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Computational and Predictive Analysis of the Aerodynamic Performance of the Eppler 423 Airfoil Using Artificial Intelligence

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Abstract:

The search for alternatives that combine energy efficiency and cost reduction has been a significant driving force behind the transformation of various industrial and technological sectors, including the field of aerodynamics. This study investigated the application of advanced machine learning algorithms, specifically artificial neural networks (ANNs), for the prediction and optimization of the aerodynamic coefficients of the Eppler 423 airfoil. The analysis considered Reynolds numbers ranging from 100 000 to 500 000, a typical operational range in applications such as small wind turbines and model aircraft. Airfoils play a critical role in controlling aerodynamic forces, and variations in the trailing edge thickness notably influence performance: thin trailing edges tend to perform better at higher speeds, whereas thicker trailing edges demonstrate enhanced efficiency at lower Reynolds numbers. A dataset comprising 360 data points was generated through comprehensive simulations conducted with the XFLR5 software, covering a broad spectrum of angles of attack and Reynolds numbers. This dataset was employed to train the ANN. To improve the generalization ability and prevent overfitting, techniques including cross-validation, feature engineering, and early stopping were applied during training. The resulting model exhibited excellent predictive accuracy, with a coefficient of determination (R^2) of 98.98%, a mean squared error (MSE) of 12.83, and a mean absolute error (MAE) of 2.8355, indicating high consistency and reliability. Moreover, the system successfully predicted the optimal operational condition of the airfoil, estimating an efficiency of 100.75%. This result was validated by subsequent simulations in XFLR5, which presented an efficiency of 100.62%, thereby confirming the robustness and precision of the machine learning approach. This methodology offers a rapid and cost-effective alternative to traditional experimental wind tunnel testing, which is typically more time-consuming and expensive. Overall, the study highlights the substantial potential of neural networks as agile and effective tools for aerodynamic airfoil optimization, benefiting domains such as renewable energy and model aircraft design, while promoting innovation and sustainability in aeronautic engineering.

Keywords: Computational optimization; aerodynamic efficiency; predictive modeling; numerical simulation

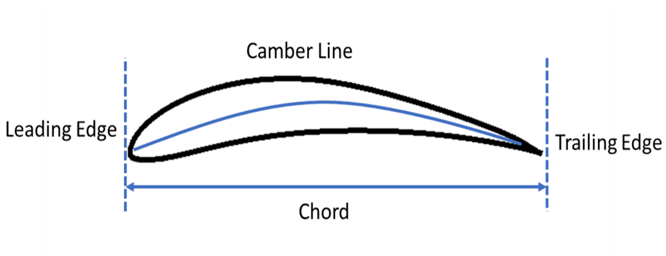
Abbreviations: C_L. Lift Coefficient; C_D. Drag Coefficient; C_M. Moment Coefficient; R^2. Coefficient of Determination; MSE. Mean Squared Error; MAE. Mean Absolute Error; ANNs. Artificial neural networks

1. Introduction

The increasing demand for efficient and innovative solutions in aerospace engineering drives the pursuit of methods that enable faster and more cost-effective optimization of aerodynamic airfoil performance. By definition, an airfoil's purpose is to control the airflow behavior around its surface, generating forces that enable flight or enhance the efficiency of systems interacting with the air [1].

The characteristics of an airfoil are based on its geometry (Figure 1), specifically its chord line, camber, thickness, and the contours of the leading and trailing edges, which directly influence the generation of lift, drag, and aerodynamic moments exerted by the airfoil itself. Furthermore, there are various types of airfoils, each adapted for specific applications, such as symmetric, asymmetric, for high or low speeds, with different levels of camber and thickness [2].

Figure 1: Geometry of an airfoil



Among the well-known airfoils, some stand out for their specific properties tailored to different operating regimes. Airfoils with thin trailing edges are commonly used at high speeds, while those with thicker trailing edges tend to be more efficient at low speeds and lower Reynolds numbers, typical of applications in model aircraft. The selection of the appropriate airfoil is essential to ensure efficiency, stability, and performance in the system where it will be applied, whether it is an airplane wing, a wind turbine blade, or an experimental model [3].

Of the aerodynamic profiles, the Eppler 423 stands out as a recurring choice for low Reynolds number applications due to its high efficiency under laminar flow conditions and its distinct geometry, such as a thick trailing edge. Traditionally, the evaluation of the aerodynamic performance of these profiles requires extensive experimental testing or high-cost computational simulations, which demand considerable time and resources for development and optimization [4].

In this context, machine learning techniques have been increasingly established as promising alternatives for predicting essential aerodynamic parameters such as C_L, C_D, and C_M. The integration of these tools not only accelerates the analysis and optimization process but also provides greater flexibility to explore a wide range of operating conditions [5].

Thus, the use of ANNs has proven to be a powerful tool for the optimization and prediction of complex parameters in aerospace engineering. Their ability to model nonlinear relationships among multiple variables allows for the estimation of aerodynamic coefficients, such as lift, drag, and moment, based on data obtained from numerical simulations or experiments. Through training with representative datasets, ANNs learn to reproduce the aerodynamic behavior of airfoils under varying operating conditions, even within high-dimensional design spaces [6].

