Pressure Distribution Prediction of Supercritical Airfoils at Multiple Flight Conditions Using Deep Learning Approach

Tuliang MA\textsuperscript{a}, Hairun XIE\textsuperscript{b} and Jing WANG\textsuperscript{c,*}

Shanghai Aircraft Design and Research Institute, Shanghai 201210 China

\textsuperscript{a}matuliang@comac.cc, \textsuperscript{b}xiehairun@163.com, \textsuperscript{c,*}wangjinger1218@163.com

Abstract. Supercritical airfoils are commonly found in modern civil airplanes. Effective access to pressure distribution around an airfoil under various flight situations is vital for enhancing the quality of supercritical airfoils. With the rapid development of deep learning, the rise of neural networks has provided new powerful tools for obtaining pressure distribution quickly. This paper proposed a deep learning based model to predict the surface pressure distribution around a supercritical airfoil under multiple flight conditions. The airfoil geometry parameters and various flight conditions are taken as input, and the corresponding surface pressure distributions are taken as output. The statistical results show that the proposed method is accurate and generalized in predicting pressure distributions around supercritical airfoils. Our method, in particular, achieves accurate prediction results over the double shock or strong shock area, demonstrating its superiority in handling complex flows.

Keywords: Supercritical airfoil, Pressure distribution, Multiple flight conditions, Deep learning

1. Introduction

The characteristic of supercritical airfoils leads to improvement of cruise efficiency of airplane at transonic region. During the aerodynamic design process, pressure distribution provides much more important informations for engineers\cite{1}. Experienced designers, in particular, do not seek the highest lift/drag ratio supercritical airfoil, but rather a design that best compromises the performances of different disciplines or at different flight conditions \cite{2,3}. Furthermore, they place a strong emphasis on design robustness, such as the buffet onset lift coefficient, the drag divergence Mach number, etc. As a result, the pressure distribution under different flight conditions is critical in supercritical wing aerodynamic design.

Conventionally, the pressure distribution over a supercritical airfoil is obtained using Computational fluid mechanics (CFD), which has been widely used in aircraft model design\cite{4,5}. However, the current aircraft design involves multi-disciplinary and multi-objective tasks, requiring massive iterations of simulations. As a result, there is a requirement for the development of an efficient and accurate method for obtaining pressure distributions around supercritical airfoils.

The development of machine learning techniques over the last decade has provided new powerful tools, resulting in a series of breakthroughs to meet this demand. \cite{6}, several researchers \cite{7,8} performed the inverse design of airfoil using neural network to map the pressure coefficient to its corresponding airfoil. Liao\cite{9} proposed a hybrid airfoil leading edge pressure distribution prediction method based on deep learning technology, which significantly improved the analysis efficiency. However, a reasonable target pressure distribution($C_p$) is usually hard to give during an inverse design. Zhang et al. \cite{10} and Chen et al. \cite{11} proposed deep learning-based prediction methods for aerodynamic coefficient of airfoil.
with good prediction accuracy. However, no detailed flow structures are given to provide continuous
and in-depth support for aerodynamic design. Sekar et al.[12] implemented deep learning methods to
predict the flow fields under subsonic conditions. Guo et al.[13] predicted velocity flow fields of various
airfoil types with convolutional neural networks. Wang et al.[14] proposed a systematic method based
on generative deep learning for predicting the entire flow fields around supercritical airfoils under a
single flight condition. Initially, predictions from geometric to aerodynamic flow fields were achieved,
but the generalization of the learning model is insufficient and difficult to apply in practice because all
the predictions were carried out under single flight condition.

To summarize, effective and accurate access to obtain the pressure distribution around an airfoil
under different flight conditions is vital for enhancing the quality of supercritical airfoils. This paper
proposes a model that can quickly and accurately predict the surface pressure distribution of a
supercritical airfoil under multiple flight conditions based on deep learning approach. The detailed
method proposed in our study, as well as the predictive results of the network are presented and
discussed in the following section.

2. Data preparation

2.1. Supercritical airfoil preparation

In deep learning, the quality of the dataset is one of the most critical factors affecting the models. To
ensure the generalization of the proposed model, pressure distribution should cover as far as possible.
In total, there are 1500 supercritical airfoils. Figure 1 shows the airfoil of the subset of the samples.
Airfoil geometry is represented and generated through the class shape transformation (CST) method
with 14 control points. Each airfoil includes 301 points with coordinates encoded as a tuple (x, y). The
x-coordinates are identical for all airfoil types.

Figure 1. A subset of airfoils. Figure 2. The entire and zoomed-in view of the C-mesh.

