APPLYING ARTIFICIAL NEURAL NETWORKS TO THE TASKS OF DESIGNING AIRFOIL SECTIONS OF A HELICOPTER´S MAIN ROTOR

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Abstract
An original system for designing aerodynamic profiles using artificial neural networks (ANN) is presented. A panel method was applied for a quick assessment of the quantitative aerodynamic characteristics of the profiles. This approach eliminates the problems of CFD modeling associated with the necessity to use large computational power. The developed methodology and the algorithms based on were applied to the design of aerodynamic profiles. As test NACA23012 base profile has been selected, on the basis of which was generated by a plurality of profiles acceptable to analysis. The analysis carried out with ANN methods revealed a limited area of the most promising candidate profiles for the further optimization of the geometry from the point of view of the chosen criteria. The profile design process is iterative. Already at the first iteration, it can be shown that the resulting profile family in aerodynamic characteristics exceeds the base profile.

1. INTRODUCTION

Aerodynamic researches play an important role at designing helicopters. This role is particularly important at the stage of aerodynamic designing a helicopter´s main rotor. One of the biggest challenges during designing a helicopter´s main rotor is the choice of basic aerofoils providing the required aircraft performance at the full range of flight modes. At the same time the data of calculated studies as well as experimental researches is widely used. Choosing and designing airfoils for a helicopter´s main rotors is not a new research area. By now considerable experience in the area has been accumulated. Earlier works were mostly based on the results of wind channel experiments. At the moment designing is usually based on the results of calculating with the help of software of various degrees of complexity followed by an experimental check of the sections obtained [1,2,3]. In these works the criteria for choosing aerofoils which have most influence on rotor´s characteristics are formulated:

– low moments at zero lift relative to an aerodynamic centre,

– high carrying capacity at low *M* ranging from 0.3 to 0.5,

– low drag at high subsonic *M* values, which is characteristic of a blade tip flow.

The progress made in the computing methods makes it possible to calculate aerodynamic characteristics of the airfoils before conducting wind channel tests, i.e. to develop the aerofoils experimentally, which makes designing of the main rotor blade considerably faster and more cost-efficient. However, the actual application of modern numeral methods for computing of aerodynamic characteristics at the stage of preliminary design makes the process far more time-consuming and labour-intensive.

Traditionally mathematical models based on "the process physics" and describing physical processes and phenomena which occur as an object functions with the help of complicated partial differential equations with boundary conditions (for example, boundary value problems for a Reynolds-averaged Navier-Stokes equation) are used to estimate aerodynamic characteristics. Software packs for analysing such models implement various numeral methods for solving the respective equations.

The numeric methods being used have a considerable computational intensity both of the calculations themselves and of preparing the input data. This limits the possibilities to use the models based on the "process physics" to a great extent, especially at the stage of preliminary (conceptual) design, during which a lot of solution options are considered and the price to pay for choosing a wrong solution would be high.

Over the past few years data-based mathematical models have started developing 4. Such models are based on the data obtained experimentally and/or using computational experiments conducted with various objects of a class under

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consideration, with a minimal involvement of knowledge subject area (the physics of processes). In other words, the models "learn" from a set of input and output data prototypes. The "data based" models actually imitate (replace) both the sources of data based on an initial model and the models which are built on studying the physics of processes. As a result, adaptive models built this way are also sometimes called surrogate models. Both models (the initial and the surrogate ones) must have the same set of input and output data, and the results for both models (for the same input data) must be close.

The technology of developing surrogate models and the methods used are based on uniting the methods of the subject area and cognitive technologies which build on the achievements of general scientific disciplines (mathematics, artificial intelligence and data analysis, information technologies), and are largely invariant to the subject area.

The data accumulated as a result of experimental research over the past years, the computing methods and the software units based on them enable us to create advanced design systems. A combination of machine learning technologies, neural networks, computational fluid dynamics (CFD) methods and accumulated data sets (calculated and experimental ones) on aerodynamic characteristics of helicopter´s main rotors elements could serve as a basis for such systems. Using fast neural network approximators for estimation of aerodynamic characteristics in the course of designing seems rather promising, as a learnt neural network requires little computational resources and is characterised with high speed of operations. At the same time, the information necessary for learning a network may build on the data obtained earlier while developing aircrafts of a similar class and it may be added to in the course of the design. The application of artificial neural networks to solving a series of tasks in applied aerodynamics is presented in the collected papers [5].

