IDENTIFICATION OF AIRCRAFT RESPONSES IN ITS FLIGHT ENVELOPE AND ESTIMATION OF ITS AERODYNAMIC DERIVATIVES USING ARTIFICIAL NEURAL NETWORKS

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Abstract. *The area of aircraft dynamics has reached a high level of development and due to the increasing availability of computers continuously faster and with bigger processing capacity, the application of numerical identification techniques in this area also had great advance. This work presents two methodologies, one for identification of aircraft responses within a pre-established flight envelope using recurrent neural networks and another one for estimation of its aerodynamic derivatives using feedforward neural networks. To get data sets to train the neural networks, a combat aircraft flight dynamics non-linear model was implemented and simulated in nine points of the flight envelope to obtain its behavior. The simulated responses corresponding to a four points of the flight envelope were used to train the neural network and after that, it was possible to verify that this net satisfactorily captured the dynamics of the aircraft, identifying with great success the longitudinal motion responses of the aircraft at all the considered flight envelope positions. After the simulation and identification of the aircraft responses inside the flight envelope, the solution of the inverse problem is presented, i.e., using scalar and angular aircraft velocities together with its geometric data as input to the feedforward neural network, a neural estimator model of aerodynamic derivatives is obtained. In order to show the capacity of this neural estimator model, this model is applied to the estimation of the derivatives of the simulated aircraft. These proposed methodologies reduce the cost of obtaining the aerodynamic derivatives and show the estimation effectiveness of the neural networks to estimate the responses of an aircraft inside a pre-defined flight envelope.*

Keywords: *Flight envelope, Identification, Recurrent and Feedforward neural networks.*

1. INTRODUCTION

With the use of new materials and new technologies, aircraft have normally operated with a high performance index and maneuverability in flight regimes in which the aerodynamics is highly non linear. The flight envelope increased in such a way that the variations in ram pressure started to become significant; the aerodynamic coefficients are affected by compressibility (mach number) and by the orientation of the aircraft in relation to the speed vector and obviously the properties of mass also are modified during flight, in accordance with the shipment or with the fuel consumption. That is, the modern aircraft are susceptible to a variety of complex limits in the flight envelopes and these, normally are difficult for the pilot to discover. In practice it is common to impose operational limits in order not to run risks, thus restricting the true performance and maneuverability of the aircraft (Horn et al., 1998). All of this, in one form or another, affects the dynamic behavior of the aircraft. All these reasons make the expansion of the flight envelope of an aircraft an extremely important question, but for the expansion of the flight envelope to be possible, it is necessary that it is completely know and identified.

Identification of systems is one technique that establishes a mathematical model of a dynamic system from measurements of the input and output data of the same (Klein, 1989). The application of identification techniques in the area of aircraft dynamics reached a high level of development with the increasing availability of faster and faster computers and with bigger processing capacity.

Hamel and Jategaonkar (1996) presented a brief revision of some modern methods of parameter estimation and a little of the history of identification of systems in aeronautics. They also showed the success of identification methodology applied systems to a wide field of problems in the modeling of flight vehicles.

Iliff and Wang (1997) applied the output error method to study the characteristics of stability and control of the F-18 aircraft, this being considered for flights at high angles of attack. Maneuvers were performed and analyzed. The main objective of this work was the attainment of the derivatives of lateral-directional stability and control. These were estimated and compared with values found in tests made in the wind tunnel and with results gotten in flight. The results obtained, were reasonable and located in graphs showing the tolerance interval of error for each one of the derivatives.

Morelli (1999) presented a method for parameters estimation using the equation of error in the frequency domain and the Fourier transformaior for the analysis of real time data. To demonstrate that the technique produces good results, they used linear and non linear simulated examples for the above mentioned flights of the F-18. It was concluded that the method has a low computational requirement, it filters the noise automatically and it can be implemented on board. In Morelli (2002) a collection of programs for aircraft identification can be found. Jategaonkar et al. (2003) used another approach to create methods and criteria of aircraft parameter estimation. They supplied a general vision of some activities of identification systems made during the last decade in a German aerospace center.

In Mendonça and Góes (2003) an application of a method in the frequency domain, the output error method, and the parameter identification of a linear model of the longitudinal dynamics of a regional aircraft of the Embraer was described. They used "3-2-1-1" input data of maneuver and identified the aircraft angle of attack, the aircraft acceleration and the pitch-up speed. The assumption of a linear model showed to be reasonable, since the results of the model and the data of the test in flight if had presented coherent.

In this context of system identification, the aim of this work is to use simulated answers for an attack aircraft, referring to certain flight conditions for the training of recurrent artificial neural networks to identify their dynamic behavior. The simulated model is non linear and is presented in SOUZA et. al. (2005). After the simulation and identification of the aircraft answers within of the flight envelope, the inverse problem will be decided: Answers for obtained angular and scalar velocities of the aircraft through the identification, at varied points of the flight envelope together with geometric data will be supplied as entry data to other neural network aiming at the attainment of a neural model to estimate of stability aerodynamic derivatives. This proposed technique reduces cost of attainment of the aerodynamic derivatives and shows the effectiveness of the neural networks in estimative esteem the aircraft answers to of daily pay-define flight envelope.

2. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANN's) are information processing systems with learning capability through examples (Haykin, 1994). Based on concepts derived from neuro-biology, ANN's are composed by a set of processing interconnected units, called *neurons*. The neurons process the signals presented to the neural network by accumulating each stimulus and by transforming the total value using a function; that is, the *activation function*. The stimulus to and from a neuron are modified by the real value called *synaptic weight*, which characterises the respective connection between neurons. Artificial Neural Networks have shown efficient in problems of identification systems and parameters estimation applied to aircraft, as is shown in some works cited in this article. In SOUZA (2002), the basic theory of RNA's is described and the algorithms used for training is shown.

Horn et al. (1998) presented a neural network model to supply information on flight envelope limits. They applied the method to provide information on normal load factors and limit attack angles of the aircraft V-22 tilt-rotor. The ANN they used was first trained off-line using simulated data and after that some tests were done simulating the responses in order to know if it could be used to predict, in real-time, which deflection of the longitudinal control would make the aircraft exceed the safe flight limit. The results have shown that the aircraft could be maneuvered throughout the flight envelope without exceeding the limits. They concluded that ANNs have great potential for limits prediction of a complex flight envelope.

Raisinghani and Ghosh (2000) have shown an ANN's application on aeroelastic aircraft modeling problem and parameters estimation without measuring elastic deflections or derivatives. Specifically, an feedforward ANN associated with two developed methods called method Zero and method Delta was proposed to predict coefficients of force and moment using simply measurements of the movement and control variables. They found and have shown in the paper sufficiently coherent results for different conditions of aircraft flexibility, making clear the applicability of ANN's in parameters estimation.

Allen & Dibley (2003) successfully used an ANN to identify bending moments, torsion loads and hinge moments of control surfaces of the active wing of the aeroelastic airplane (AAW).

Neto et. al. (2005) presented an adaptable algorithm for training an ANN known as Functional Link Network applied to parameters estimation problems. To show the results of the proposed technique, they studied a case of the longitudinal dynamics of the F-16 aircraft using simulated data, to estimate the aerodynamic derivatives. The results had been sufficiently satisfactory and had shown that this method can be applied to control and identification problems. They had also concluded that this algorithm can easily be implanted in the computer of an aircraft for identification of its derivatives in flight.

2.1. Identification of flight envelope using recurrent neural networks

The aircraft data used in simulation was obtained of McRUER et al. (1973) and of SCHIMIDT (1998). The simulated aircraft is of the military and of combat type and its geometric data, important for simulation are presented in Table 1.

Table 1 – Geometric data of simulated aircraft (SCHIMIDT, 1998).

Weight	*Airplane mass*	*Wing area*	*Airplane span*	*Semi-chord*
W = 78186.9 [N]	m = 8512.1 [kg]	S = 24.1548 [m^2]	b = 8.3820 [m];	c = 3.2918 [m].

Nine cases will be analyzed, whose parameters are shown in Table .2. The corresponding data to cases 1, 2, 3, 4, 8 and 9 had been removed of SCHIMIDT (1998) and the corresponding data to cases 5, 6 and 7 of McRUER et al. (1973), being all duly converted for SI units.

Table 2 – Altitudes, velocities, Mach number, pitching moment of inertia, dynamic pressure, air density data used for aircraft simulation (McRUER et al., 1973; SCHIMIDT, 1998).

Data	case 1	case 2	case 3	case 4	case 5	case 6	case 7	case 8	case 9
Altitude h [m]	0	4572	4572	10668	0	10668	4572	4572	10668
Mach number M	0.4	0.4	0.6	0.6	0.2	0.5	0.4	0.9	0.9
V [m/s]	136	129	193	178	68	148	129	290	267
Q [N/m^2]	11347	6416	14411	6033	2834.4	4165.4	6415.6	32413	13549
Iy [kg/m^2]	35106	35106	35106	35106	39715	35106	35106	35106	35106
α_{trim} [degree]	4.7	8.9	3.4	8.8	19.5	13	8.9	0.7	2.9
ρ [kg/m^3]	1.22500	0.77082	0.77082	0.37960	1.22500	0.37960	0.77082	0.77082	0.37960

As it can be observed in Table 2, there are two flight conditions in transonic regime (Mach number = 0.9) and two conditions with zero altitudes, not meaning that the aircraft is flying at exactly this level. It can be flying slightly above the sea. In Table 3, the aircraft dimensional longitudinal derivatives used are shown correspondingly to each case under study. As the implemented mathematical model was based on the one presented by Etkin and Reid (1996), it is necessary to do some conversions of units.

Table 3 – Longitudinal derivatives (dimensional) (McRUER et al., 1973; SCHIMIDT, 1998).

