A Hybrid Framework for Airfoil Optimization: Combining PINNs and Genetic Algorithm (Student Abstract)

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Abstract

Achieving optimal design is a crucial aspect of any design process for safe and efficient operation. Such tasks typically require numerous simulations over many iterations, which can become computationally expensive. This paper proposes a novel method that combines Physics-informed Neural Networks (PINNs) with a Genetic Algorithm to optimize the parameters of an airfoil that aims to achieve favourable aerodynamic conditions. Traditional solvers are computationally expensive for performing such tasks, but using PINNs can significantly reduce this while keeping accuracy high. The proposed approach shows the advantage of using PINNs in optimizing complex engineering problems.

Introduction

Aerodynamics studies the behaviour of objects moving through the air; it plays a pivotal role in aviation and automotive designs. The cross-sectional profile of an object plays a vital role in influencing the aerodynamic properties of an object and failing to consider it may lead to structural or functional failures. Computational fluid dynamics (CFD) is used to predict fluid behaviour around these structures. It uses numerical methods to solve the Navier-Stokes equations, to simulate the fluid and body interaction under specified conditions. However there are certain challenges, CFD happens to be resource intensive requiring a lot of power and time. Large-scale simulations can take days or even weeks to complete, depending on the complexity of the design and the desired accuracy of the results. This makes the process both time-consuming and expensive, especially for industries that rely on iterative testing and refinement. The design of an airfoil is a critical aspect of aerodynamics invested heavily in. Achieving an optimal airfoil design involves balancing lift and drag coefficients to maximize efficiency and stability. Companies in the aerospace and automotive sectors spend substantial resources on simulations, wind tunnel tests, and design iterations to reach the best possible aerodynamic performance.

Background

PINNs

PINNS is a neural network framework which is at its core has the knowledge of physics embedded into it. It was introduced by (Raissi, Perdikaris, and Karniadakis 2019) and has the capability to solve the partial differential equations (PDEs). The traditional method like FEM and FVM for solving the PDEs are very resource expensive requiring a lot of time and computation power.PINNs has 3 loss functions one is the data based loss function, the boundary condition based loss function and the other is the physics based loss function. The data-based loss function ensures that the prediction done by the neural network is accurate, the boundary condition loss keeps a check if the initial boundary conditions are satisfied, and the physics-based loss function ensures that the prediction satisfies the governing equations (the Navier-stokes in this case).

NSGA-II

NSGA-II is a genetic algorithm introduced by (Deb et al. 2002) which has emerged as a robust method for solving complex optimization problems. It is one of the evolutionary algorithms built on the foundation of genetic principles, using a combination of parent and offspring populations to evolve toward optimal solutions. NSGA-II uses nondominated sorting, where solutions are ranked based on their dominance in the objective space. By leveraging an elitist strategy and ensuring diversity through the crowding distance, NSGA-II ensures that the final set of solutions lies on a Pareto front, thus balancing multiple objectives as well as a single objective effectively.

Numerical Setup

The dataset for this research was generated through Computational Fluid dynamics (CFD) analysis using the ANSYS Fluent software. First, we made an unoptimized airfoil in the software using the design modeler for ease of generating the dataset, as we were required to run multiple simulations. We parameterized 5 points on the upper profile of the airfoil and then 5 coordinates on the lower profile of the airfoil in a total of 10 spatial coordinates that describe the airfoil, with the leading and the trailing edge fixed at the origin and (1,0) keeping a chord length of 1 meter throughout the

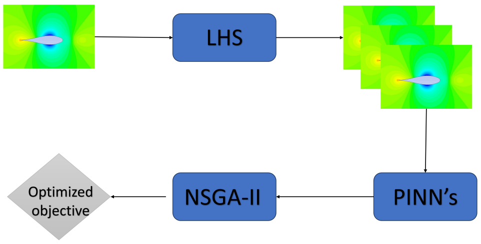

Figure 1: Overall Architecture

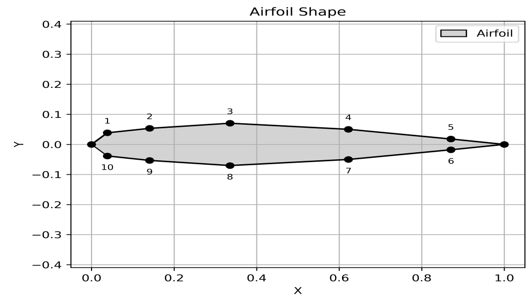

Figure 2: Airfoil Plot

dataset after that we defined the fluid domain in our sketch. After completing the sketch, we created a C-type mesh for the problem with quadrilateral elements. The conditions for the simulation are Re = 6000000; the free stream velocity was found to be around 52.08 m/s and the kinematic viscosity was around 8.68 x 10^{-6} m^2/s. The simulation yielded converged values of C_l and C_d after 2700 iterations. The simulation was repeated for different angle of attack (AOA) from 0 to 15 degrees. Then we validated the simulations result with the experimental results of NACA 0012 to check if the simulation was set up properly and accurately. We employed the Latin Hypercube Sampling (LHS) technique to obtain more data points for our dataset. We provided it with the upper and lower bounds of both the x and y, and it generated all the possible combinations we could have. This way it is easy to change the parameterized coordinates and run the simulation quickly. Once all the coordinates were given as input, the simulation is started. When the results converged, they were exported into a CSV file.

Methodology

In order to optimize the design of the airfoil to we get maximum lift and minimum drag we incorporated a Physics informer Neural Networks (PINNs) as a surrogate model. The dataset was given input to our network. The PINNs network we built has 5 layers in total, the first has 11 neurons, then 64 in the next 3 layers, and the final layer has a single neuron. The activation function used is tanh, and the optimizer used for the initial training is Adam with a learning rate of 0.001, and for the later stage of training, we used an L-BFGS optimizer. After training for the optimization of the airfoil geometry, we employed our NSGA-II algorithm, which has 11 decision variables, consisting of the control points of the airfoil. The objective of this study is to maximize the C_l/C_d ratio, a critical performance metric in aerodynamic design. However, since NSGA-II is designed to minimize objectives by default, we negate the predicted values of C_l/C_d in the evaluation phase to align with the algorithm's mechanics. A population of 100 individuals comprising both parents and offspring evolving for over 200 generations. The population is created by generating offspring from parents using crossover and mutation operators, forming a combined pool of solutions. Only the best solutions are selected for the next generation. Selection is made using a crowded tournament mechanism.

Experimental Analysis and Result

The PINNs model outperformed the traditional Artificial Neural Network (ANN) Surrogate model as summarized in Table 1. The value of C_l/C_d when the control points of the airfoil were optimized by the NSGA-II when coupled with PINNs was around **44.49**, which shows that the optimized coordinates yielded a configuration having better aerodynamics showing a greater lift and minimum drag as compared to when coupled with ANN which was around **16.89** indicating to a greater drag and smaller lift.

Metric	PINNs	ANN
MSE	64.824	125.470
MAE	5.832	9.037
R^2	0.483	0.001
MAPE	0.390	0.615

Table 1: Evaluation Metrics

Conclusion

The results showed that PINNs have better prediction than the traditional ANN, with an overall better performance in predicting the flow parameters. Thus, it can be employed in the field of CFD to accurately predict desired parameters.

Acknowledgements

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References

Deb, K.; Pratap, A.; Agarwal, S.; and Meyarivan, T. 2002. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, 6(2): 182–197.

Raissi, M.; Perdikaris, P.; and Karniadakis, G. 2019. Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational Physics*, 378: 686–707.