IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 14, No. 1, February 2025, pp. 240~251
ISSN: 2252-8938, DOI: 10.11591/ijai.v14.i1.pp240-251

Unmanned aircraft vehicles/unmanned aerial systems digital twinning: Data-driven lift and drag prediction for airfoil design

Ali Aghazadeh Ardebili[1,3], Angelo Martella[1,4], Adem Khalil[2], Sabri Khalil[2], Antonella Longo[1,4], Antonio Ficarella[1]
[1]Data Lab-CRISR Research Center, Department of Engineering for Innovation, University of Salento, Lecce, Italy
[2]Department of Aeronautical Engineering, Faculty of Engineering and Architecture, Istanbul Gelisim University, Istanbul, Turkey
[3]Department of Research and Development, HSPI-Roma, Rome, Italy
[4]ICSC-International Center of Super Computing, Big Data and Quantuum Computing, Italy

Article Info

Article history:

Received Jan 9, 2024
Revised Aug 3, 2024
Accepted Aug 30, 2024

Keywords:

Aerodynamic
Airfoils
Data-driven design
Data-driven performance analysis
Digital twin
Machine learning
Neural network

ABSTRACT

This study investigates the innovative application of neural networks algorithms in the aviation industry's mechanical design process, motivated by the pursuit of creating a more accurate and efficient method for performance prediction. Traditional approaches, such as computational fluid dynamics (CFD) simulations based on solving Navier-Stokes's equations, demand substantial computational power and often exhibit limited accuracy, particularly when compared with complex geometries. The state-of-the-art review unveils a growing research trend advocating for data-driven methodologies to revolutionize design practices, addressing the limitations of conventional techniques. The primary objective of this study is to explore how neural network algorithms can overcome the drawbacks of CFD simulations, offering a more effective alternative for predicting the performance of airfoils. To achieve this objective, we conducted a performance analysis of airfoils using neural network algorithms. The results presented a promising avenue for a more accurate and efficient performance prediction method through digital twinning. The study highlights the advantageous features of neural network methods in unmanned aircraft vehicles (UAV) component mechanical design, showcasing their potential to outperform traditional methods and offering practical recommendations for integration into the design process.

Corresponding Author:

Ali Aghazadeh Ardebili
Data Lab-CRISR Research Center, Department of Engineering for Innovation, University of Salento
Lecce, Italy
Email: ali.a.ardebili@unisalento.it

1. INTRODUCTION

The aviation industry is undergoing a paradigm shift, driven by the rapid advancements in digital technologies. Among these, machine learning and neural networks methods hold undiscovered potential to revolutionize the design process and unlock new possibilities for unmanned aerial systems (UAS) [1], [2]. This study investigates the application of neural networks to predict airfoil lift and drag coefficient, crucial parameters in UAS design and performance.

While traditional simulation and analysis methods have been the mainstay in aircraft design, they often rely on assumptions and may not accurately capture real-world complexities [3], [4]. This can lead to suboptimal designs and missed opportunities for innovation. Conversely, data-driven approaches based on machine learning and neural networks offer a powerful alternative. By leveraging real-world data, these methods can learn complex relationships and make accurate predictions, leading to improved efficiency, reduced costs, and enhanced performance [5], [6].

Several successful applications of machine learning algorithms in the aviation sector demonstrate their potential. For instance, decision tree learning has proven effective in aircraft engine failure diagnosis, while neural networks have been utilized to predict aircraft maintenance needs with high accuracy [7]. These examples highlight the ability of artificial intelligence to transform critical aspects of aircraft design and operation. In the realm of UAS, optimizing airfoil performance is paramount for maximizing range, endurance, and maneuverability. The lift coefficient, a key aerodynamic parameter, plays a crucial role in determining an airfoil's lift generation at different angles of attack. Traditionally, computational fluid dynamics (CFD) simulations have been employed to predict lift coefficients, but they can be computationally expensive and time-consuming.

This study explores the use of neural networks as a data-driven alternative for predicting airfoil lift and drag coefficients. This approach aims to achieve fast and accurate predictions, potentially streamlining the UAS design process and enabling rapid prototyping and optimization. By employing neural networks, this research seeks to: i) develop a model for predicting airfoil lift and drag coefficients, ii) compare the performance of the neural network model with traditional CFD simulations, and iii) demonstrate the potential of data-driven design for UAS development and optimization. This research contributes to the ongoing effort to integrate machine learning into the aviation industry and explore its potential benefits for UAS design. By harnessing the power of data-driven approaches, we can usher in a new era of innovation and efficiency in the development of next-generation UAS.

2. BACKGROUND REVIEW

In the domain of engineering, the utilization of neural networks has increased across diverse applications, ranging from image, and text recognition [8], [9], maintenance [10], production [11], cutting edge technologies like internet of things (IoT) [12], [13]. However, despite the myriad use cases, a notable gap persists in harnessing the potential of neural networks for designing machine components under the influence of aerodynamic loads. Bridging this gap holds immense promise not only for enhancing the efficiency and performance of machine components, but also for pushing the boundaries of what neural networks can achieve in the field of engineering design.

In aircraft engineering, having a wing designed with appropriate aerodynamic features is critical for achieving efficient and successful flight. The initial phase of this process involves meticulously exploring various wing cross-sections through a combination of experimental, computational, and theoretical methods. This iterative process often culminates in creating a customized wing profile tailored to the specific requirements of the aircraft.

