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# NEURO-FUZZY SYSTEMS APPLIED ON A FIXED-WING AIRCRAFT CONTROL

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***Abstract.*** *The loss of the aircraft's control during the flight is the main cause of death in aircraft accidents. Because of that, it becomes highly important the development of an efficient controller, that many times cannot be obtained through the classic techniques. In this study, the control of a fixed wing aircraft is done using Neuro-fuzzy systems with parameters obtained through Differential Evolution and Simulated Annealing. The MATLAB® software will be used to obtain the controller and to evaluate the system's performance and stability. The obtained results indicate that the controller is able to compensate occasional system's disturbance. Besides that, the Simulated Annealing presents a shorter runtime to find an optimal controller, in contrast, this method shows a greater results standard deviation, which suggests a greater randomness and imprecision than the Differential Evolution method.*

***Keywords:*** *Intelligent Control, Neuro-fuzzy systems, Differential Evolution, Stability*

## 1. INTRODUCTION

On countries that have a large territorial extension, such as Brazil, United States, China, among others, it is necessary a transportation structure that allow geographic population's mobility and convenience in the distribution of goods, overcoming the landform with no difficulties. It is observed that the Brazilian economic development in the last decades caused a considerable growth in the civilian aviation market and, consequently, the aircraft accidents. According to studies made by CENIPA (Cenipa, 2017) (Center of investigation and prevention of aircraft accidents), in the last 10 years (2008-2017) there were 1187 registered accidents, in an average of 119 per year. The largest percentage of crashes have as main cause the engine's failure during the flight and the loss of control on ground and on air. In this context, the reporting records show a considerable number of fatal victims and costly damages which could be reversed if the system was able to autonomously overcome a possible failure. Therefore, it is helpful that an aircraft's control is developed that has the goal to decrease the occurrence of air crashes, ensuring a better safety, efficiency and reliability for global air transportation.

Until now, the PID (Proportional Integral Derivative) controller is one of the most commonly used control design techniques in the world. However, these controllers may not work in a satisfactory way (Gianelli, 2013) when disposed by nonlinear procedures, which may have delays on the transport or variations in time. Hence, it is recommended to use other control techniques that can be able to adapt to the complex systems and provide an optimal response. For instance, in these cases, Artificial Intelligence can be used to estimate the controller gains for a designed control structure.

The main goal of Artificial Intelligence (AI) methods, being a branch of computer's science, is to build algorithms capable of simulating the intelligence through the input of data and explain the output. These mechanisms must, through the combination of large amounts of data with fast and interactive processing and intelligent algorithms, learn with information or patterns presented on the data and make a decision (Brasil Escola, 2019; SAS, 2019).

In this project, the AI is of major importance to design a proper controller that have as main feature the adaptability, and capacity of obtaining the parameters in an efficient and fast manner. Furthermore, the techniques used on the controller design can be summarized as below:

- **Neuro-fuzzy System**: hybridization system of the modelling techniques of Neural Networks and disturbance Fuzzy systems.
- **Differential Evolution**: robust method of functions minimizations, used to obtain the Neuro-fuzzy system's parameters.
- **Simulated Annealing**: optimization method derivated of the metals annealing analogy, also used to obtain the

Neuro-fuzzy system's parameters.

The present study has as main objective the development of a intelligent controller applied to a Cessna 172 airplane, which is based on Neuro-fuzzy systems and the parameters will be obtained using the methods: Differential Evolution and the Simulated Annealing, who will be compared in the following.

## 2. SYSTEM MODEL

According to (Valavanis, 2007), for any conventional aircraft configuration, its dynamical model can be derived using Newton-Euler formulation applied for 6 degree of freedom rigid body representing the aircraft translation and rotation on space. Hence, for the system modeling, it is commonly used two reference systems: the first, is a earth fixed reference system denoted by $I_{cs}$; the second, known as body coordinate system $B_{cs}$ is fixed on the body center of gravity translating and rotating with the aircraft. Then, the equations of motions are derived on the $B_{cs}$ once the external moments and forces are applied on the body. In summary, the concerned forces and moments are: the aerodynamic interaction of the body with the surrounding fluid, the propulsion system thrust and the gravitational forces.

