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Using convolutional neural networks to predict airfoil dynamic stall response

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Abstract. *Convolutional neural network models are developed to predict the aerodynamic coefficients from images of the flow field of an airfoil under dynamic stall. The networks are capable of identifying relevant flow features present in the images and associate them to the airfoil response. Results demonstrate that the models are effective in interpolating between flow parameters. This shows that CNN-based models may offer a promising alternative for sensors in experimental campaigns and for building robust surrogate models of complex unsteady flows.*

Keywords: *Convolutional neural networks (CNN), Machine learning, Unsteady aerodynamics, Dynamic stall*

1. INTRODUCTION

Although capable of delivering accurate results, high-fidelity numerical simulations of unsteady separated flows require large amounts of computational power and time. Extracting high-resolution spatiotemporal results from experiments is also a challenging and time consuming task. As such, the broad parameter space encompassed by unsteady separated flows hamper exhaustive characterization by computational or experimental means. This precludes prediction and control across the broad range of conditions likely to be encountered in flight regime.

Fortunately, the emerging of machine (deep) learning techniques could provide more ideas for leveraging surrogate models. It should be clear that such machine learning models should not replace CFD and experiments, but improve the arsenal of tools available for solving unsteady flows with a broad range of spatial and temporal scales. The era of big data and the significantly improved computing power have laid a good foundation for applying machine learning techniques to complex problems. Therefore, the provided massive labeled flowfield data makes it promising to expand these techniques to unsteady fluid mechanics applications.

Since the 1990s, researchers have shown that neural networks can predict flowfield evolution under static (Linse and Stengel, 1993; Ha, 1995) and dynamic conditions (Faller *et al.*, 1994; Schreck *et al.*, 1995), and also construct accurate models and efficient real-time control strategies for highly time-dependent, unsteady separated flows such as those encountered in dynamic stall problems (Kawthar-Ali and Acharya, 1996). Overall, these early attempts demonstrate the capacity of neural networks to model aerodynamic coefficients from simulated flight-test data with a few hidden layers and nodes when compared to the current state-of-the-art network architectures. Despite their success, deep neural networks were mostly abandoned in the early 2000s due to the unstable gradients observed as the algorithm progresses down to the lower layers. It was only after Glorot and Bengio (2010) that some light was shed on the causes of the unstable gradients, making deep learning popular again.

In recent years, machine learning has emerged as a promising technique for various applications in fluid mechanics, such as turbulence modeling (Ling *et al.*, 2016; Wu *et al.*, 2018; Maulik *et al.*, 2019; Duraisamy *et al.*, 2019; Ahmed *et al.*, 2021), reduced order modeling (Rowley and Dawson, 2017; Lui and Wolf, 2019; Wang *et al.*, 2019; Eivazi *et al.*, 2020; Fukami *et al.*, 2021), flow control (Raibaudo *et al.*, 2020; Zhou *et al.*, 2020; Cornejo Maceda *et al.*, 2021; Oliveira and Wolf, 2022), among others. To mention a few examples, Lui and Wolf (2019) presented a numerical methodology for construction of reduced order models of fluid flows through the combination of flow modal decomposition and nonlinear regression analysis. Their approach allowed the prediction of the flow field beyond the training window and with larger time increments than those used by the full order model. Kochkov *et al.* (2021), in turn, used deep learning inside traditional fluid simulations to improve both accuracy and speed even on examples very different from the training data. Their method uses machine learning to interpolate better at a coarse scale, achieving the same accuracy as traditional finite difference/finite volume methods, but with a much coarser resolution. As a result, they were capable of expanding the Pareto frontier of efficient simulation in CFD. Complementary information on the use of machine learning for fluid dynamics can be found in many recent reviews (see Brunton *et al.* (2020); Willard *et al.* (2022); Rabault *et al.* (2020);

Pandey *et al.* (2020); Fukami *et al.* (2020); Kou and Zhang (2021); Brunton (2021) for instance).

