JOURNAL OF THEORETICAL
AND APPLIED MECHANICS
44, 1, pp. 31-50, Warsaw 2006

PRACTICAL ASPECTS OF IDENTIFICATION OF THE AERODYNAMIC CHARACTERISTICS

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

Key words: dynamics of flight, non-linear model, flight simulation, aerodynamic characteristics identification

1. Introduction

An 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 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 the identification.

Aerodynamic characteristics of an aircraft change according to velocity and flight altitude variations. It is, therefore, necessary to apply identification methods which could follow up those variations. The contemporary problem of system identification (assume shape as flying object), can be divided into three main parts (Fig. 1):

- Measurement equipment – a subsystem logging measurement data and recording them through appropriate on-board and on-ground equipment with respect to their "quality" – knowledge of measurement errors.

- Flight test techniques – a subsystem selecting adequate test flight programs of the flying object. Input signals are optimized in terms of their spectrum so that parameters of the object could be estimated.

- Flight data analyzer – a subsystem based on a mathematical model of the flying object and estimation criteria to find a solution to the given computational identification algorithm from initial conditions or specified *a priori* estimates of unknown parameters and to minimize the error system response of the best estimate parameter.

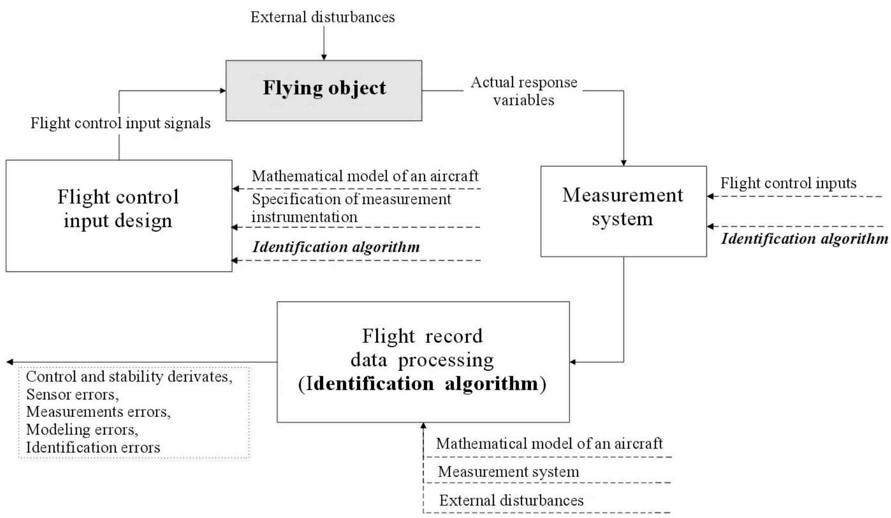

Fig. 1. Correlation in the process of identification of aerodynamic characteristics

Identification of aerodynamic characteristics of a flying object (with control and stability derivates) depends on numerical solution of values based on test flights. In preparation of an identification method to practical use, we must assume its applicability in a step by step manner (Giergiel and Uhl, 1990). We divide the development of the method into three phases (Fig. 2):

- Phase 1 – depends on numerical simulation of a tested object aimed at the identification of flight regimes, for example the problem of high angles of attack.

- Phase 2 – depends on an identification algorithm determining the influence of object control and measurement errors on recorded data processing.

- Phase 3 – depends on practical use of Phase 1 and 2 which are applied to data processing recorded during flight tests.

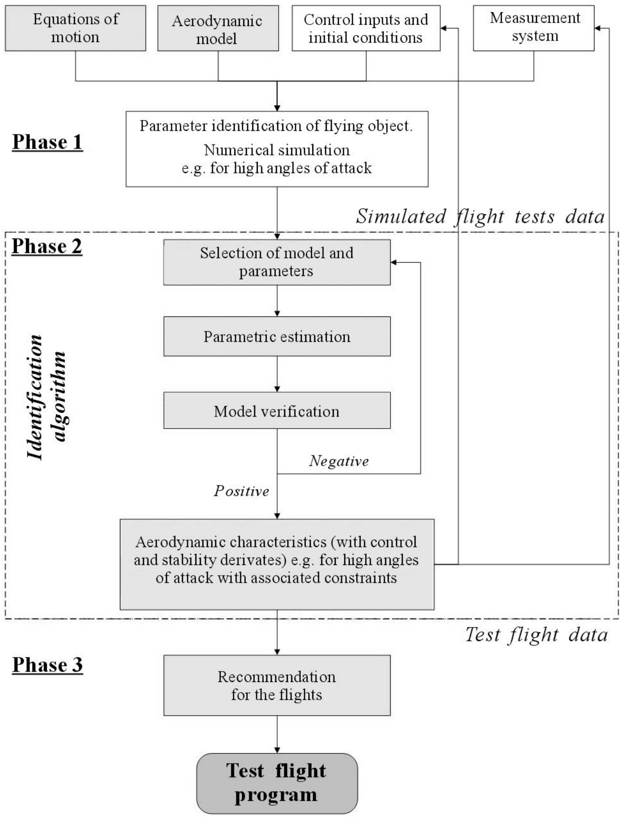

Fig. 2. Phases of practical identification of aerodynamic characteristics of a flying object (Giergiel and Uhl, 1990; Goszczyński, 2000)

