# Aerodynamics Prediction of Airfoil using Artificial Neural Network


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## Abstract


In this study, an artificial neural network (ANN)-based method is proposed to predict the aerodynamic characteristics of NACA 0012 airfoil, approximating the flow around the airfoil as a function of Reynolds number (*Re*), angle of attack ($\alpha$), airfoil coordinates (*X, Y*), and lift coefficient ($C_L$) and drag coefficient ($C_D$) without extensive software packages. Wind turbine data for $C_L$ and $C_D$ were obtained for $\alpha$ ($0^\circ \le \alpha \le 180^\circ$) and *Re* ($10^4 \le Re \le 10^7$). An ANN model was trained to have an *MSE* of 0.0144 and 0.00062 for $C_L$ and $C_D$, respectively. The trained model used to evaluate new data had an *MSE* of less than 0.0081 for $C_L$ and 0.0144 for $C_D$. The results were validated in a two-dimensional numerical domain using RANS-CFD simulations and experimental data, showing that the proposed ANN approach is in good agreement for predicting the stall shape and aerodynamic characteristics at an angle of attack ($\alpha$) ranging from ($0^\circ \le \alpha \le 30^\circ$).


## Background & Objectives

The airfoil shape is responsible for producing lift and drag for wind turbines, aircraft wings, and ship rudders. Therefore, the precision of the lift coefficient ($C_L$) and drag coefficient ($C_D$) has a significant impact on the airfoil design process. The analysis of the flow field tends to be the most computationally intensive and time-consuming part of the process. Because of

- **massive computational resources needed, especially with the increased number of DOFs;**
- **for the final results, the machine experience gained during the simulation is lost.**

Trained artificial neural network (ANN) models have recently gained attention for learning the responses of large, complex, and nonlinear systems[1]. Previous studies that used ANN models to predict aerodynamic characteristics relied heavily on different CFD simulation software tools to generate training data[2,3,4,5]. However, CFD simulation software tools have certain real-world limitations. Consequently, ANN models generated from these data will eventually mimic those limitations because the accuracy of the ANN is heavily dependent on the data quality during the training phase. Therefore, the goal of this study is

- **to use reliable training data from wind turbine experiment[6];**
- **to reduce extensive dependence on software packages;**
- **to reduce the time needed to solve.**

## Methodology

### 1. Geometric modeling

1. NACA 0012 airfoil section is used.
2. Airfoil tools is used to generate 201 airfoil coordinates.

Figure 1: Geometry of NACA 0012 airfoil with 0.154 m chord length.

### 2. Meshing

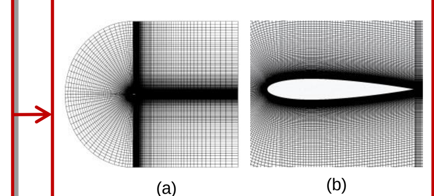



Figure 2: (a) Mesh around NACA 0012 airfoil and (b) detail close to the NACA 0012 airfoil.

### 3. Boundary conditions

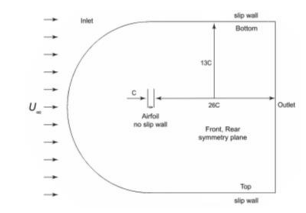
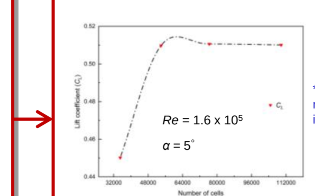



Figure 3: Flow past NACA 0012 airfoil simulation in the C-type domain.

### 4. Turbulence models

1. Realizable $k$ - $\varepsilon$ model
2. SST $k$ - $\omega$ model
3. Spalart - Allmaras model

### 5. Mesh convergence study




*76400 cells are required for mesh independent solution.

Figure 4: Mesh convergence study for NACA 0012 airfoil using the Realizable $k$-$\varepsilon$ model.

### 6. Numerical simulation

1. Numerical simulations of NACA 0012 were conducted using three different turbulence models for angle of attacks ($\alpha$) ranging from $0^\circ$ to $30^\circ$.

2. The simulations were carried out using Ansys fluent students version 2022.

**RANS-CFD analysis**

### 1. Dataset preparation

1. The dataset includes airfoil coordinates (*X, Y*), angle of attack ($\alpha$), Reynolds number (*Re*), lift coefficient ($C_L$), and drag coefficient ($C_D$).
2. An online database for airfoil profile generator, was used to generate a total of 201 airfoil coordinates (*X, Y*) for NACA 0012 airfoil.
3. Wind turbine experimental data[6] from was used for the rest of the features, where for $\alpha$ ($0^\circ \le \alpha \le 180^\circ$) $C_L$ and $C_D$ was obtained at different values of *Re* ($10^4 \le Re \le 10^7$) for NACA 0012 airfoil.

### 2. Dataset splitting

1. A total of 606 observations were used.
2. 16 observations with Re of $1.6\text{x}10^5$ were used as test data.
3. Of the remaining observations of 590, 10% were used to validate the model.

