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THE USE OF ARTIFICIAL NEURAL NETWORKS IN THE DESIGN OF AERODYNAMIC PROFILES OF A ROTOR OF A HELICOPTER

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Abstract

The authors showed the possibility of using mathematical models based on artificial neural networks to determine the aerodynamic characteristics of helicopter profiles, as well as the ability to design new profiles with specified aerodynamic characteristics. At the first stage of work, an approximation model based on a neural network of the multilayer perceptron type was created to determine the coefficients of lift, drag, and pitch moment of the profiles. This topology has a number of distinctive features and is well suited for solving such problems. Neural network training was conducted. As a training set, the calculated data of 3692 aerodynamic profiles were used. The accuracy of the approximation of aerodynamic characteristics was estimated. The expediency of using artificial neural networks to solve this class of problems was substantiated. At the second stage of work, to obtain the geometry of new profiles, a mathematical model was created on the basis of special classes of artificial replicative neural networks, which allowed us to significantly reduce the dimension of the space used to describe the surface of the aerodynamic profile and create a qualitatively new design system. Examples were given of using the system for creating profile families in the region of specified aerodynamic characteristics and limiting the maximum relative thickness of the profile

Keywords

Design, aerodynamic profile, neural network, data interpolation, neural network approximator

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Introduction. It is known that in the design of a new helicopter a reliable determination of the aerodynamic characteristics of all its elements is of fundamental importance. At the same time, the flight characteristics of the new machine largely depend on the aerodynamic perfection of the rotor, which cannot be achieved without the choice of basic aerodynamic profiles that provide the required aerodynamic characteristics of the rotor blade in the entire range of flight modes [1–5]. Currently, methods of both CFD and experimental aerodynamics are widely used to search for optimal parameters of aerodynamic profiles.

In the early stages of the development of the aircraft industry, the design of profiles was based mainly on the methods of experimental aerodynamics. Progress in computational approaches allows calculating the aerodynamic characteristics of profiles, which significantly speeds up and cheapens the process of designing a rotor blade. However, the direct application of modern numerical approaches for calculating aerodynamic characteristics at the preliminary design stage leads to a significant increase in the time and complexity of this process.

The methods currently used to determine the characteristics of aerodynamic profiles can be divided into two large groups:

- based on the numerical solution of the system of equations of continuum mechanics;
- based on the generalization and interpolation of previously obtained experimental and calculated data.

Traditionally, to evaluation the aerodynamic characteristics, the methods based on the numerical solution of the system of gas dynamics equations and describing the physical processes and phenomena when the flow around the profile occurs, were used. Numerical methods, as a rule, require the attraction of significant computing recourses for the calculations themselves and labor for the preparation of the source data. This significantly reduces the possibilities of their use, especially at the stage of preliminary (conceptual) design, where a large number of variations are considered and the price of an incorrectly chosen solution is high.

Attempts to circumvent the shortcomings of the above methods of mathematical simulation have led to the development in recent years of mathematical models based on a generalization of the available experimental and calculated data. Such models are based on the results of field and/or computational experiments conducted with various objects of the class in question, with minimal involvement of knowledge from the subject area (process physics) [6, 7]. In other words, models are “trained” on a variety of input and output data prototypes.

They are capable of imitating (replacing) both data sources based on some initial model, and models created on the basis of solving gasdynamic equations. Adaptive models constructed in this way are also called surrogate models. Both models (initial and surrogate) should have the same set of input and output data, and the results of both models (for the same input data) should be close.

Currently, surrogate models created on the basis of neural networks are successfully used in solving various problems of aerodynamic design. Reviews of the use of such models in the field of aerodynamic design are presented in [7, 8]. The advantages of surrogate models are as follows: they have high speed (hundreds of thousands of times faster than modern numerical methods), require minimal computational resources, allow the use of previously obtained calculation and experimental data, and prevent cases of non-receipt of the result due to a solution divergence, which is typical for numerical methods. The disadvantages of neural network surrogate models include the need for a large amount of data to configure and train neural networks and model verification. Examples of the use of neural network models in the design of aerodynamic profiles for aircraft for various purposes are given in [9–12].

This paper presents the results of applying neural network models to the problem of designing an aerodynamic profile with structural and aerodynamic constraints typical of helicopter rotor profiles.