In the second phase, a selection of critical elements for the identification process are used for estimation of parameters verification of the formulated mathematical model.

Requirements of the above phases indicate fundamental need for aerodynamic tunnel tests and knowledge of the flying object physics.

As a matter of fact an aerodynamic model of a flying object in the deterministic sense must reflect particularly strongly nonlinear components of aerodynamic forces and moments.

2. Mathematical models

An aircraft is defined as a flying object (FO) considered in a flight configuration as a rigid body with movable control surfaces. A mathematical model of FO is defined in the FO body-fixed co-ordinate system (Hamel and Jategaonkar, 1996; Main and Iliff, 1985; Maryniak, 1985), see Fig. 3.

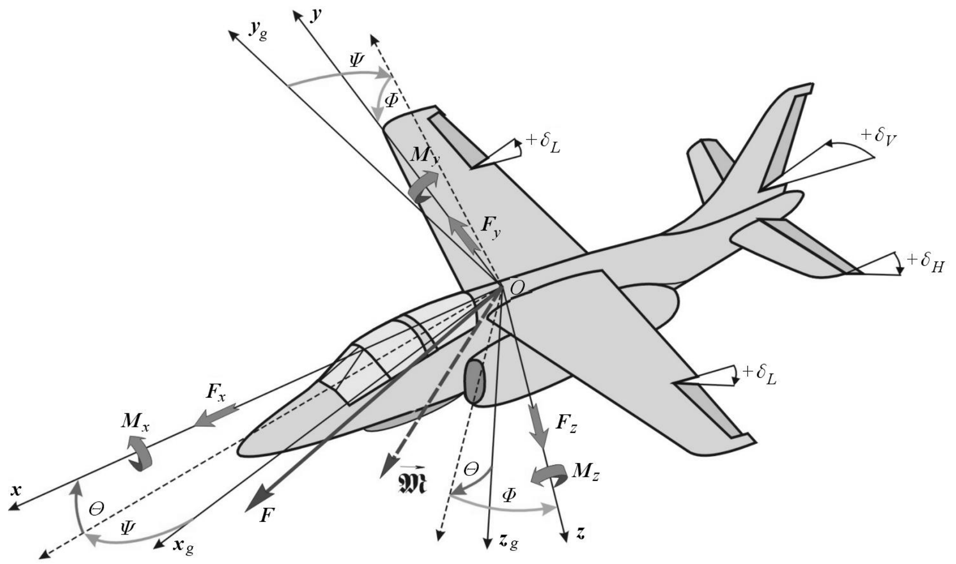

Fig. 3. Assumed FO co-ordinate systems and displacements of control surfaces

Within the framework of analytical mechanics, we arrive at the following equations of motion (Goszczyński, 2000; Goszczyński *et al.*, 2000; Maryniak, 1985; Sibilski, 1998)

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

where

$\boldsymbol{x}_d$ – dynamical part of the state vector

$$\boldsymbol{x}_d = [U, V, W, P, Q, R]^\top \tag{2.2}$$

$\mathbf{B}$ – matrix of inertia
$\mathbf{V}_\omega$ – matrix of linear and angular velocities
$\boldsymbol{F}_M$ – vector of external forces and moments

$$\boldsymbol{F}_M = \begin{bmatrix} \boldsymbol{F} \\ \boldsymbol{M} \end{bmatrix} = [F_x, F_y, F_z, M_x, M_y, M_z]^\top \tag{2.3}$$

and the kinematic relations

$$\dot{\boldsymbol{x}}_k = \mathbf{T}(\boldsymbol{x}_k)\boldsymbol{x}_d \tag{2.4}$$

where $\mathbf{T}$ denotes the transformation matrix from the FO body-fixed axes to the earth-fixed co-ordinate system

$$\boldsymbol{x}_k = [\varPhi, \varTheta, \varPsi, x_1, y_1, z_1]^\top$$

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

$$\boldsymbol{F}_M = \boldsymbol{F}_M^G + \boldsymbol{F}_M^T + \boldsymbol{F}_M^A \tag{2.5}$$

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

$$\boldsymbol{F}_M^A = [P_x, P_y, P_z, L, M, N]^\top \tag{2.6}$$

have to be estimated basing on recorded digital signals of FO motion with filtering and smoothing techniques used. These estimates are unknown polynomials of the state variables, control function and Mach number. Their forms and coefficients are to be identified (Goszczyński *et al.*, 2000).