Derivatives	case 1	case 2	case 3	case 4	case 5	case 6	case 7	case 8	case 9
X_u [s^{-1}]	-0.0160	-0.0148	-0.0129	-0.0128	-0.0826	-0.01687	-0.01482	-0.0635	-0.0353
X_α [m/s^2]	-0.5310	-3.7978	-1.1342	-6.2819	-2.1207	-5.0172	-4.7833	-13.8013	-14.3378
Z_u [s^{-1}]	-0.156	-0.160	-0.104	-0.114	-0.26	-0.1291	-0.1518	-0.135	-0.120
Z_α [m/s^2]	-121.462	-66.9341	-158.160	-66.5378	-20.8669	-5.0172	-67.0438	-428.0916	-178.8262
M_u [m . s]$^{-1}$	0.0013	0.0016	0.0013	0.0013	0.0095	0.0017	0.0015	-1094.2	-575.8858
M_α [s^{-2}]	-10.233	-5.639	-12.97	-5.402	-2.2746	-3.6963	-5.6597	-35.96	-14.99
$M_{\dot{\alpha}}$ [s^{-1}]	-0.342	-0.204	-0.353	-0.160	-0.1441	-0.1232	-0.2039	-0.858	-0.389
M_q [s^{-1}]	-1.151	-0.670	-1.071	-0.484	-0.48	-0.389	-0.670	-1.934	-0.876
X_{δ_e} [m/s^2]	1.2619	0.7772	1.2253	0.8199	0	0	0	-50976	-14700
Z_{δ_e} [m/s^2]	-12.9723	-6.9921	-17.3797	-7.2329	-2.1549	-4.8189	-6.9921	-31.3883	-13.07592
M_{δ_e} [s^{-2}]	-13.73	-7.40	-19.46	-8.10	-2.21	-5.26	-7.40	-33.81	-14.8

2.2. Presentation of the flight envelope

A flight envelope scheme to be identified can be observed in Figure 1, where the red points correspond to the referring altitudes and Mach number of each one of the known flight conditions. To simulate the behavior of the aircraft in these points, the mathematical model presented in SOUZA et al (2005) is used. Some of these sets of answers, specifically 4 of them, will be used for training the ANN and the others will be used in the generalization tests

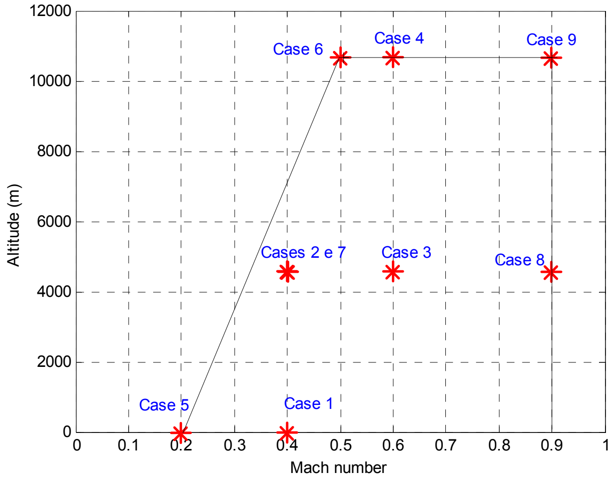


Figure 1. Scheme of flight envelope.

2.3 Identification of longitudinal dynamics

To obtain the data sets to train the ANN, three simulations using data of case 5, three simulations using data of case 6, three simulations using data of case 8 and other three simulations using data of case 9 were done, using only elevators step inputs with different values. Cases 5, 6, 8 and 9 were chosen for training, therefore these represented all the known flight altitudes of the aircraft. Also, since relatively large elevator step inputs provoke highly non linear responses, if the ANN was able to identify the corresponding responses it would identify the response to any another input.

Firstly a feedforward neural network was implemented to identify the horizontal velocity of the aircraft. To compose the input matrix for the ANN, 3 data sets obtained in simulations with data referred to cases 5, 6, 8 and 9 were used, all using input steps with different values in the elevators and applied at the time 20s. These inputs had been associated to the Mach number and to the corresponding altitudes of the flight envelope thus forming a dynamic input composed by the step input signals applied to the elevator and two static inputs that were Mach number and the corresponding air density of the simulated case.

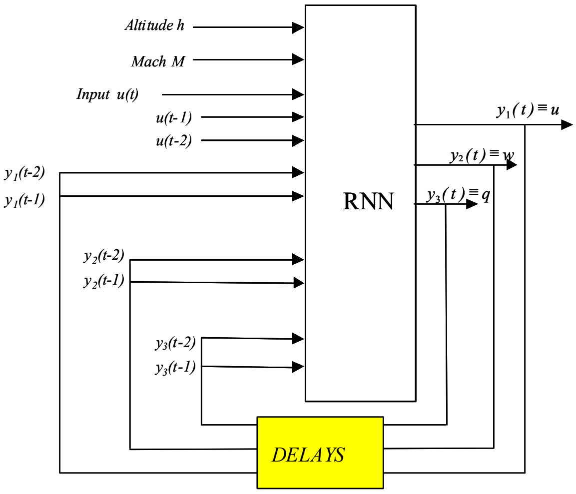
The ANN that better presented results had 3 layers of neurons, with 2 delays in each input, 10 neurons in the hidden layer and 1 neuron in the output layer. They produced little reasonable results in generalization tests, since it did not identify the speed for case 4. These first results were obtained with a smaller flight envelope, without the two conditions at Mach number 0.9, are shown in SOUZA et al. (2005).

After that, already with the two flight conditions Mach number of 0.9, a recurrent neural network (RNN) was used, placing a feedback of the output layer to the input one, resulting on small improvements, concluding then that the RNN did not still captured correctly the dynamics of the aircraft.

