Airfoil Optimization using Convolutional Neutral Network

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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 others. This Study aims to investigate the application of CNN model in gradient based aerodynamic optimization. Three separate models are trained to predict aerodynamic coefficients and an optimization is solved using the trained models and a conventional low fidelity approach. Results shows that CNN optimizer,though is 15 times faster than the conventional approach, is rather equivocal in accuracy. A further experiment points out that CNN models might serve as an efficient pre-processor of baseline geometry in methods of higher complexity.

I. Nomenclature

C_d	=	drag coefficient
C_l	=	lift coefficient
C_m	=	moment coefficient around quarter chord
C_p	=	pressure coefficient
Re	=	Reynolds number
α	=	angles of attack
$\mathcal{X}$	=	design variables

II. 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 others[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, C_m, 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).

III. Model Training

Models to predict aerodynamic coefficients are trained based on a modified version of model provided by Liu et al. [3]. CNN is selected for its common application in image recognition [8]. Predicting aerodynamic coefficients using CNN is not a novel topic, and multiple studies has shown significant accuracy with a well trained model [9]. For this study, a six layer CNN is used, and the input image is of size 128×128 to discriminate between minuscule differences in airfoil OML.

Training Data is obtained from running XFOIL direct analysis on all airfoil downloaded from UIUC Airfoil Database [6] at zero angle of attack and Reynolds number of 5,000,000. The images are augmented in the y direction for higher sensitivity of the trained model to changes in OML. A sample input is shown as in figure 1.

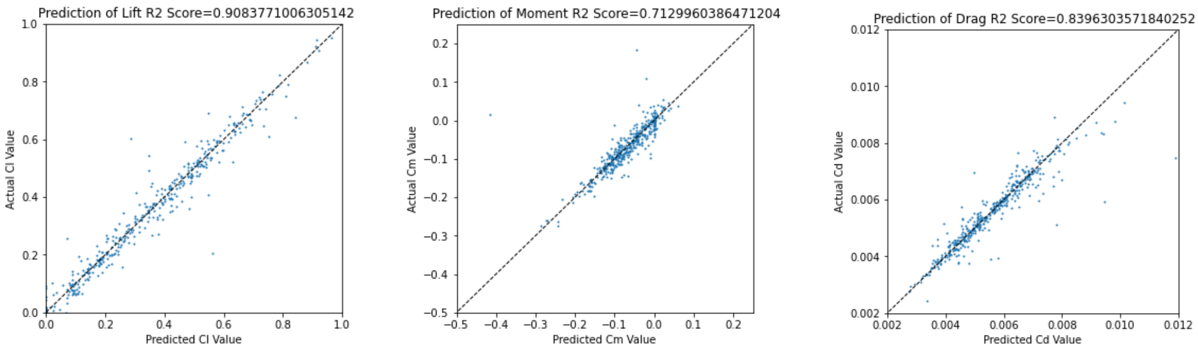
(a) Input Image of NACA 2412　　(b) Input Image of RAE 2822

Fig. 1　Examples of Input Images for CNN Model

A total of 1,287 images of airfoil at zero angle of attack is generated, and distributed into three batches, namely train (920), validation (873), and test (414). Note that training data and validation data includes about 70 % of same input sets.

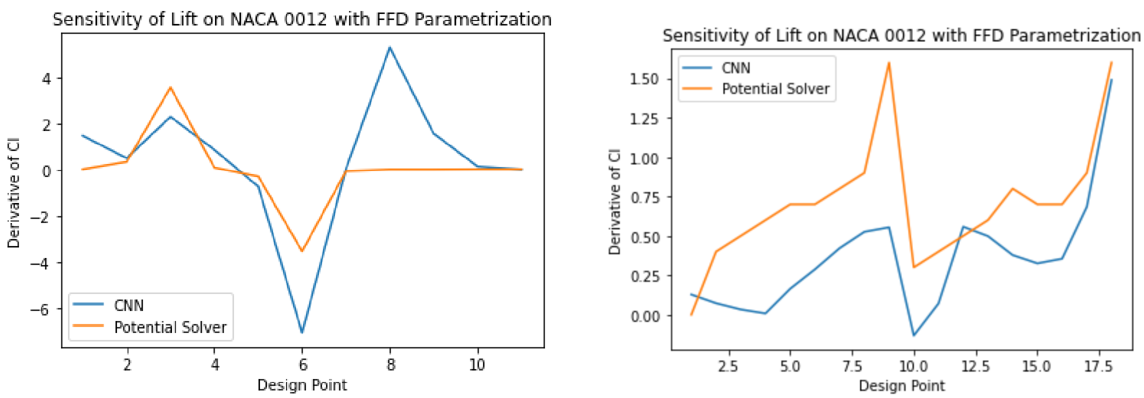
The trained model shows appreciable accuracy in testing, as is shown in figure 2, with R^2 score ranging from 70 to 90 percent. Note the low accuracy in predicting C_m is due to change in activation function used in each layer of the model.

