Development of an ANN-Based Predictive Model for an Airfoil with a Trailing-Edge Flap

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Abstract. This work makes use of a data-driven approach to predict the aerodynamic performance of the wind turbine airfoil equipped with an active trailing-edge flap. The NACA 4412 airfoil is considered to investigate the effect of the trailing-edge flap angle on the efficiency, measured in terms of the lift-to-drag ratio (Cl/Cd). A vast set of aerodynamic data is generated to consider the angle of attack (α) from $-20°$ to $20°$ and various flap angles (TE). Based on the generated database, an Artificial Neural Network (ANN) model is formulated to predict the value of Cl/Cd in terms of the angle of attack and the flap angle. The ANN model was trained using 81 iterations with 75% of the dataset used for training, 15% for validation, and 10% for testing. The predictions of the ANN model are then compared to the reference solutions from the Computational Fluid Dynamics (CFD) simulation in the form of systematic plots. The high level of agreement between the predictions of the two approaches emphasizes the validity and accuracy of the proposed data-driven ANN model. The model presented in this work provides an approach to efficiently and accurately overcome the repetitive simulation of aerodynamics and represents an attractive tool in the analysis of smart airfoils with active trailing-edge flaps. The ANN model provides an R^2 value of more than 0.9898 on the test data.

1. Introduction

The increasing need for energy and the need for reducing emissions of greenhouse gases has led to significant research in wind energy technology. The need for improved wind energy technology and overcoming challenges in wind speed fluctuations and turbulence has remained an area of concern in this sector for quite some time now. The conventional airfoil technology is only sufficient in certain areas and has numerous drawbacks in situations involving variations in airflows. The need for overcoming such drawbacks has led researchers to work on smart airfoils with actuators and sensors for managing airflows in real time, which is quite pertinent in the present situation [**1**].

Among the different techniques that have been employed for aerodynamic flow control, the use of trailing edge flaps has been found to be very effective. By providing the airfoil with autonomous control functions, the flap is able to react dynamically to the changing conditions of the wind in real time, which is very helpful for wind turbines [**2, 3**]. Various tests have shown that these flaps are able to affect the lift and drag forces and even delay flow separation [**4, 5**]. The influence of leading edge slats combined with slotted trailing edge flaps has also been studied [6].

However, more recent intelligent control methods have emerged with the aim of optimizing the real-time deflection of the trailing edge flap. For instance, the efficacy of a fuzzy logic control system on a trailing edge flap was demonstrated by Lakhal et al. [7] for improving the aerodynamic performance of wind turbine airfoils.

In order to help in understanding the phenomena, ultra-high resolution models are used to calculate airflow in various geometries. As much as these models are valuable in understanding the phenomena, their high cost and time complexity mean that they are not useful in control and optimization applications in a short time, such as in the optimization of wind turbine design. Simplified models that are less costly and faster are also being explored.

This paper discusses the continuous improvement of airfoil simulation efforts, coupled with parallel studies of applying machine learning methodologies for airflow simulation and understanding performance for various geometries. Artificial Neural Networks (ANNs) and other machine learning techniques have proved to be remarkably successful over the past few years, especially regarding the complex interplay of airspeed, geometry, and forces of lift and drag [1]. In this context, Haiek et al. [8] presented a metamodeling method for simulating wind turbine airfoils using ANN, highlighting the ability of these models to effectively lower costs of simulation while maintaining their level of accuracy. More advanced techniques have been investigated for adaptive flow control and wing geometry optimization, exploiting the potential of high-performance computing for autonomous learning [2, 3].

Recent studies have also focused on integrating trailing-edge flap control with aerodynamic actuators to enhance energy extraction efficiency in turbines [9]. Moreover, the design of turbine blades increasingly considers structural optimization to reduce material usage while maintaining performance [10].

The purpose of this research is the development of an ANN model that has the capability of estimating the efficiency of a specific airfoil with a trailing flap using a large dataset of aerodynamic tests carried out on different models. With the use of the ANN model that can substitute the expensive CFD simulations, this research has the potential of being utilized in the wind turbine blades' optimization process[**7,** 8].

Unlike conventional ANN-based aerodynamic surrogate models that focus on fixed airfoil geometries, the present work incorporates the effect of active trailing-edge flap deflection, enabling the prediction of aerodynamic performance for morphing airfoils.

The rest of this paper will have the following structure. In Section 2, an overview of existing research on this subject will be given. The building of the aerodynamic database will then be explained in detail in Section 3. The structure of the artificial neural network used in this study will then be introduced in Section 4. The final results of this study will then be presented in Section 5.

