# Enhancement of Unsteady and 3D Aerodynamics Models using Machine Learning

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**Abstract.** Unsteady aerodynamics will be an important part of the floating wind turbines of the future operating under high shear across the rotor disk coupled with platform motion and atmospheric turbulence. We develop an unsteady aerodynamics and dynamic stall model using a long short-term memory variant of recurrent neural networks. The neural network model is trained using the oscillating airfoil data set from Ohio State University. The predictions from our machine learning (ML)-based model show good agreement with the experimental data and other state-of-the-art dynamic stall models for a wide range of airfoils, Reynolds numbers and reduced frequencies. In some cases the predictions are better than the Beddoes-Leishman model implementation in OpenFAST, when using the default coefficients. The ML-based model is also able to capture the key physics associated with dynamic stall, such as the precedence of moment stall before lift stall and cycle-to-cycle variations in the aerodynamic response. The new unsteady aerodynamics model is expected to improve prediction of fatigue loads for yaw-based wake-steering control scenarios in actuator-line and actuator-disc simulations of wind farms. Our methodology for training the ML-model provides a pathway for improving design level tools using high-fidelity computational fluid dynamics (CFD) simulations in the future.

## 1. Introduction

Unsteady aerodynamic response and the associated fluid-structure interaction are important phenomena in increasingly larger wind turbines with more slender and flexible blades designed with bend-twist coupling. The reduced frequency $\kappa = \omega c/2V_{loc}$ of the variation in angle of attack is a key non-dimensional parameter that determines the level of deviation from quasi-steady aerodynamics, where $\omega$ is the angular frequency of the variation in angle of attack, $c$ is the airfoil chord and $V_{loc}$ is the local freestream velocity at the airfoil. Figure 1 shows that a significant portion of the blades on commercially relevant wind turbines can experience major unsteady aerodynamic effects when subjected to angle of attack variations at 3 per-rev. Floating wind turbines of the future operating under high shear across the rotor disk coupled with platform motion and atmospheric turbulence could easily experience 3 per-rev fluctuations in the local angle of attack. The unsteady aerodynamic effects become more pronounced when operating under yawed flow and wind veer. Control of future wind farms using wake steering will place more wind turbines under yawed and partially waked inflow conditions. The design of such turbines will have to trade off between increased power capture at the farm level and fatigue loads on individual turbines. The ability to accurately predict unsteady aerodynamic effects will be crucial for the successful adoption of yaw-based control for wake steering within wind farms.

Unsteady aerodynamics phenomena are characterized by the *aerodynamic lag* that is usually seen as a *hysteresis loop* in the airfoil polars (e.g., lift coefficient $C_l$) as a function of angle of attack, $\alpha$. When
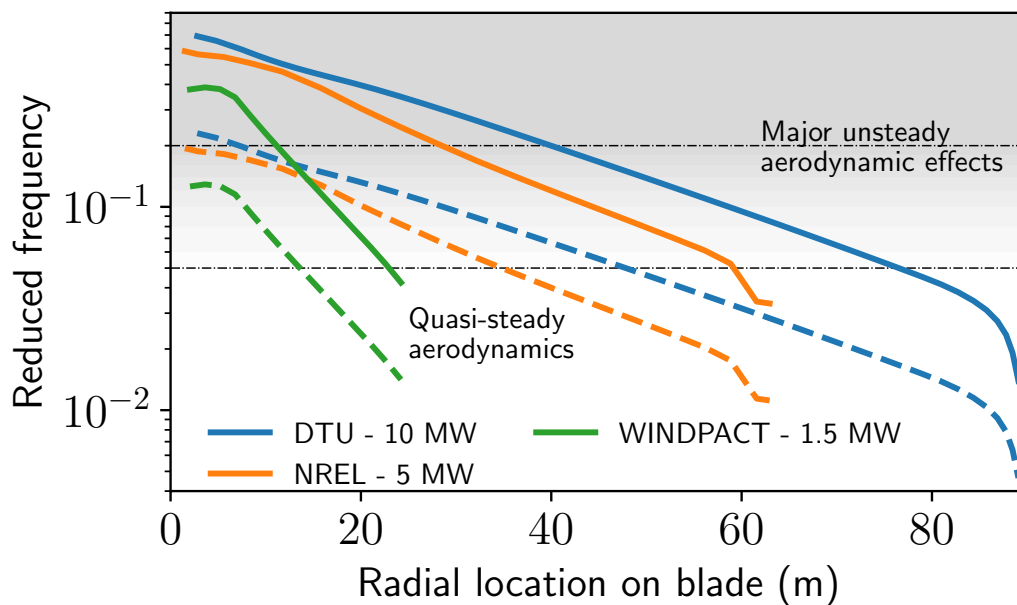
Figure 1: Variation of reduced frequency $\kappa = \omega c / 2 V_{loc}$ over the blade length at a forcing of 1 per-rev (dashed lines) and 3 per-rev (solid lines) for three commercially relevant wind turbines: DTU 10 MW [1], NREL 5 MW [2], WINDPACT 1.5 MW [3].

the mean angle of attack is high enough, flow separation would lead to dynamic stall phenomenon: flow separation on the suction side leading to moment stall, followed by lift stall, and subsequent reattachment of the flow at a much lower angle of attack than the static stall angle of attack. Any unsteady aerodynamic model must be able to accurately model time-histories of the circulatory and non-circulatory components [4] in response to changes in angles of attack resulting from change in inflow conditions and blade structural response (e.g., elastic twist from blade torsional dynamics).

