Forest Chemicals Review
www.forestchemicalsreview.com
ISSN: 1520-0191
March-April 2022 Page No. 921-930
Article History: Received: 08 February 2022, Revised: 10 March 2022, Accepted: 02 April 2022, Publication: 30 April 2022

Airfoil Aerodynamic Coefficient Prediction Based on GA-BP

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Abstract:

The acquisition of aerodynamic parameters of wings is an important part of aircraft aerodynamics. The traditional acquisition methods include wind tunnel test measurement and computational fluid dynamics modeling calculation, but there are disadvantages of large amount of calculation and high cost. In this paper, the GA-BP algorithm is used to predict the lift coefficient , drag coefficient and moment coefficient under different angles of attack, Mach number and Reynolds number for various airfoils, which greatly reduces the calculation time. At the same time, the feasibility of NACA4, 5-bit mixed data set prediction is proved, and comparative experiments are done to prove the superiority of GA-BP

Keywords: *GA-BP; machine learning; aerodynamic coefficient.*

I INTRODUCTION

[1] Airfoil design is a major aspect of aircraft aerodynamics.[2] The traditional methods of obtaining aerodynamic parameters of airfoils can be summed up in two ways: measurement by wind tunnel experiment and calculation by computational fluid dynamics modeling. Although this method has been proved to be effective, it has the disadvantages of large amount of calculation and high experimental cost [3]. Therefore, how to realize the rapid prediction of the aerodynamic parameters after the change of the wing state has become a major difficulty. The basic idea of the traditional fast prediction method is to obtain the mathematical relationship between geometric parameters, flight state and aerodynamic parameters by mathematical fitting according to the statistical law of aerodynamic parameters, so as to realize the rapid calculation of aerodynamic parameters. However, this method is generally applicable to a small range, and can not guarantee the prediction accuracy for the system with strong nonlinear problems. [4].

With the rapid development of neural network in recent years, its outstanding nonlinear mapping ability attracts more and more scholars to apply this method to aerodynamic parameter prediction. This method takes airfoil design parameters and aerodynamic coefficients as learning objects, establishes a prediction model through neural network or Support Vector Machine (SVM), and predicts the aerodynamic coefficients of unknown airfoils, thereby avoiding a large number of numerical operations

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and tests. Reference [5] established an RBF neural network model to predict the lift coefficient and drag coefficient of the wing at any displacement point in the frequency range 1-5 in the movement from the trough to the peak under a specific amplitude. Reference [6] and reference [7] take the angle of attack, Mach number, Reynolds number, and airfoil geometry as design inputs, and establish a neural network model to predict the aerodynamic coefficient of the airfoil. Reference [8] combines evolutionary programming algorithm with support vector regression algorithm to predict lift, drag and roll moment coefficients of airfoils with different geometric parameters under different angles of attack.

[9] However, artificial neural networks have two obvious shortcomings: there is instability in the system training process and local convergence will occur. In order to solve these two problems, some researches introduce GA into artificial neural networks for optimization. As an evolutionary computing technology based on biological evolution model, we can avoid the local convergence problem by introducing the GA algorithm, and greatly reduce the amount of information retrieval [10]. Second, many parametric prediction models cannot represent airfoils, but only predict specific airfoils without using airfoils as features. Based on the above research status, a GA-BP algorithm based airfoil parameter prediction model was established in this paper. By taking airfoil shape coordinates, Angle of attack, Mach number and Reynolds number as inputs, the lift coefficient, drag coefficient and moment coefficient of airfoil were predicted. By comparing the prediction results with ANN and GP Network, the superiority of GA - BP neural network in airfoil parameter prediction is proved .