2. Related Work

Active flow control technology on airfoils has made significant progress in the past two decades. The initial work on trailing-edge flaps in wind turbines primarily focused on aerodynamic performance evaluation by analytical modeling or algorithms. Later,Qian et al. [4] investigated deformable trailing-edge flaps in thick airfoils of a wind turbine by numerical simulations and observed a great improvement in aerodynamic performance and a decrease in loading.

The more recent studies have focused on various trailing edge modification techniques such as slots, serrations, and their combinations with high-lift devices. Tanürün et al. [5] studied the aerodynamic performance of NACA airfoil with a slotted trailing edge, while Arra et al. [6] studied the influence of slats on the NACA airfoils with slotted trailing edge flap.

Taken together, it is clear that trailing-edge flow control is an important area of research for airfoil design. The use of computational fluid dynamics (CFD) simulation results has gained importance in analyzing complicated flow control designs due to increasing computational power. Karthikeyan & Harish [1] used machine learning algorithms along with CFD simulation for analyzing hybrid flow control on NACA 4412 airfoil.

Recent trends have also combined reinforcement learning and deep learning techniques alongside classical supervised learning in adaptive and intelligent flow control. A deep supervision network combined with reinforcement learning for morphing trailing-edge wings was introduced by Dai et al. [2], while Portal-Porras et al. [3] directly used reinforcement learning for active flow control on airfoils. Although these methods offer potential for real-time decision-making tasks, they may involve significant data and computational costs during training.

In the context of wind turbine optimization, Wang et al. [**9**] and Han et al. [**10**] explored control strategies combining pitch and trailing-edge flap actuation in vertical axis wind turbines. Mansi & Aydin [**11**] studied the effect of trailing edge flaps on small-scale horizontal axis wind turbines. Li et al. [**12**] investigated nonlinear modeling and adaptive control of smart rotor wind turbines. Sanaye & Farvizi [**13**] developed an ANN-based approach with genetic algorithms for optimizing helical-blade vertical axis wind turbines.

Environmental impact assessments have become an important consideration for wind energy projects, as highlighted by Nazir et al. [**14**].

However, there still remains a requirement for effective and accurate aerodynamic models to successfully forecast values of Cl/Cd for airfoils with trailing-edge flaps. In fact, there is a lack of focus regarding surrogate models developed for flow data or for a control-oriented model. In point of fact, it should be noted that this paper will focus on addressing these concerns by creating and validating a model for a NACA 4412 airfoil with a trailing-edge flap via ANN.

3. Aerodynamic Database Generation

3.1 Airfoil and Trailing-Edge Flap Configuration

The aerodynamic study is done using NACA 4412 airfoil, which is commonly used in wind turbine blades because of its excellent lifting abilities at low to moderate Reynolds numbers. The NACA 4412 airfoil has maximum camber of 4% at 39.5% of chord length with relative thickness of 12%.

The trailing edge flap is an addition made to the basic airfoil to alter actively its aerodynamic characteristics. The geometry is described by a rigid hinged surface placed 80% on the chord and located 50% thick, covering 20% of the chord length. Flaps are tested by varying their angles of deflection (TE), varying the angles of attack (α) and maintaining a constant flap length (Fig. 1). Angles of deflection varying from -20° to 20° are tested, and their effect is observed on aerodynamic characteristics

Polar curves are created for angles of attack ranging from -20° to 20°. The ratio of lift to drag (Cl/Cd) is chosen as the criterion of excellence because this parameter directly indicates airfoil efficiency. In this way, it is possible to create an organized airfoil data base concerned with training and verifying the new proposed ANN prediction model.

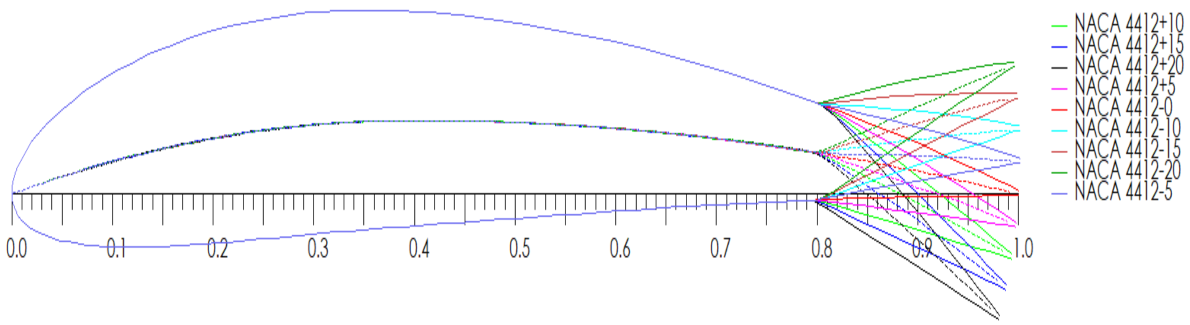

Fig. 1. Schematic of NACA 4412 with Variable Trailing-Edge Flap

3.2 Airfoil Simulation Methodology for ANN Training Data

The aerodynamic simulations were performed using QBlade, which relies on the XFOIL aerodynamic solver. The flow solution is obtained using a panel method coupled with a boundary-layer solver that accounts for viscous effects and boundary-layer development along the airfoil surface.

