FAST AERODYNAMIC DESIGN TECHNOLOGIES

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Abstract

The paper offers fast aerodynamic calculation technology for passenger aircraft in cruise flight regime, based on the application of efficient direct methods of aerodynamic calculation, mathematical apparatus of artificial neural nets and information technologies. Examples are given of the application of the methods concerned in the phase of preliminary design.

1 Introduction

Creation of fast modules for evaluating the aerodynamic characteristics of passenger aircraft in cruise flight regime is an urgent problem of practical value [1-2]. Any design system may be conventionally divided into two modules: a generator of the design objects and a module for evaluating the design object characteristics.

To begin with, it is necessary to develop a mathematical model of the aircraft (A/C) layout class involved and a module for random generation of aerodynamic layouts and their elements in the prescribed parameter range, using dimensionality reduction techniques. The ability to create objects having desired properties is the most important feature of the object generation module. The design process is, in this case, significantly simplified.

Then, it is necessary to calculate the flow about the layouts concerned in the prescribed range of free stream parameters and create the database. It is but natural that the choice of the design method and the field of its application imposes certain requirements on the method of describing the data used, in particular, on the mathematical model structure and method of the aircraft surface description.

The data obtained enable the approximators for the output parameters studied to be created [3]. In the present case the approximators are developed, based on the artificial neural nets (ANN), which allows the time of the design process to be significantly reduced. Creation of the qualitative object generation module is of great importance in the phase of the ANN learning sets production in the aerodynamic characteristics evaluation module.

2 Description of the A/C layout mathematical model

As an object of study passenger aircraft layouts in “wing – fuselage” and “wing – fuselage – tail unit” configurations (Fig. 1) are considered for which cruise flight aerodynamic characteristics are to be calculated.

Detailed description of the aircraft surface is used as source information both for grid methods of aerodynamic calculation (CFD codes) and engineering approaches. To describe the three-dimensional aircraft surface in detail a huge dimension vector is used that contains thousands of parameters whose greater part, if separately considered, have no explicit meaning. It is impossible to use vectors of such dimensionality as the approximator (ANN) input data. To describe the aircraft surface requires another methods.

The 3D surface description dimensionality can be reduced only in case of restricting the class of layouts considered. Formally, surfaces of the aircraft class considered should be described by a moderate number of parameters (several hundred) which involve all the principal integral geometric characteristics routinely used to describe the layouts of the class considered and fully specifying the most essential aerodynamic and structural properties. The parameter dimensionality and structure are supposed to be the same for layouts of the class concerned.

Fig. 1. Passenger aircraft layouts under consideration

A small set of parameters may definitely characterize a layout only if additional aircraft surface assumptions have been made. In other words, at issue is construction of an aircraft surface mathematical model defined by a small number of parameters. The model should be selected so that in varying its parameters (within the limits prescribed) the existing aircraft and those under design may be described in sufficient detail to determine the aerodynamic characteristics with an adequate degree of accuracy and a comparative analysis of similar layouts different in the model parameters conducted.

Generally accepted is the practice of using approximate mathematical models of the surface instead of its detailed description. In the phase of preliminary design and drafting approximate aircraft mathematical models are used that allow aerodynamic characteristic to be calculated with accuracy adequate for the stages involved. Thereby, the aircraft surface mathematical model comprises:

- a variety of surface assumptions that limit the class of layouts considered and allow the surfaces to be specified by a small number of parameters;
- a set of the model parameters that are explicitly determined through detailed surface description;
- a range of the model parameter values.

Wing Model (Fig. 2) is defined by describing its planform, selecting the dihedral angles, tables of airfoil coordinates in the selected sections, spanwise distribution of twist angle ε and airfoil thickness ratio $\overline{C}$. The planform is specified by the total area aspect ratio (AR), base trapezium taper ratio (TR = C_2/C_0), relative areas of the leading edge (S_1/S_0) and trailing edge (S_2/S_0) extensions, leading edge (x_1, y_1) and trailing edge (x_2, y_2) kink position, quarter-chord base trapezium sweep angle (χ_{25}), dihedral angles of the root (ψ_0) and tip (ψ_1) wing parts.

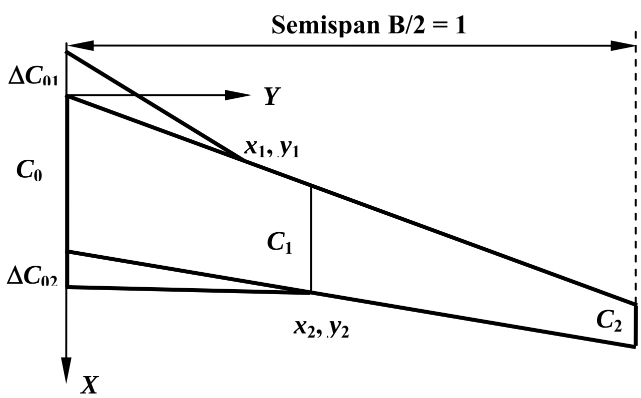


Fig. 2. Wing model

In forming a **fuselage model** the following assumptions have been made. The fuselage is composed of a nose, cylindrical and tail parts (Fig. 3). Each part has some fixed forms of upper, lower and side lines. All the fuselage cross sections $S(x)$ are of the same form. The cross section form difference from ellipse is determined by an additional form parameter. The fuselage lines for the nose, central and tail sections are described by different analytical functions.