State-of-the-art unsteady aerodynamics and dynamic stall models use empirical corrections to the 2D steady-state polars based on physical intuition and engineering approximations. Typical dynamic stall models used in wind energy applications are based on the Beddoes-Leishman (BL) model [4] that was originally developed for helicopter applications. The model coefficients were originally tuned for thin symmetric airfoils like National Advisory Committee for Aeronautics (NACA) 0012 airfoil, operating in the compressible flow regime and the primary stall mechanism was the onset of leading-edge separation. For wind turbines flow separation is usually observed at the inboard sections composed of thick, cambered airfoil sections (for structural reasons) where the primary stall mechanism is trailing-edge stall. Since the development of the original BL model, several researchers have attempted to modify it for cambered airfoils operating at low Mach numbers relevant to wind turbine applications. Hansen et al. [5] developed a Beddoes-Leishman type dynamic stall model in state-space using indicial formulation. Øye [6] attempted to develop a dynamic stall model for wind energy applications. Guntur et al. [7] have recently tuned the Beddoes-Leishman model to thicker, cambered airfoils typically used on wind turbines operating at low Mach numbers without much leading-edge separation. In typical wind turbine design and analysis codes, the 2D aerodynamic polars are also corrected to account for 3D effects such as rotational augmentation and root and tip loss. Engineering models for corrections due to 3D, unsteady aerodynamics and dynamic stall use a limited number of model parameters and inputs including the angle of attack and its derivatives at the current time and optionally inputs at a time lag for tuning. It is difficult to tune the existing dynamic stall models to account for the strong nonlinearity of the flow response to

time history and airfoil shape under all possible operating conditions. Loads analysis processes therefore often use the same model coefficients regardless of the airfoil geometry, operating Reynolds number and reduced frequency in the design and optimization loops. Modern wind turbines use very thick airfoils ($t/c \sim 30 - 35\%$) with flat-back trailing edges near the root and thin ($t/c \sim 12 - 15\%$) airfoils near the tip to improve overall aerodynamic performance. Figure 3 shows the variation in airfoil shapes and thickness for the 10 airfoils used in the present study. The lack of easy and readily available methods to tune the coefficients of the unsteady aerodynamics models for airfoils of different shapes and thickness is expected to be a significant concern with future wind turbines.

As an alternative, unsteady aerodynamic models based on deep neural networks (DNN) can mitigate the aforementioned shortcomings of the traditional models. These unsteady aerodynamic models can be trained on a large number of input parameters that can represent the operating conditions as well as the airfoil characteristics in a comprehensive manner that is impossible with traditional models. Depending on the number and arrangement of the layers within the neural network, these models can be tuned to capture all relevant aerodynamic effects for a large range of airfoil families. These models also have the added benefit that they can be trained on both experimental data from wind tunnels as well as data generated from high-fidelity Reynolds-averaged Navier-Stokes (RANS), or detached eddy simulations (DES) of airfoils. Furthermore, the training process for DNN-based models can be automated and thus integrated into the design process.

In the present work, we develop a DNN surrogate model to account for the unsteady aerodynamics and dynamic stall phenomena in loads analysis in comprehensive wind turbine analysis codes (e.g., OpenFAST [8]). The model is trained using a subset of experimental data from the Ohio State University (OSU) wind tunnel tests [9]. The model is then validated against the remaining data set from experiments. Finally, the performance of the model is compared with that of the Morten-Hansen (MHH) model [5], Øye model [6] and the existing Beddoes-Leishman model available in OpenFAST.

## 2. Methods

We use a variant of recurrent neural networks (RNN) to develop a data-driven model for the unsteady aerodynamics phenomenon. RNNs are very popular in areas where a sequence of data needs to be modeled and output depends on the history of states previously observed [10]. We use a network comprising of long short-term memory (LSTM) [11] networks to construct an unsteady aerodynamics model. LSTMs are very attractive because they can handle long-term dependencies and provide a solution to the vanishing gradient problem typically seen with RNNs. A schematic of the network architecture is shown in Fig. 2. The model consists of two layers of LSTM, each with 64 hidden layers, stacked on top of each other with a fully connected layer. The input parameters for the LSTM model contains parameters related to the airfoil operating conditions as well as airfoil geometry. Input parameters for operating conditions provided to the LSTM model include angle of attack $\alpha$, the angular velocity $\dot{\alpha}$, angular acceleration $\ddot{\alpha}$, and Reynolds number, $Re$. The aerodynamic response of the airfoil to pitching and heaving motions are both modeled using only the change in the angle of attack and its derivatives with respect to time.

The airfoil shapes are parameterized with a universal parametric geometric representation (UPGR) method [12] that Boeing developed specifically to represent aerodynamic shapes. The UPGR parametrization uses high order polynomials to represent the upper and lower surfaces of the airfoil separately along with another parametrization to represent the trailing edge. This parametrization is a reasonable choice as input to machine learning (ML)-based models to capture the camber and thickness variations across the airfoil efficiently.