The computation of the aerodynamic database is done for every trailing-edge flap setting. The simulations are done with a Reynold number equal to 1000000 and within an angle of attack range of -20° through 20° and This allows a broad spectrum of aerodynamic conditions to be analyzed. This range includes pre-stall as well as post-stall conditions.

For each working condition, the values of the lift coefficient and the drag coefficient are calculated, and thereafter the resulting lift-to-drag ratios (Cl/Cd) are determined (Fig. 2). This approach results in a methodical generation of a dataset that interprets the nonlinear relationship between aero efficiency, angle of attack, and trailing flap deflection.

The obtained data is used as a basis for establishing a referential database used for testing and training the model of the artificial neural network for predictive evaluation purposes.

The generated aerodynamic coefficients for the NACA 4412 airfoil were validated against **well-established polars from the literature** at the same Reynolds number, showing good agreement and confirming the reliability of the QBlade/XFOIL simulations.

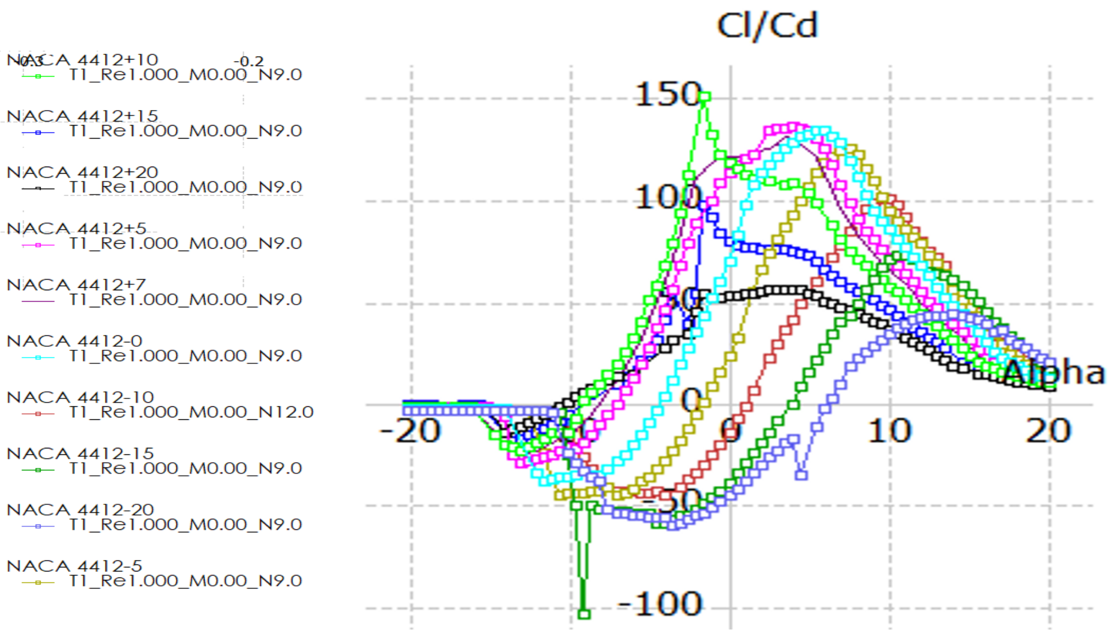

Fig. 2. Lift-to-Drag Ratio (Cl/Cd) vs. Angle of Attack for Various Flap Deflections

A mesh independence study was conducted to ensure that the numerical results were not affected by the grid resolution. Several meshes with increasing refinement levels were generated around the NACA 4412 airfoil, particularly near the airfoil surface and in the wake region. The aerodynamic coefficients (Cl and Cd) were monitored for each mesh configuration. The results showed that further mesh refinement produced negligible variations in the aerodynamic coefficients (less than 1%). Therefore, the selected mesh was considered sufficiently refined to ensure grid-independent results while maintaining a reasonable computational cost.

The aerodynamic database used for training the ANN model was generated using CFD simulations over a wide range of operating conditions. The angle of attack (α) was varied from −20° to 20° with a step size of 0.5°, while the trailing-edge flap deflection angle (TE) was varied from −20° to 20° with a step size of 5°.