2. APPLYING ANN TO ESTIMATE THE AERODYNAMIC CHARACTERISTICS OF AIRFOILS

This work considers applying artificial neural networks to aerodynamic design tasks via the example of designing airfoils for a helicopter´s main rotor for whose geometric and aerodynamic characteristics have been set. Any design system must, as a rule, contain at least the following components: design criteria, a module for assessing these criteria and a module for generating the objects of design in a set area. The major part of time spent on aerodynamic design is accounted for by the necessity to calculate the flow of aerodynamic objects at a lot of modes, which do not allow using modern CFD codes based on solutions to Reynolds-averaged Navier-Stokes equations. Modules based on artificial neural networks are used in order to provide a fast quantitative assessment of design criteria, which will make it possible to reduce the time spent on choosing promising airfoils dramatically and eliminate the problem typical for all computational CFD methods, when it is impossible to obtain all aerodynamic characteristics at all modes in question for a series of designed objects due to the divergence of the computational process.

Fig. 1 shows a diagram of how determining the coefficient of an airfoil´s maximum lift with the help of a neural network diverges. The x-axis shows the calculated values of the coefficient, while the y-axis shows their estimation by a neural network. The network has been trained on a set 3,540 airfoils, the average absolute approximation error *CLmax* being 0.0066. It took less than 10^{-5}c. at CPU Intel Core i7-3820 3.60GHz to estimate one variant.

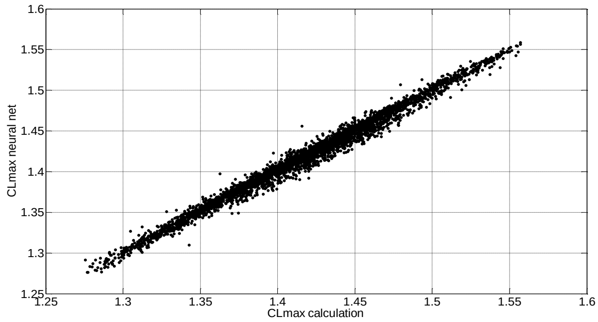

Fig.1 - A comparison of the computational data with a neural network approximation

Application of artificial neural networks to develop surrogate models and to assess object´s characteristics quickly is far from unusual nowadays. The table below shows integral estimates of deviation for the main aerodynamic coefficients obtained through approximating the calculated data with artificial neural networks such as multilayer perceptron.

Table 1

Neural network	σ	***mae***
$C_D=C_D(Geom,M,\alpha)$	**2.4e-04**	**1.6e-04**
$C_D=C_D(Geom,M,C_L)$	**2.62e-04**	**1.71e-04**
$C_L=C_L(Geom,M,\alpha)$	**0.0062**	**0.0042**
$C_m=C_m(Geom,M,\alpha)$	**0.741e-03**	**0.531e-03**
$C_m=C_m(Geom,M,C_L<0.7)$	**0.316e-03**	**0.232e-03**
$\alpha=\alpha(Geom,M,C_L<0.7)$	**0.0119**	**0.0087**

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$C_{Lmax}=C_{Lmax}(Geom,M=0.3)$	**0.0066**	**0.0050**
$C_{m0}=C_{m0}(Geom,M=0.3, C_L=0)$	**0.241e-03**	**0.071e-03**

Computational data for 3692 airfoils with the range of angles of attack from -1.5 to 16.5 and Mach numbers from 0.3 to 0.82 with a constant number $Re=3.0\cdot10^6$ have been used as the learning set. The learning set contained 342000 computational points. The computational points of the set for coordinates (M, α) are shown in the fig. 2.

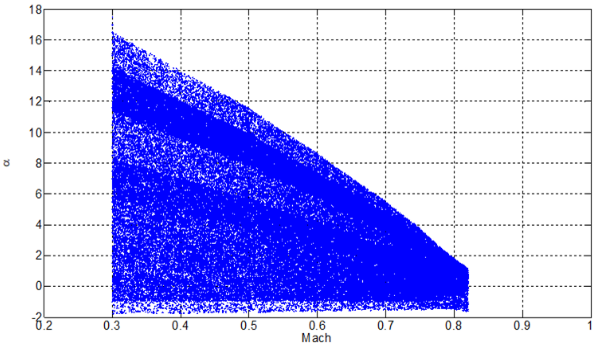

Fig. 2 - Points of the learning set

A typical distribution of the density for drag coefficient approximation error in comparison with normal distribution with the same parameters (dispersion and average) is presented in fig. 3.