Success on ImageNet Classification[1] obtained with convolutional neural networks (CNNs) makes this class of NNs an interesting approach due to its fewer connections and parameters (Krizhevsky *et al.*, 2012). CNNs have been successfully applied to identify features in fluid flows by Strofer *et al.* (2019). Jin *et al.* (2018) designed a CNN architecture to predict the velocity field around a cylinder using measurements of the surface pressure as input. Ye *et al.* (2020) used the classical simple network LeNet-5 to predict the pressure on a cylinder from the velocity distributions along its wake. CNNs were also shown to be viable alternatives for detecting shock waves, with less time consumption than traditional methods (Liu *et al.*, 2019). This class of network was also employed in a new technique to extract underlying flow features from the original flow field data, as proposed by Obayashi *et al.* (2021). These authors made use of the nonlinear decomposition from the CNN process to extract flow features different from those of proper orthogonal decomposition in each mode. Guastoni *et al.* (2021) and Güemes *et al.* (2021) used CNNs to predict two-dimensional instantaneous velocity-fluctuation fields at different wall-normal locations from wall measurements.

The studies mentioned above demonstrate the possibilities that CNNs exhibit for feature detection in fluid mechanics. For this reason, here, we chose this class of artificial neural networks to study the flowfields from our high-fidelity numerical simulations. Different CNN architectures are employed in the hope of finding the mapping relation between the flow structures and the underlying airfoil responses. Dynamic stall is taken here as an example since the flow has a common structure owning certain complexity as well. Despite that, the concepts applied herein can be easily extended to other branches of fluid mechanics where a regression task is involved. That said, based on any fluid property from the unsteady flowfield, the network between the existing flow structures and some concerned flow feature is constructed. This CNN-based deep learning method, then, links the map of fluid property to the aerodynamic coefficients, which represents the feature learned from the flow field. In the following sections, we present the methodology employed in the present work to predict the response of airfoils undergoing dynamic stall by using CNNs. Then, results are provided aiming to interpolate solutions for different flow conditions. More results recently published by the authors (Miotto and Wolf, 2023) show that the present methodology is also able to extrapolate the source domain.

2. METHODOLOGY

In this work, we train a deep neural network model to capture relevant flow structures and establish a mapping relationship between these structures and the flow aerodynamic coefficients. Both the location and the morphology of the flow structures with respect to the airfoil must be properly inferred by the neural network for an accurate estimation of the aerodynamic loads. For that, we use convolutional neural networks (CNNs) for their success in identifying flow features.

