JOURNAL OF THEORETICAL
AND APPLIED MECHANICS
1, **38**, 2000

ON FAST IDENTIFICATION PROBLEM OF THE AERODYNAMIC AIRCRAFT CHARACTERISTICS SOLVED BY MEANS OF CURRENT FLIGHT PARAMETERS RECORDING

JACEK A. GOSZCZYŃSKI

Institute of Aviation, Warsaw
e-mail: jagoszcz@ilot.edu.pl

The problem of fast aircraft aerodynamic characteristics identification performed by means of current flight parameters recording is presented in the paper. Basic concepts of fast identification algorithms; e.g., Nonlinear Filtering (NF) (based on the Lipcer and Sziriajev theory) and Estimation Before Modelling (EBM) are presented, as well.
Tips on how to implement EBM and NF methods in practice are shown, as well. The numerical results presented seem to be very interesting.

Key words: flight dynamics, parameters identification, numerical research, aerodynamic characteristics

1. Introduction

Aircraft is a complex dynamic system that moves in real atmosphere and executes dynamic controlled manoeuvres. Aerodynamic loads acting upon the aircraft as well as the surrounding atmosphere (environmental conditions) exert fundamental influence on its behaviour and dynamic properties. One of the effective ways of determination of aerodynamic coefficients appearing in the formulae for aerodynamic forces and moments in the aircraft flight is identification.

The aircraft aerodynamic characteristics changes according to the velocity and flight altitude variations. It is, therefore, necessary to apply the identification methods, which could follow up those variations (cf Hamel and Jategaonkar, 1996; Iliff, 1989; Klein, 1989).

The problem of identification consists in determination of parameters of the aircraft mathematical model in the way ensuring that the best approximation of the test data in terms of a chosen identification coefficient (Fig.1) is achieved.

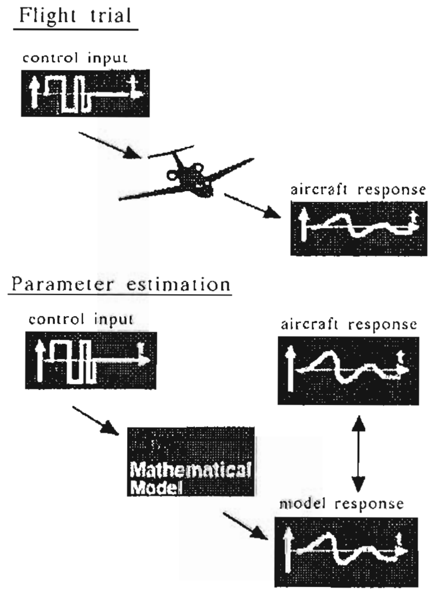

Fig. 1. Aircraft parameters identification process (see National Research Council, Canada)

The problem formulated in that way requires some additional information, especially on the following two aspects:

1. Identifiability (i.e., the possibility of identification) of the models
2. *On-line* identification.

The term "identifiability" is associated with a structure of mathematical model and the possibility of its determination as well as estimation of the model parameters using both the a priori information about the modelled object and test data (Giergiel and Uhl, 1990). In this paper we assume that the aircraft is identifiable.

The essence of the *on-line* identification can be presented straightforward, basing on the *off-line* identification, which consists in test data processing, in which all the recorded data are used at one instant in determination of the estimator. Whereas in the *on-line* identification, the parameters are being determined in the course of taking measurements (cf Niederliński, 1983).

In the fast identification of the aircraft aerodynamic characteristics based on current flight parameters recording the recursive identification methods are used (i.e., estimation of the unknown parameters is performed basing only on the results of the previous calculation step and current measurements, with no necessity for the parameter histories to be stored), which reveal the following properties:

- No high requirements imposed on PC memory capacity, since there is no need for all test data storing
- Applicability to the real-time algorithms, used in time-dependent parameters monitoring is straightforward
- Possibility of the *on-line* construction (at each instant) of a model of the considered process.

A number of recursive algorithms are available for the systems with time-dependent parameters. Since in those algorithms the old information is being put away to allow for responding only to current changes of the process, the parameter estimator is divergent as t tends to infinity, even for constant parameters (cf Elbert, 1985; Söderström and Stoica, 1997).