The first part describes the aerodynamic characteristics of neural network profiles used as approximators. The obtained estimates of the accuracy of approximation of the main aerodynamic characteristics of the profiles are presented. The second part is devoted to the creation on the basis of neural networks of a special type of profile geometry generation module with specified aerodynamic and structural characteristics. The final part provides an example of the application of the proposed approach for generating a series of aerodynamic profiles with predefined properties.

The use of ANN to assess the aerodynamic characteristics of profiles. To approximate the aerodynamic characteristics of the profile, neural networks of the multilayer perceptron type (multilayer forward propagation network) were used. Such networks, as a rule, consist of many sensory elements (input nodes) that form the input layer of one or more hidden layers of computational neurons, and one output layer of neurons. Multilayer perceptrons have three distinguishing features:

- each neuron has a smooth (everywhere differentiable) nonlinear activation function (usually sigmoidal) [6];
- the network contains one or more layers of hidden neurons that are not part of the input or output of the network;

• the network has a high degree of connectivity through synoptic connections.

The combination of these properties provides high processing power of the multilayer perceptron. It is known that such a network has sufficient accuracy and rate to predict [6].

At this stage, the training of neural networks was conducted. Training of a neural network is understood as the process of minimizing the deviation of output values on the available data (training set) by determining the weight coefficients of neurons.

As a training set we used calculated aerodynamic lift coefficient C_y, resistance coefficient C_x and pitching moment coefficient m_z for 3692 aerodynamic profiles in the range of angles of attack from −1.5° to 16.5° and Mach numbers M from 0.3 to 0.82 with a constant Reynolds number Re = $3 \cdot 10^6$. In total, the training set contained 342 000 calculation points. The approximation errors (RMS deviations) by the neural networks of aerodynamic coefficients were: drag coefficient C_x $\sigma(C_x) \approx 0.00025$, pitch moment coefficient m_z $\sigma(m_z) \approx 0.00032$, lift coefficient C_y $\sigma(C_y) \approx 0.0062$. The calculated data was obtained using the VISTRAN code [13].

A comparison of the calculated (obtained using numerical methods) and approximation (obtained using neural networks) dependences of the lift coefficient C_y on the angle of attack α and polar for randomly selected profiles are shown in Fig. 1. The results obtained for two Mach numbers 0.3 and 0.78 presented.

The results show that the use of artificial neural networks allows a fairly reliable assessment of the basic aerodynamic characteristics of the profiles. At the same time, neural networks provide high productivity: less than one was needed to evaluate one variation 10^{-5} s at CPU Intel Core i7-3820 3.60GHz.

The use of a special type of ANN to generate many random objects similar to the original. To create many new aerodynamic profiles similar to those on which the training took place, a mathematical model was applied based on replicative neural networks, which are one of the subspecies of multilayer perceptrons. These networks have a symmetrical architecture. Mandatory attributes of such neural networks are the first and last layers, which have the same number of neurons equal to the length of the input vector, and a narrow "throat" — the middle layer of a significantly smaller dimension. One of the options for a replicative neural network is a three-layer perceptron, in which the number of elements of the input and output layers is the same, and the number of elements of the middle hidden layer is much smaller.

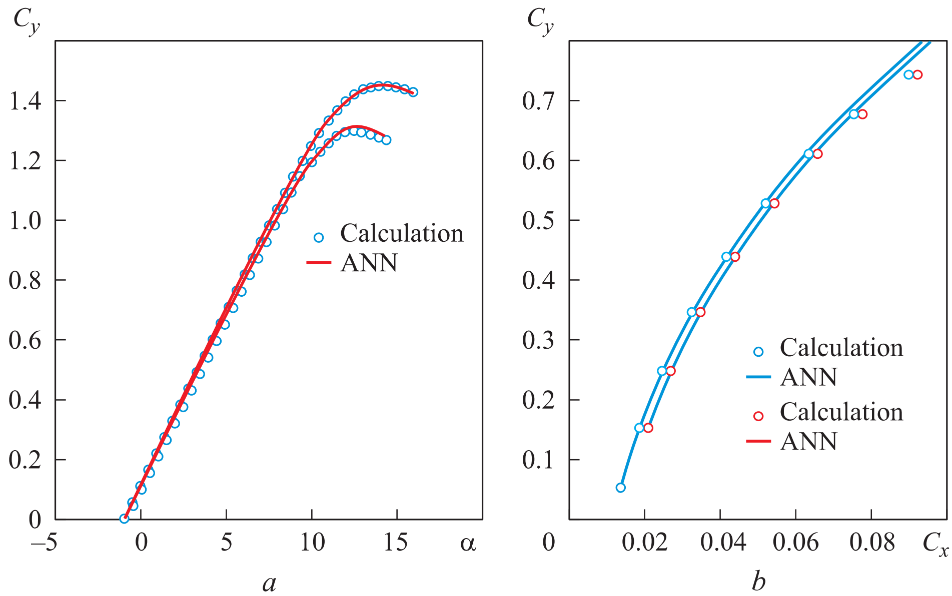


Fig. 1. Comparison of calculated and approximation aerodynamic characteristics for two Mach numbers: M = 0.3 (*a*) and 0.78 (*b*)