Firstly, one can define the aircraft kinematic relations used to describe the aircraft position and attitude throughout its operation. Any vector on the $B_{cs}$ can be written on the $I_{cs}$ using the Euler angles, which represents the aircraft attitude the earth fixed reference frame defined by: pitch ($\theta$), roll ($\phi$) and yaw ($\psi$). From (Roskam, 1997), it is possible to obtain the kinematic relation from any vector on the $B_{cs}$.

From Fig. 1 it is possible to visualize the axes, velocity (U, V, W, P, Q, R), forces (X, Y, Z), moments (L, M, N) and Euler angles ($\Phi$, $\Theta$, $\Psi$) of the aircraft.

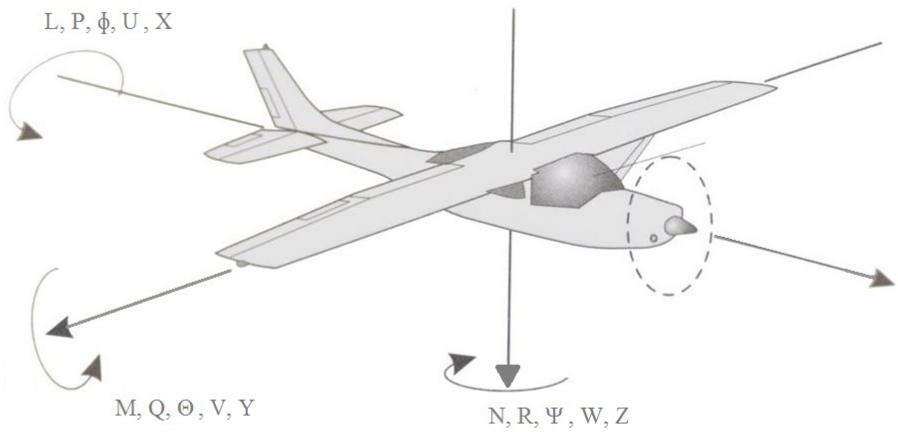


Figure 1. Definition of axes, velocity, forces, moments and Euler angles of the aircraft

### 2.1 SMALL PERTURBATION THEORY

The Small Perturbation Theory is a valuable tool used to linearize nonlinear equations based on Taylor series expansion (Roskam, 1997). According to it, any state or control variable ($\vec{\xi}$) can be written as a sum of a nominal or trimmed value ($\vec{\xi_0}$) and a perturbed variable ($\delta\vec{\xi}$). The first represents the system equilibrium condition while the second expresses the perturbation of the state variable around the linear boundary of the equilibrium point, from this, any state variable, external forces and moments can be denoted by:

$$\vec{\xi} = \vec{\xi_0} + \delta\vec{\xi} \tag{1}$$

The trimmed variables $\vec{\xi_0}$ are obtained from (Roskam, 1997) assuming that the system is operating on steady state, i.e. the system is dynamically on stable while all the forces and moments acting on the body are in equilibrium.

As previously stated, the linear model will be later used to train the system and to validate the designed controller.

## 3. NEURO-FUZZY SYSTEMS

The Adaptive neuro-fuzzy inference system (ANFIS) is a system consisting of a hybridization of Artificial Neural Network (ANN) and Fuzzy Inference System (FIS) modelling techniques. The ANFIS presents the FIS structure which consists of: the fuzzifier, the rule base, the fuzzy inference engine and the defuzzifier. However, they present the same ANN structure arrangement and learning ability.

The ANFIS has 5 layers. The layer 1 represents the system inputs. In layer 2 occurs the fuzzification of the system data input. The membership functions (MF) are built for each input data, in this project was defined the gaussian membership function. In layer 3 occurs the ANFIS rule base creation with a propositions collection "If.... Then ... " and the logical operators AND and OR are mathematically modeled as product and maximum, respectively. In layer 4 occurs the consequents' definition of each node, which is defined by $f_L = f(I_1, \ldots, I_i, \ldots, I_n, w_{1L}, \ldots, w_{jL}, \ldots, w_{oL}, k)$, where $w_1L, \ldots, w_{jL}, \ldots, w_{oL}$ are the weights determined in ANFIS training (Takagi e Sugeno, 1985; Chen, Lin e Lin, 2008; Pereira, 2017). In layer 5 occurs the defuzzification and the evaluation of the ANFIS output.