However, with the ever-increasing wing geometry and design complexity, traditional CFD approaches have become computationally expensive and resource-intensive. Additionally, the accuracy of CFD methods can be compromised when dealing with highly complex geometries, potentially leading to misleading results. Consequently, researchers have focused on data-driven approaches and real-world measurements to develop more accurate predictive models. This shift towards data-driven methodologies is further supported by a significant gap in the existing literature regarding the application of artificial neural networks (ANNs) in aerodynamics, particularly in the context of wing cross-section design in Figure 1. This underscores the immense potential of ANNs to contribute significantly to the advancement of aerodynamic design and analysis.

One key approach involves using convolutional neural networks (CNNs) [14]. By leveraging their ability to extract spatial features from image data, CNNs can be trained on airfoil geometry data to predict the lift coefficient directly. This eliminates the need for complex simulations and allows for faster design iterations. Additionally, recurrent neural networks (RNNs) and long short-term memory (LSTM) architectures are being investigated for their capability to capture the temporal dependencies between different angles of attack, leading to more accurate lift predictions throughout the entire range of operation [15], [16]. Furthermore, advanced data augmentation techniques are being employed to address the often limited availability of high-quality airfoil data. By artificially generating new data based on existing samples, researchers can significantly expand the training set and enhance the generalization ability of the neural network models [17]. This is particularly beneficial for unconventional airfoil designs with scarce experimental data.

Another promising avenue involves integrating domain knowledge into the neural network architecture. This can be achieved through physics-informed neural networks (PINNs) [18], which utilize partial differential equations governing the flow around the airfoil to guide the learning process. By incorporating these physical constraints, PINNs can achieve superior accuracy and robustness compared to traditional neural networks, mainly when dealing with extreme or unseen conditions. These advancements demonstrate the immense potential of neural networks and related data-driven techniques in revolutionizing the design of airfoils for UAS. By enabling rapid prototyping, exploring unconventional designs, and ensuring robust performance across various operating conditions, this approach is paving the way for a new era of innovation in unmanned aircraft systems.

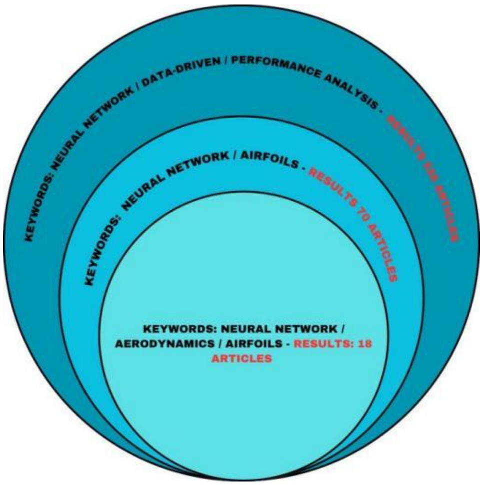


Figure 1. Results from ScienceDirect

3. THE REVIEW OF DIFFERENT TECHNIQUES

3.1. Physical model and mathematical approach

Predicting aerodynamic forces acting on an airfoil is crucial for the design and analysis of UAS. Traditionally, two main approaches have been employed: physical models based on theoretical equations and numerical simulations like finite element analysis (FEA) and CFD. Early attempts to understand and predict the lift force generated by an airfoil relied on simple physical models based on the Bernoulli equation, which relates the pressure difference between the upper and lower surfaces of the airfoil to its lift. This equation, expressed as [19]:

$$L = \frac{1}{2} \times \rho \times V^2 \times cl \times A$$

Where ρ is the air density, V is the air velocity, cl is the lift coefficient, and A is the wing area.

However, this equation only provides an approximation of the lift force and does not account for various factors such as viscosity, turbulence, and compressibility. To address these limitations, more complex mathematical models were developed based on the Navier-Stokes equations, which govern the flow of viscous fluids. These equations are a set of coupled partial differential equations that can be used to solve for the pressure, velocity, and temperature distribution around the airfoil. However, solving these equations analytically is often impossible, and numerical methods are required.

3.1.1. Mathematical background of navier-stokes equations

The Navier-Stokes equations are derived from the fundamental principles of conservation of mass, momentum, and energy. They can be written in the following general form [20]:

– Continuity equation

$$\frac{\partial \rho}{\partial t} + \nabla (\rho v) = 0$$

– Momentum equation

$$\frac{\partial (\rho v)}{\partial t} + \nabla \cdot (\rho v v) = -\nabla p + \nabla \cdot \tau + \rho g$$

– Energy equation

$$\frac{\partial (\rho E)}{\partial t} + \nabla \cdot (\rho v E) = \nabla \cdot (k \nabla T) + \nabla \cdot (\tau \cdot v) + \rho q$$

Where ρ is the density, v is the velocity, p is the pressure, τ is the stress tensor, g is the acceleration due to gravity, T is the temperature, k is the thermal conductivity, and q is the heat source. These equations are solved with appropriate boundary conditions to determine the flow field around the airfoil.

Limitations: solving the Navier-Stokes equations directly can be computationally expensive. Especially for complex geometries and turbulent flows. This limits their application to simple cases or requires powerful computing resources.

3.1.2. Joukowski and lifting line theory

Joukowski's airfoil theory provides a relationship between the lift force and the circulation around the airfoil. It can be expressed as [20]:

$$L = \rho * V * \Gamma$$

Where Γ is the circulation. The Prandtl lifting line theory is a fundamental concept in aerodynamics, developed by Ludwig Prandtl and his colleagues in the early 20th century. It offers a simplified model to predict a three-dimensional wing's lift distribution and aerodynamic performance.

a) Key assumptions
- Wing is represented by a line vortex: The actual wing is replaced by a line vortex along its span, where the vortex strength varies to represent the varying lift distribution. This simplifies the complex 3D flow around the wing.
- Elliptic lift distribution: The lift distribution is assumed to be elliptical, with the highest lift at the wing root and gradually decreasing towards the tips.

