

Research Article

Inverse Design of Airfoils Using Artificial Neural Network

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Abstract

With the development of science and technology, application of UAV is increasing in the world. In order to improve the flight performance of UAV, it is important to inversely design the airfoil that generates lift. Inverse design of airfoils has been a challenging task and subject of investigation for a long time, date back to the beginning of airfoil research. In this paper, an inverse design method of airfoil using ANN and profile database is proposed. In preliminary design phase of the UAV, airfoil database and ANN are constructed and validated to design a profile that satisfied the aerodynamic character of the airfoil for a given flight performance and availability are verified. Many types of airfoils are parameterized using the PARSEC method. For the NASA SC, RAE, HQ, and NACA series of airfoil, the aerodynamic characteristics at the specified Reynolds number and angle of attack are calculated and database are created. These aerodynamic characters are trained by ANN to establish the inverse design process of the airfoil. For the airfoil obtained through the reverse design process, the lift and drag values obtained using CFD calculations are in relatively good agreement with the setting target values.

Keywords

Airfoil, Artificial Neural Network, Inverse Design

1. Introduction

The improved aerodynamic configuration can improve cruise efficiency and safety by reducing the drag of the aircraft, which greatly depends on the aerodynamic design of the wing and airfoil of aircraft. The conventional aerodynamic design method first obtains the aerodynamic characteristics of a given airfoil under certain flow conditions by CFD or wind tunnel experiments, modifies the airfoil geometry according to aerodynamic knowledge and experience, and then repeats the above procedure until the results are satisfactory. This process greatly increases the computational cost and computational time [1-6, 11].

Conversely, the inverse design can directly obtain the ge-

ometry from the desired aerodynamic characteristics. In this case, ANN is used to set up a network connecting aerodynamic and geometric data. Once the network is trained, the results can be obtained very quickly. The steps to establish the inverse design method of airfoil and wing are as follows.

Step 1: Obtain essential parameters from the geometry of the airfoil.

Step 2: Obtain the aerodynamic characteristics of the airfoil under the corresponding flow conditions.

Step 3: Construct an ANN with the obtained drag characteristics and geometric parameters as a database.

In recent years ANN has entered the inverse design of air-

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foils where ANN plays a role as a calculator based on a pre-set model [12-14].

Hassan Moin described the implementation of ANN for airfoil geometry determination. Instead of using full coordinates of the airfoil, Bezier-PARSEC parameters were used to describe an airfoil [3, 7-10, 15-17]. However, the number of design variables used in this method is eleven and cannot accurately represent various type of airfoil shapes, especially the trailing edge of the airfoil.

2. Inverse Design Process of Airfoil

2.1. Parameterization of Airfoil

The premise of ANN application is a parameterized database. Many parameterization methods such as orthogonal basis function method, B-spline method, PARSEC and CST method have been discussed. The five main principles of parameterization are as follows.

Minimization: it should include as few variables as possible.

Completeness: the equality of the parameterized airfoil and the original airfoil should be good.

Orthogonality: a set of parameters should not correspond to two or more aerodynamic types.

Integrity: do not show abnormal shapes.

Intuition: the correlation between parameters and geometric features should be clear.

PARSEC contains several parameters as follows: upper airfoil leading edge radius r_{leup} , lower airfoil leading edge radius r_{lelo}

The thickest position of the upper airfoil surface x_{up} , the thickest position of the lower airfoil surface x_{lo} , maximum thickness of upper airfoil z_{up} , maximum thickness of lower airfoil z_{lo} , upper curvature z_{cup} , lower curvature z_{clo} , tail width δz_{te} , tail vertical height z_{te} , tail wedge angle β_{te} , tail angle α_{te} .

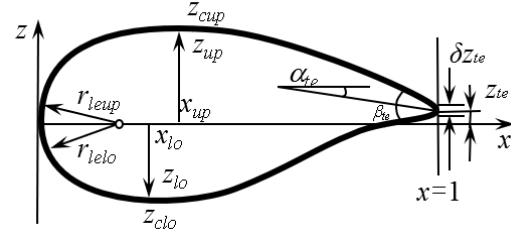


Figure 1. Geometric representation of airfoil by PARSEC method.

The tail wedge angle and the azimuth angle are measured in the clockwise direction. The upper and lower profiles can be obtained by the following equation

$$z(x) = \sum_{n=1}^6 a_n x^{n-1/2} \quad (1)$$

where a_n of upper and lower wing surface is provided by matrix equation as below.