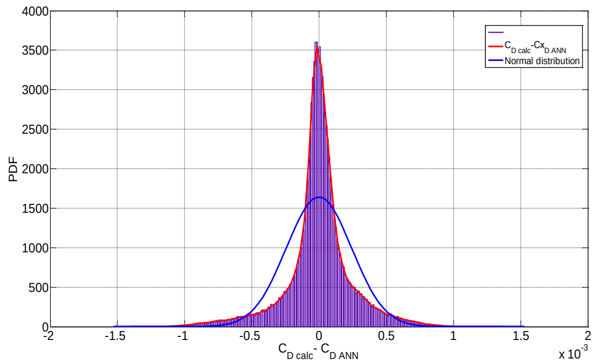

Fig. 3 - The distribution of approximation error density

The comparison of calculated to approximated dependences of lift coefficient from the angle of attack and polars for two arbitrary airfoils from the set is shown in fig. 4.

The above results demonstrate that artificial neural networks enable us to estimate the main aerodynamic characteristics of airfoils with enough precision. At the same time, a learnt neural network requires very little computational resources for operating.

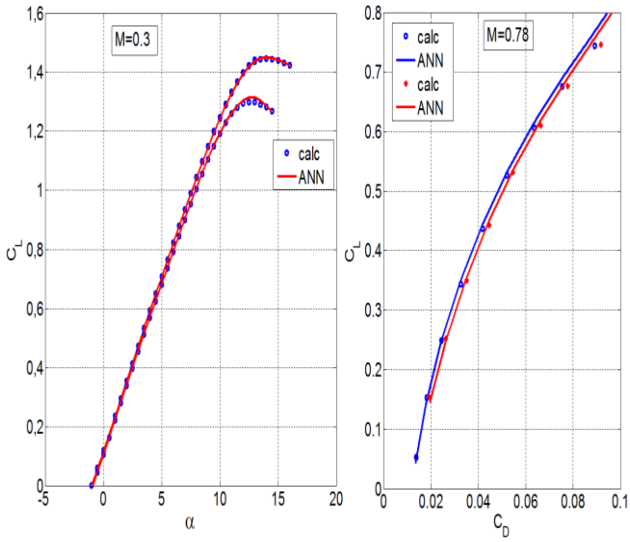

Fig. 4 - Comparison of calculated to Approximated dependences

3. APPLYING ANN OF A SPECIAL TYPE TO GENERATE AIRFOILS WITH PRE'SET CHARACTERISTICS

Developing a high-quality module for generating objects is no less important for a high quality design system. A particularly important feature of the object generation module is the ability to create objects with the given properties. This simplifies the designing process dramatically.

This work considers using specific classes of artificial neural networks (replicative and autoenconder) for generating objects with the given aerodynamic and geometric properties taking airfoil sections as an example. Applying such neural networks makes it possible to reduce the dimensionality of the space used to describe the surface of an airfoil section and to develop cutting-edge design systems.

Autoencoder neural networks constitute a subclass of multi-layer perceptrones. These networks have a symmetrical architecture. These networks must have the first and the last layer with the same numbers of neurons equal to the length of the input vector, and a bottleneck - the middle layer with a considerably lower dimensionality. The first and the last layers are called the input and the output layers respectively, while the middle layer is referred to as a hidden layer. Fig. 5 shows the architecture of an autoencoder network.

