FLIGHT DYNAMICS PARAMETER ESTIMATION OF A ROTARY WING AIRCRAFT USING THE OUTPUT ERROR MINIMIZATION WITH NATURAL AND META HEURISTIC METHODS

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Abstract. Flight simulators are employed by civil and military pilots, as well by engineers, in order to increase the security in training of crew, and to find out the behavior of the aircraft under different operational conditions. However, it is necessary to calibrate the simulator software to have good adherence to real flight. In this process, parameters of the mathematical model of the flight simulation need to be identified, such that the simulation is as close as possible to the real flight dynamic. With appropriated values of these parameters, the simulator will be ready for training or assessing the aircraft dynamics. This can be described as an inverse problem or parameter identification, formulated as an optimization problem. The simulator is designed to represent the dynamics of the helicopter AS355-F2, for testing two types of maneuverswere employed: a sinusoidal input and 3-2-1-1 pulse input. The aerodynamic derivatives estimation methodology is also known as quad-M scheme, since it involves four different processes: Measurement, Maneuver, Model, and Methods of error minimization. The tested helicopter was equipped with the Aydin Vector Data Acquisition System (AVDAS) PCU-816-I, ATD-800 digital recorder The system measures a total of thirty-five different parameters. The calibration of a dynamic flight simulator is achieved by two meta-heuristics: a Genetic Algorithm and a new approach named Multiple Particle Collision Algorithm (MPCA). Preliminary results show a good performance of the employed optimization methods.

INTRODUCTION

The Helicopter flight is quite expensive as compared with other similar fixed wing aircrafts. Helicopter Flight Simulators (HFS) can provide a suitable alternative to real flight experience to increase the flight security through training of the crew, prior evaluation of flight tasks and data acquisition procedures to validate and certificate onboard aircraft systems. However, the HFS must convey high degree of realism in order to be truly effective.

The area of parameter estimation and model identification have several applications in astronomy, aerospace, economics, biology, electrical, geological areas [1], [2], [3]. The strategy is to adjust the unknown model parameters in order to achieve the best fit between the predictions of the mathematical model and the experimentally observed system response. Tools and techniques of system identification have evolved to match the complexity of the models and the increasing need for correction and precision in the results. This methodology is more accurate than the corresponding values predicted by other methods such as analytical and numerical differentiation, [4], [5], [6].

The presence of noise such as state noise or measurement noise, [6], affect the identification methods, and this process becomes more difficult as the number of degrees of freedom (DOFs) and model parameters increase [7]. The identification of parameters methodology uses techniques such as the maximum likelihood method, equation error method, output error method, filter error method, and stochastic method [8], [9]. These methods require a mathematical model of the aircraft with a set of initial values for the parameters to begin the algorithm ([10], [11]). Concerning helicopter system identification techniques, very few articles have used stochastic method. One can cite [12], [13] in the longitudinal mode system identification of the Twin Squirrel helicopter and [14] in the identification of a small unmanned helicopter model. In this work, we used a well-known Quad-M methodology for parameters identification [15] as shown schematically in Figure 1.

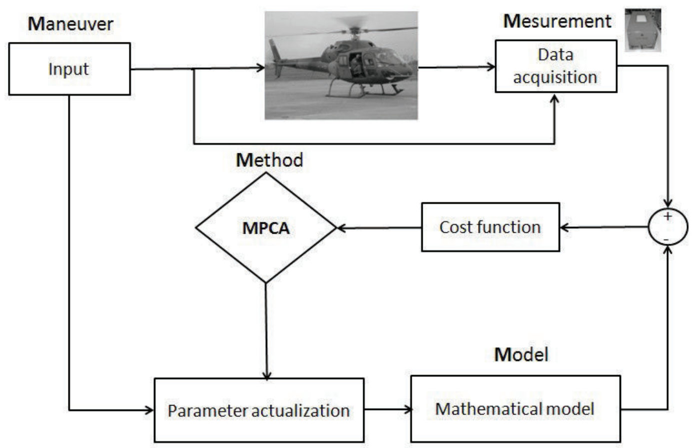

Figure 1: Adaptation Quad-M Method with MPCA.

This methodology takes into account the main elements of rotorcraft system identification, including the rotorcraft excitation maneuvers, the aerodynamic data measurements, the mathematical model of the helicopter equations of motion, and the parameter estimation methods used to minimize the predicted output-error between the proposed aerodynamic model and the real data. With respect to the optimization of the output error, the method used was MPCA. Each one of these four different processes will be discussed in the following sections.