This sampling strategy resulted in 81 values of angle of attack and 9 values of flap deflection, leading to a total of 729 CFD simulation cases, which were used to build the dataset for ANN training and validation.

The selected range of α ensures that the dataset includes aerodynamic conditions corresponding to pre-stall, near-stall, and post-stall regimes, which allows the ANN model to capture the nonlinear aerodynamic behavior of the airfoil over a wide range of operating conditions.

Therefore, the dataset provides a balanced representation of aerodynamic regimes, ensuring reliable training and generalization capability of the ANN model.

4 ANN-Based Predictive Model

In this paper, we have designed a supervised learning-based prediction model intended to forecast the aerodynamic characteristics of airfoils featuring a trailing edge flap. The prime goal of such a prediction model is to deliver a more efficient and useful alternative to traditional, time-consuming computational fluid dynamics calculations by directly estimating lift-to-drag ratios (Cl/Cd) based on airfoil geometric properties and trailing edge flap deflection angles.

The inputs of the ANN are two important geometric and aerodynamic characteristics of the wing:

- Angle of attack (α),
- Trailing-edge flap deflection parameter (TE).

These inputs are assembled into a vector $x \in \mathbb{R}^2$. The network is trained to predict the lift-to-drag ratio (Cl/Cd), with data created from numerical simulations of the airfoil at different flap deflections.

The proposed ANN model offers several advantages over traditional surrogate modeling techniques:

1. **Ability to capture strong nonlinearities:** Unlike classical response surface or spline interpolation methods, the ANN can accurately model the complex nonlinear relationship between lift-to-drag ratio (Cl/Cd), angle of attack, and trailing-edge flap deflection.
2. **Flexibility and adaptability:** The ANN structure can be easily retrained or extended for different airfoil geometries or operating ranges without redesigning the entire model.
3. **Computational efficiency:** Once trained, the ANN predicts Cl/Cd values almost instantly, avoiding the need for repeated CFD simulations or time-consuming interpolations.
4. **Robustness to large datasets:** The ANN can efficiently handle large CFD datasets, maintaining high predictive accuracy even across pre-stall and post-stall conditions.

Overall, these advantages make the ANN a powerful and practical tool for fast and accurate aerodynamic performance prediction, especially in the context of smart airfoils with active trailing-edge flaps.

4.1 Neural Network Architecture

A feedforward artificial neural network is employed within this study. The network consists of an input layer that is 2 neurons in number representing the angle of attac k(α) and the trailing edge flap deflection angle (TE), a hidden layer that is 10 neurons in number using a sigmoid activation function meant to handle nonlinearities, and an output layer that is a single neuron meant to predict the lift-to-drag ratio (Cl/Cd) (Fig. 3) .

This architecture is chosen in order to guarantee a proper level of learning, together with simplicity and numerical stability.