The *in-real-time* method is one of the *on-line* identification methods imposing, however, in contrast to the *on-line* and *off-line* ones (revealing a spatial character) strict time requirements. We can monitor any change in parameter values in the course of the process variable in time properties.

When selecting the identification method we should take into account its goal, since it may determine a desirable model accuracy. A detailed description of the process and verification of physicals models require high accuracy of estimation. When choosing the method of identification we indirectly select the model structure. The chosen method must, therefore, result from a compromise between the required accuracy and calculation costs.

In a real aircraft motion we can measure the input and output signals. However, it should be remembered that stochastic disturbances take place during the motion and deteriorate and falsify the measurement results (cf Manerowski, 1990).

For unification purposes the dynamical model of the aircraft is assumed in the following general form

$$
\begin{aligned}
\dot{\boldsymbol{x}} &= f\Big(\boldsymbol{x}(t),\boldsymbol{u}(t),\boldsymbol{p}(t)\Big) + \boldsymbol{w}(t) \\
\boldsymbol{y} &= h\Big(\boldsymbol{x}(t),\boldsymbol{u}(t),\boldsymbol{p}(t)\Big) + \boldsymbol{v}(t)
\end{aligned}
\tag{1.1}
$$

where

$\boldsymbol{x}$ – state vector the components of which are co-ordinates and generalised velocities
$\boldsymbol{u}$ – control vector, the components of which are control surface deflections and the thrust
$\boldsymbol{y}$ – output vector (measurement vector)
$\boldsymbol{p}$ – unknown parameters vector
$\boldsymbol{w}$ – state disturbance vector
$\boldsymbol{v}$ – measurement error vector.

As a rule, it is assumed that the vectors $\boldsymbol{w}$ and $\boldsymbol{v}$ are stochastically independent processes of zero mean values and given covariance matrices.

The Nonlinear Filtering (NF) and EBM methods (Goszczyński, 1998) have been selected from among a variety of *on-line* identification methods (cf Elbert, 1984; Giergiel and Uhl, 1990; Mańczak and Nahorski, 1983; Stalford, 1979; Söderström and Stoica, 1997).

2. Mathematical models of the flying object

The aircraft is defined as a flying object (FO) considered in flight configuration as a rigid body with movable control surfaces. A mathematical aircraft model is defined in the FO body-fixed co-ordinate system (Goszczyński, 1998; Maryniak, 1985; Sibilski, 1999), see Fig.2.

Within the framework of analytical mechanics we arrive at the following equations of motion

$$\dot{\boldsymbol{x}}_d = \mathsf{B}^{-1}(\mathsf{V}_\omega \mathsf{B}\boldsymbol{x}_d + \boldsymbol{F}_M) \tag{2.1}$$

where

$\boldsymbol{x}_d$ – dynamical part of the state vector, $\boldsymbol{x}_d = [U, V, W, P, Q, R]^\top$
B – matrix of inertia
V_ω – linear and angular velocities matrix
$\boldsymbol{F}_M$ – vector of external forces and moments, $\boldsymbol{F}_M = [F_x, F_y, F_z, M_x, M_y, M_z]^\top$

and the kinematic relations

$$\dot{\boldsymbol{x}}_k = \mathsf{T}(\boldsymbol{x}_k)\boldsymbol{x}_d \tag{2.2}$$

where

T – transformation matrix from the FO body-fixed axes to the earth-fixed co-ordinate system
$\boldsymbol{x}_k$ – vector of co-ordinates, $\boldsymbol{x}_k = [\Phi, \Theta, \Psi, x_1, y_1, z_1]^\top$.