This assumption is based on empirical observations and approximates many wings well.

b) Concepts and formulas

Lift and induced drag: The theory relates the lift generated by the wing to the induced downwash velocity field created by the line vortex. This downwash velocity reduces the effective angle of attack at different sections along the wing, leading to a variation in lift distribution. The induced drag arises from the work done against the downwash. Here are some important formulas used in Prandtl lifting line theory [20].

- Lift coefficient

$$CL = \frac{2\pi\, \varepsilon}{\sqrt{(1+\varepsilon^2)}}$$

Where ε is the elliptic parameter related to the aspect ratio of the wing.

- Induced drag coefficient

$$CDi = \frac{CL^2}{\pi AR}$$

Where AR is the aspect ratio of the wing.

- Downwash velocity

$$w(x) = \frac{-\Gamma(s)}{2\pi b} \times \sqrt{\frac{(x-s)^2}{b^2}} ds$$

Where Γ(s) is the vortex strength at spanwise location s, b is the half-span of the wing, and x is the spanwise location where the downwash is being calculated.

c) Limitations
- Assumptions limit accuracy: The theory relies on simplifying assumptions like elliptical lift distribution, which may not hold perfectly for all wings or flight conditions [20].
- Limited to subsonic flows: The theory is primarily valid for subsonic flow regimes and may not accurately predict the behavior of wings at transonic and supersonic speeds [20].

3.2. Numerical approach and Simulations like finite element analysis and computational fluid dynamics

Numerical simulations are necessary for more accurate predictions of aerodynamic forces. While physical models offer valuable insights into the underlying principles of airfoils. FEA and CFD are two widely used numerical techniques.

3.2.1. Finite element analysis

FEA discretizes the geometry of the airfoil into a mesh of finite elements. The Navier-Stokes equations are then solved for each component, and the results are combined to obtain an overall solution for the flow field. FEA is typically used to analyze the structural integrity of airfoils and other aerospace components [21].

3.2.2. Computational fluid dynamics

CFD solve the Navier-Stokes equations on a grid of points surrounding the airfoil. The grid can be structured or unstructured, and the equations are solved using various numerical methods such as finite volume, finite difference, or spectral methods. CFD is widely used for predicting the aerodynamic performance of airfoils and other aerospace components [22].

3.2.3. Limitations of computational fluid dynamics and finite element analysis

While FEA and CFD offer powerful tools for analyzing solid and fluid mechanics, they do come with limitations [22]. Both methods rely on discretizing the domain of interest, which can lead to inaccuracies, especially near complex geometries or sharp gradients. FEA, while adept at stress and deformation analysis, struggles with fluid flow and heat transfer, while CFD excels in these areas but can be computationally expensive for complex systems. Additionally, both methods require significant user expertise for accurate model generation, boundary condition definition, and result interpretation [22].

4. METHOD

The primary objective of this study is to develop a predictive model employing neural networks. This model aims to forecast alterations in the lift coefficient in response to variations in the angle of attack and predicting the drag coefficient across the lift coefficient, as specified by the user-defined geometry, the outline of the research design is shown in Figure 2. The forthcoming subsections will elaborate on this process.

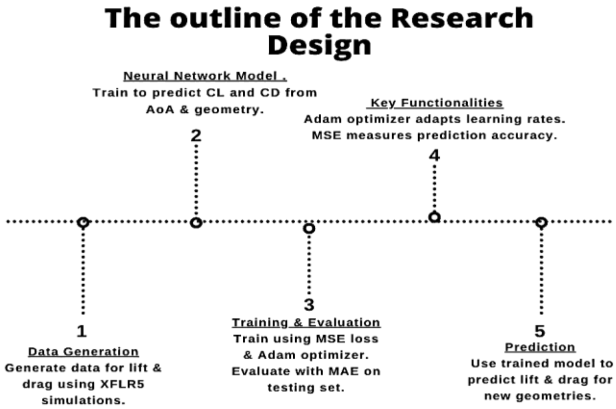


Figure 2. The outline of the research design

4.1. Dataset generation

In this case study, due to the absence of real-life data, lift coefficient and various drag coefficient data for various angles of attack on different wing sections was generated using CFD simulation extracted from the XFLR5 software. This simulated data was subsequently transferred to an Excel file. The file was organized into columns with headers for angle of attack (Alpha values), GeoX (X coordinates of wing sections), GeoY (Y coordinates), drag coefficient (CD), and lift coefficient (CL) creating a dataset for the ANN model. The simulation condition used in XFLR5 is shown in Table 1.

Table 1. Simulation condition

Reynolds number	1000000
Mach number	0.3
Angle of attack range	[-10,15]
Angle of attack rate of change	0.5
Airfoil pannels	50

After repeating the same simulation on different geometries, the different National Advisory Committee for Aeronautics (NACA) 4-digit wing section data have been saved in Excel files. The NACA wing sections to be used for training the model are as follows: NACA0006, NACA0018, NACA0024, NACA1408, NACA2410, NACA2412, NACA2415, NACA4412, NACA4418, NACA442, NACA6409, and NACA6412. The Figures 3 and 4 shows a sample of the results obtained from the XFLR after running the simulation showed on Table 1.