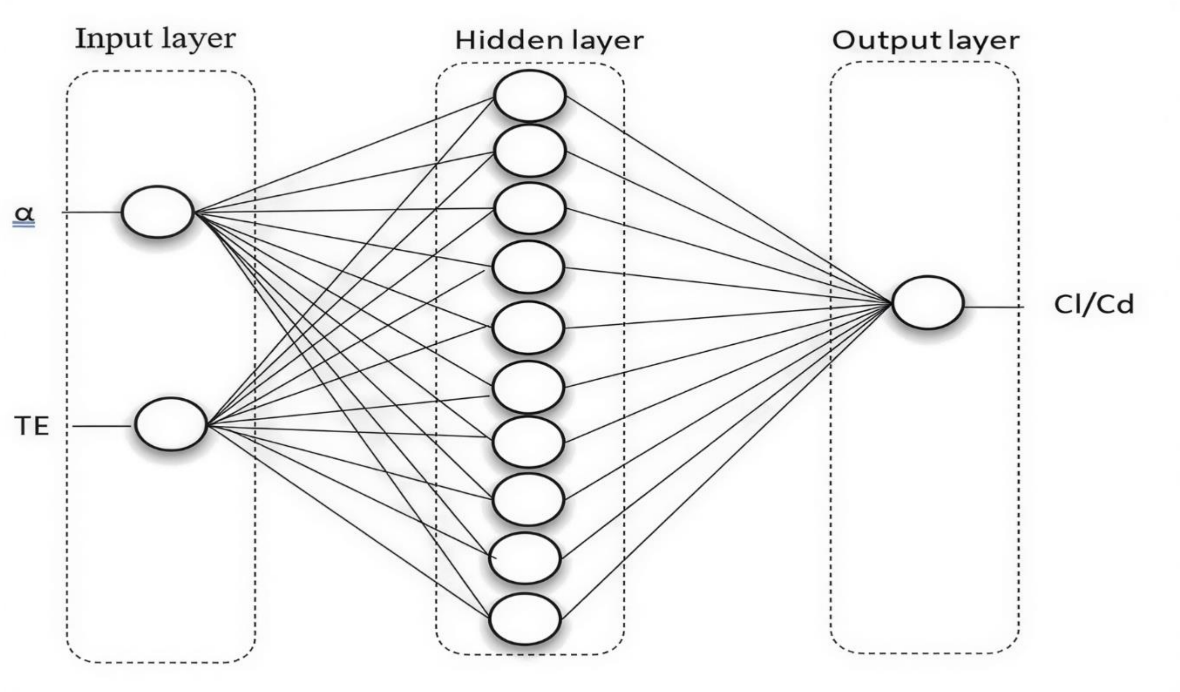

Fig. 3. Neural network architecture for ANN-Based Predictive Model

4.2 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 architecture used in this study consists of an input layer with two neurons corresponding to the angle of attack (α) and the trailing-edge flap deflection angle (TE), one hidden layer composed of 10 neurons, and an output layer with a single neuron predicting the lift-to-drag ratio (Cl/Cd). The sigmoid activation function was used in the hidden layer to capture nonlinear aerodynamic relationships, while a linear activation function was applied in the output layer.

The dataset was divided into three subsets for model development: 75% of the data were used for training, 15% for validation, and the remaining 10% for testing. This split strategy ensures that the model is trained efficiently while maintaining its ability to generalize to unseen data.

To reduce the risk of overfitting, a validation-based early stopping strategy was employed during the training process. The Levenberg–Marquardt optimization algorithm was used to minimize the mean squared error (MSE) between predicted and reference values. The network hyperparameters, including the number of hidden neurons and training iterations, were selected based on preliminary tests to achieve a good compromise between prediction accuracy and computational efficiency.

For the training of the Artificial Neural Network (ANN), a total number of 81 iterations were carried out. Unlike the random or stratified sampling approach followed in traditional methods, the training dataset was developed using a specific ordering of the NACA 4-digit airfoil 4412 according to the trailing edge flap deflection angles. The validation dataset was obtained through random sampling of the total dataset in order to test the ability of the ANN in generalizing airfoil geometries.

The training process used the Levenberg-Marquardt method, which is better suited for gradient descent algorithms and the Gauss-Newton method for quick convergence to a local minimum of the mean squared error (MSE).

The performance assessment of the proposed model was carried out by giving major emphasis to the value of the statistic of the coefficient of determination (R^2) as the primary assessment statistic, and Mean Squared Error (MSE) was considered as the secondary assessment statistic. These metrics were observed to monitor the learning process and ensure that there was no overfitting.

The quantitative performance of the ANN model during training, validation and testing phases is summarized in Table 1.

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

	Observations	MSE	R
Training	511	63.3588	0.9847
Validation	109	37.9958	0.9905
Test	109	50.8051	0.9898

4.3 Test and Validation

The validation step is the test of the ability of the predictive model based on ANN to correctly predict the value of the ratio of lift to drag (Cl/Cd) for trailing edge flap angles not presented during the training step.This is an important step to verify that the network is able to generalize and not simply memorize.

The model is guaranteed to be reliable if it meets the following criteria:

- High value of coefficient of determination ($R^2 \approx 1$) for both training and validation datasets;

- The convergence of mean squared error (MSE) to a stable point after a certain number of training epochs;

- Convergence and stabilization of the damping parameter μ in the Levenberg-Marquardt optimization algorithms.

Moreover, the tools for qualitative assessment such as the path followed by the MSE values during the epochs and the graphs showing the predictions against the actual values offer tangible proof about the ability of the model to approximate the reference behavior.

The convergence of the learning process can be analyzed through the evolution of the mean squared error shown in Fig. 4.