II. GA -BP NEURAL NETWORK

[11]BP neural network is a widely used artificial neural network, including input layer, hidden layer and output layer. The neurons in the input layer interact with the real world to receive input, the output layer is presented in a visual way, and the neurons in the hidden layer are not visible [12] . Taking the three-layer BP neural network shown in Figure 1 as an example, the neurons in the input layer are a_m, the hidden layer neuron is b_u, and the output layer neuron is c_n. Let ω_{mn} be the connection weight between the m-th neuron in the input layer and the U-th neuron in the hidden layer, and v_{un} be the connection weight between the U-th neuron in the hidden layer and the n-th neuron in the output layer, then, neuron of hidden layer and neuron of output layer can be obtained successively, as shown in Equations (1) and (2):

$$b_u = f(\sum_u \omega_{mu} a_m + k_u) \tag{1}$$

$$c_n = f(\sum_u v_{un} b_u + p_n) \tag{2}$$

Among them: the excitation function is the sigmoid function, k_u is the hidden layer neuron threshold, p_n is the output layer neuron threshold. The output value of each time is compared with the expected output. If the mean square error does not meet the predetermined requirements, the back propagation

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process is performed, and the mean square error is returned in the form of gradient and distributed to the neurons of each layer. Repeat this process until the mean square error converges[13].

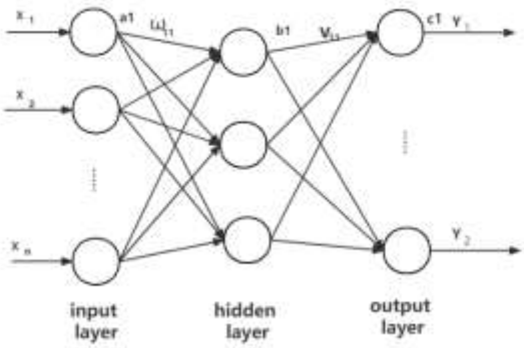

Figure 1: BP Neural Network

[14] Since no reliable method has been found to determine the initial weights and thresholds of the neural network, the determination of the initial weights and thresholds of the neural network has a certain randomness, and the BP neural network algorithm is easy to fall into the local optimal solution, making the The neural network cannot fit normally[15] , and the genetic algorithm with nonlinear optimization ability can just solve this problem. Among them, the real number array composed of the weights and thresholds of the BP network is the chromosome population of GA, and each individual in the population represents the distribution of the weights and thresholds of a neural network, that is, the length N of each individual is the sum of the total weight and the number of thresholds of the neural network, where N is shown in Formula (3) :

$$N=mu+un+u+n. \tag{3}$$

In the process of searching for optimal weights and thresholds, the mean square error function is used to judge the survivability of individuals, and each new individual is generated according to a certain crossover probability and mutation probability. We optimize the weights and thresholds of the BP network through the genetic algorithm, and finally establish the GA -BP neural network.

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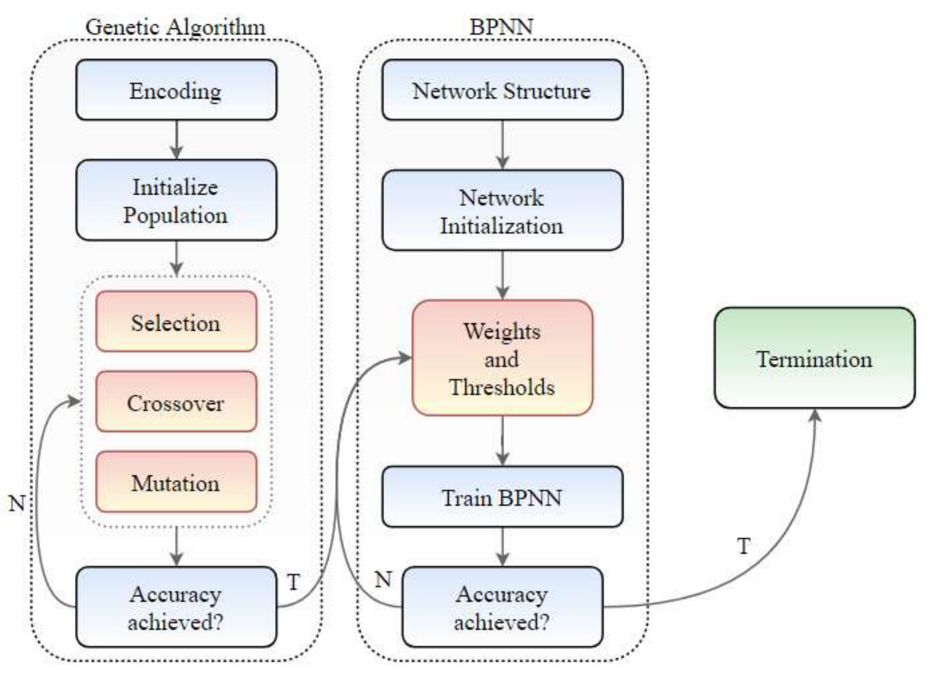