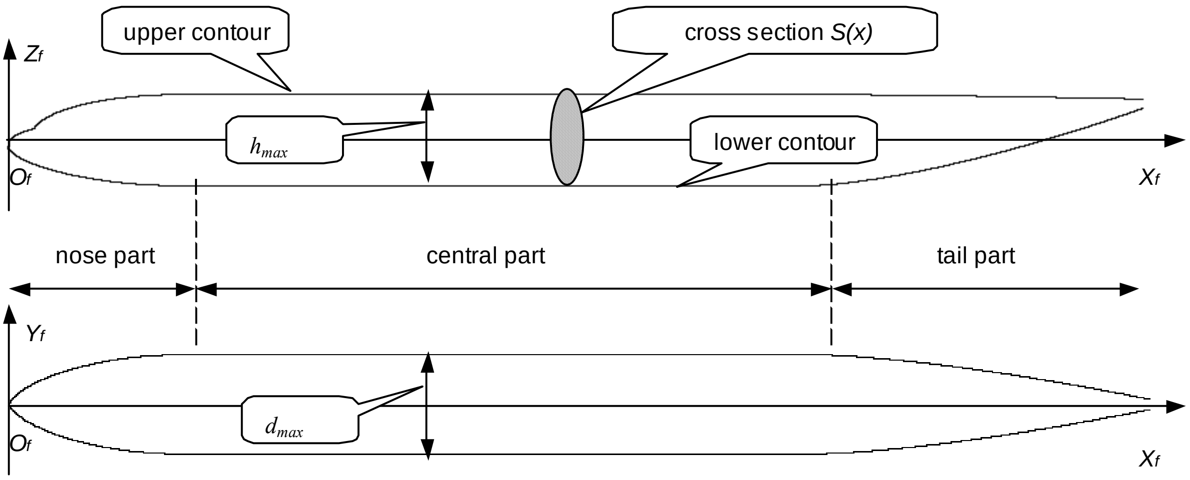


Fig. 3. The fuselage view in longitudinal vertical section and horizontal projection

Tail unit model includes models of horizontal (HT) and vertical (VT) tails that are fully specified by the two end (root and tip) sections with symmetrical airfoils installed in them. The model of the relative position of the layout components specifies the relationship of the airframe base elements.

The ranges of variation in geometric parameters of the wing, fuselage and tail unit models are chosen in conformity with the actual values of the existing airliner parameters.

2 Forming the set of A/C layouts

To form the learning set about 10000 "wing–fuselage–tail unit" and over 12000 "wing–fuselage" layouts have been preliminary generated by the vector component random generation within the ranges prescribed. Used is a method of object generation with the aid of replicative ANN [4] described below. Airfoil wing sections were selected at random from the base of airfoils or formed with the aid of replicative ANN.

These are available to download at address with airfoils taken as an example, considered is the replicative ANN application for generating objects with prescribed aerodynamic and geometric parameters. The usage of the ANN concerned allows the dimensionality of space applied for describing the airfoil surface to be significantly decreased and qualitatively new A/C design systems to be developed [5].

The replicative (duplicating) ANN are one of the subtypes of multilayer perceptrons. The architecture of these nets is symmetrical (Fig. 4) with the first and last layers having the same number of neurons equal to the input vector length and with the mid-layer being a narrow throat of significantly smaller dimension. The first and the last layer are called an input and output layer, respectively, the middle one is called a hidden layer.

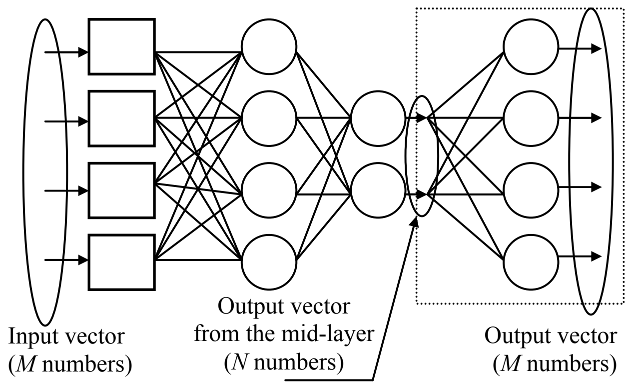


Fig. 4. Replicative ANN

The replicative ANNs were first suggested for solving the problems of data compression [4]. Consider a three-layer perceptron having the same number of neurons in input and output layers. Let the number of the hidden mid-layer elements be much less then in input and output layers and as a result of learning the ANN can duplicate the same output vector as that fed to the input layer. The ANN concerned compresses the data over the area from the input layer to the hidden one and decompresses them from the hidden to the output layer. Hidden layer elements generate representation of each vector whose dimension is smaller than the length of the input vector (Fig. 5). In fact, the replicative ANNs enable data dimensions to be reduced by transition to the so-called "natural" coordinates. In case the neurons with linear transfer functions are used, the present approach results in the known method of principal components analysis (PCA) [6].