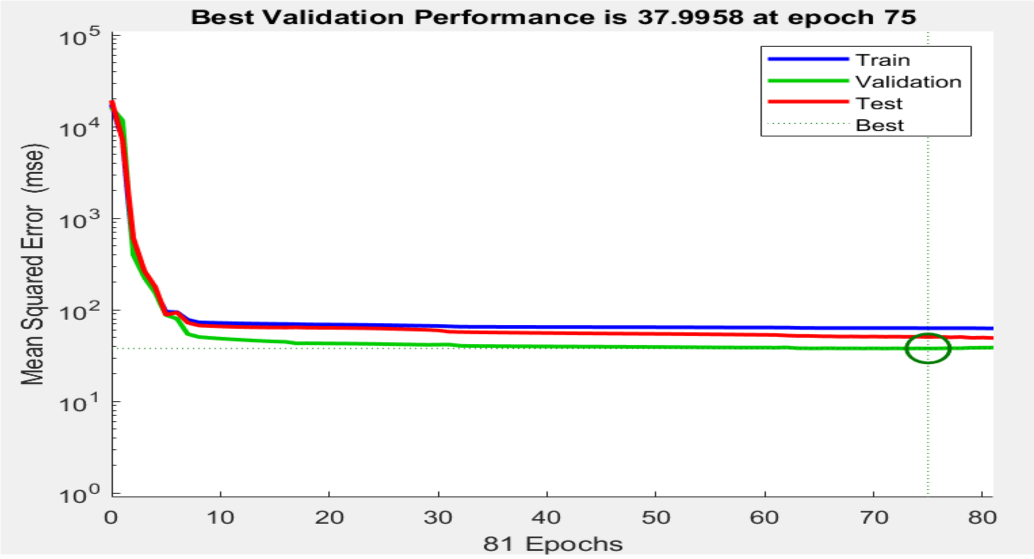

Fig. 4. Mean Squared Error (MSE)

A comparison of the error evolution in the different phases of model construction is presented in Fig. 5.

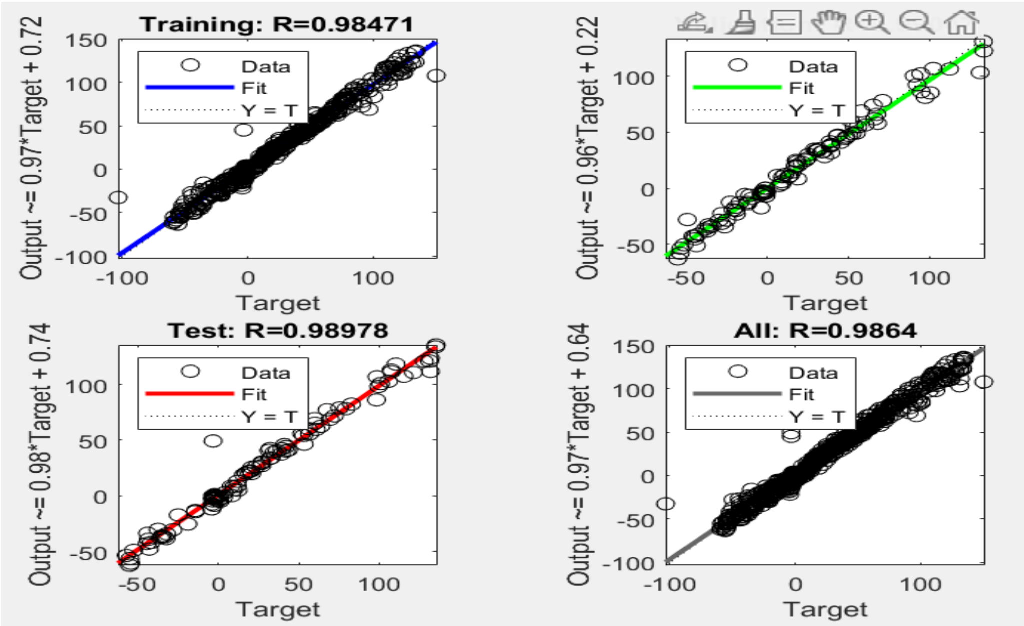

Fig. 5. MSE of different phase of ANN model building

4.4 Analysis on Unseen trailing-edge flap deflections

A set of trailing edge flap deflections, not practiced during the training procedures, is chosen to validate the prediction capability of the ANN model. For each flap deflection, the set of inputs provided to the model is the geometric variables set, the trailing edge flap deflection (TE), and the angle of attack parameter (α). The resulting output from the model is the lift-to-drag ratio (Cl/Cd), which is compared to the reference value obtained from the CFD databases.

As shown in Fig. 6. Cl/Cd ratio values generated by the ANN predictive model for a trailing-edge flap deflection equal to −17.5 demonstrate an almost perfect convergence across all angles of attack considered.