2 THE QUAD-M METHODOLOGY

The Quad-M or M^4 methodology [15] takes into account the main elements of aircraft system identification, including the aircraft excitation **maneuvers**, the aerodynamic response **measurements**, the mathematical **model** of the aircraft equations of motion, and the parameter estimation **methods** used to minimize the output-error between the predicted model response and the real data observation. Each one of these functional elements is discussed below.

2.1 Maneuvers

The dynamic response of the helicopter in flight is excited by the application of different control inputs to the cyclic and collective flight commands including pulse signals, step, doublet, multistep, sinusoidal, and 3-2-1-1 pulse sequence, among others. Hence, a wide variety of manoeuvres can be specified to excite the specific modes of the aircraft.

The choice of a proper flight test maneuvers, by shaping the excitation signals, is very important to minimize the uncertainties in the parameter estimation procedures and to maximize the information in the flight test data content. The optimization of the excitation signal can be realized from a priori knowledge of the initial dynamic parameters of interest. However, since there are no priori studies available for AS355-F2 helicopter, the experimental manoeuvres were specified applying conventional flight test procedures and taking into account flight safety constraints. Since this work focuses the determination of the lateral-directional flight derivatives at forward and level flight, special sequences of sharp-edge pulses known as the 3-2-1-1 using the lateral cyclic and pedal inputs were used to excite the dutch-roll mode with 80 kts indicated airspeed at 5,000 ft of altitude pressure.

The identification procedure used the 3-2-1-1 sequence with both lateral cyclic and pedal inputs, while the validation procedure utilized two different sequences, one with lateral cyclic inputs and pedal fixed and the other with pedal input and fixed cyclic control, [12].

2.2 Measurements

The helicopter flight test data was recorded with the Aydin Vector Data Acquisition System (AVDAS) PCU-816-I and the ATD-800 digital recorder, this system measures a total of thirty-five different flight parameters. Some of the measured data channels include fuel quantity in each tank, nose boom static and dynamic pressures, external stagnation temperature, aerodynamic angle of attack (α) and sideslip (β), roll, pitch, and yaw angular rates (p, q, r), load factors, longitudinal (θ) and lateral (φ) aircraft body attitudes, nose heading, and the flight command deflections, comprised of collective, longitudinal and lateral cyclic, and pedal command deflections (δ_c, δ_b, δ_a and δ_p).

The earth axis speeds (u, v, w) were obtained with the aid of a Z12 Differential Global Positioning System DGPS from Astech, whose antenna is fixed in the top of the helicopter vertical fin. The DGPS and AVDAS data synchronization was done inserting a simultaneous event in both systems. The DGPS data is represented with the same AVDAS data sampling rate by means of linear interpolation procedure.

The wind direction and intensity were obtained comparing the body axis speeds with the aerodynamic speed from the flight-test air data system, mounted on a nose boom, at trim conditions. Consequently, the body axis speeds (u, v, w) are easily calculated adding wind vector to the Earth axis speeds [13].

2.3 The Helicopter Model

The helicopter equations of motion are derived from Newton second law for the rigid body translational and rotational degrees of freedom, and are given by [16],[17], and [18] as:

$$X = m(\dot{u} - rv + qw) + mg\sin\theta \quad (1)$$

$$Y = m(\dot{v} - pw + ru) - mg\cos\theta\sin\phi \quad (2)$$

$$Z = m(\dot{w} - qu + pv) - mg\cos\theta\cos\phi \quad (3)$$

$$L = I_{xx}\dot{p} - I_{zx}(\dot{r} + pq) - (I_{yy} - I_{zz})qr \quad (4)$$

$$M = I_{yy}\dot{q} - I_{zx}(r^2 - p^2) - (I_{zz} - I_{xx})rp \quad (5)$$

$$N = I_{zz}\dot{r} - I_{zx}(\dot{p} - qr) - (I_{xx} - I_{yy})pq \quad (6)$$

where X, Y and Z represents the external force components (longitudinal, lateral and vertical); L, M and N are respectively, the roll, pitch and yaw moments; and I(index) stands for the moments and products of inertia of the aircraft rotating body. The kinematic relation for the pitch rate and roll rate about Y and X-axis are written as:

$$d\theta/dt = q\cos\varphi - r\sin\varphi \quad (7)$$

$$d\varphi/dt = p + q\sin\varphi\tan\theta + r\cos\varphi\tan\theta \quad (8)$$

The helicopter equations of motion are nonlinear, but a meaningful analysis can be employed by converting them into linear differential equations, by considering only small perturbations about a trimmed equilibrium point (represented by subscript 0) in the rotorcraft flight envelope. In matrix notation, a linearized dynamical model is given by [16], and [18],