2.1. A particular mathematical model of an aircraft

In a simplified case, we can analyze a rigid and symmetrical aircraft moving through atmosphere which moves with a uniform speed over a flat earth (Maryniak, 1985). Using the body-fixed reference frame $Oxyz$ with the origin in the centre of gravity, are obtains equations of motion (2.3) as presented below

$$\begin{aligned}
X &= m(\dot{U} + QW - RV) + mg\sin\varTheta \\
Y &= m(\dot{V} + RU - PW) - mg\cos\varTheta\sin\varPhi \\
Z &= m(\dot{W} + PV - QU) - mg\cos\varTheta\cos\varPhi
\end{aligned} \tag{2.7}$$

$$\begin{aligned}
L &= I_x\dot{P} - (I_y - I_z)QR - I_{xz}(\dot{R} + PQ) + \\
&\quad -I_{Ti}\omega_{Ti}(R\sin\varphi_{Tzi} + Q\cos\varphi_{Tzi}\sin\varphi_{Tyi}) \\
M &= I_y\dot{Q} - (I_z - I_x)RP - I_{zx}(R^2 - P^2) + \\
&\quad +I_{Ti}\omega_{Ti}(R\cos\varphi_{Tzi}\cos\varphi_{Tyi} + P\cos\varphi_{Tzi}\sin\varphi_{Tyi}) \\
N &= I_z\dot{R} - (I_x - I_y)PQ - I_{zx}(\dot{P} - QR) + \\
&\quad -I_{Ti}\omega_{Ti}(Q\cos\varphi_{Tzi}\cos\varphi_{Tyi} - P\sin\varphi_{Tzi})
\end{aligned} \tag{2.8}$$

Equations (2.7) and (2.8) take the form of first order differential equations for, respectively for translational velocities, angular velocities and attitude angles in the body-fixed reference frame $Oxyz$. The forces X, Y, Z represent components of the *total aerodynamic force*, including aerodynamic effects of propulsion systems. L, M, N denote the *total aerodynamic moments* (including any aerodynamic effects of the propulsion system) about the body axes $Oxyz$. Both components (2.7) and (2.8) define a form of an aerodynamic vector (2.6).

Completing equations (2.7) and (2.8) with kinematic relations (2.4) and components of the total aerodynamic force and moment (known also as the *aerodynamic model*) leads to the full set of aircraft dynamic equations of motion.

It is worth noting here that the "physical" input variables such as displcements of control surfaces and engine thrust (or power changes) also serve as inputs to the above set of differential equations as they should appear as independent variables in the aerodynamic model of the flying object.

In the written above kinematic model of an aircraft, the measured variables, i.e. *specific aerodynamic forces* and *body rotation rates* appear as forcing functions.

The specific force is defined here as an external non-gravitational field force per mass unit. The specific forces are variables measured by "ideal" accelerometers in the body's centre of gravity, irrespective of whether the body is influenced by the gravitational field or not (Mulder *et al.*, 1994; Stalford, 1979). In flight tests, such ideal accelerometers would measure the specific aerodynamic forces according to

$$X = A_x m \qquad\qquad Y = A_y m \qquad\qquad Z = A_z m \tag{2.9}$$

in which A_x, A_y, A_z denote the specific aerodynamic forces along the body reference axes $Oxyz$.

Substitution of (2.9) into (2.7) and division by m leads to the following expressions

$$\begin{aligned}
\dot{U} &= A_x - g\sin\Theta - QW + RV \\
\dot{V} &= A_y + g\cos\Theta\sin\Phi - RU + PW \\
\dot{W} &= A_z + g\cos\Theta\cos\Phi - PV + QU
\end{aligned} \tag{2.10}$$

As the mass has been eliminated, equations (2.10) represent a set of what might be called kinematical relations. The two sets of equations, (2.9) and

(2.10), may be solved numerically if the specific forces A_x, A_y, A_z and the angular rates P, Q, R are taken as input variables.

