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A Surrogate ANN–BEM Framework for Aerodynamic Modeling of Smart Wind Turbine Blades

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KEYWORDS

NACA, airfoil, artificial neural networks (ANN), morphing blade, smart blades.

ABSTRACT

Accurate prediction of aerodynamic coefficients is essential for the design and control of smart blades featuring morphing airfoils. This study presents a datadriven metamodel based on Artificial Neural Networks (ANNs) developed to predict the aerodynamic behavior of airfoils within the NACA series. The model accepts geometric descriptors of airfoils along with the angle of attack (AoA) as input and outputs corresponding lift (Cl) and drag (Cd) coefficients. A high-fidelity aerodynamic database was generated through systematic simulations across a wide range of AoAs and NACA profiles to train and validate the ANN.

The model is trained on NACA 4-digit series profiles covering a wide range of AoA and geometric parameters. The ANN model achieved a mean squared error of 2.10805 e-3 and an R^2 above 0.997 on test data. The trained metamodel demonstrates excellent generalization accuracy while drastically reducing computational requirements compared to conventional CFD or BEM-based methods. The model is particularly suited for integration into larger

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simulation frameworks, such as Blade Element Momentum (BEM) codes or adaptive control systems, enabling real-time performance estimation for morphing smart blades. This work contributes a scalable and efficient surrogate modeling approach for aerodynamic prediction across diverse airfoil geometries.

إطار بديل قائم على الشبكات العصبية الاصطناعية وطريقة عنصر الريشة لنمذجة الديناميكا الهوائية لشفرات توربينات الرياح الذكية

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ملخص: تُعدّ القدرة على التنبؤ الدقيق بالمعامات الهوائية أمرًا أساسيًا في تصميم والتحكم في الشفرات الذكية المزودة بمقاطع هوائية متحوّلة. يقدم هذا البحث نموذجًا استبداليًا (metamodel) يعتمد على الشبكات العصبية الاصطناعية (ANNs) تم تطويره للتنبؤ بالسلوك الهوائي للمقاطع الهوائية من سلسلة NACA. يستقبل النموذج واصفات هندسية للمقاطع الهوائية إلى جانب زاوية الهجوم (AoA) كمدخات، ويُنتج معاملات الرفع(Cl) ومعاملات الجر (Cd) المقابلة. تم إنشاء قاعدة بيانات هوائية عالية الدقة من خال محاكاة منهجية تغطي نطاقًا واسعًا من زوايا الهجوم (AoAs) ونماذج NACA لتدريب والتحقق من أداء الشبكة العصبية. وقد تم تدريب النموذج على مقاطع من سلسلة NACA ذات الأربع خانات، تشمل نطاقًا واسعًا من زوايا الهجوم والمعامات الهندسية. حقق نموذج ANN خطأً تربيعيًا متوسطًا مقداره $2.10805e^{-3}$ ومعامل تحديد (R^2) يتجاوز 997.0 على بيانات الاختبار. يُظهر النموذج المُدرّب دقة عالية في التعميم مع تقليص كبير في متطلبات الحساب مقارنة بطرق CFD أو BEM التقليدية. يُعتبر النموذج مناسبًا بشكل خاص للدمج ضمن أطر محاكاة أكبر، مثل شفرات نظرية عنصر الريشة (BEM) أو أنظمة التحكم التكيفية، مما يتيح تقدير الأداء في الزمن الحقيقي للشفرات الذكية المتحوّلة. تسهم هذه الدراسة في تقديم مقاربة استبدالية (surrogate modelling) قابلة للتوسع وفعّالة للتنبؤ الهوائي عبر هندسيات مختلفة للمقاطع الهوائية.

الكلمات المفتاحية: NACA، المقطع الهوائي، الشبكات العصبية الاصطناعية (ANN) ، الشفرة المتحوّلة، ، الشفرات الذكية.

