



Improvement of aerodynamic coefficients of the airfoil with free form deformation with the aid of Artificial Neural Networks and Genetic Algorithm

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ABSTRACT: With the advent of morphing airfoils, the aerodynamics of wind turbines and wings underwent many changes. In this study, the aerodynamic coefficients of morphing airfoil based on NACA 0015 are optimized in the range of Reynolds number 105 to 106 and the angle of attack 0 to 12 degrees using Artificial Neural Network (ANN) and Genetic Algorithm (GA). First, the airfoils were created in MATLAB software by random control points and mesh generated in Gambit software, then in two-dimensional Ansys software were simulated. The simulation results, including lift and drag coefficients, separation point and pressure center, with control points were used to train the Artificial Neural Network (ANN). The trained function is given as an input function to the Genetic Algorithm (GA) to optimize the desired coefficients. Lift coefficient, center of pressure, separation point and lift to drag ratio were optimized as a single objective, In single-objective optimization, the lift coefficient was increased by 18% using the morphing airfoil. Also, the lift coefficient and the center of pressure, the lift coefficient and the drag coefficient were optimized as the dual-objectives optimization. In the optimization of the dual objectives, lift and drag coefficients were controlled by 0.8 and 0.03, respectively, by the morphing airfoils.

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1. INTRODUCTION

The use of smart materials in airfoil manufacturing has caused a significant change in wings and wind turbines. Smart materials are a group of unique materials that undergo significant deformation under conditions such as electric field, magnetic field, and thermal field. Materials that deform under an electric field are known as piezoelectrics.

Gardner et al. [1] optimized the airfoil using genetic algorithms and X-Foil software, and they used the Bezier curve to generate the airfoil geometry. Research results show that by optimizing the airfoil's velocity distribution, the airfoil's best possible aerodynamics can be achieved. Lee et al. [2] showed that the airfoil's trailing edge wing in aerodynamically active mode could reduce the airfoil forces. Numerical and laboratory results indicate the feasibility of using morphing wings to reduce the load on the wings. Gaspari and Ricci [3] optimized the 3D morphing airfoil for a commercial aircraft. They pursued optimization using the genetic algorithm method in a multi-objective manner. By minimizing the amount of drag coefficient, they were able to reduce it by about 6%.

Weishuang et al. [4] optimized the morphing wing at the end edge of the airfoil. The results showed an 8% increase in the ratio of lift to drag. Stall angle also increased by 1.3%.

Wen et al. [5] used the back propagation genetic algorithm to optimize wind turbine airfoil. Bessel curve features and 1446 layers were used to train the neural network. The results show a 71% increase in the maximum lift coefficient. The maximum lift coefficient and the lift to drag for the optimal airfoil were 1.8 and 96, respectively. Ma et al. [6] optimized the Darius wind turbine blade's geometry to increase the power coefficient by a genetic algorithm. The turbine is simulated with NACA 0018 airfoil with three different rotor diameters in three dimensions. The results show an increase in the turbine power coefficient for the tip speed ratio of 0.4 to 1.5, the largest increase in the tip speed ratio of 0.9 to 26.82% occurred.

2. COMPUTATIONAL SETUP

Optimization of the wind turbine's airfoil as an input variable requires a function to produce a smooth and continuous surface for the airfoil. The morphing airfoil varies in the direction of the airfoil thickness by 20% of the airfoil's total thickness. For each of the airfoil surfaces, 4 points were selected as control points to produce the airfoil surface. 2 control points are located at the leading and trailing edge of the airfoil, and 2 points create the main variations in the shape of the airfoil. Fig. 1 shows the variation range of upper and lower bands of the morphing airfoils.