We can interpret (2.4), (2.10) as to represent the dynamical system and define the *state vector*

$$\boldsymbol{x}_a = [U, V, W, \Phi, \Theta, \Psi, x_1, y_1, z_1]^\top \tag{2.11}$$

as well as the *input vector*

$$\mathbf{u} = [A_x, A_y, A_z, P, Q, R]^\top \tag{2.12}$$

The *equation of the system state* may be written as

$$\dot{\boldsymbol{x}}_a = \boldsymbol{f}(\boldsymbol{x}_d, \boldsymbol{u}) \tag{2.13}$$

where $\boldsymbol{f}$ denotes a non-linear vector function of $\boldsymbol{x}_a$ and $\boldsymbol{u}$.

While the accelerometers and gyroscopes serve to measure components of the input vector, the barometric and other sensors may be used to measure components of the observation vector.

2.2. The aerodynamic model of a flying object

Aerodynamic models are defined as mathematical models of aerodynamic forces and moments in the body-fixed $Oxyz$ or wind-fixed $Ax_ay_az_a$ reference frames.

Development of aerodynamic models from dynamic flight test data requires an initial "guess" of the mathematical structure of the model. The initial guess is referred as an *a priori* model, indicating that no flight data was used to build the model. *A priori* models can be based on physical knowledge, semi-empirical databases, results found from Computational Fluid Dynamics (CFD) or Wind Tunnel measurements.

A generalized aerodynamic force (2.6) may be written as follows (Main and Iliff, 1985, 1986; Mulder *et al.*, 1994)

$$\begin{aligned}P_A = P_S(\alpha,\beta) &+ \sum_n P_A^{\delta_n}(\alpha,\beta)\delta_n + P_A^p(\alpha,\beta)P + P_A^q(\alpha,\beta)Q + P_A^r(\alpha,\beta)R + \\ &+ P_A^{pq}(\alpha,\beta)PQ + P_A^{p^2}(\alpha,\beta)P^2 + P_A^{pr}(\alpha,\beta)PR + P_A^{q^2}(\alpha,\beta)Q^2 + \\ &+ P_A^{qr}(\alpha,\beta)QR + P_A^{r^2}(\alpha,\beta)R^2\end{aligned} \tag{2.14}$$

where $P_S(\alpha,\beta)$ is a part of the aerodynamic force depending on the angle of attack and angle of sideslip, P_A^p, P_A^q, P_A^r, P_A^{pq}, $P_A^{p^2}$, P_A^{pr}, $P_A^{q^2}$, P_A^{qr}, $P_A^{r^2}$ are parts of the aerodynamic force in function of the roll, pitch and yaw rate, $P_A^{\delta_n}$ are parts of the aerodynamic force depending on aileron, elevator and rudder (δ_n) deflections.

As estimated parameters are likely to be compared with results determined from wind tunnel experiments (or CFD), a standard way of system modelling through Taylor series of dimensionless aerodynamic coefficients (Maryniak, 1985) should be used

$$
\begin{aligned}
C_D &= C_{D0} + C_{D\alpha}\alpha + C_{D\alpha^2}\alpha^2 + C_{Dq}\frac{qc_a}{V} + C_{D\delta_e}\delta_e \\
C_Y &= C_{Y0} + C_{Y\beta}\beta + C_{Yp}\frac{Pb}{2V} + C_{Yr}\frac{Rb}{2V} + C_{Y\delta_a}\delta_a + C_{Y\delta_r}\delta_r \\
C_L &= C_{L0} + C_{L\alpha}\alpha + C_{Lu}\frac{u}{V} + C_{Lq}\frac{qc_a}{V} + C_{L\delta_e}\delta_e \\
C_l &= C_{l0} + C_{l\beta}\beta + C_{lp}\frac{Pb}{2V} + C_{lr}\frac{Rb}{2V} + C_{l\delta_a}\delta_a + C_{l\delta_r}\delta_r \\
C_m &= C_{m0} + C_{m\alpha}\alpha + C_{mq}\frac{qc_a}{V} + C_{m\delta_e}\delta_e \\
C_n &= C_{n0} + C_{n\beta}\beta + C_{np}\frac{Pb}{2V} + C_{nr}\frac{Rb}{2V} + C_{n\delta_a}\delta_a + C_{n\delta_r}\delta_r
\end{aligned}
\tag{2.15}
$$

where α and β denote the angle of attack and sideslip, P, Q, R are the roll, pitch and yaw rates, δ_a, δ_e, δ_r are aileron, elevator and rudder deflections, $C_D,\dots,C_n$ are dimensionless aerodynamic coefficients, $C_{D\alpha}, C_{L\alpha},\dots$ are aerodynamic parameters which denote partial derivatives $\partial C_D/\partial\alpha, \partial C_L/\partial\alpha,\dots$.

