

A machine learning approach for online IPC controller selection based on wind features

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- Motivation
- The idea

2 Methodology

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- Results
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Context

Wind Energy growth

Wind energy capacity is **exponentially growing**, involving billions of €.

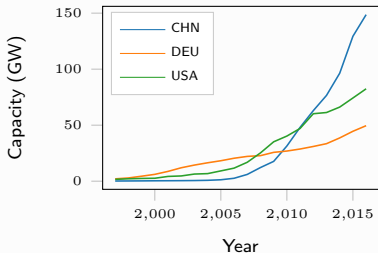


Figure: Cumulative installed capacity of wind energy (ourworldindata.org).

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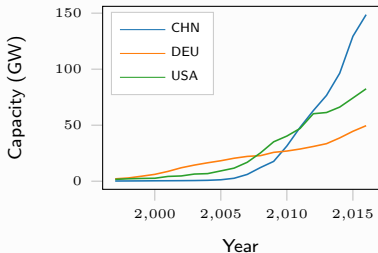


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Cost reduction

Slight decrease on Wind Turbine (WT) operational cost can result in **saving millions of €**.

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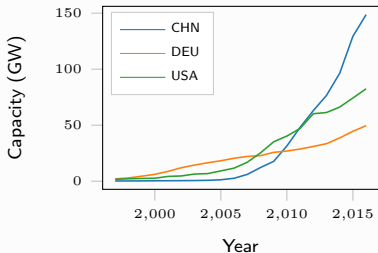
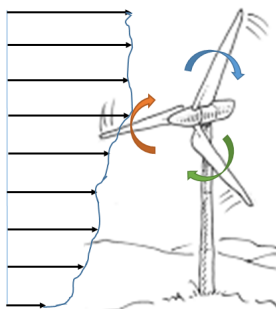


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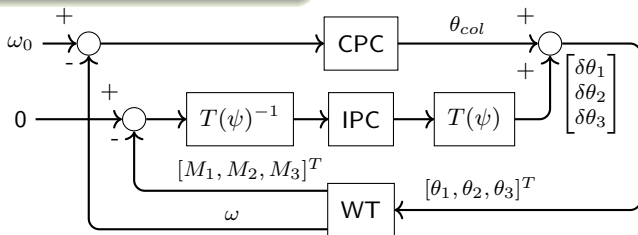
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Individual Pitch Control (IPC)

- In **addition to** Collective Pitch Control (**CPC**)

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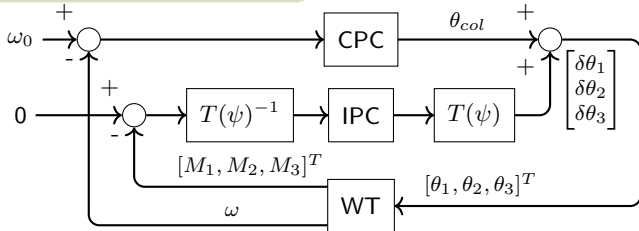


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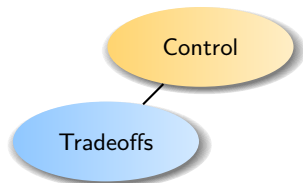
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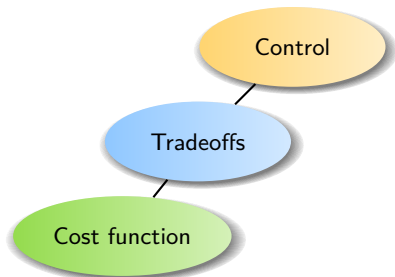
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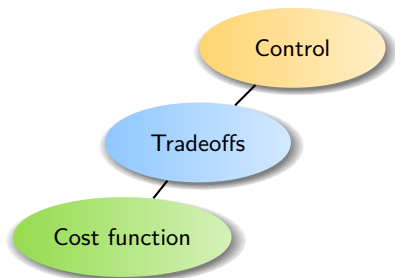
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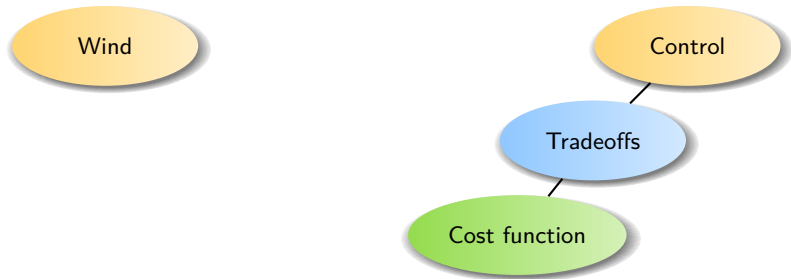
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Individual Pitch Control (IPC)