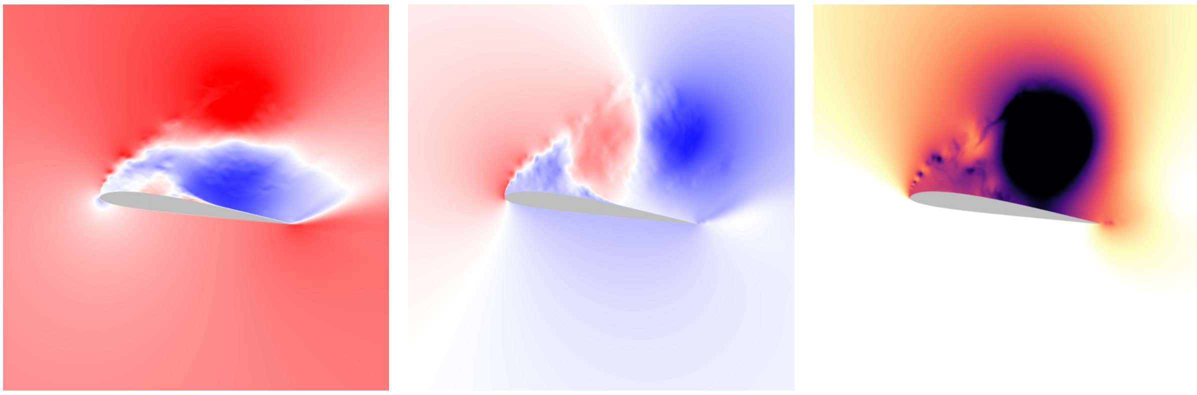
2.1 Input data

The starting point of the method is the input images of flowfields obtained from high-fidelity simulations, such as those from a 2D cross section or spanwise averaged data. The images were obtained from the simulations of Miotto *et al.* (2022b) and Miotto *et al.* (2022a). In these references, the authors were interested in understanding the mechanisms of dynamic stall onset and on the conditions for pitch and plunge equivalence to occur. Although the databases used in this work were obtained from numerical simulations, the same approach could be done with experimental results. Any physical property of interest could be used as input of the network. Here, we trained a CNN that takes u- and v-velocity components as input and another one that uses the pressure coefficient (C_p) field. The rationale for choosing these quantities is that the velocity fields can be directly obtained experimentally, through PIV techniques, and the pressure is closely related to the airfoil aerodynamic loads. Figure 1 shows examples of snapshots used as an input to the CNN. These images are not at scale, though. They had to be resized to fit in the present document.

Our dataset consists of nearly 20,000 RGB images for each physical property and of size 600×600 pixels each. These images consider all simulations of dynamic stall cases reported in Refs. (Miotto *et al.*, 2022b,a), which include a periodic plunging airfoil and constant ramp pitching and plunging airfoils for Mach numbers 0.1 and 0.4. When generating the images, it is important to keep a fixed range for the contour levels of the property of interest. We used the values $[-2, 2]$ for both velocity components and $[-4, 0]$ for C_p. Notice that the velocity components are already non-dimensionalized by the freestream velocity. Finally, this collection of images was shuffled and arbitrarily divided into groups of nearly 16,000, 2,000 and 2,000 images to form the training, validation, and test sets, respectively. In Table 1, we present which simulations were used to train the neural network.

Data augmentation is used to artificially increase the size of the training set. Realistic variants of each training instance were generated by shifting, rotating, and resizing every picture through preprocessing layers (Shorten and Khoshgoftaar, 2019). The transformations applied to the input images are only geometrical and, therefore, preserve the semantics of the images. Moreover, the dynamic stall vortex (DSV) and the entire airfoil are fully framed in all generated instances.

[1] ImageNet is a large database of images classified into many classes, commonly used to evaluate computer vision systems



(a) u-velocity (b) v-velocity (c) C_p

Figure 1. Examples of images used as input to the CNN.

Reynolds	Motion	Mach	Rate / Reduced frequency
60,000	Plunge periodic	0.1	0.25
60,000	Plunge periodic	0.4	0.25
60,000	Plunge ramp	0.1	0.05
60,000	Plunge ramp	0.1	0.10
60,000	Plunge ramp	0.4	0.05
60,000	Plunge ramp	0.4	0.10
60,000	Pitch ramp	0.1	0.05
60,000	Pitch ramp	0.1	0.10
60,000	Pitch ramp	0.4	0.05
60,000	Pitch ramp	0.4	0.10

Table 1. Simulations used to train the neural network.

2.2 CNN architecture

In this work we seek for regression models capable of predicting one or more scalar quantities, in this study, we work with the aerodynamic coefficients. Particularly, two models were built, one for predicting lift, drag and quarter-chord pitching moment, and another for the distribution of C_p along the airfoil suction side. The convolutional layers process the pressure information by extracting features, which are gathered by the fully connected layers to obtain the aerodynamic coefficients. Hence, the difference between these two models resides only in the fully-connected layers.

To speed up the training process and yield more accurate results, we used an InceptionV3 network (Szegedy *et al.*, 2016) pre-trained on ImageNet dataset. This model takes 299$\times$299 RGB images of pressure coefficient field and estimates lift, drag and quarter-chord pitching moment coefficient. The InceptionV3 uses subnetworks called inception modules, which were initially proposed by Szegedy *et al.* (2015). These modules allow for more computationally efficient and deeper networks through a dimensionality reduction with stacked 1$\times$1 convolutions. In an InceptionV3 model, several techniques for optimizing the network have been put for easier model adaptation. This includes exploring factorized and asymmetric convolutions, and the use of an auxiliary classifier as a regularizer (Szegedy *et al.*, 2016).