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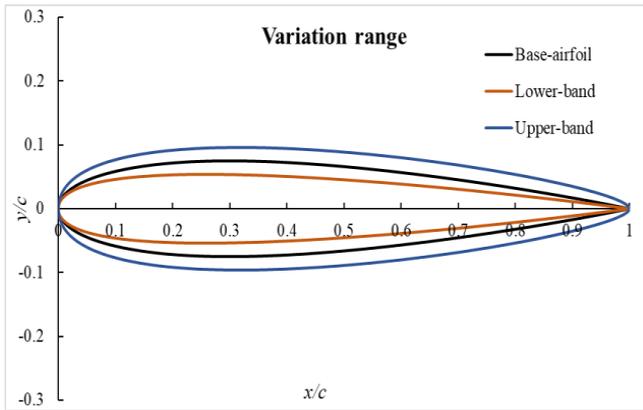


Fig. 1. Upper and lower bands of airfoil variations

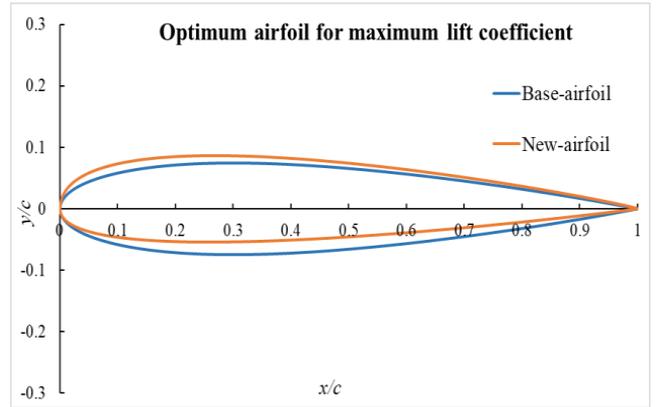


Fig. 3. New airfoil for maximum lift coefficient

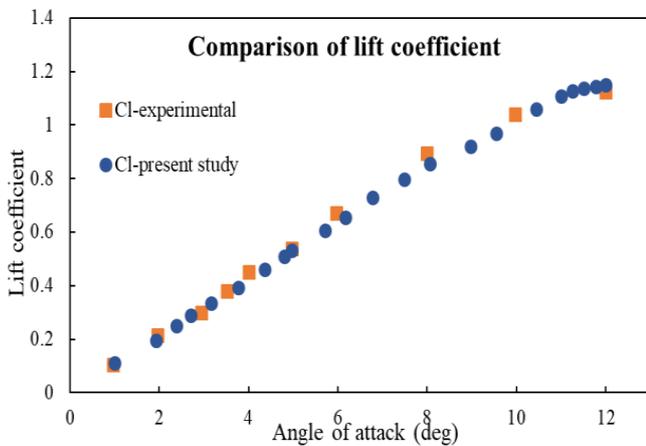


Fig. 2. Validation of lift coefficient at $Re=10^6$

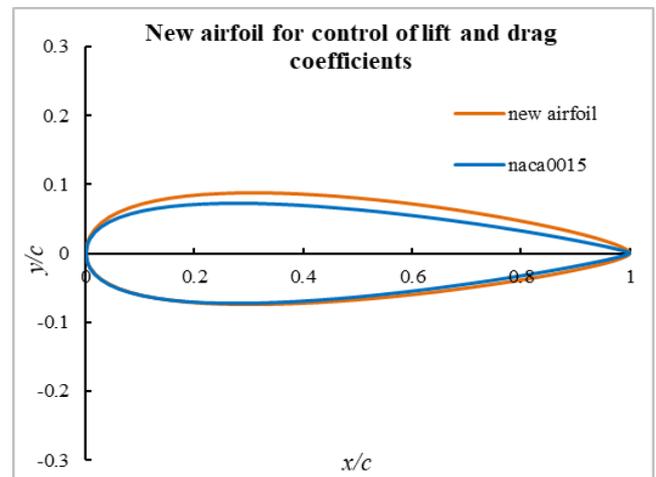


Fig. 4. New airfoil at $AOA=8^\circ$

Calculation of equation solved by Ansys Fluent 19 software. The flow governing of problem is turbulent, steady-state and incompressible, and the $k-\omega$ SST turbulence approach has been used to solve the turbulent flow. The problem is solved by Pressure based method using coupled algorithm, and all discretizations are of second order. In SIMPLE method, the momentum and pressure equations are solved separately, and the convergence is relatively slow. In contrast, the coupled method explicitly solves these equations and has a high convergence speed.

