Computer Assisted Methods in Engineering and Science, **21**: 257–265, 2014.

MPCA for flight dynamics parameters determination

Ivana Y. Sumida[1,2], Haroldo F. de Campos Velho[1],
Eduardo F.P. Luz[1], Ronaldo V. Cruz[3], Luiz Carlos S. Góes[3]

[1] *National Institute of Space Research*
São José dos Campos, Brazil
e-mail: ivanayoshie@yahoo.com.br, haroldo@lac.inpe.br, eduardofpl@gmail.com
[2] *Flight Test Research Institute*
São José dos Campos, Brazil
[3] *Technological Institute of Aeronautics*
São José dos Campos, Brazil
e-mail: ronaldocruz@hotmail.com, goes@ita.br

Aircraft have become increasingly costly and complex. Military and civil pilots and engineers have used flight simulators in order to increase safety of flight through the training of crew. It is necessary to calibrate the simulation for simulators to have good adherence to reality, that is, to identify the parameters that make the simulation as close as possible to the actual dynamics. After determining these parameters, the simulator will be ready to be used in human resources training or assessing the aircraft. Parameter identification characterizes the aerodynamic performance of the aircraft and can be formulated as a problem optimization. The calibration of a dynamic flight simulator is achieved by a new meta-heuristic called multiple particle collision algorithm (MPCA). Preliminary results show a good performance of the employed approach.

Keywords: flight dynamic, parameter identification, multiple particle collision algorithm (MPCA).

1. Introduction

Looking at the adaptation of automatic control systems and flight simulators we see that flight dynamics are critical for aircraft design. Identification techniques applied to flight dynamics has had an improvement due to the increasing availability of faster computers.

The identification of parameters methodology has various applications areas (e.g., astronomy, aerospace, economics, biology, electrical, geological, etc.) [1–3]. This is the strategy to adjust the unknown parameters in order to have the best fit of a mathematical model of the phenomenon to the observations. Tools and techniques of identification have evolved to match the complexity and the increasing need for correction and precision in the results. The proposed methodology is more accurate than the corresponding values predicted by other methods such as analytical and numerical differentiations [4, 7]. Thus, identification of parameters has become a significant tool for applications such as model validation, handling qualities evaluation, control law design, and flight vehicle design and certification [6].

Specifically for helicopter parameter estimation, Hamel and Kaletka [8] presented an overview of the progress in this field up to 1997 and Padfield [5] described a comprehensive theoretical model of flight dynamics, flight qualities criteria development, flight test techniques, and several results of this research conducted in the United Kingdom.

It is important to notice that most works use local optimization algorithms based on gradient search methods such as Gauss-Newton and Levenberg-Marquadt methods for finding a local minimum of the prediction error function at the system output. Concerning the use of global optimization algorithms and, more specifically, stochastic algorithms (e.g., genetic algorithm (GA)) have been used by Hajela and Lee [9] in rotor blade design, by Wells et al. [10] in the acoustic level reduction rotor design, and by Zaal et al. [11] in the estimation of parameters of multichannel pilot models, among others.

Regarding helicopter system identification techniques, very few articles have used GA for global optimization of a cost function based on the prediction error. In this framework, one can cite Cruz et al. [14, 15] in the longitudinal mode system identification of the Twin Squirrel helicopter and Cerro [17] in the identification of a small unmanned helicopter model.

Thus, parameter identification associated with the aerodynamic performance of the aircraft can be formulated as an optimization problem. In this paper, a new meta-heuristic, named multiple particle collision algorithm (MPCA) [12], was applied to the calibration of a dynamic flight simulator [13]. The MPCA optimization algorithm was inspired by some typical phenomena inside nuclear reactors during the neutron travel, that is, absorption and scattering of multiple particles. The results obtained with MPCA are compared to the ones obtained by Cruz [13], where a GA was used to find the parameters.

2. Parameter identification methodology

The methodology for the identification of parameters used in this work is the well-known Quad-M, proposed by Jategaonkar [19]. 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 model and the real data, as shown in Fig. 1. Here it is important to notice that the method used was MPCA. Each of these elements will be discussed below.