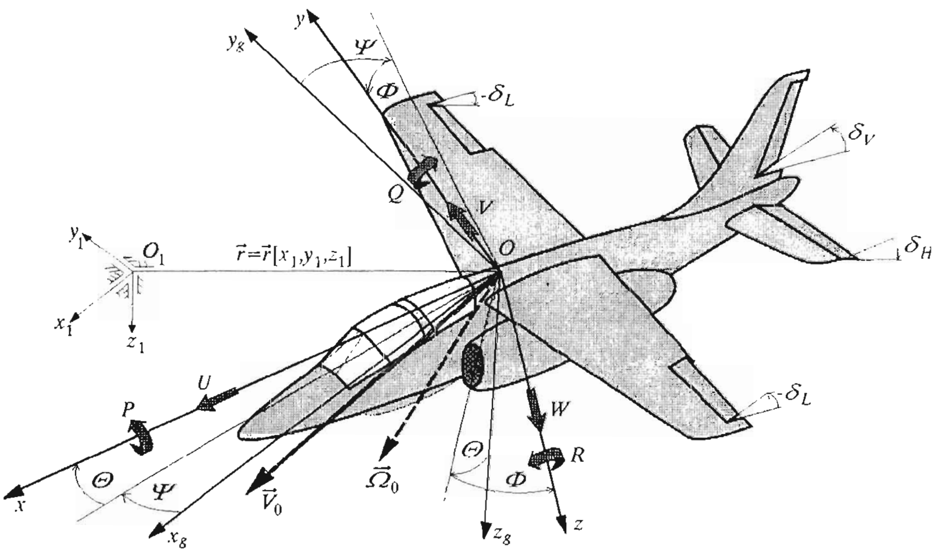

Fig. 2. Assumed FO co-ordinate systems and control surfaces deflections

$\boldsymbol{F}_M$ vector is represented as a sum of gravity, thrust and aerodynamics forces and moments

$$\boldsymbol{F}_M = \boldsymbol{F}_M^G + \boldsymbol{F}_M^T + \boldsymbol{F}_M^A \tag{2.3}$$

We assume that the gravity and thrust forces and moments are known, while the aerodynamic forces and moments

$$\boldsymbol{F}_M^A = [P_x^A, P_y^A, P_z^A, L^A, M^A, N^A]^\top \tag{2.4}$$

have to be estimated basing on the recorded digital signals of the FO motion using filtering and smoothing techniques. These estimates are unknown polynomials of the state variables, control function and Mach number, forms and coefficients of which are to be identified (Goszczyński et al., 1998b; Stalford et al., 1977).

3. Nonlinear Filtering (NF) method

3.1. Fundamentals

The NF theory formulated by Lipcer and Sziriajev (1981) (cf Anderson and Moore, 1984; Ocone, 1981) consists in finding a pair of stochastic processes in a nonlinear form of the Stochastic Differential Equations (SDE)

$$\begin{aligned} d\boldsymbol{x}_t &= [\mathsf{a}(t,y) + \mathsf{b}(t,y)\boldsymbol{x}_t]dt + \mathsf{c}(t,y)d\boldsymbol{u}_t \qquad && \boldsymbol{x}_{t=0} = \boldsymbol{x}_0 \\ d\boldsymbol{y}_t &= [\mathsf{A}(t,y) + \mathsf{B}(t,y)\boldsymbol{x}_t]dt + \mathsf{C}(t,y)d\boldsymbol{w}_t \qquad && \boldsymbol{y}_{t=0} = \boldsymbol{y}_0 \end{aligned} \tag{3.1}$$

where only the process y_t is observed, whereas $\boldsymbol{u}_t$ and $\boldsymbol{w}_t$ are the independent Wiener processes.

Solution to the filtering problem is possible on the following assumptions:

- Right-hand side of the SDE $(3.1)_2$ depends linearly on the Unknown Parameters Vector (UPV), which is independent of stochastic excitations (this vector describes the FO in flight, while stochastic terms represent external disturbances)
- A priori distribution of the UPV is normal. The unknown parameters have often physical or technical meaning, thus we can often determine their limiting values. However, if it is impossible to determine the range of those parameters it is reasonable to make the aforementioned assumption
- UPV is stochastically independent of the Wiener process $\boldsymbol{w}_t$
- There exists the inverse of the matrix $(\mathsf{C}^\top(t,y)\mathsf{C}(t,y))^{-1}$, i.e. the stochastic disturbances must affect the FO adequately
- Right-hand side of Eq $(3.1)_2$ has a strong solution, what imposes the requirement for existence and uniqueness of the classic solution of the ordinary differential equation resulting from Eq $(3.1)_2$ when neglecting the noises.