3. Results

In this section, we present the results obtained with our CNN models, starting with the prediction of lift, drag and pitch moment coefficients. After training, we achieved a loss of 2.2693×10^{-4} with mean square error of 3.5242×10^{-4} and a validation loss of 2.5085×10^{-4} with mean square error of 3.8655×10^{-4} at the 126th epoch. An early stopping with patience of 50 epochs was set to prevent unnecessary computation, which means that the neural network trained for 176 epochs. Results for the aerodynamic coefficients for 100 random images of the test set are compared against their true values in Fig. 2. In this figure, we observe that all 100 randomly selected images predicted the airfoil response with a great accuracy.

The previous result shows that the CNN is capable of processing the pressure information by extracting relevant features from the input image. This information was then translated into surface-integrated measurements, such as lift, drag and quarter-chord pitch moment coefficients. However, these responses come with easy in an experimental procedure. A more interesting result is the pressure distribution over the airfoil surface, as this type of measurement requires the installation of several probes, which can be structurally prohibitive or even very expensive. To this end, it is necessary to

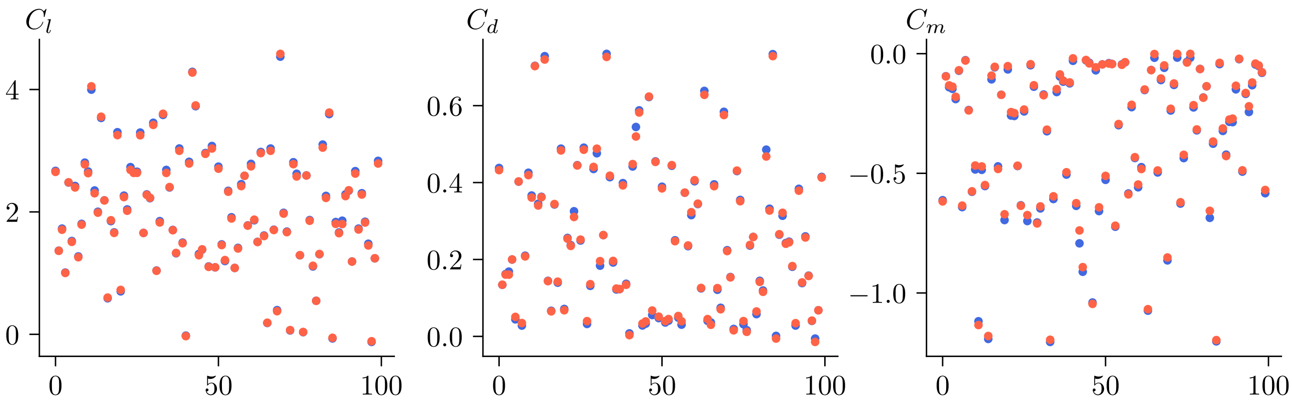


Figure 2. Comparison between true (red) and predicted (blue) lift, drag and quarter-chord pitching moment coefficients for 100 examples of the test set.

change the fully-connected layers of our CNN. The model mentioned above outputs 3 values in the last fully-connected layer, being one for each aerodynamic coefficient. Now, we want the outputs to represent the probe values over the airfoil surface. To train this new model, it is possible to reuse the convolutional layers of our previously trained model and fine tune it. But here, we considered the convolutional block pretrained on the ImageNet dataset since this training only took about 9.5 hours in an NVIDIA Tesla A100.

