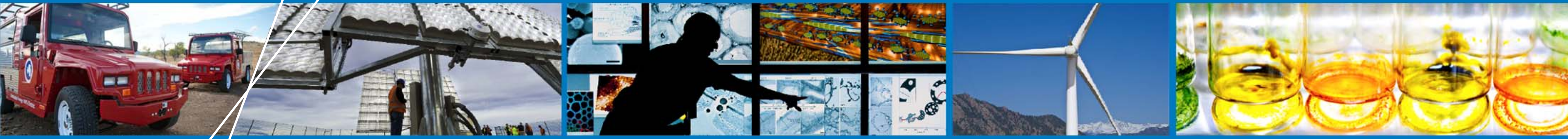
Using Machine Learning To Create Turbine Performance Models



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Yesterday's approximation – stream tube

Air Density

Rotor Diameter

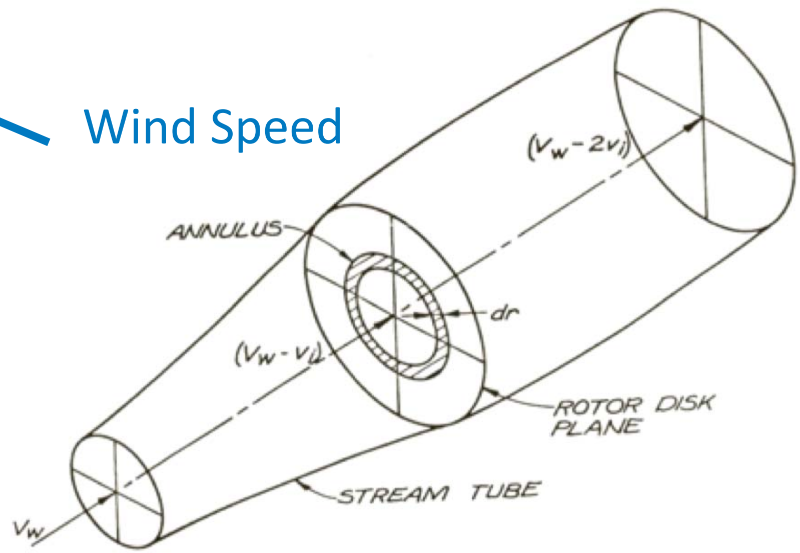
$$P = \frac{1}{2}\rho C_P \frac{\pi D^2}{4} U^3$$

Wind Speed

Efficiency

The Betz Limit

$$C_p = \frac{16}{27}$$



In low shear *and* low turbulence,
hub-height wind speed is a useful metric

Today's need – include the real atmosphere

How can we include the atmospheric boundary layer in turbine performance predictions?