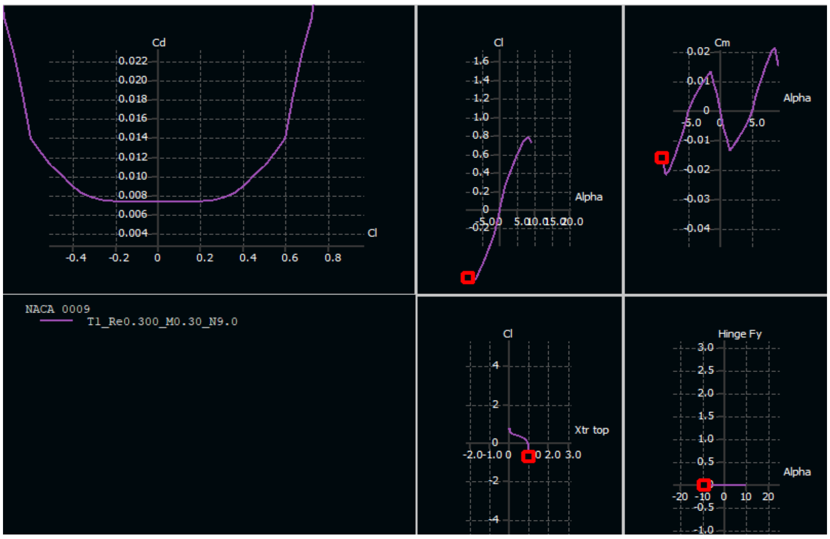


Figure 3. Aerodynamics coefficients from XFLR5

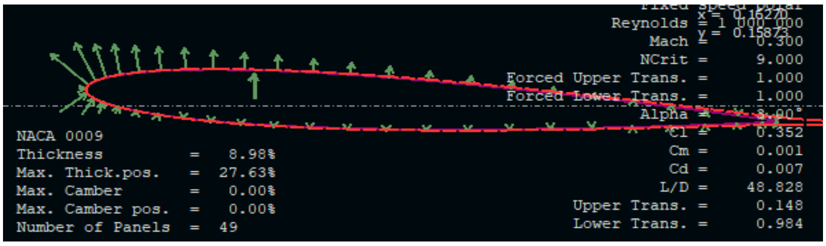


Figure 4. Pressure distribution along the airfoil

4.2. Neural network model

According to The Buckingham Pi Theorem applied on resultant forces as the lift and drag forces we obtain the following:

$$Cr = \frac{R}{\frac{1}{2}\times\rho\times V^2\times D^2} = f(G,Re,M)$$

Where R: Force, Cr: Force Coefficient, V: Velocity, D: Distance, G: Geometry, Re: Renolds number, and M: Mach number. Which tells that the lift and drag coefficients are only influenced by the geometry, Reynolds number and Mach number. In this study case Reynolds number and Mach number will be fixed and train the model on different geometries.

This study presents a TensorFlow neural network model for predicting the CL and CD trained on different airfoil geometries at various angles of attack (Alpha/AoA). The model reads data from Excel files containing airfoil coordinates, Alpha, CD, and CL values from different geometries and concatenates them into a single dataset. The dataset is then split into training and testing sets, as shown in Figures 5 and 6 (training) and Figure 7 (test).

The neural network model consists of two dense layers with 64 units and 1 unit, respectively. The mean squared error (MSE) loss function was chosen to train the model, and the Adam optimizer was used to minimize the loss function 1. The model was trained for 100 epochs for CL v AoA, and CD v CL. But two dense layers with 32 units and 1 unit, respectively. The MSE loss function (section 4.2.2) was chosen because it is a popular choice for regression problems, such as predicting the lift coefficient of airfoils. The Adam optimizer (section 4.2.1) was chosen because it is an efficient optimization algorithm that is well-suited for large datasets and high-dimensional parameter spaces.

The training history was recorded, and the model's performance was evaluated by calculating the test loss and mean absolute error (MAE). The MAE helps build a predictive model for CL based on airfoil geometry and angle of attack, which can be used in aerodynamic simulations and analysis. Overall, the TensorFlow model was chosen because it is a powerful and flexible tool for building and training neural networks. The MSE loss function and Adam optimizer were chosen because they are well-suited for regression problems and large datasets, respectively. The model's performance was evaluated using the MAE, which is a common metric for regression problems.

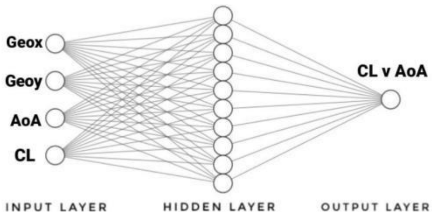


Figure 5. The training architecture for CL v AoA

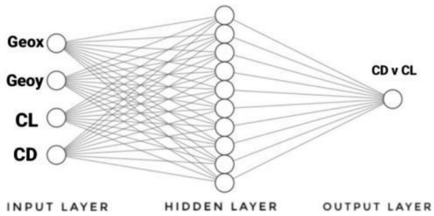


Figure 6. The training architecture for CD v CL

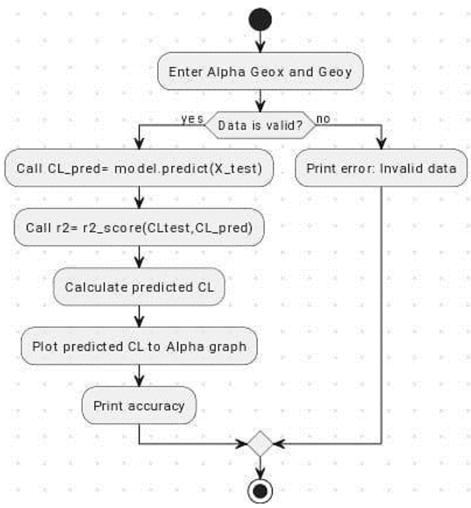


Figure 7. The test algorithm for testing CL v AoA

4.2.1. Adam optimizer

The adaptive moment estimation (ADAM) optimizer, widely used in deep learning, addresses the shortcomings of traditional stochastic gradient descent (SGD) by adaptively adjusting the learning rate for each parameter. It accomplishes this by maintaining two exponential moving averages: the first moment (mean) $\hat{m}_t$ and the second moment (uncentered variance) w_t of the gradient. These moments are used to update the parameters w_t according to:

$$w_{t+1} = w_t - \alpha \times \frac{\hat{m}_t}{(\sqrt{\hat{v}_t} + \varepsilon)}$$

Where α is the learning rate, ε is a small constant to prevent division by zero, and $\hat{m}_t$ and $\hat{v}_t$ are the bias-corrected versions of the first and second moment estimates, respectively. This adaptive learning rate allows for faster convergence and efficient training of deep neural networks [23], [24].