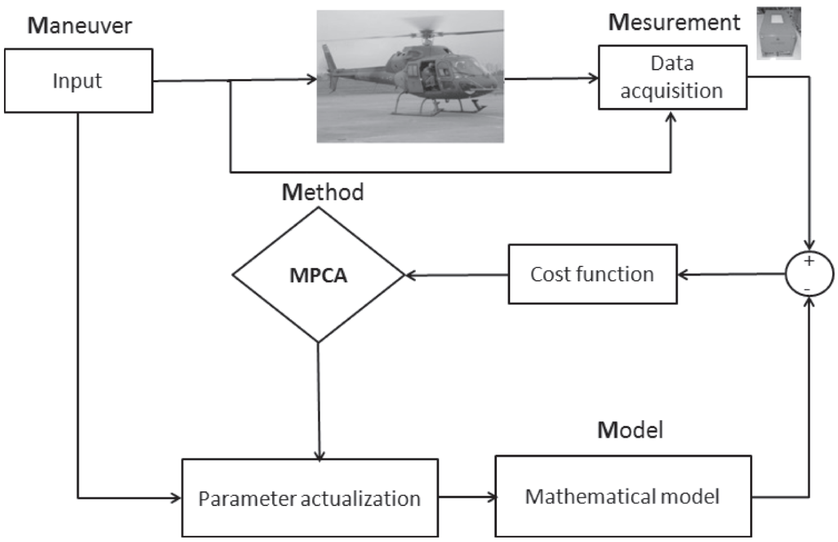

Fig. 1. Methodology for Quad-M adaptation.

2.1. Maneuver

The dynamic response and results from the application of inputs such as pulse, step, doublet, multistep, sinusoidal, 3-2-1-1, among others are obtained. Thus, a wide variety of maneuvers can be specified. We considered the following basic principle in identification systems: the data records of the flight test must contain the information of the dynamic characteristics to be obtained in the model [13]. In this work, only the sinusoidal frequency input will be used.

2.2. Measurements

The tested helicopter was equipped with the Aydin Vector data acquisition system (AVDAS) PCU-816-I, ATD-800 digital recorder, this system consists in a total of thirty-five different 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 rates (p, q and r, respectively), load factors, longitudinal (θ) and lateral (ϕ) body attitudes, heading, collective, longitudinal and lateral cyclic as well as pedal command deflections (δ_c, δ_b, δ_a and δ_p, respectively).

The Earth's axis speeds (u, v, w) are obtained with the aid of a Z12 differential global positioning system (DGPS), an Ashtech whose antenna is fixed on the top of the vertical fin. The DGPS and AVDAS data synchronization is made by inserting a simultaneous event in to 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 are obtained by 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's axis speeds [16].

2.3. Linearized model of flight dynamics

The helicopter equations of motion, deduced from the Newton second law for translational and rotational movements are given in [20] and [21] as:

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

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

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

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

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

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

where X, Y and Z represent the external force components (longitudinal, lateral and vertical), L, M and N are respectively, the roll, pitch and yaw moments, and $I_{()}$ corresponds to the moments and product of inertia of a rotating body. The kinematic relation for the pitch rate and the roll rate about Y- and X-axis are written as

$$\dot{\theta} = q\cos\phi - r\sin\phi, \tag{7}$$

$$\dot{\phi} = p + q\sin\phi\tan\theta + r\cos\phi\tan\theta. \tag{8}$$

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 on a trimmed equilibrium point (represented by subscript 0) in the rotorcraft flight envelope. In matrix notation, a linearized dynamical model is given in [13]:

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

$$\cdot \begin{bmatrix} \Delta u \\ \Delta w \\ \Delta q \\ \Delta\theta \\ \Delta v \\ \Delta p \\ \Delta\phi \\ \Delta r \end{bmatrix} + \begin{bmatrix} \frac{X_{\delta_B}}{m} & \frac{X_{\delta_C}}{m} & \frac{X_{\delta_A}}{m} & \frac{X_{\delta_P}}{m} \\ \frac{Z_{\delta_B}}{m} & \frac{Z_{\delta_C}}{m} & \frac{Z_{\delta_A}}{m} & \frac{Z_{\delta_P}}{m} \\ \frac{M_{\delta_B}}{I_{yy}} & \frac{M_{\delta_C}}{I_{yy}} & \frac{M_{\delta_A}}{I_{yy}} & \frac{M_{\delta_P}}{I_{yy}} \\ 0 & 0 & 0 & 0 \\ \frac{Y_{\delta_B}}{m} & \frac{Y_{\delta_C}}{m} & \frac{Y_{\delta_A}}{m} & \frac{Y_{\delta_P}}{m} \\ L'_{\delta_B} & L'_{\delta_C} & L'_{\delta_A} & L'_{\delta_P} \\ 0 & 0 & 0 & 0 \\ N'_{\delta_B} & N'_{\delta_C} & N'_{\delta_A} & N'_{\delta_P} \end{bmatrix} \begin{bmatrix} \delta_b \\ \delta_c \\ \delta_a \\ \delta_p \end{bmatrix}. \tag{9}$$