On the above assumptions it can be proved that the conditional expected value is the best mean square estimator of the non-observed stochastic process (SP) $\boldsymbol{x}$ when observing the process $\boldsymbol{y}$ in the time interval $[0,t]$. The optimal estimator and minimal error are given by a finite system, i.e.:

- Filtration tasks have finite dimensions and, therefore, can be realised technically
- Optimal estimator is represented directly by the dynamic of processes $\boldsymbol{x}$ and $\boldsymbol{y}$
- Optimal estimation at the instant t+dt results from the optimal estimation at the instant t, supplied with a new observation in the interval $[t, t+dt]$, what allows for construction a recursive filter
- Solution is of the *on-line* type

- When using fast computer systems, is possible to reach the real-time solution. So as to formulate properly the parameter estimation in terms of the filtering problem, the stochastic process $\boldsymbol{x}$ should be stationary and represented by the same UPV. That leads directly to formulation of the filtering problem in a specific form (Goszczyński, 1998).

3.2. Requirements imposed on the state and output (measurement) vectors

For the UPV estimation purposes by means of the NF method the FO equation of motion in flight should be represented in terms of the measurement vector, since this is the only information about the real FO motion we are provided with. Eq $(3.1)_2$ should therefore satisfy the following conditions:

- Noises encountered in the course of the state vector measurement are negligible when compared to the external stochastic disturbances affecting the FO in flight. If the noises arise also in the measurement process, the estimation task of both the state vector and UPV are infinite multidimensional (Goszczyński, 1998)
- Relation between the state and measurement vectors has the following linear form

$$\boldsymbol{y} = \mathbf{H}\boldsymbol{x} \tag{3.2}$$

where $\mathbf{H}$ is a constant or time-dependent matrix and

$$\det \mathbf{H}^\top \mathbf{H} \neq 0 \tag{3.3}$$

Thus, we can rewrite Eq (3.2) as follows

$$\boldsymbol{x} = (\mathbf{H}^\top \mathbf{H})^{-1} \mathbf{H}^\top \boldsymbol{y} \tag{3.4}$$

By virtue of Eq (3.4) the equation of motion $(3.1)_1$ representing evolution of the process $\boldsymbol{x}$, may be presented in terms of the measurement vector.

3.3. Application

The model of the controlled aircraft in 3D-flight (2.1) within the framework of nonlinear filtering theory (NF) can be represented in the form

$$\dot{\boldsymbol{x}}_d = \mathbf{B}^{-1}\boldsymbol{g}(\boldsymbol{x}_d, t) + \mathbf{B}^{-1}\boldsymbol{f}(\boldsymbol{x}_d, t) + \boldsymbol{k} \tag{3.5}$$

where

$\boldsymbol{k}$ – vector of constants
$\boldsymbol{g}$ – gravity and thrust forces vector
$\boldsymbol{f}$ – aerodynamic forces vector.

The vector of aerodynamic forces has the following linear form with respect to the unknown parameters

$$\boldsymbol{F}_M^A = \boldsymbol{f}(\boldsymbol{x}_d, t) = \mathbf{X}(\boldsymbol{x}_d, t)\boldsymbol{p} \tag{3.6}$$

which determines the structure of both the vector $\boldsymbol{p}$, and matrix $\mathbf{X}(\boldsymbol{x}_d, t)$, unknown at the moment.

Having the matrix $\mathbf{X}(\boldsymbol{x}_d, t)$ determined, after substitution of Eq (3.6) into Eq (3.5) and introducing the formulae for external stochastic disturbances in flight we arrive at the stochastic equation of motion

$$d\boldsymbol{x}_{d_t} = [\boldsymbol{k} + \mathbf{B}^{-1}\boldsymbol{g}(\boldsymbol{x}_{d_t}, t) + \mathbf{B}^{-1}\mathbf{X}(\boldsymbol{x}_{d_t}, t)\boldsymbol{p}]dt + \mathbf{D}d\boldsymbol{\omega}_t \tag{3.7}$$

which we consider as the observation equation (in the NF theory sense), where $\boldsymbol{\omega}_t \leqslant 0$ is the 6D Wiener process, representing the influence of stochastic factors on aerodynamic forces and moments and $\mathbf{D}$ is the inverse matrix of modified matrix $\mathbf{B}$.