After training, such a network can reproduce at the output the same vector that is fed to the input layer of the perceptron. Such a network compresses information in the area from the input layer to the middle and restores it on the layers from medium to output. Moreover, on the elements of the middle layer there is a representation of each vector, which is shorter than the length of the vector supplied to the input. In fact, replicative networks can reduce the dimensionality of data by moving to the so-called natural coordinates. This approach was first applied to image compression. [14]. In the case of using neurons with linear activation functions, this approach leads to the well-known as principal component analysis (PCA) [6].

The problem of using a replicative neural network to generate new objects was solved by the example of the generation of aerodynamic profiles. The three-layer replicative network was trained on a variety of aerodynamic profiles, the ordinate vectors of the profiles being the input and output of the network. The network has an input and output layers of dimension M = 59 and a narrow throat — the middle layer of a significantly smaller dimension of $K = 6$ neurons. To generate a new profile, a signal in the form of a K component vector was applied to the output of the middle layer or to the input of the output (which is the same thing). The components of this vector are random numbers with a uniform distribution law, which are limited by the extreme values of the corresponding components from the original set. After that, a vector with M components was obtained from the output layer, defining a new generated profile. Typical profile forms obtained using this approach are shown in Fig. 2. The original profile is marked with dots.

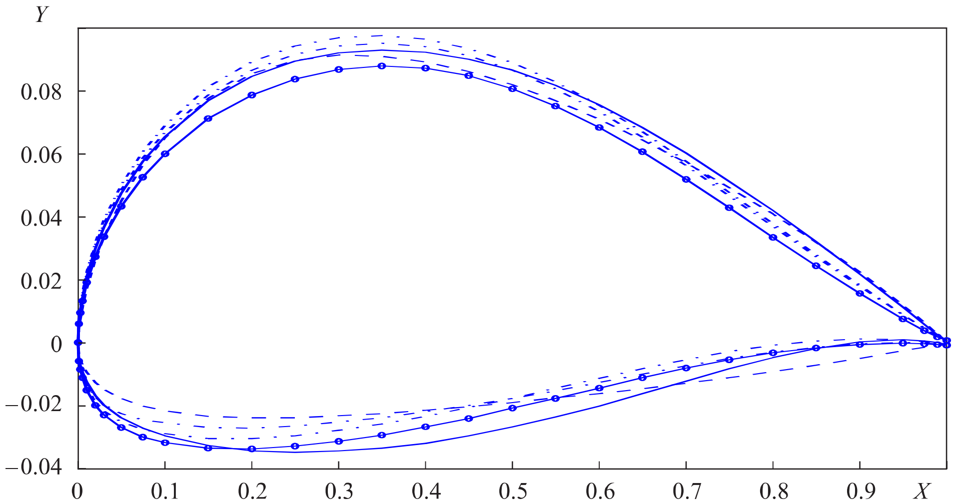


Fig. 2. A set of profiles randomly generated in 6-dimensional space (M = 59, K = 6); X, Y — profile coordinates normalized to the chord

The use of ANN of a special type for generating a series of aerodynamic profiles with desired properties. To generate a series of aerodynamic profiles with desired properties, a modification of replicative neural networks is proposed, in which part of the input vector components (describing the characteristics) go directly to the output layer. In this case, after training the network, it is possible to create profiles by supplying a random vector to the output links of the middle layer and the given values of the characteristics, to the corresponding input neurons.

The following problem was solved as an example of applying this approach to designing the rotor profiles of a helicopter. We need to construct a series of aerodynamic profiles with a given maximum thickness t = 12 %, a given pitch moment at zero lifting force m_{z0} = −0.01 at M_∞ = 0.3, a given drag coefficient C_{x0} = 0.0180 at M_∞ = 0.80 and a maximum lifting force coefficient $C_{y\,\max}$ at M_∞ = 0.3, varying from 1.35 to 1.55 in increments of 0.05.