The LSTM model is trained on the oscillating airfoil dataset from OSU provided by the National Wind Technology Center (NWTC) Information Portal [9]. The OSU dataset provides a comprehensive description of unsteady lift, drag and moment characteristics of the S8XX airfoil family and the N4415 airfoil (see Fig. 3) under a wide range of oscillating conditions (e.g. [13]). They provide a time history of the angle of attack and aerodynamic forces on the airfoil through multiple cycles of stall and reattachment.
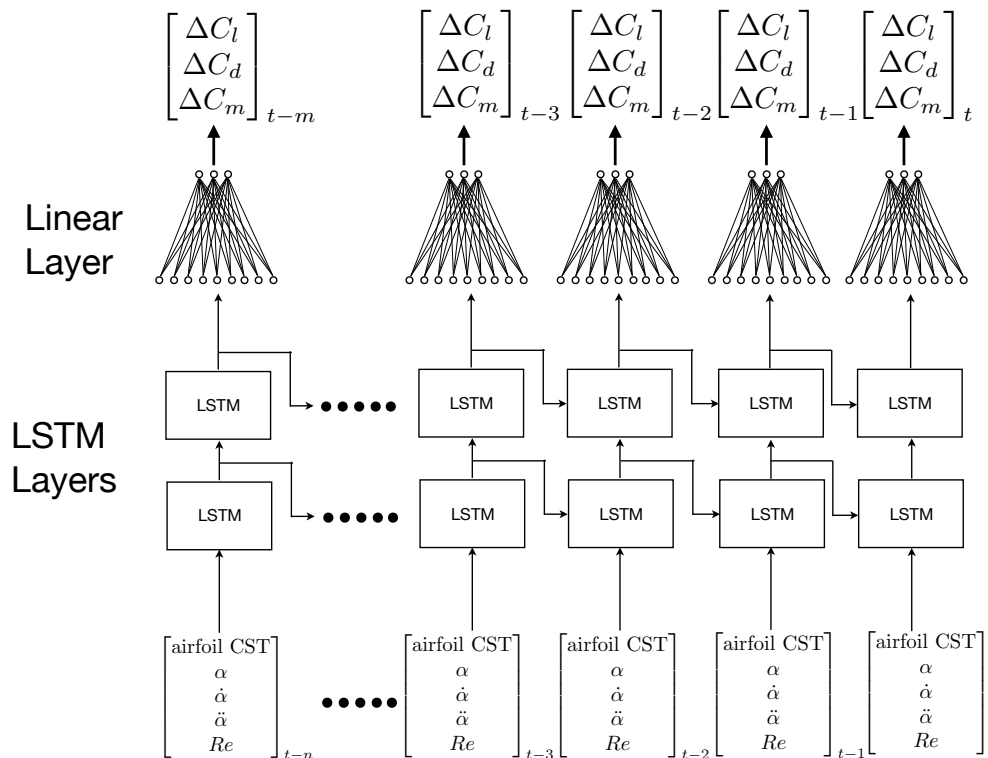
Figure 2: Illustration of LSTM model to predict difference in aerodynamic coefficients from steady state polars.

The detailed description makes this experimental dataset an ideal test case to demonstrate the viability to construct a model for unsteady aerodynamics and dynamic stall using machine learning. Figure 4 shows the variation of the lift coefficient $C_l$ of the S809 airfoil in response to a periodic oscillation of the angle of attack at the lower and higher extremes of the reduced frequency range. The flow morphology as the airfoil sections undergo airfoil stall has several stages that can be clearly observed in Figure 4d. As the angle of attack increases, the aerodynamic lag response causes the dynamic lift to exeed the static maximum lift. Between the angles of attack where static stall and the dynamic stall occurs, a leading edge separation bubble forms leading to moment stall (not shown in the figure). The lift continues to increase as the separation bubble convects over the suction side. The dynamic lift stall occurs when the separation bubble moves past the trailing edge and the flow enters a state of full separation. Finally, as the angle of attack decreases the flow eventually reattaches. Figure 4 is representative of the entire dataset available through the NWTC Information Portal [9]. The data contains experimental errors, high frequency fluctuations in loads and cycle-to-cycle variations that are expected to present challenges to the development of any unsteady aerodynamics model. To simplify our analysis, we only consider the datasets with the leading edge grit applied in order to make the flow fully turbulent over the airfoil. The methodology developed in the present work will be extended in future to handle laminar-turbulent transition effects.