## 4. CONTROLLER STRUCTURE

It's possible to decouple the perturbed equations of motion on two independent state-space models: longitudinal and lateral-directional. Hence, for autonomous flight navigation, a control strategy built on two control loops is commonly used for aeronautical systems.

The longitudinal and lateral-directional controllers has a cascade structure. The longitudinal control is responsible for controlling the aircraft altitude using the Cessna 172 elevator deflection. The lateral-directional control accomplishes the adaptation of aircraft yaw angle using two actuators deflection from its structure: the aileron and the rudder.

Both of the controllers structures are observed in Fig 2 and Fig 3.

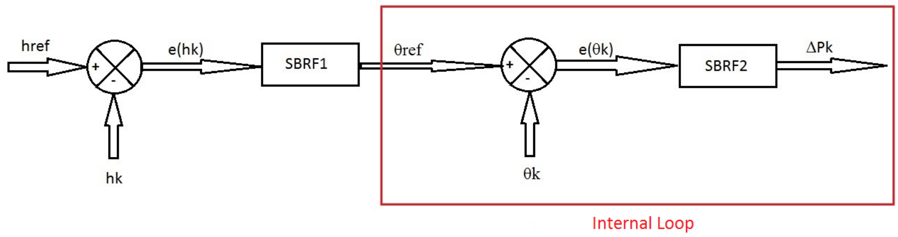


Figure 2. Longitudinal Control System

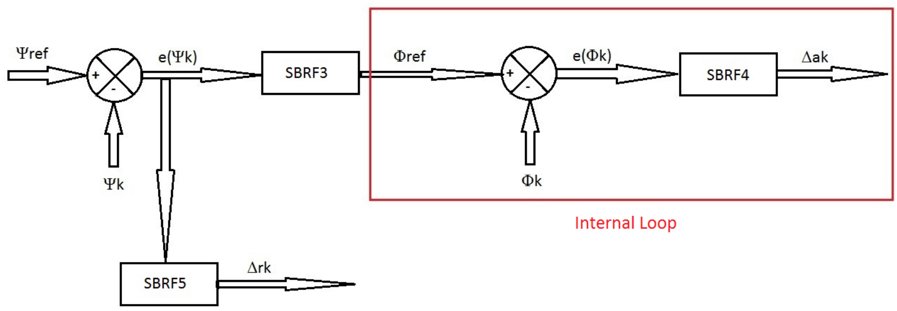


Figure 3. Lateral-directional Control System

Firstly, the internal loop parameters are found for both controllers, then the external loop parameters will be calculated.

## 5. RESULTS AND DISCUSSIONS

The pole value, $p$, of the longitudinal control internal loop is initially fixed on 0.1. During the entire simulation, the desired pitch angle set point ($\theta ref$) is defined as $0°$.

The Fig. 4 represents the controller action using Differential Evolution. Note that in the instant of $t = 0$ s, that the initial condition is $30°$. In accordance to the reference signal, it is possible to verify that the control action minimizes the error over the system. As expected from control theory, it is observed that the system accommodates around the set point value in time $t = 40$ s, since:

∘

$$T_a = 4T \quad (2\%), \qquad T = \frac{1}{p} \tag{2}$$

Where $T_a$ is the system settling time and $T$ is the time constant. For $t > 50$ s, the system has reached steady state.