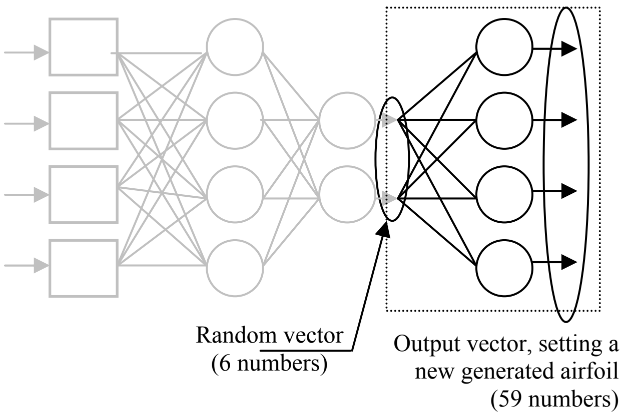


Fig. 5. New airfoil generator: setting the airfoil geometry from the random vector in the compressed data space

Generation of random objects similar to those on which learning occurred is another application of the replicative ANN. Using a random number transducer, points are generated in the N-dimensional space region restricted by the minimum and maximum values of the neuron mid-layer outputs. If these N-dimensional vectors are to be fed to the output layer of the learnt replicative ANN, vectors of the original M-dimensional space are obtained corresponding to the points in the space of natural coordinates. The objects generated refer to the same class as the original ones.

With airfoils taken as an example, the following problem is solved. There is a set of airfoils for three-layer replicative ANN learning. The net has an input and output layer of great dimensionality (59 inputs – outputs) and a narrow throat which is a hidden layer of much less dimension (6 neurons). The ANN involved is capable of compressing data from the input layer dimension to that of the hidden mid-layer. The task is to generate new airfoils using the learnt net mentioned.

The initial set used for ANN learning consisted of about 300 airfoils whose shape is specified by 59 points. The replicative ANN with linear activation functions was used, i.e. the method of principal components was actually applied.

The decompression part of this net learnt was used as an airfoil generator. To this effect a signal in the form of a 6-component vector is applied to the hidden layer output (the input of the output layer). The vector components are randomly distributed and limited by extreme values of the respective initial set components. That is, they lie in the dense set of compressed data. Thereafter, a 59-componenet vector is obtained from the output layer that specifies a new airfoil. Fig. 6 gives typical shapes of the airfoils obtained by the present approach.

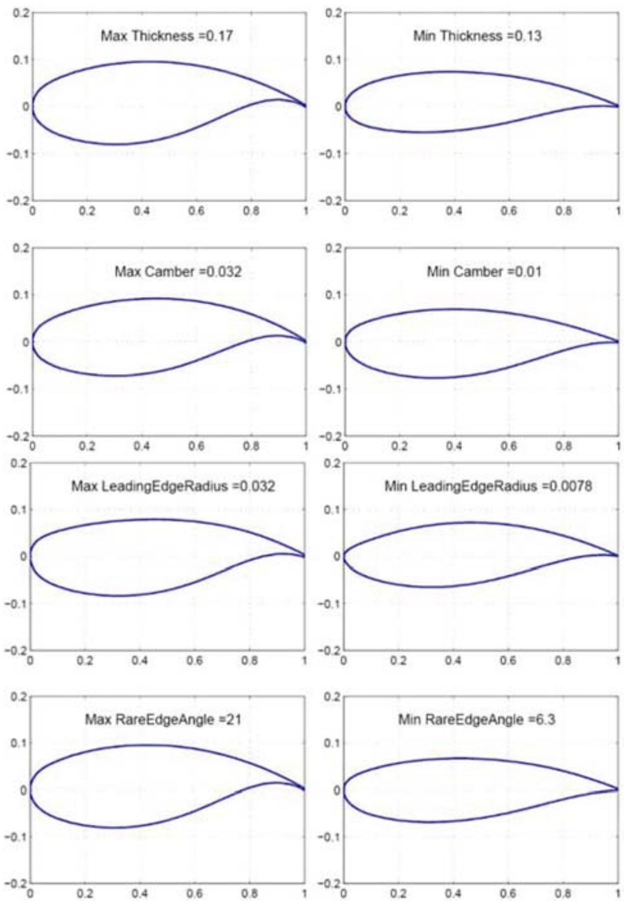


Fig. 6. Airfoils of the set randomly generated in the 6-dimensional space

3. Artificial neural nets tuning and learning, evaluation of the aerodynamic characteristics determination accuracy

To determine the aerodynamic characteristics calculations have been made using CFD-code BLWF [7] in which a boundary-value problem is solved for full velocity potential equation. Viscosity is allowed for in the boundary layer approximation with fixed position of the laminar-to-turbulent transition. The method concerned simulates the occurrence of local supersonic areas and shock waves, provides computation flows with small separation zones and is reliably verified.