1. INTRODUCTION

The growing need for renewable and clean forms of energy has provided substantial incentive for optimizing the performance of wind turbines. Of many different methods currently being investigated, use of adaptive or 'smart' blades that can vary their aerodynamic shapes based on operating conditions has been identified as a viable method for increasing aerodynamic effectiveness, minimizing loads, and improving turbine longevity [1][2]. However, assessment of such blade configurations accurately and efficiently poses a computational challenge because complex relationships between geometry, flow conditions, and a chosen measure of performance exist. The Blade Element Momentum (BEM) approach has gained widespread usage due to its ease and effectiveness in simulating wind turbines, particularly at early design stages [3]. However, conventional BEM is based on pre-calculated aerodynamic coefficient tables and is typically limited to fixed-profile airfoils and does not account for the morphing geometries' dynamic behavior. At the opposite extreme, high-fidelity Computational Fluid Dynamics (CFD) simulations provide rich information but have a computation cost that is too high when utilized within iterative optimization or real-time control loops [4]. To overcome this limitation, recent research literature has suggested utilizing Artificial Neural Networks (ANNs) as surrogate models for swift aerodynamic estimation [5]-[6]. Recent surrogate models based on deep learning achieved drag reduction exceeding 80% for rotor airfoils while requiring significantly less computation time than CFD [7]. ANNs can learn intricate nonlinear mappings between airfoil geometry, angle of attack, and aerodynamic coefficients and can provide real-time estimates of lift and drag with very good accuracy. Haiek et al. [1], for instance, showed the possibility of utilizing ANN-based metamodels for estimating the NACA series airfoil's performance over a large range of geometrical parameters and angles of attack. Their work also shows promise for combining the machine learning models and physical solvers and building hybrid frameworks for simulation of performance. Unlike traditional surrogate methods such as Kriging or Radial Basis Functions (RBF), artificial neural networks (ANNs) offer superior scalability for highdimensional nonlinear aerodynamic spaces, as demonstrated in recent studies [6]. "Multi-fidelity deep learning approaches have also demonstrated their ability to optimize airfoil performance while balancing data complexity and computational cost [8]-[9]." "A recent review outlines how ML-based methods, such as ANN, Kriging, and SVR, are increasingly used in aerodynamic design tasks due to their flexibility and predictive accuracy [10]."In addition to these modeling advances, various physical strategies have also been explored to enhance blade performance [11-14].

By way of background, the work put forward here involves a new coupled approach that incorporates an ANN-based aerodynamic predictor within a BEM solver to model variableairfoil-geometry smart blades. The ANN is trained on predicting lift and drag coefficients for NACA 4-digit shapes from geometric attributes and angle of attack while physics-based rotor dynamics are addressed by the BEM model. This combined structure inherits the twofold benefits of accuracy and computational speed and is thus appropriate for integration within design loops and optimization studies and real-time use.

The rest of this paper is organized as follows: Section 2 gives the entire framework architecture. Section 3 gives the mathematical foundation of the BEM method. Section 4 outlines the building of the ANN metamodel and verifies the predictions of ANN. Section 5 gives the coupling strategy and shows simulation results. Section 6 provides concluding remarks, including a synthesis of the main results and prospects for future work.

2. ARCHITECTURE OF COUPLED ANN-BEM MODEL

The proposed modeling framework (Fig.1) is designed to simulate and predict the aerodynamic behavior of smart blades equipped with morphing airfoils. It integrates two key components: a physics-based Blade Element Momentum (BEM) model for system-level performance evaluation, and a data-driven Artificial Neural Network (ANN) surrogate model for rapid and accurate estimation of local aerodynamic coefficients (Cl and Cd). This hybrid structure combines the strengths of both methods:

BEM provides a reliable and computationally efficient method for estimating the performance of rotating blades, widely used in wind turbine and propeller analyses.

ANN is used to replace traditional lookup tables or analytical expressions for airfoil data, enabling flexibility in geometry (across NACA series) and operational conditions (e.g., varying AoA).

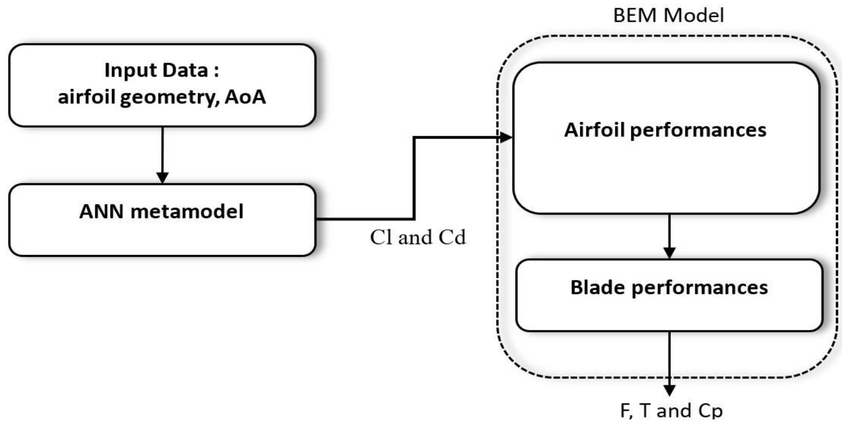

Figure 1: Architecture of coupled ANN-BEM framework for smart blade.