4.2.2. The mean squared error

In deep learning, the MSE serves as a vital tool for evaluating the performance of regression models. It measures the average of the squared differences between predicted and actual values, providing a quantitative assessment of the model's accuracy. Mathematically, MSE is defined as [25]:

$$\text{MSE} = \frac{1}{n} \times \Sigma(y\_i - \hat{y}\_i)^2$$

Where n is the number of data points, y_i is the actual value of the i-th data point, and ŷ_i is the predicted value of the i-th data point.

The squaring operation in the equation magnifies the impact of larger errors, making MSE sensitive to outliers. This characteristic can be both an advantage and a disadvantage. On the one hand, it ensures that models are penalized more for significant deviations from the true values, encouraging them to learn accurate predictions across the entire dataset.

MSE is widely used in various deep learning tasks, including regression problems such as price prediction and time series forecasting. It offers a simple and interpretable metric for model evaluation, allowing developers to easily assess the performance of different models and compare them against each other. However, it is important to acknowledge its limitations, particularly its sensitivity to outliers, and consider alternative loss functions like MAE when dealing with datasets containing significant outliers.

5. RESULTS AND DISCUSSION

Following the training process, the model's capabilities were evaluated using a new wing cross-section, NACA 4412, to assess its performance. This evaluation involved a comprehensive comparison of the predicted results with the CFD data presented in Figures 8 to 10. The comparison employed both graphical visualizations for qualitative insights and quantitative metrics for precise accuracy assessment.

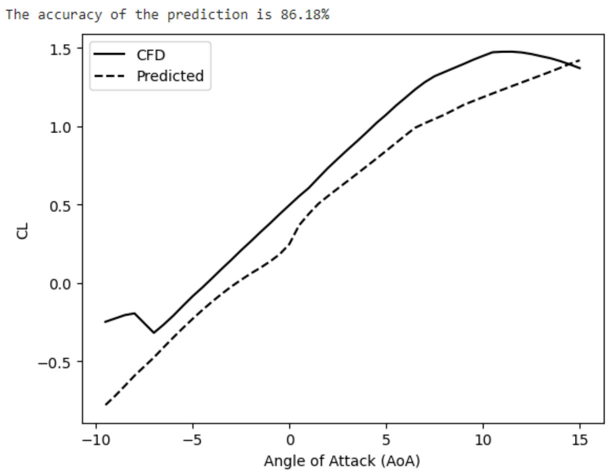


Figure 8. Results for CL v AoA

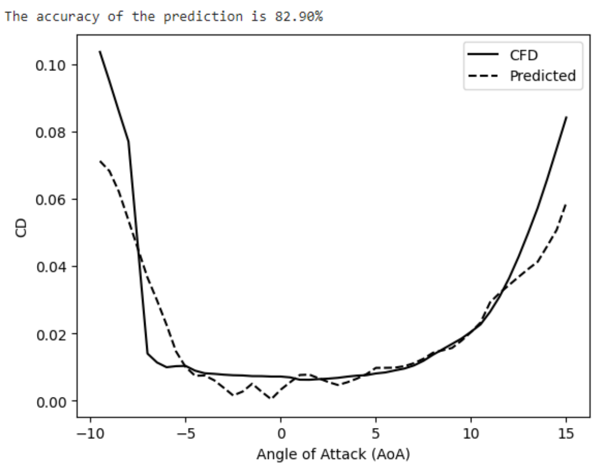


Figure 9. Results for CD v AoA

This study focuses on investigting the performance of ANN in predicting aerodynamic coefficients, specifically focusing on the lift coefficient and drag coefficient, utilizing airfoils' geometry coordinates. Unlike previous research endeavors, which have predominantly centered on employing PINNs using mathematical methodologies and CNN trained on visual data of airfoils, this investigation seeks to fill crucial gaps mentioned in section 2. Prior studies have indeed explored the effects of various factors on aerodynamic coefficients, yet they have not explicitly examined the performance of ANN trained on geometry coordinates.

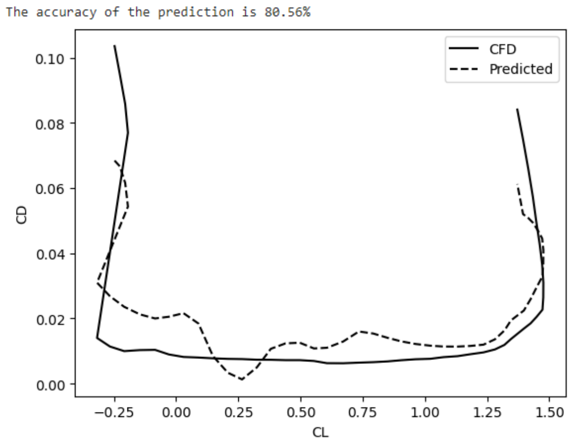


Figure 10. Results for CD v CL

The analysis revealed promising results for all parameters, even with a limited dataset. Further study is required to optimize hyperparameters, particularly with a larger dataset. The CL across the AoA achieved an impressive accuracy of 86.18%, while the CD showed strong performance with 82.90% accuracy across the angle of attack and 80.56% across the lift coefficient. Despite the small dataset, these results indicate the potential of the model. Moving forward, a more extensive hyperparameter optimization study, with a larger dataset, will likely lead to even more accurate predictions.

