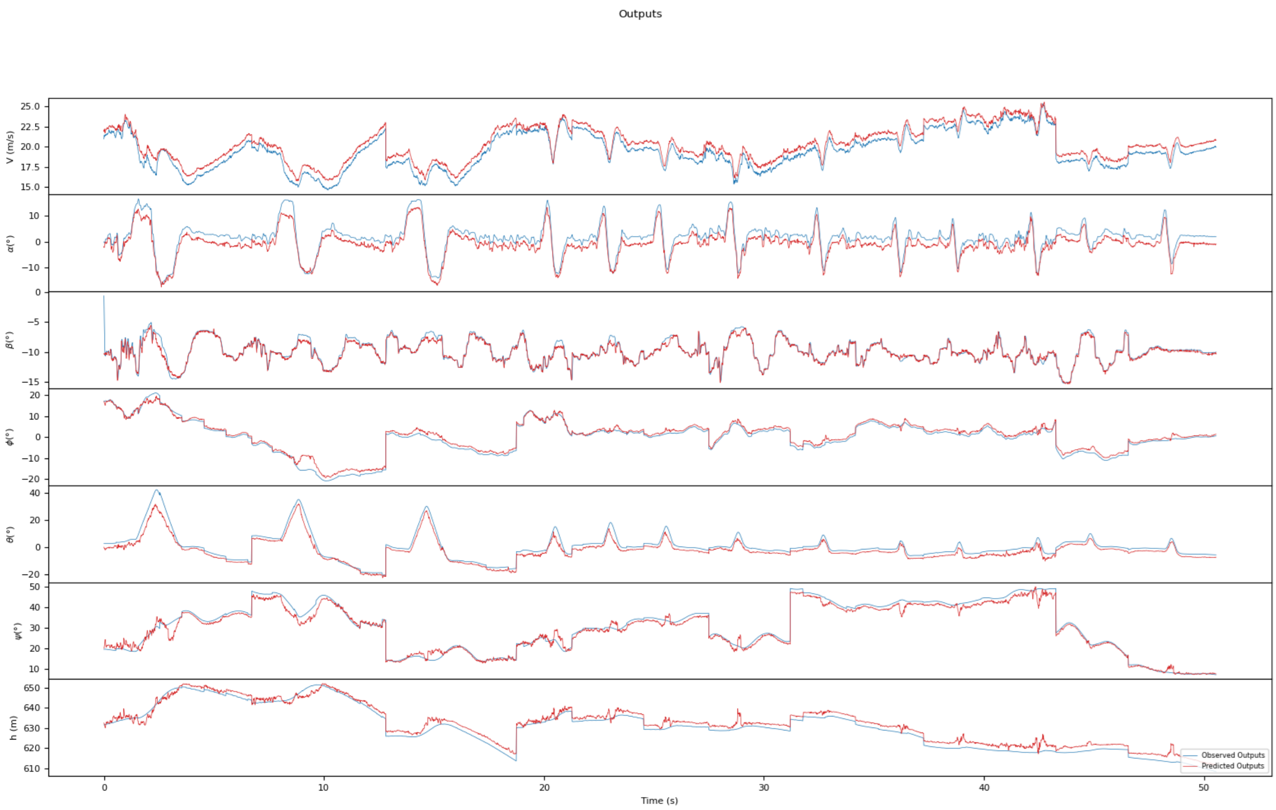

Figure 6. Predicted Outputs (in red) of the FFFNN and Expected Outputs (in blue) of EOLO aircraft