$$\begin{bmatrix} \Delta\dot{u} \\ \Delta\dot{w} \\ \Delta\dot{q} \\ \Delta\dot{\theta} \\ \Delta\dot{v} \\ \Delta\dot{p} \\ \Delta\dot{\phi} \\ \Delta\dot{r} \end{bmatrix} = \begin{bmatrix} \frac{X_u}{m} & \frac{X_w}{m} & \frac{X_q}{m} - w_0 & -g\cos\theta_0 & \frac{X_v}{m} & \frac{X_p}{m} & 0 & \frac{X_r}{m} + v_0 \\ \frac{Z_u}{m} & \frac{Z_w}{m} & \frac{Z_q}{m} + u_0 & -g\cos\phi_0\sin\theta_0 & \frac{Z_v}{m} & \frac{Z_p}{m} - v_0 & -g\sin\phi_0\cos\theta_0 & \frac{Z_r}{m} \\ \frac{M_u}{I_{yy}} & \frac{M_w}{I_{yy}} & \frac{M_q}{I_{yy}} & 0 & \frac{M_v}{I_{yy}} & \frac{M_p}{I_{yy}} & 0 & \frac{M_r}{I_{yy}} \\ 0 & 0 & \cos\phi_0 & 0 & 0 & 0 & 0 & -\sin\phi_0 \\ \frac{Y_u}{m} & \frac{Y_w}{m} & \frac{Y_q}{m} & -g\sin\phi_0\sin\theta_0 & \frac{Y_v}{m} & \frac{Y_p}{m} + w_0 & g\cos\phi_0\cos\theta_0 & \frac{Y_r}{m} - u_0 \\ L'_u & L'_w & L'_q & 0 & L'_v & L'_p & 0 & L'_r \\ 0 & 0 & \sin\phi_0\tan\theta_0 & 0 & 0 & 1 & 0 & \cos\phi_0\tan\theta_0 \\ N'_u & N'_w & N'_q & 0 & N'_v & N'_p & 0 & N'_r \end{bmatrix} \begin{bmatrix} \Delta u \\ \Delta w \\ \Delta q \\ \Delta\theta \\ \Delta v \\ \Delta p \\ \Delta\phi \\ \Delta r \end{bmatrix}$$

$$+ \begin{bmatrix} \frac{X_{\delta_B}}{m} & \frac{X_{\delta_C}}{m} & \frac{X_{\delta_A}}{m} & \frac{X_{\delta_P}}{m} \\ \frac{Z_{\delta_B}}{m} & \frac{Z_{\delta_C}}{m} & \frac{Z_{\delta_A}}{m} & \frac{Z_{\delta_P}}{m} \\ \frac{M_{\delta_B}}{I_{yy}} & \frac{M_{\delta_C}}{I_{yy}} & M_{\delta_A} I_{yy} & \frac{M_{\delta_P}}{I_{yy}} \\ 0 & 0 & 0 & 0 \\ \frac{Y_{\delta_B}}{m} & \frac{Y_{\delta_C}}{m} & \frac{Y_{\delta_A}}{m} & \frac{Y_{\delta_P}}{m} \\ L'_{\delta_B} & L'_{\delta_C} & L'_{\delta_A} & L'_{\delta_P} \\ 0 & 0 & 0 & 0 \\ N'_{\delta_B} & N'_{\delta_C} & N'_{\delta_A} & N'_{\delta_P} \end{bmatrix} \begin{bmatrix} \delta_b \\ \delta_c \\ \delta_a \\ \delta_p \end{bmatrix} \tag{9}$$

therefore, Equation 9 may also be written as:

$$\frac{d}{dt}\begin{bmatrix} X_l \\ X_d \end{bmatrix} = \begin{bmatrix} A_l & C_1 \\ C_2 & A_d \end{bmatrix}\begin{bmatrix} X_l \\ X_d \end{bmatrix} + \begin{bmatrix} B_l & D_1 \\ D_2 & B_d \end{bmatrix}\begin{bmatrix} \Delta\delta_l(t-\tau) \\ \Delta\delta_d(t-\tau) \end{bmatrix} + \dot{x}_{bias} \tag{10}$$

here X_l and X_d represent the state space vector for the longitudinal and lateral movements, respectively.