Apart from the test and prediction confusion matrix, a sensitivity analysis on the models are made to determine whether they are suitable for application in a gradient descent optimization problem. A NACA 0012 airfoil is parametrized using two different PARSEC and Free Form Deformation (FFD) techniques, and the sensitivity of lift coefficient with respect to each design variable is compared against that of XFOIL direct analysis in figure 3. It is observed that though the accuracy of gradient calculation is off, the model prediction generally follows the trend shown by XFOIL, which suggest that the model might be applicable in a gradient based optimization problem.



(a) Confusion matrix of Lift Coefficient (b) Confusion matrix of Moment Coefficient (c) Confusion matrix of Drag Coefficient

Fig. 2 Examples of Input Images for CNN Model



(a) C_l sensitivity using PARSEC (b) C_l sensitivity using FFD

Fig. 3 Sensitivity Analysis of Lift Coefficient

IV. Numerical Framework

The optimization problem aims to deform a baseline airfoil to reach desired lift characteristics and minimizing drag while retaining a small moment coefficient at zero angles of attack and Re of 5,000,000. NACA 0012 is selected as baseline airfoil and NACA 2412 is selected as a target airfoil for demonstration purposes. The optimization problem is formally stated in equation 1, where C_l^* represents target lift coefficient, in this case C_l of NACA 2412 at 0 α, and C_d^* is a very small number to minimize drag. w_1 and w_2 are weighting factors to ensure that two parts of the objective function are within the same order of magnitude. The gradient of objective function is thus equation 2, where derivative of aerodynamic coefficient with respect to design variables are calculated using finite difference scheme.

$$\begin{aligned} \min_{\mathcal{X}} \quad & F(\mathcal{X}) = w_1(1 - \frac{C_l(\mathcal{X})}{C_l^*})^2 + w_2(1 - \frac{C_d(\mathcal{X})}{C_d^*})^2 \\ \text{s.t.} \quad & \alpha = 0 \\ & Re = 5,000,000 \\ & C_l^* = 0.3 \\ & C_d^* = 0.001 \\ & C_m \leq 0.05 \end{aligned} \tag{1}$$

$$\frac{\partial F(\mathcal{X})}{\partial \mathcal{X}} = \frac{-2w_1}{C_l^*}(1 - \frac{C_l(\mathcal{X})}{C_l^*})\frac{\partial C_l(\mathcal{X})}{\partial \mathcal{X}} - \frac{2w_2}{C_d^*}(1 - \frac{C_d(\mathcal{X})}{C_d^*})\frac{\partial C_d(\mathcal{X})}{\partial \mathcal{X}} \tag{2}$$

The airfoil is parametrized using FFD, in which design points are chosen to draw two Bezier curve to outline the airfoil OML [10]. The initial FFD box is chosen to be of height 0.2 chord length and width of 1 chord length, as is shown in figure 4. The first and the last set of design variables remains unchanged to fix leading edge and trailing edge thus not inducing any angles of attack. Optimization is solved in an iterative fashion using Method of Moving Asymptotes (MMA) [11] embedded in NLopt package[12] within python environemnt.