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ x_{te}^{1/2} & x_{te}^{3/2} & x_{te}^{5/2} & x_{te}^{7/2} & x_{te}^{9/2} & x_{te}^{11/2} \\ x_{up}^{1/2} & x_{up}^{3/2} & x_{up}^{5/2} & x_{up}^{7/2} & x_{up}^{9/2} & x_{up}^{11/2} \\ \frac{1}{2}x_{te}^{-1/2} & \frac{3}{2}x_{te}^{1/2} & \frac{5}{2}x_{te}^{3/2} & \frac{7}{2}x_{te}^{5/2} & \frac{9}{2}x_{te}^{7/2} & \frac{11}{2}x_{te}^{9/2} \\ \frac{1}{2}x_{up}^{-1/2} & \frac{3}{2}x_{up}^{1/2} & \frac{5}{2}x_{up}^{3/2} & \frac{7}{2}x_{up}^{5/2} & \frac{9}{2}x_{up}^{7/2} & \frac{11}{2}x_{up}^{9/2} \\ -\frac{1}{4}x_{up}^{-3/2} & \frac{3}{4}x_{up}^{-1/2} & \frac{15}{4}x_{up}^{1/2} & \frac{35}{4}x_{up}^{3/2} & \frac{63}{4}x_{up}^{5/2} & \frac{99}{4}x_{up}^{7/2} \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \\ a_6 \end{bmatrix} = \begin{bmatrix} \sqrt{2r_{le-up}} \\ z_{te} + \frac{\delta z_{te}}{2} \\ z_{up} \\ -\tan(\alpha_{te} + \beta_{te}) \\ 0 \\ z_{xx,up} \end{bmatrix} \quad (2)$$

Calculation of lower wing surfaces is similar to that of upper wing surface, as follows:

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ x_{te}^{1/2} & x_{te}^{3/2} & x_{te}^{5/2} & x_{te}^{7/2} & x_{te}^{9/2} & x_{te}^{11/2} \\ x_{lo}^{1/2} & x_{lo}^{3/2} & x_{lo}^{5/2} & x_{lo}^{7/2} & x_{lo}^{9/2} & x_{lo}^{11/2} \\ \frac{1}{2}x_{te}^{-1/2} & \frac{3}{2}x_{te}^{1/2} & \frac{5}{2}x_{te}^{3/2} & \frac{7}{2}x_{te}^{5/2} & \frac{9}{2}x_{te}^{7/2} & \frac{11}{2}x_{te}^{9/2} \\ \frac{1}{2}x_{lo}^{-1/2} & \frac{3}{2}x_{lo}^{1/2} & \frac{5}{2}x_{lo}^{3/2} & \frac{7}{2}x_{lo}^{5/2} & \frac{9}{2}x_{lo}^{7/2} & \frac{11}{2}x_{lo}^{9/2} \\ -\frac{1}{4}x_{lo}^{-3/2} & \frac{3}{4}x_{lo}^{-1/2} & \frac{15}{4}x_{lo}^{1/2} & \frac{35}{4}x_{lo}^{3/2} & \frac{63}{4}x_{lo}^{5/2} & \frac{99}{4}x_{lo}^{7/2} \end{bmatrix} \begin{bmatrix} a_7 \\ a_8 \\ a_9 \\ a_{10} \\ a_{11} \\ a_{12} \end{bmatrix} = \begin{bmatrix} -\sqrt{2r_{le-lo}} \\ z_{te} - \frac{\delta z_{te}}{2} \\ z_{lo} \\ -\tan(\alpha_{te} - \beta_{te}) \\ 0 \\ z_{xx,lo} \end{bmatrix} \quad (3)$$