Therefore, Eq. (9) may also be written as

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

where X_l and X_d represent respectively the longitudinal and lateral movements. Therefore, the longitudinal movement is expressed by

$$\frac{dX_l}{dt} = A_l X_l + B_l \Delta\delta_l(t-\tau) + \dot{x}_{bias}, \tag{11}$$

$$X_l = [\Delta u \quad \Delta w \quad \Delta q \quad \Delta\theta]^T, \tag{12}$$

$$\Delta\delta_l = [\Delta\delta_b \quad \Delta\delta_c]^T. \tag{13}$$

The elements of matrix A (stability derivatives), matrix B (control derivatives), and τ the delays associated with the aircraft response are the values of interest for system identification. Furthermore, the addition of a tendency vector x_{bias} is constant and unknown. This vector is introduced in the mathematical model to represent measurement errors and noise produced by transducers and instrumentation [18]. Let $J(\Omega)$ be the cost function, given by

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

$$\Omega = \left(\frac{X_u}{m}, \frac{X_w}{m}, \frac{X_q}{m}, \frac{Z_u}{m}, \frac{Z_w}{m}, \frac{Z_q}{m}, \frac{M_u}{I_{yy}}, \frac{M_w}{I_{yy}}, \frac{M_q}{I_{yy}}, \frac{X_{\delta_B}}{m}, \frac{X_{\delta_C}}{m}, \frac{Z_{\delta_B}}{m}, \frac{Z_{\delta_C}}{m}, \frac{M_{\delta_B}}{I_{yy}}, \frac{M_{\delta_C}}{I_{yy}}, \right.$$
$$\left. \Delta\dot{u}_{bias}, \Delta\dot{w}_{bias}, \Delta\dot{q}_{bias}, \Delta\dot{\theta}_{bias}, \Delta u_{ref}, \Delta w_{ref}, \Delta q_{ref}, \Delta\theta_{ref}, \tau_c, \tau_b \right), \quad (15)$$

where n is the number of measurements.

2.4. Method of multiple particle collision algorithm

The cost function to be minimized is a function of the parameters of the 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 Eq. (14) can be seen as an optimization problem and will be solved by a new meta-heuristic named the MPCA.

MPCA is a meta-heuristic based on the canonical PCA [22]. 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 a nuclear reactor. The use of PCA was effective for several test functions and real applications [23].

The PCA starts with a selection of an initial solution (Old-Config), it is modified by a stochastic perturbation (*Perturbation*{.}), leading to the construction of a new solution (New-Config). The new solution is compared with previous solution (function *Fitness*{.}), and a decision is made on whether it can or cannot be accepted. If the new solution is not accepted, the scheme of scattering (*Scattering*{.}) 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 [12].

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 [12]. The pseudo-code for the MPCA is presented in Table 1.

Table 1. MPCA: psedo-code for the 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 shown in Figs. 2–5. The GA used Matlab Toolbox, and the MPCA was also implemented in Matlab R2011b. Computer tests were conducted on Linux operating system with an Intel Core I5 2.27 GHz processor. The sinusoidal