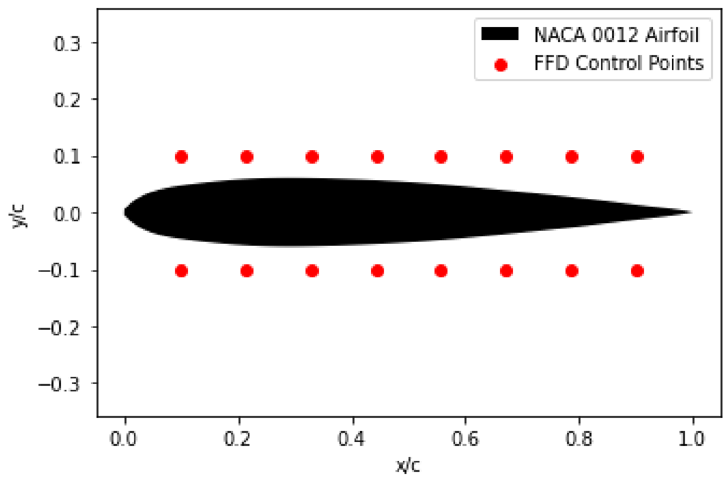
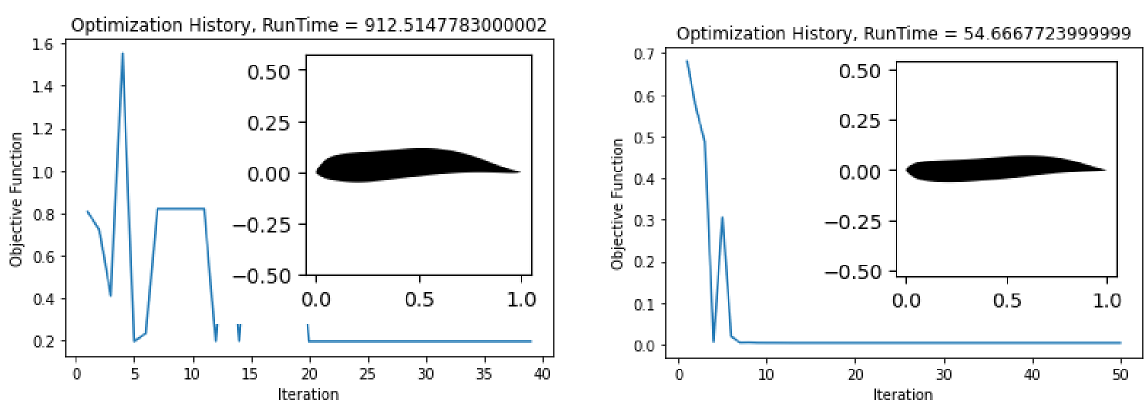


Fig. 4 NACA 0012 Baseline Airfoil and Design Variable

V. Results

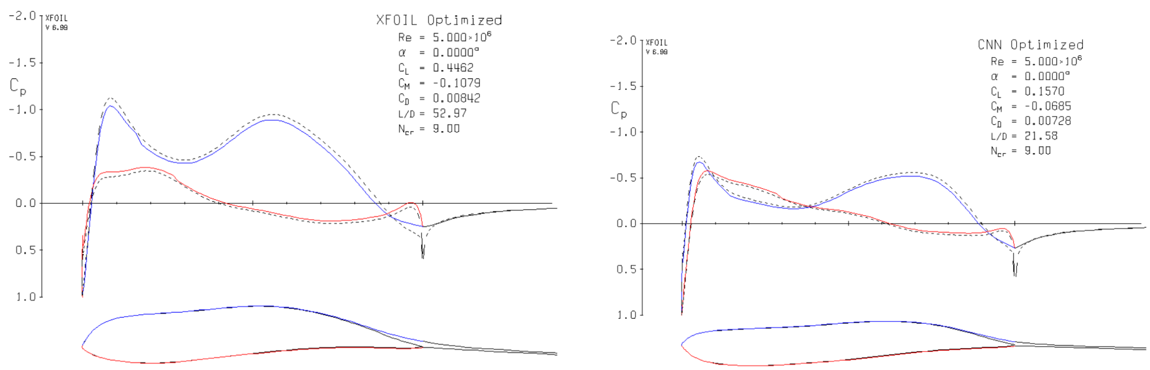
Optimization history using trained model and XFOIL is shown in parallel as in figure 5. XFOIL took significantly longer to converge to a solution in comparison to CNN, and a few iterations in between saw a diverged output from XFOIL. The trained model, albeit faster, took more iterations to converge. Optimized airfoils resulted from two different approaches differs in thickness, but arguably follows the same deformation compared to the baseline case. Performance of both airfoil is solved for using XFOIL with the given flight condition, and is presented in figure 6. The one optimized using XFOIL is closer to the performance specified in equation 1.