3. Identification algorithms

3.1. Non-Linear Filtering (FN) method

The FN theory formulated by Lipcer and Sziriajev (Anderson and Moore, 1984; Lipcer and Sziriajev, 1981; Ocone, 1981) consists in finding *a pair* of *stochastic processes* in a non-linear form of *Stochastic Differential Equations* (SDE)

$$
\begin{aligned}
dx_t &= [a(t,y) + b(t,y)x_t]dt + c(t,y)du_t \qquad & x_{t=0} = x_0 \\
dy_t &= [A(t,y) + B(t,y)x_t]dt + C(t,y)dw_t \qquad & y_{t=0} = y_0
\end{aligned}
\tag{3.1}
$$

where only the process y_t is observed, whereas u_t and w_t are independent *Wiener processes.*

Finding a solution to the filtering problem is possible on the following assumptions:

a) The right-hand side of 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).

b) The *a priori* distribution of the UPV is normal. Unknown parameters have often physical or technical meaning, thus we can determine their limiting values. However, if it is impossible to determine the range of those parameters, it is reasonable to make the aforementioned assumption.

c) The UPV is stochastically independent of the *Wiener process* w_t.

d) There exists an inverse to the matrix $[C^\top(t,y)C(t,y)]^{-1}$, i.e. the stochastic disturbances must affect the FO adequately.

e) The right-hand side of Eq. $(3.1)_2$ has a strong solution, which imposes the requirement for existence and uniqueness of the classic solution to the ordinary differential equation resulting from Eq. (2.10) 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) x when observing the process 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.
- The optimal estimator is directly represented by dynamics of the processes x and y.
- The optimal estimation at the instant $t+dt$ results from the optimal estimation at the instant t, supplied with a new observation in the interval $[t,t+dt]$, which allows for construction of a recursive filter.
- The solution is of the *on-line* type.
- When using fast computer systems, it is possible to reach *the real-time* solution.

So as to properly formulate the parameter estimation in terms of the filtering problem, the stochastic process x should be stationary and represented by the same UPV. That directly leads to formulation of a filtering problem in a specific form (Goszczyński, 2000).

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

For the UPV estimation purposes by means of the NF method, the equation of motion of the FO 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. Equation $(3.1)_2$ 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, 2000).

- The 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), equation of motion (2.3), representing evolution of the process x, may be presented in terms of the measurement vector.

3.1.2. Application

The model of a controlled aircraft in 3D-flight (2.3) within the framework of non-linear filtering theory (FN) can be represented in the form
$$\dot{\boldsymbol{x}}_d = \mathbf{B}^{-1}\boldsymbol{g}(\boldsymbol{x}_d, t) + \mathbf{B}^{-1}\boldsymbol{f}(\boldsymbol{x}_d, t) \tag{3.5}$$

where

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

It 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

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

which we consider as the *observation equation* (in the NF theory sense), where $\omega_t \geqslant 0$ is the 6D *Wiener process* representing the influence of stochastic factors on the aerodynamic forces and moments.

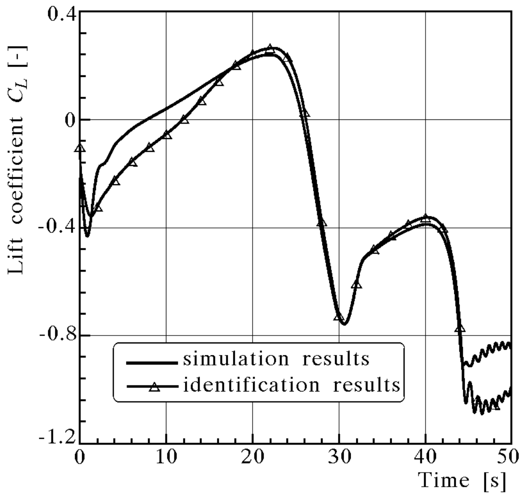

Fig. 4. Identification of the lift coefficient C_L (FN)

3.2. Estimation Before Modeling (EBM)

The EBM consists of the following two-steps (Goszczyński *et al.*, 2000)[7]:

Step 1 – estimation of the state vector using a filter;

Step 2 – modelling itself, e.g. by means of the regression method

$$\widehat{\boldsymbol{z}} = \mathbf{A}\widehat{\boldsymbol{p}} + \widehat{\boldsymbol{\varepsilon}} \tag{3.8}$$

where

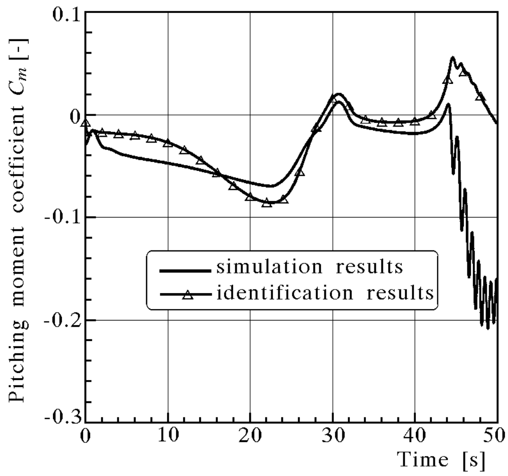

Fig. 5. Identification of the pitching moment coefficient C_m (FN)