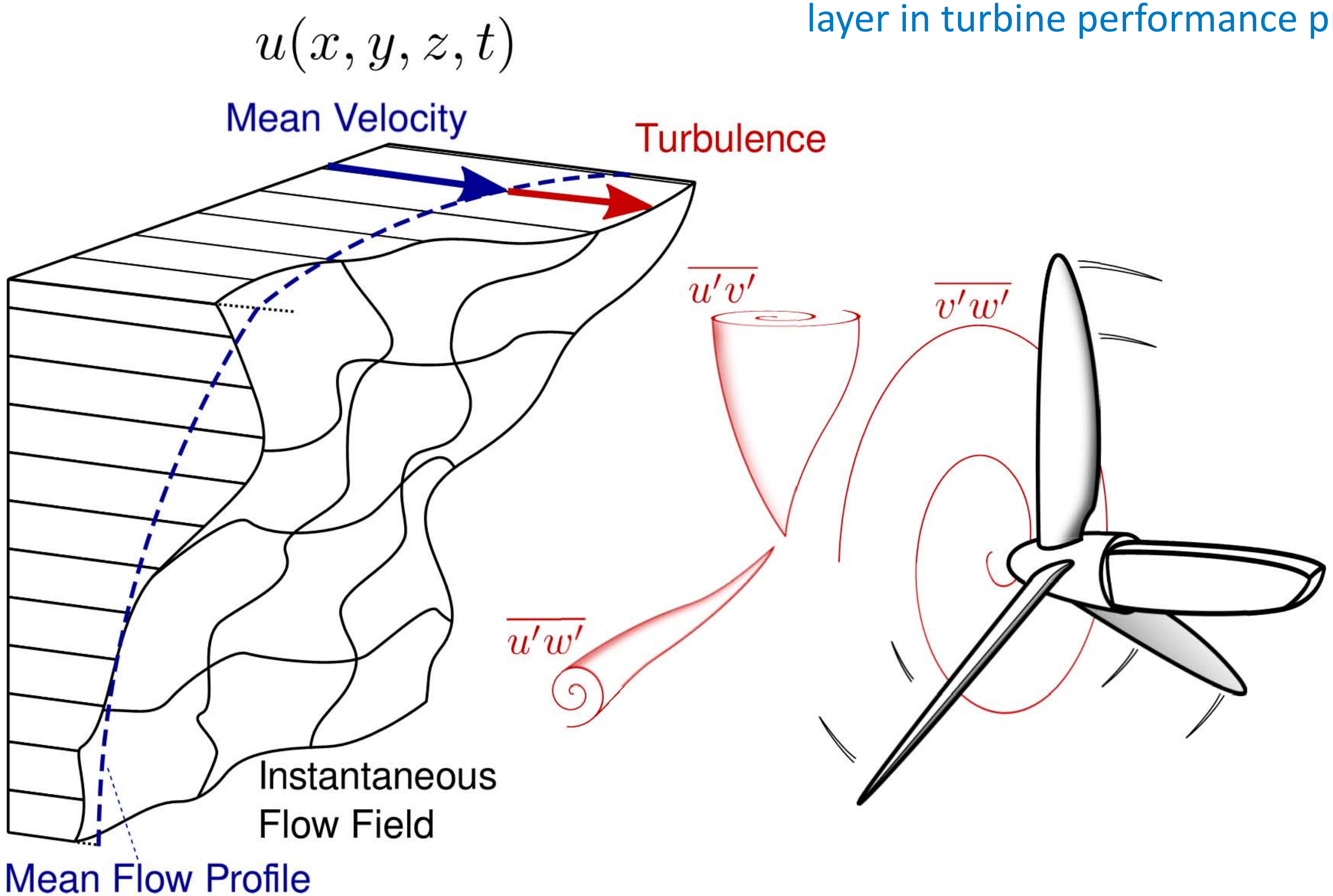
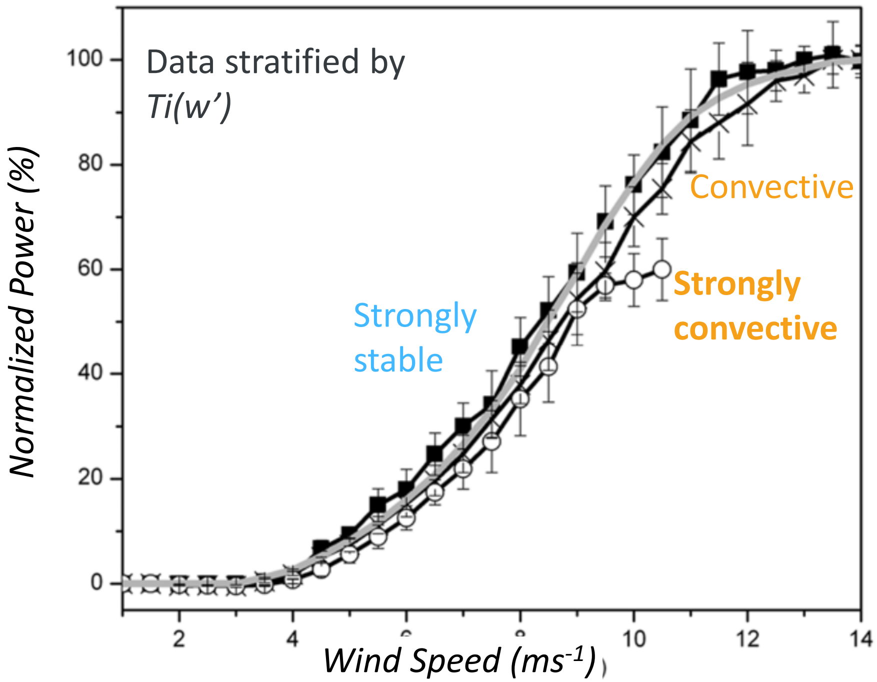


