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LATERAL-DIRECTIONAL AERODYNAMIC MODELLING FOR NUMERICAL RESULTS USING NEURO-FUZZY WITH DIFFERENTIAL EVOLUTION

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Abstract

This work presents a methodology to obtain an unsteady aerodynamic model of an aircraft with the help of a computational intelligence technique known as Neuro-fuzzy (NF) combined with the differential evolution optimization. The Neuro-fuzzy has the interpretability of Fuzzy Inference Systems (FIS) combined with the adaptability of Artificial Neural Networks (ANN). The artificial intelligence (AI) technique is fed by numerical data of the lateral-directional axis inputs and outputs variables of a reduced scale Cessna 182 airplane model, acquired from the FAA-certified flight simulation tool XPLANE. After accomplishing the aerodynamic model validation graphs are built to ensure the reliability of the trained model.

Keywords: Aerodynamic Model, Differential Evolution, Lateral-Directional, Neuro-fuzzy, Reduced scale model

1. Introduction

Reliable aerodynamic models are highly required in aeronautic industries especially in unsteady and non-linear aerodynamics. This work has the intention to propose an alternative methodology to identify unsteady aerodynamics forces and moments coefficients only by using input data information, which depends on the studied aerodynamic axis. In this work, only the lateral-directional aircraft axis will be explored and according to [4], the variables which most influences this axis force and moments are the sideslip angle (β) and the aileron and rudder deflections (δ_a and δ_r).

To use of Fuzzy logic for aerodynamic model creation is not new. In the work by [8], stall modelling has been performed using information from numerical CFD simulations of an airfoil. The methodology used for that application was the Neuro-fuzzy and Orthogonal Functions. The work presented by Roy and Peyada in [6, 5] shows the lateral-directional aerodynamic model of a full-scale aircraft obtained using the Neuro-fuzzy methodology with the Takagi-Sugeno inference method and Genetic Algorithm optimization algorithm.

In this work, this method has been applied for the aerodynamic modelling of the lateral-directional force and moments. The proposed method includes an offline data-driven learning/tuning mode. The necessary time to train the aerodynamic model will depends on the number of the input variables and will also depends on the amount of data. Thereafter, the created (aerodynamic) metamodel requires only extreme lite calculation power so that it can be used in real-time applications, cyber-physical simulations with a necessity on execution speed (magnitudes faster than real time), or on embedded systems with limited calculation performance to identify unsteady aerodynamic effects.

2. State of Art

In this section, the Fuzzy Inference System (FIS) in combination with the Takagi-Sugeno inference method, the Neuro-fuzzy architecture, and the aircraft lateral-directional force and moments will be described and analysed.

2.1 Fuzzy Inference Systems

The Fuzzy Logic is a reasoning that contradicts the Boolean logic idea, which consider only two membership degree conditions, 0 or 1, do not belong and totally belong respectively. The FIS allows for continuous ranks ranging from 0 to 1, allowing intermediate ranks between 0 and 1. The fuzzy subsets are called membership functions and they are defined as functions varying from 0 to 1, and these subsets are, in general, triangular, rectangular, or Gaussian functions. In this work the membership functions will be Gaussian functions. The operators for the prepositions OR and AND in the rule base are maximum and minimum, respectively.

According to [1], the FIS has four main substructures, the Input Processor, Inference Machine, Rule Base and Output Processor. They are described in the following items.

- **Input Processor:** The input processor converts a real number into numbers with a certain degree of belonging in fuzzy sets. This process is called fuzzification.
- **Inference Machine:** The interference machine establishes the correlation between the input fuzzy sets with the output fuzzy sets, according with the Rule base.
- **Rule Base:** The rule base are prepositions like `IF...THEN` that correlate the input variables with the output variables.
- **Output Processor:** The output processor is responsible to convert the fuzzy sets number into real numbers. This process is called defuzzification.