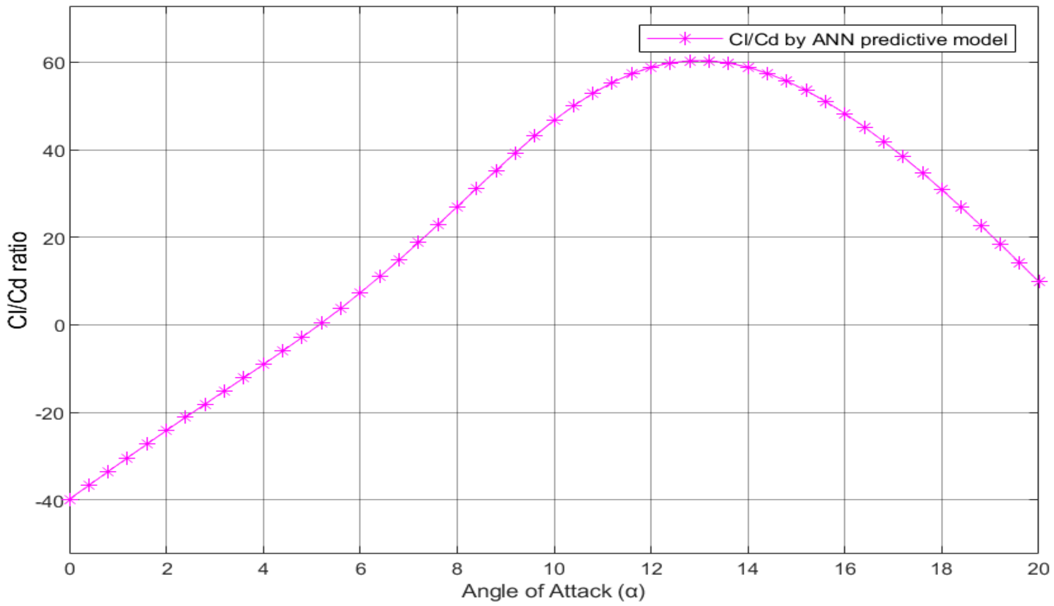

Fig. 6. Cl/Cd ratio values generated by the ANN predictive model for a trailing-edge flap deflection equal to -17.5

In Fig. 7. Cl/Cd ratio values obtained through CFD simulations for a trailing-edge flap deflection equal to −17.5 confirm this agreement, with only slight discrepancies at higher angles of attack, while maintaining the correct trend and accurately identifying the efficiency peaks.

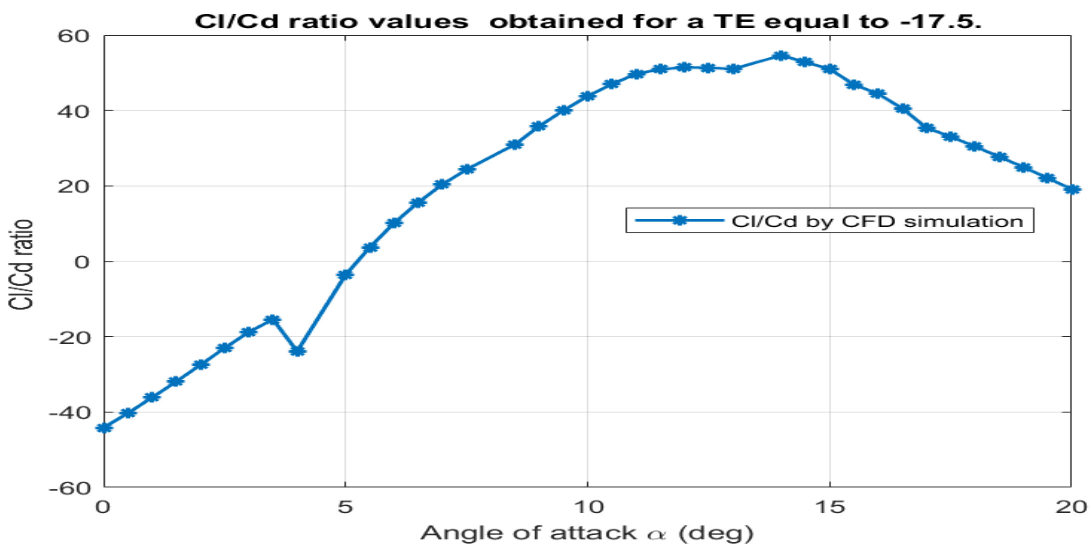

Fig. 7. Cl/Cd ratio values obtained through CFD simulations for a trailing-edge flap deflection equal to -17.5

In addition to the comparison with CFD simulations, the predictive capability of the proposed ANN model can be discussed with respect to previous research on data-driven aerodynamic modeling. Similar approaches using artificial neural networks for airfoil performance prediction have been reported in the literature. For instance, Haiek et al. [8] demonstrated that ANN-based metamodels can effectively reproduce aerodynamic trends while significantly reducing computational cost. In the present study, the obtained coefficient of determination ($R^2 \approx 0.9898$) confirms that the proposed model achieves a comparable level of predictive accuracy.