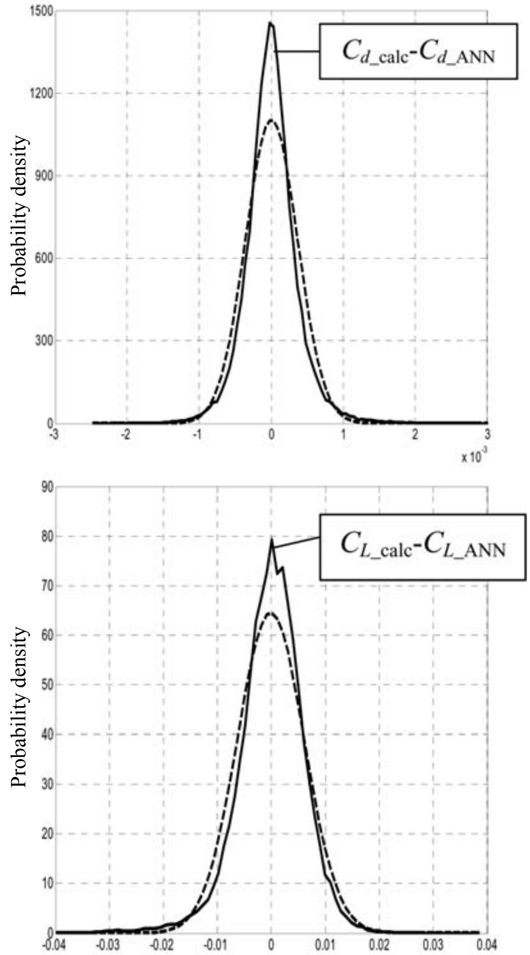
The results obtained have been used to form the database (a variety of patterns) to be used for ANN learning and testing. To produce the aerodynamic characteristics approximators an ANN of a multilayer perceptron type were used.

Fig. 7 gives an error density distributions of the drag coefficient C_d and lift coefficient C_L evaluation. Difference in values obtained in direct calculation and from approximation is shown by a solid line. The dashed line shows normal distribution with the same standard deviation. The accuracies obtained are quite adequate for carrying out the aerodynamic layout analysis in the phase of preliminary design.

Table 1 gives mean absolute and relative errors in evaluating drag coefficient C_d, lift coefficient C_L and derivatives of the lift coefficient and pitching moment by angle of attack C_L^a, C_m^a and HT setting angle C_L^{IHT} and C_m^{IHT}.

Characteristic	Mean absolute error	Mean relative error, %
C_L	0.00390	0.8
C_L^a	0.00200	1.4
C_L^{IHT}	0.00026	1.1
C_m^a	0.00470	2.3
C_m^{IHT}	0.00076	0.9
C_d	0.00030	1.5

Table 1



a
b

Fig. 7. Error density distribution of C_d and C_L evaluation (Re = $3{\cdot}10^7$)

4 Comparative analysis of aerodynamic perfection

In solving the design problems it is necessary to evaluate and compare the aerodynamic perfection of several layouts that differ in a number of parameters such as sweep, aspect ratio, leading edge extension value and wing thickness distribution. As a rule, direct recalculation does not show to what extent one layout is better or worse than the other. It is very often impossible to define what the difference in characteristics is due to – the planform or wing shaping. And naturally, it is impossible to assess how well the wing shaping has been chosen without solving the surface shape optimization problem with prescribed limitations. Application of neuronet technologies enables the problems concerned to be solved and modules to be created which, in the process of design, allow the perfection of the version obtained to be practically instantly compared to the base level.

In the previous examples a parameter vector fully describing the layout was applied to the ANN input. Consider the case when a vector of smaller dimension including only parameters of the wing planform and its average thickness is applied to the input. After ANN learning an actual approximation function is obtained allowing the aerodynamic characteristics to be determined with a small number of parameters specifying the wing planform.

Fig. 8 shows comparison of the total drag $C_{d\ \mathrm{total}}$ evaluation accuracy obtained using the full and shortened input vector, in the form of the error probability density distribution. The results cited show that allowance for wing airfoil shaping in ANN learning several times improves the aerodynamic characteristics evaluation accuracy.