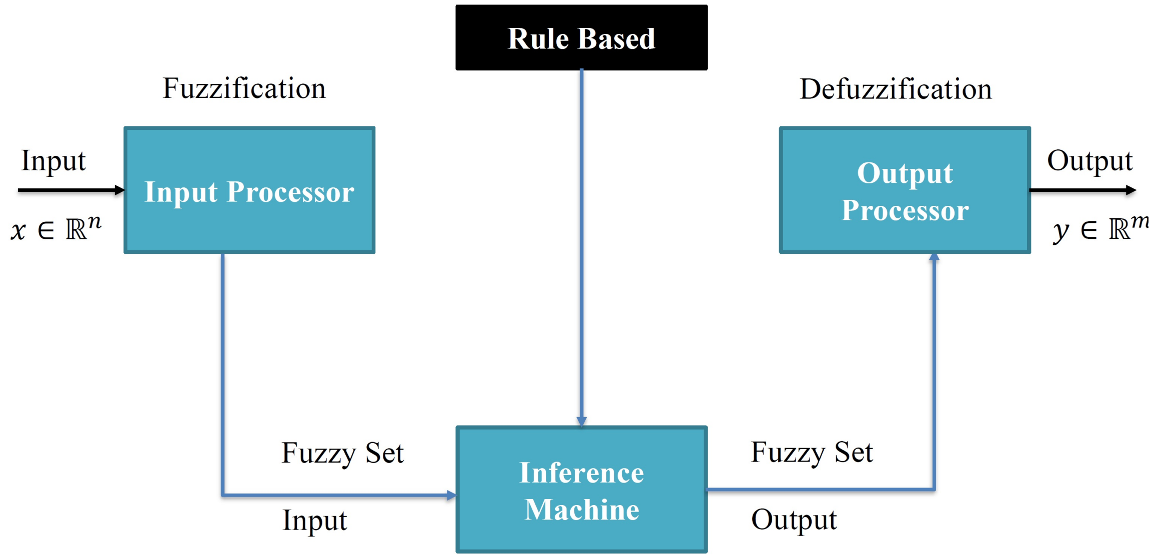


Figure 1 – A representation of the Fuzzy Inference System.

To explain the Takagi-Sugeno inference method, as shown in Fig. 2, it is necessary to elaborate two rules arbitrary, for example:

$$\begin{array}{c}\textbf{Rule 1: If (X is } A_1 \textbf{ AND Y is } B_1\textbf{) Then (Z is } C_1\textbf{)}\\ \textbf{Rule 2: If (X is } A_2 \textbf{ AND Y is } B_2\textbf{) Then (Z is } C_2\textbf{)}\end{array} \tag{1}$$

In this case, the consequent C_1 and C_2 are composed by functions of type $f_i = f(x_1, x_2, \ldots, x_n)$ where x_i are the input variables. The weights w_i are the resultant values of each rule.

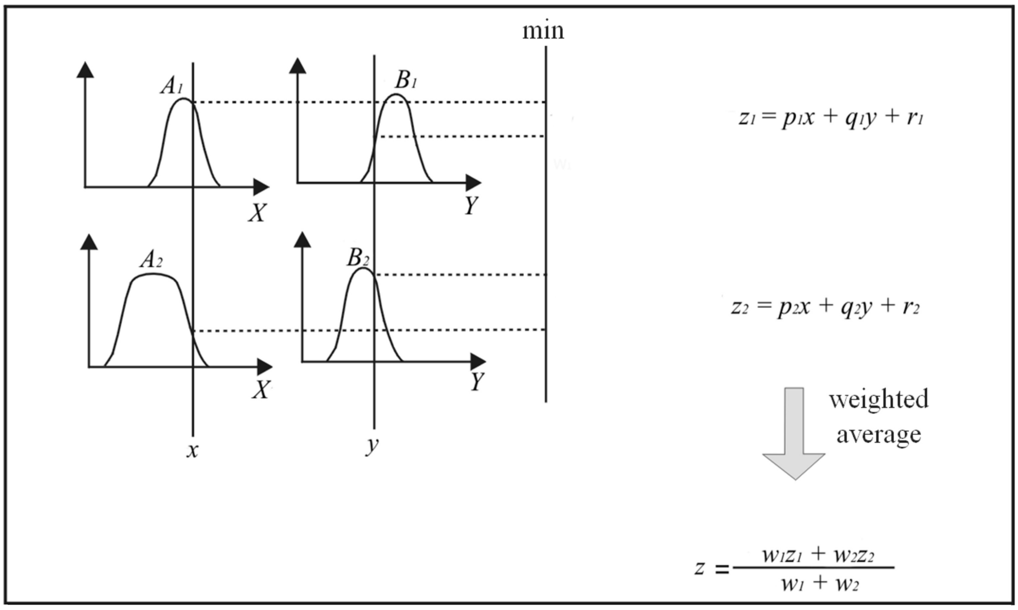


Figure 2 – Takagi-Sugeno Fuzzy Inference System.