To solve this problem, a modification of the replicative neural network of the “utoencoder” type was used [15]. The first and second hidden layers compress information, the third and fourth — restore it (Fig. 3). Moreover, at the output of the second hidden layer, a compressed representation of the input vector appears.

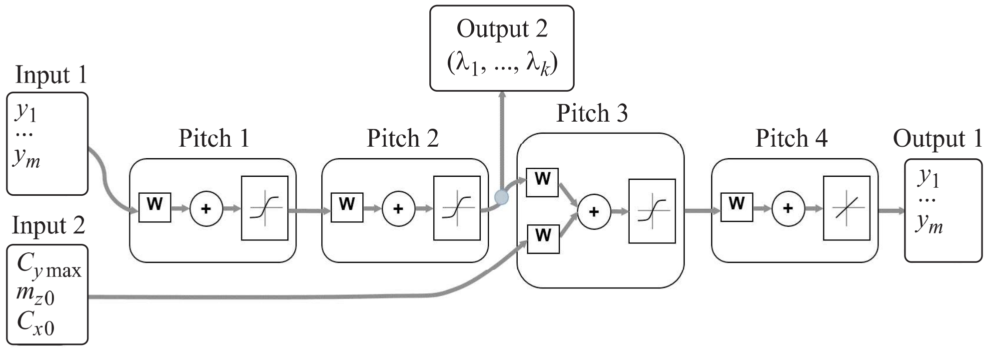


Fig. 3. Modified neural network

Two vectors served as a network input. The first vector (Input 1, see Fig. 3) contained the ordinates of the profile and was fed to the first layer of the network, the second vector (Input 2, see Fig. 3) contained the specified aerodynamic characteristics: pitch moment at zero lifting force m_{z0} and number $\mathrm{M}_\infty = 0.3$, drag coefficient at zero lifting force C_{x0} and number $\mathrm{M}_\infty = 0.8$ and maximum lift coefficient $C_{y\,\max}$ at $\mathrm{M}_\infty = 0.3$. The second vector was fed to the input of the 3rd hidden layer located behind the narrow second layer. The network output (Output 1, see Fig. 3) was the profile ordinate vector.

For training, we used data obtained by calculation for a set of 3379 profiles. To create this set, the replicative neural network considered earlier was used. It should be noted that the maximum thickness for all profiles of the set was $t = 12$ %.

The training consisted in minimizing the deviation of the output vector (4th layer) from the input vector containing the ordinates of the profiles of the base set (Input 1, see Fig. 3). In this case, the maximum and minimum values of the components (λ_i) of the output vector of the 2nd layer, which displays the profile in a compressed form, were determined.

After training, a generating neural network was formed, which consists of the 3rd and 4th hidden layers of the original network and two vectors were fed to its input. The components of the first vector are limited by the extreme values of the corresponding components of the output vector of the 2nd layer and correspond to the compressed image of the profile, the components of the second are the specified aerodynamic characteristics of the profile.

Further, the obtained neural network was used to solve the problem of creating a series of profiles formulated at the beginning of the section. The profile NACA23012 is selected as the base profile. A vector was supplied to the first input of the generating neural network, which is an image of the NACA23012 profile in compressed space, and to the second input, the values of the specified aerodynamic characteristics. In the obtained series, the profiles differed only in the values of the maximum lift coefficient, which was supplied to the second input of the generating neural network.

The forms of the obtained profiles are shown in Fig. 4, markers highlighted the base profile of NACA23012. It should be noted that the obtained profiles differ slightly from each other, the maximum deviation of the ordinates from NACA23012 is less than 0.15 % of the profile chord.