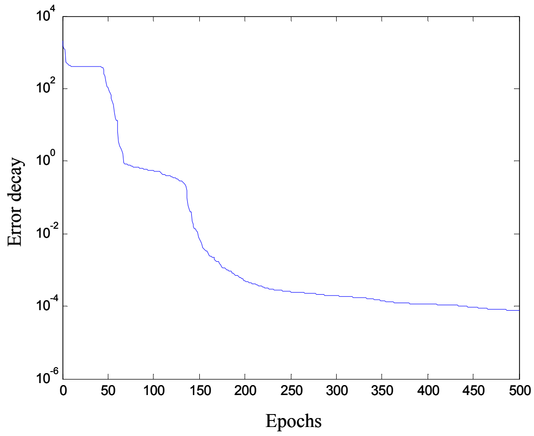
The idea then was to mount only one representative neural network of the aircraft, that is, with elevator angle input and containing the 3 outputs u, w and q. The neural network implemented continued being recurrent with 3 neurons layers. Some tests were then carried out, being that in a first one, 4 delays in each input and each output, 12 neurons in the hidden layer and 3 neurons in the output layer were placed. Then, the results obtained in the training had been sufficiently satisfactory. After, as a test, the number of delays was diminished to 3 and later diminished to 1 and still, one could observe many good results. To verify the results of the training, tests with other results of simulation had been carried through, confirming that the neural network had exactly captured the dynamics of the system, concluding then that, for this problem, it was not necessary more than one delay.

Then, a RNN with three neurons layers, 2 delays in the inputs and 2 delays for each output, 9 neurons in the hidden layer and 3 neurons in the output layer was adopted. Figures 2 (a) and 2 (b) respectively present the representative blocks diagram of the RNN used in the identification and the performance curve of the error during the training process.

In the previous blocks diagram (Figure 2 (a)), the applied elevator dynamic input is presented together with its respective delays, the fixed inputs altitude (h) and Mach number(M) associated to the dynamic input, $y_1(t)$, $y_2(t)$ and $y_3(t)$ representing the outputs horizontal velocity u, vertical velocity w and pitch velocity q, all with its respective delays. The ANN was trained during 500 epochs after which the variation of the error it stabilized and, as it can be observed in Figure 2 (b), the training result was sufficiently satisfactory, reaching an order of 10^{-6} .



(a)



(b)

Figure 2. (a) Representative scheme of the RNN used and (b) Error performance of the ANN training process.

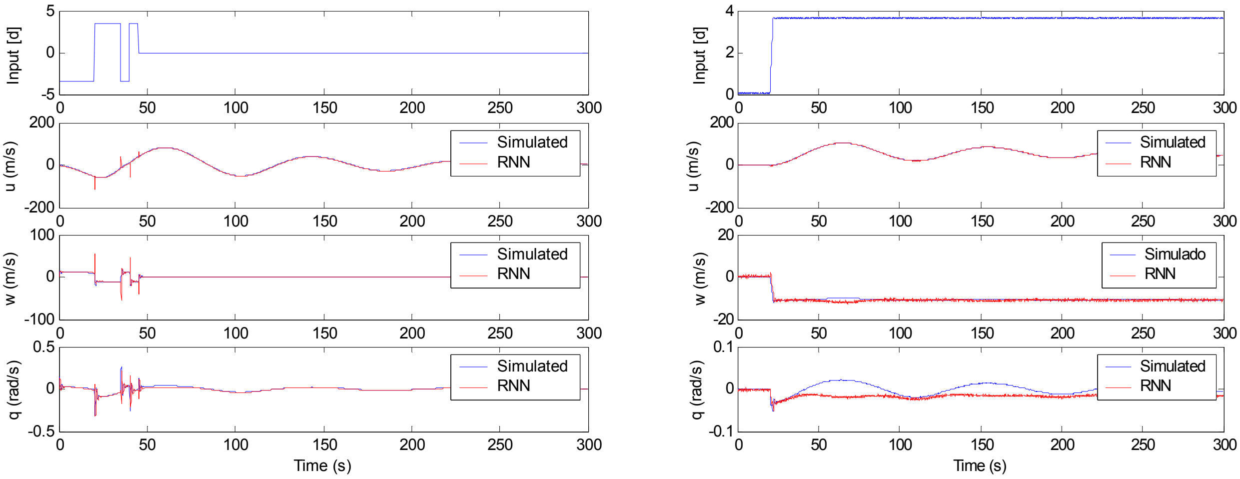
One can therefore conclude that the step input associated with each output separately, was not representative of the problem, while the input applied to the elevator associated with all the outputs together represent the dynamic behavior of the aircraft since the resulting RNN identified its states in any point of the envelope under consideration. As said previously, the RNN was trained simultaneously with the data of cases 5, 6, 8 and 9, using as fixed inputs the values of altitude and Mach number and the dynamic ones the elevator step input.