4. Estimation Before Modelling (EBM) method

The EBM consists of the following two-step (Goszczyński, 1998; Hoff and Cook, 1996; Stalford, 1979, 1981; Sibilski, 1999):

Step 1 – estimation of the state vector using a filter

Step 2 – the "properly" modelling itself e.g. by means of the regression method (Draper and Smith, 1973)

$$\widehat{\boldsymbol{z}} = \mathbf{A}\widehat{\boldsymbol{p}} + \widehat{\boldsymbol{\varepsilon}} \tag{4.1}$$

where
$\widehat{\boldsymbol{z}}$ – estimation of the output vector (resulting from the filter)
$\mathbf{A}$ – estimation matrix of the vector $\boldsymbol{x}$ (cf the observation matrix $\mathbf{X}$ in Lipcer and Sziriajew (1981))
$\widehat{\boldsymbol{\varepsilon}}$ – vector of error with zero mean values and a constant covariance matrix
$\widehat{\boldsymbol{p}}$ – estimation of unknown parameters vector.

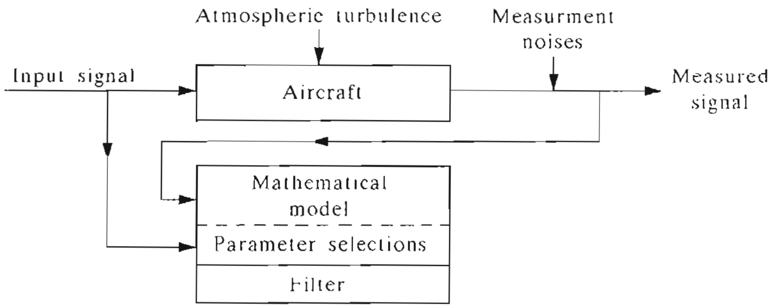

Fig. 3. Concept of the EBM method

The problem of the model parameters identification is schematically presented in Fig.3. The EBM method is one of the equation error methods, with its name representing adequately the order of the operations to be performed (Goszczyński, 1998; Hoff and Cook, 1996).

4.1. State estimation

At the first step, realised by means of the filtering technique the extended Kalman filter is applied (Goszczyński et al., 1998b,c). The loading introduced this way can be reduced by means of linear smoothing, e.g. employing the modified Bryson-Frazier filter. An alternative approach consists in application of smoothing with a constant delay, which may occur to be a simpler and less time-consuming way, giving at the same time both smoothing and estimation of the state variable derivatives.

A crucial role in the EBM plays the aerodynamic modelling in terms of the state equation, for the requirements of Kalman filter theory to be met. To this end each component of the aerodynamic forces and moments vector is represented in the form of Gauss-Markov process

$$\dot{\boldsymbol{x}}_{di}(t) = \mathsf{K}_i(t)\boldsymbol{x}_{di}(t) + \mathsf{G}_i\boldsymbol{\zeta}_i(t) \qquad \boldsymbol{x}_{di}(0) = \boldsymbol{x}_{di0} \qquad i = 1,...,6 \tag{4.2}$$

where

$\boldsymbol{\zeta}_i(t)$ – white (gaussian) noise
G_i – output matrix
$\boldsymbol{x}_{di}$ – state vector
K_i – state matrix in the form

$$\mathsf{K}_i = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \tag{4.3}$$

The state estimates obtained at the first step of the EBM method are the input data at the second step. Therefore, the identification problem is addressed in a completely different way, in contrast to a typical identification process of parameters. In the EBM method a structural identification is performed as well.

4.2. Estimation of parameters

The second step of the EBM method is reasonably called "modelling". This approach gives a insight into the mechanical models of flight being currently in use (Goszczyński et al., 1998b). Whenever the identification is to be made within the area of substantial changes in values of the physical quantities, which of course affect strongly the values of parameters, it must be preceded by a proper subdomain selection. In each subdomain a separate identification is realised (Batterson and Klein, 1989).