2.2 Differential Evolution

The differential evolution method was first developed by [7] and the step by step of how this optimization method works is presented in Fig. 3.
The differential evolution is used to optimize the means and standard deviations from the membership functions of the input variables and is also used to optimize the consequences of the output variable.

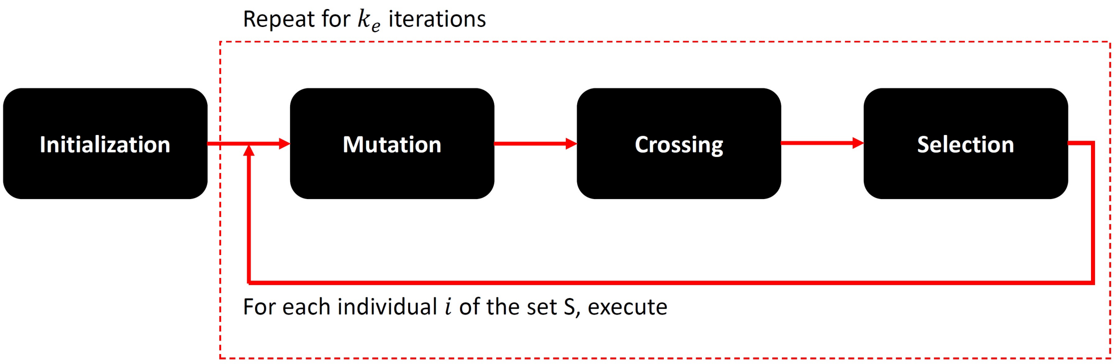


Figure 3 – Simplified representation of the differential evolution.

2.3 Neuro-Fuzzy

The Neuro-Fuzzy technique was first presented by [2], as a combination of the learning and adaptability from Artificial Neural Networks (ANN) with the logic presented by Fuzzy Inference Systems (FIS). The Neuro-Fuzzy architecture, according to [3], is divided into five layers, as Fig. 4 shows. Using the Takagi-Sugeno inference system, the purpose of each layer is given by the following definitions:

First Layer: Each node receives one input variables $I_i(k)$ that will be used in the training process. The output from i node from the first layer at time k, $u_i^{(1)}(k)$ is given by:

$$u_i^{(1)}(k) = I_i(k) \tag{2}$$

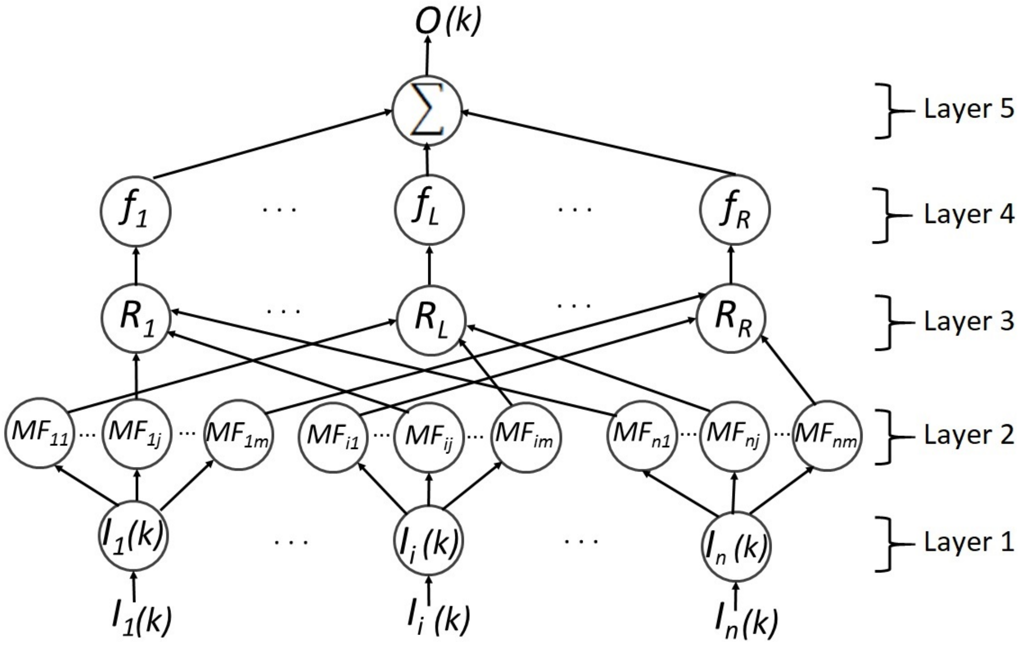


Figure 4 – Neuro-Fuzzy architecture.

