# Reinforcement Learning for Wind Turbine Load Control

## How AI can drive tomorrow‘s wind turbines

**Nico Westerbeck // Julius Gonsior // David Marten // Sebastian Perez-Becker**

## Problem

Operating a modern windturbine requires **control** systems that adjust the wind turbine parameters to the operating situation. The load controller is a particularly complex control system, as it adjusts the large, inert **rotor and generator** to the dynamics of the incoming wind situation with split-second accuracy. Load controllers for wind turbines are typically based on a PID-controller or an equivalent **linear mechanism**. Currently, load controllers typically operate with 4 output signals (3 blade pitches, generator torque) and 4 input signals (blade bending moments, rotor speed). However, current research in wind turbines requires a higher number of outputs through the integration of **active flow control** elements on the wing and a higher number of inputs through integration of **advanced sensors** such as LIDAR [1]. Designing linear control systems for such a high dimensional task is difficult, thus adopting a more powerful framework for control becomes relevant. Reinforcement learning has proven capable at **solving high-dimensional control** problems, which potentially makes it a suitable candidate for the next generation of wind turbine load controllers.

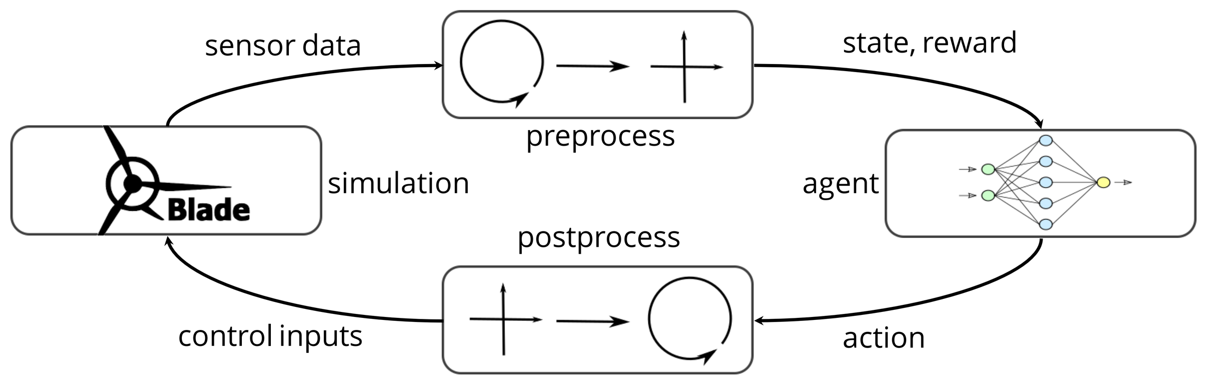



Figure 2: Closed-loop control with WINDL includes the QBlade simulation, Coleman-transforming preprocessor, a smooth reinforcement learning agent and Coleman-backtransforming postprocessing

## Method

We present WINDL, a method for training a **model-free** reinforcement agent as a load-controller. In our work, we use the algorithm SAC [2] adjusted with a **smoothness regularizer** to learn an assistive control policy for the wind turbine simulated in QBlade [3]. As **large-scale** grid-searching was required, we develop a distribution framework tailored to the requirements of the expensive simulation and the Lise HPC. By Coleman-transforming the inputs and outputs, the controller can learn a **rotation-invariant policy**. Further transformations, normalizations and a novel frame-stacking technique are used to satisfy environment requirements of the algorithm. To aid training, we employ a **surrogate reward** function that is dense, more convex and closely related to the true optimization goals of fatigue- and extreme-load reductions.