Selection of the model structure consists in multiple application of the linear regression technique (3.6) (Goszczyński et al., 1998b). It results from the step by step introducing and removing of the independent variables. The independent variable, which might be the best single variable at the previous stage, could be needless at the next stage, which we can check using the Fisher-Snedecor test (test F) (Draper and Smith, 1973).

Selection of the aerodynamic model structure is of crucial importance. Usually, the linear regression technique is used, in which n parameters $(N \leqslant n)$ are determined from N measurements and a simple parametrical model in the following form (corresponding to Eq (3.6)) is assumed

$$\boldsymbol{y}_i = \mathsf{X}_i \boldsymbol{p}_i + \boldsymbol{e}_i \qquad i = 1, ..., 6 \tag{4.4}$$

where

$\boldsymbol{y}_i$ – vector of aerodynamic forces or moments of N order
X_i – matrix of independent variables of $N \times n$ order
$\boldsymbol{p}$ – vector of unknown parameters of n order
$\boldsymbol{e}$ – error vector of N order.

Applying the least square method, by virtue of Eq (3.4) (the relation between the state and measurement vectors is linear) we arrive at the equation

$$\widehat{\boldsymbol{p}}_i = (\mathsf{X}_i^\top \mathsf{X}_i)^{-1} \mathsf{X}_i^\top \boldsymbol{y}_i \tag{4.5}$$

representing explicitly the identification process.

4.3. EBM conclusions

Usually, at high angles of attack the aerodynamic characteristics are strongly nonlinear depending on the state and control vectors (2.1) in an unknown way. The function $\mathbf{X}_i(\boldsymbol{x}_d, t)$ is represented in the form of splines or polynomials with unknown coefficients $\boldsymbol{p}_i$ (cf Goszczyński et al., 1998b; Stalford, 1979; Hoff and Cook, 1996). Basing on the dynamical limitations imposed on all degrees of freedom (flight modelling) it is possible to estimate $\boldsymbol{x}_{di0}$ and the coefficients $\boldsymbol{p}_i$, which completes the first step of the EBM identification method – the state estimation.

The EBM method can be most efficient for determination of aerodynamic characteristics at high angles of attack (Sibilski, 1998; Stalford, 1979, 1981; Stalford et al., 1977). Several advantages should be maintained here:

- A priori estimation of aerodynamic characteristics before modelling allows for more accurate determination of input data at the modelling stage
- Estimation and identification of aerodynamic derivatives do not require construction of the models depending on the state parameters
- Simultaneous reconstruction of many manoeuvres allows for better precision in aerodynamic derivatives identification.

The most advantageous feature of the EBM method consists in the fact that the model structure is constructed basing on measurement of dynamical parameters of the aircraft.

5. Final remarks

The results of numerical tests of the presented methods are promising (see Fig.4, Fig.5 and Goszczyński, 1998). A good convergence of the numerical algorithms and low sensitivity to initial errors has been found. These features are hopeful, particularly for aerodynamic characteristics, the values of which can be precisely, a priori estimated. Actually, investigations into application of the presented methods to the problem of six-degree-of-freedom aircraft are being conducted. An expected number of estimates equals about 200 (Goszczyński, 1998).

Acknowledgement

The work has been financially supported by the State Committee for Scientific Research under grants No. 9T12C01813 and No. 0T00A 03617.