Second Layer: In this layer the fuzzification of input variables is performed, that is, the real numbers are transformed into Fuzzy subsets with a certain degree of pertinence. In this step, the membership functions (MF) are built for the description of the inputs. Considering that the membership functions are approximated by Gaussians, the output of node ij from layer 2 at time k, $u_{ij}^{(2)}(k)$, is given by:

$$u_{ij}^{(2)}(k) = e^{\frac{(u_i^{(1)}(k)-m_{ij}(k))^2}{\sigma_{ij}^2(k)}} \tag{3}$$

where $m_{ij}(k)$ and $\sigma_{ij}^{(2)}(k)$ are the mean and standard deviation, respectively, of the Gaussian membership function MF_{ij}.

Third Layer: Here the propositions of type If...Then... are realized, forming the rule base for Adaptive Neuro-Fuzzy Inference Systems (ANFIS). For each rule, the AND and OR operator are treated as minimum or maximum, respectively, so the output of the L node from this layer, $u_L^{(3)}(k)$, is a function of the layer 2 selected output from rule R_L.

Fourth Layer: The nodes from this layer are treated as constants, and are defined as a function $f_L : R^n \to R$ such that $f_L = f(I_1, ..., I_i, ..., I_n, w_{1L}, ..., w_{jL},$ $..., w_{oL}, k)$, where $w_{1L}, ..., w_{jL}, ..., w_{oL}$ are weights that will be determined in the ANFIS training phase. Thus, the output from node L of layer 4, $u_L^{(4)}(k)$, is calculated by:

$$u_L^{(4)} = u_L^{(3)}(k) f_L(I_1, ..., I_i, ..., I_n, w_{1L}, ..., w_{jL}, ..., w_{oL}, k) \tag{4}$$

Fifth Layer: The last layer releases the Neuro-Fuzzy response, given by equation:

$$O(k) = \frac{\sum_{L=1}^{R} u_L^{(4)}(k)}{\sum_{L=1}^{R} u_L^{(3)}(k)} \tag{5}$$

2.4 Aircraft Lateral-Directional Force and Moments

The Lateral-Directional axis of an aircraft encompass the moment L (moment in X-axis), the Y-axis force and the moment N (moment in Z-axis). The Cessna 182 body axis can be observed in Fig. 5.

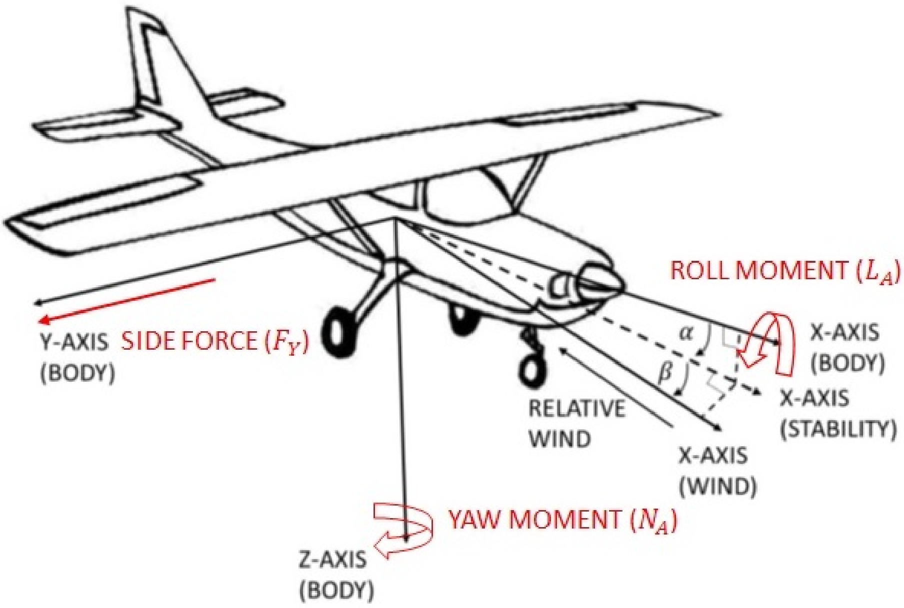


Figure 5 – Aircraft (Cessna 182) body axis.

