Postprint of "Research on Aerodynamic Optimization Methods for Wind Turbine Blades Based on Deep Learning"

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Abstract

To address the issues of large computational cost and long computation time associated with traditional computational fluid dynamics methods in evaluating the aerodynamic performance of blades, a wind turbine blade aerodynamic optimization method based on deep learning is proposed. First, a rapid airfoil aerodynamic force prediction model based on a multilayer perceptron is constructed to achieve fast optimization of the aerodynamic performance of wind turbine airfoils. Subsequently, in combination with blade element momentum theory, a rapid calculation method for the aerodynamic performance of wind turbine blades is established, thereby enabling the optimization of blade geometry. Using a 1.5 MW wind turbine as an example, airfoil optimization and blade shape optimization are carried out with respect to the maximum lift-to-drag ratio and annual energy production, respectively. The results show that the airfoil aerodynamic force prediction model based on a multilayer perceptron achieves an overall prediction accuracy greater than 99% on both the training and test sets. The wind turbine blade optimized by this method exhibits a 13.74% increase in power coefficient and a 4.04% increase in annual energy production, demonstrating the practical value of deep learning in the field of aerodynamic optimization of wind turbine blades.

Full Text

Research on Aerodynamic Optimization Method for Wind Turbine Blades Based on Deep Learning

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Abstract

To address the computational inefficiency and time-consuming nature of traditional computational fluid dynamics (CFD) methods in evaluating blade aerodynamic performance, this paper proposes a novel aerodynamic optimization method for wind turbine blades based on deep learning. The method first constructs a fast aerodynamic force prediction model for airfoils using a multi-layer perceptron (MLP), enabling rapid optimization of airfoil aerodynamic performance. Subsequently, combined with blade element momentum theory, a fast calculation method for wind turbine blade aerodynamic performance is established to conduct shape optimization studies. Using a 1.5 MW wind turbine as a case study, airfoil optimization targeting maximum lift-to-drag ratio and blade shape optimization for maximum annual energy production are performed separately. The results demonstrate that the MLP-based aerodynamic force prediction model achieves overall prediction accuracy exceeding 98% on both training and test sets. The optimized wind turbine blade exhibits a 13.74% improvement in power coefficient and a 4.04% increase in annual energy production, validating the practical value of deep learning in wind turbine blade aerodynamic optimization.

Keywords: deep learning; wind turbine blade optimization; blade element momentum theory; airfoil optimization

1. Introduction

With the continuous development of clean and renewable energy technologies, wind energy utilization has gained significant attention worldwide, particularly in China where wind power technology advancement is actively promoted. As the primary energy conversion component in wind turbines, blade performance is crucial for efficient turbine operation, making blade optimization design research essential. The airfoil is a key determinant of wind turbine blade aerodynamic performance, and optimization typically begins with airfoil design. Developed countries such as Denmark have established specialized airfoil families like NREL-S and RisØ series, while China' s research in this area started relatively later, with contributions from institutions such as Northwestern Polytechnical University (NPU-WA series) and the Chinese Academy of Sciences.

Traditional aerodynamic performance evaluation relies heavily on CFD methods, which require extensive computational time through iterative processes, resulting in long optimization design cycles. There is an urgent need to establish rapid optimization methods for wind turbine airfoils to advance specialized airfoil development. With the rise of artificial intelligence, deep learning has found extensive applications in turbomachinery optimization design. Convolutional neural networks (CNN) have been employed for airfoil inverse design, while reinforcement learning and neural network surrogate models have demonstrated the ability to rapidly and credibly predict aerodynamic forces, significantly reducing computational costs and shortening optimization cycles.

This study proposes an efficient wind turbine blade optimization method based on deep learning, aiming to improve computational efficiency while optimizing blade performance. The approach establishes a deep learning-based airfoil aerodynamic characteristic prediction model and integrates it with blade element momentum theory for comprehensive aerodynamic optimization.