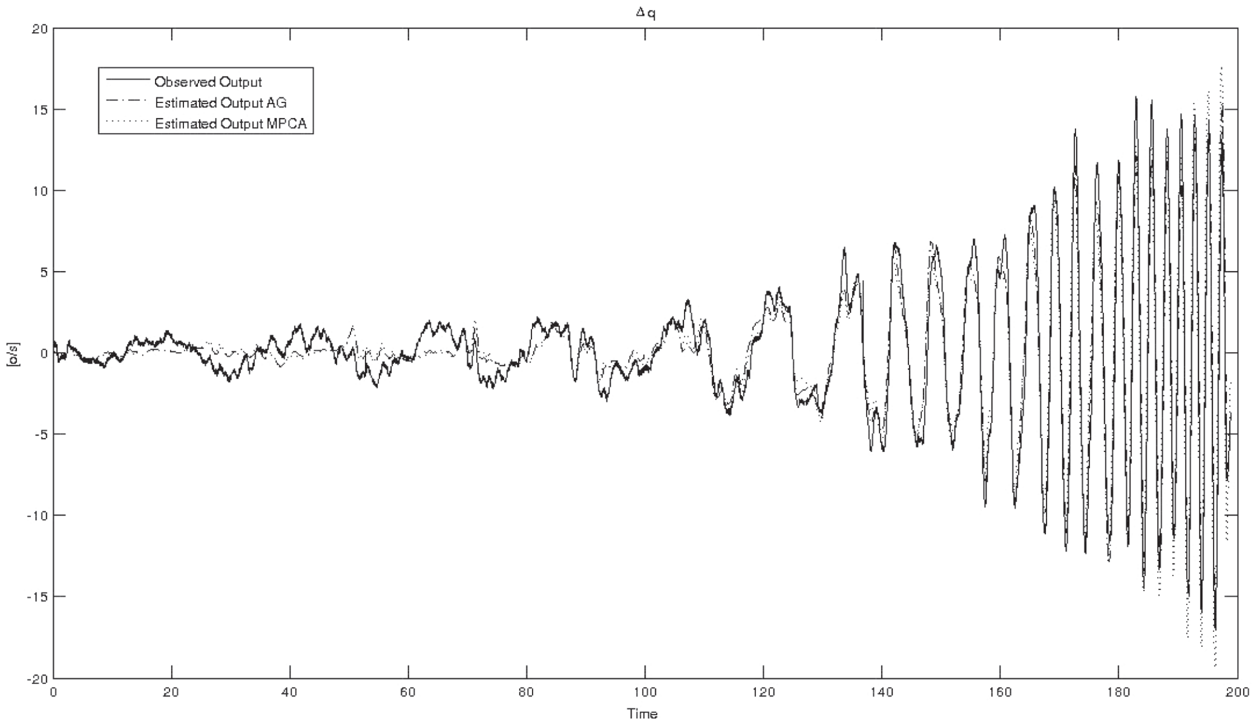

Fig. 2. Pitch rate.