In Fig. 3, we show the results for the C_p distribution over the airfoil suction side for some selected snapshots, which are reproduced in the right hand side of the figure. These images belong to the test set, so they were never seen by the network. From the graphs, we observe an excellent agreement between the actual distribution of C_p and that predicted by the network. Some high-frequency fluctuations appear to be filtered out by the CNN, possibly due to the limited resolution of the input image. But, the significance of these results is much more optimistic: they tell us that if we can operate this model on experimental images, the pressure sensors could be replaced by a CNN-based model. This would have a huge impact on experimental campaigns. Before that, however, there are many issues that need to be addressed. For example, how does the model generalize to other flows or motion parameters? Can another fluid flow property be used as an input, such as velocity, which can be obtained directly from PIV?

As this is a work in progress, we do not yet have all the answers to these questions. But efforts have already been made in this direction. We start by investigating the model's ability to predict the airfoil response in a flow with an intermediate Mach number. For this, we run an LES of a periodically plunging airfoil at freestream Mach number of $M_\infty = 0.2$. Other parameters such as Reynolds number, reduced frequency, etc. were kept the same (see (Miotto *et al.*, 2022a) for details). Despite never seen an image of dynamic stall problem for $M_\infty = 0.2$, the network successfully predicted the airfoil response, as shown in Fig. 4. Remember that the model was trained with pictures of $M_\infty = 0.1$ and $M_\infty = 0.4$ flows. Thus, we verify that the model is able to interpolate between different compressible regimes. Here, we consider the network with 3 outputs (C_l, C_d and C_m), but similar conclusions are also drawn for the network that predicts the C_p distribution along the airfoil surface.

The model capability to perform extrapolation between flow parameters should also be sought. However, this is probably a more delicate question, because depending on how far this extrapolation goes, the fluid behavior can be very different from what the network was trained for. For example, if we significantly increase the Mach number, the mechanism of dynamic stall formation will involve shock waves, which have never been seen by the neural network. We do not expect the model to be able to correctly interpret scenes with semantics very different from those on which it was trained. In the final version of the paper, extrapolation results will be provided together with a discussion on the best practices for such applications.

The final question that we address here is that of using another fluid flow property as input of the CNN. For being directly obtained from a PIV technique, the velocity field is a good candidate for input. So, we build a model that takes images of u- and v-velocity components, concatenated channelwise, and predict the aerodynamic coefficients. We are using the same InceptionV3 architecture from before (pretrained on ImageNet dataset) with 3 outputs in the fully-connected layers. The only difference is that it receives 2 input images at the same time. The results are shown in Fig. 5, obtained after training for 131 epochs, which corresponds to a loss of 0.0114 with mean square error of 0.0225, and a validation loss of 0.0043 with mean square error of 0.0077. The graphics displayed in this figure refer to the pitching-up airfoil with $\Omega^+ = 0.05$ in a $M_\infty = 0.1$ flow and they contain data from train, validation and test sets.

From Fig. 5, we observe that the predicted coefficients oscillate around their true values. This could be due to a high-bias model or an irreducible error in the velocity data itself. By irreducible data error, we are not saying that the velocity field is wrong, but rather that this image is inherently too noisy for the task. To verify if the underfitting occurs due to high bias, more complex networks should be used. So far, to generate these results that consider velocity components as