2. Fast Prediction Method for Wind Turbine Blade Aerodynamic Characteristics

2.1 Airfoil Parameterization and Database Construction This study employs the Class-Shape Function Transformation (CST) method for airfoil shape parameterization. The CST method first defines a class function to determine the fundamental airfoil category, then uses shape functions to define the specific geometry. The basic expression is:

$$y(x) = C(x) \cdot S(x) + x \cdot \Delta y_{te}$$

where $C(x)$ represents the class function, $S(x)$ represents the shape function expressed as a Bernstein polynomial, x denotes the chordwise coordinate, y denotes the vertical coordinate, Δy_{te} is the trailing edge offset, and A represents the shape function coefficients.

A Multi-Layer Perceptron (MLP), a powerful artificial neural network, is constructed to simulate biological signal transmission. The computational expression for a single neuron is:

$$z = f\left(\sum_{i=1}^{n} w_i x_i + b\right)$$

where x_i are input data, w and b are weights and biases between connections, and f represents the nonlinear activation function.

For wind turbine airfoil optimization, the primary focus is on lift and drag coefficients. XFOIL software is used to calculate aerodynamic coefficients at various Mach numbers and angles of attack, establishing a comprehensive database with one-to-one correspondence between airfoil geometry and aerodynamic data. To address potential limitations in airfoil shape diversity or insufficient sample size that may affect model prediction accuracy across different operating conditions, Latin Hypercube Sampling (LHS) is employed. Each parameter range is divided into equal intervals, with samples selected from each interval to ensure uniform distribution in the multidimensional design space.

The design space for airfoil shapes is illustrated in [Figure 3: see original paper]. To enable aerodynamic coefficient prediction across varying Mach numbers and angles of attack, the Mach number range is set to [0.05, 0.4] and the angle of attack range to [-5°, 20°], sampled at 0.5° intervals. XFOIL calculations provide the aerodynamic database for wind turbine airfoil optimization.

A deep branching structure model is adopted, with geometric parameters (airfoil shape coefficients) and operating parameters (Mach number and angle of attack) processed through separate branches since they belong to different parameter categories. The model structure is shown in [Figure 4: see original paper].

2.2 Model Training and Performance Evaluation The dataset is divided into training and test sets, with 163,666 training samples and 3,523 test samples. The initial learning rate is set to 0.0002, with a standard batch size. The SELU activation function is used. Model accuracy is calculated using relative error:

$$\text{Accuracy} = \left(1 - \frac{|y_{\text{pred}} - y_{\text{true}}|}{y_{\text{true}}}\right) \times 100\%$$

[Figure 5: see original paper] and [Figure 6: see original paper] compare predicted and calculated values for the training and test sets. The majority of sample points cluster near the $y = x$ line, indicating excellent agreement between predictions and XFOIL calculations. The model demonstrates outstanding predictive capability on the training set and maintains strong performance on the test set, proving its generalization ability.

The error distributions are shown in [Figure 7: see original paper] and [Figure 8: see original paper]. For the test set, the average prediction accuracy for drag coefficient is 98.5527%, while for lift coefficient it reaches 99.7054%. The overall prediction accuracy exceeds 98.4767%, with most samples having prediction errors below 0.5% and an average accuracy of 99.7036%.

3. Wind Turbine Aerodynamic Characteristics Prediction Method Based on Blade Element Momentum Theory

The blade element momentum (BEM) theory is the most widely used method for wind turbine blade aerodynamic calculation. The velocities and forces acting on a blade element are shown in [Figure 9: see original paper]. Let U be the incoming flow velocity, B the number of blades, U_a the axial induced velocity, U_b the tangential induced velocity, and Ωr the tangential velocity.

Based on the corrected BEM theory, a wind turbine aerodynamic calculation model is established. The NREL 20 kW three-bladed wind turbine is used as a validation case. lists its basic design parameters. [Figure 10: see original paper] compares calculated and experimental power output, showing good agreement and validating the accuracy of the corrected BEM theory.