(a) Optimization History using XFOIL

(b) Optimization History using Trained CNN

Fig. 5 Optimization History and Results



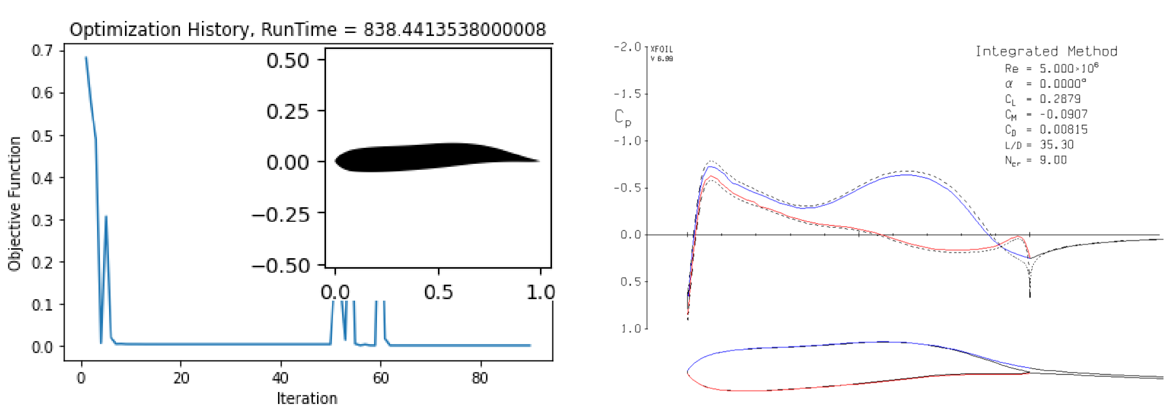
(a) C_p distribution of airfoil optimized using XFOIL (b) C_p distribution of airfoil optimized using CNN

Fig. 6 Optimization History and Results

VI. Conclusion

This study serves as a proof of concept on application of data-driven method in aerodynamic optimization. Three models are trained to predict C_l, C_m, and C_d, respectively, and is used to optimize an airfoil under a given flight condition. Result of the optimization problem is then compared with that solved using XFOIL. While two resultant airfoil shows geometrical similarity, the one optimized using a more conventional approach is closer to the optimization target. This is unsurprising in that the sensitivity analysis aligns only in trend but not magnitude, and errors from model prediction would prone to accumulate during the iteration process.

While the performance of CNN optimized airfoil is not as desirable, the method might still shines in its execution time required and robustness. The optimization using CNN converged 15 times faster than that using XFOIL, and arrives at an arguably similar geometry. Therefore it is reasonable to hypothesis, given the accuracy of the model trained, that data-driven solver is still applicable in gradient based aerodynamic optimization, and would serve as a good pre-processor of baseline geometry to rapidly reduce computation time. To settle such hypothesis, an experimental trail of the same problem posted in equation 1 is made by feeding the optimization result of optimizer based on trained CNN to optimizer based on XFOIL. The optimization history is shown in figure 7. The integrated method is indeed faster and more robust than using XFOIL alone, but the improvement in computation time is rather trivial considering the cost related to training respective models. Nevertheless, this may serve as a good pre-processing technique in methods with higher fidelity and, thus, complexity.



(a) Optimization History using Itegrated Method (b) C_p distribution of airfoil optimized using Integrated Method

Fig. 7 Optimization History and Results

VII. Future Work

While the study is merely a proof of concept, it shine light in future studies of interests. To begin with, the model could be trained for higher accuracy by feeding in better data. This could be done by shifting from low fidelity method such as XFOIL to CFD packages, such that the "ground truth" is more sensitive to OML changes. Training data could also be improved by generating a set of ortho-normal design variables, and replace the "shotgun approach" of using airfoil database with more mathematically meaningful inputs.

Furthermore, a comparison between application of data-driven methods in gradient based optimization and surrogate based optimization. The later of which has been widely studied as well due to its independent of gradient and thus the ability to detect minor deformation of OML. This result will offer insight in how machine learning will be integrated into the field of computational aerodynamics.

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.

[8] Valueva, M., Nagornov, N., Lyakhov, P., Valuev, G., and Chervyakov, N., "Application of the residue number system to reduce hardware costs of the convolutional neural network implementation," *Mathematics and Computers in Simulation*, Vol. 177, 2020. https://doi.org/10.1016/j.matcom.2020.04.031.

[9] Zhang, Y., Sung, W., and D., M., "Application of artificial neutral network to predict airfoil lift coefficient," *AIAA SciTech Forum*, 2018.

[10] Nilesh, S., Juned, A., and Channiwala, A., "Airfoil parameterization techniques: a review," *American Journal of Mechanical Engineering*, Vol. 2, 2014. https://doi.org/DOI:10.12691/ajme-2-4-1.

[11] Krister, S., "A class of globally convergent optimization methods based on conservative convex separable approximations," *SIAM Journal on Optimization*, Vol. 12, No. 2, 2002. https://doi.org/DOI:10.12691/ajme-2-4-1.

[12] Steven, J., "The NLopt nonlinear-optimization package," , 2020. URL http://github.com/stevengj/nlopt.