Author Comments.

When a WES paper is published, the journal editors completely retype set the paper. They rescale figures etc.. All of the figure sizes are intended for the final paper rather than the draft. For these reasons, the figures are all over the place etc.. The final visual presentation of the paper is determined by the journal, not me.

Referee #1

Thank you for the detailed comments on the paper. It may appear in the following section that I am hostile to your comments, this is not the case, I appreciate the feedback even if I have responded in an argumentative fashion in the following sections.

Please note that while the experiments mostly inspect dynamic stall, my literature review places dynamic stall in the wider context of unsteady aerodynamics.

Comment regarding training method.

I would like to start with the topic of a machine learning approach to unsteady aerodynamics. For my description to make sense it is important to understand that methods such as neural networks are trained in steps using stochastic gradient descent. In short, this means that we put a data point into the network, we then measure the difference between the correct output and the output of the current configuration of the model. We then slightly nudge the model in the direction of creating the correct output. A deep learning neural network architecture has enormous flexibility, while this is great because we can approximate any function, by definition most of these functions will be the wrong function. To constrain the neural network from all possible functions down to something that looks like an aerodynamic response of an airfoil, we need a good deal of data. As you rightly point out, it would be silly to attempt this with CFD.

Here is the important part of the argument. Because we can use stochastic gradient descent to train the model, we don't need to use the same input data over the whole training process. We can use low resolution data in the early training stages to bring the neural network into the correct neighbourhood. Out of the all of the possible functions that a neural network can create, the poor quality approximation of the aerodynamics which lacks turbulence etc. is still much closer to CFD or field data than all possible outputs. Is it a good model at this stage? No. But it is relatively well behaved, it could do a nice impersonation of the Beddoes Leishman model for instance.

What now? Once we have a model that contains something that looks roughly like unsteady aerodynamics, we can begin refining the model with a much smaller amount of higher quality data. To use a metaphor, the poor quality data got us into the neighbourhood like a bad quality street map, the better quality data is like a good quality street map of a very limited area, it helps us find the right street.

The ideas that I have presented here have a precedent. Jeremy Howard was able to win a neural network image identification challenge using much smaller amounts of computational time by first training the neural network on 16bit images and then only training on 256 right at the end.

The important question is of course: will this all work? My answer is, I don't know. 3D effects, different time scales all these things will make it a difficult model to train. However, I believe that the innovations of modern machine learning approaches have opened this new avenue of model building. My exploration of this topic was intended communicate the existence of this new avenue rather than prescribing an exact solution to unsteady aerodynamics.

Comment Regarding Airfoil stall is bad.

I understand your point but I disagree.

1. Stall reduces lift. We see vortex generators in the inner and outer regions of wind turbines to mitigate this effect for increased power production and noise reduction (for this I only have anecdotal evidence admittedly)
2. Stall causes phase lags which can result in instabilities. (I will come back to this point)
3. Review papers such as Holierhoek, J. (2013). An Overview of Possible Aeroelastic Instabilities for WIND ENGINEERING, 44(0). Make a very long list of instabilities, a great deal of them being stall driven.
4. While smaller wind turbines were stall regulated, the design methodology of modern wind turbines uses pitch and variable speed to regulate wind turbines. In part due to the instabilities highlighted in point three. In short, modern wind turbines seem to be designed to avoid using stall as a regulation of lift which seems to be reflect that on balance, wind turbines stall is bad.

While there may be certain load cases where as you pointed out, stalling of the blades will reduce extreme loads, in the very next sentences I provide the context for the statement. While you do make an interesting counter point, I would prefer not to change the sentence. With respect, the boundary case you present does not present a strong enough argument to say: "simply not correct". It's not a critical premise in a syllogism, I believe that the balance of the argument is on my side, and I believe that it is a succinct way open opening the topic. I would happily hear an expansion of your point, perhaps I have missed your point.

Stall Flutter

I will clarify this point with a few references to literature, because their explanations are far better than mine. Stall flutter doesn't imply dynamic stall. In fact, while you may get a large response from deep stall, light stall will tend to drive down the aerodynamic damping in the torsional direction. If you look in the figure below you can see the hysteresis loops have much larger negative damping than the deep stall case, you alluded to this effect in your comments. If you read the paragraph carefully I clearly state that I am talking about light stall. In page 303 of the reference, the distinction is made between stall flutter and dynamic stall, though it is my experience that stall flutter can be applied as a named to many many different phenomena. I believe my description was fairly careful.