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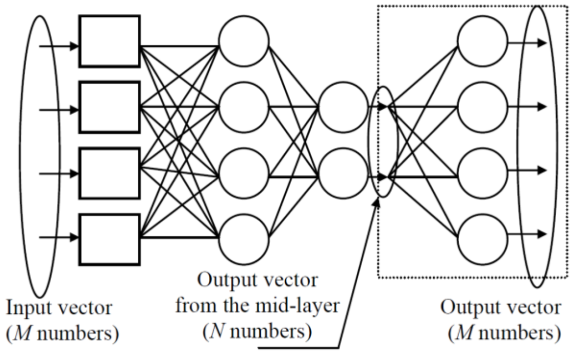

Fig. 5 - Autoencoder ANN

Autoencoder networks were first proposed as a solution to information compression problems [6]. Let us consider a 3-layer perceptron which has an equal number of elements on its input and output layers, but whose middle hidden layer contains much fewer elements. After training the network can output the same vector that enters the perceptron's input layer. Such network compresses information on the interval from the input to the hidden layer and decompresses it from the hidden to the output layer. It is noticeable that a representation of each vector appears on the elements of the hidden layer, and that this representation is shorter than the input vector. In effect, artificial neural networks allow reducing the dimensionality of the data by transitioning to the so-called "natural" coordinates. In the case of using neurons with linear activation functions this approach leads to the known method of principal components.

Autoencoder networks find one more application in generating random objects which are similar to those used for the learning. A random number generator gives points in an area of the *N*-dimensional space. The area is restricted by minimal and maximal values of the middle neuron layer output signal. If these *N*-dimensional vectors are sent to an output layer of a trained autoencoder network, we will get the vectors for the original *M*-dimensional space which corresponds to points in the space of natural coordinates. The generated objects belong to the same class as the original ones.

The following task is solved taking airfoils as an example. We have a set of airfoils from which a 3-layer autoencoder network learns. This network has the input and output layers of a large dimensionality (*M* inputs-outputs) and a bottleneck - a hidden layer whose dimensionality is considerably lower (*N* neurons). Such a network compresses the data from the dimensionality of the input layer to the one of the middle hidden layer. The task is to generate new airfoils with the help of this trained network. In order to do this a signal in the form of an *N*component vector is sent to the output of the hidden layer or the input of the output layer (which is the same). The vector´s components are randomly distributed and limited by the extreme values of the respective components from the original set, that is, they lie within a dense set of compressed data. After this we get a vector with *M* components from the output layer which gives a new generated airfoil. Typical forms of airfoils obtained using this approach, are given in fig. 6.

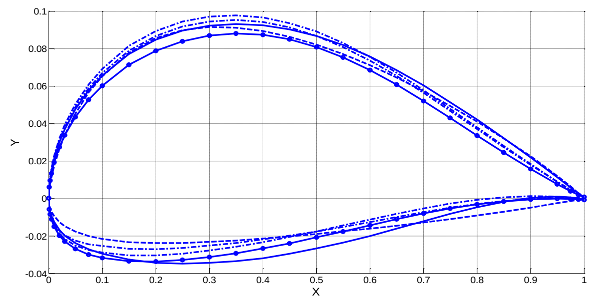

Fig. 6 - Aerofoils of a set generated randomly in a 6-dimensional space, (M=59, N=6)

The ability to create objects with the given characteristics is desirable for aerodynamic design. A modification of autoencoder neural networks in which some components of the input vector (describing the characteristics) go directly to the output layer has been proposed for solving such tasks. (fig. 7). In this case it is possible to create airfoils by sending a random vector to the output links of the middle layer, while sending the set values of the characteristics to the respective input neurons after training the network.

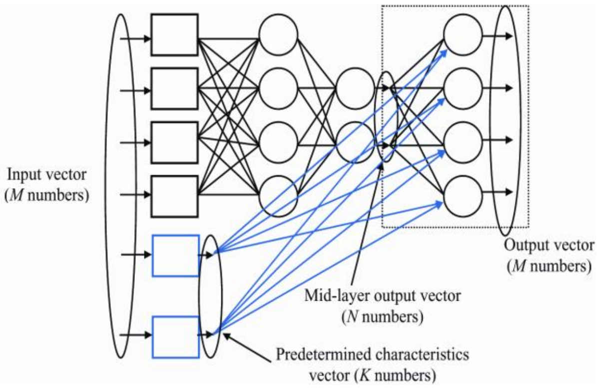

Fig. 7 - A modification of an autoencoder ANN, which allows generating objects with the given

A module for generating airfoils which have geometric (the maximum thickness is set) and aerodynamic (*CLmax* is set) limitations has been created to illustrate using such networks. A lot of aerofoils have been obtained using this generator. The thickness is set equal to 15% and *CLmax*=1.55. The calculations showed that the characteristics of the generated random set of

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airfoils lie close to the given values. The distributions by the maximum lift coefficient of the original set (used to learn the network) and by the generated set of airfoils are shown in fig. 8.