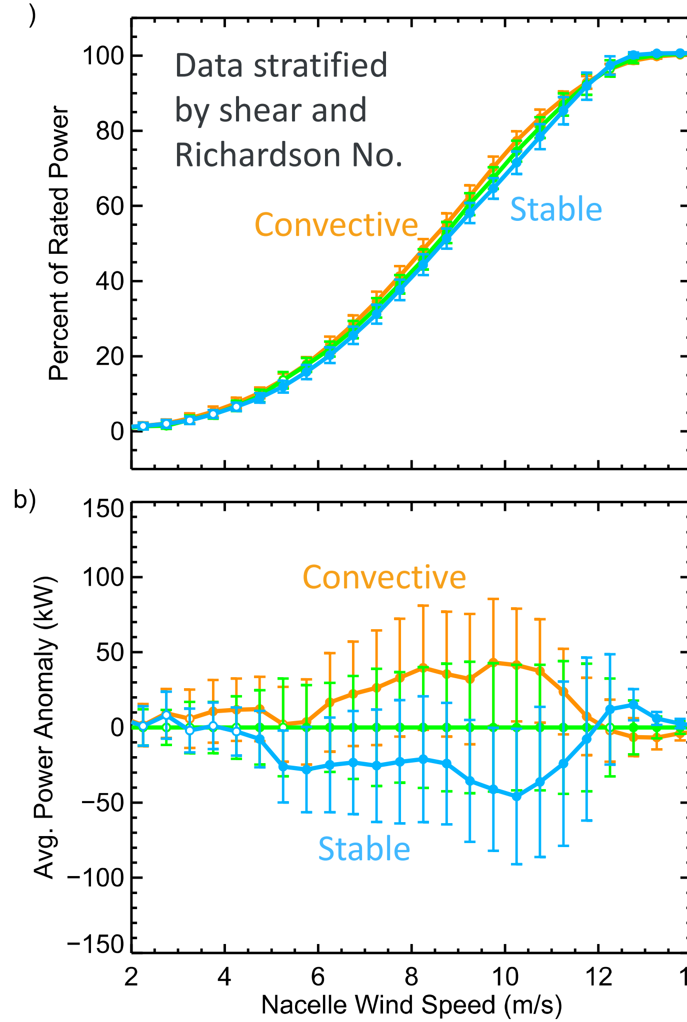
Illustration courtesy Levi Kilcher, NREL

Stability is just one part of the puzzle

There's no clear link between stability and power production.

Is it better to look at shear and turbulence?





S. Wharton and J. K. Lundquist, *Atmospheric stability affects wind turbine power collection*, Environmental Research Letters **7** (2012)