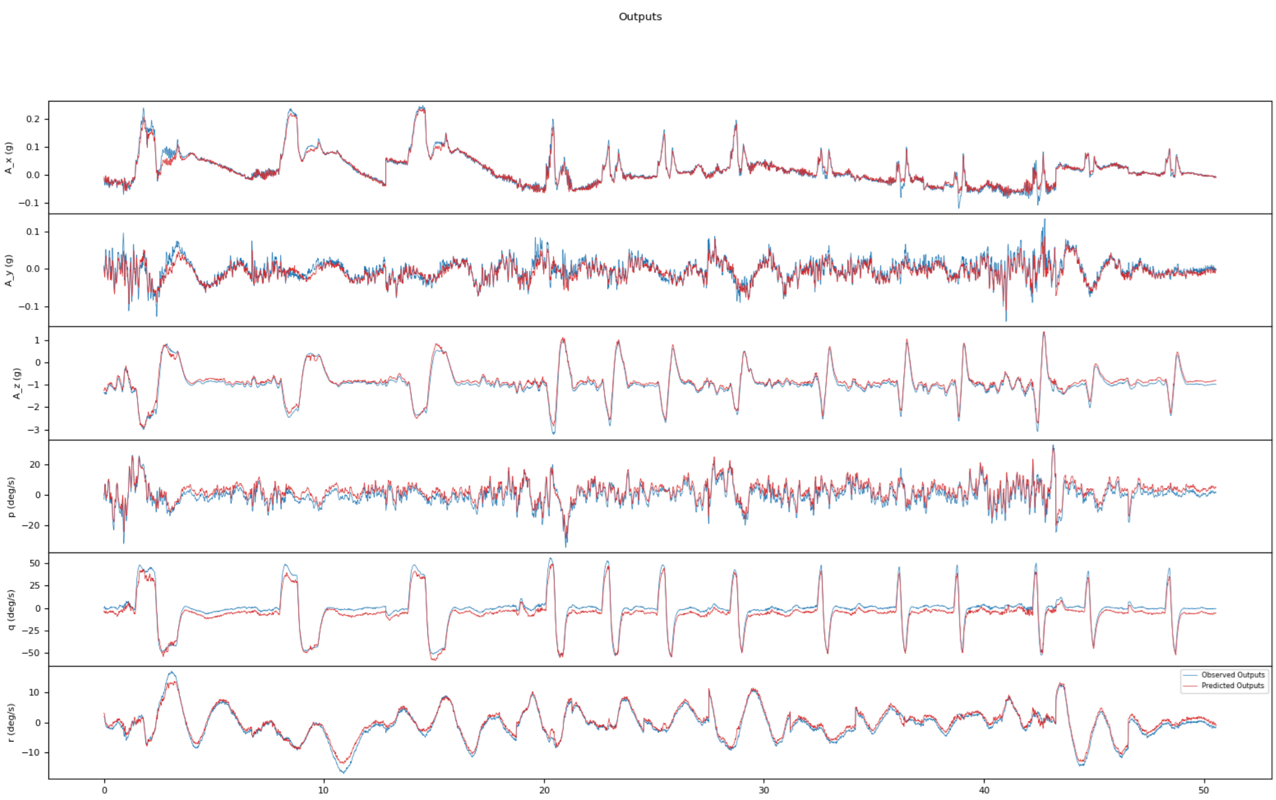

Figure 7. Predicted Outputs (in red) of the FFFNN and Expected Outputs (in blue) of EOLO aircraft (Continuation)

5. CONCLUSIONS

The Artificial Neural Networks are a very powerful resource to simulate unknown systems (black box systems), correlating input versus output adjusting its neurons weight and activation functions. The Feedforward Neural Network