- In **addition to** Collective Pitch Control (**CPC**)
- Many works implemented, with **different control architectures**
- **Trade offs** between pitch activity, blade fatigue reduction and tower fatigue increase
- The most efficient **controller architecture** might **depend on the disturbance** characteristics



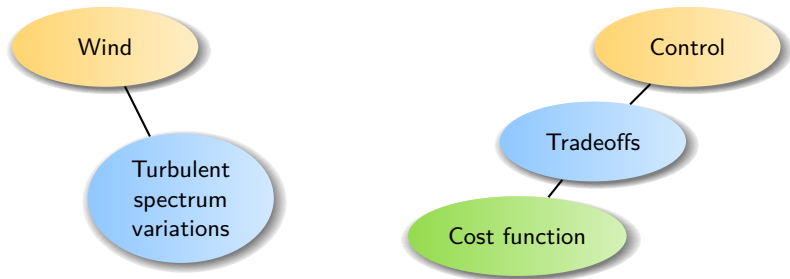
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Wind resource assessment

- Wind turbulent spectrum varies with **diurnal** and **synoptic** variations [Van der Hoven, 1957]

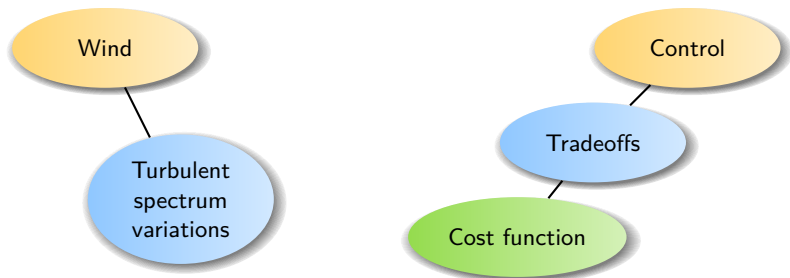
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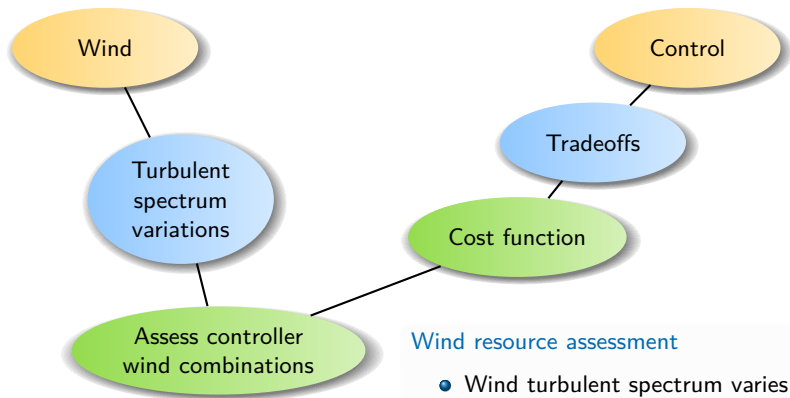
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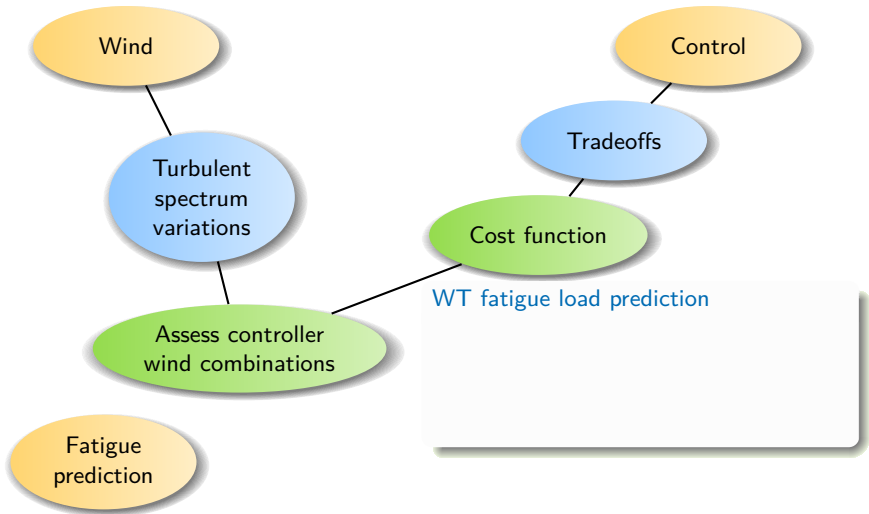
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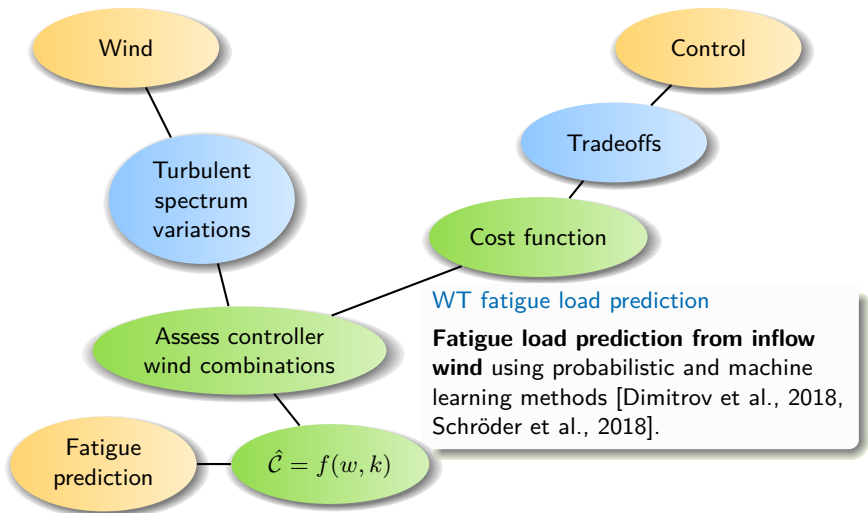
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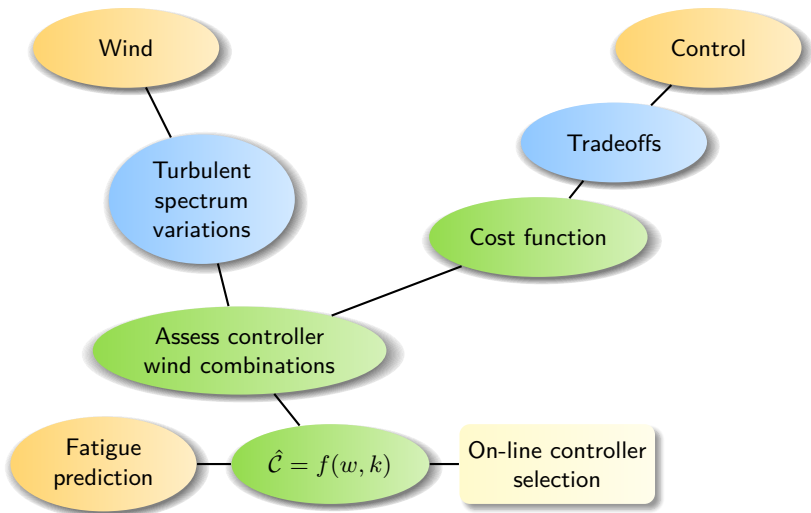
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Economic cost function computation