2.4 Results of the identification of the aircraft responses in the flight envelope

To train the ANN, the backpropagation algorithm was used with the Levenberg-Marquardt optimization technique which are presented in SOUZA et al. (2005). After being verified that the ANN had been adequately trained, the set of weights and bias were saved in an archive to be used in the generalization tests. To show the good training attained, the generalization of the ANN was tested at points of the flight envelope where it wasn't trained. It is observed that there have been used, during training, elevator inputs varying from $0,5^{o}$ up to 3^{o} and, during generalization, inputs up to 12^{o} and the results obtained were sufficiently satisfactory. In Figures 3 (a) and (b), results of the identification of the aircraft at point 1 are presented, where the aircraft if found flying at an altitude of 10,800 meters and Mach number 0.4 and in the Figures 4 (a) and (b) two responses at point 3, where the aircraft flies at Mach number 0.2 and altitude of 4,572 meters. As it can be verify, in both the cases the results of the identification of u, w and q had been sufficiently satisfactory. Various other tests had been carried out but, in order to not extend much the text, only two results for each one of the points of the envelope that were not used during the training process will be presented.

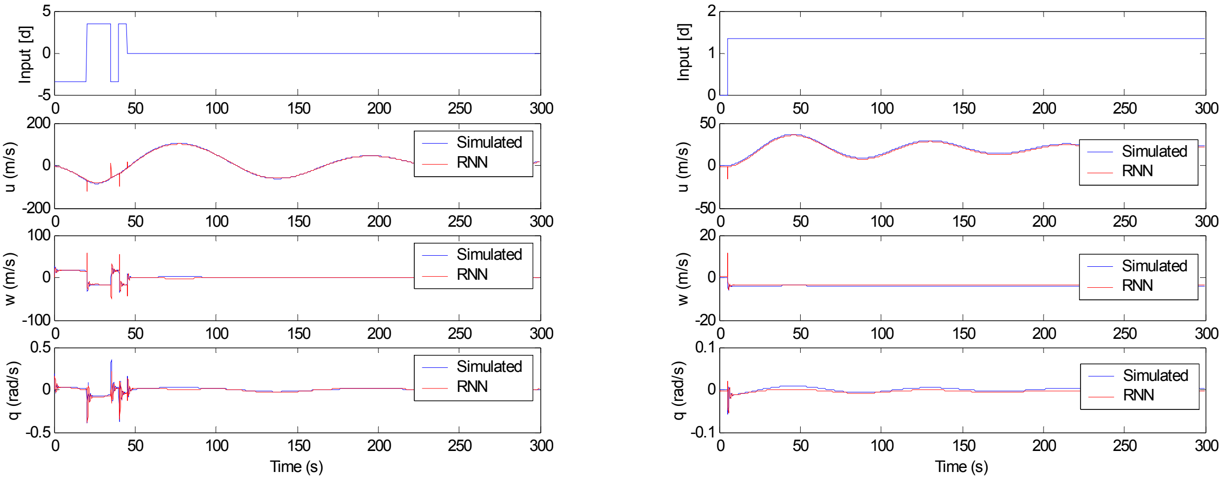
Figures 5 (a) and (b) present some results of the identification of the aircraft responses at point 2 of the flight envelope. One can observe in Figure 1 that the corresponding altitude to Case 2 is 4,572 meters and Mach number 0.4. The results obtained, corresponding to this point, had shown that the RNA captured the dynamics of the aircraft.

Analogously, Figure 6 (a) shows results of the identification after application of an elevator pulse train, with period of 50 seconds and amplitude of 0.5 degrees for the aircraft at point 7 of the flight envelope and Figure 6 (b) presents the results of the identification, also at this point, using elevator sine type input, with frequency of 1 rad/s and amplitude of 0.5 degrees. Finally the results of some tests carried out for the flight envelope case 4 will be presented. The results obtained, as it can be observed in Figures 7 (a) and (b), had also been sufficiently satisfactory.



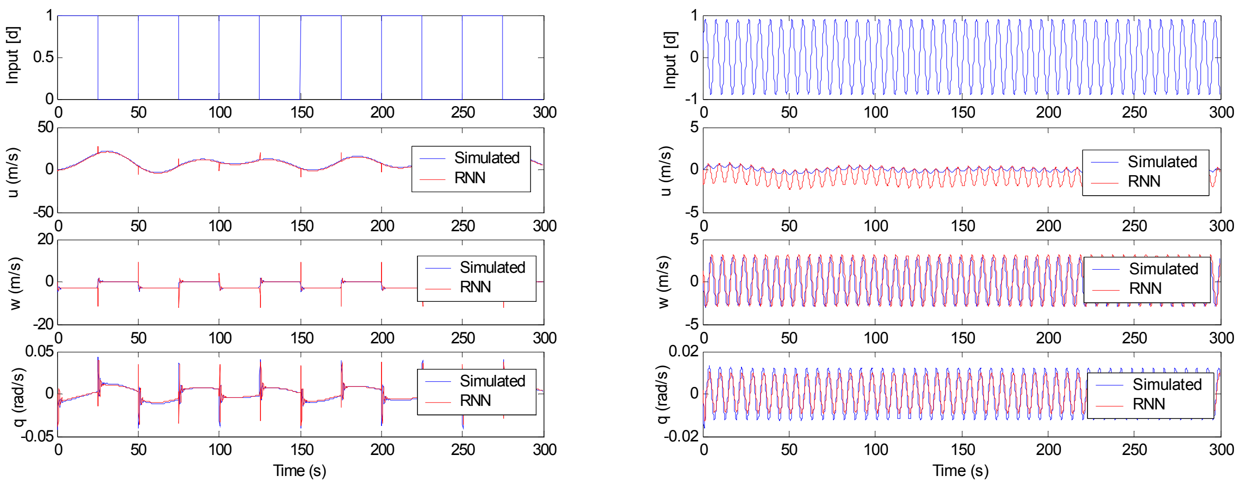
(a) (b)

Figure 3. (a) Identification in the point 1 after application of 3-2-1-1 input. (b) Identification after signal slope together with noise in the elevator.