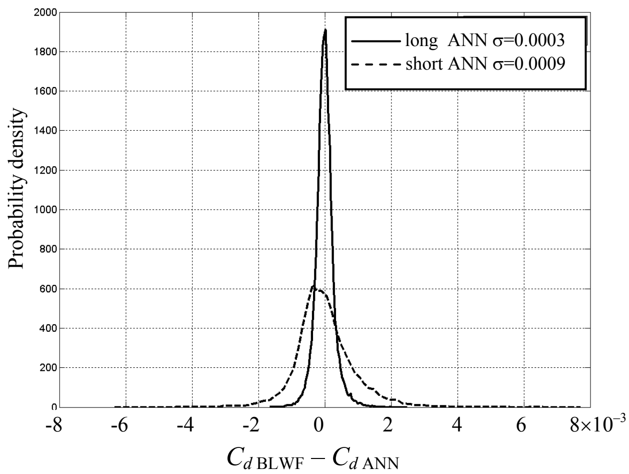


Fig. 8. Error probability density distribution in determining $C_{d\mathrm{total}}$. Solid line is “long” ANN, dotted line – “short” ANN input vector

Therewith, difference in the aerodynamic characteristics obtained with the use of “long” and “short” ANN, depending on the number of the input parameters, makes it possible to assess the quality of the choice of wing airfoil shaping for the layout involved. In fact, estimation of aerodynamic characteristics using ANN with a small number of input parameters gives an average level of aerodynamic characteristic for the planform and mean wing thickness ratio concerned based on the sample of versions used for ANN learning. Calculation or estimation of aerodynamic characteristics using ANN with full input vector gives aerodynamic characteristics of a particular version. The more it differs (to the better) from the average, the more qualitative is the choice of wing airfoil shaping. Based on this consideration, it is easy to create a module ensuring fast design system version sorting.

Figs. 9-10 demonstrate results of application of the approach concerned for the wing design, with replicative ANN being used in the capacity of the data generator.

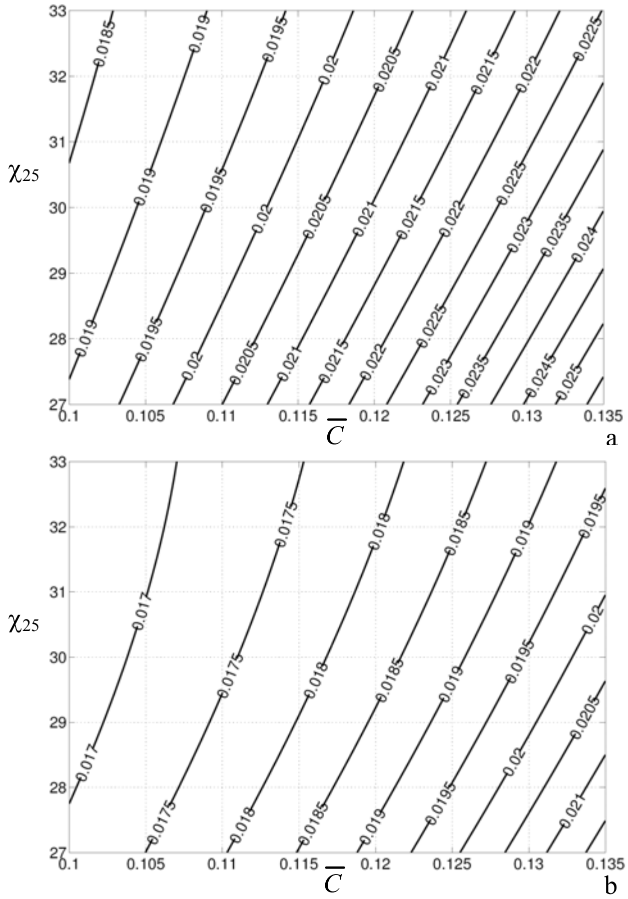


Fig. 9. $C_{d\mathrm{total}}$ distribution in variables $\overline{C}$ – χ_{25}
a) initial, b) obtained

Values of $C_{d\mathrm{total}}$ corresponding to the initial wing sample are given in Fig. 9a against wing mean thickness ratio $\overline{C}$ and sweep at quarter chord χ_{25}. After the sorting procedure only those wing forms were left which exceed the average level of lift to drag ratio at $C_L = 0.5$ within the range of M numbers from 0.7 to 0.8. The sample obtained was used for learning the replicative ANN with 41 neurons in the hidden layer. After learning ANN was used as a data generator and the aerodynamic characteristics were evaluated using BLWF code computation. 3998 layouts were created. The computational data obtained were used for learning new ANN with short input vector.

Fig. 9b gives $C_{d\text{total}}$ values consistent with the new wing sample. Drag coefficient level for the new sample is seen to have decreased, on average, by 0.0030. Contour patterns in variables $\overline{C}$ – χ_{25} are obtained for the layout with invariable fuselage shape and constant wing aspect ratio, taper ratio, leading and trailing edge extension values (Fig. 10).