In this work, it is considered the parameter estimation of the lateral dynamic motion, whose simplifies model is expressed by:

$$\frac{dX_d}{dt} = A_d X_d + B_d \Delta\delta_d(t-\tau) + \dot{x}_{bias} \tag{11}$$

$$X_d = [\Delta v \quad \Delta p \quad \Delta\phi \quad \Delta r]^T \tag{12}$$

$$\Delta\delta_d = [\Delta\delta_a \quad \Delta\delta_p]^T \tag{13}$$

The parameter values of interest for system identification are the elements of matrix A_d (stability derivatives), matrix B_d (control derivatives), and the delays associated with the aircraft response (τ). Furthermore, the parameters include the estimation of an unknown bias vector, x_{bias}. This vector is introduced in the mathematical model to represent measurement errors and noise produced by transducers and signal condition instrumentation [4].

The model parameter vector (Ω) is estimated by a minimization process of the cost function, $J(\Omega)$, related to the output error between the measured and predicted system response,

$$J(\Omega) = \sum_{i=1}^{n} \| X_i^{obs} - X_i^{mod}(\Omega) \|_2^2 \tag{14}$$

$$\Omega = \left(\frac{Y_v}{m}, \frac{Y_p}{m}, \frac{Y_r}{m}, L'_v, L'_p, L'_r, N'_v, N'_p, N'_r, \frac{Y_{\delta_a}}{m}, \frac{Y_{\delta_p}}{m}, L'_{\delta_a}, L'_{\delta_p}, N'_{\delta_a}, N'_{\delta_p}, \right.$$
$$\left. \Delta\dot{v}_{bias}, \Delta\dot{p}_{bias}, \Delta\dot{\phi}_{bias}, \Delta\dot{r}_{bias}, \Delta v_{ref}, \Delta p_{ref}, \Delta\phi_{ref}, \Delta r_{ref}, \tau_a, \tau_p \right) \tag{15}$$

where n is the number of observed measurements.

2.4 The MPCA Optimization Method

The cost function to be minimized is the output error between the model prediction response and the actual measured response. This objective function depends on the parameters of the proposed dynamic model, such as the helicopter aerodynamic stability and control derivatives, sensor bias, and sensitivities. Therefore, the determination of a parameter vector Ω that minimizes the cost function given by Equation 14 can be seen as an optimization problem and will be solved by a new meta-heuristics, named the Multiple Particle Collision Algorithm (MPCA).

The MPCA optimization algorithm was inspired on typical physical phenomena related to neutron particle transport inside a nuclear reactor core, where during the neutron travel multiple particles absorption and scattering are observed. The results obtained with MPCA in this study are compared to the ones obtained by Cruz ([13]) where a Genetic Algorithm (GA) was used to find the helicopter aerodynamic and control derivatives.

The MPCA is a meta-heuristic optimization method based on the canonical PCA [19]. This version uses multiple particles in a collaborative way, organizing a population of candidate solutions. The PCA was inspired by the traveling process (with absorption and scattering) of a particle (neutron) in the core of a nuclear reactor. The use of the PCA was effective for several test functions and real optimization applications [20].

The PCA starts with a selection of an initial solution (Old-Config), and is modified by a stochastic perturbation (Perturbation{.}), leading to the construction of a new solution (New-Config). The new solution is compared (function Fitness{.}), and the new solution can or cannot be accepted. If the new solution is not accepted, the scheme of scattering (Scaterring{.}) is used. The exploration around closer positions is guaranteed by using the functions Perturbation{.} and Small-Perturbation{.}. If the new solution is better than the previous one, this new solution is absorbed. If a worse solution is found, the particle can be sent to a different location of the search space, such that it enables the algorithm to escape from a local minimum [21].

The implementation of the MPCA algorithm is similar to PCA, but it uses a set with N particles, where a mechanism to share the particle information is necessary. A blackboard strategy is adopted, where the best-fitness information is shared among all particles in the process. This process was implemented in Message Passing Interface (MPI), looking for application into a distributed memory machine [21]. The pseudo-code for the MPCA is presented by Table 1.

Table 1: MPCA: pseudo-code for the optimization algorithm.

```
Generate an initial solution: Old-Config
Best-Fitness = Fitness{Old-Config}
Update Blackboard
For n = 0 to # of particles
    For n = 0 to # iterations
    Update Blackboard
    Perturbation{.}
        If Fitness{New-Config} > Fitness{Old-Config}
            If Fitness{New-Config} > Best-Fitness
                Best-Fitness = Fitness{New-Config}
            End If
            Old-Config = New-Config
            Exploration{.}
        Else
            Scattering{.}
        End If
    End For
End For
```

3. RESULTS

The computational results obtained with MPCA and GA are show in Figures 2, 3 and 4. The GA and the MPCA have been implemented in the Matlab/Simulink environment. Computer tests were conducted under Linux operating system, in an Intel Core I5 2.27 GHz. The sinusoidal maneuver is represented by δ and the results presented take into consideration the average of 4 experiments with seeds generate with different random numbers and experimental data generating artificially. The parameters used are: 2 particles; 10 iterations (exploration). The stopping criterion used was the total number of iterations (30) and the initial estimative were the derivatives of stability and control of BO105 improved by the GA

Figure 2 shows the lateral velocity as function of time. The red curve corresponds to the real data obtained during the test, the dotted blue is the result of the identification produced by the GA, and the results achieved by the MPCA are represented by the dotted curve in magenta. The results show that a small discrepancy between the measured data and the data obtained by both algorithms.