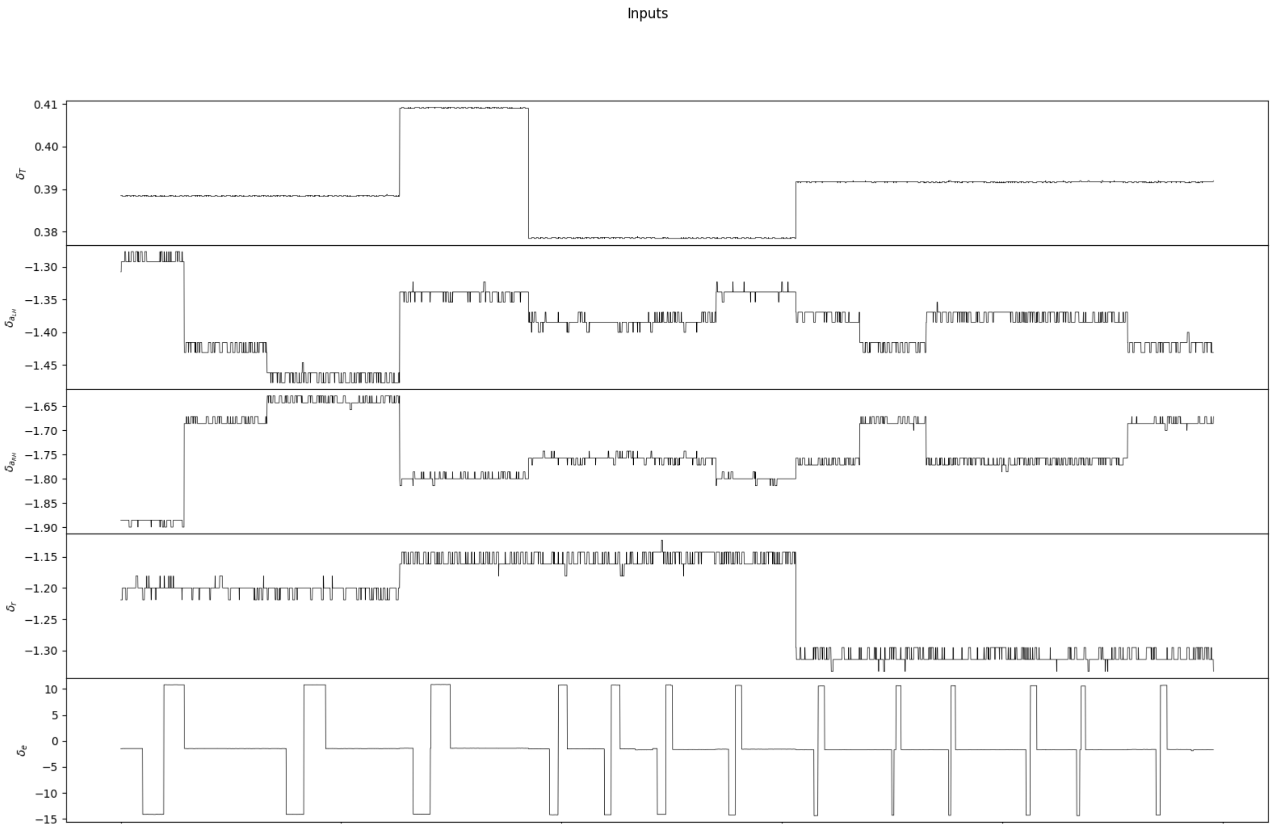

Figure 8. Inputs of the identified maneuvers - LSTM Neural Network