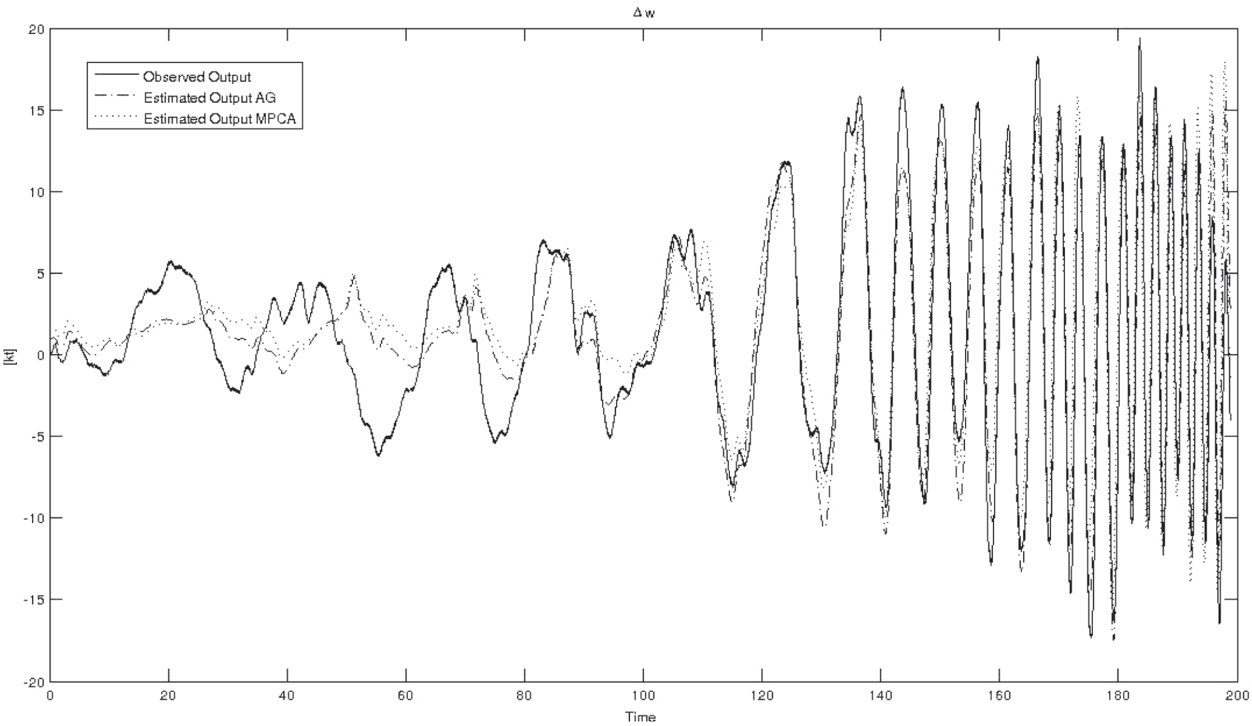

Fig. 3. Vertical velocity in helicopter body axis.

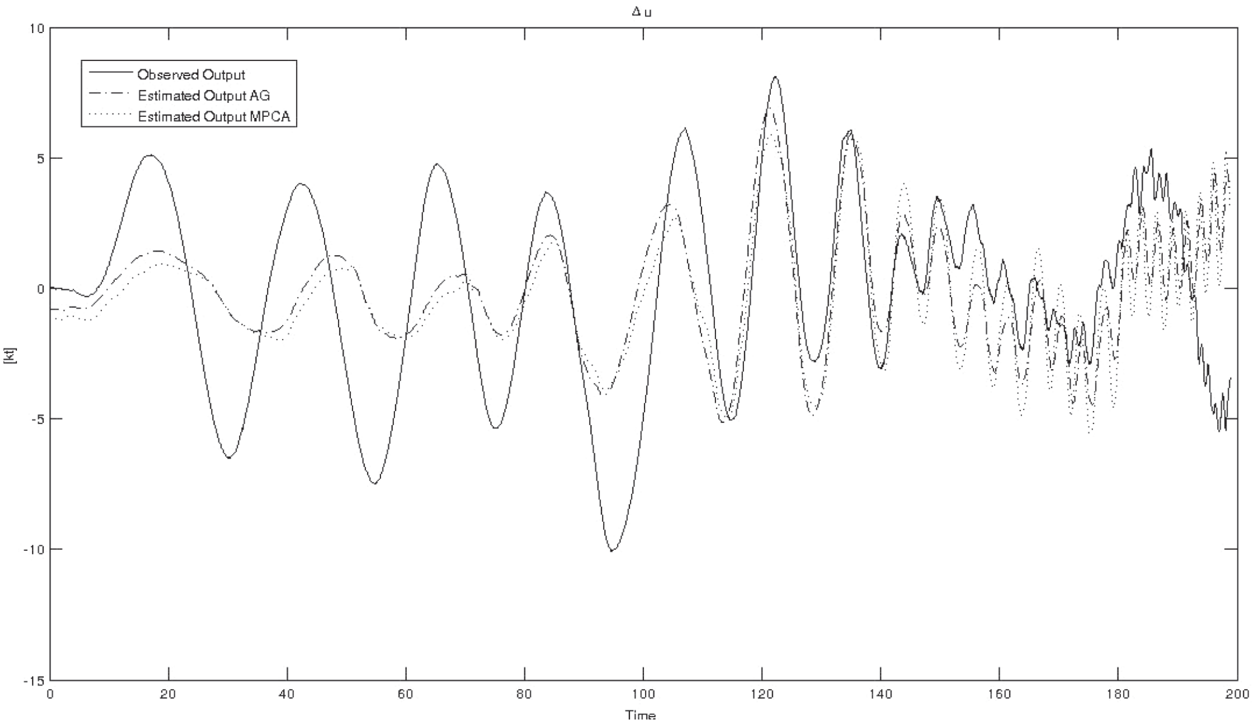

Fig. 4. Longitudinal velocity in helicopter body axis.