The overall architecture follows a sequential workflow where blade geometry and operating conditions, such as rotational speed, inflow velocity, and the number of blade elements, are first defined. For each element along the blade span, the local angle of attack (AoA) is computed using the BEM model, and the corresponding airfoil geometry (typically a NACA profile) is identified. The AoA, along with key geometric parameters including airfoil thickness, position of maximum thickness, camber, and position of maximum camber, are then fed into an Artificial Neural Network (ANN). The ANN outputs the corresponding lift and drag coefficients, Cl and Cd, which are passed back into the BEM loop to calculate the local aerodynamic forces and moments. These are integrated across the blade to compute the overall performance of the rotor, including torque, thrust, power, and the power coefficient. The hybrid ANN-BEM framework offers significant advantages: it is flexible, easily adaptable to other airfoil families such as NACA 5-digit or morphing profiles; it is fast, eliminating the need for time-consuming CFD simulations at each evaluation; and it is integration-ready, making it suitable for use in iterative design loops, control simulations, and real-time optimization environments.

3. BLADE ELEMENTS MOMENTUM FOR BLADE MODELING

The momentum part of BEM is derived from the conservation of linear and angular momentum applied to an annular control volume through which air flows as it interacts with the rotating blade.

Assuming axial flow and a steady-state, incompressible system, the thrust T produced by a rotor disk of radius R is:

$$T = \dot{m}(V_\infty - V_d) = \rho A v(V_\infty - v) \tag{1}$$

Where:

V_∞: freestream wind speed,

V_d: wind speed downstream of rotor,

v: induced axial velocity at rotor plane,

$A=\pi R^2$: rotor disk area, ρ : air density.

By defining the axial induction factor a such that:

$$v = aV_\infty \Rightarrow T = 2\rho A V_\infty^2\, a(1-a) \tag{2}$$

This equation provides the total thrust generated by the rotor disk using momentum balance. In the blade element part, the blade is divided into radial segments. For each segment, aerodynamic forces are computed using 2D airfoil theory:

$$dL = \frac{1}{2}\rho V_{rel}^2 c C_L dr\ ;\ \ dD = \frac{1}{2}\rho V_{rel}^2 c C_D dr \tag{3}$$

Where:
c : chord length of the blade element,
dr: radial thickness of the segment,
V_{rel} : relative wind speed at the segment,
C_L, C_D : lift and drag coefficients from the ANN.
The relative wind speed V_{rel} at radius r is:

$$V_{rel} = \sqrt{(V_\infty(1-a))^2 + (\omega r(1+a'))^2} \tag{4}$$

Where:
ω : angular speed of the rotor,
a : axial induction factor,
a' : tangential induction actor.
The inflow angle ϕ (between relative wind and rotor plane) is:

$$\phi = \tan^{-1}\left(\frac{V_\infty(1-a)}{\omega r(1+a')}\right) \tag{5}$$

The local angle of attack is:

$$\alpha = \phi - \theta \tag{6}$$

Where: θ : local pitch angle (blade twist + collective pitch).
Once C_L and C_D are computed from the ANN surrogate model, the axial and tangential forces on the blade element are:

$$dT = dF_x = \frac{1}{2}\rho V_{\mathrm{rel}}^2 c(C_L\cos\phi + C_D\sin\phi)\, dr \tag{7}$$

$$dQ = dF_\theta = \frac{1}{2}\rho V_{\mathrm{rel}}^2 cr(C_L\sin\phi - C_D\cos\phi)\, dr \tag{8}$$

Then:

$$\text{Total thrust } (T) = \int dT \tag{9}$$

$$\text{Torque } (Q) = \int dQ \tag{10}$$

$$\text{Power } (P) = \omega Q \tag{11}$$

4. ANN METAMODEL BUILDING

4.1. Airfoil Dataset and Problem Formulation

The National Advisory Committee for Aeronautics (NACA) developed a standardized system for defining airfoil geometries, which remains a foundational reference in aerodynamic analysis. In this work, we focus on the NACA 4-digit series (Fig.2), where the airfoil shape is defined by three parameters: maximum camber, position of maximum camber, and maximum thickness — all expressed as percentages of the chord length. This parametric structure allows for systematic variation of geometry and supports the generation of a wide design space suitable for training a generalizable machine learning model.

Each NACA 4-digit airfoil is encoded using a 4-digit code (e.g., NACA 2412), where:

- The first digit indicates the maximum camber as a percentage of the chord.
- The second digit gives the location of the maximum camber (in tenths of the chord).
- The last two digits specify the maximum thickness.

A large dataset was generated by varying these parameters across the feasible domain (Fig.3, Fig.4), resulting in hundreds of unique airfoil shapes.