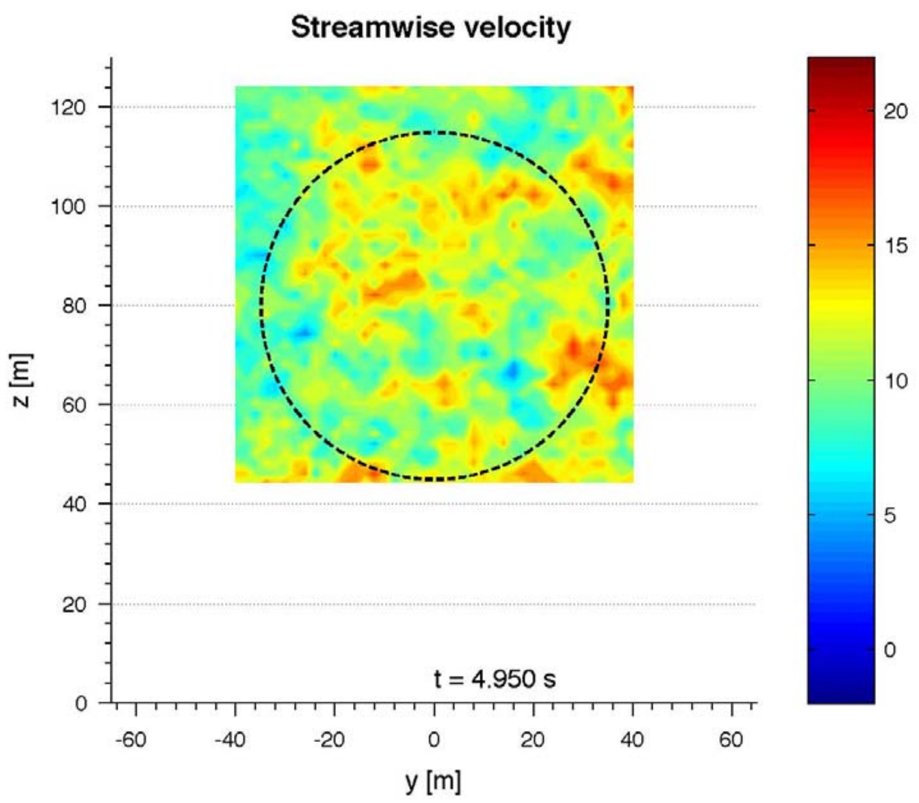
B. Vanderwende and J. K. Lundquist, *The modification of wind turbine performance by statistically distinct atmospheric regimes*, ERL **7** (2012)

Research question

- **How do we include the effect of shear and turbulence on the performance of a turbine? Do we**
  - Remove it – find a zero turbulence power curve?
  - Acknowledge it – provide power curves for different turbulence intensities and shear?
  - Embrace it – figure out ways to include more variables?