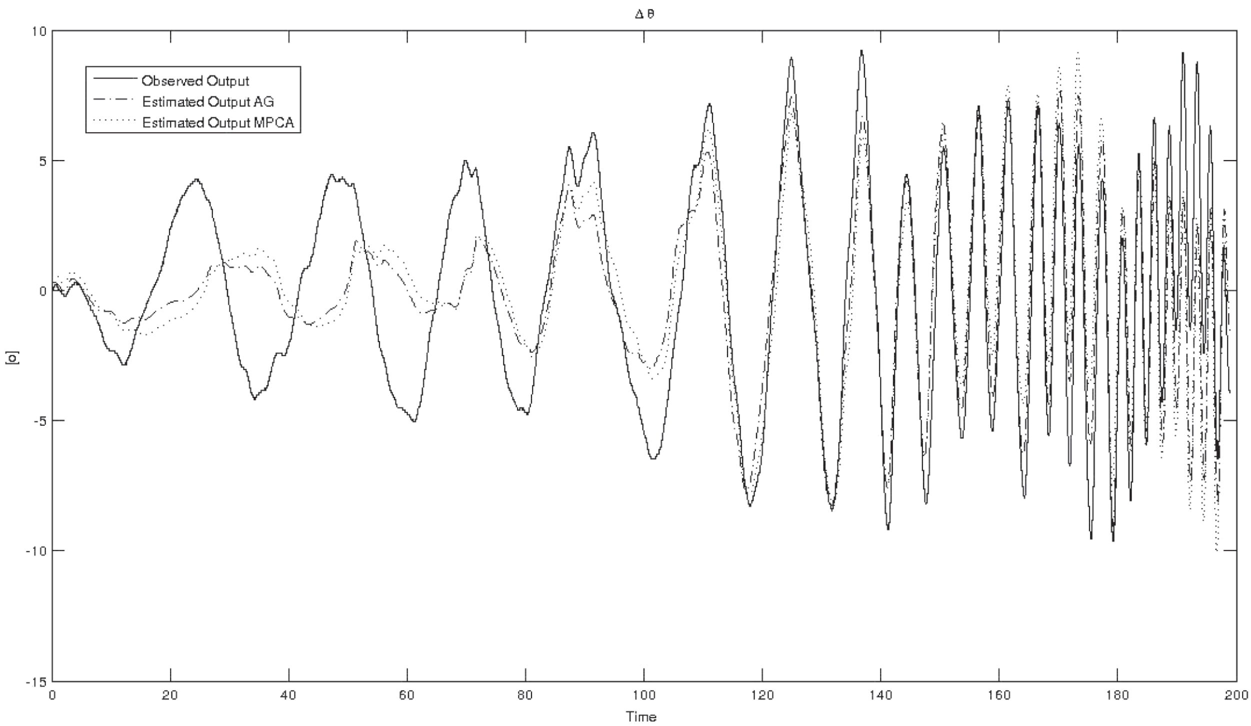

Fig. 5. Pitch attitude.

maneuver is represented by δ and the results presented take into consideration the average of four experiments with seeds generating different random numbers and experimental data being generated artificially. The parameters used are: 2 particles; 10 iterations (exploration). The stopping criterion used was the total number of iterations (30).

The solid curve corresponds to the real data obtained during the test, the dash-dotted curve is the result of identification produced by the GA and the results achieved by the MPCA are represented by the dotted curve. The results show that especially for u and w there is a slight discrepancy between the measured data and the data obtained by both algorithms. However, for high frequencies there is an improvement in the identification.

4. Conclusions

In this work, we compared two stochastic algorithms, GA and MPCA, for a helicopter parameter identification. The techniques were applied only in the estimation of the aerodynamic parameters of the longitudinal motion. The problem is formulated as an optimization process. The 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 it is a little bit better for 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.

Acknowledgements

We wish to thank for the partial support given by ITA and IPEV, especially the 2013 class Flight Teste Course (EFEV) Students, for providing the experimental data. Also, we would like to thank FINEP under agreement 01.13.0518.00 that funded the development of this tool and the presentation trip.

References

[1] H.F. Campos Velho, F.M. Ramos. Numerical inversion of two-dimensional geoelectric conductivity distributions from electromagnetic ground data. *Brazilian Journal of Geophysics*, **15**(2): 133–143, 1997.

[2] E.S. Chalhoub, H.F. Campos Velho. Estimation of the optical properties of sea water from measurements of exit radiance. *Journal of Quantitative Spectroscopy & Radiative Transfer*, **72**(5): 551–565, 2002.