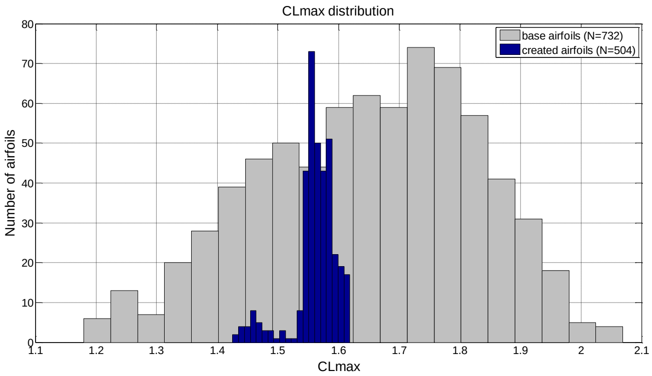

Fig. 8 - Distribution by maximum lift coefficient C_{Lmax}

A similar distribution by maximum airfoil thickness is shown in fig. 9. Typical forms of airfoils obtained using this approach, are given in fig. 10.

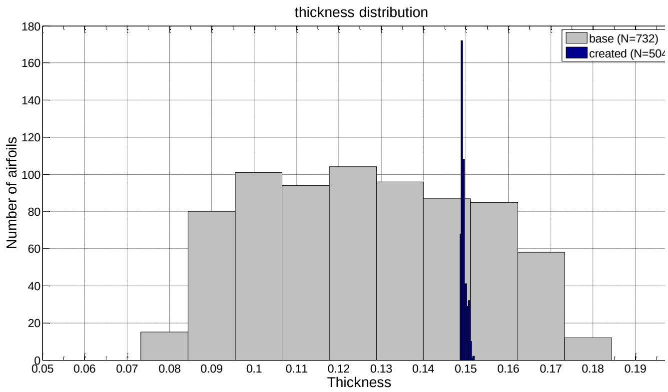

Fig. 9 - Distribution by maximum aerofoil thickness

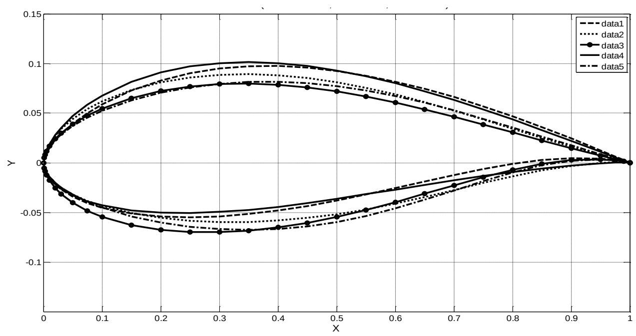

Fig. 10 - Aerofoils from the set with geometric and areodynamic limitations, (C_{Lmax}=1.55, thickness=0.15)

4. DESIGNING A SERIES OF AIRFOILS WITH PRE-SET VALUES FOR THICKNESS, FOR COEFFICIENTS OF MAXIMUM LIFT, PITCHING MOMENTS AND DRAG

The following problem has been solved as an example of applying this approach to designing airfoils of the main rotor of a helicopter. A series of airfoils with pre-set maximum thickness t = 12%, with set pitching moment at zero lift, C_{m0} = -0.01 at M=0.3, with set drag coefficient C_{D0} = 0.0180 at M=0.80 and the maximum lift coefficient C_{Lmax} at M=0.3, which change from 1.35 till 1.55 at the increments of 0.05 must be designed.

A modification of autoencoder neural net considered above was used to solve this task. The network schematic is shown below in fig. 11. The first and the second hidden layers compress the information, while the third and the forth restore it. Moreover, a compressed representation of the input vector appears at the output of the second hidden layer.

The net's input consisted of two vectors. The first vector contained the airfoil's ordinates and was sent to the net's first layer, while the second layer contained set aerodynamic characteristics: the pitching moment at zero lift, c_{m0} and number M=0.3, drag coefficient C_{D0} at zero lift and number M=0.80 and the maximum lift coefficient C_{Lmax} at M=0.3. The second vector was sent to the 3rd hidden layer's input lying after a "narrow" second layer. The net's output was the vector of an airfoil's ordinates.