2.4.1 Roll moment (L_A)

According to [4] the roll moment L_A can be described as Eq. 6.

$$L_A = C_l \bar{q} S b \tag{6}$$

Where C_l is the rolling moment coefficient and it depends on of many variables during the perturbed flight, like sideslip angle (β) and the control surfaces deflections (δ_a and δ_r). In this work, the rolling moment will depends on the sideslip angle (β) and rudder deflection (δ_r).
The Taylor first order series form to the rolling moment coefficient according to [4] is presented in Eq. 7.

$$C_l = C_{l_0} + C_{l_\beta}\beta + C_{l_{\delta_a}}\delta_a + C_{l_{\delta_r}}\delta_r \tag{7}$$

2.4.2 Side Force (F_Y)

The aerodynamic force in Y-axis is also known as side force and according to [4] it can be written as in Eq. 8.

$$F_{Y_A} = C_Y \bar{q} S \tag{8}$$

Where C_Y is the Y-axis force coefficient and it depends on the same variables of moment L. Eq. 9 shows the Taylor first order series for C_Y.

$$C_Y = C_{Y_0} + C_{Y_\beta}\beta + C_{Y_{\delta_a}}\delta_a + C_{Y_{\delta_r}}\delta_r \tag{9}$$

2.4.3 Yaw moment (N_A)

Finishing the equations that describe the aircraft aerodynamics force and moments, the yawing moment N is calculated by Eq. 10.

$$N_A = C_n \bar{q} S b \tag{10}$$

In this work, the yawing moment of the aircraft will depend only on the rudder and aileron deflections, δ_r and δ_a respectively.
In the same way of the past terms, the Taylor first order series for the yawing moment N coefficient, according to [4], can be seen in Eq. 11.

$$C_n = C_{n_0} + C_{n_\beta}\beta + C_{n_{\delta_a}}\delta_a + C_{n_{\delta_r}}\delta_r \tag{11}$$

3. Results

This section will show the results from the data training and validating for each lateral-directional force and moments. The forces and moments are obtained from an output text document from XPLANE, which is a FAA-certified flight simulator software. The values for sideslip angle (β), aileron deflection (δ_a) and rudder deflection (δ_r), are the input variables for this setup. This data set serves for the training using the methodology explained in Section 2.
To obtain representative (and realistic) data from XPLANE, a 1:10 reduced scale model of the Cessna 182 has been modelled with the help off the XPLANE draft section. The resulting model is depicted in Fig. 6.

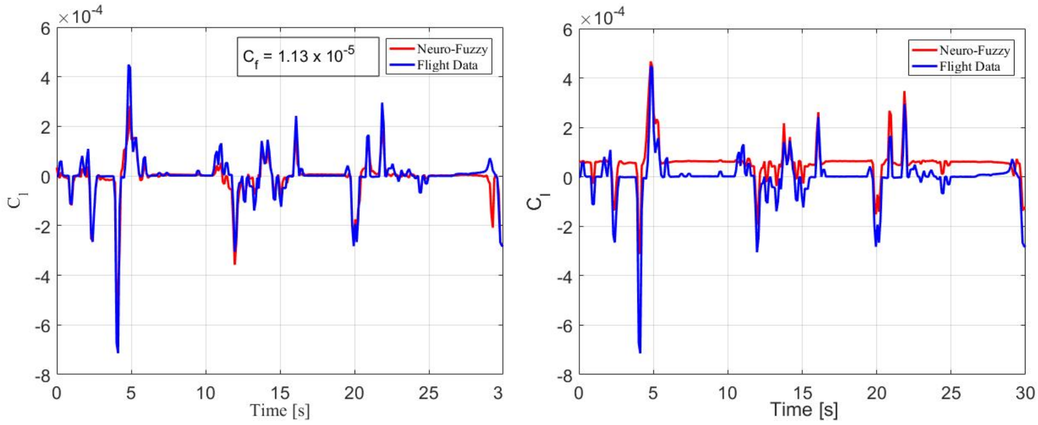
Figure 6 – Reduced scale model of Cessna 182 in XPLANE flight simulation.

3.1 Roll Moment L_A

The roll moment (around the body system X-axis) is known as moment L_A. It is usually controlled with the help of ailerons (opposite-deflecting trailing edge control surfaces at the outer section of the wing). However, the roll moment is also influenced by the rudder control surface deflection, the sideslip angle, the sideslip angle variation rate ($\dot{\beta}$), the velocity and the acceleration in Y-axis (v and $\dot{v}$, respectively) and the angular velocity P (roll), according to [4]. For this study, only the derivatives through time of the deflections of the ailerons and rudder was taken in considering. The results of the training data and the validation data can be observed in Fig. 7.