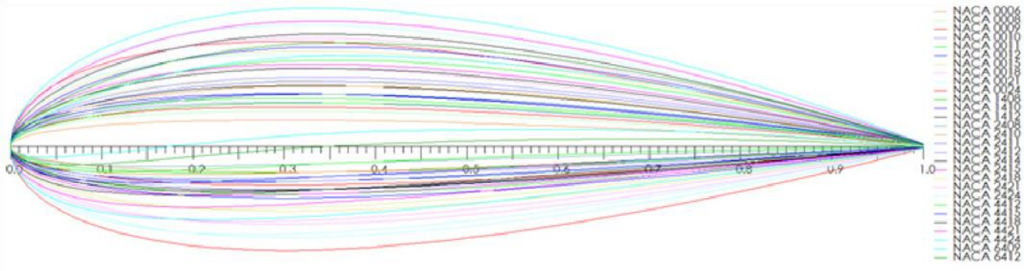

Figure 2: Sets of NACA airfoils used to learn the ANN model.

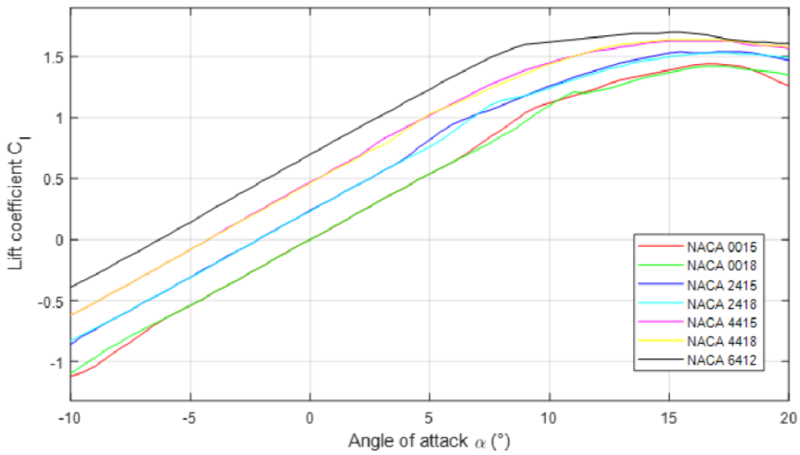

Figure 3 : lift coefficient for each NACA airfoil.

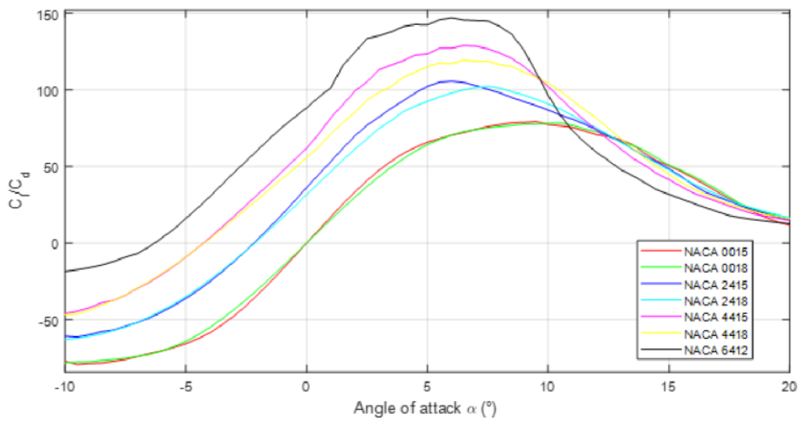

Figure 4: Cl/Cd for each NACA airfoil.

4.2. Development of the ANN-Based Surrogate Model

In this study, we developed a supervised learning-based surrogate model designed to predict the aerodynamic performance of wind turbine blade profiles. Similar studies using Random Forest and Gradient Boosting also reported high accuracy for Cl/Cd prediction across wide AoA ranges [15]. The aim of this surrogate is to replace costly CFD simulations by rapidly estimating lift (Cl) and drag (Cd) coefficients from airfoil geometry and angle of attack.

The neural network receives five characteristic parameters of the airfoil as inputs: α : angle of attack,

Tm : maximum relative thickness,

Pt : position of maximum thickness,

Cm : maximum camber,

Pc : position of maximum camber.

These inputs form a vector $x \in R^5$. The network is trained to predict an output vector y∈R^2, which contains the aerodynamic coefficients C_L and C_D, based on a numerically generated dataset.

4.3. Neural Network Architecture

The surrogate model is implemented as a feedforward artificial neural network with three layers (Fig.5):

An input layer of 5 neurons, corresponding to the five airfoil parameters.

A hidden layer with 10 neurons using a sigmoid activation function, designed to capture complex nonlinear relationships.

An output layer of 2 linear neurons, responsible for predicting C_L and C_D.

This architecture was chosen to provide a good trade-off between generalization ability and computational simplicity.