Training was conducted using data obtained through calculation for a set of 3379 airfoils. The autoencoder neural net shown in fig.5 was used to create this set. Some airfoils of the set obtained are shown in the picture below, fig. 12. It should be pointed out that the maximum thickness for all airfoils of the set was t = 12%.

The training consisted in minimizing the deviation of the output vector (the 4th layer) from the input vector containing the ordinates of the main set's airfoils. At the same time, the maximum and minimum values of the components of the 2nd layer's output vector folding the airfoil were determined.

After training a generating neural network (fig. 13) consisting of the 3rd and the 4th hidden layers of the original network were formed, and two vectors were sent to its input. The components of the first vector are limited to extreme values of respective components of the 2nd layer's output vector and match the airfoil's compressed image, while the components of the second one are the airfoil's set aerodynamic characteristics.

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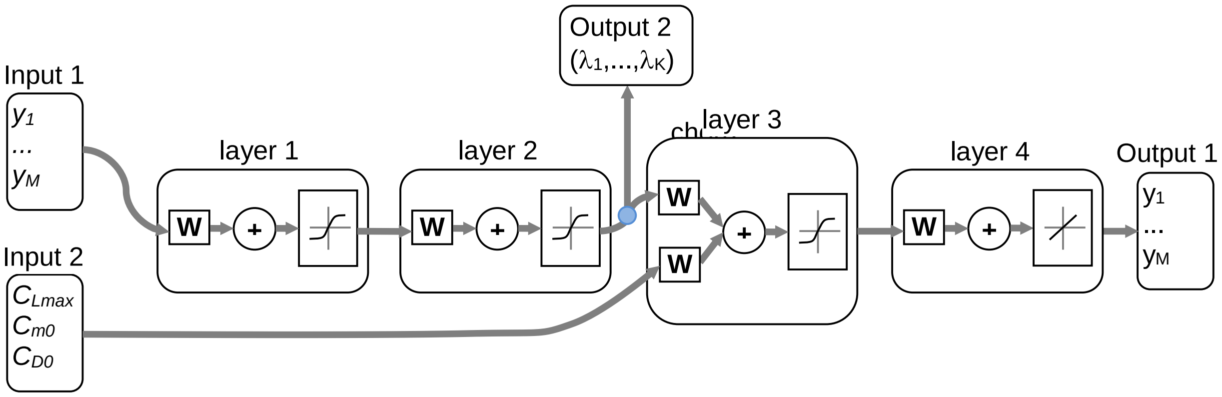

Fig. 11 - Modification autoencoder neural net

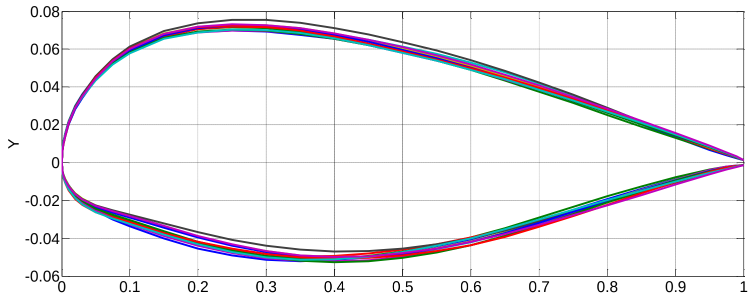

Fig. 12 - The geometry of basic set's airfoils

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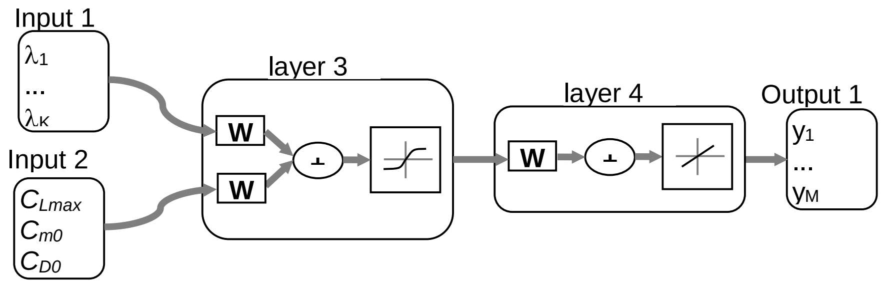