Moreover, previous studies such as those of Sanaye and Farvizi [13] , as well as Li et al., have shown that intelligent modeling techniques can be successfully integrated into wind turbine optimization frameworks. The results obtained in this work are consistent with these findings, highlighting the ability of machine learning approaches to capture the nonlinear aerodynamic behavior of airfoils equipped with control devices such as trailing-edge flaps.

In addition to the quantitative agreement between the ANN predictions and the CFD results, the model is also able to reproduce the main aerodynamic trends typically observed for airfoils. In particular, for moderate angles of attack corresponding to the pre-stall region, the predicted aerodynamic performance follows a smooth and nearly linear evolution with increasing angle of attack. This behavior is consistent with the classical lift curve slope observed in airfoil aerodynamics. As the angle of attack approaches the stall region, the model captures the peak aerodynamic efficiency, followed by a gradual decrease at higher angles of attack corresponding to post-stall conditions. This confirms that the ANN model is capable of reproducing the nonlinear aerodynamic behavior associated with flow separation and stall phenomena.

A sensitivity analysis of the predicted aerodynamic performance was also conducted to examine the influence of the angle of attack (α) and the trailing-edge flap deflection angle (TE) on the lift-to-drag ratio (Cl/Cd). The results indicate that the angle of attack plays a dominant role in determining the aerodynamic efficiency of the airfoil, as it directly controls the flow behavior and lift generation. Variations in α lead to significant changes in the Cl/Cd ratio, particularly near the stall region.

On the other hand, the trailing-edge flap deflection modifies the aerodynamic performance by adjusting the effective camber of the airfoil. Although its influence is generally smaller than that of the angle of attack, the flap deflection allows fine control of the aerodynamic efficiency and can shift the optimal operating conditions. This demonstrates that the ANN model is able to capture the combined influence of both parameters on airfoil performance.

From a practical perspective, the results provide insight into the optimal range of trailing-edge flap deflections for wind turbine applications. The analysis shows that moderate positive flap deflections improve aerodynamic efficiency by increasing the effective camber of the airfoil. For example, for angles of attack between **4° and 10°**, the lift-to-drag ratio (Cl/Cd) increases from approximately **55–60 for TE = 0°** to about **60–65 for TE = 5°**.

However, larger flap deflections tend to increase drag and reduce aerodynamic efficiency. For instance, when the flap deflection reaches **15°**, the Cl/Cd ratio decreases to approximately **45–50** due to the significant drag penalty. Based on these observations, the optimal flap deflection range for maximizing aerodynamic efficiency is typically between **0° and 10°**, depending on the operating angle of attack.

These results suggest that moderate flap deflections can be beneficial for wind turbine blade performance, particularly for fine aerodynamic control under varying wind conditions.

5 Conclusion

In the present study, an artificial neural network (ANN)-based model has been proposed for predicting the aerodynamic efficiency, in terms of the Cl/Cd ratio, for a NACA 4412 airfoil section provided with a trailing-edge flap. A look-up table for aerodynamic performance has been created by carrying out computational fluid dynamics (CFD) calculations for a variety of angles of attack ranging between −20° and 20°, as well as for different flap deflection configurations. The proposed ANN model has been found to be very accurate in predicting the reference Cl/Cd ratios.

Furthermore, the aerodynamic database used for training the ANN model was generated from 729 CFD simulations corresponding to different combinations of angle of attack and trailing-edge flap deflection. A typical CFD simulation required several minutes of computational time depending on the mesh resolution and solver convergence criteria.

In contrast, once the ANN model is trained, the prediction of the lift-to-drag ratio (Cl/Cd) for a new operating condition is obtained almost instantaneously, typically within a fraction of a second. This represents a significant reduction in computational cost compared to running a full CFD simulation for each configuration.

Although the training phase of the ANN requires the initial CFD dataset, it is performed only once. After training, the model can rapidly predict aerodynamic performance for a large number of operating conditions, which makes it particularly suitable for optimization studies and real-time aerodynamic control strategies.

Therefore, the proposed ANN model provides a promising framework for integration into real-time control systems for smart airfoils equipped with trailing-edge flaps, where rapid prediction of aerodynamic performance is required to adapt flap deflection to changing wind conditions.

However, the performance of the model is necessarily dependent on the quality and comprehensiveness of the training database. Expanding the training database to include Reynolds numbers and unsteady aerodynamics is expected to improve the generalization ability of the model. Thus, future studies will focus on improving the model to include unsteady flow conditions, as well as integrating the ANN model with control methods for trailing edge flaps.

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