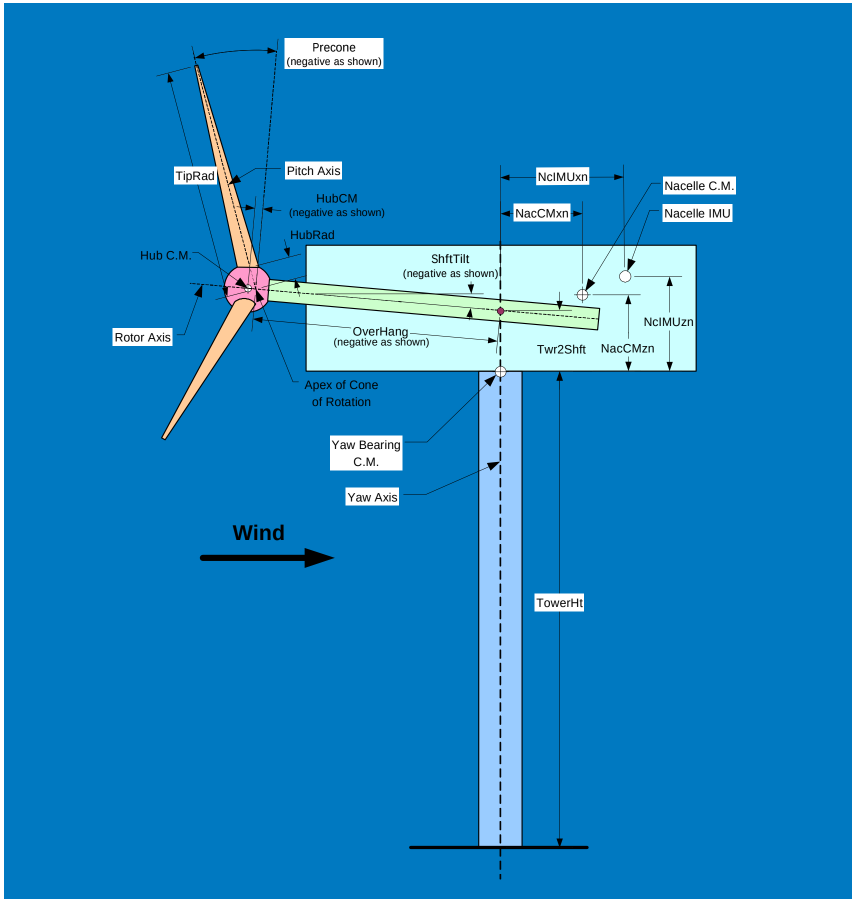
Tools for exploring turbine behaviour

TurbSim – flow simulator



http://wind.nrel.gov/designcodes/preprocessors/

FAST – turbine simulator

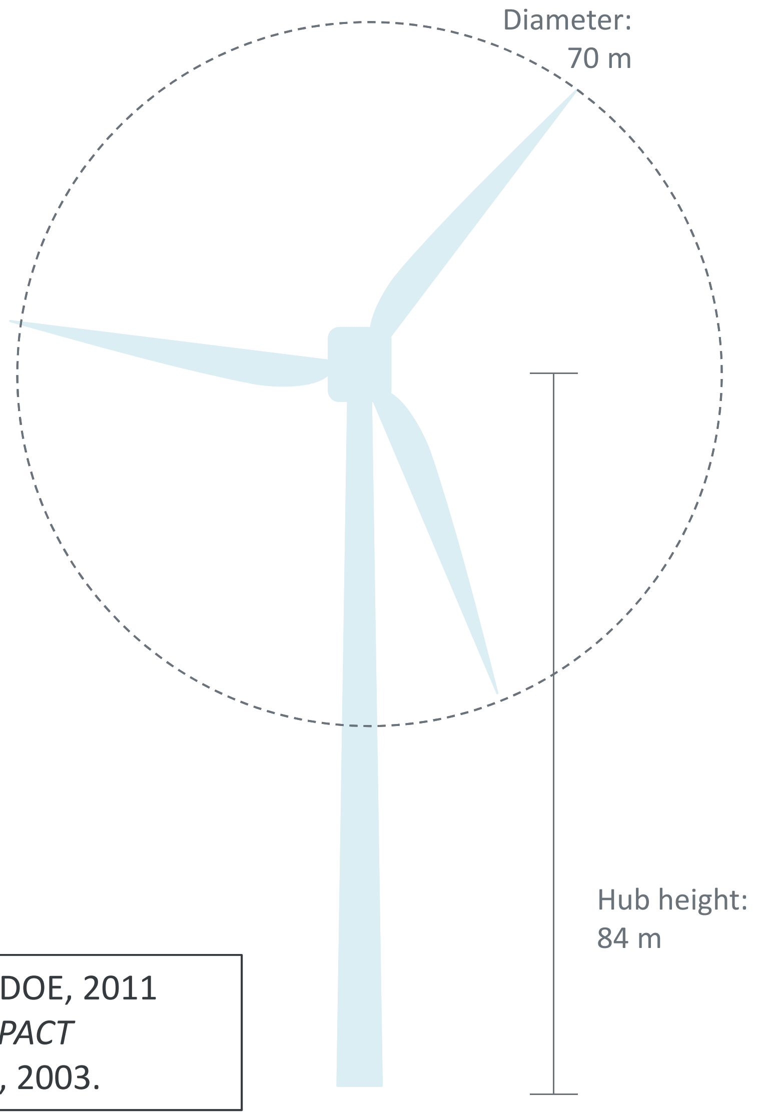


http://wind.nrel.gov/designcodes/simulators

The WindPACT 1.5MW baseline turbine

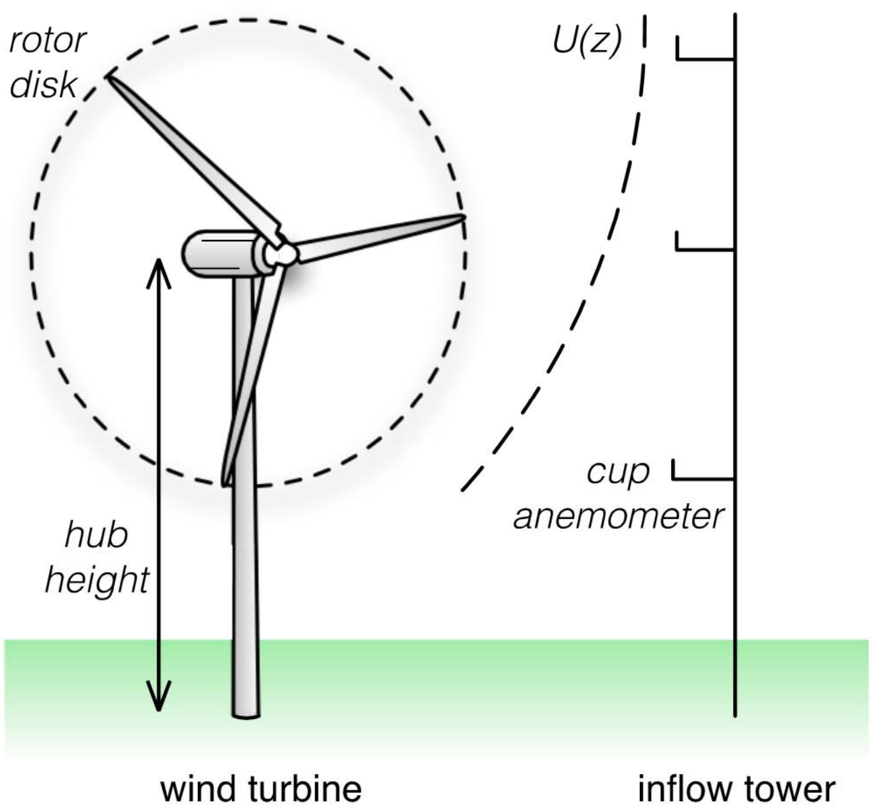
More than 50% of turbines installed in the USA from 2002-2011 were 1-2 MW[1]

Parameter	Value[2]
Hub height	84 m
Rotor diameter	70 m
Cut-in	3 m/s
Rated speed	11.5 m/s
Power power	1500 kW
Rated RPM	20.5 RPM
Cut-out	27.6 m/s



[1] R. Wiser and M. Bollinger, *2011 Wind technologies market report*, DOE, 2011