2.2. Comparison of calculation results

The flow fields of all the airfoils are evaluated in this study at a series of fixed lift coefficients (Cl=0.6,
0.64, 0.68, 0.72, 0.76, 0.8, 0.84) with Mach number of 0.76 and Reynolds number of 5.0×10^6. The shear
stress transport (SST) turbulence model is used in RANS (Reynolds Average Navier-Stokes)
simulations. For reconstruction, spatial discretization, and time propulsion, the MUSCL scheme, the
Roe scheme, and the lower-upper symmetric Gaussian-Seidel method are used. In the wraparound and
normal directions, structured C-meshes with dimensions 381×81 are generated. Figure 2 shows the
whole and near-body meshes. Through a comparative study of the pressure distribution of RAE2822
airfoil shown in Figure 3, it is verified that CFD solver agrees with the experiment well.
3. Pressure distributions prediction model

The Deep Neural Network (DNN) is a type of neural network that consists of numerous neurons linked together to build a complicated network. The neuron receives multiple input signals and generates an output. The output of a neuron in the lth layer is given in Eq. (1).

\[ a^l_j = \sigma \left( \sum_{k=1}^{N(l-1)} w^l_{jk} a^{l-1}_k + b^l_j \right) \] (1)

where \( \sigma \) indicates the nonlinear activation function; \( w^l_{jk} \) denotes the weight connection from the j-th neuron of the current layer to the k-th neuron in the previous layer; The bias terms are denoted by b, while the output of each layer is denoted by a. The feed-forward technique is used to derive the output of each neuron from the given input. The weighted and bias parameters are optimized using a backpropagation operation.

The DNN architecture used in this paper is shown in Figure 4. The proposed prediction network’s accuracies are measured using the error assessment metrics listed below:

\[ \text{MSE} = \frac{1}{m} \sum_{i=0}^{m} (y_i - y_i^{'})^2 \] (2)

\[ \text{MAE} = \frac{1}{m} \sum_{i=0}^{m} |y_i - y_i^{|} \] (3)

\[ \text{R}^2(y, \hat{y}) = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \] (4)

where \( y_i \) is the true value, \( \hat{y}_i \) is the predicted value and \( \bar{y} = \frac{1}{n} \sum_{i=1}^{n} y_i \). Especially, the \( R^2 \) score, also known as the determination coefficient, is very important for evaluating the performance of a regression model. The value of \( R^2 \) score reflects the relative degree of regression contribution.

4. Experiments and results

4.1. Hyperparameters and training implementation

A total of 15186 samples of pressure distribution under different flight conditions are involved in our study. During the training stage, a random combination of 80% of the total number of airfoils is used for training, with the remaining 20% used for validation. The input of the model is the y coordinates of the airfoils together with the flight condition, and the output is the corresponding pressure distributions obtained by CFD, therefore input layer size is set to 302 and output layer size is set to 301.

DNN involves many hyperparameters, such as, learning rate, nonlinear activation function, optimizer, number of hidden layers and number of neurons in each layer. To properly train the model, it is critical to select optimal hyperparameters. Table 1 shows an example of learning rate selection, with 1e-3 being the best option for minimum error for both training and validation set.
The optimized network features three fully connected hidden layers with 512, 256 and 512 neurons, respectively. The Sigmoid activation function and the Adam optimizer are chosen. The cost function is defined by SmoothL1 loss, which evaluates the difference between the estimated and desired output tensors. To reduce errors from numerical precision during the training stage, the data are standardized to \([0, 1]\) range using a min–max normalization preprocessing step. The batch size is set to be 64. With the settings of hyperparameters, both the loss of the training set and the loss of the validation set decrease steadily and tend to converge, as shown in Figure 5.

| lr  | 1e-1 | 1e-2 | 1e-3 | 1e-4 | 1e-5 |
|-----|------|------|------|------|------|
| train(MSE) | 0.000898 | 0.000050 | 0.000003 | 0.000024 | 0.000062 |
| Valid(MSE)  | 0.000897 | 0.000048 | 0.000011 | 0.000023 | 0.000058 |

Figure 5. Convergence process.

Figure 6. R² Score for different Cl

4.2. Geometry data driven prediction model

The performance of the R² score defined in Eq. (4) and the distribution statistics of the MAE defined in Eq. (3) under different flight conditions are shown in Figure 6 and 7, respectively, in order to demonstrate the predictive abilities of our proposed method. It can be seen that the model performs nearly as well in the valid datasets as it does in the training datasets. Even at the worst performance, Cl=0.6, the R² score is greater than 0.99, demonstrating the proposed model's generalization ability. Furthermore, the model for the higher Cl behaves better than the lower Cl, this is because double shock and other complicated phenomenon are involved under lower Cl.