While PINNs, CNNs, and RNNs have gained traction in aerodynamics for airfoil applications and performance prediction, each exhibits inherent limitations. PINNs excel at solving partial differential equations governing aerodynamic simulations but demand substantial training data and computational resources. CNNs adeptly analyze image data for flow field prediction, yet struggle with time-dependent data and show sensitivity to input variations. RNNs, while suitable for time-dependent flow field prediction, can be computationally expensive and data-hungry. Furthermore, a common pitfall across these models is the "overlook geometry" disadvantage, where complex airfoil geometries are not adequately captured, leading to inaccurate predictions. This necessitates a critical evaluation of model selection and potential integration with traditional methods for robust and reliable aerodynamic predictions [26]–[29].

This methodology has showcased a new approach to analyzing the performance of airfoils using ANN and geometry coordinates, addressing the limitations mentioned earlier. This methodology can be applied in various industries, including the energy sector for designing turbine blade airfoils. Additionally, since the algorithm is trained on data separate from the fluid characteristics, it can be utilized in any other context where training data is available, eliminating the need for costly simulation approaches that consume time and high computational power.

6. LIMITATIONS, CHALLENGES AND FUTURE STUDIES

This study demonstrates valuable insights but acknowledges limitations arising from the small dataset used for training. To address the hard problem of limited data, future studies should prioritize expanding data acquisition, particularly for additional aerodynamic coefficients. Additionally, exploring data augmentation technique and advanced optimization strategies could enhance model performance and robustness. Regularization techniques are also crucial to avoid the non-obvious mistake of overfitting often associated with limited data. Furthermore, the potential of hybrid approaches and adapting the framework for 3D geometries opens doors for broader applications in the future, paving the way for a wider range of possibilities in aerodynamic design and optimization.

7. CONCLUSION

As a solution this investigative study put in theory that neural networks can potentially solve these problems without explicitly relying on differential equations or images by building models directly from airfoil geometry and data. This approach leverages the inherent non-linearity and feature extraction capabilities of neural networks to capture the complex relationships between geometry and aerodynamic performance. By encoding airfoil parameters, surface features, and experimental data into the network architecture, neural networks can learn the underlying physics and directly predict aerodynamic coefficients, lift, and drag. This eliminates the need for solving complex partial differential equations or interpreting flow field images, potentially leading to faster predictions and less reliance on high-resolution data. However, this approach requires careful design of the network architecture and selection of relevant features, as well as robust training datasets to avoid overfitting and ensure generalizability to unseen airfoil geometries. Compared to traditional methods, neural networks-based geometry-driven models offer a potentially faster and data-driven alternative for aerodynamic prediction, although further research is needed to fully validate their accuracy and robustness. To conclude, the study assessed the use of a neural network model to predict CL based on the angle of attack for various geometries. Despite the use of small datasets, the model showed promising performance, highlighting its potential for aerodynamic analysis and wing design. To enhance accuracy and generalization, future research should focus on using larger and more diverse datasets.

ACKNOWLEDGEMENTS

The research was partially supported by the Italian Research Center on High Performance Computing, Big Data and Quantum Computing (ICSC) grant, funded by EU – NextGenerationEU (PNRR-HPC, CUP:C83C22000560007), and the RIPARTI regional project - dataEnrichment for Resilient UAS (assegni di RIcerca per riPARTire con le Imprese)-POC PUGLIA FESRTFSE 2014/2020, CUP F87G22000270002.

REFERENCES

[1] I. Kabashkin, B. Misnevs, and O. Zervina, "Artificial intelligence in aviation: new professionals for new technologies," *Applied Sciences*, vol. 13, no. 21, 2023, doi: 10.3390/app132111660.

[2] A. A. Ardebili, A. Ficarella, A. Longo, A. Khalil, and S. Khalil, "Hybrid turbo-shaft engine digital twinning for autonomous aircraft via ai and synthetic data generation," *Aerospace*, vol. 10, no. 8, 2023, doi: 10.3390/aerospace10080683.

[3] J. R. R. A. Martins, "Aerodynamic design optimization: Challenges and perspectives," *Computers and Fluids*, vol. 239, 2022, doi: 10.1016/j.compfluid.2022.105391.

[4] M. Panzeri, A. Savelyev, K. Anisimov, R. D'Ippolito, and A. Mirzoyan, "Uncertainty quantification and robust design optimization applied to aircraft propulsion systems," *Transportation Research Procedia*, vol. 29, pp. 289–302, 2018, doi: 10.1016/j.trpro.2018.02.026.

[5] S. D. Longueville, J. Jézégou, E. Bénard, and Y. Gourinat, "Enhancing preliminary aircraft design through operational considerations: A data-driven approach," *IOP Conference Series: Materials Science and Engineering*, vol. 1024, no. 1, 2021, doi: 10.1088/1757-899X/1024/1/012057.

[6] A. D. Fentaye, V. Zaccaria, and K. Kyprianidis, "Aircraft engine performance monitoring and diagnostics based on deep convolutional neural networks," *Machines*, vol. 9, no. 12, 2021, doi: 10.3390/machines9120337.

[7] A. Altay, O. Ozkan, and G. Kayakutlu, "Prediction of aircraft failure times using artificial neural networks and genetic algorithms," *Journal of Aircraft*, vol. 51, no. 1, pp. 47–53, 2014, doi: 10.2514/1.C031793.