Fig. 10. View of the layout

5 Aerodynamic drag minimization

Application of fast models in designing minimum drag wing at M = 0.8 and $C_L = 0.5$ is considered. In the course of design airfoil shapes were varied in 10 wing sections. The wing planform, thickness distributions and twist remained constant and were specified by the initial layout selection. The problem was solved according to the diagram in Fig. 11. Here σ_{PCL} is root-mean-square deviation in the space of the compressed (natural) coordinates.

12 iterations of generation, estimation and choice of the minimum drag layout have been performed. Fig. 12a shows variation in the total drag coefficient $C_{d\text{total}}$ where the layout number is plotted on abscissa axis. The first number corresponds to the initial layout. Drag reduction is seen to occur during the first 7 – 8 iteration. Changes in the components of drag coefficient are shown in Fig. 12b (induced $C_{d\text{ind}}$), Fig. 13a (profile $C_{d\text{FP}}$) and Fig. 13b (wave $C_{d\text{wave}}$).

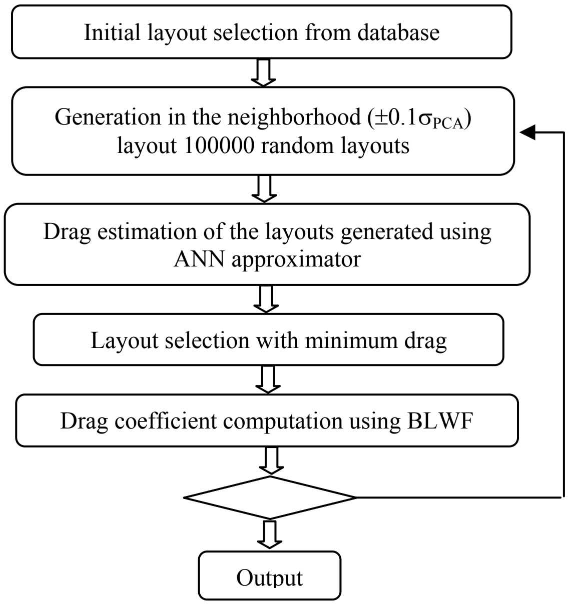


Fig. 11. Diagram of the problem solution

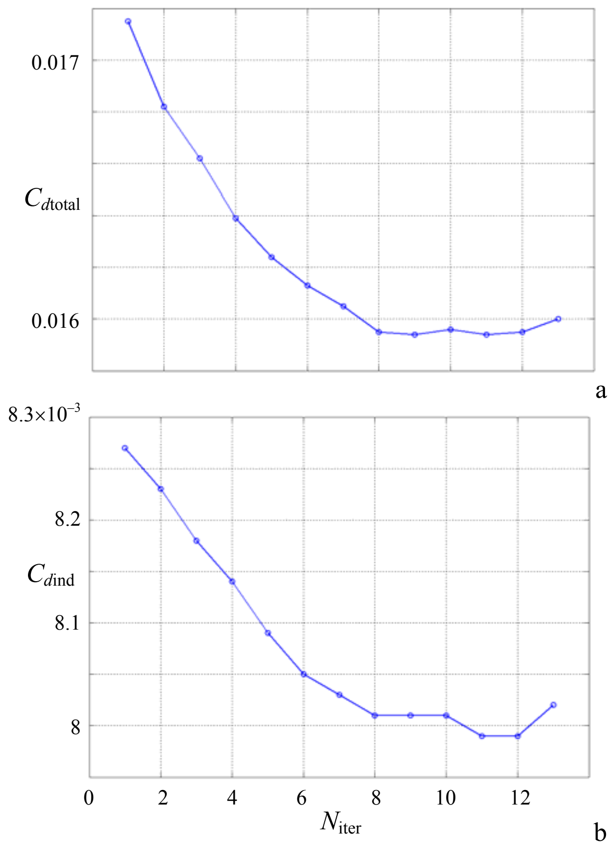


Fig. 12. Variations in total and induced drag coefficients

Fig. 14 shows spanwise distribution of the wing twist ε and thickness $\overline{C}$. Shapes of aerodynamic airfoils in wing sections $\overline{Y} = 0.1$; 0.5; 1.0 obtained for the initial layout No. 0 and layouts Nos. 8 and 9 are shown in Fig. 15. The layout overall view is shown in Fig. 16. Fig.17 gives isobar patterns.