3.2 Side Force F_Y

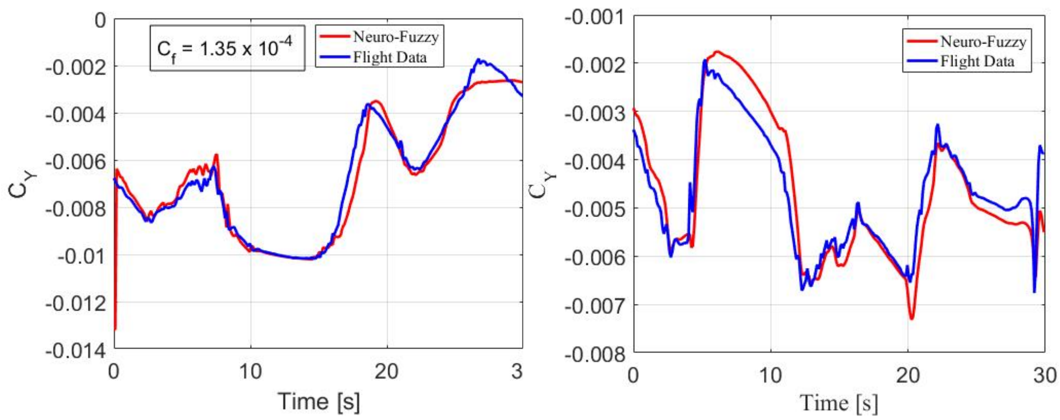
The side force (in Y-axis) is the lateral force that pulls the aircraft to the right-wing direction. This force is influenced by the sideslip angle (β), by the rudder and aileron deflection (δ_r and δ_a, respectively), and by some other flight variables described in 3.1 in according to [4].



(a) Training graph. (b) Validation graph.

Figure 7 – Training and validation graphs for the rolling moment coefficient (C_l).

In this work, the sideslip angle (β) and the rudder deflection (δ_r) are the input variables to train the force coefficient in Y-axis (C_Y). Fig 8a and Fig. 8b show the training data and the validation data results, respectively.



(a) Training graph. (b) Validation graph.

Figure 8 – Training and validation graphs for the Y-axis force coefficient (C_Y).

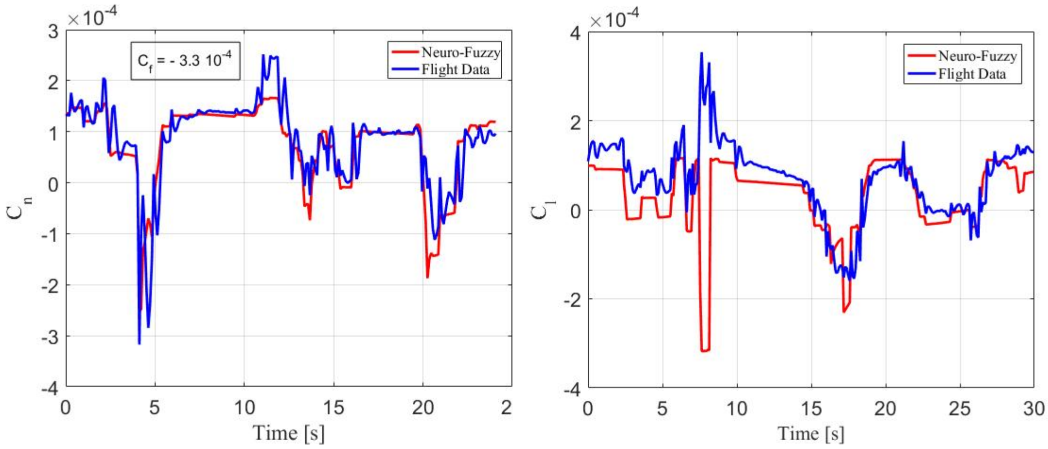
3.3 Yaw Moment N_A

The yaw moment N (around the Z-axis) is influenced by the lateral-directional variables, which are sideslip angle (β), rudder and aileron deflection (δ_r and δ_a, respectively), and by other variables that were cited in 3.1 according to [4].