[8] B. Shi, X. Bai, and C. Yao, "An end-to-end trainable neural network for image-based sequence recognition and its application to scene text recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 11, pp. 2298–2304, Dec. 2016, doi: 10.1109/tpami.2016.2646371.

[9] H. Ohmaid, S. Eddarouich, A. Bourouhou, and M. Timouyas, "Comparison between svm and knn classifiers for iris recognition using a new unsupervised neural approach in segmentation," *IAES International Journal of Artificial Intelligence*, vol. 9, no. 3, pp. 429–438, 2020, doi: 10.11591/ijai.v9.i3.pp429-438.

[10] T. Zonta, C. A. D. Costa, F. A. Zeiser, G. D. O. Ramos, R. Kunst, and R. D. R. Righi, "A predictive maintenance model for optimizing production schedule using deep neural networks," *Journal of Manufacturing Systems*, vol. 62, pp. 450–462, Jan. 2022, doi: 10.1016/j.jmsy.2021.12.013.

[11] W. Cardoso *et al.*, "Modeling of artificial neural networks for silicon prediction in the cast iron production process," *IAES International Journal of Artificial Intelligence*, vol. 11, no. 2, pp. 530–538, 2022, doi: 10.11591/ijai.v11.i2.pp530-538.

[12] M. Chen, U. Challita, W. Saad, C. Yin, and M. Debbah, "Artificial neural networks-based machine learning for wireless networks: a tutorial," *IEEE Communications Surveys & Tutorials*, IEEE, vol. 21, no. 4, pp. 3039–3071, Jan. 2019, doi: 10.1109/comst.2019.2926625

[13] M. Almiani, A. AbuGhazleh, A. Al-Rahayfeh, S. Atiewi, and A. Razaque, "Deep recurrent neural network for IoT intrusion detection system," *Simulation Modelling Practice and Theory*, vol. 101, Nov. 2019, doi: 10.1016/j.simpat.2019.102031.

[14] M. I. Kim and H. S. Yoon, "Geometric modification for the enhancement of an airfoil performance using deep CNN," *Ocean Engineering*, vol. 266, 2022, doi: 10.1016/j.oceaneng.2022.113000.

[15] S. Suresh, S. N. Omkar, V. Mani, and T. N. G. Prakash, "Lift coefficient prediction at high angle of attack using recurrent neural network," *Aerospace Science and Technology*, vol. 7, no. 8, pp. 595–602, 2003, doi: 10.1016/S1270-9638(03)00053-1.

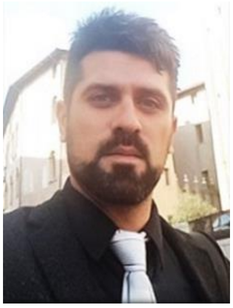
[16] J. Hu and W. Zhang, "Flow field modeling of airfoil based on convolutional neural networks from transform domain perspective," *Aerospace Science and Technology*, vol. 136, 2023, doi: 10.1016/j.ast.2023.108198.

[17] H. Wu, X. Liu, W. An, and H. Lyu, "A generative deep learning framework for airfoil flow field prediction with sparse data," *Chinese Journal of Aeronautics*, vol. 35, no. 1, pp. 470–484, 2022, doi: 10.1016/j.cja.2021.02.012.

[18] Y. Sun, U. Sengupta, and M. Juniper, "Physics-informed deep learning for simultaneous surrogate modeling and PDE-constrained

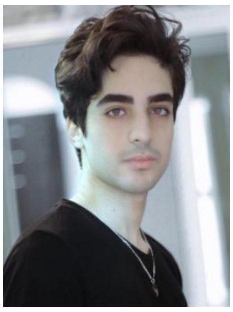
optimization of an airfoil geometry," *Computer Methods in Applied Mechanics and Engineering*, vol. 411, 2023, doi: 10.1016/j.cma.2023.116042.
[19] J. David, *Introduction to flight*, New York: Mcgraw Hill, pp. 17–30, 2012, doi: 10.4324/9780080477787-6.
[20] J. D. Anderson, F*undamentals of aerodynamics*, New York: Mcgraw-Hill, 2016, doi: 10.2514/152157.
[21] H. K. Versteeg and W. Malalasekera, *An introduction to computational fluid dynamics: the finite volume method*, Essex, England: Pearson Education, 2014.
[22] J. D. Anderson, *Computational fluid dynamics, the basic with applications*, United States of America: Mcgraw-Hill, 1976.
[23] Z. Zhang, "Improved Adam optimizer for deep neural networks," *2018 IEEE/ACM 26th International Symposium on Quality of Service, IWQoS 2018*, 2019, doi: 10.1109/IWQoS.2018.8624183.
[24] M. Reyad, A. M. Sarhan, and M. Arafa, "A modified Adam algorithm for deep neural network optimization," *Neural Computing and Applications*, vol. 35, no. 23, pp. 17095–17112, 2023, doi: 10.1007/s00521-023-08568-z.
[25] G. Tsiotas, "Regression analysis using asymmetric losses: a Bayesian approach," *Journal of Quantitative Economics*, vol. 20, no. 2, pp. 311–327, 2022, doi: 10.1007/s40953-022-00289-9.
[26] S. Bhatnagar, Y. Afshar, S. Pan, K. Duraisamy, and S. Kaushik, "Prediction of aerodynamic flow fields using convolutional neural networks," *Computational Mechanics*, vol. 64, no. 2, pp. 525–545, 2019, doi: 10.1007/s00466-019-01740-0.
[27] S. Cai, Z. Mao, Z. Wang, M. Yin, and G. E. Karniadakis, "Physics-informed neural networks (PINNs) for fluid mechanics: a review," *Acta Mechanica Sinica/Lixue Xuebao*, vol. 37, no. 12, pp. 1727–1738, 2021, doi: 10.1007/s10409-021-01148-1.
[28] Z. Yuan, Y. Wang, Y. Qiu, J. Bai, and G. Chen, "Aerodynamic coefficient prediction of airfoils with convolutional neural network," *The Proceedings of the 2018 Asia-Pacific International Symposium on Aerospace Technology (APISAT 2018)*, vol. 459, pp. 34–46, 2019, doi: 10.1007/978-981-13-3305-7_3.
[29] R. L. Liu, Y. Hua, Z. F. Zhou, Y. Li, W. T. Wu, and N. Aubry, "Prediction and optimization of airfoil aerodynamic performance using deep neural network coupled Bayesian method," *Physics of Fluids*, vol. 34, no. 11, 2022, doi: 10.1063/5.0122595.