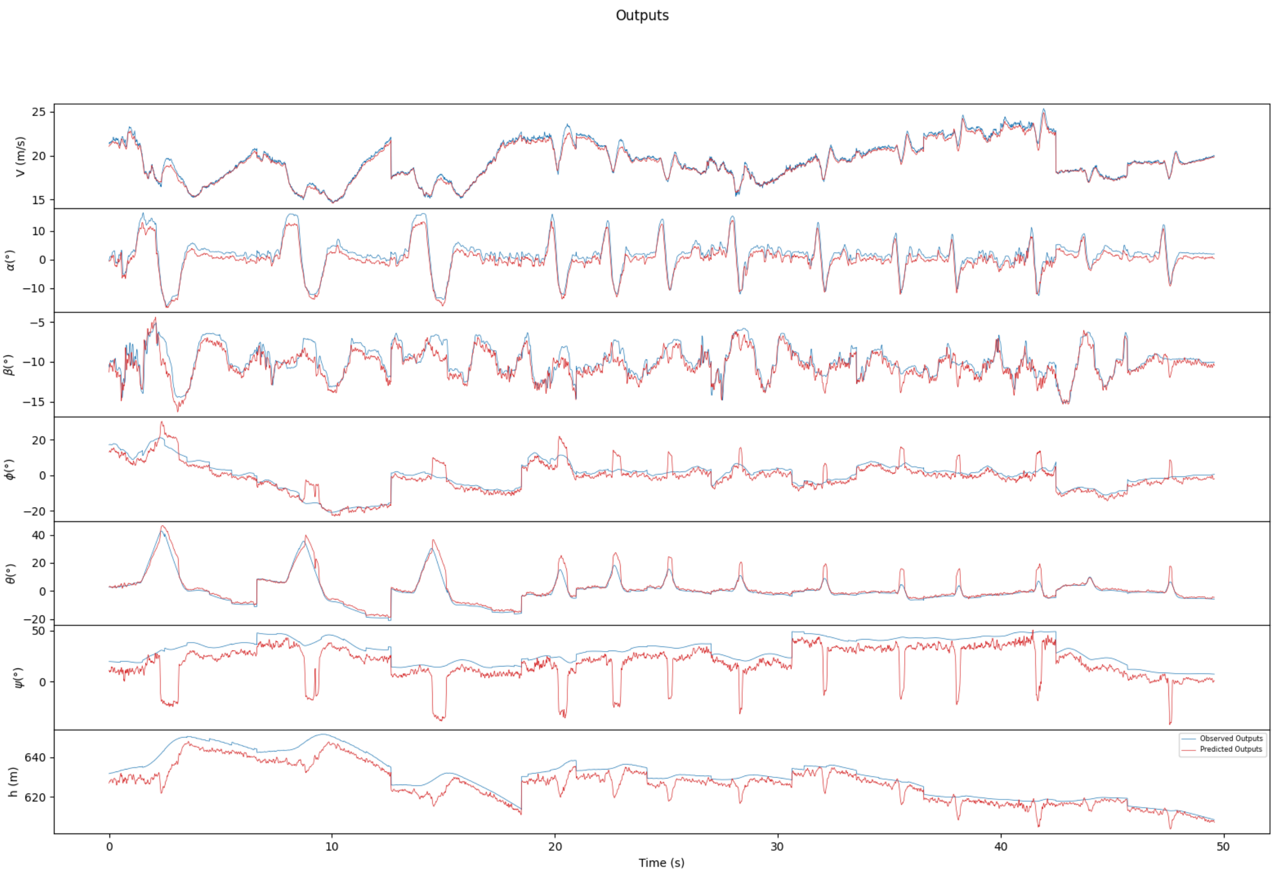

Figure 9. Predicted Outputs (in red) of the LSTM and Expected Outputs (in blue) of EOLO aircraft