## 3. Results
The ML-based unsteady aerodynamics model is trained on the datasets at high and low reduced frequencies and tested against against the validation dataset in the middle of the reduced frequency range.
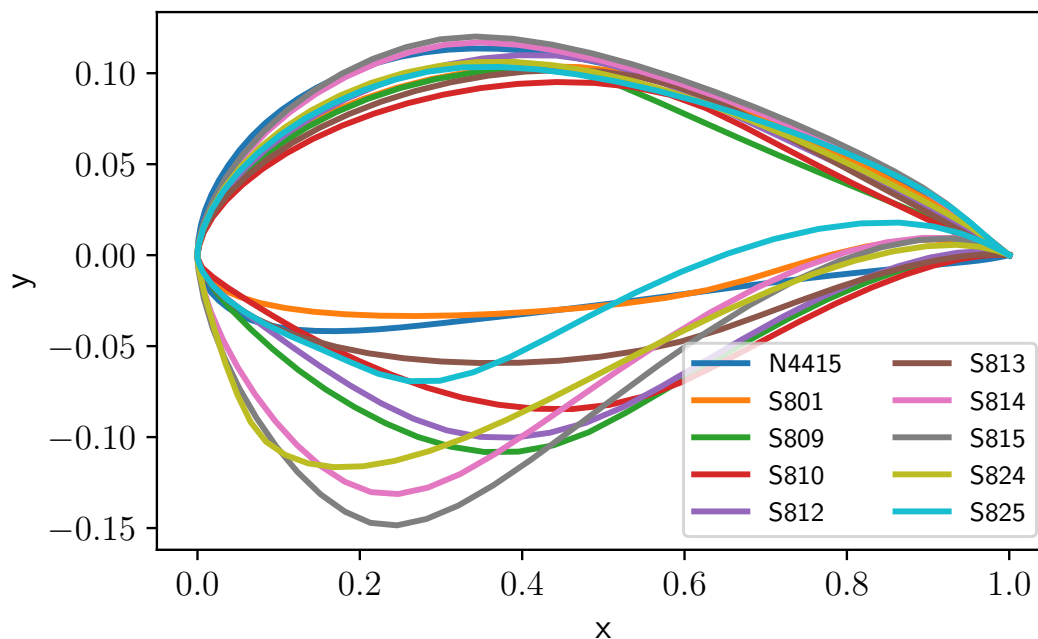
Figure 3: Airfoil shapes for 10 different airfoils used in the current study.

We separate the The OSU dataset into training and validation datasets based on the reduced frequency, $\kappa$ as shown in Fig. 5. The datasets with $0.035 < \kappa < 0.045$ are marked as validation datasets and are excluded from the training dataset for the ML-based model. Thus the ML-based model is trained on data at low and high reduced frequencies and tested on data in the middle of the reduced frequency range. We compare the performance of the ML-based model with that of the Morten-Hansen (MHH) model [5], Øye model [6] and the state-of-the-art unsteady aerodynamics model used in OpenFAST [8] that is based on the Beddoes-Leishman model [4], hereafter referred to as the Uns-AeroDyn model.

Figures 6 - 8 show the prediction of the aerodynamic response (lift and moment coefficient) of S809, S825 and N4415 airfoils to a sinusoidal variation in the angle of attack around a reduced frequency of $\kappa \sim 0.04$. They compare the response predicted by the ML-based model with that from the Uns-AeroDyn model, and experimental data. These figures show that the response predicted by the new machine learning model performs better than the Uns-AeroDyn model without the spurious kinks and on-par with the Morten-Hansen [5] and Øye model [6]. For the S809 airfoil, Figs. 6b- 6d show that the ML-based model is able to capture the physical phenomenon of moment stall before the lift stall when the angle of attack exceeds the static stall angle. Figures 6a-6b show that the ML-based model is able to capture the peak in the lift coefficient on the upstroke fairly well, when the angle of attack does not far exceed the static stall angle. The above conclusions apply fairly well to the very different S809, S825 and N4415 airfoil families as shown in Fig. 7 and 8. The ML-based model is also capable of predicting realistic cycle-to-cycle variations as shown in Fig. 9 unlike other models based on the Beddoes-Leishman model.

## 4. Conclusions

We developed an unsteady aerodynamics and dynamic stall model using a long short-term memory variant of recurrent neural networks. The neural network model is trained using the oscillating airfoil dataset from the Ohio State University [9]. Predictions from the model show good agreement with the experimental data for a wide range of airfoils, Reynolds numbers and reduced frequencies. In some cases the predictions are better than those from the Beddoes-Leishman model implementation in OpenFAST [8],
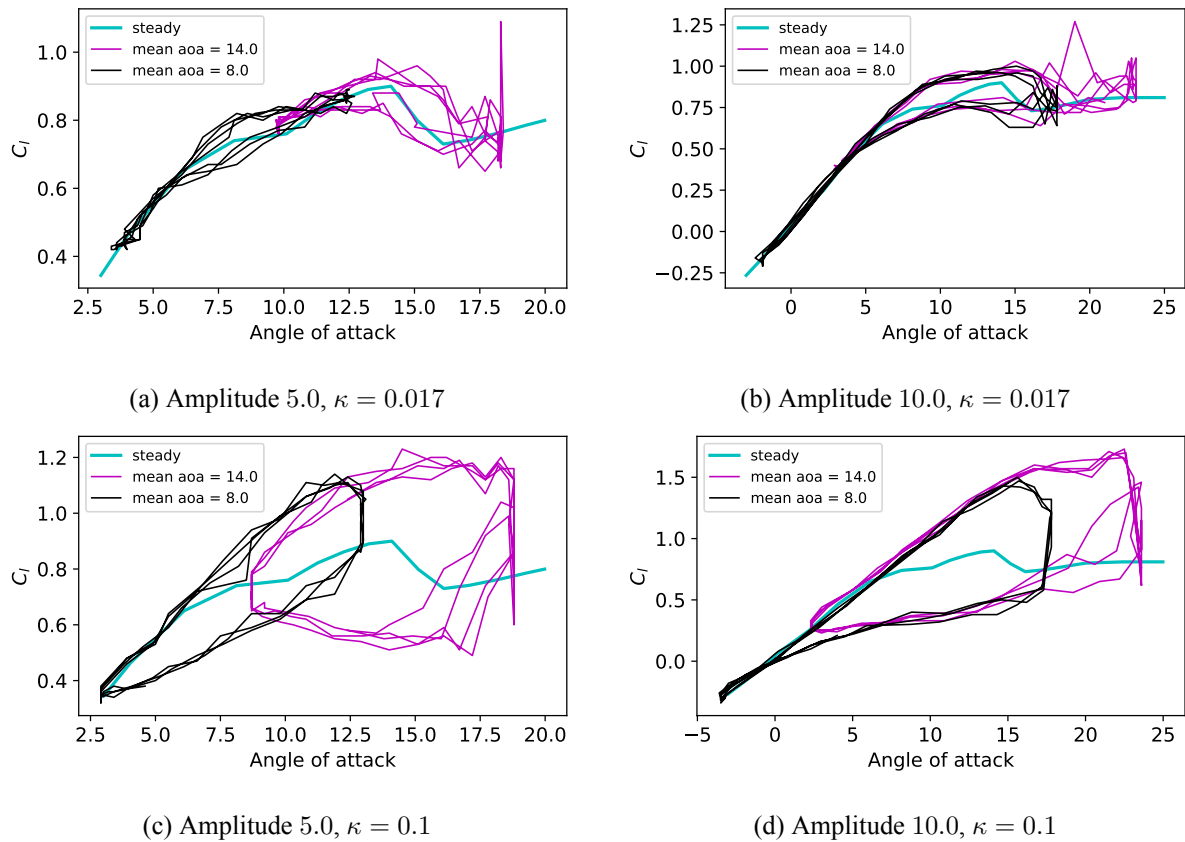
(a) Amplitude 5.0, $\kappa = 0.017$