Fig. 13 - A generating neural network

Then the formed network was used for solving the task of creating a series of airfoils stated at the beginning of the task. Airfoil NACA23012 was chosen as the basic one. A vector which is an image of NACA23012 airfoil in a compressed space was sent to the first input entry of the autoencoder neural net, while the values of set aerodynamic characteristics were sent to the second one. In the resulting series the only difference between the airfoils was the value of the maximum lift coefficient which was sent to the second input of the generating neural net.

The forms of the airfoils obtained are given in fig. 14, the basic NACA23012 aerofoil is being marked. It should be pointed that the resulting airfoils differ one from another only slightly, with the maximum deviation of the ordinate from NACA23012 is less than 0.15% of the airfoil's

The created series of airfoils was then calculated in order to check whether the computational goal set has been achieved. The calculation results are given in fig. 15 and fig. 16. In fig. 15 were marked the values of zero pitching moment depending on maximum lift coefficient which have been obtained for a series of airfoils. This figure also shows the points which correspond to a set of airfoils used to train the neural net.

Similar data for the airfoils of the series and the basic set are given in fig. 16 in coordinates (C_{Lmax}, C_{D0}).

Fig. 17 shows the calculated dependence of the lift coefficient from the angle of attack for the obtained series of airfoils for number M=0.3.

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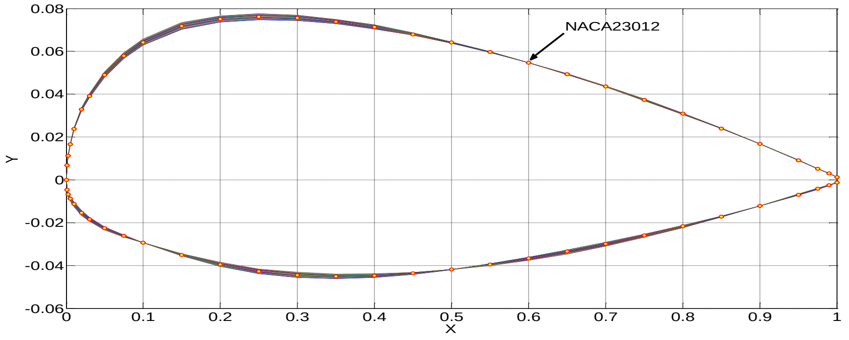

Fig. 14 - The geometry of a series of airfoils

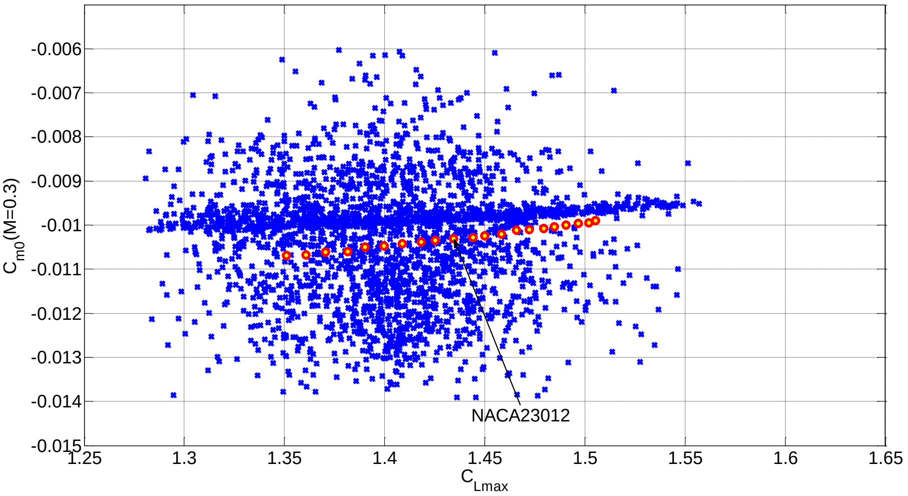

Fig. 15 - Aerodynamic characteristics of airfoils in coordinates (C_{Lmax}, C_{m0})