Table 1: Partition of the dataset

| Dataset | Observations |
|---|---|
| Training data | 530 |
| Validation data | 60 |
| Test data | 16 |
| Total | 606 |

### 3. Network architecture

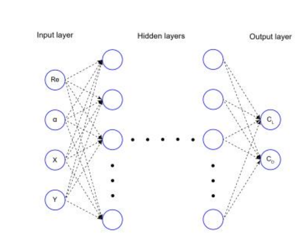



Figure 5: ANN architecture used in the aerodynamic characteristics prediction network.

### 4. ANN models training

1. Five different ANN models were trained.
2. The models were trained for 300 epochs.
3. All training data fed to the network in batches of 8 observations before the weights were allowed to update using the batch's Mean Square Error (*MSE*).

### 5. Prediction

1. Among five ANN models, the best performed model is used to predict the aerodynamic characteristics.
2. The model is used to predict the lift coefficient ($C_L$) and drag coefficient ($C_D$) of NACA 0012 airfoil at Reylonds number (*Re*) of $1.5\text{x}10^5$ for angle of attacks ($\alpha$) ranging from $0^\circ$ to $30^\circ$.

### Comparison

1. Numerical simulations of NACA 0012 were conducted using three different turbulence models for angle of attacks ($\alpha$) ranging from $0^\circ$ to $30^\circ$.

1. The simulations were carried out using Ansys fluent students version 2022.

**ANN model creation**

## Results & Discussion

### RANS-CFD approach

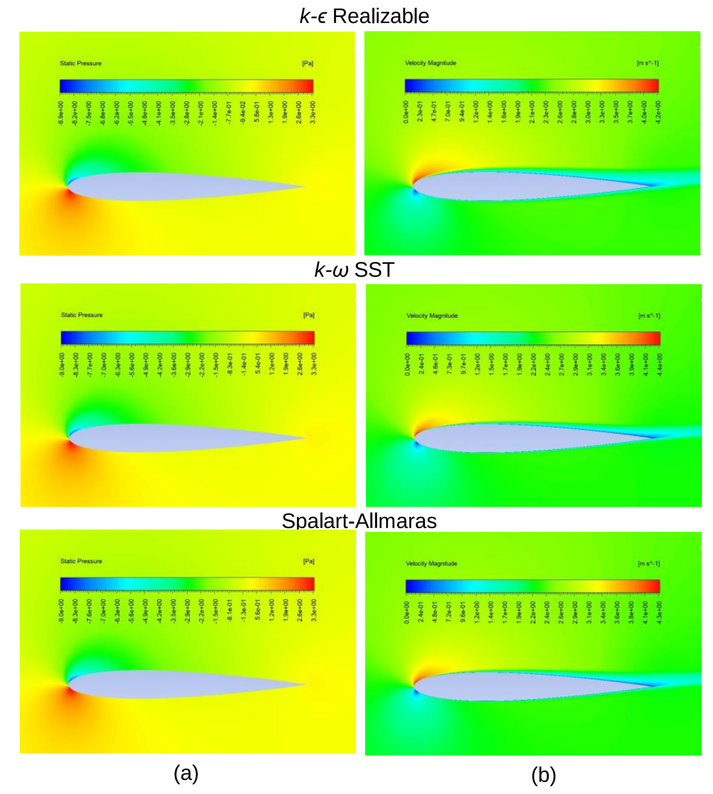



Figure 6: The (a) pressure and (b) velocity contours of NACA 0012 airfoil at $7^\circ$ angle of attack ($\alpha$) with Reynolds number (*Re*) of $1.6\times10^5$ using three turbulence models.

### ANN approach

Table 2: ANN performance for five different models.

| ANN model | No. of hidden layers | No. of nodes | MSE | |
|---|---|---|---|---|
| | | | $C_L$ | $C_D$ |
| Model 1 | 6 | 80 | 0.014979 | 0.00142 |
| **Model 2** | **6** | **128** | **0.01353** | **0.00062** |
| Model 3 | 5 | 64 | 0.019839 | 0.0018 |
| Model 4 | 6 | 256 | 0.017756 | 0.00088 |
| Model 5 | 5 | 256 | 0.019991 | 0.00114 |

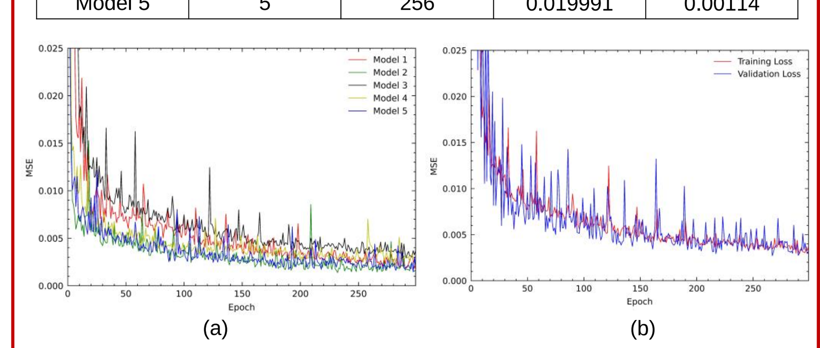



Figure 7: (a) Training losses of ANN's after 300 epochs, (b) Training & validation losses after 300 epochs for Model 2.