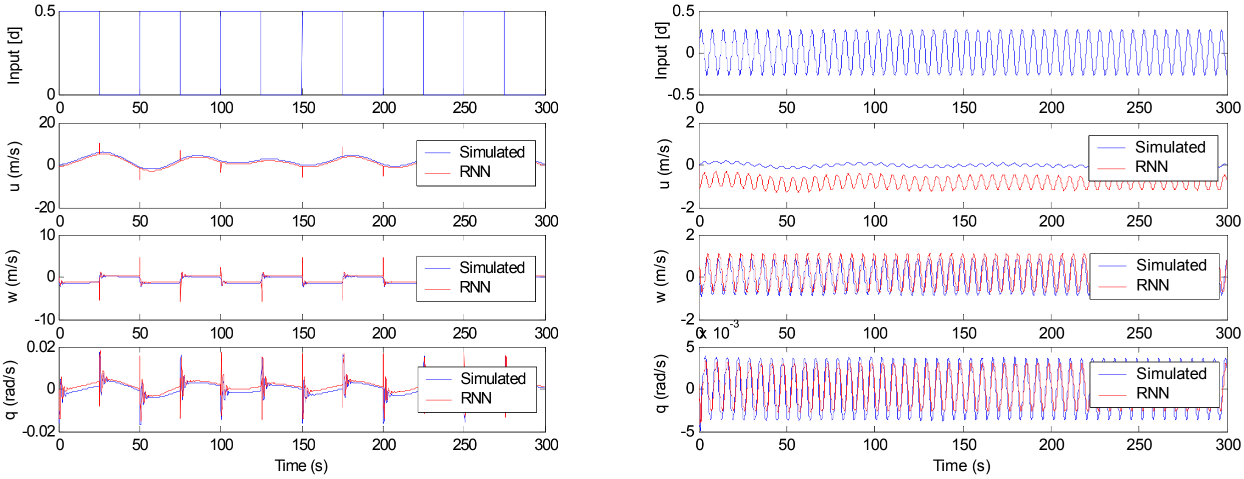
(a) (b)

Figure 4. (a) Identification in point 3 of the flight envelope after application 3-2-1-1 input (b) Identification after application step.



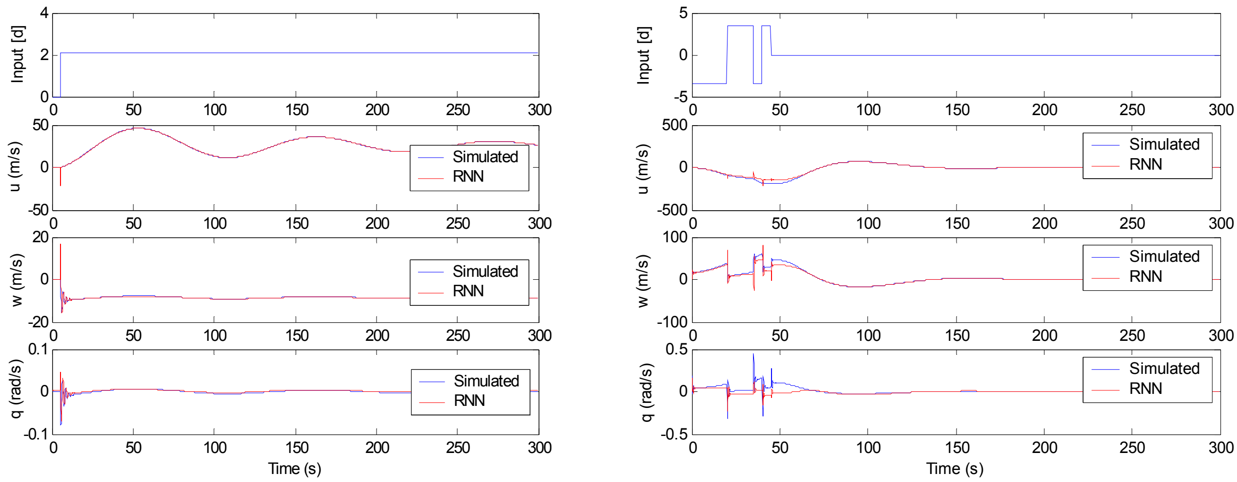
(a) (b)

Figure 5. (a) Identification of the answers of the aircraft flying in corresponding conditions to point 2 of the flight envelope after application of pulse train in the elevators. (b) Identification after application of sine input.



(a) (b)

Figure 6. (a) Identification of the answers of the aircraft in point 7 of the flight envelope after application pulse train input in the elevators. (b) Identification of the answers after sine type input in the elevators.



(a) (b)

Figure 7. (a) Identification of the answers of the aircraft in point 4 of the flight envelope after application of step input of 1,8$^{\mathrm{o}}$ in the elevators. (b) Identification after application of 3-2-2-1 input in the elevators.

2.5 Resolution of the inverse problem: estimation of aerodynamic derivatives using simulated results of an aircraft in an flight envelope using ANN.