(b) Amplitude 10.0, $\kappa = 0.017$



(c) Amplitude 5.0, $\kappa = 0.1$



(d) Amplitude 10.0, $\kappa = 0.1$

Figure 4: Variation of lift coefficient $C_l$ in response to periodic oscillation of the angle of attack. Data reproduced from Ramsay et al. [13].
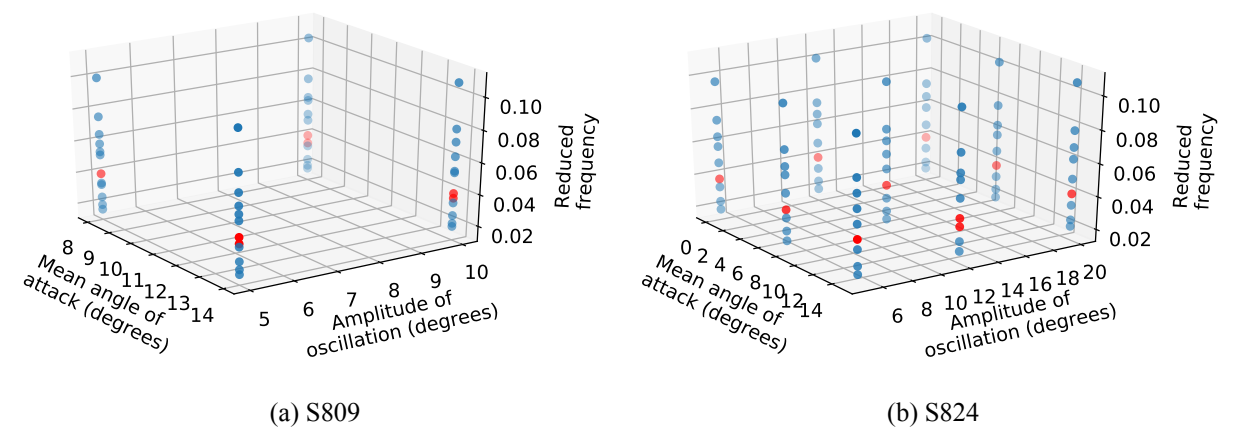


(a) S809



(b) S824

Figure 5: Scatter plot of OSU data used for training (blue dots) and validation (red dots) of the machine-learning model for unsteady aerodynamics. (a) S809 airfoil (Ramsay et al. [13]) and (b) S824 airfoil (Ramsay and Gregorek [14].)