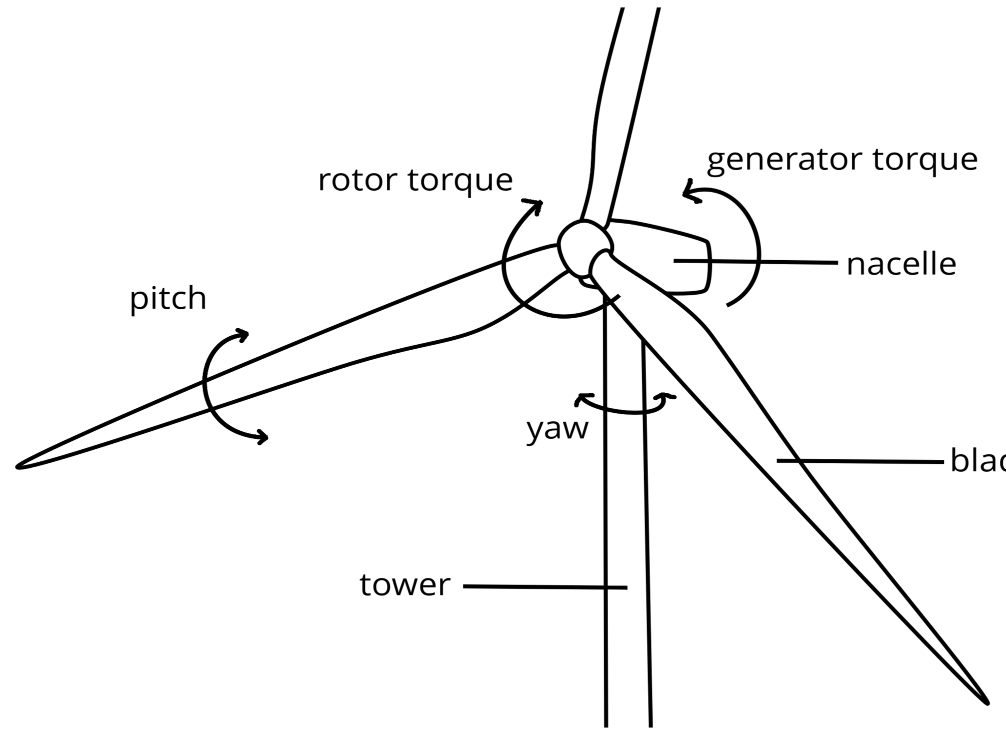



Figure 1: Schema of a wind-turbine with named components

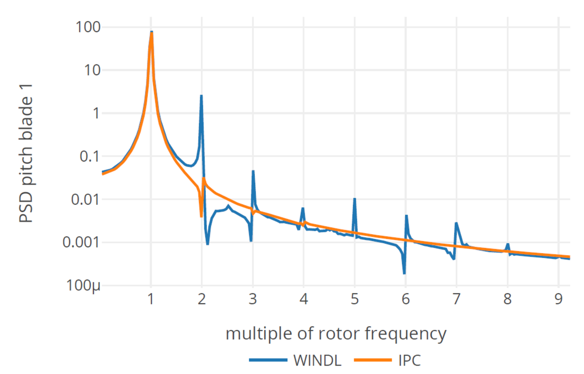
## Aim

Evaluate the use of reinforcement learning to train a wind turbine load controller

- in an idealized **steady wind** situation
- in a **turbulent wind** situation

Compared to two baselines

- Collective Pitch Controller (CPC)
- Individual Pitch Controller (IPC)