$\widehat{\boldsymbol{z}}$ – 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 Mańczak and Nahorski (1983))
$\widehat{\varepsilon}$ – vector of errors with zero mean values and a constant covariance matrix.

The problem of the model parameters identification is schematically presented in Fig. 6. The EBM method is one of the *equation error methods*, with its name adequately representing the order of operations to be performed (Goszczyński *et al.*, 2000).

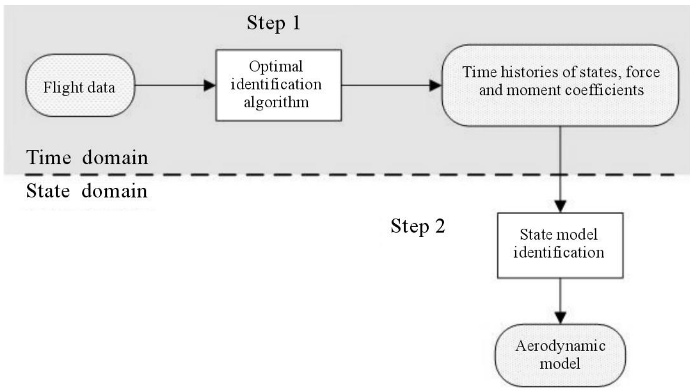

Fig. 6. Overwiew of the Estimation Before Modelling technique (Stalford, 1979)

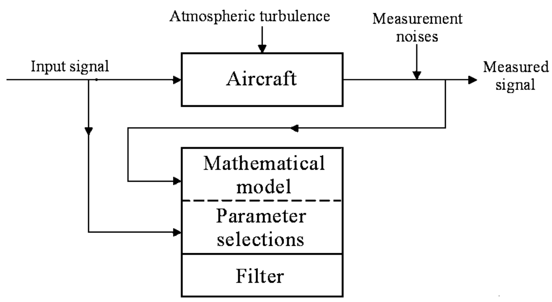

Fig. 7. Concept of the EBM method (Goszczyński *et al.*, 2000)

A crucial role in the EBM plays the aerodynamic modelling in terms of the state equation, for the requirements of Kalman's filter theory to be met. To this end, each component of the vector of aerodynamic forces and moments is represented in the form of the Gauss-Markov process $(i = 1, \dots, 6)$

$$\dot{\boldsymbol{x}}_{di}(t) = \mathbf{K}_i(t)\boldsymbol{x}_{di}(t) + \mathbf{G}_i\boldsymbol{\zeta}_i(t) \qquad \boldsymbol{x}_{di}(0) = \boldsymbol{x}_{di0} \tag{3.9}$$

where

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

$$\mathbf{K}_i = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \tag{3.10}$$

The state estimates obtained in the first step of the EBM method are the input data for 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.

Selection of the aerodynamic model structure is of crucial importance. Usually, the linear regression technique is used, in which n parameters $(N \geqslant n)$ are determined from N measurements, and a simple parametrical model in the following form (corresponding to Eq. (3.5)) is assumed

$$\boldsymbol{y}_i = \mathbf{X}_i\boldsymbol{p}_i + \boldsymbol{e}_i \qquad i = 1, \dots, 6 \tag{3.11}$$

where

$\boldsymbol{y}_i$ – vector of aerodynamic forces or moments of the Nth order
$\mathbf{X}_i$ – matrix of independent variables of the $(N \times n)$th order
$\boldsymbol{p}_i$ – - vector of unknown parameters of the nth order
$\boldsymbol{e}_i$ – - error vector of the Nth order.

Applying the least square method, by virtue of Eq. (3.3) (the relation between the state and measurement vectors is linear) we arrive at the equation

$$\widehat{\boldsymbol{p}}_i = (\mathbf{X}_i^\top \mathbf{X}_i)^{-1} \mathbf{X}_i^\top \boldsymbol{y}_i \tag{3.12}$$

representing explicitly the identification process.

Usually, at high angles of attack, aerodynamic characteristics are strongly non-linear depending on the state and control vectors (2.3) in an unknown way. The function $\mathbf{X}_i(\mathbf{x}_d, t)$ is represented in the form of splines or polynomials with unknown coefficients $\boldsymbol{p}_i$. 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.