The inflow angle ϕ at a blade element is:

$$\phi = \arctan\left(\frac{U(1-a)}{\Omega r(1+b)}\right)$$

where a and b are axial and tangential induction factors. The local angle of attack α is:

$$\alpha = \phi - \beta$$

with β being the local twist angle. The Prandtl tip loss correction factor F is:

$$F = \frac{2}{\pi} \arccos\left[\exp\left(-\frac{B(R-r)}{2r\sin\phi}\right)\right]$$

The corrected axial and tangential induction factors are:

$$a = \frac{1}{\frac{4F\sin^2\phi}{\sigma C_n} + 1}, \quad b = \frac{1}{\frac{4F\sin\phi\cos\phi}{\sigma C_t} - 1}$$

where σ is the solidity, and C_n and C_t are normal and tangential force coefficients. The rotor thrust T, torque M, power P, and power coefficient C_p are calculated accordingly.

4. Airfoil Aerodynamic Optimization Method Based on Deep Learning

Airfoil optimization is crucial for designing high-quality wind turbine airfoils. The genetic algorithm is selected as the optimization algorithm, with parameters detailed in . The optimization uses 30 design variables representing the upper and lower surface shape coefficients, with variation ranges limited to $±$10% of original values. The objective is maximizing lift-to-drag ratio, with the constraint that the optimized airfoil' s lift coefficient must not be lower than the initial airfoil' s.

The optimization model is formulated as:

$$\begin{aligned} \max \quad & \frac{C_l}{C_d} \\ \text{s.t.} \quad & C_l \geq C_{l,\text{initial}} \\ & \text{shape constraints} \end{aligned}$$

The wind turbine airfoil aerodynamic optimization platform is built using Isight software. The platform inputs initial airfoil parameters and design conditions (angle of attack and Mach number), uses the MLP-ClCd aerodynamic coefficient predictor to rapidly output lift and drag coefficients, and employs genetic algorithm selection, crossover, and mutation operations to generate new airfoil designs. The optimization iterates until convergence, outputting the airfoil with maximum lift-to-drag ratio. The optimization flowchart is shown in [Figure 12: see original paper].

5. Blade Shape Optimization Method Based on Blade Element Momentum Theory

For blade shape optimization, the annual energy production E is maximized:

$$E = \sum_i P(U_i) \cdot f(U_i) \cdot t$$

where $P(U_i)$ is power output at wind speed U_i, $f(U_i)$ is the probability of wind speed U_i, and t is time. The chord lengths c_i and twist angles β_i at different spanwise positions are used as optimization variables, with constraints ensuring monotonic variation.

The optimization model is:

$$\begin{aligned} \max \quad & E \\ \text{s.t.} \quad & c_{\min} \leq c_i \leq c_{\max} \\ & \beta_{\min} \leq \beta_i \leq \beta_{\max} \\ & \text{monotonicity constraints} \end{aligned}$$

The blade is divided into sections, and the BEM-based code performs optimization by initializing a population of blade designs, evaluating aerodynamic performance for each, and iterating until convergence to the blade geometry with maximum annual energy production.

6. Optimization Results and Analysis

6.1 Initial Wind Turbine Blade Model A 1.5 MW wind turbine blade is selected as the research object. The blade uses S814, S830, and S831 airfoils at different spanwise sections, suitable for inland areas with low average wind speeds and small variations. The basic design parameters are listed in . The wind field is described using a Weibull distribution [Figure 13: see original paper], yielding an initial power coefficient of 0.4350 and annual energy production of 6.609×10^6 kWh.

6.2 Airfoil Aerodynamic Optimization The established aerodynamic optimization platform optimizes the three airfoils. The optimization status is detailed in . [Figure 14: see original paper] compares the initial and optimized airfoil shapes. The optimized airfoils show improved aerodynamic performance:

- **S814**: Lift coefficient changes from 1.1351 to 1.1922, drag coefficient from 0.0209 to 0.0203, lift-to-drag ratio improves by 9.45%
- **S830**: Lift coefficient changes from 1.0754 to 1.1433, drag coefficient from 0.0160 to 0.0154, lift-to-drag ratio improves by 9.12%
- **S831**: Lift coefficient changes from 1.0887 to 1.1553, drag coefficient from 0.0129 to 0.0121, lift-to-drag ratio improves by 13.13%

All three airfoils demonstrate enhanced aerodynamic performance.