Cost function

$$C = \sum_i \pi_i D_i$$

- C **Cost** of the simulation in €
- π_i Component i **price of replacement** (construction + transportation + installation)
- D_i Component i **damage** under the simulation, $D_i = 1 \rightarrow$ the component is broken

Relating wind to fatigue with machine learning

Wind features

Wind characteristics likely to **explain fatigue variance**:

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RAWS Rotor Averaged Wind Speed

δ_y Horizontal shear

δ_z Vertical shear

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CPC Proportional Integral (PI) controller designed as in [Jonkman et al., 2007]

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This results in $588 \text{ winds} \times 100 \text{ controllers} = 58,800$ simulations, which takes 2 weeks on a standard computer parallelized on CPU.

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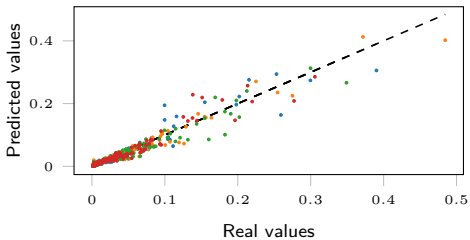
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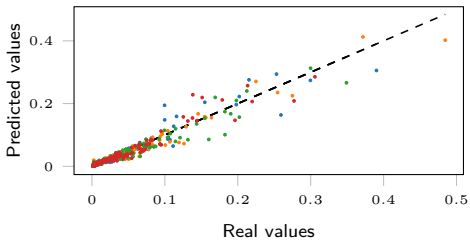
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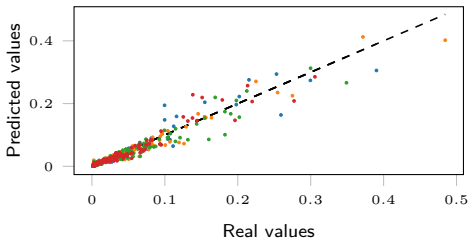


Controller	R_2	Decrease
1	0.93	0.23
2	0.96	0.35
3	0.93	0.36
4	0.92	0.26

Preliminary results

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- The regression algorithm manages to predict fatigue cost from wind features
- A relative **fatigue cost decrease of 23%** could be achieved **from the best candidate**

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- **On-line validation** in simulation on realistic wind scenarios with varying spectrum parameters
- Step up to **advanced control** techniques
- Extend wind space definition and **improve regression scores**
- **Study** more thoroughly **wind evolution on long time scales** (day, week)

References I

-  Clifton, A., Schreck, S., Scott, G., Kelley, N., and Lundquist, J. K. (2013). Turbine inflow characterization at the national wind technology center. *Journal of Solar Energy Engineering*, 135(3):031017.
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Data Generation

Wind generation

- NREL wind generator TurbSim
- Coherent turbulent wind field generated from a wind spectrum
- Modification of spectrum parameters (direction, speed, turbulence intensity)
- 588 winds generated

Simulations

- NREL WT aeroelastic simulator FAST
- Each controller candidate is simulated with all the winds

Fatigue theory

Palmgren-Miner rule

$$D = \sum_i \frac{n_i}{N_i(L_i)}$$

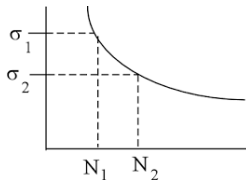
$D \in [0, 1]$ is the damage endured $D = 1 \rightarrow$ The component is broken

n_i is the number of hysteresis cycle i

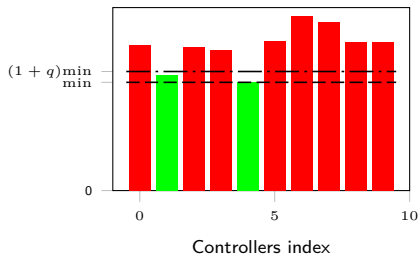
N_i is the number of hysteresis cycle i that the component can endure in its lifetime

L_i is the amplitude of hysteresis cycle i

Hysteresis cycles are counted with a rainflow-counting algorithm.