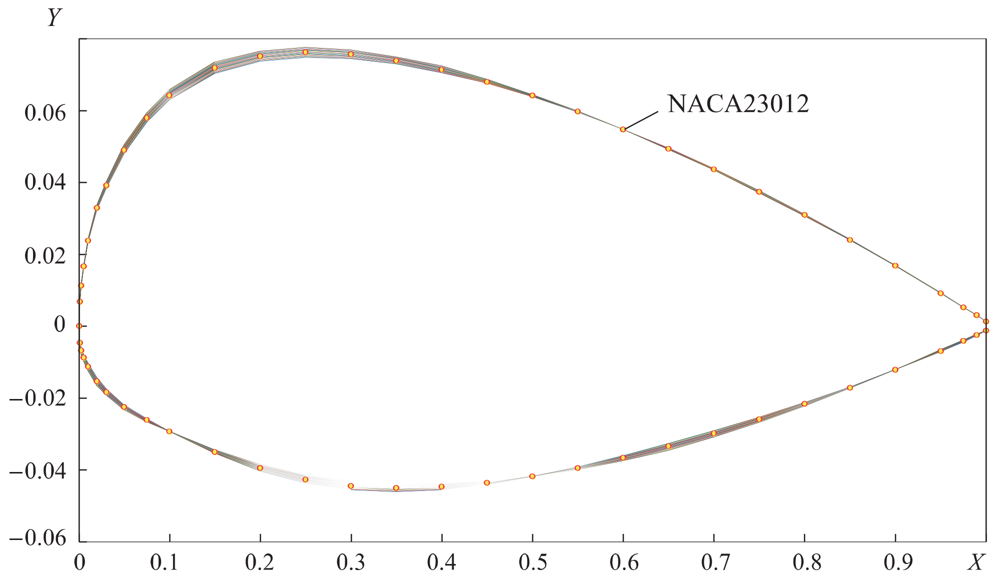
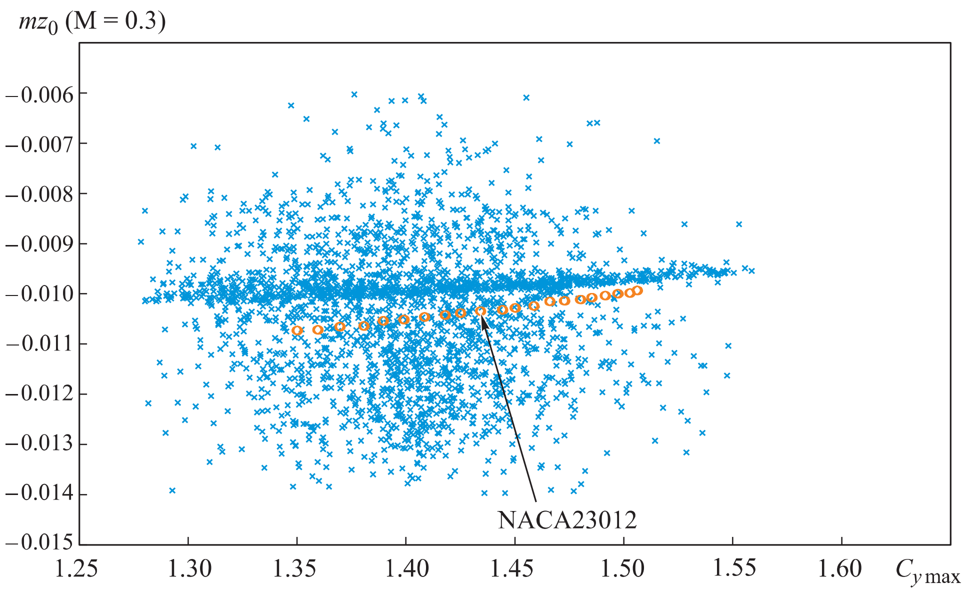