6.3 Wind Turbine Blade Shape Optimization Results The optimized airfoils are stacked to form the wind turbine blade, and blade shape optimization is performed. [Figure 15: see original paper] shows the optimization results for chord length and twist angle distribution. Significant changes are observed: chord length reduces from 5.96 m to 5.24 m at the root, and twist angle decreases from 30.25° to 25.26°.

At a tip speed ratio of 7, the optimized blade achieves a power coefficient of 0.4948, representing a 13.74% improvement over the initial blade' s 0.4350. For tip speed ratios below 7, the optimized blade's power coefficient is slightly lower, but this region corresponds to high wind speeds with low probability. [Figure 16: see original paper] shows the power coefficient variation with tip speed ratio, while [Figure 17: see original paper] shows output power variation with wind speed. The optimized blade produces more power at the same wind speed.

Assuming continuous operation without mechanical losses, the optimized blade' s annual energy production is 6.876×10^6 kWh, a 4.04% increase over the initial blade, proving the aerodynamic superiority of the optimized design.

7. Validation of Optimization Results

To further validate the deep learning-based optimization method, CFD simulations are performed using FLUENT. The computational domain consists of stationary and moving regions connected by an interface, with a total mesh count of approximately 3.6×10^6 and first layer height of 4.84×10^{-5} m. [Figure 18: see original paper] shows the blade modeling and mesh division.

Boundary conditions are set as velocity inlet and pressure outlet, with 12 m/s wind speed and 21.68 r/min rotational speed. The Navier-Stokes equations are solved using the finite volume method with the k-ω SST turbulence model. [Figure 19: see original paper] compares pressure contours between initial and optimized blades in the X-Z plane.

The output power comparison is shown in . The maximum error between BEM theory and CFD results is 2.97%, confirming the reliability of BEM theory for evaluating optimization effects. The optimized blade shows significant power output improvement over the initial blade.

8. Conclusion

This study proposes an efficient wind turbine blade optimization method based on deep learning to address the high computational cost of traditional flow field calculations. The method constructs an MLP-based airfoil aerodynamic force prediction model achieving over 98% accuracy on both training and test sets, effectively replacing traditional CFD and significantly accelerating the airfoil optimization process. Combined with blade element momentum theory, the method optimizes blade shape.

For the 1.5 MW wind turbine case study, the optimized blade achieves: - Power coefficient improvement of 13.74% - Annual energy production increase of 4.04%

The results demonstrate that the proposed optimization method not only significantly improves wind turbine blade aerodynamic performance but also reduces optimization time and computational cost, representing an efficient and feasible optimization strategy.

References

[1] Zhonghua Z, Zhenghong H, Wenping W. Airfoil research: history, current status, and future directions[J]. Acta Aerodynamica Sinica, 2021, 39(6): 1-36.

[2] Zhide Z, Wenping W, Yongwei Z. Design and experimental research of NPU-WA airfoil family for wind turbines[J]. Acta Aerodynamica Sinica, 2012, 30(2): 260-265.

[3] Jingyan W, Chenwu H. Inverse design of wind turbine airfoils[J]. Journal of Engineering Thermophysics, 2012, 33(11): 1884-1887.

[4] Fuglsang P, Madsen H A. Optimization method for wind turbine rotors[J]. Journal of Wind Engineering and Industrial Aerodynamics, 1999, 80(1/2): 191-206.

[5] Zhu W J, Sørensen J N. Integrated airfoil and blade design method for large wind turbines[J]. Renewable Energy, 2014, 70: 227-238.

[6] Huishe W, Jianzhong X, Pengcheng L. Optimization design method research for high-performance wind turbine airfoils based on XFOIL technique[J]. Journal of Engineering Thermophysics, 2007, 28(4): 586-588.