Figure 7. Loss Distribution for different Cl

A comparison of the pressure distributions are presented in Figure 8 to depict the flow details. At flight condition of Cl=0.6, the pressure distribution of upper surface shows multiple peaks, indicating a double or triple weak shock. Due to the complex distribution, prediction has relative large error at curve turning, especially at the shock position. At flight conditions above Cl=0.6, the pressure distribution
shows mono-shock behaviour, however the slope of shock position is different. The oscillation before and after shock is the key error for the pressure distributions, if the transition of shock slope is gentler, there is less oscillation. In general, the trained model have excellent performance to predict the pressure distribution at all given flight conditions, the accuracy is acceptable for engineering design.

Table 2 shows the training and inference time requirements, as well as the speedup of our method over the CFD simulation. Because neural network can predict several samples in parallel using a matrix operation, the average time cost for various batch sizes is listed. When compared to traditional CFD simulation, the current approach is much faster, taking less than 1s to predict the entire flow fields. The statistical results show that our proposed model outperforms traditional CFD solvers by more than 3000 times.

Figure 8. Pressure distribution of Prediction and Ground truth for different Cl
Table 2. Companions of time requirement and speedup

| Operation                      | Time          |
|-------------------------------|---------------|
| CFD simulation                | 120s (CPU)    |
| Training network              | 40 min (GPU)  |
| Prediction:batch size=1       | 0.033s (GPU)  |
| Prediction:batch size=10      | 0.040s (GPU)  |
| Prediction:batch size=100     | 0.055s (GPU)  |

CPU: Intel® Xeon® Gold 6258R GPU: NVIDIA® Tesla® V100

5. Conclusions
This paper proposed a deep neural network to predict the surface pressure distribution around supercritical airfoils under multiple flight conditions quickly and accurately. The statistical results show that the proposed method has excellent predictive performance and generalization to predict pressure distributions for a wide range of flight conditions with $R^2$ score higher than 0.99. When compared to traditional CFD solvers, the model can achieve over 3000 speedups. Accurate prediction results are obtained, in particular, over the double shock or strong shock area, demonstrating the superior ability to conduct complex flow at high Mach numbers.

References
[1] Zhang M, Liu T, Ma T, et al. High speed aerodynamic design of large civil transporter based on CFD method. Acta Aeronautica et Astronautica Sinica, 2016,37(1):244254.
[2] Chen Y, Song B, Liu H. General civil aircraft design. Shanghai: Shanghai Jiao Tong University Press, 2010. 44–54 (in Chinese).
[3] Zhang X, Song W, Zhang M. Model Aerodynamics Design. Shanghai: Shanghai Jiao Tong University Press, 2020. 74–92 (in Chinese).
[4] Johnson T, Yu N. Thirty years of development and application of CFD at Boeing Commercial Airplanes, Seattle. Computers & Fluids, 2005,34(10):1115-1151.
[5] O’Porter E. Aerodynamic design in transport aircraft. GUSF, WUXS, YANGXI, translated. Shanghai: Shanghai JiaoTong University Press, 2010:61-103 (in Chinese).
[6] Chen H, Deng K, LI R. Utilization of machine learning technology in aerodynamic optimization. Acta Aeronautica et Astronautica Sinica, 2019,40(1): 522480 (in Chinese).
[7] V. Sekar, M. Zhang, C. Shu, B.C. Khoo, Inverse design of airfoil using a deep convolutional neural network, AIAA J. 57 (3) (2019) 993 – 1003.
[8] Wang J, Li R, He C, et al. An inverse design method for supercritical airfoil based on conditional generative models
[9] Liao P, Yao L, Bai G, et al. Prediction of hybrid airfoil leading edge pressure distribution based on deep learning. Journal of Aerospace Power, 2019,34(8): 1751-1758.
[10] Zhang Y, Sung W, Mavris D N. Application of convolutional neural network to predict airfoil lift coefficient, in: 2018 AIAA/ASCE/AHS/ASC Structures, Struc- tural Dynamics, and Materials Conference, 2018, p. 1903.
[11] Chen H, Qian W, He L. Aerodynamic coefficient prediction of airfoils based on deep learning. Acta Aerodynamica Sinica, 2018, 36(2): 294-299.
[12] Sekar V, Jiang Q, Shu C, Khoo B C, Fast flow field prediction over airfoils using deep learning approach, Phys. Fluids 31 (5) (2019) 057103.
[13] Guo X, Li W, Iorio F, Convolutional neural networks for steady flow approxi- mation, in: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, ACM, 2016, pp. 481–490.
[14] Wang J, He C, Li R, et al. Flow field prediction of supercritical airfoils via variational autoencoder based deep learning framework, Physics of Fluids 33, 086108 (2021)