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A framework for quick identification of inflow conditions inducing destructive aeroelastic instabilities in wind turbines

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1 Introduction

Stall-Induced Vibrations (SIV) are an aeroelastic instability that happen when large portions of a wind turbine blade experience an angle of attack such that the slope of the lift coefficient is negative ($\partial C_L/\partial\alpha < 0$) [1]. With a rising necessity to design larger and more flexible wind turbine blades, SIV are an important design consideration as the loads generated during the occurrence might severely damage the blades. The severity of SIV depends on the blade design and inflow conditions.

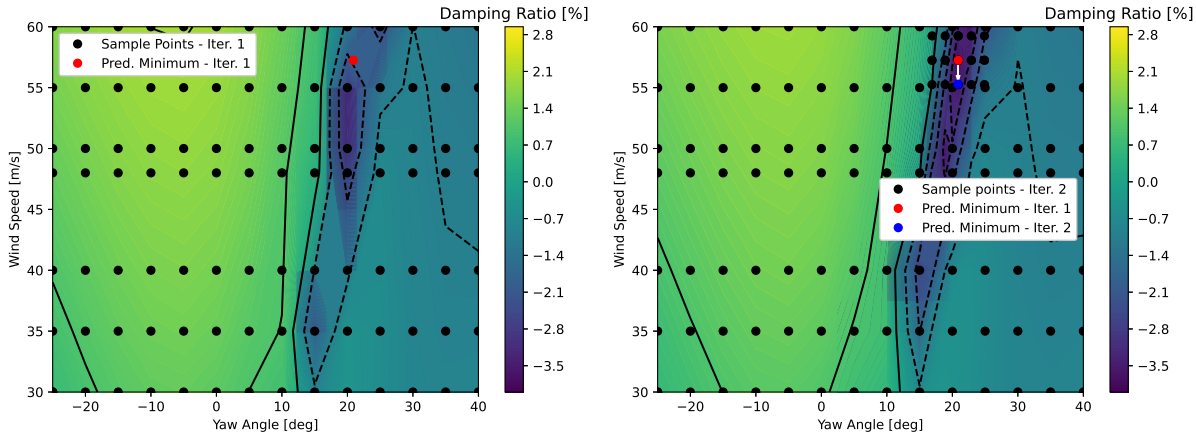
Exploration of the design and inflow space that cause SIV has a high computational cost, since it involves high fidelity aeroelastic simulations. The aim of this work is to formulate a framework based on an aeroelastic simulator, a surrogate model and an optimizer that can automatically identify the conditions that maximize SIV in a wind turbine with the minimal number of simulations. The framework is based on a type of an optimization algorithm called Surrogate-Based Optimization (SBO), which makes use of surrogate models to approximate an expensive objective functions in the design space and guide the selection of new sample points towards the optimum [2].

2 Methodology, setup and SIV characterisation

In this work, the IEA 10 MW [3] turbine is chosen for investigation. The occurrence and characteristics of SIV in this turbine are studied for a parked rotor with a 90 deg pitch angle, 0 deg azimuth angle (blade 1 pointing upwards) and constant wind conditions. The inflow conditions and simulation setup are similar to the considerations in the AVATAR project [4], where the characteristics of SIV was studied on a large wind turbine rotor. In this work, we have focused on the effects of wind speed and yaw angle on SIV, therefore we have defined a first regular grid of inflow conditions. The aeroservoelastic tool HAWC2 [5] is used to simulate the motion of the wind turbine.

The edgewise bending moment at the root of blade 1 is chosen as the response to characterise SIV. For certain inflow conditions, the system is asymptotically stable. For some others the system is unstable, and the response grows exponentially, until it stabilizes on a nonlinear limit cycle oscillation. The initial part of the simulation is discarded to remove the effect of the initial condition. Then, the length of the signal is truncated to limit the response to the linear range. The severity of SIV is estimated by band pass filtering the response around the frequency of the first blade edgewise mode, and identifying the damping ratio.

Different methods were attempted to identify the damping ratio. The classical logarithmic decrement method and a variant, based on computing the slope of the straight line passing through the logarithm of the signal peaks, the half power bandwidth, and fitting an Auto Regressive model. The results from the different methods were found to be in good agreement with each other. The variation of the log decrement method has been eventually chosen for its robustness. The key difference with respect to the classical



(a) *First simulation grid, minimum damping* -2.46% (b) *Refined simulation grid, minimum damping* -3.58%

Figure 1: Simulation grid and contour of damping ratio over iterations.

version is that it uses all peaks, as opposed to the classical one which uses only two. By indicating with (t_i, y_i) the time and value of the i-th signal peak, ω the mode frequency and ζ the mode damping ratio, we can write

$$\log(y_i) = -\zeta\omega t_i + c \tag{1}$$

where c is the line intercept. The mode damping ratio is finally computed with the least-squares method.

3 Optimization

We have identified the damping ratio for all points of the initial inflow grid, and then trained an Artificial Neural Network (ANN) on it, so as to convert it into a continuous variable. The ANN is trained using the TensorFlow library [6], with 2 hidden layers containing 8 neurons each. The ANN function is then minimized to obtain the inflow conditions that leads to the minimum damping ratio (i.e. maximum SIV). After the first optimization, new inflow conditions are defined around the one of the minimum damping ratio, and the procedure is repeated. The grid and minimum damping ratio for the first two iterations is shown in Fig. 1.

The improvement in the estimated minimum damping ratio due to the inclusion of the additional simulations is nearly 1.12% measured in absolute value. It can be seen that the framework drastically limits the number of simulations needed to find the most critical inflow condition.

4 Conclusion

In this work we have studied Stall-Induced Vibrations on the IEA 10 MW wind turbine. We have developed a framework based on an Artificial Neural Network, that allows to find the most critical inflow conditions with the minimum number of high fidelity simulations. Future works will regard the conversion of the framework to OpenMDAO [7], and the application to Vortex-Induced Vibrations.

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