[3] S. Stephany, H.F. Campos Velho, F.M. Ramos, C.D. Mobley. Identification of inherent optical properties and bioluminescence source term in a hydrologic optics problem. *Journal of Quantitative Spectroscopy & Radiative Transfer*, **67**(2): 113–123, 2000.

[4] G.D. Padfield. *Helicopter flight dynamics: the theory and application of flying qualities and simulation modeling.* AIAA Education Series, AIAA, Reston, 1999.

[5] G.D. Padfield. Applications of system identification in rotorcraft flight dynamics. *Vertica*, **13**(3): 207–412, 1989.

[6] R. Kumar, R. Ganguli, S.N. Omkar. Rotorcraft parameter identification from real time flight data. *Journal of Aircraft*, **45**(1): 333–341, 2008.

[7] *Agard Rotorcraft System Identification.* AGARD AR 280, LS 178, 1991.

[8] P.G. Hamel, J. Kaletka. Advances in rotorcraft system identification. *Progress in Aerospace Sciences*, **33**(3–4): 259–284, 1997.

[9] P. Hajela, J. Lee. Genetic algorithms in multidisciplinary rotor blade design, *Proceedings of the 36th AIAA Structures, Structural Dynamics, and Materials Conference*, New Orleans, USA, 1995.

[10] V.L. Wells, A.Y. Han, W.A. Crossley. *Acoustic design of rotor blades using a genetic algorithm*, AGARD CP 552, 1995.

[11] P.M.T. Zaal, D.M. Pool, Q.P. Chu, M.M.V. Paassen, M. Mulder, J.A. Mulder. Modeling human multimodal perception and control using genetic maximum likelihood estimation. *Journal of Guidance, Control, and Dynamics*, **32**(4): 1089–1099, 2009.

[12] E.F.P. Luz, *Parallel meta-heuristics on the solution of inverse problems* [in Portuguese: *Meta-heurísticas paralelas na solução de problemas inversos*]. PhD thesis, National Institute of Space Research, São José dos Campos, 2012.

[13] R.V. Cruz, *Development Dynamic Model for Helicopter Simulators* [in Portuguese: *Desenvolvimento de um Modelo Dinâmico para Simuladores de Helicóptero*]. PhD Thesis, Technological Institute of Aeronautics, São José dos Campos, 2009.

[14] R.V. Cruz, N.S.B. Neto, L.C.S. Góes. Preliminary results of longitudinal helicopter system identification using genetic optimization algorithm. *Proceedings of the 5th Brazilian Conference on Dynamics, Control and their Apllications*, Guaratinguetá, Brazil, (2006).

[15] R.V. Cruz, L.C.S. Góes. Results of longitudinal helicopter system identification using output-error and both genetic and Levenberg-Marquardt optimization algorithm. *Proceedings of the 19th Brazilian Congress of Mechanical Engineering*, Brasília, Brazil, 2007.

[16] R.V. Cruz, L.C.S. Góes. Results of short-period helicopter system identification using output-error and hybrid search-gradient optimization algorithm. *Mathematical Problems in Engineering*, **2010**: 17, 2010, Article ID 231594.

[17] J. del Cerro, J. Valero, A. Barrientos. Identification of small unmanned helicopter model using genetic algorithms. *Proceedings of the International Conference on Intelligent Robots and Systems*, Edmonton, Canada, 2005.

[18] M.B. Tischler, R.K. Remple. *Aircraft and rotorcraft system identification*. AIAA Education Series, 2006.

[19] R.V. Jategaonkar. Flight vehicle system identification: a time domain methodology. *Progress in Aerospace Sciences*, Reston, USA, 2006.

[20] R.W. Prouty. *Helicopter performance, stability and control*. Krieger Publishing Company, Malabar, 2005.

[21] A.K. Cooke, E.W.H. Fitzpatrick. *Helicopter test and evaluation*. AIAA Education Series, AIAA, Reston, 2002.

[22] W.F. Sacco, C.R.E.A. Oliveira, A new stochastic optimization algorithm based on a particle collision metaheuristic. *Proceedings of the 6th World Congress of Structural and Multidisciplinary Optimization*, 2005.

[23] W.F. Sacco, D.C. Knupp, E.F.P. Luz, A.J.S. Neto. *Particle Collision Algorithm* [in Portuguese: *Algoritmo de Colisão de Partículas*]. Nature Inspired Computational Intelligence Techniques: Applications in Inverse Problems in Radiative Transfer, 2009.