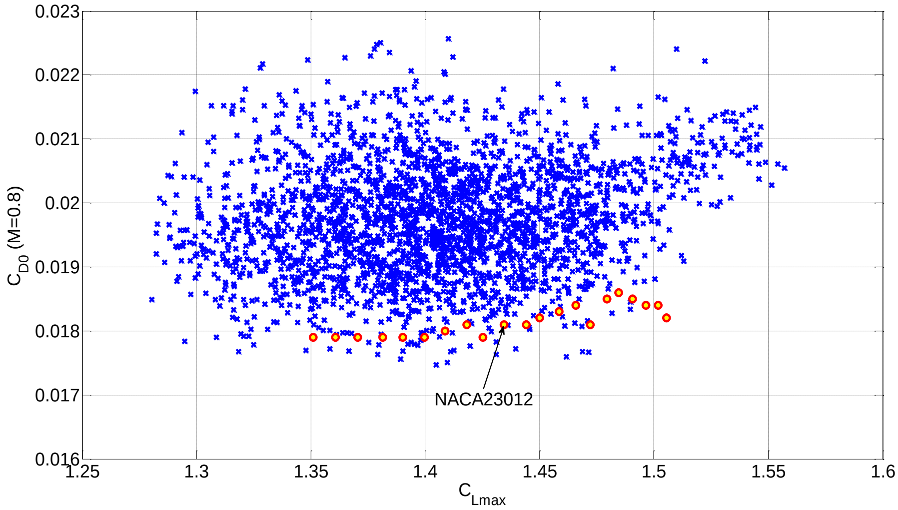

Fig. 16 - Aerodynamic characteristics of airfoils in coordinates (C_{Lmax}, C_{D0})

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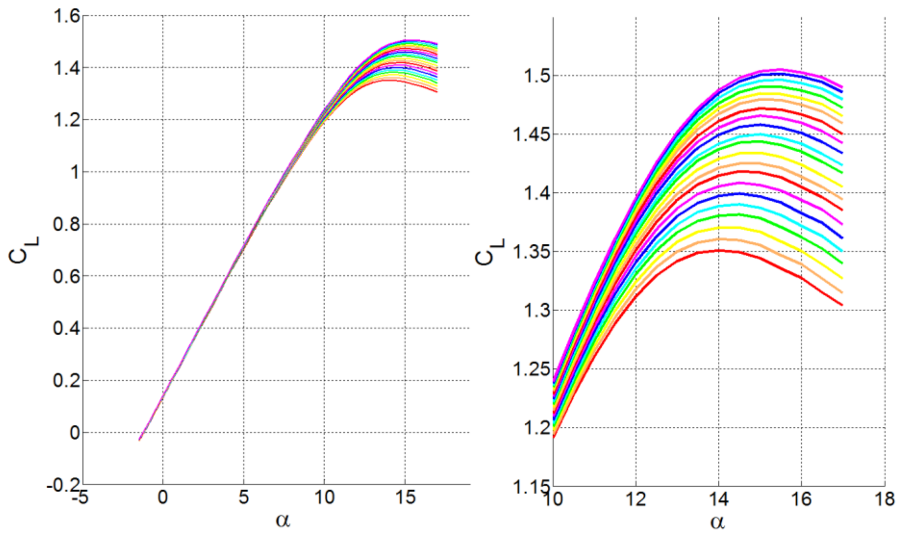

Fig. 17 - Dependences C_L=C_L(α), M=0.3

It should be mentioned that the calculated coefficients of the pitching moment and drag for the airfoils obtained are close to the ones pre-set which were sent to the neural net's input. There is a deviation from the set values for values $C_{Lmax} > 1.47$ for the maximum lift coefficient. This deviation is caused by a lack of data used for learning the neural net in this field.

5. CONCLUSION

The work has considered the possibilities to apply artificial neural networks to aerodynamic designing of an aircraft's elements. A specific class of artificial neural networks - the so-called autoencoder or replicative neural networks is used for generating designed objects in a given area. It is demonstrated that autoencoder neural networks can be used to generate airfoil sections with given aerodynamic and geometric characteristics. Examples of generating families of airfoils in the area of set values for the coefficients of maximum lift, pitching moment, drag and maximum thickness are given. The suggested approach to the design tasks is not restricted to the subject area of choosing airfoil sections for a helicopter´s main rotor.

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