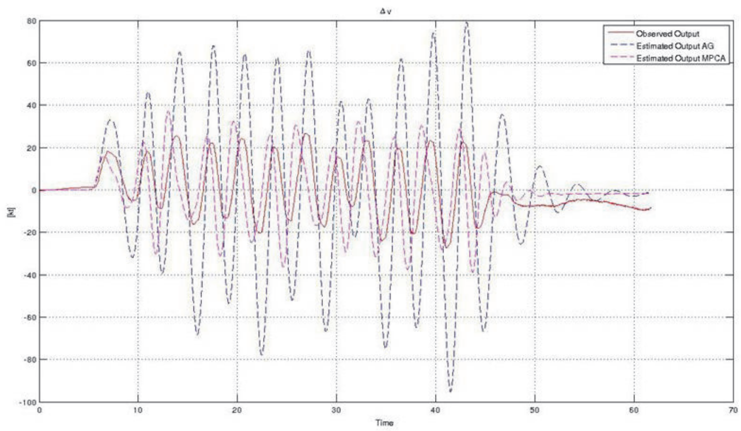

Figure 2: Linear velocity variation along the Y-axis.

A similar behavior is observed for the roll rate and the bank angle attitude of the aircraft as shown by Figures 3 and 4.

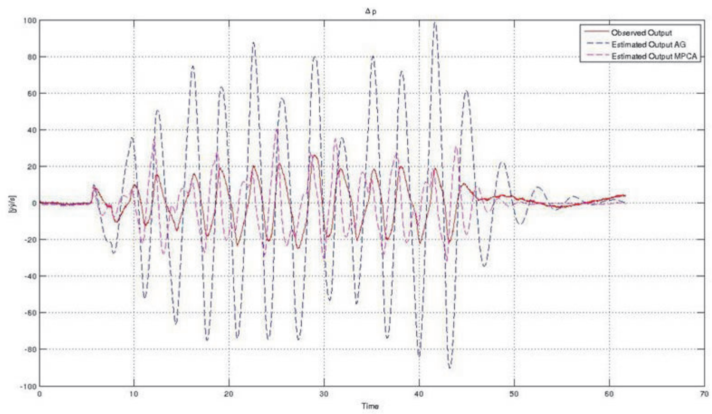

Figure 3: Angular velocity (roll rate) variation along the X-axis.

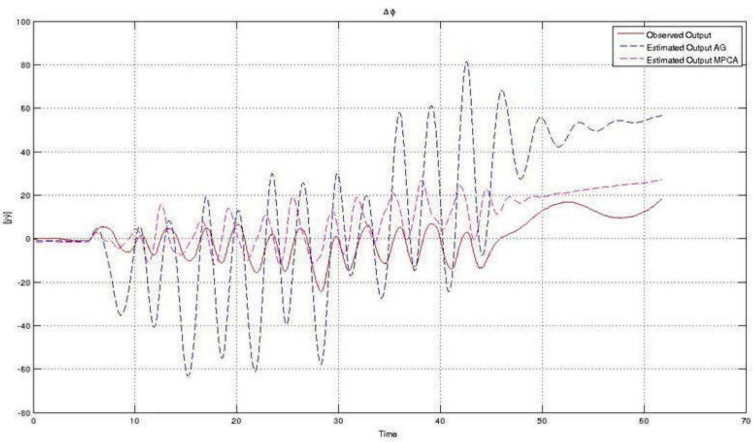

Figure 4. Bank angle as function of time.

3 CONCLUSIONS

In this work, we compared two stochastic algorithms, GA and MPCA, for helicopter parameter identification. The techniques were applied only in the estimation of the aerodynamic parameters of the lateral motion. The problem is formulated as an optimization process. Different heuristic search algorithms (GA and MPCA) were employed to address the solution of the optimization problem. The results indicate that GA and MPCA present a good agreement, but the results are better with the MPCA implementation. Further work is suggested to apply MPCA in lateral-directional dynamic mode and in a more complex model which includes both longitudinal and lateral-directional dynamic modes of the helicopter.

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