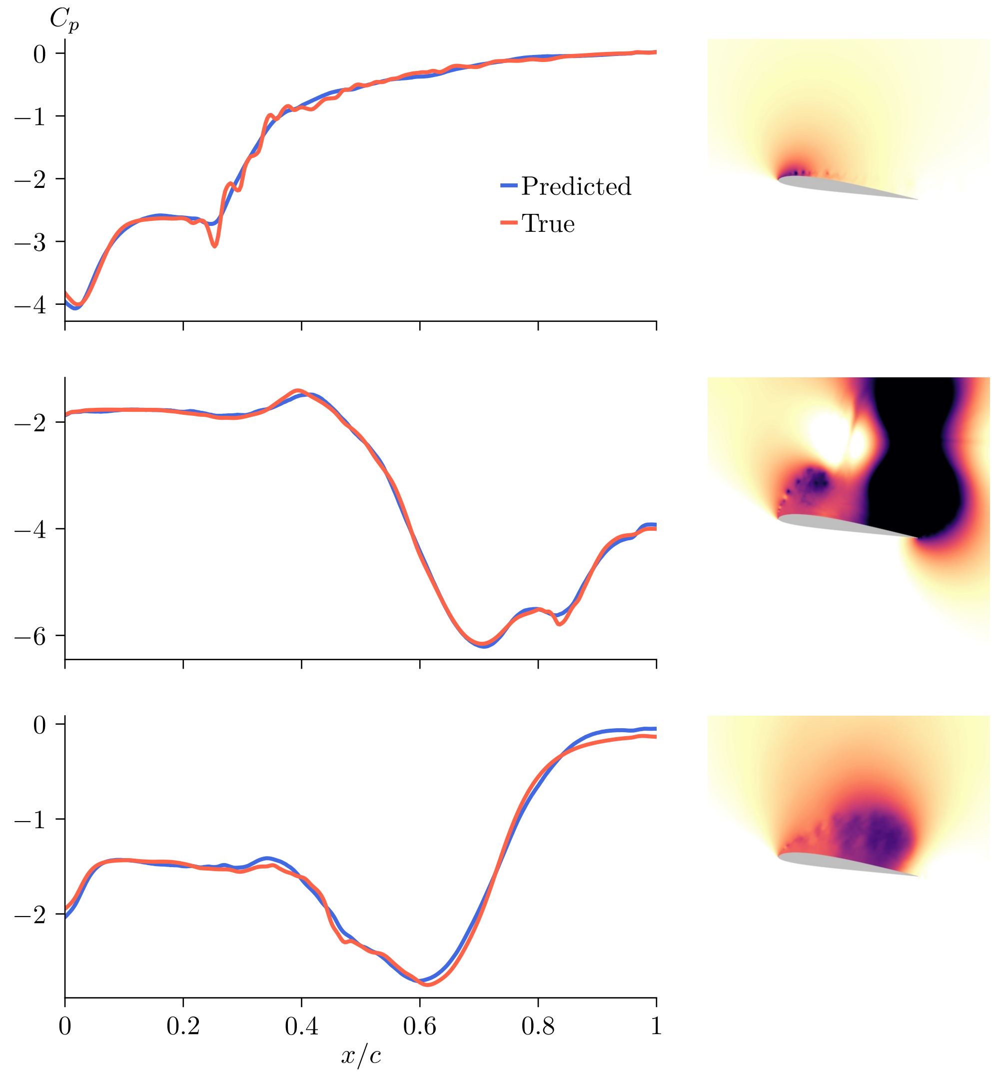


Figure 3. Pressure coefficient distribution over the airfoil suction side (left) and corresponding snapshot of pressure coefficient field (right). Top: plunge constant ramp with $\Omega^+ = 0.05$ and $M_\infty = 0.1$. Middle: plunge constant ramp with $\Omega^+ = 0.1$ and $M_\infty = 0.1$. Bottom: plunge periodic with $k = 0.25$ and $M_\infty = 0.4$.