when using the default coefficients. The predictions are also on par with those from the Morten-Hansen model [5] and the Øye model [6]. One key advantage of the machine learning (ML) model is that the automation of the model tuning can be readily integrated into the design workflow. The ML-based model can capture the key physics associated with dynamic stall, such as the precedence of moment stall before
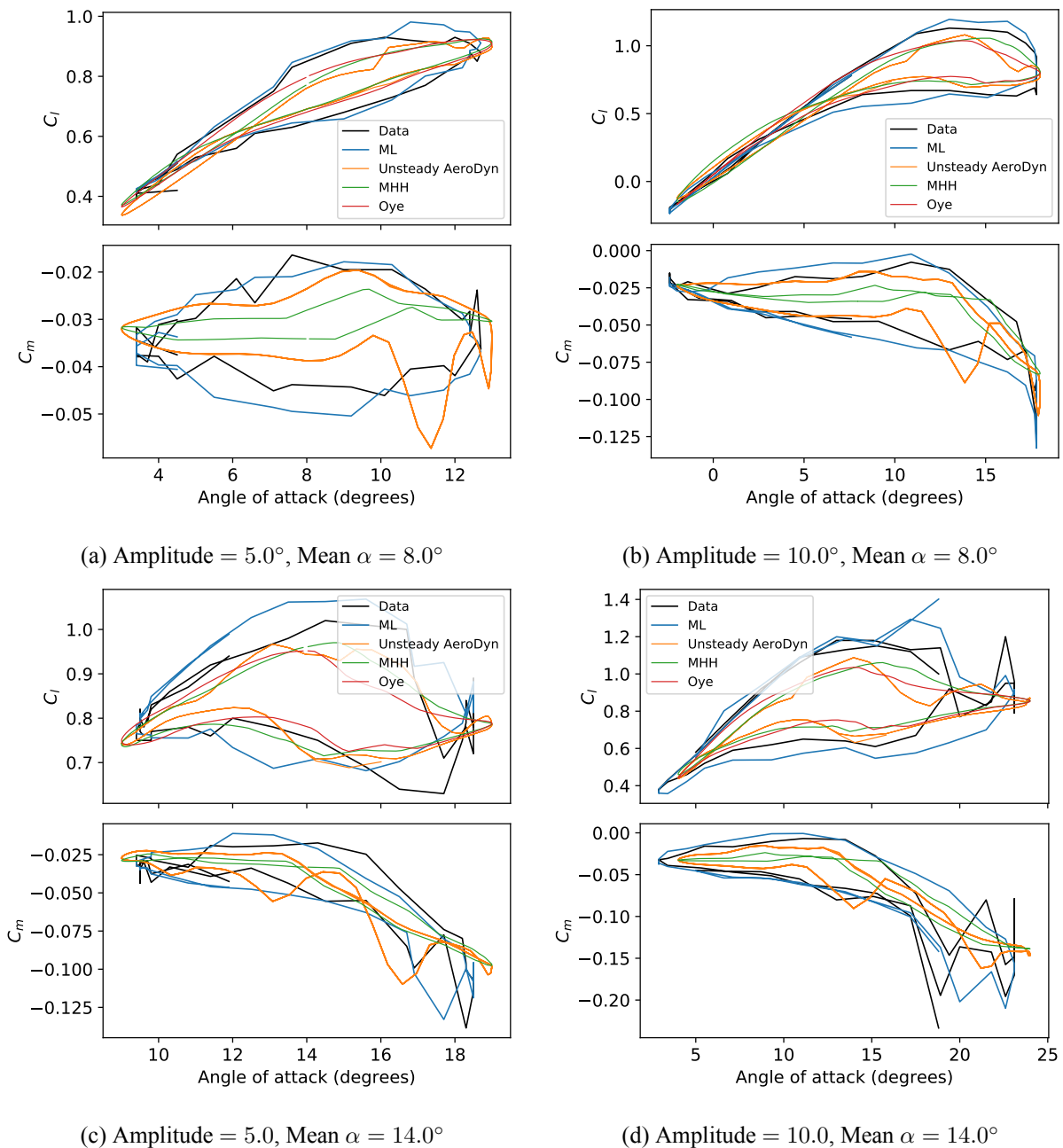
(a) Amplitude = 5.0°, Mean $\alpha = 8.0°$

(b) Amplitude = 10.0°, Mean $\alpha = 8.0°$

(c) Amplitude = 5.0, Mean $\alpha = 14.0°$

(d) Amplitude = 10.0, Mean $\alpha = 14.0°$

Figure 6: Prediction of lift ($C_l$) and moment ($C_m$) coefficient response to sinusoidal flucutuation of angle of attack ($\alpha$) on the S809 airfoil at a reduced frequency $\kappa = 0.04$: comparison between experimental data, ML-based model, Morten-Hansen (MHH) model [5], Øye model [6] and unsteady aerodynamics model in AeroDyn15 [8].