In this study, two input variable were used to predict the moment N coefficient (C_n); aileron deflection (δ_a) and the rudder deflection (δ_r). The results from the training data and the validation is shown in Fig. 9a and Fig. 9b. In Fig. 9b it is possible to identify a wrong prediction of the C_n between the interval of 5 to 10 seconds. This occurs because of the value of the N moment coefficient exceeded the maximum value used during the training which was $+2,5 \times 10^{-4}$.

3.4 Result Discussion

The presented methodology is able to predict the lateral-direction force and moments coefficient axis using the information of five input variables, sideslip angle (β), aileron deflection (δ_a), rudder deflection (δ_r) and its derivatives through time ($\dot{\delta}_a$ and $\dot{\delta}_r$). It has been shown that this methodology is not capable to extrapolate values from the training data interval, which means that it only works within the training data interval.



(a) Training graph.

(b) Validation graph.

Figure 9 – Training and validation graphs for the yawing moment coefficient (C_n).

Each input variable counts with three membership functions, which represents low set, medium set and high set of each value. Each output variable count with five consequent values. The values are being optimized with the differential evolution for the input membership functions for each output variable in lateral axis. The obtained values of the membership functions are listed in the Tab. 1. The Neuro-fuzzy developed for this work suggest five consequent parameters for each output variable. These values are given in Tab. 2.

Table 1 – Mean and standard deviation values for the membership functions of the input variables

	Mean	**Std**	**Mean**	**Std**
	$\dot{\delta}_a$		$\dot{\delta}_r$	
C_l	(-0.133, -0.100, 0.021)	(0.045, 0.064, 0.072)	(-0.024, 0.006, 0.044)	(0.029, 0.005, 0.048)
	β		δ_r	
C_Y	(-0.697, -0.350, -0.169)	(0.298, 0.300, 0.300)	(-0.040, -0.030, 0.050)	(0.008, 0.021, 0.006)
	δ_a		δ_r	
C_n	(-0.015, -0.002, 0.000)	(0.003, 0.006, 0.007)	(-0.014, 0.004, 0.006)	(0.003, 0.005, 0)

Table 2 – Consequent values for the output variables according to Takagi-Sugeno FIS.

	Consequent (C)
C_l	-0.0004, -0.0003, 0, 0.0001, 0.0005
C_Y	-0.0125, -0.0080, -0.0064, -0.0020, -0.0002
C_n	$-3.17 \times 10^{-4}, -5.00 \times 10^{-5}, 0.00, 6.74 \times 10^{-5}, 2.50 \times 10^{-4}$

4. Conclusion

This work presents a Neuro-fuzzy based method to obtain a model of the lateral-directional force and moments coefficients knowing only three parameters about the aircraft configuration during flight, which are the sideslip angle (β), the aileron and rudder deflections (δ_a and δ_r) and its derivatives through time ($\dot{\delta}_a$ and $\dot{\delta}_r$). The Neuro-fuzzy approach was chosen based on literature sources ([6, 5]) where the algorithm showed great performance for aerodynamic modelling.

The Neuro-fuzzy methodology performed good results on the aerodynamic modelling of numerical results from a reduced scale aircraft, as it can be seen in Fig. 7, 8 and 9. This algorithm works well if enough data samples – preferably addressing the completed design space – are available to train the algorithm sufficiently. The total training time depends on the processing capacity. On a 32 GB

RAM computer, it took less than 1 minute to train each force and moment using a training data set of 200 data points for each variable (consisting of two input and one output floating point parameters).

The result shows that the Neuro-Fuzzy with Differential Evolution is not capable to extrapolate the training boundaries, so the validation needs to fit the training interval, otherwise the model will not be able to predict the force and moments in lateral-directional axis of the numeric reduced scale model. However, with a limited flight envelope of an aircraft and a vast amount of (real operation) measurement data exploring the whole design space, the presented methodology may be used to generate precise aerodynamic models (as a kind of surrogate/response surface models) with extreme less calculation effort, e.g., for embedded sub-simulations or envelope protection.

The algorithm was implemented in MATLAB®and does not have the ability to refine the trained model by adding additional data yet, it needs to start over again the training phase each time. As a future work, the option to update the model with additional data could be implemented to the Neuro-fuzzy code. After that modification, the Neuro-fuzzy code could be e.g., implemented in a Pixhawk (Arduino-based autopilot for RC aircraft models) to self-update the aerodynamic model after each flight of a remote controlled (sub-scaled) test aircraft.

5. Copyright Statement

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