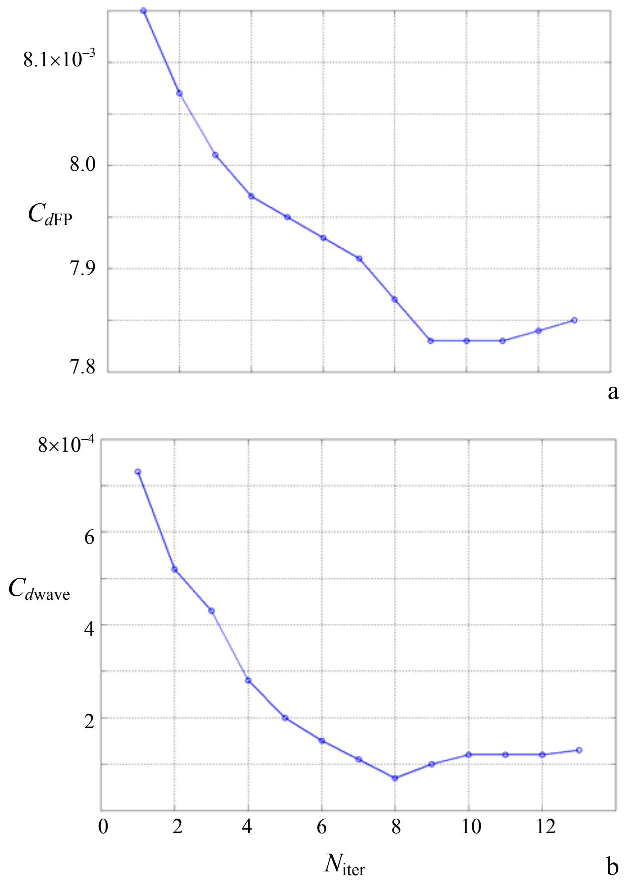


Fig. 13. Variations in pressure and wave drag coefficients

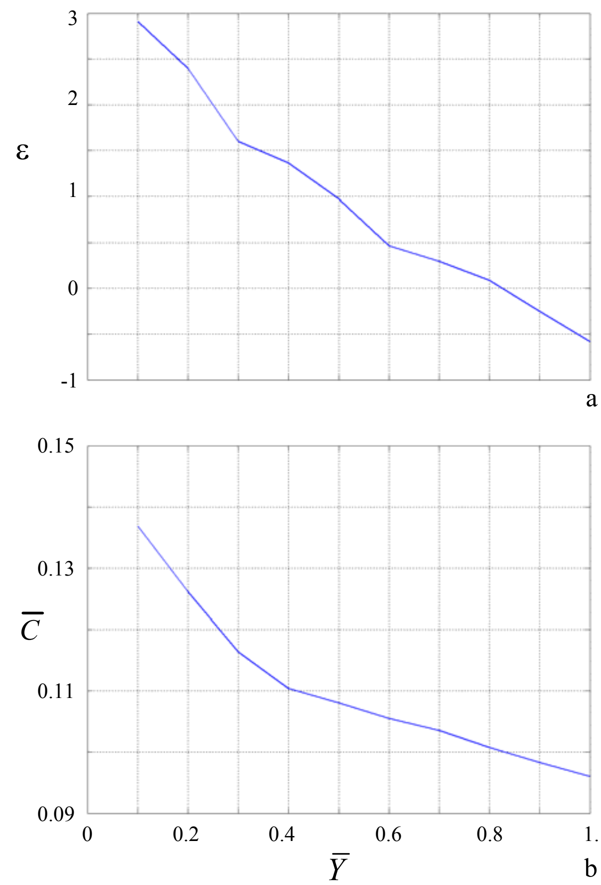


Fig. 14. Spanwise distributions of twist and airfoil section thickness

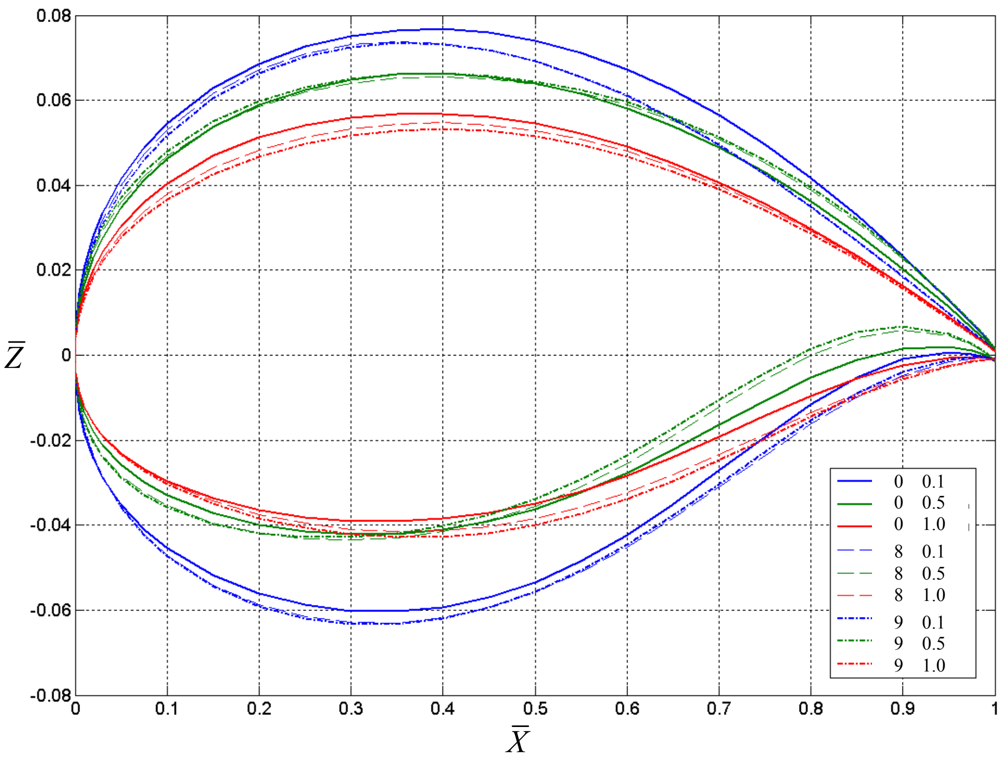


Fig. 15. Airfoil shapes obtained

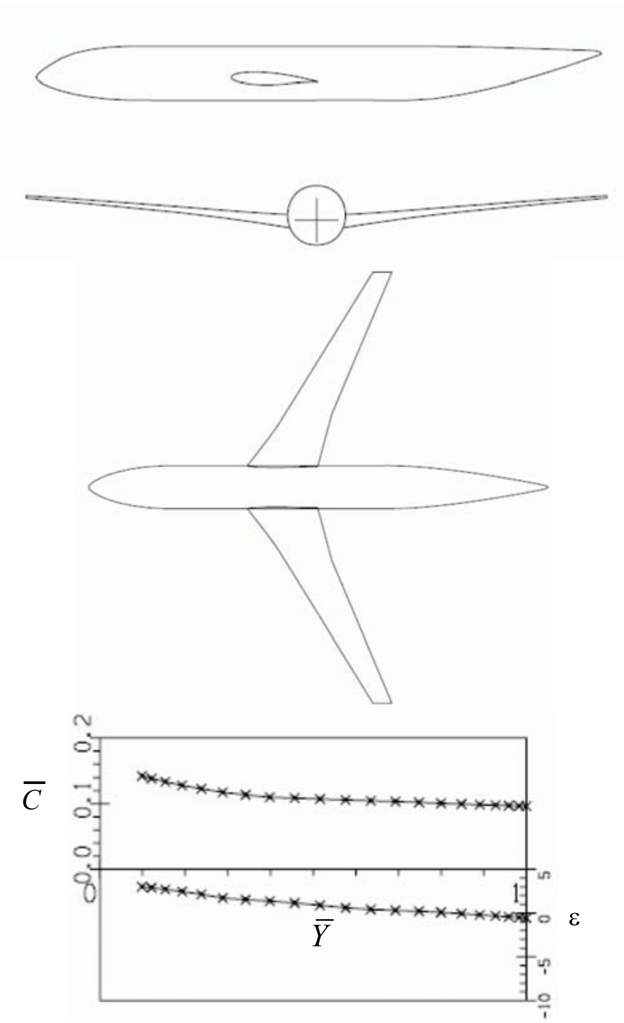


Fig. 16. Overall view of the layout

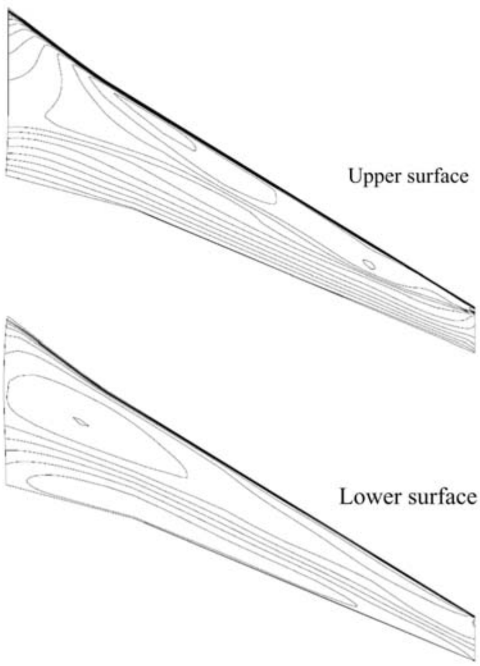


Fig. 17. Isobar pattern (M= 0.8, α = 0.65°)

Total time for CPU to perform one iteration on PC amounted to 11.3 seconds, with generation of 100 000 layouts taking 1.1 seconds, evaluation of aerodynamic characteristics using fast model of 100 000 layouts – 3.2 seconds and BLWL code computation of one the best layout – 7 seconds.

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