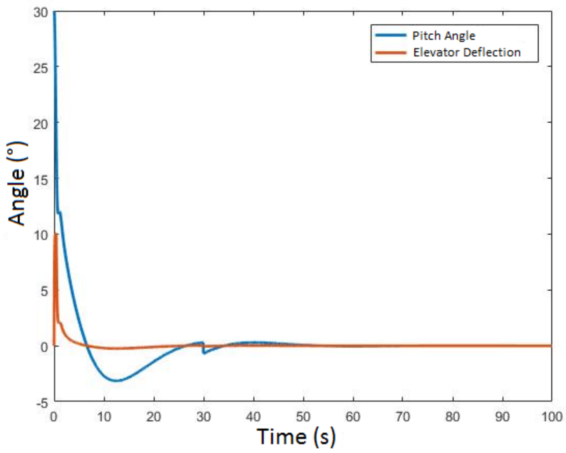


Figure 4. Pitch Angle and Elevator Deflection using Differential Evolution

From Fig. 5, using Simulated Annealing, it is known that the system control response is faster than the Differential Evolution response since the pitch angle responds more quickly to the elevator deflection action. The theory comprobation is verified since the system accomodates in the instant of $t = 40$ s and in the instant of $t = 50$ s , the system is effectively in the steady state.

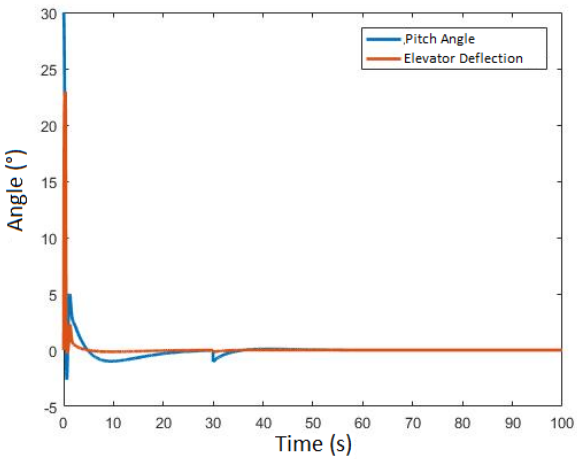


Figure 5. Pitch Angle and Elevator Deflection using Simulated Annealing

The altitude set point, $h_{ref}$, of the longitudinal control external loop is defined such as $h_{ref} = 50$ m for $t = [0, 75]$ s, and $h_{ref} = 0$ m for $t = [75, 150]$ s. From Fig. 6 (a), using Differential Evolution, one can conclude that when $t = [0, 25]$ s the height is in transient state, oscillating around the set point of 50 meters. When $t = [25, 50]$ s, the system reaches the steady state condition.

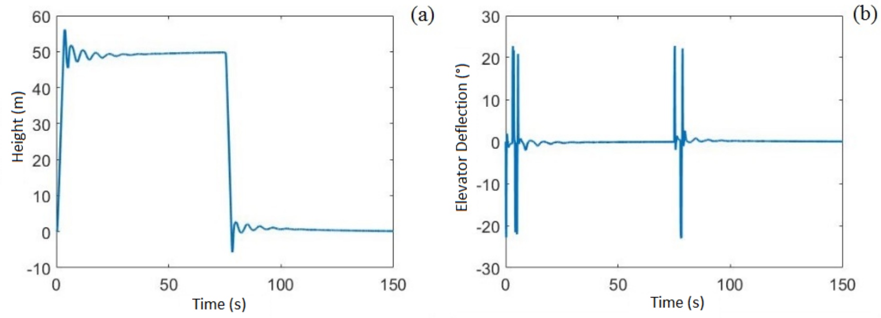


Figure 6. Height and Elevator Deflection using Differential Evolution

In Fig.6 (b) the controller has a high gain in the presence of major disturbances, decreasing its action magnitude until reaches the equilibrium condition, when it remains close to zero.

From Fig.7, using Simulated Annealing, it is observed that the height and elevator deflection curves have the same behavior than the curves presented in Fig.6 using Differential Evolution.