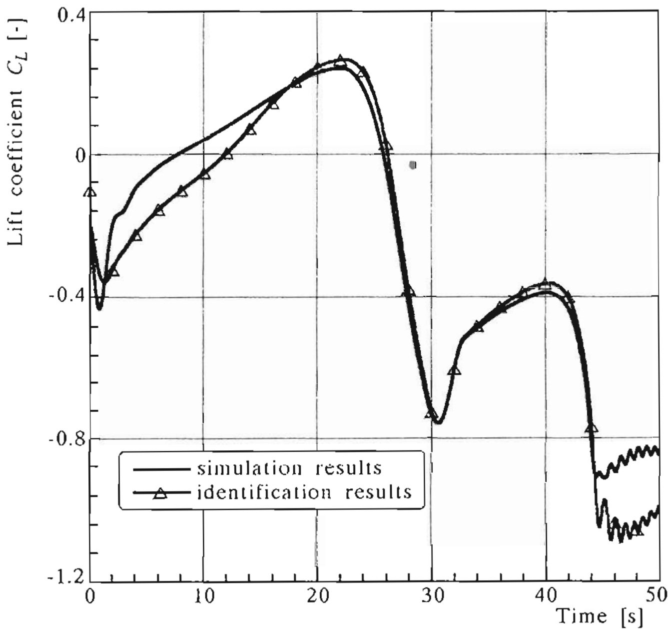

Fig. 4. Identification of the lift coefficient C_L (NF)

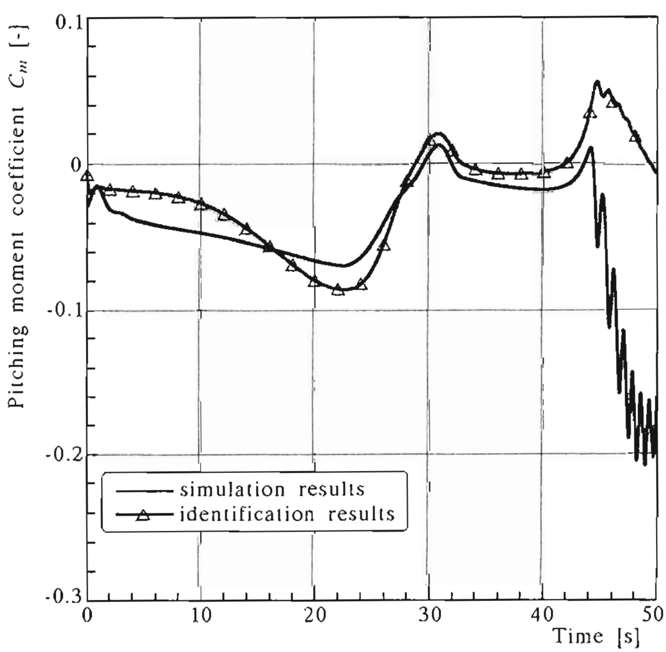

Fig. 5. Identification of the pitching moment coefficient C_m (NF)

References

1. ANDERSON B.D.O., MOORE J.B., 1984, *Filtracja optymalna*, WN-T, Warszawa

2. BATTERSON J.G., KLEIN V., 1989, Partitioning of Flight Data for Aerodynamic Modeling of Aircraft at High Angles of Attack, *Journal of Aircraft*, **26**, 4, 334-339

3. DRAPER N.R., SMITH H., 1973, Analiza regresji stosowana, PWN-BNI, Warszawa

4. ELBERT T.F., 1984, *Estimation and Control of Systems*, Van Nostarand Reinhold

5. GIERGIEL J., UHL T., 1990, *Identyfikacja układów mechanicznych*, PWN, Warszawa

6. GOSZCZYŃSKI J.A., 1998, Identyfikacja w czasie rzeczywistym parametrów obiektu latającego z zastosowaniem do symulacji numerycznej ruchu, Raport merytoryczny projektu badawczego KBN nr 9T12C 006 08, Instytut Lotnictwa, Warszawa

7. GOSZCZYŃSKI J.A., GOETZENDORF-GRABOWSKI T., MARYNIAK J., MICHALSKI W.J., PIETRUCHA J.A., PYRZ J., 1998a, Algorytm identyfikacji parametrów obiektu latającego w czasie rzeczywistym – część 2 – zastosowanie, *Zeszyty Naukowe Politechniki Rzeszowskiej*, nr 168, *Mechanika*, **51**, *Awionika*, **1**, Rzeszów, 141-148

8. GOSZCZYŃSKI J.A., GOETZENDORF-GRABOWSKI T., MARYNIAK J., MICHALSKI W.J.J., PIETRUCHA J.A., PYRZ J., 1998b, Identyfikacja charakterystyk aerodynamicznych obiektu latającego w czasie rzeczywistym, *Materiały II Międzynarodowej Konferencji Uzbrojeniowej "Naukowe Aspekty Techniki Uzbrojenia"*, WAT, Warszawa, **2**, 127-134