The lift coefficient of the present study at Reynolds 10^6 flow has been compared and validated in terms of different attack angles with the laboratory research of Rethmel et al. [7] in Fig. 2. The average error in the validation coefficient is 7.3%.

3. OPTIMIZATION

First, the control points that produce the airfoils' shape are generated by the Bezier curve in MATLAB and then sent to Gambit to draw the airfoil and its meshing. In the next step, airfoils are sent to Ansys software for simulation. The outputs

of Ansys, which are the power coefficient, are sent to the artificial neural network in MATLAB, and the control points to be trained in the artificial neural network. The trained neural network is given as a function to the genetic algorithm to optimize and control the aerodynamic coefficients, the center of pressure, the separation point, and related control points. The genetic algorithm also reports these desirable values as their output along with their control points.

4. RESULTS AND DISCUSSION

The speed of 50 m/s and the 6° angle of attack were optimized in this section. The lift coefficient for the NACA 0015 airfoil is 0.61. The Lift coefficient's optimization objective was 0.8, which was increased to 0.72 by the morphing airfoils and the limitation of the angle of attack and the flow velocity. In other words, the deformation of the airfoil increased the coefficient of performance by 18%. Fig. 3 shows these changes well.

The lift and drag coefficients are simultaneously controlled in Reynolds at a speed of 45 m/s and an angle of attack of 0 to 12° in the values of 0.8 and 0.03, respectively. Fig. 4 shows these changes at $AOA=8^\circ$

5. CONCLUSIONS

Artificial neural networks have a high ability to learn nonlinear problems. With proper training of artificial neural networks and accurately predicting the parameters, optimization operations can be performed more quickly. With the use of morphing airfoils, the performance of systems such as wind turbines and aircraft wings can be significantly controlled.

In this research, airfoil optimization was performed as single-objective and multi-objective, and the results show the control of aerodynamic coefficients, center of pressure and separation point with the help of airfoil deformation with acceptable accuracy. lift coefficient of single-objective increased by %18 with optimization of lift coefficient, control of pressure center at 0.25 point of airfoil chord with 100% accuracy, control of separation point at 0.18 point, airfoil chord with 100% accuracy, control of the ratio of lift coefficient to drag coefficient at 30 with high accuracy, control of lift and drag coefficients with error of 2.1% and 20%, respectively, in specific values in dual-objective optimization was one of the optimization results of this study.

REFERENCES

- [1] B. Gardner, M. Selig, Airfoil design using a genetic algorithm and an inverse method, in: 41st Aerospace Sciences Meeting and Exhibit, 2003, pp. 43.
- [2] J.-W. Lee, J.-H. Han, H.-K. Shin, H.-J. Bang, Active load control of wind turbine blade section with trailing edge flap: Wind tunnel testing, *Journal of intelligent material systems and structures*, 25(18) (2014) 2246-2255.
- [3] A. De Gaspari, S. Ricci, Knowledge-based shape optimization of morphing wing for more efficient aircraft, *International Journal of Aerospace Engineering*, 2015 (2015).
- [4] L. Weishuang, T. Yun, L. Peiqing, Aerodynamic optimization and mechanism design of flexible variable camber trailing-edge flap, *Chinese Journal of Aeronautics*, 30(3) (2017) 988-1003.
- [5] H. Wen, S. Sang, C. Qiu, X. Du, X. Zhu, Q. Shi, A new optimization method of wind turbine airfoil performance based on Bessel equation and GABP artificial neural network, *Energy*, 187 (2019) 116106.
- [6] N. Ma, H. Lei, Z. Han, D. Zhou, Y. Bao, K. Zhang, L. Zhou, C. Chen, Airfoil optimization to improve power performance of a high-solidity vertical axis wind turbine at a moderate tip speed ratio, *Energy*, 150 (2018) 236-252.
- [7] C. Rethmel, J. Little, K. Takashima, A. Sinha, I. Adamovich, M. Samimy, Flow separation control using nanosecond pulse driven DBD plasma actuators, *International Journal of Flow Control*, 3(4) (2011).

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