3.2.1. State estimation

In the first step, realised by means of the filtering technique, the extended Kalman filter is applied (Goszczyński, 2000; Goszczyński *et al.*, 2000). The loading introduced this way can be reduced by means of linear smoothing, e.g. by employing the modified Bryson-Frazier filter. An alternative approach consists in application of the smoothing with a constant delay, which may occur to be simpler and less time-consuming, giving at the same time both the smoothing and estimation of the state variable derivatives.

3.2.2. Estimation of parameters

The second step of the EBM method is reasonably called "modelling". This approach gives an insight into mechanical models of flight being currently in use (Goszczyński *et al.*, 2000). Whenever an identification is to be made within the area of substantial changes in values of physical quantities, which of course strongly affect values of parameters, it must be preceded by a proper selection of subdomains. In each subdomain, a separate identification is realised (Batterson and Klein, 1989).

The selection of the model structure consists in multiple application of the linear regression technique (3.5) (Goszczyński *et al.*, 2000). It results from the step-by-step introduction and removal of independent variables. An independent variable, which might be the best single variable at the previous step, could be needless in the next step, which can be checked by using the Fisher-Snedecor test (test F) (Draper and Smith, 1973).

The EBM method can be most efficient for determination of aerodynamic characteristics at high angles of attack (Mulder *et al.*, 1994; Stalford, 1979, 1981; Stalford *et al.*, 1977). Several advantages should be mentioned (Sibilski, 1998):

- *A priori* estimation of aerodynamic characteristics before modelling allows for more accurate determination of input data at the modelling step.

- Estimation and identification of aerodynamic derivatives do not require construction of models depending on state parameters.

- Simultaneous reconstruction of many manoeuvres leads to better precision in the identification of aerodynamic derivatives.

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

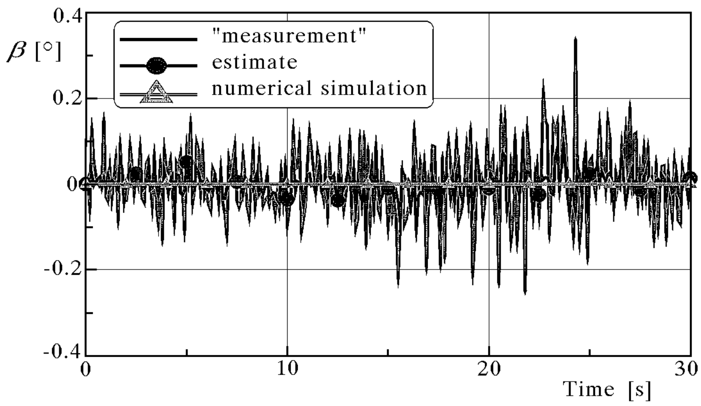

Fig. 8. History of the sideslip angle β (EBM)

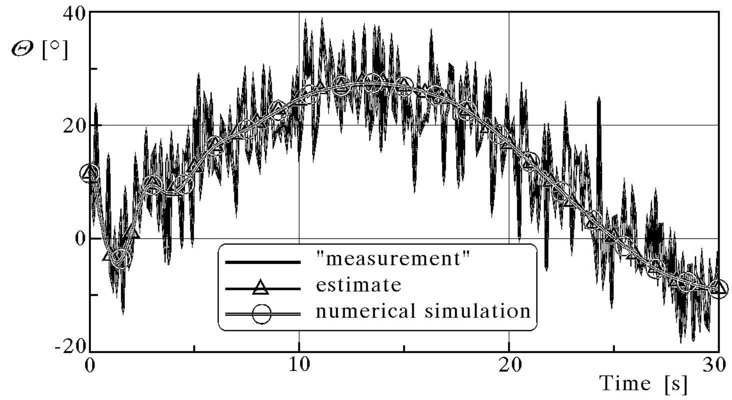

Fig. 9. History of the pitch angle Θ (EBM)

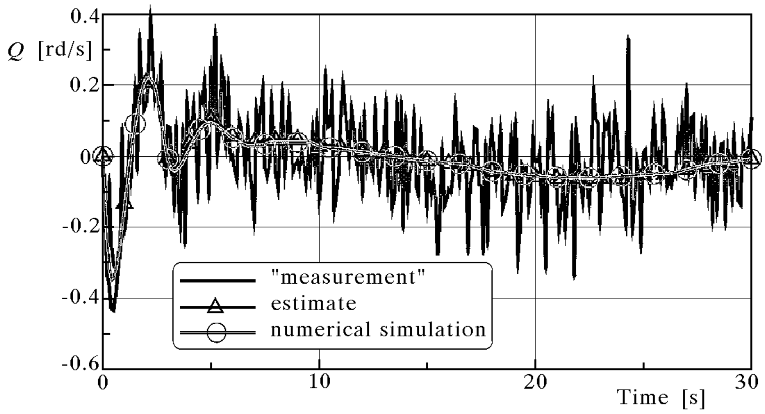

Fig. 10. History of the pitch angular velocity Q (EBM)