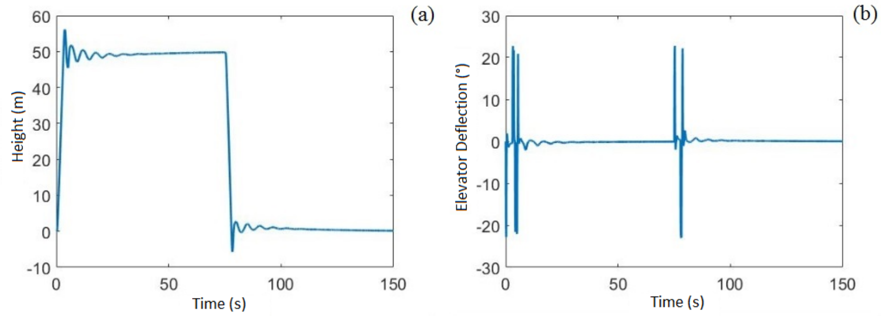


Figure 7. Height and Elevator Deflection using Simulated Annealing

For the lateral-directional control analysis, during the internal loop entire simulation, the roll angle set point, $\Phi_{ref}$, is defined as $0°$, with disturbances in two instants ($t = 0$ s and $t = 30$ s), Fig.8. From Differential Evolution Analysis,the pole value, $p$, is initially fixed on $0.1$. One can infer that in the interval of $t = [50, 100]$ s the system is operating on steady state.

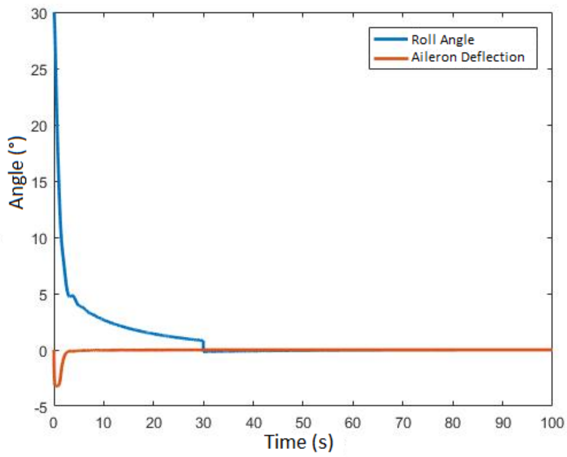


Figure 8. Roll Angle and Aileron Deflection using Differential Evolution

From Simulated Annealing analysis, the roll angle and aileron deflection curves presented in Fig.9 presented variations when compared to the curves presented in Fig.8. It is observed that the system accommodates around the instant of $t = 7$ s and the roll angle oscillates around the set point until it reaches the steady state in the interval of $t = [10, 100]$ s.

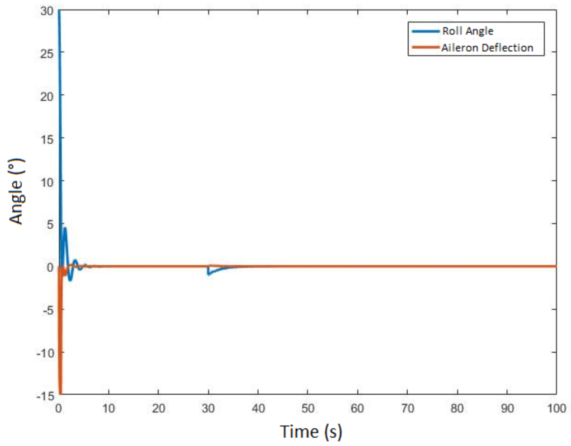


Figure 9. Roll Angle and Aileron Deflection using Simulated Annealing

In lateral-directional external loop, for $t = [0, 50]$ s, the yaw angle set point, $\Psi_{ref}$, is defined as $90°$ for $t = [0, 50]$, and $\Psi_{ref} = 0°$ for $t = [50, 100]$ s. From Fig. 10, using the Differential Evolution, it is observed that the aircraft yaw angle has a smooth curve with small oscillations around the desired set point. The system reaches the steady state around the set point close to the instant of $t = 30$ s. For $t = [50, 100]$ s, the yaw angle response has the same behaviour, reaching the steady state around $0°$.