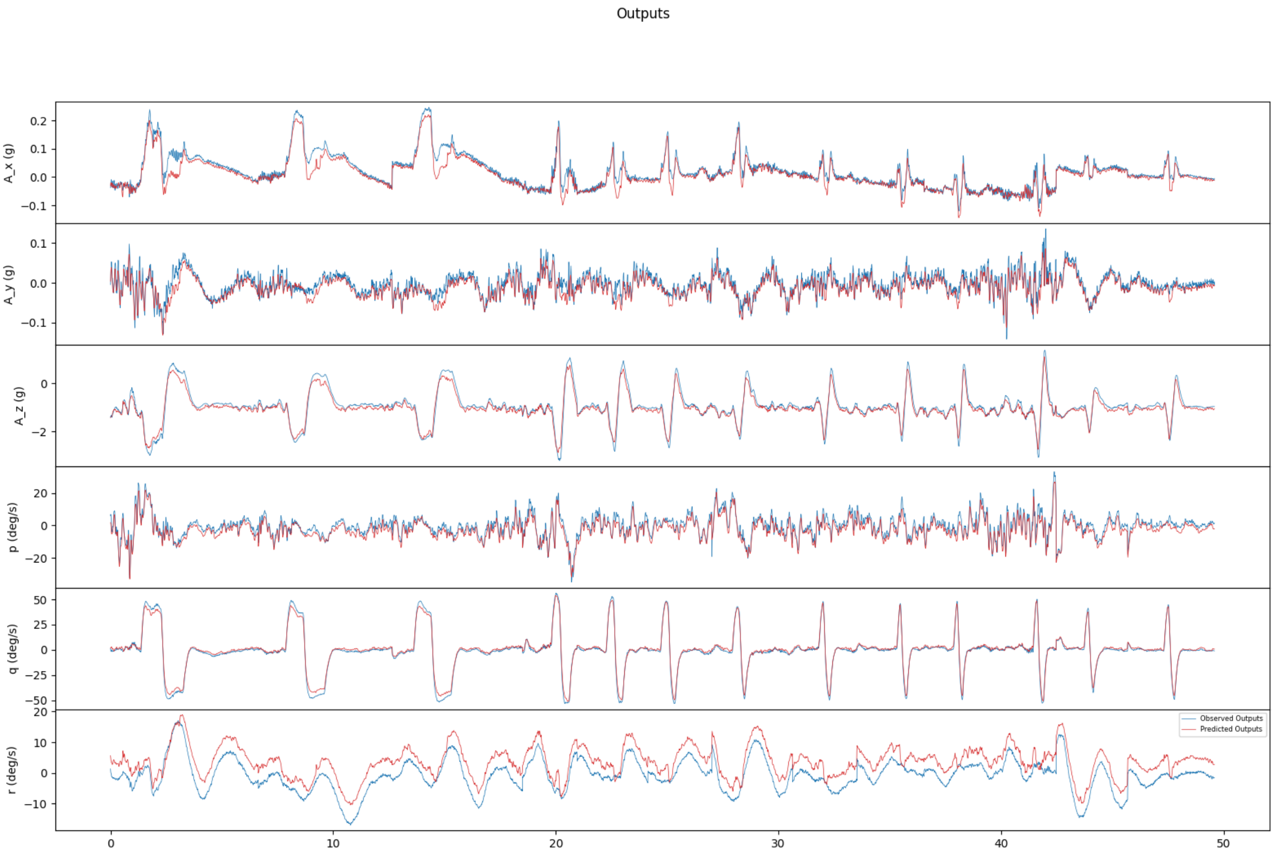

Figure 10. Predicted Outputs (in red) of the LSTM and Expected Outputs (in blue) of EOLO aircraft (Continuation)

requires much less computational power, there is no need to have huge amounts of data, but it can sometimes not have a good generalization. However, this is the most popular Neural Network used worldwide and it has a great power in therms of usage at many kind of disciplines.

The LSTM Neural Network is a Neural Network that can be more suitable for temporal data, like the Flight Test data. Most of the aerodynamic data are time dependent. However, since it is time dependent and what is trained is a sequence of data and not the data at a given instant, lots of data are needed to train the Neural Network and more different maneuvers are needed.

Finally, for an aircraft with a flexible wing, which flexibility plays a lot of influence at the aerodynamic results, the use of Neural Networks can simplify the complex modeling that is needed to model this interaction between aerodynamics and structural flexibility.

6. REFERENCES

Bodin, C., 2020. *Automatic Flight Maneuver Identification Using Machine Learning Methods*. Ph.D. thesis, Master of Science Thesis in Electrical Engineering, Linköping University, Linköping, Sweden.