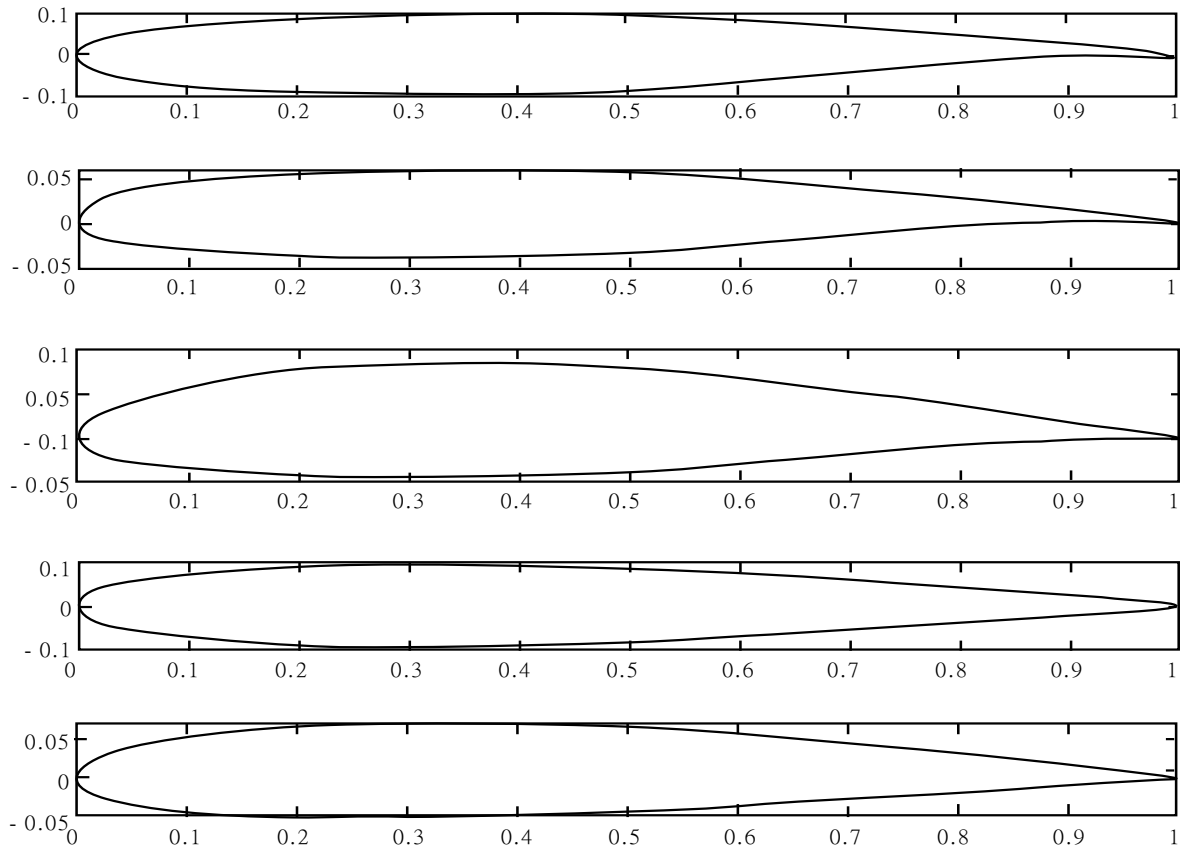


Figure 2. Airfoil reconstruction with PARSEC method.

To verify the PARSEC reconstruction results from the airfoils of NASA SC (2)-0518, RAE (NPL) 5213, HQ20 0-13, NACA0018, and NACA1412 shown in Figure 2 are reconstructed by PARSEC method. The obtained results show that the parameterization of the profile by the PARSEC method is quite reasonable for a series of profiles.

2.2. Artificial Neural Network

Artificial neural network is a computational model that mimics the animal's brain and calculates output data from input data similar to what an animal think. Artificial neural networks are constructed in which a certain number of neurons form a layer and a layer is connected. Here, the first layer is the input layer, the last layer is the output layer, and the middle layers between them are the hidden layers.

Neural networks for function approximations usually use feedforward or cascade networks. A feedforward network consists of several layers connected in series, the first layer connected to the input of the network. Each layer is connected to a layer just ahead of it, and the last layer generates the output of the network. The cascade network is similar to the

feedforward network, except that all the layers ahead of it are connected to the chosen layer.

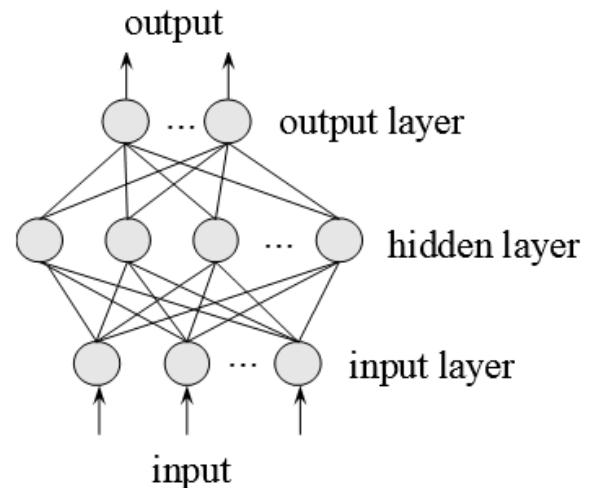


Figure 3. General structure of artificial neural network.