A methodology for resolution of the inverse problem of the shown will be presented, that is, from the answers of velocities and aircraft data the the derivatives of stability of this will be esteem using static neural networks. To obtain the data set of training for the neural network, some corresponding flight conditions to each one of the cases of the flight envelope had been simulated using different inputs in the elevator. They had been used the type pulse train, sine and random step inputs. Three data sets for each one of the conditions of the flight envelope had been simulated.

First it was thought about implementing only one ANN to esteem the aircraft longitudinal aerodynamic derivatives, but had to the very great number of inputs, that is, had to the high computational cost, he was determined to implement separate ANN to esteem the derivatives. They had been implemented a net esteem the derivatives in *u*, the case, X_u, Z_u e M_u, other to esteem the derivatives in *w*, X_w, Z_w e M_w e one other esteem the derivatives $M_{\dot{w}}$ e M_q.

For the attainment of all these derivatives, static neural networks had been used, that is, of the type feedforward, with two intermediate layers of neurons and to train them was used the backpropagation algorithm. In all the neural networks had been used also two types of inputs: dynamic, in the case aircraft velocities answers the and input static, that are aircraft data and air density. These signals in the time domain had been discretized and thus considered 1 point to each 50 of the total of 10000 points, forming themselves with these signals two vectors of size 200 to supply as inputs. It could be verified that making this discretization the signal continued characterized. Specifically, the static inputs used had been aircraft mass (m), inertia moment I_y, air density ρ, initial velocity U_0 e Mach number M. It is observed that *Matlab®* software was used to work with the ANN. Figure 8 (a), (b) and (c) show architectures schemes.

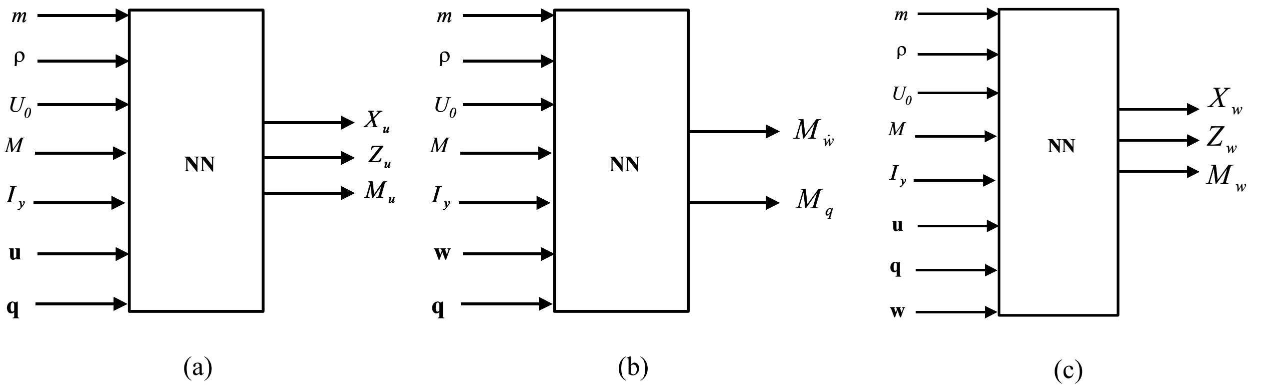


Figure 8. Blocks diagrams showing ANN schems used to steem respectively: (a) X_u, Z_u e (b) M_u, $M_{\dot{w}}$ e (c) M_q .e X_w, Z_w ***e*** M_w

2.5.1 Results of longitudinal aerodynamics derivatives X_u, Z_u e M_u

First the identification results of the derivatives X_u, Z_u e M_u will be presented. As said previously, beyond the static inputs, dynamic inputs had been used also, in this in case that, answers in the time of variations of linear u and angular q velocities. Some tests had been made and the joined results had been sufficiently next. The results to follow presented are referring to a RNA with 12-11-13 neurons. The training error reached 10^{-5} order and after 3000 epochs it stabilized. Presenting to the ANN, values for it unknown correspondents to cases 1, 2, 3, 4 and 7 respectively to verify its capacity of estimation parameters, that is, to verify if the RNA had acquired generalization capacity. The results obtained are presented in Tables 4, 5 and 6.

Table 4. Comparison of the estimated and theoretical derivatives.

X_u (Kg/s)	case 1	case 2	case 3	case 4	case 7
Real	-108.9	-109.8	-126.1	-125.9	-127.5
Estimated	-1109	-111.1	-127.01	-177.3	-128.4

Table 5. Comparison of the estimated and theoretical derivatives.

Z_u (Kg/s)	case 1	case 2	case 3	case 4	case 7
Real	-970.4	-885.3	-1292.1	-1361.9	-1243.6
Estimated	-975.7	-886.4	-1161.4	-1264.5	-1064.5

Table 6. Comparison of the estimated and theoretical derivatives.

M_u $(Kg.m/s)$	case 1	case 2	case 3	case 4	case 7
Real	46.07	46.07	53.9	57.5	46.07
Estimated	45.7	43.7	52.6	63.1	55.2

Analogous to the fact with the results desired and the data obtained by ANN, the averages of correlation between the desired and the estimates derivatives had been calculated, getting themselves to X_u, Z_u e M_u derivatives respectively 0.68, 0.95 and 0.78 that they show that the derivatives X_u has great correlation and and strong are correlated.