Curvo, M., 2001. *Modelagem aerodinâmica e controle estocástico adaptativo de aeronaves de alto desempenho por redes neurais artificiais e estimação de parâmetros*. Ph.D. thesis, Doctoral Thesis, INPE, São José dos Campos, Brasil.

Fethalla, N., 2019. *Modelling, Identification, and Control of a Quadrotor Helicopter*. Ph.D. thesis, Doctoral Thesis École de Technologie Supérieure, Université du Québec, Montreal, Canada.

Goodfellow, I., 2016. *Deep Learning*. ISBN 978-0262035613.

Han, Z., Zhao, J., Leung, H., Ma, K.F. and Wang, W., 2021. "A review of deep learning models for time series prediction". *IEEE Sensors Journal*, Vol. 21, No. 6, pp. 7833–7848. doi:10.1109/JSEN.2019.2923982.

Haykin, S., 2008. *Neural Networks and Learning Machines*. Prentice Hall, 3rd edition. ISBN 978-0131471399.

Hochreiter, S. and Schmidhuber, J., 1997. "Long Short-Term Memory". *Neural Computation*, Vol. 9, No. 8, pp. 1735–1780. ISSN 0899-7667. doi:10.1162/neco.1997.9.8.1735. URL `https://doi.org/10.1162/neco.1997.9.8.1735`.

Hornik, K., Stinchcombe, M. and White, H., 1989. "Multi layer feed forward neural networks are universal approximators". *Neural Networks 2*, pp. 359–366.

Kriegeskorte, N. and Golan, T., 2019. "Neural network models and deep learning". *Current Biology*, Vol. 29, No. 7, pp. R231–R236. ISSN 0960-9822. doi:https://doi.org/10.1016/j.cub.2019.02.034. URL https://www.sciencedirect.com/science/article/pii/S0960982219302040.

Machado, R.C., 2019. *Closed-loop Subspace Identification of an Unmanned Aerial System (UAS) with Flexible Wings*. Ph.D. thesis, Doctoral Thesis in Aeronautical Engineering, Instituto Tecnológico de Aeronáutica, São José dos Campos, Brasil.

Majeed, Singh, J. and Kar, I.N., 2012. "Identification of aerodynamic derivatives of a flexible aircraft". *J. Aircr.*, Vol. 49, No. 2, pp. 654–658.

Manaswi, N.K., 2018. *RNN and LSTM*, Apress, Berkeley, CA, pp. 115–126. ISBN 978-1-4842-3516-4. doi:10.1007/978-1-4842-3516-4_9.

Newton, L.J., 2020. "Learning neural network representations of aircraft flight dynamics". *CS230: Deep Learning, Winter 2020*.

Raisinghani, S.C. and Ghosh, A.K., 2000. "Parameter estimation of an aeroelastic aircraft using neural networks". *Sadhana*, Vol. 25, No. 2, pp. 181–191.

Raisinghani, S., Ghosh, A. and Kalra, P., 1998. "Aircraft lateral-directional parameter estimation via neural networks". *Proceedings of 49th AGM of the Aeronautical Society of India, Bangalore*, pp. 6–1.

Waszak, M.R. and Schmidt, D.K., 1988. "Flight dynamics of aeroelastic vehicles". *J. Aircr.*, Vol. 25, No. 6, pp. 563–571.

Yu, Y., Si, X., Hu, C. and Zhang, J., 2019. "A Review of Recurrent Neural Networks: LSTM Cells and Network Architectures". *Neural Computation*, Vol. 31, No. 7, pp. 1235–1270. ISSN 0899-7667. doi:10.1162/neco_a_01199. URL https://doi.org/10.1162/neco_a_01199.

Zuñiga, D.F.C., 2019. *Aeroelastic testing of flexible aircraft using acceleration and strain sensors*. Ph.D. thesis, Doctoral Thesis in Aeronautical Engineering, Instituto Tecnológico de Aeronáutica, São José dos Campos, Brasil.

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