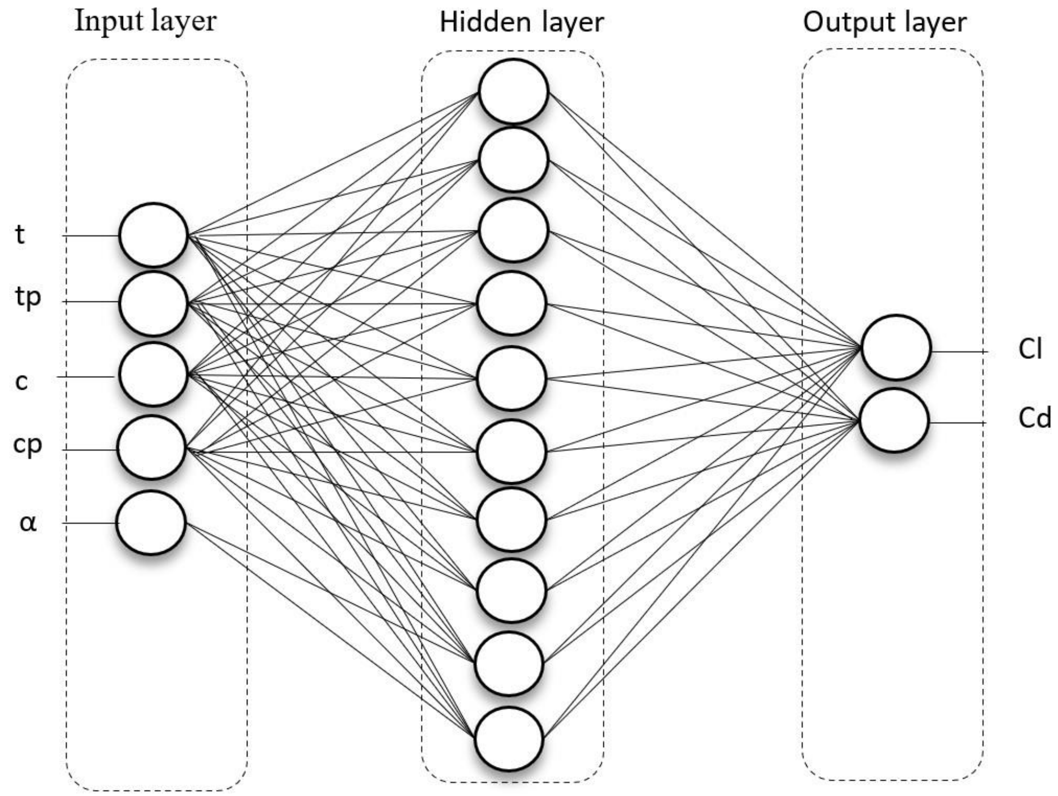

Figure 5: neural network architecture for airfoil metamodel.

4.4. Training Methodology

The training process was carried out in three sequential phases:

1. Training using 75% of the data,
2. Cross-validation on 15% of the data,
3. Testing on the remaining 10%.

The ANN was trained for 200 epochs with a learning rate of 0.001 and a batch size of 32. Instead of using random or stratified sampling, the dataset was built by ordering NACA 4-digit profiles by increasing relative thickness. This deterministic sampling strategy guarantees a controlled exploration of aerodynamic variations as a function of airfoil thickness. Validation airfoils were randomly selected from the full dataset to ensure generalization to unseen geometries. The Levenberg-Marquardt optimization algorithm was used for training, known for its efficiency in nonlinear regression tasks. It blends the advantages of gradient descent and the Gauss-Newton method, allowing fast convergence toward a local minimum of the mean squared error (MSE), Table 1.

The main performance indicator was the coefficient of determination (R^2), supported by MSE as a complementary metric. These metrics were used throughout all three phases to monitor learning progress, prevent overfitting, and assess the model's robustness on unseen data.

Table 1. Values of R^2 and MSE during the construction of the metamodel.

	Observations	**MSE**	**R^2**

Training	9677	1.98410 e-3	9.97483 e-1
Validation	2074	2.34837 e-3	9.97016 e-1
Test	2074	2.10805 e-3	9.97221 e-1

4.5. Test and validation

The validation phase aims to assess the ability of the artificial neural network (ANN)-based metamodel to reliably predict the aerodynamic coefficients Cl and Cd for airfoil profiles that were not encountered during training. This step is crucial to ensure that the model does not merely memorize the data, but can generalize effectively to new geometric configurations and different angles of attack.