lift stall and cycle-to-cycle variations in the aerodynamic response. The new ML-based model is expected to provide a replacement option for the unsteady aerodynamics models in wind turbine design codes like OpenFAST and HAWC2 [15]. We anticipate that the use of the new unsteady aerodynamics model will improve the prediction of turbine response in actuator-line and actuator-disc simulations of wind farms. Finally, we also expect increased adoption of the new model in wind farm controls research to improve prediction of wake-generation for yaw-based control scenarios that significantly increase
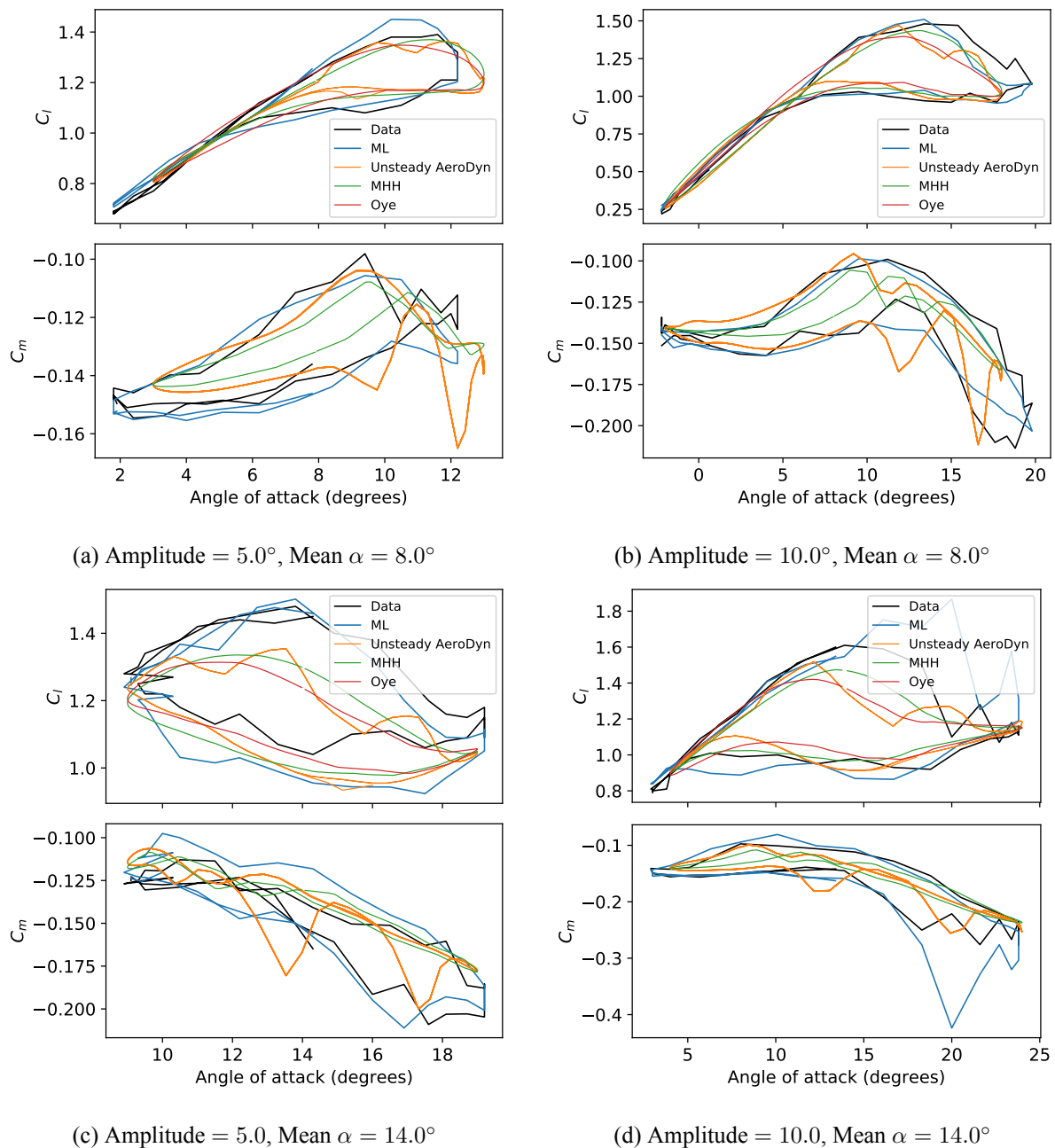
(a) Amplitude = 5.0°, Mean $\alpha$ = 8.0°

(b) Amplitude = 10.0°, Mean $\alpha$ = 8.0°

(c) Amplitude = 5.0, Mean $\alpha$ = 14.0°

(d) Amplitude = 10.0, Mean $\alpha$ = 14.0°

Figure 7: Prediction of lift ($C_l$) and moment ($C_m$) coefficient response to sinusoidal flucutuation of angle of attack ($\alpha$) on the S825 airfoil around a reduced frequency $\kappa \sim 0.04$: comparison between experimental data, ML-based model, Morten-Hansen (MHH) model [5], Øye model [6] and unsteady aerodynamics model in AeroDyn15 [8].

unsteady aerodynamics effects.