This characteristic makes neural networks extremely suitable for accelerating design and optimization processes, reducing the need for detailed and costly analyses. Moreover, the integration of ANNs into iterative and multidisciplinary processes offers flexibility for rapid adjustments and timely predictions, contributing to more efficient and innovative development of aerodynamic airfoils.

This work proposes the use of predictive models based on machine learning, trained on an extensive dataset generated with the XFLR5 software, to predict the aerodynamic coefficients of the Eppler 423 airfoil and identify optimized operational configurations.

2. Methodology

2.1. Data Collection

The input data were generated through simulations using the XFLR5 software, widely used for airfoil analysis at low Reynolds numbers [7]. The simulations were conducted under different operating conditions by varying the Reynolds number (100 000 – 500 000) and the Angle of attack (α) (0° – 20°) to analyze the various coefficients resulting from these operating conditions, such as the lift coefficient (C_L), drag coefficient (C_D), moment coefficient (C_M), and aerodynamic efficiency.

2.2. Computational Environment

The modeling was performed in Python using deep neural networks, as proposed by Sêcco & Mattos [8] and Chen et al. [9], utilizing the pandas, numpy, scikit-learn, and tensorflow libraries. The data, imported from an Excel spreadsheet, were organized into a DataFrame. Numeric variables were standardized using StandardScaler, applied simultaneously via ColumnTransformer. The dataset was split into 80% for training and 20% for testing. During training, the early stopping technique was applied to halt the process when the performance on the validation set ceased to improve, thus preventing overfitting. After finding the optimal hyperparameter configuration, the final model was trained with these parameters and evaluated on the test set.

2.3. Performance Evaluation

The model validation was conducted following the recommendations established by Chicco et al. [10], employing widely recognized metrics for performance evaluation in regression analysis, such as the coefficient of determination (R^2), mean absolute error (MAE), and mean squared error (MSE). These measures are essential to quantify the predictive capability and accuracy of the model. For a more comprehensive assessment of the algorithm's performance, comparative tests were also carried out through simulations, following the methodology applied by Moin et al. [11]. The R^2, MAE, and MSE metrics were implemented as described in Equations 1, 2, and 3, allowing the evaluation of the model's ability to correctly predict the data and optimize its functionalities. This multidimensional approach in validation ensures the robustness and reliability of the result.

$$R^2 = 1 - \frac{\Sigma_{i-l}^{N}(Y_{i\,predicted} - Y_{i\,real})^2}{\Sigma_{i-l}^{N}(Y_{i\,predicted} - \overline{Y}_{i\,real})^2} \quad (1)$$

$$MAE = \frac{1}{N}\Sigma_{i=l}^{N}\left|Y_{i\,real} - Y_{i\,predicted}\right| \quad (2)$$

$$MSE = \frac{1}{N}\Sigma_{i=l}^{N}\left|(Y_{i\,real} - Y_{i\,predicted})\right|^2 \quad (3)$$

Where N is the number of samples, $Y_{i\,real}$ are the target values, $Y_{i\,predicted}$ are the estimated values, and $\bar{Y}$ is the mean of the target values.

3. Results and discussion

3.1. Model Performance

The computational model was developed using a sequence of 16-8-1 neurons with the ReLU function as the activation function. Accordingly, the model's performance was analyzed using a neural network with the early stopping technique to find the optimal operating conditions for the Eppler 423 airfoil at low Reynolds numbers. Early stopping was applied during the network training to halt the adjustment process once the performance on the validation set ceased to improve, preventing overfitting and promoting better generalization capability. This approach yielded a model with robust performance, whose results are detailed in Table 1.

Table 1: Performance Analysis Metrics

Metrics	Value
R^2	0.9898
MSE	12.83
MAE(%)	2.3865

The coefficient of determination (R^2) was 0.9898, indicating that the model is able to explain approximately 98.98% of the variability present in the experimental data. This value reflects a very high degree of fit between the predicted values and the actual values of the optimal conditions of the Eppler 423 airfoil. The mean absolute error (MAE), equal to 2.3865, represents the average of the absolute differences between the predicted and observed values, indicating that, on average, the neural network predictions deviate by only 2.39 percentage points from the experimentally obtained optimal conditions [10].

The mean squared error (MSE) of 12.83 indicates low error dispersion, reinforcing the model's accuracy. According to the literature, the use of these indicators is fundamental to evaluate and more severely penalize larger deviations, ensuring the model's reliability in complex applications [8]. These results demonstrate that the neural network with early stopping is a robust and efficient tool for modeling nonlinear processes in the context of aerodynamic development, such as the optimization of the Eppler 423 airfoil in aerodesign projects.

3.2. Prediction

After evaluating the statistical indicators that demonstrated the model's accuracy, the prediction of the optimal point for the Eppler 423 airfoil was carried out. Using the neural network with early stopping, the model identified the best operating conditions to maximize aerodynamic efficiency in the context of the aerodesign project.