BIOGRAPHIES OF AUTHORS



Ali Aghazadeh Ardebili holds a Ph.D. in Engineering Risk Analysis from the University of Trieste and is about to conclude 2nd Ph.D. at the UniSalento in Complex Decentralized Energy System's Resilience; he is currently working at the CRISR research center as a post-doc researcher in Unmanned Aircraft Systems for Smart Cities and Advanced Air Mobility (AAM) for Urban Services. His research field is digital twins, UAS/RPAS/AAM, cyber-physical-social systems, uncertainty analysis/assessment, engineering/project risks, critical infrastructures resilience, and data-oriented solutions. He has 4 patents, and 8 years of professional career experience in international engineering design/consultant companies. He speaks English, Italian, Persian, Azerbaijani, and Turkish. In 2018 he was selected among the 13 redefiners of the next 100 years in N100 symposium out of 650 applicants from 55 countries; he was peace ambassador certified by the global peace chain from 2018 to 2020. In 2019 he won the TATA Steel challenge award for a sustainable solution for HYSARNA industrial steel production process. He is a member of the Italian Industrial engineering association (AIDI) and Iran construction engineering organization (IRECO). He can be contacted at email: ali.a.ardebili@unisalento.it.

Adem Khalil is Aeronautical Engineering student at Istanbul Gelisim University(ongoing). He has a keen interest in aerospace technology, renewable energies, and the aviation industry. He has achieved finalist status in two editions of the TEKNOFEST competition in Turkey, specifically in the categories of flying car design, international UAV free mission competition, and fighter drone competition. He speaks Arabic, French, English, and Turkish. His aspiration is to contribute to the field through research and development activities in both industry and academia. He can be contacted at email: 190414137@ogr.gelisim.edu.tr.



Sabri Khalil is Aeronautical engineering student at Istanbul Gelisim University (ongoing) with a strong interest in aeronautics, unmanned aerial vehicles, artificial intelligence, and network. With a proven ability to quickly learn and apply new technologies, He has contributed to a UAV project for rescue operations. He showcased his project at TEKNOFEST 2021, an esteemed aerospace and technology festival held in Istanbul, Turkey. He speaks in Arabic, French, English, and Turkish. He can be contacted at email: sabri.khalil@ogr.gelisim.edu.tr.

Angelo Martella is a junior researcher at the DataLab of the University of Salento. He is an academic lecturer in big data management and data science and engineering at the same department. The research topics he is involved in are related to developing the digital twins paradigm and data space concept. Consequently, his areas of expertise encompass all stages of the design, development, and implementation of digital twins for smart cities, emphasizing adopting data spaces as essential facilitators of the resulting data ecosystem by managing data flows in distributed edge-cloud environments. Currently, he is involved in various research projects, mostly related to ICSC - Spoke9 "Digital Society and Smart Cities". He can be contacted at email: angelo.martella@unisalento.it.

Antonella Longo is Associate Professor at the Department of for Innovation of the University of Salento, and received the Ph.D. in Information Engineering in 2004. She teaches database, data management, big data management, data engineering, and security of critical infrastructures at computer engineering, management engineering, and engineering for the security of critical infrastructures (bach and Ms.C. classes). Her research interests include information systems and databases, service-oriented architectures design for cloud and edge infrastructure, and tools for enhancing citizen science. Her current research focuses on models and tools for big data management and the exploration of edge/cloud architecture in cyber-physical systems. She has published over 100 papers on these topics in peer-reviewed journals and international conference proceedings. She is the coordinator of DataLab (datalab.unisalento.it), the data lab at University of Salento and the DidaLab (didalab.unisalento.it), the lab about innovative models in education based on digital tools. She is also an Associate Editor of the IEEE Journal of the Internet of Things and of Taylor's Software and Practice. She is also a member of the Scientific Advisory Board of Fiware Foundation. He can be contacted at email: antonella.longo@unisalento.it.

Antonio Ficarella is full Professor of energy and environment systems at University of Salento (Italy); former Dean of the Faculty of Industrial Engineering. Member of the Board of Directors of the Aerospace Technological Cluster (DTA), Inter-university Consortium of Apulian Region (CIRP), Inter-university Consortium for Research on Sustainable Development (CIRPS). Professor of machinery, energy systems, aeronautical propulsion, design and management of energy systems, industrial energy management, fluid-dynamics, sustainability of propulsion and energy systems. The scientific activities were developed in the fields of unsteady and two-phase fluid-dynamic inside machines and apparatus, thermo and fluid dynamic applied to industrial processes simulation, diesel engines and related direct injection systems, sensor development, industrial energy applications and related environmental subjects, energy recovery from biomass, wastes, industrial processes. He can be contacted at email: antonio.ficarella@unisalento.it.