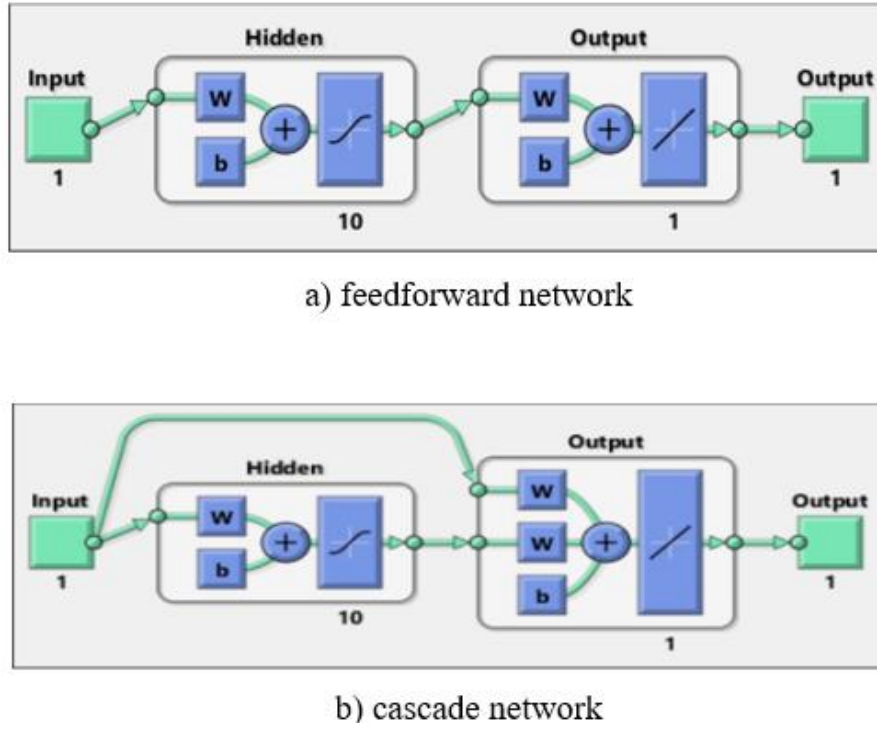


Figure 4. A typical neural network architecture for function approximation.

In a neural network, a nerve cell is modelled by the weighting factor w_{ij} of the input signal, the threshold θ_j , and the transfer function f . Then, the output of the nerve cell, o_j , is calculated as

$$o_j = f\left(\sum_{i=1}^n w_{ij}x_i - \theta_j\right) \quad (4)$$

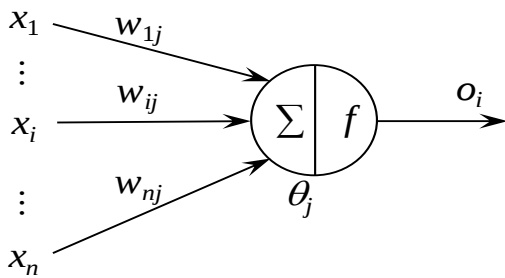


Figure 5. Operation process of nerve cell.

Figure 5 shows the operation process of the nerve cell. When performing function approximations, we usually use the tansig function in the hidden layer and the purelin function in the output layer. The training process of ANN is the process of adjusting the weighting factor and threshold in each cell to obtain the desired output. To train ANNs, we usually perform error back propagation. Algorithms of error back propagation include the elastic back propagation algorithm, the Leven-

berg-Marquardt (LM) back propagation algorithm, and the Bayesian organized back propagation algorithm. Elastic back propagation is applicable for all networks where the weights, inputs, and transfer functions have derivatives. Using back propagation, we calculate the derivative of performance for the weight and threshold variables x and adjust the variables as follows

$$dx = \Delta x * \text{sgn}(gx) \quad (5)$$

Where, gx is the gradient.

In LM back propagation, the error is back propagated as follows.

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \quad (6)$$

Where J is the Jacobian matrix, e is the error vector, and e is the variable controlling the propagation velocity. When μ is zero, this method is the same as the Newton method, and when μ is large, it is the same as the gradient method. The Newton method is faster and more accurate in the vicinity of the minimum error, thus increasing the training speed by adjusting μ .

In order to apply ANNs in practice, it is important to ensure that the neural network does not lose generality during the training process. To do this, a certain number of test data sets should be selected from the training data set and the performance monitoring of the network on the test set should be carried out.