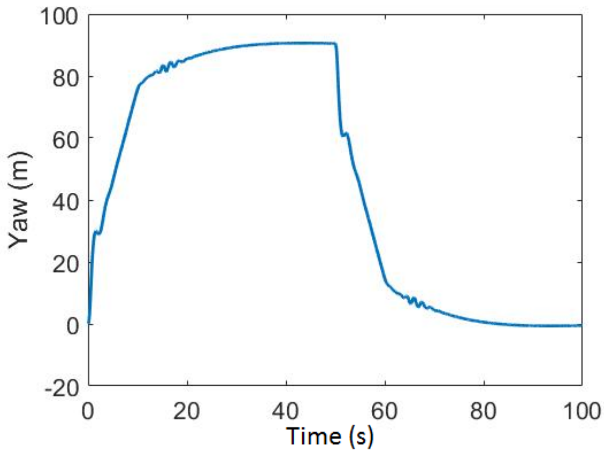


Figure 10. Yaw Angle using Differential Evolution

It is noted that the control actions provided by the aileron deflection and rudder deflection, observed in Fig.11, have high gain in the instants of set point change and are almost null close to the instant of the system steady state ($t = 30$ s and $t = 70$ s).

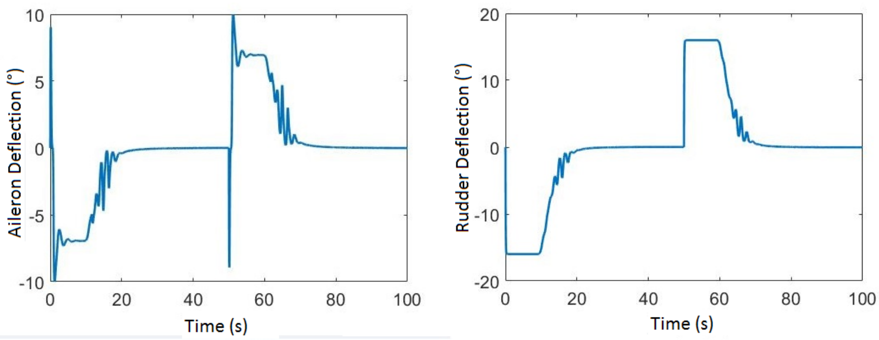


Figure 11. Aileron Deflection and Rudder Deflection using Differential Evolution

It is observed, comparing Fig.12 and Fig.10 that the yaw angle response using Simulated Annealing does not behave as expected, not reaching the accommodation in the instant of $t = 8$ s, according to the theory.

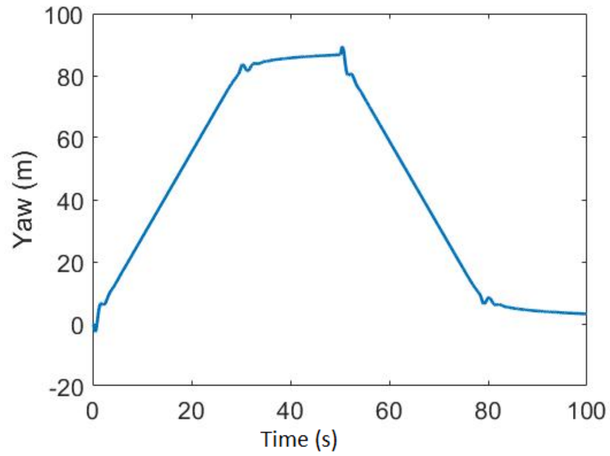


Figure 12. Yaw Angle using Simulated Annealing

From Fig.13, it is possible to observe that the control action due to the aileron deflection occurs more abruptly in certain moments and remains close to 0° during a longer time of the simulation. The rudder deflection is smoother than the aileron deflection.