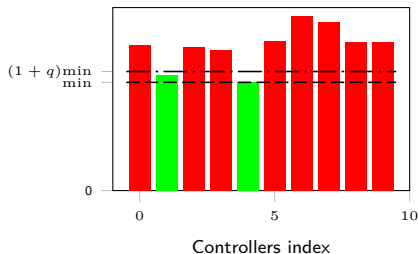


Controller selection



A 'close-to-the-first' parameter q is defined to consider as equally first the controller minimizing the cost and a close second or first.

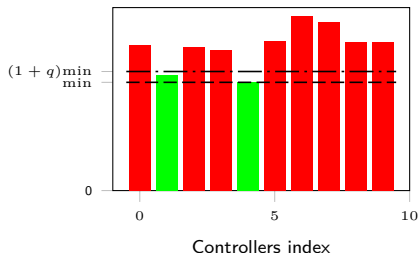
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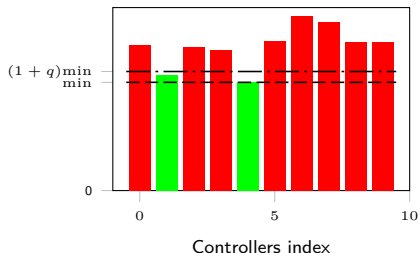


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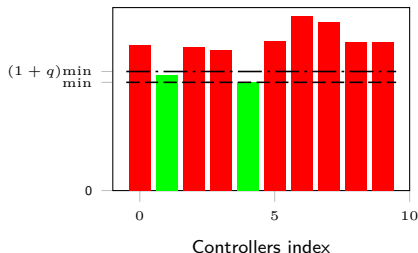


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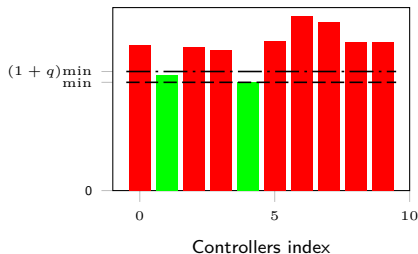


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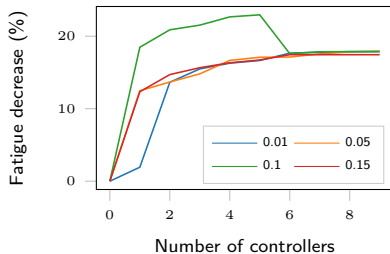
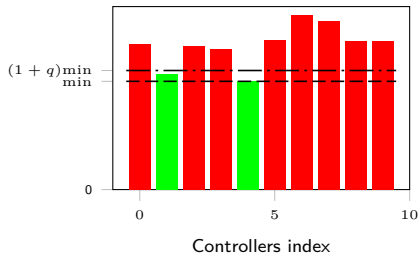


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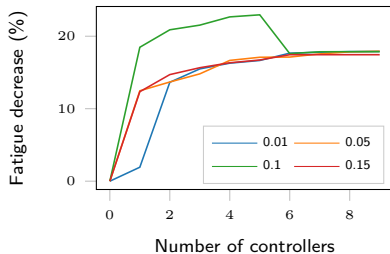
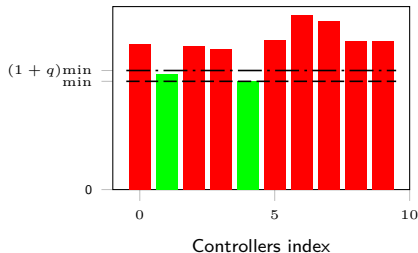


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Parameters chosen: $q = 0.1$ and $n = 4$