3. Inverse Design of Airfoil

3.1. Design of Airfoil Database

From the system design of the UAV, the aerodynamic characteristics required for airfoil are as follows.

$Re = 3\,977\,000$

At attack of angle $\alpha=0^\circ$, $C_L = 0.467\,1$, $C_D = 0.008\,8$, $C_M = 0.098$

At attack of angle $\alpha=2^\circ$, $C_L = 0.722\,6$, $C_D = 0.009\,5$, $C_M = 0.103\,3$

Where, C_L , C_D and C_M are the lift coefficient, drag coefficient and moment coefficient, respectively.

The aerodynamic characteristics of the standard airfoils provided in Profili 2 software were trained by ANN to establish the airfoil inverse design system. The standard airfoils were parameterized by the PARSEC method to calculate 12 parameters, and the aerodynamic characteristics at the specified Reynolds number and angle of attack were obtained using Software Profili 2.

Input parameter: C_{L0} , C_{D0} , C_{M0} , C_{L2} , C_{D2} , C_{M2}

Where, the subscripts denote the angle of attack.

Output parameter: r_{leup} , r_{lelo} , x_{up} , x_{lo} , z_{up} , z_{lo} , z_{cup} , z_{clo} , δz_{te} , z_{te} , β_{te} , α_{te}

Database of 175 airfoils in NASA SC, RAE, HQ, and NACA series is established. The number distribution of airfoils per series is shown in the Figure 6.

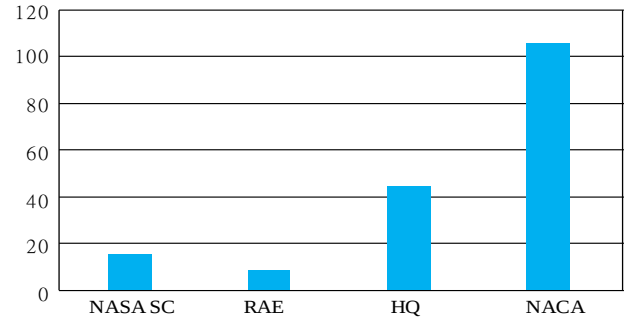


Figure 6. Configuration state of airfoil database.

The ranges of the parameters are shown in Table 1.

Table 1. Ranges of the parameters.

Parameter	Minimum	Maximum	Parameter	Minimum	Maximum
C_{L0}	-0.048 4	0.691 8	z_{up}	0.015 1	0.147 3
C_{D0}	0.005 1	0.018 4	z_{cup}	-1.598 9	-0.081 5
C_{M0}	-0.154 1	0.014 5	x_{lo}	0.048 5	0.522 4
C_{L2}	0.177 4	0.903 3	z_{lo}	-0.105 8	-0.008 3
C_{D2}	0.006 2	0.018 6	z_{clo}	0	3.636 2
C_{M2}	-0.150 5	0.013 8	z_{te}	-0.014 7	0.002
r_{leup}	0.000 9	0.057 6	δz_{te}	0	0.003 4
r_{lelo}	0.000 8	0.043 8	α_{te}	-5.707 3	17.415
x_{up}	0.225 9	0.461 1	β_{te}	-2.097 3	28.165 5

3.2. Design of Artificial Neural Networks

A general methodology for selecting the structure of a neural network does not exist. The network structure was

selected as the cascade type and the number of hidden layers was chosen as five. The number of layer cells was chosen as {2, 7, 11, 15, 15}. Figure 7 shows the structure of the selected ANN.

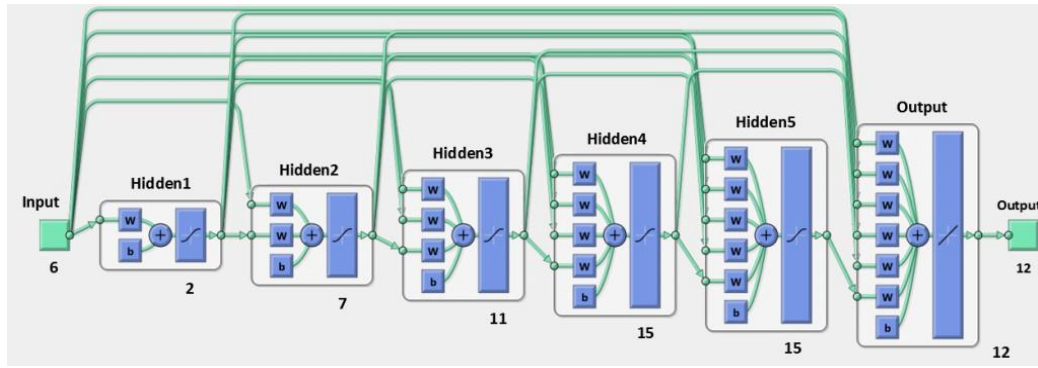


Figure 7. Structure of the selected ANN.