Table 2 presents the *MSE* of the models and the network architectures. Model 2, with six hidden layers and 128 nodes, performed better, and the *MSE* values of $C_L$ and $C_D$ were 0.01353 and 0.00062, respectively. Therefore, Model 2 was used to predict the aerodynamic characteristics. The models training loss is shown in Fig. 7a. From Table 2 it is evident that model 2 does better, it's training and validation loss is shown in Fig. 7b.

### RANS-CFD *versus* ANN

Table 3: The *MSE* of turbulence models and ANN model.

| Range ($\alpha$) | $k$-$\epsilon$ Realizable | | $k$-$\omega$ SST | | Spalart-Allmaras | | ANN | |
|---|---|---|---|---|---|---|---|---|
| | $C_L$ | $C_D$ | $C_L$ | $C_D$ | $C_L$ | $C_D$ | $C_L$ | $C_D$ |
| 0 - 10 | 0.002833 | 0.000324 | 0.000986 | **$1.78\text{x}10^{-05}$** | **0.000707** | $2.7\text{x}10^{-05}$ | 0.011164 | $6.92\text{x}10^{-05}$ |
| 11 - 20 | 0.419295 | 0.003171 | 0.51439 | 0.00192 | 0.470994 | **0.004738** | **0.001845** | **0.000132** |
| 21 - 30 | 0.010106 | 0.001164 | 0.008748 | 0.000771 | 0.010752 | **0.000347** | **0.001442** | **$1.22\text{x}10^{-05}$** |

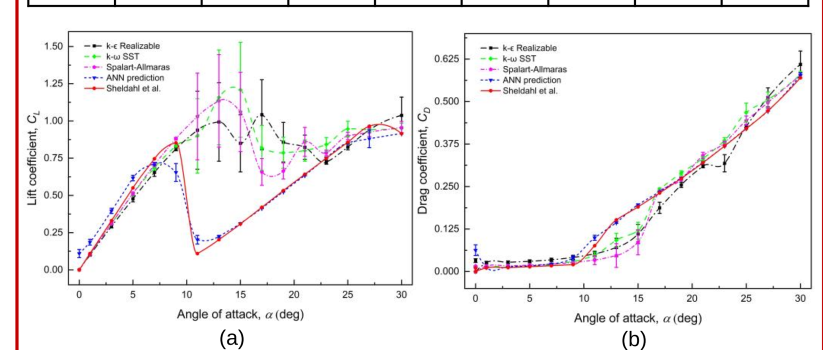



Figure 8: Result comparisons of NACA 0012 with Reynolds number (*Re*) of $1.6 \times 10^5$ for (a) lift coefficient ($C_L$), (b) drag coefficient ($C_D$).

The MSE of turbulence models and ANN model for NACA 0012 airfoil were calculated, shown in Table 3. The curve of the lift coefficient ($C_L$) and the drag coefficient ($C_D$) for NACA 0012 airfoil is shown in Fig. 8, for angle of attack ($\alpha$) ranging from $0^\circ$- $30^\circ$, predicted with ANN model, computed with three turbulence models and compared with experimental data. In most of the cases, The Spalart-Allmaras and the k-ω SST turbulence model did better calculating $C_L$ and $C_D$ when the angle of attack ($\alpha$) was in the range of $0^\circ$- $10^\circ$. However, for $\alpha$ ranging from $11^\circ$- $30^\circ$ ANN model outperformed all the turbulence model's results while predicting the shape of the stall as well whereas turbulence models failed to do so.

## Conclusions

This study developed a neural network model to predict airfoil aerodynamic characteristics using experimental data to test the feasibility of deep learning in flow analysis. To validate the ANN model, RANS-based CFD simulations with three turbulence models in a two-dimensional domain were performed. Evidently, when compared with the experimental data, the ANN model easily outperformed each of the three turbulence models. More specifically, when the angle of attack ($\alpha$) was in the range of $11^\circ$-$30^\circ$, the ANN model produced the most precise outcome or, in other words, had the least amount of error compared to all other turbulence models. When α was in 0°-10° range, different turbulence models performed better. Even at α (0°-10°), the ANN model outperformed all other turbulence models. Additionally, the ANN model successfully predicted the stall shape for airfoil, whereas the turbulence models failed to do the same. Also, The ANN model used much less computational power than RANS-based CFD analysis. Thus, the proposed ANN approach can accurately predict the aerodynamic characteristics of marine rudders and other airfoil-shaped geometries.

## References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