Fig. 4. Profile series geometry, *X, Y* — chord normalized profile coordinates

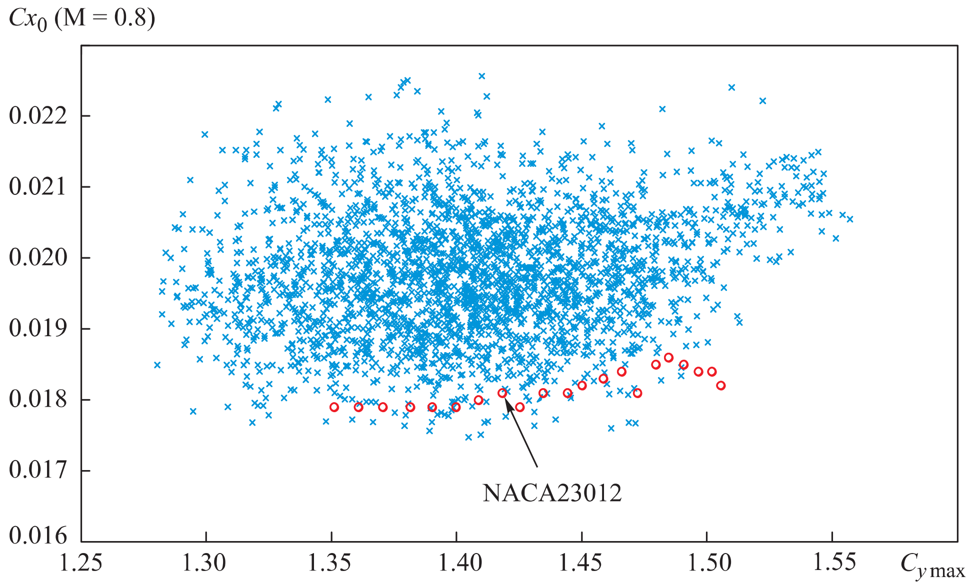
To verify the achievement of the design goal, the obtained series of profiles were calculated according to the program [13]. The calculation results are shown in Fig. 5. In Fig. 5, *a* the markers show the characteristics of zero pitch moment m_{z0} obtained for a series of profiles depending on maximum lift coefficient $C_{y\ \max}$. Here are the points corresponding to the set of profiles on which the neural network was trained and the point corresponding to the NACA23012 profile is shown. Similar data for the dependence of the resistance coefficient C_{x0} at zero lifting force from the coefficient of maximum lifting force $C_{y\max}$ are given in Fig. 5, *b*.

The calculated dependences of the lift coefficient of the profiles on the angle of attack for the number M = 0.3 are shown in Fig. 6.

It should be noted that the calculated coefficients of the pitch moment m_{z0} and drag C_{x0} for the obtained profiles are close to the given, which were



a



b

Fig. 5. Aerodynamic characteristics of profiles in coordinates:
a — $C_{y\,\max}$, m_{z0}; *b* — $C_{y\,\max}$, C_{x0}

fed to the input of the neural network. For the coefficient of maximum lifting force, there is a discrepancy with the specified values for the values $C_{y\,\max} > 1.47$. The discrepancy occors because of the fact that in this area of values there is not enough data that was used to train the neural network.

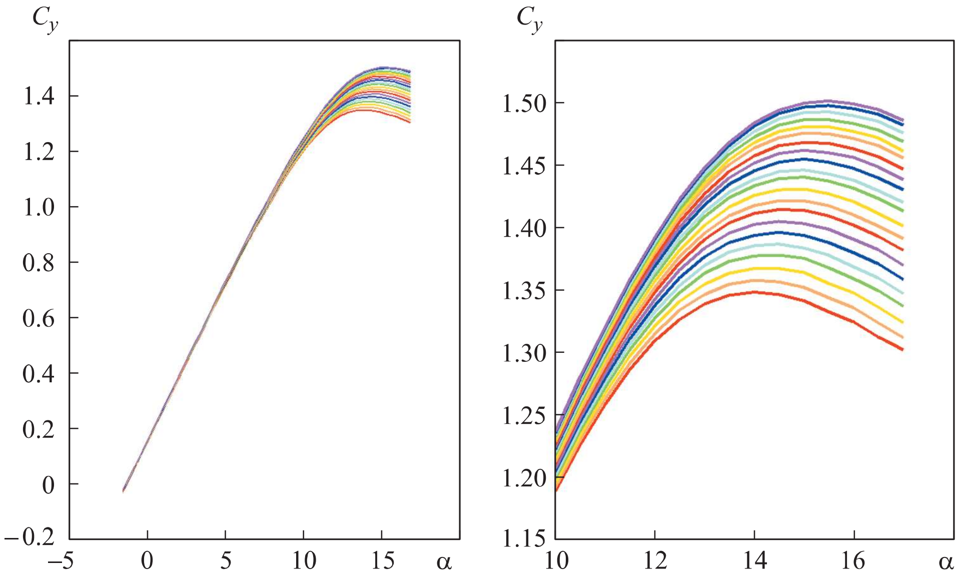


Fig. 6. Dependencies $C_y = C_y(\alpha)$, M = 0.3

Conclusion. The possibilities of using artificial neural networks in the tasks of aerodynamic design of aircraft elements are considered. A special class of neural networks — the so-called replicative or replicating neural networks is used to build design objects in a given area. It is shown that replicative neural networks can be used as generators of aerodynamic profiles with specified aerodynamic and geometric characteristics. Examples of constructing families of profiles in the area of the given values of the coefficient of maximum lifting force, pitch moment, drag and maximum thickness are given. The proposed approach to design problems is not limited to the subject area of choosing aerodynamic profiles for the rotor of a helicopter.

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