Our grand vision is to improve aerodynamics models in comprehensive wind turbine analysis codes and design level tools using data from high-fidelity CFD simulations using the ExaWind framework [16, 17]. This will allow us to generate lower order aerodynamics models for airfoils and blade shapes for which no experimental data exist. However the state-of-the-art turbulence models used in the high-fidelity CFD simulations suffer from a loss of accuracy under highly stalled conditions. Machine-learning models
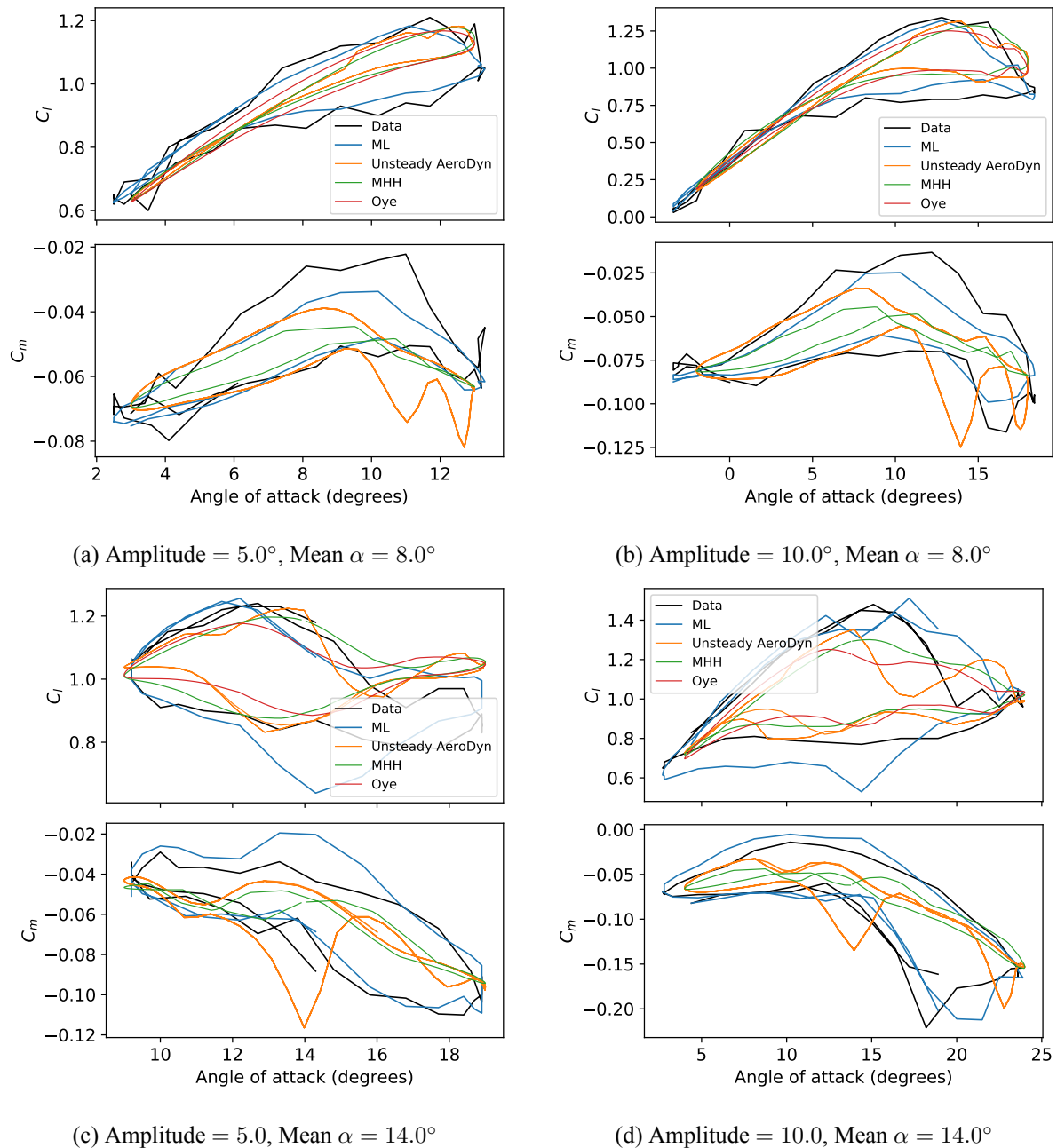
(a) Amplitude = 5.0°, Mean $\alpha = 8.0°$

(b) Amplitude = 10.0°, Mean $\alpha = 8.0°$

(c) Amplitude = 5.0, Mean $\alpha = 14.0°$

(d) Amplitude = 10.0, Mean $\alpha = 14.0°$

Figure 8: Prediction of lift ($C_l$) and moment ($C_m$) coefficient response to sinusoidal flucutuation of angle of attack ($\alpha$) on the N4415 airfoil at a reduced frequency $\kappa = 0.04$: comparison between experimental data, ML-based model, Morten-Hansen (MHH) model [5], Øye model [6] and unsteady aerodynamics model in AeroDyn15 [8].

offer an attractive alternative to correct the results from CFD simulations using experimental data. In the future, we will use this pathway to augment experimental data using CFD simulations before developing ML-based models for various aerodynamic phenomena. Future work will extend the machine learning model to account for 3D flow effects including rotational augmentation.
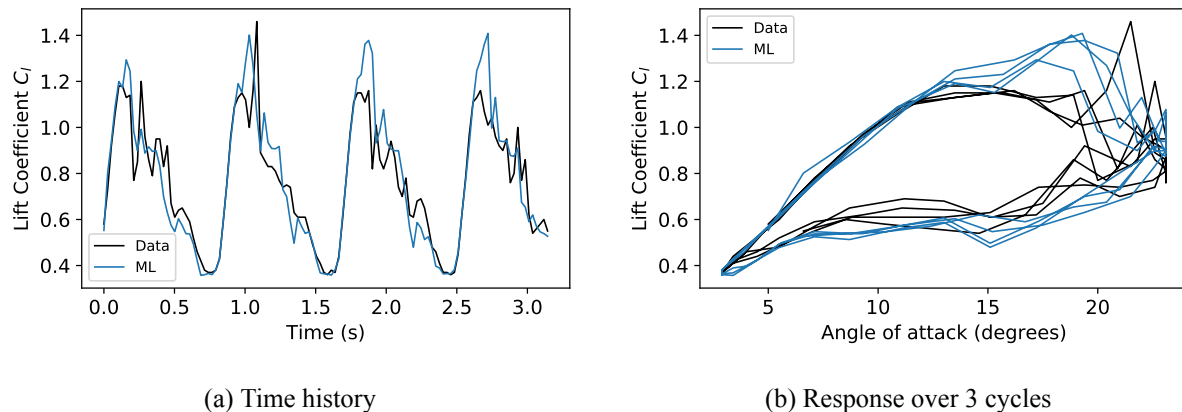
(a) Time history

(b) Response over 3 cycles

Figure 9: Prediction of lift coefficient response to sinusoidal flucutuation of angle of attack on the S809 airfoil at a reduced frequency $\kappa = 0.04$: comparison between experimental data and ML-based model over 3 cycles.

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