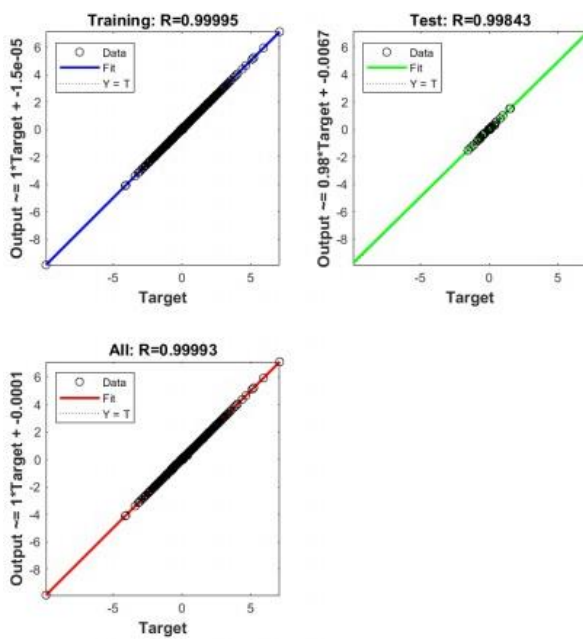


Figure 8. Regression characteristics of the trained ANN.

$$Y = \frac{1}{10} \sum_{i=1}^{10} y_i \quad (7)$$

The inversed airfoil with the required aerodynamic characteristics as input data is shown in Figure 9.

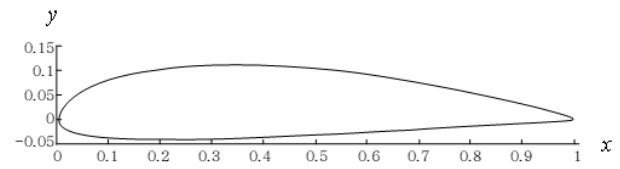


Figure 9. Shape of inversely designed airfoil.

The pressure distribution characteristics obtained through CFD calculation of the airfoil are shown in Figure 10. The error between the CFD analysis results and the target values is shown in Table 2.

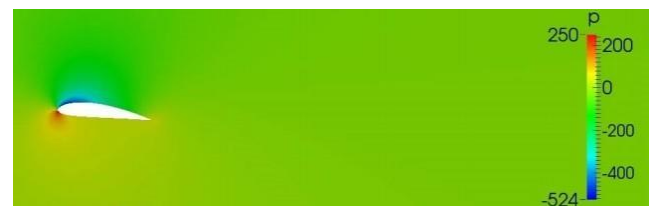


Figure 10. Pressure distribution around the airfoil.

To improve the generality of the trained neural network, 10 networks without loss of generality were obtained by early interruption while monitoring the test performance during training. Figure 8 shows the regression characteristics of the trained ANN.

For the corresponding input data, the output is calculated by averaging the outputs obtained in these networks.

Table 2. Error Analysis of Aerodynamic Characteristics.

	Attack of angle, 0 °			Attack of angle, 2 °		
	C_{L0}	C_{D0}	C_{M0}	C_{L2}	C_{D2}	C_{M2}
Target	0.467 1	0.008 8	-0.098 0	0.722 6	0.009 5	-0.103 3

	Attack of angle, 0 °			Attack of angle, 2 °		
	C_{L0}	C_{D0}	C_{M0}	C_{L2}	C_{D2}	C_{M2}
CFD analysis	0.454 0	0.009 2	-0.101 1	0.704 5	0.009 9	-0.106 8
Error (%)	2.8	4.6	3.2	2.5	4.8	3.4

4. Conclusions

Based on the trained ANN, we proposed a method to design the airfoil that satisfied the aerodynamic character required in the preliminary design phase of the UAV. Errors of all aerodynamic coefficients are within 5%. This method can be widely used to design airfoils that satisfies the requirements of system design of UAV.

Abbreviations

ANN	Artificial Neural Network
UAV	Unmanned Aerial Vehicles
CFD	Computational Fluid Dynamics

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Conflicts of Interest

The authors declare no conflicts of interest.

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