## **AE 416 Term Project**

Wanzheng Zheng

## I. Introduction

Machine learning and data mining techniques has been widely applied in many fields and businesses, yet application of which in the field of aerodynamics are somewhat new compared to other[1]. Complex flow behaviours around body of interest are usually simulated and predicted using computational fluid dynamics (CFD) methods of various fidelity. Though these methods has reached acceptable levels of maturity, they usually implies high computational cost. Such cost is augmented when CFD is applied in multidisciplinary optimization, which is usually an iterative process. To overcome such limitation, researchers has been investigating the application of machine learning and data-driven approaches for aerodynamic analysis. Esther [1] showed that machine learning have huge potentials in making quick predictions of aerodynamic coefficients. Hui et al. [2] trained a model to predict pressure distribution over airfoils based on Convolutional Neutral Network (CNN) without solving governing equations. Liu et al. [3] trained and published a CNN that is able to predict airfoil lift to drag ratio, and shows that the method of CNN has competitive level of accuracy compared to conventional CFD methods while being potentially 5,000 times faster.

While the potential of data-driven method in the field of aerodynamics is apparent, it is necessary to note that physical relations are not considered during the prediction process of CNN, which implies that the gradient of aerodynamic parameters with respect to change in topology cannot be calculated by taking derivatives of the underlying governing equations. This issue implies that application of machine learning in aerodynamic optimization needs to either use a gradient independent algorithm or use finite difference technique to approximate for the gradient. The former of which was accomplished by Haryanto et al. [4] by applying Genetic Algorithm (GA) as an optimizer based on Artificial Neutral Network to optimize lift to drag ratio of turbine blade airfoil. The later case however, was barely considered in the writer's knowledge. Drela [5] acknowledged the versatility of parameter gradient calculation methods in airfoil optimization, and pointed out that unforeseen difficulties and surprising results arise as design parameters increase. Drela mentioned that one of the cons of airfoil optimization is that increase of DOFs requires also the increase of near-continuous sampling of operation space, which will be very expensive and optimized aerodynamic shapes from such approaches usually appears to be noisy and needs smoothing.

It is therefore interesting to consider the effectiveness of applying data-driven method in gradient based airfoil optimization problem. If it is shown to be efficient, such approach can potential resolve the computation expenses in solving governing equations during iterative process, and pre-processing airfoil geometry data into images in utilizing CNN models to predict aerodynamic coefficient can potentially leads to smoother and realistic optimized geometry. Thus the purpose of this project is to train a CNN model using UIUC airfoil database [6] to predict aerodynamic coefficients, namely  $C_l$  and  $C_d$  using the method provided by Liu [3]. The model is then used to solve for an airfoil optimization problem using conventional gradient decent approach and the result of which is compared to solving the same problem by using viscous coupled vortex lattice method provided by XFOIL[7]. The comparison should offer insight in application of machine learning in aerodynamic optimization and, potentially, multi-disciplinary optimization (MDO).

The project will be delivered by a small presentation (proposal 1), as well as a written deliverable and a published code on Github.

## References

- [1] Esther, A., "Data mining and machine learning techniques for aerodynamic databases: introduction, methodology and potential benefits," *Energies*, Vol. 13, No. 21, 2020, p. 5870. https://doi.org/10.3390/en13215807.
- [2] Hui, X., Bai, J., Wang, H., and Zhang, Y., "Fast pressure distribution prediction of airfoils using deep learning," *Aerospace Science and Technology*, Vol. 105, No. 8, 2020, p. 105949. https://doi.org/10.1016/j.ast.2020.105949.
- [3] Liu, H., Li, Z., and Lu, F., "An airfoil aerodynamic parameters calculation method based on convolutional neural network," *Asia-Pacific international symposium on aerospace technology*, 2018, pp. 34–46. https://doi.org/10.1007/978-981-13-3305-7\_3.
- [4] Haryanto, I., Utomo, T. S., Sinaga, N., Rosalia, C. A., and Putra, A. P., "Optimization of maximum lift to drag ratio on airfoil

- design based on artificial neural network utilizing genetic algorithm," *Applied Mechanics and Materials*, Vol. 493, 2014, pp. 123–128. https://doi.org/10.4028/AMM.493.123.
- [5] Drela, M., Pros and cons of airfoil optimization, World Scientific, 1998, pp. 363–381. https://doi.org/10.1142/9789812815774\_0019.
- [6] Selig, M. S., "UIUC airfoil data site," 1996.
- [7] Drela, M., "XFOIL: An analysis and design system for low Reynolds number airfoils," *Conference on Low Reynolds Number Airfoil Aerodynamics*, Vol. 54, 1989. https://doi.org/10.1007/978-3-642-84010-4\_1.