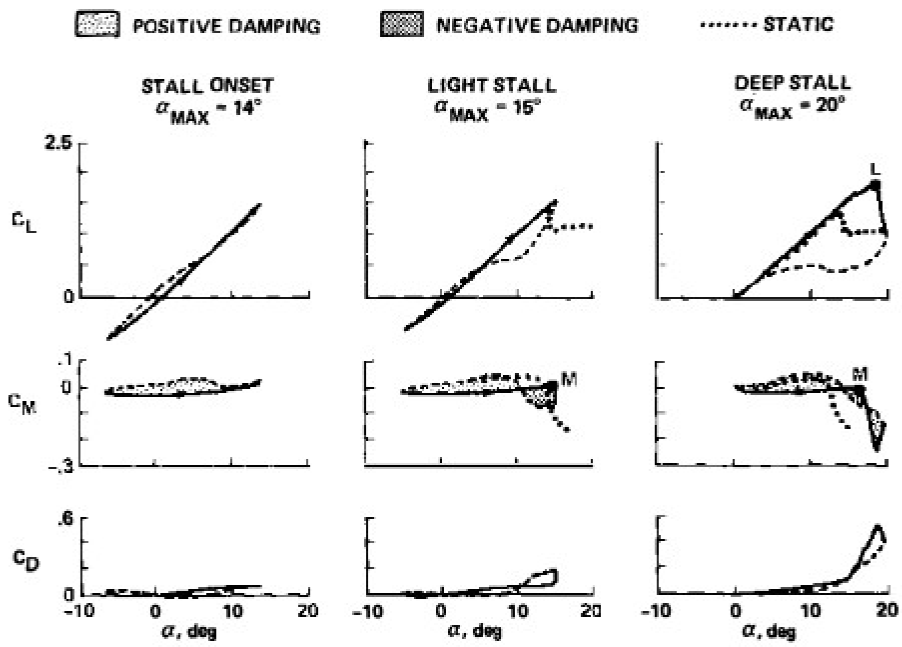

Figure 9 Unsteady forces and moments in three dynamic-stall regimes: $M_\infty = 0.3$, $\alpha = \alpha_0 + 10° \cos \omega t$, $k = 0.10$.

McCroskey, W. J. (1982). Unsteady Airfoils. *Annual Review of Fluid Mechanics*, *14*(1), 285–311. https://doi.org/10.1146/annurev.fl.14.010182.001441

Regarding phase shift, remembering that work or the energy absorbed or dissipated is defined as the boundary integral of these loops.

$$W \equiv \oint M_R \, \mathrm{d}\alpha_R$$

This is just one way of looking at the equations. Another way is the decomposition of the lift into complex values in the same manners as Theodorsen. Carta and Niebanck sum it up neatly.

and after Eqs. (15) and (16) are substituted into Eq. (14), the result is

$$C_W = -\int_0^{2\pi} \left[C_{M_M} + \bar{C}_{M_{UR}} \cos\omega t - \bar{C}_{M_{UI}} \sin\omega t \right] \bar{\alpha} \sin\omega t \; d(\omega t) \tag{17}$$

(The integration range, $0 \leq \omega \leq 2\pi$, is equivalent to one complete cycle of motion.) After the integrations indicated in Eq. (17) are performed, it is found that the term involving the mean moment vanishes as well as the term containing the real part of the unsteady moment; the final result for the theoretical work coefficient is given by

$$C_W = \pi \bar{\alpha} \bar{C}_{M_{UI}} \tag{18}$$

This is the work done by the air on the airfoil; hence, a positive value of C_W will indicate an unstable motion, since this implies a net energy exchange from the surrounding medium to the airfoil, whereas a negative value of C_W will indicate a stable, or damped motion.

Carta, F. O., & Niebanck, C. F. (1969). *Prediction of rotor instability at high forward speeds.* (Vol. III, Stall).

I draw your attention to formula 18 where the unsteady component is responsible for the work done in a single degree of freedom system. This means that the phase shift between the angle of attack and the moment leads to aerodynamic damping.

The following paper dives into this topic in greater detail. This and another paper were provided as citations in the offending sentence to give this very context.

Bowles, P. O., Corke, T. C., Coleman, D. G., Thomas, F. O., & Wasikowski, M. (2014). Improved Understanding of Aerodynamic Damping Through the Hilbert Transform. *AIAA Journal*, *52*(11), 2384–2394. https://doi.org/10.2514/1.J052630

I find the description in terms of $\frac{dC_l}{d\alpha}$ or $\frac{dC_m}{d\alpha}$ less succinct. The phase difference description is applicable to different modes of instability.

Cycle to Cycle Variations.

While in the long run the system may oscillate around an attractor it can have large departures from that attractor in the short run, do we still want to call that cycle stable? The work done formula presented on the previous page presents the boundary integral over a cycle, not over a long run range of cycles, so stability is determined cycle to cycle and can even be determined with in the cycle referencing Bowles and Corke again.

Towing Tank Outlier Case

The towing tank case presents data on a single pressure port because as you said, we didn't have full lift available. In the limited part of the aerodynamic data that I had available, there weren't any good examples to demonstrate the outlier detection.

Figure 22

There is only a small different between the clusters this was already highlighted but I have extended the comment. The misplaced reference was fixed.

Figure 12

The colors represent z-scores- it's standardized, added comment to caption.

Figure 14-16

The probability distributions are presented with minimum possible detail.

Section 4.1

I agree. I have moved it and I believe it reads better now.

Page 15 Complicated Case

From the limited set of data available to me, this demonstrated the effects best.

Unnecessary figures.

I removed some figures.

Referee #2 Tuhfe Gocmen

Section 3

1. Fixed
2. Moved to later but final placement will be done by the editors.
3. The clustering algorithm receives a time series as input.
4. A full study about the downsampling is published in my students thesis I have highlighted this.

Section 4.

- Agreed and rearranged.
- Regarding the CNN architecture. I am in a split mind. I used the generic pictures to try and educate the reader in broad terms.
- You are right about the uncertainties on the training data. This is why I said I assume the training data is correct. I did a few trials seeing how different my clicks were on the same figure, it was less than the difference in the convection speeds by a good margin. It’s not a perfectly satisfying answer, but the best approach I could think of. The approach is intended to be used to analyse experimental data. If it was an online system, I would definitely want to be more rigorous.
- I added some explanations of the training process.

Regarding my suggestions for future unsteady aerodynamics models, I was talking in the sense of future work and where ML could be applied, it would be a different model completely however.

The code example will have some of the dataset.