Figure 2: GA-BP flow chart

III. EXPERIMENT

3.1 Data acquisition and preprocessing

In this paper, the target of prediction is the lift coefficient, drag coefficient and moment coefficient of airfoil (as labels of the data set), because these coefficients are related to the airfoil shape and conditions such as Angle of attack, Mach number and Reynolds number (as features of the data set), we refer to the data generation method in reference [1] and use the NACA 4-bit and NACA 5-bit airfoil data sets generated by Javafoil with macro, as shown in Table 1.

TABLE 1: NACA 4-bit and NACA 5-bit airfoil data sets generated by Javafoil with macro

	Data sets	Coordinate points i（yU_i,yD_i,）
NACA 4 bit	NACA4_05.csv	5
	NACA4_10.csv	10
	NACA4_15.csv	15
NACA 5 bit	NACA5_05.csv	5
	NACA5_10.csv	10
	NACA5_15.csv	15

In each dataset, the first (2i + 3) columns are features:

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The shape of the airfoil is represented by the coordinates (yU_i, y L _i) of the upper and lower surfaces of the airfoil . yU_i consists of the y coordinates of the upper surface at equal intervals x_i, and y L _i consists of the y coordinates of the lower surface at the same x_i position . A total of 2i columns.

The next three columns are ReynoldsNumber, MachNumber, alpha (angle of attack).

The last three columns are labels, which are lift coefficient C_L, drag coefficient C_D and moment coefficient C_M.

Next, we examine the dataset and weed out some anomalies, mainly those that Javafoil cannot compute when the alpha (angle of attack) is particularly large.

After that, we standardize the (2i+3) features X by column by formula (4) , and the final partial data is shown in Table 2.

$$(X - \text{mean})/\text{std} \tag{4}$$

Mean is the mean of each column and std is the variance.

TABLE 2: NACA5_05.csv

	yU_1	yU_2	yU_3	yU_4	yU_5	yL_1	yL_2	yL_3
0	0.016659	0.024604	0.021796	0.01277	0.003794	-0.01666	-0.0246	-0.0218
1	0.016659	0.024604	0.021796	0.01277	0.003794	-0.01666	-0.0246	-0.0218
2	0.016659	0.024604	0.021796	0.01277	0.003794	-0.01666	-0.0246	-0.0218
…	…	…	…	…	…	…	…	…
171430	0.152298	0.227349	0.23408	0.184544	0.084534	-0.08594	-0.12191	-0.07577

	yL_4	yL_5	ReynoldsNumber	MachNumber	alpha	Cl	Cd	Cm
0	-0.01277	-0.00379	100000	0.1	-10	-0.334	0.1614	0.001
1	-0.01277	-0.00379	100000	0.1	-9	-0.392	0.13236	0.001
2	-0.01277	-0.00379	100000	0.1	-8	-0.442	0.10163	0.001
…	…	…	…	…	…	…	…	…
171430	0.000438	0.015683	500000	0.3	10	3.207	0.05764	-0.434

3.2 Model training

For the GA-BP neural network, if the data distribution is more uniform, the accuracy is higher, the stability is better, and the model after training is more suitable. Therefore, we randomly shuffle the data to ensure the randomness and uniformity of the training data, and divide the training set: test set: validation set = 7 : 1.5 : 1.5 for training.