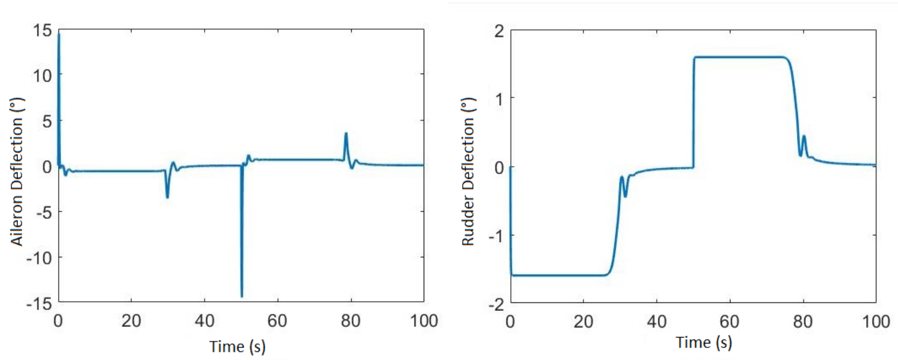


Figure 13. Aileron Deflection and Rudder Deflection using Simulated Annealing

From Fig. 14, one can notice that RMS error along the execution of Differential Evolution Algorithm decreases until iteration k = 8 is reached, continuing almost constant until k = 30. However, it is noted that RMS error values have a small scale due to the decay factor of desired pole. The same behaviour occurs analogously for all presented cases.

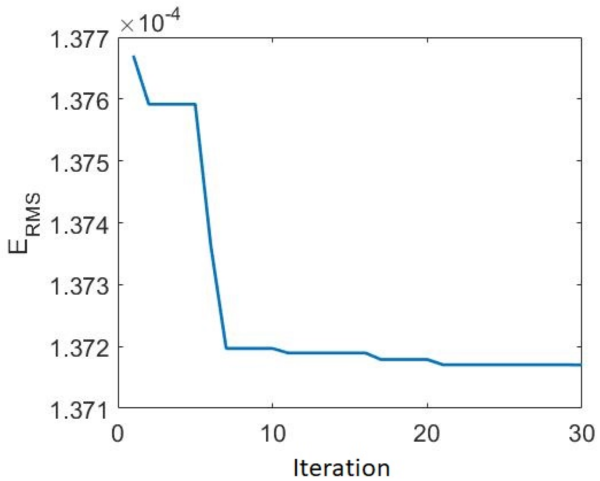


Figure 14. RMS Error using Differential Evolution

In comparison with Differential Evolution method, from Fig.15 using Simulated Annealing, it is observed a change in the RMS error behaviour, which has a curve that presents peaks due to the search for the global minimum and the permission for highest energy points in the iteration $k + 1$.

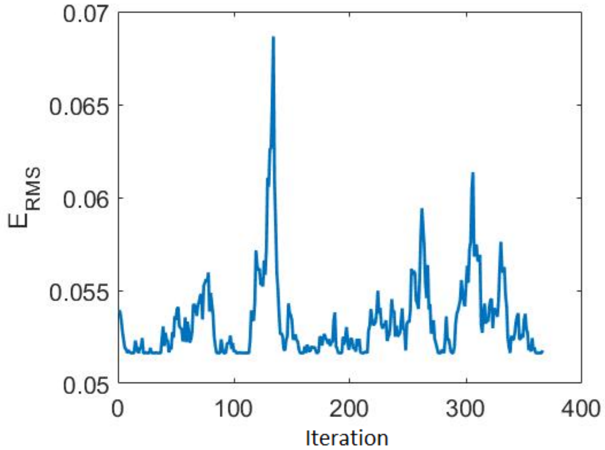


Figure 15. RMS Error using Simulated Annealing

## 6. CONCLUSION

This Paper presented the application of intelligent control techniques in analysis and Cessna 172's control in real scale. In order to accomplish this, the equations of motion for fixed wing aircraft were presented and linearized to enable the control parameters calculation. Later, a control architecture based on Neuro-Fuzzy systems was proposed with the ambition of making the aircraft autonomously reestablish a equilibrium condition when susceptible to a state perturbation for the model and control validation. Simulations involving the use of Differential Evolution and Simulated Annealing as function optimization methods were performed in order to obtain the proposed controller design parameters.

From the presented results, one can conclude that, for each system analysis performed and for each function optimization method, the controller operated effectively, producing on the input a response which converged to the defined set point, and was able to restore the equilibrium condition after suffering a disturbance.

The Differential Evolution is a method which is assertive in the controller calculation, producing smaller errors. However, has a longer runtime, compromising the controller efficiency when used in online applications. The Simulated Annealing presents a greater dispersion in RMS error, which can influence in the controller response for each simulation performed. In contrast, the method runtime is lower enabling its use in online applications.

## 7. ACKNOWLEDGEMENTS

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