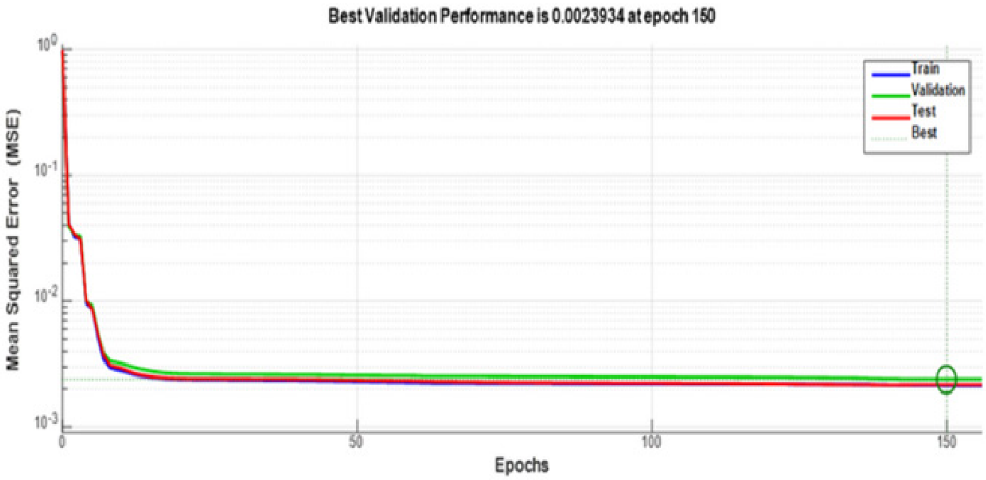

Figure 6: Mean Squared Error (MSE).

The model is considered successful if it satisfies the following conditions:

- $R^2 \approx 1$ on training and validation sets,
- A low and stable MSE after a reasonable number of training epochs,
- Convergence of gradients and stabilization of the damping parameter μ in the LevenbergMarquardt algorithm.

Visual tools such as the MSE curve across epochs (Fig.6) and scatter plots comparing predicted vs. target values (Fig.7) further demonstrate the strong agreement between model predictions and reference aerodynamic data.

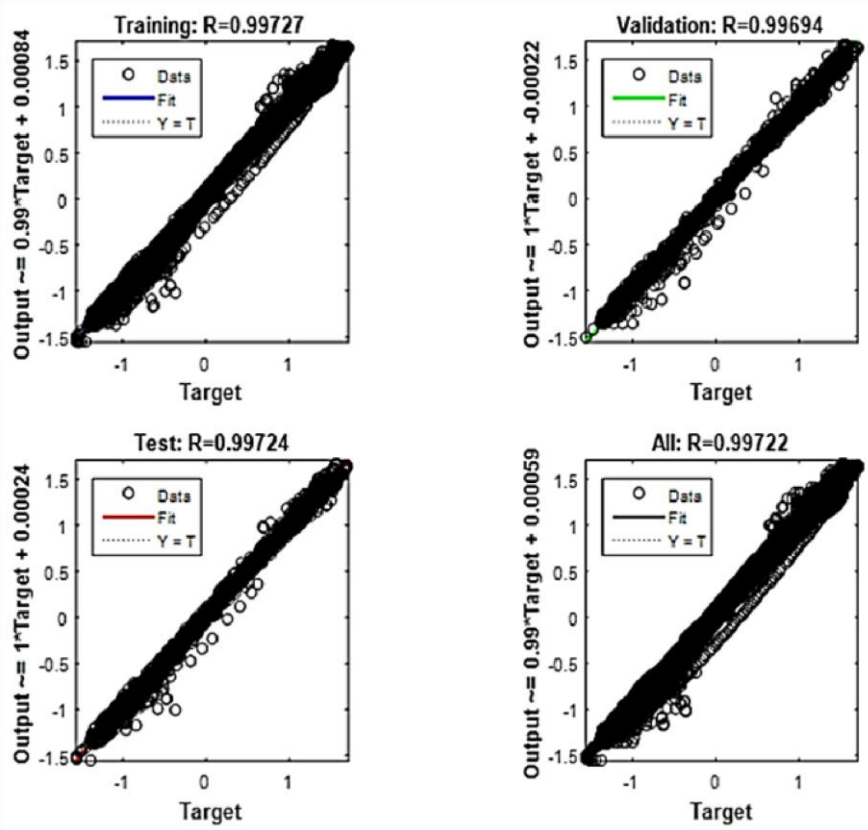

Figure 7: MSE of different phase of ANN model building.

4.6. Analysis on Unseen Airfoil Profiles

A subset of NACA profiles not used during training (e.g., NACA 2315, 0012, 4415...) was selected to evaluate the metamodel on real-case scenarios. For each profile:

- The model receives as input the geometric parameters (t,tp,c,cp) along with the angle of attack α,
- It outputs the corresponding aerodynamic coefficients,
- These predictions are then compared with reference values obtained from BEM simulations or validated CFD databases (Fig.8).