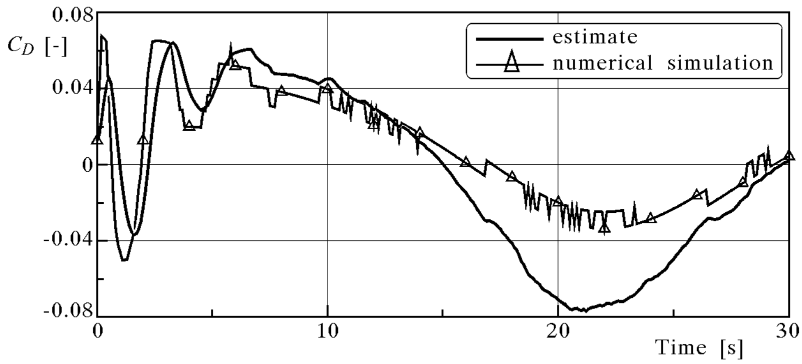

Fig. 11. Estimation history of the aerodynamic drag coefficient $C_D = f(t)$ (EBM)

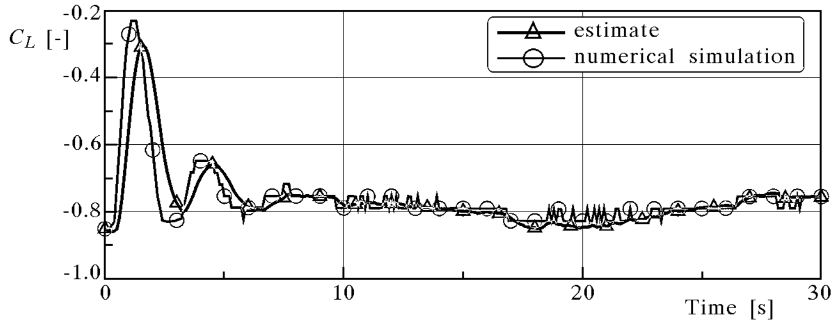

Fig. 12. Estimation history of the aerodynamic lift coefficient $C_L = f(t)$ (EBM)

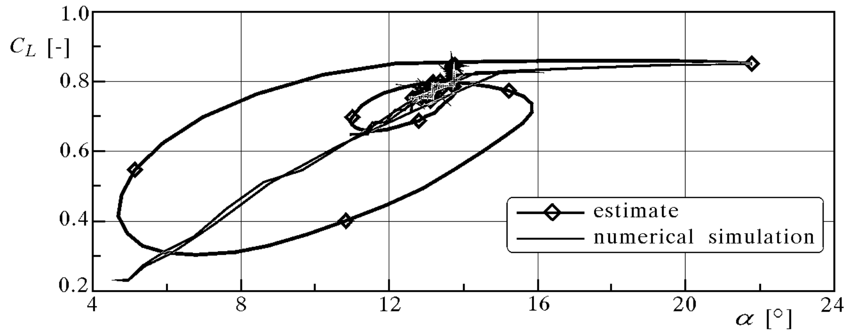

Fig. 13. Estimation of the aerodynamic lift coefficient $C_L = f(\alpha)$ (EBM)

4. Conclusions

The results of numerical tests of the presented methods are promising. 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. Investigations of the application of the presented methods to the problem of a six-degree-of-freedom aircraft are being conducted (Goszczyński *et al.*, 2000) based on real flight data records.

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Praktyczne uwagi w identyfikacji charakterystyk aerodynamicznych

Streszczenie

W pracy przedstawiono metodę estymacji przed modelowaniem (EBM), znaną również pod nazwą metody dwu etapowej identyfikacji charakterystyk aerodynamicznych (i ich pochodnych). Przedstawiona technika jest szczególnie przydatna do identyfikacji charakterystyk samolotu poruszającego się na dużych kątach natarcia i ślizgu. W pracy przedstawiono podstawowe cechy i zależności metody. Uzyskane wyniki, wraz z posiadaną wiedzą o zakończonych badaniach innych zespołów, pozwalają określić przedstawioną technikę jako potencjalnie integralną część badań rozwojowych i oceny każdego samolotu.

Manuscript received August 4, 2005; accepted for print September 26, 2005