9. GOSZCZYŃSKI J.A, MICHALSKI W.J.J., PIETRUCHA J.A., 1998c, Metoda estymacji przed modelowaniem w identyfikacji samolotu, *Zeszyty Naukowe Katedry Mech. Stosowanej Pol. Śląskiej*, **6**, 121-126

10. HAMEL P.G., JATEGAONKAR R.V., 1996, Evolution of Flight Vehicle System Identification, *J. of Aircraft*, **33**, 1, 9-28

11. HOFF J.C., COOK M.V., 1996, Aircraft Parameter Identification Using on Estimation – Before – Modelling Technique, *Aeronautical Journal*, 259-268

12. ILIFF K.W., 1989, Parameter Estimation for Flight Vehicles, *J. of Guidance*, **12**, 5, 609-622

13. KLEIN V., 1989, Estimation of Aircraft Aerodynamic Parameters from Flight Data, *Progress in Aerospace Sciences*, **26**, 1-77

14. LIPCER R.S., SZIRIAJEW A.N., 1981, *Statystyka procesów stochastycznych – filtracja nieliniowa i zagadnienia pokrewne*, PWN, Warszawa
15. MANEROWSKI J., 1990, Identyfikacja modelu dynamiki lotu odrzutowego samolotu oraz jego układów sterowania, *Informator ITWL*, **296**, Warszawa
16. MAŃCZAK K., NAHORSKI Z., 1983, *Komputerowa identyfikacja obiektów dynamicznych*, PWN, Warszawa
17. MARYNIAK J., 1985, Ogólny model symulacji samolotu, Zespół N-B DOR, ITLiMS PW, Sprawozdanie nr 141/85, Warszawa
18. NIEDERLIŃSKI A., 1983, *Systemy i sterowanie. Wstęp do automatyki i cybernetyki technicznej*, PWN, Warszawa
19. OCONE D., 1981, Finite Dimensionally Computable Statistics and Estimation Algebras in Nonlinear Filtering, *Proceedings of International Symposium of Mathematical Theory of Networks and Systems*, Santa Monica, CA, 5-17
20. SIBILSKI K., 1998, Modelowanie dynamiki granicznych stanów lotu statków powietrznych o podwyższonej manewrowości, WAT, rozprawa habilitacyjna, Warszawa
21. SÖDERSTRÖM T., STOICA P., 1997, *Identyfikacja systemów*, PWN, Warszawa
22. STALFORD H.L., 1979, Application of the Estimation Before Modeling (EBM) System Identification Method to the High Angle of Attack/Sideslip Flight of the T2C Jet Trainer Aircraft. Vol. 1: Executive Summary, *NASA Technical Report*, NADAC-76097-30-Vol-1
23. STALFORD H.L., 1981, High-Alpha Aerodynamic Model Identification of T-2C Aircraft Using the EBM Method, *J. of Aircraft*, **18**, 10, 801-809
24. STALFORD H.L., RAMACHANDRAM S., SCHNEIDER H., MASON J.D., 1977, Identification of Aircraft Aerodynamic Characteristics at High Angles of Attack and Sideslip Using the Estimation Before Modeling (EBM) Technique, *AIAA Atmospheric Flight Conference Proceedings*, Holywood, FL

Problem szybkiej identyfikacji charakterystyk aerodynamicznych samolotu w oparciu o bieżąc rejestrację parametrów lotu

Streszczenie

W pracy zostało przedstawione zagadnienie szybkiej identyfikacji charakterystyk aerodynamicznych samolotu w oparciu o bieżąc rejestrację parametrów lotu. Przedstawiono podstawy teoretyczne opracowanych algorytmów identyfikacji, tj. filtracji nieliniowej (opierając się na teorii Lipcera i Sziriajewa) oraz estymacji przed modelowaniem. Zamieszczono opis zastosowania opracowanych logarytmów oraz przykład interesujących wybików testów numerycznych.

Manuscript received June 30, 1999; accepted for print September 1, 1999