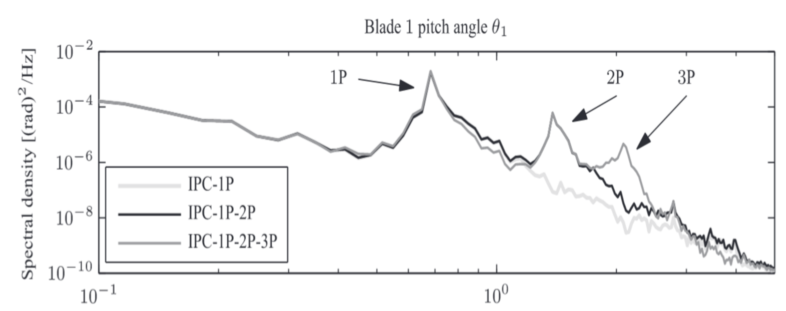



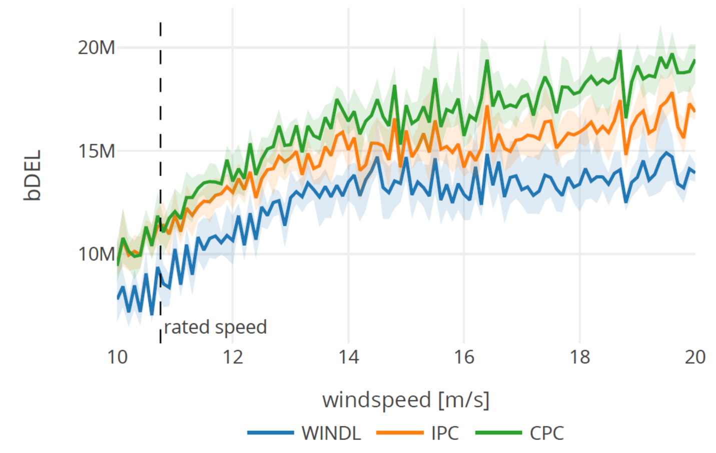

Figure 3.1: PSD-plot of WINDL and IPC pitch activity

Figure 3.2: PSD-plot of 1p-2p-3p and 1p IPC pitch activity from [4]

Figure 3: In the steady wind, a 1p-2p-3p controller emerges from the training.

## Results

In the steady wind, a control policy similar to the 1p-2p-3p controller [4] emerges from the training, which beats both baseline controllers in terms of blade fatigue loads measured in DEL. Also in the turbulent wind, blade fatigue- and extreme loads are lower across the entire operating range for load controllers. In both scenarios, WINDL exhibits higher pitch bearing fatigue loads and shows a slight asymmetry between the blades.



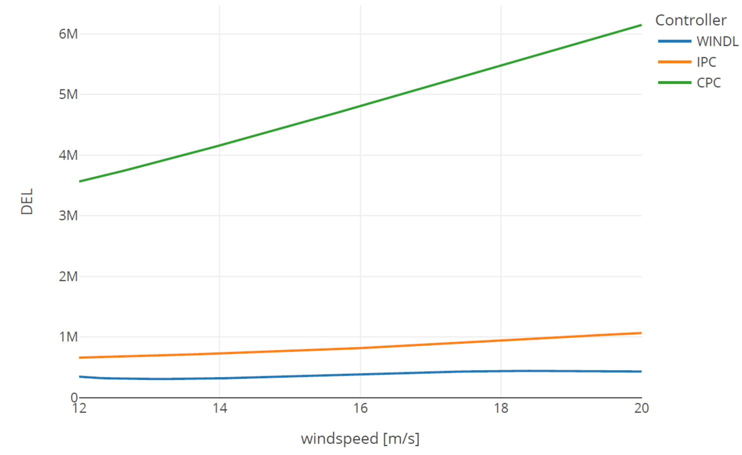




Figure 4.1: Blade DELs in turbulent wind, lower is better

Figure 4.2: Blade DELs in steady wind, lower is better

Figure 4: Both in turbulent wind and in steady wind, WINDL exhibits lower blade fatigue loads than baselines

## Conclusion

We show that reinforcement-learning can match or exceed the performance of traditional control systems. It can easily balance between multiple optimization goals and scale to more inputs and outputs than traditional control. Combining this work with safety guarantees likely yields a capable and industry-ready control framework for future generations of wind turbine load controllers and follow-up work in this topic is recommendable.

Literature:

[1] Sebastian Perez-Becker, David Marten, and Christian Oliver Paschereit. Active flap control with the trailing edge flap hinge moment as a sensor: Using it to estimate local blade inflow conditions and to reduce extreme blade loads and deflections. Wind Energy Science, 6(3): 791–814, June 2021. ISSN 2366-7451. doi: 10.5194/wes-6-791-2021

[2] Tuomas Haarnoja, Aurick Zhou, Pieter Abbeel, and Sergey Levine. Soft Actor-Critic: Off-Policy Maximum Entropy Deep Reinforcement Learning with a Stochastic Actor. arXiv:1801.01290 [cs, stat], August 2018.

[3] David Marten. QBlade: A modern tool for the aeroelastic simulation of wind turbines. 2020. doi: 10.14279/DEPOSITONCE-10646.

[4] E. van Solingen and J.W. van Wingerden. Linear individual pitch control design for twobladed wind turbines: Wind Energy, 18(4):677–697, April 2015. ISSN 10954244. doi: 10.1002/we.1720.

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