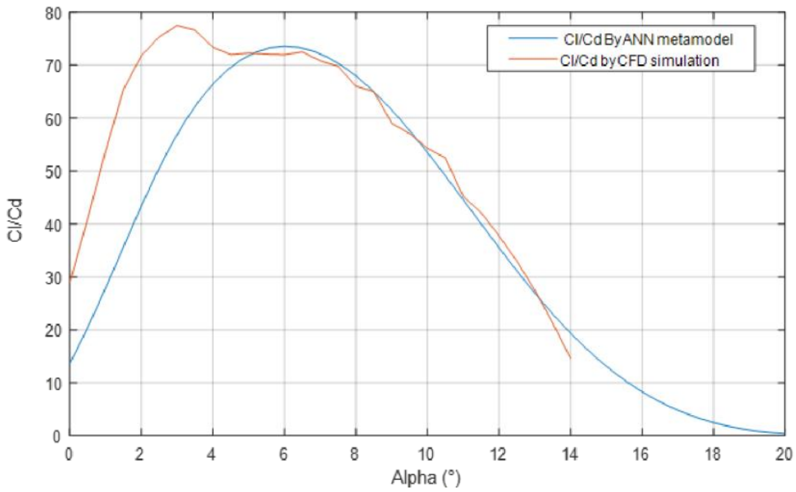

Figure 8 : Comparison between the Cl/Cd ratio values generated by the metamodel and those obtained through simulations for NACA 2315.Zaa.

The results demonstrate that the ANN is capable of accurately capturing the C_l (α) and C_d (α) curves, with a relative error of less than 3% across most of the angle of attack range.

The metamodel demonstrates strong generalization capability, even for geometries outside the training distribution. This characteristic makes it particularly suitable for integration into optimization tools or fast simulation frameworks (such as BEM), where thousands of profile evaluations are required.

However, it should be noted that the model's performance may decline at very high angles of attack, where stall phenomena are difficult to predict without turbulence models or enriched CFD data.

5. COUPLING THE ANN METAMODEL WITH THE BEM MODEL

Integrating the artificial neural network (ANN) into the Blade Element Momentum (BEM) model enables the construction of a hybrid simulator capable of rapidly assessing the aerodynamic performance of a smart blade, while accounting for geometric variations in airfoil profiles (e.g., morphing). This section presents the coupling strategy, algorithmic implementation, and results derived from the combined simulation framework.

In a classical BEM formulation, the aerodynamic coefficients C_l and C_d are typically obtained from:

- Experimental lookup tables (applicable only to fixed profiles), • CFD-generated polar curves (which are computationally expensive),
- Simplified analytical models (which are often limited in accuracy).
- The ANN metamodel provides an efficient alternative by:
- Delivering real-time predictions of C_l and C_d based on the local angle of attack and the instantaneous geometry of each blade element,
- Enabling the simulation of variable-geometry or morphing blades, which are otherwise difficult to model using static aerodynamic databases.

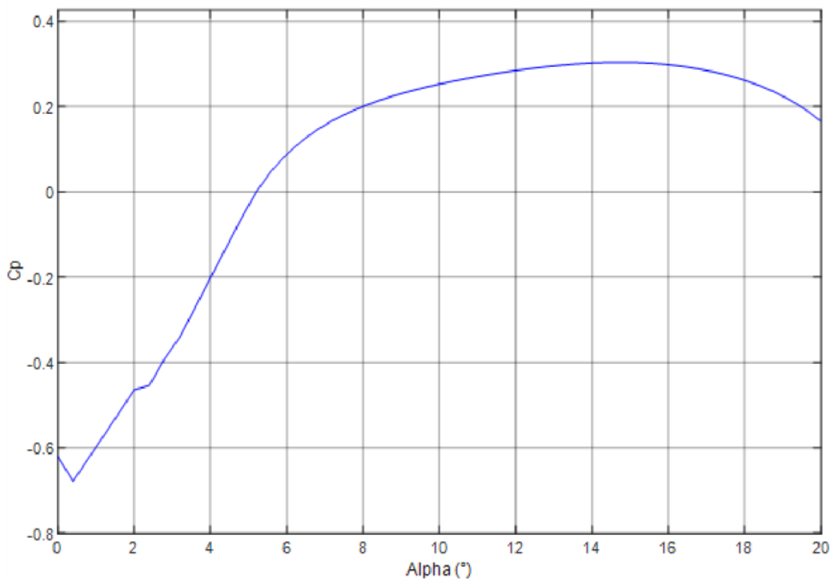

Figure 9: Cp variation function Angle of attack.