2.5.2 Results of longitudinal aerodynamic derivatives $M_{\dot{w}}$ e M_q

Again the answers of the aircraft in points 5, 6, 8 and 9 of the flight envelope will be used for training and will be verified the answers for Cases 1, 2, 3, 4 and 7 respectively. As inputs for the ANN to get the derivatives and, the answers of variations of w and q also discrete in the time will be used, represented for vectors with 200 points and the static data, representing characteristic of the aircraft in each point of the used envelope during training. The first tested architecture presented 11-8-2 respectively neurons in the intermediate layers and of exit. Some tests had been carried through and analyzed and all they had presented resulted sufficiently satisfactory, adopting then this first model to esteem $M_{\dot{w}}$ e M_q. The performance error he also reached 10^{-5} order and stabilized after 3000 epochs. To verify the train results, they had been presented inputs corresponding to 1, 2, 3, 4 and 7 cases respectively, that they are unknown values by the ANN. As they show Tables 7 and 8 the generalization results had been sufficiently satisfactory

The average values of correlation coefficients and the respective values to $M_{\dot{w}}$ e M_q they had been 0.994 e 0.813 showing that for both $M_{\dot{w}}$ e M_q, estimated and desired values were strong correlated.

Table 7. Comparison of the estimated and theoretical derivatives.

$M_{\dot{w}}\ (Kg.m)$	case 1	case 2	case 3	case 4	case 7
Real	-31.6	-64.1	-55.5	-55.5	-88.1
Estimated	-31.7	-63.8	-50.6	-54.8	-90.3

Tabela 8. Comparison of the estimated and theoretical derivatives.

$M_q\ (Kg.m^2/s)$	case 1	case 2	case 3	case 4	case 7
Real	-16991	-37599	-23521	-23521	-40407
Estimated	-16998	-30600	-25549	-29728	-31621

2.5.3 Results of longitudinal aerodynamic derivatives X_w, Z_w e M_w

To esteem X_w, Z_w e M_w derivatives, in a first test, was implemented a ANN using as dynamic input variations of w and q and as static inputs same the used ones in other RNA' s previously presented. The results obtained had not been satisfactory. After that these inputs cited previously together with vector *u* had been supplied to all, as it showed the diagram of blocks in the Figure 5 (c), and the results had improved significantly.

Again a feedforward neural network without delays in the time was used. Will be presented the results of a topology with respectively 30-18-3 in the hidden layers and output layer. The tax of learning was 0.02. The error performance reached 10^{-4} order and stabilized after 2000 epochs. The corresponding results of generalization to Cases 1, 2, 3, 4 and 5 are shown in Tables, 9, 10 and 11 respectively.

Table 9. Comparison of the estimated and theoretical derivatives.

$X_w\ (Kg/s)$	case 1	case 2	case 3	case 4	case 7
Real	-49.9585	-300.4027	-315.8004	-250.7358	-31.0660
Estimated	-209.5821	-247.7830	-221.3919	-285.5244	-25.5142

Table 10. Resultados das derivadas estimadas e teóricas.

$Z_w\ (Kg/s)$	case 1	case 2	case 3	case 4	case 7
Real	-6966.8	-3181.8	-4426.3	-4419.1	-7106.7
Estimated	-5137.0	-2907.1	-4835.9	-4487.9	-7098.4

Table 11. Comparison of the estimated and theoretical derivatives.

$M_w\ (Kg.m/s)$	case 1	case 2	case 3	case 4	case 7
Real	-2356.2	-1065.4	-1541.1	-1535.4	-2636.7
Estimated	-2048.5	-1365.9	-1841.8	-1509.6	-2599.7

Again aiming at a quantitative analysis of the proximity it enters the stability derivatives desired and estimates, had been calculated the average factors of correlation getting itself 0.71, desired 0.86 and 0.94 that they had shown to the high correlation between the derivatives and estimates and.

3. CONCLUSIONS

This work presented a specific application of ANN for fast and efficient identification of the fixed wing aircraft answers inside. an flight envelope pay-established. Specifically, RNN with delays in the time had been assigned to identify the states of the aircraft. For the case study an attack aircraft model was simulated using data obtained in literature. The aircraft was simulated in 9 distinct points of an flight envelope with distinct Mach number and altitude. A recurrent neural network was trained in 4 of these points using dynamic input, that were the signal given in the elevator and static input that had been the data of Mach number and the aircraft altitude. To train the RNN only results of simulation using step input in the elevators had been used. After duly trained, the RNN identified with great precision the answers of q, w and u of the aircraft in the others 5 points of the flight envelope. Some tests had been presented using some inputs types in the elevators. The resolution of the inverse problem was also presented, that is, using the geometric data, corresponding answers of the aircraft and its data the 4 different points of the flight envelope to train a feedforward neural network, had been identified to the aerodynamic derivatives of this in the others 5 points of the envelope. The results obtained had been sufficiently satisfactory as it was shown. One concluded then that the neural models, since that duly trained they are capable to identify the behavior of an aircraft inside of an flight envelope, in any point of this. One also concluded that, using the answers identified together with aircraft geometric data, it is possible esteem the aircraft stability derivatives in any point of a flight envelope and in any situation of flight.

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