This approach allowed the determination of the ideal angle of attack, Reynolds number, and other variables associated with the airfoil's best performance. Table 2 presents the optimal conditions predicted by the neural network.

Table 2: Prediction proposed by the neural network

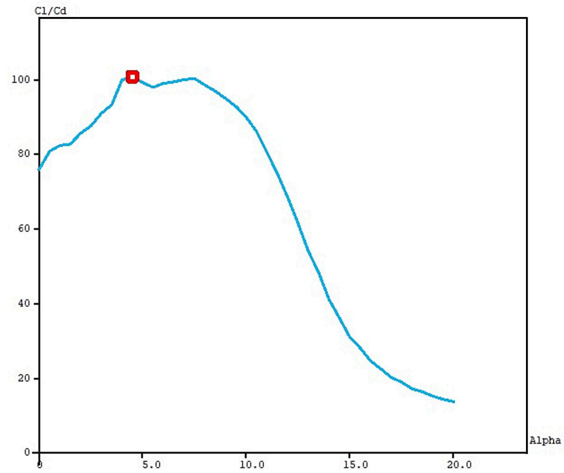
Variables	Values
Reynolds Number	350 000
Angle of attack (α)	4.5 °
C_L	1.612
C_D	0.016
C_M	-0.241
Efficiency	100.75

These values indicate a favorable combination for the airfoil used, showing high lift capacity and low aerodynamic drag, consistent with experimental data that demonstrate the Eppler 423 excels at low Reynolds numbers due to its thicker trailing edge, which reduces flow separation risks and maintains high aerodynamic efficiency around the optimal angle of attack of 4.5°.

This behavior is illustrated in Figure 2, which shows the relationship between C_L/C_D and the Angle of attack (α), with the optimal operating condition predicted by the ANN highlighted in red.

It is essential to note that this angle was identified as optimal by the neural network developed in this work, thereby reinforcing the predictive model's validity by converging on a value consistent with experimental evidence.

Figure 2: Relationship between C_L/C_D and angle of attack (α) for the Eppler 423 airfoil at Re=350 000, with the optimal condition predicted by the ANN highlighted in red.



According to Maia et al. [9], a Reynolds number near 350 000 represents an optimal point for the Eppler 423 at low speeds, where the airfoil demonstrates superior aerodynamic performance, combining efficient lift and reduced drag. Thus, the neural network's prediction confirms and complements the experimental understanding, demonstrating the network as an effective tool for optimizing and analyzing the airfoil under real operating conditions.

3.3. Validation

To verify the reliability of the predictive model based on ANNs, a cross-validation was performed using independent data obtained through simulation in the XFLR5 software, reproducing the optimal operating conditions predicted by the model: Reynolds number equal to 350 000 and Angle of attack (α) of 4.5°[10].

The results show a relative deviation of less than 3.5% for all evaluated parameters, indicating high accuracy of the neural network even under prediction conditions outside the training set [5][7].

The predicted and validated efficiency showed a difference of only 0.13 percentage points, reinforcing the model's ability to represent the real aerodynamic behavior of the Eppler 423 airfoil under low Reynolds number conditions [12].

The simulated coefficients were directly compared with the values predicted by the neural network, as shown in Table 3, using widely accepted statistical performance metrics in regression model validation, such as MAE, relative percentage error, and R^2 [11].

Table 3: Comparison between the data predicted by ANNs and simulated by XFLR5

Parameter	Value	Simulated Value	Absolute Error	Relative Error (%)
C_L	1.612	1.563	0.049	3.04
C_D	0.016	0.0155	0.0005	3.23
C_M	-0.241	-0.233	0.008	3.32
Efficiency (%)	100.75	100.62	0.13	0.13

Furthermore, additional simulations (not shown in this summary), performed at points near the optimum, indicated consistent behavior between the model's predictions and the values obtained in XFLR5, demonstrating good generalization capability of the predictive model [8].

Despite the positive results, it is important to highlight that the model is still limited to the originally simulated data and may have reduced performance outside the analyzed range. Therefore, future work is recommended to include experimental validations in a wind tunnel and to expand the database to different geometries and turbulence configurations [13].

4. Conclusion

This project demonstrated that neural networks are effective in predicting the aerodynamic coefficients of the Eppler 423 airfoil, with results validated by simulations in XFLR5 under Reynolds number conditions of 350 000 and an angle of attack of 4.5°. The adopted approach shows great potential to accelerate the aerodynamic profile optimization process, reducing the need for extensive testing and enabling fast and reliable analyses.

However, to ensure a more comprehensive and robust validation of the predictive model, it is recommended that the next steps include additional computational tests covering different ranges of Reynolds numbers and angles of attack. Furthermore, conducting experimental wind tunnel tests with physical models of the Eppler 423 airfoil will allow the acquisition of real data for comparison, calibration, and model improvement. These future steps will be essential to consolidate the reliability of the approach and expand its applicability under diverse operating conditions.

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