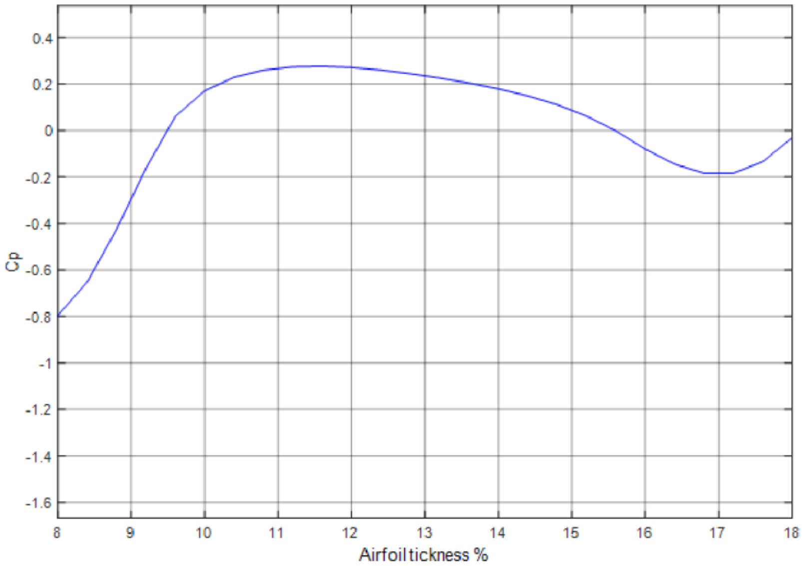

Figure 10 : Cp variation function airfoil thickness.

The last two figures (Fig.9, Fig.10) illustrate the variation of the power coefficient Cp as a function of different geometric parameters of the airfoil. These results highlight the ability of the hybrid ANN-BEM model to accurately simulate the aerodynamic performance of both individual blades and the entire rotor across a wide range of airfoil shapes. This confirms the model's flexibility in handling diverse airfoil geometries, including those with morphing characteristics. As such, the proposed framework is well-suited for optimization studies and serves as a robust tool for the simulation and control of smart blades equipped with adaptive or morphing airfoils.

Despite the good generalization ability shown by the ANN metamodel across various airfoil profiles, some limitations must be acknowledged. In particular, the model exhibits decreased accuracy at high angles of attack, where stall effects become prominent—phenomena not captured in the training dataset. Moreover, the performance may be sensitive to small perturbations in the geometric inputs, which could arise from uncertainties in morphing mechanisms or measurement noise. Additionally, prediction variability has not been formally quantified. Including standard deviation or error bars in test results would enhance the assessment of model uncertainty, particularly in applications such as active control or online optimization. Compared to conventional methods such as classical BEM models relying on static lookup tables for Cl and Cd, the proposed ANN-based approach significantly reduces computational time while maintaining comparable accuracy. Unlike CFD, which offers high fidelity but at a prohibitive computational cost, the ANN-BEM hybrid enables rapid simulation and is more suitable for integration in optimization or real-time control applications. Overall, wind turbine blades represent a promising field for research and innovation [16].

6. CONCLUSION

This work has proposed and tested a surrogate modeling approach that marries an Artificial Neural Network (ANN) metamodel with the Blade Element Momentum (BEM) theory to estimate the aerodynamic behavior of morphing airfoil geometric smart blades. The ANN is trained on key airfoil parameters and angle of attack and used to approximate lift and drag coefficients in place of conventional static aerodynamic databases. When embedded within the BEM computational routine, such a surrogate model can be used for fast and accurate and flexible simulation of rotor behavior under different geometric and operational states. The coupled ANNBEM model exhibits good predictive power and generalization among unobserved shapes of airfoil, and simulation cases exhibit a good agreement with traditional BEM and CFD solutions while achieving substantial reduction in computation time. Due to its adaptability, the model is very fit for use in tasks related to optimization, design loops, and real-time control for intelligent blades. This framework is well-suited for integration into industrial wind turbine design software to accelerate optimization and reduce prototyping costs. The inclusion of confidence intervals around ANN model predictions can enhance the assessment of result reliability, particularly in sensitive contexts such as real-time control or robust optimization.

Future work will include continuing model development with Reynolds number influences, 3D geometrical variations for blades, and integrating feedback loops for active morphing blade control in dynamically varied environments. In parallel, uncertainty quantification techniques such as adding confidence intervals or estimating prediction errors will be integrated to enhance the model's robustness and reliability in critical applications. Finally, explainable AI (XAI) methods will be investigated to shed light on the ANN's internal decision-making processes and improve interpretability, which is essential for building trust and facilitating adoption in engineering design workflows.

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