[7] Yaping J, Chuhua Z. Optimal design method for wind turbine airfoils based on artificial neural network and genetic algorithm[J]. Proceedings of the CSEE, 2009, 29(20): 106-111.

[8] Yanping R, Teng L. Research on several airfoil parameterization methods[J]. Journal of Projectiles, Rockets, Missiles and Guidance, 2011, 31(3): 160-164.

[9] Fuglsang P, Madsen H A. Optimization of wind turbine rotors[J]. Wind Energy, 2004, 7(2): 141-148.

[10] Rajakumar S, Ravindran D. Iterative approach for optimization of wind turbine rotor[J]. Renewable Energy, 2012, 38(1): 83-91.

[11] Huan L, Xuejun C, Pengcheng W. Research on wind turbine blade optimization design based on particle swarm algorithm[J]. Journal of Shenyang University of Chemical Technology, 2022, 36(6): 544-547.

[12] Chao H, Binghao S, Yong W. Optimization design of twist angle and chord length for offshore wind turbine blade based on Simulink[J]. Acta Energiae Solaris Sinica, 2021, 42(3): 135-141.

[13] Yang W, Huan Z. Optimization design method for horizontal axis wind turbine blade based on Wilson method and genetic algorithm[J]. Journal of Shanghai University of Electric Power, 2018, 34(4): 325-328.

[14] Sekar A, Jiang Z. Flow field prediction for airfoils using deep learning approach[J]. Physics of Fluids, 2019, 31(5): 054102.

[15] Liu L, Zhenxun W. Aerodynamic force calculation and inverse design of airfoils based on neural network[J]. Physics of Gases, 2018, 3(5): 41-47.

[16] Chenming C, Xueyan W, Linsen C. Research on airfoil optimization and domain adaptation based on neural network surrogate model[J]. Journal of Chinese Society of Power Engineering, 2022, 42(7): 657-663.

[17] Lou J, Linsen C. Aerodynamic optimization of airfoils based on reinforcement learning[J]. Physics of Fluids, 2023, 35(3): 034110.

[18] Liu Y, Zhang C. Airfoils optimization based on reinforcement learning to improve aerodynamic performance of rotors[J]. Aerospace Science and Technology, 2023, 134: 108108.

[19] Sobieczky H. Parametric airfoils and wings[M]//Notes on Numerical Fluid Mechanics. Berlin: Springer, 1998: 71-88.

[20] Giguère P, Selig M S. Design of a tapered and twisted blade for the NREL combined experiment rotor[R]. Golden, CO: National Renewable Energy Laboratory, 1999. NREL/SR-500-26173.

[21] Zhengrong W, Lifeng L, Xinyue H. Assessment of wind energy resources and utilization status in large-scale wind farms[J]. Practical Electronics, 2018(18): 15-16.

[22] Yilmaz A, German B. Convolutional neural network approach to training predictors for airfoil performance[C]//18th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference. Reston: AIAA, 2017: 4431.

[23] Zhang Q, Weipao Z, Linsen C. Optimal design of dynamic stall for wind turbine airfoil based on surrogate model[J]. Acta Energiae Solaris Sinica, 2023, 44(6): 331-338.

[24] Deghoum A, Gherbi S, Sultan K. Optimization of small horizontal axis wind turbines based on aerodynamic, steady-state, and dynamic analyses[J]. Applied System Innovation, 2018, 3(5): 31.

[25] Yin Z. Optimal design and aerodynamic performance prediction of horizontal small-scale wind turbine[J]. Mathematical Problems in Engineering, 2022, 2022(1): 2022.

[26] Kaviani A, Moshfeghi M. Multi-megawatt horizontal axis wind turbine blade optimization based on deep learning method[J]. Aerospace, 2023, 10(2): 174.

[27] Rodriguez C, Celis R. Design optimization methodology for small horizontal axis wind turbine blades using hybrid CFD/BEM/GA approach[J]. Journal of the Brazilian Society of Mechanical Sciences and Engineering, 2022, 44(6): 202.

Note: Figure translations are in progress. See original paper for figures.