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Next, this article sets up the hidden layer. Using too few neurons in the hidden layer leads to underfitting. Using too many neurons may lead to overfitting, while too many neurons will increase the training time and make it difficult to achieve the desired effect. Obviously, choosing an appropriate number of hidden layer neurons is critical.

This paper first bases on the following principles:

• The number of hidden neurons should be between the size of the input layer and the size of the output layer.

• The number of hidden neurons should be less than twice the size of the input layer.

Subsequently, through many experiments, it was found that the best effect was 4 layers and 12 neurons, so as to establish the neural network.

The computer configuration used for modeling and simulation in this paper is: Intel Corei7-44703.7GHz CPU, 16GB memory. The model is trained using MATLAB. The model error judgment standard adopts the mean square error (MAE), and the maximum number of iterations is set to 2000 times.

IV. EXPERIMENTAL RESULTS

4.1 Prediction accuracy

We train on 6 data sets in turn. For the convenience of description, we use NACA4_15. Data set to predict C_L as an example to illustrate the diagram. After the GA-BP training is completed, the test set data is input into the model, and the prediction C_L can be obtained, and the prediction time is less than 1s. In this paper, each experiment was carried out for 20 times. Some accidental training results were eliminated and the most average situation was selected as the result. As can be seen from Figure 3, when Epoch=927, MSE=0.0012013, with a small error, and MSE almost unchanged after Epoch=100, with rapid convergence. This paper selects the first 1000 points to compare the predicted value and the real value, as shown in Figure 4. It can be seen from Figure 4 that the real value of CL is very close to the predicted value with high accuracy.

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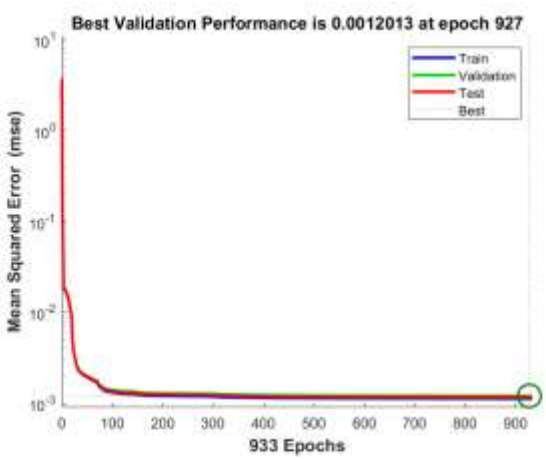

Figure 3: GA-BP MSE

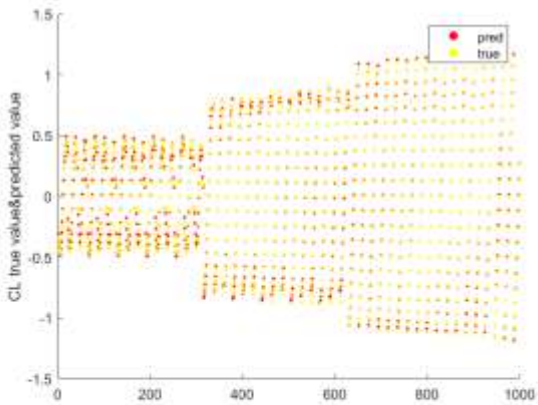

Figure 4: CL true value&predicted value

4.2 Comparative experiment

4.2.1 NACA4 and NACA5 mixed dataset training model

In the previous experiments, we used GA -BP to train the NACA4 and NACA 5 datasets respectively. In order to observe whether GA -BP can make accurate predictions on the mixed dataset of the two, we trained with the mixed dataset of NACA4_15 and NACA5_15 . GA -BP network, the maximum number of iterations is still 1 000 , and the MSE diagram is as follows:

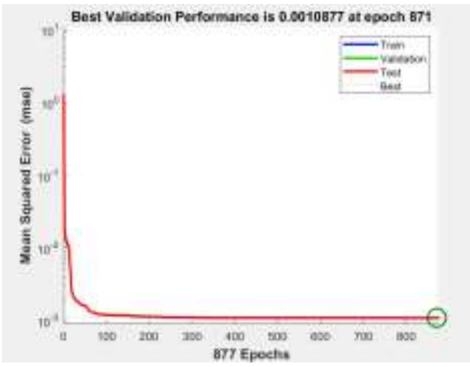

Figure 5: Mixed dataset MSE

It can be seen that after mixing the datasets, GA -BP can still have higher prediction accuracy, M SE = 0.0010877 , which indicates that a GA -BP model can have higher accuracy without training NACA4 and NACA 5 separately, Thereby reducing workload. At the same time, the hybrid dataset reaches the optimal convergence point at Epoch = 877. Compared with the MSE=0.0010877 obtained when training NACA4_15 alone to reach 927 times, it can be seen that the convergence speed becomes faster.

4.2.2 ANN, BP neural network comparison experiment

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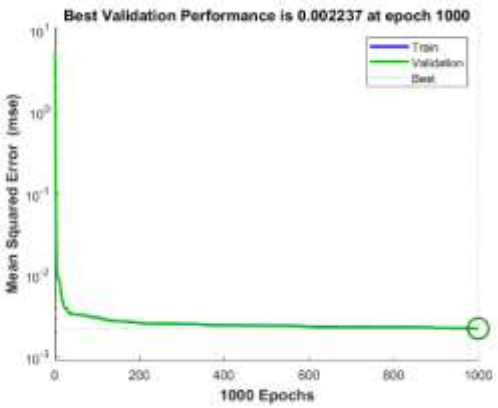
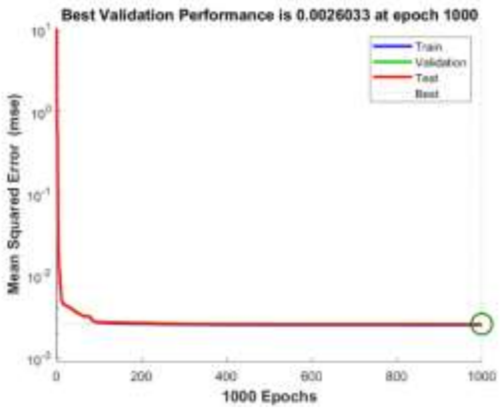
This paper takes the NACA4_15 data set to predict the lift coefficient C_L as an example, and compares the MSE of ANN, BP neural network and GA -BP to prove the superiority of the GA-BP algorithm.



ANN



BP neural network

Figure6 ANN and BP neural network

FORM 3: Table that the MSE of GA -BP is the smallest and the convergence speed is the fastest

Model	M SE
ANN	0.002237
BP neural network	0.0026033
GA-BP	0.0012013

It can be seen from the figure and table that the MSE of GA -BP is the smallest and the convergence speed is the fastest , which fully proves that the genetic algorithm makes the model have the ability of global optimization, so it can reach the target more quickly .

5 CONCLUSION

This paper, based on GA -BP , a model for predicting lift coefficient C_L , *drag coefficient* C_D *and* moment *coefficient* C_M *is* designed for various airfoils under different angles of attack, Mach number and Reynolds number . Compared with the traditional method, the calculation time of airfoil aerodynamic parameters is greatly reduced . At the same time, the research in this paper also proves that GA -BP still has a high prediction accuracy for NACA 4 -bit and 5-bit mixed datasets. This paper finally compares the prediction effect of GA-BP and ANN , BP neural network, and proves the superiority of GA -BP algorithm.

ACKNOWLEDGEMENTS

Funding Statement: This work is supported by the National Innovation and Entrepreneurship Training Program for College Students X2021-867

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

Hassan Moin and Hafiz Zeeshan Iqbal Khan and Surrayya Mobeen and Jamshed Riaz. Airfoil's Aerodynamic Coefficients Prediction using Artificial Neural Network. arXiv:2109.12149

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