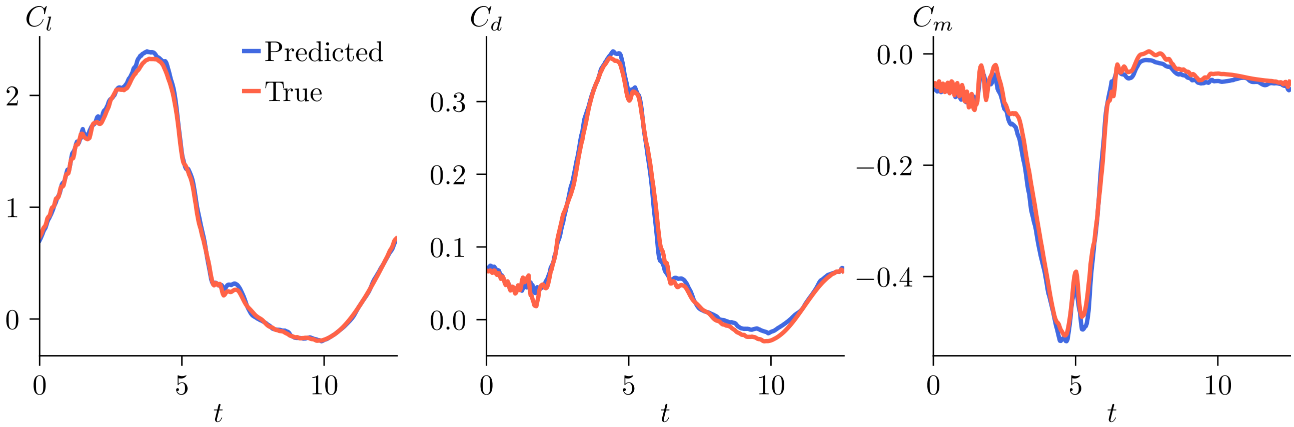


Figure 4. Lift, drag and quarter-chord pitching moment coefficient estimation for an airfoil at Mach number 0.2, never seen by the model.

input, we only used the InceptionV3 network. So, the possibility that the result will be better with other architectures is not ruled out. However, for what matters, the pressure coefficient field is preferable to velocity when it comes to building our regression model. In principle, this makes sense, since pressure is directly related to forces (and consequently to aerodynamic coefficients).

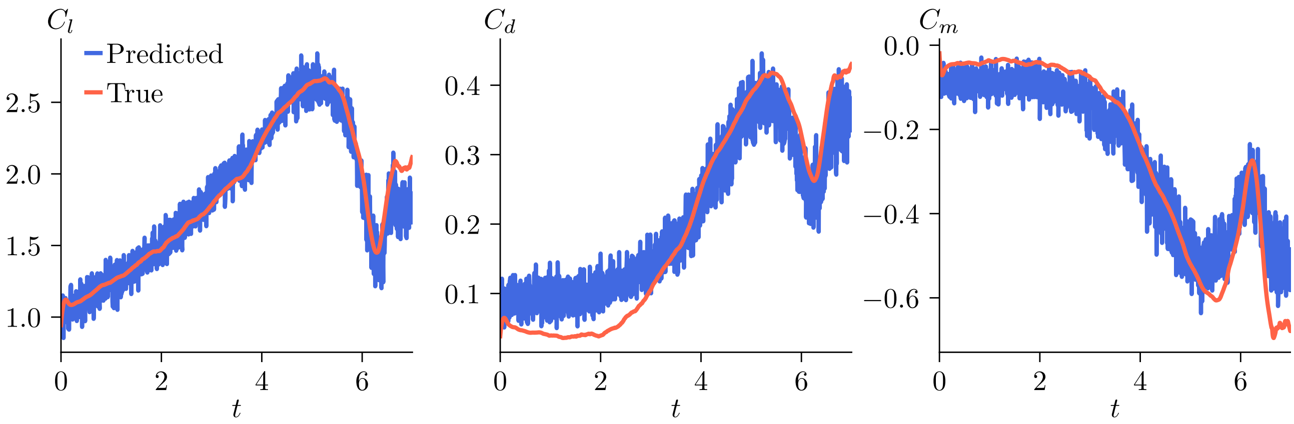


Figure 5. Lift, drag and quarter-chord pitching moment coefficient estimation using the velocity components as inputs.

4. CONCLUSIONS

Based on the pressure coefficient from the unsteady flowfield, a pre-trained InceptionV3 network rendered the backbone of a neural network model that links the existing flow structures to the aerodynamic coefficients. The CNN correctly inferred the attributes present in the flow image even in a compressible flow regime for which no annotations were given. As a result, an excellent agreement between predicted and ground truth values was obtained. This fact demonstrates that CNN-based models can be used to interpolate between flow parameters. In our recently published manuscript (Miotto and Wolf, 2023), we show that the neural network is also able to extrapolate the source domain.

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