[2] R. Poore and T. Lettenmaier. *Alternative design study report: WindPACT advanced wind turbine drive train designs study*. SR-500-33196, NREL, 2003.

Simulating a power performance test



Forcing = log-law wind fields

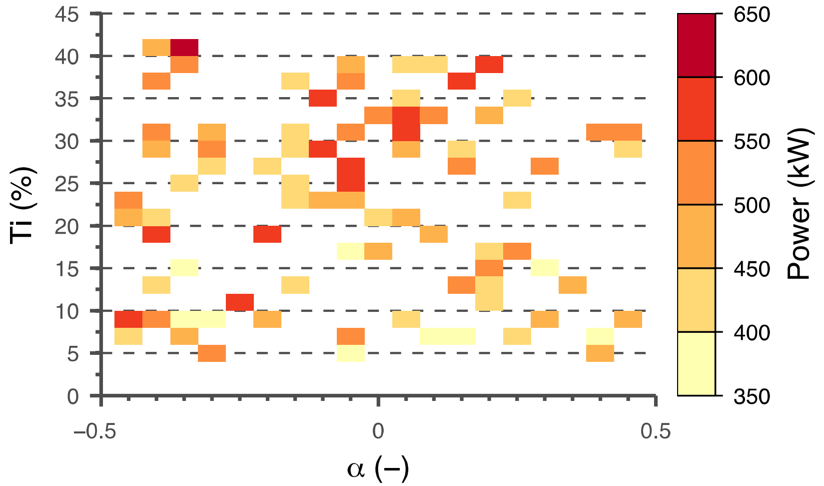
- Hub-height horizontal wind speed
  U = [3 … 25] ms^{-1}
  $$U = \overline{u}$$
- Hub-height turbulence intensity
  Ti = [5 … 40] %
  $$Ti = \frac{\sigma(u)}{U}$$
- Power-law speed profile shear exponent
  α = [-0.5 … 0.5]
  $$\frac{U_1}{U_2} = \left[\frac{z_1}{z_2}\right]^{\alpha}$$
- Constant density
  ρ = 1.225 kg m^{-3}

- **Output = 10-minute mean power**

$$P = f\left(U, \alpha, Ti\right)$$

Subsets of the data

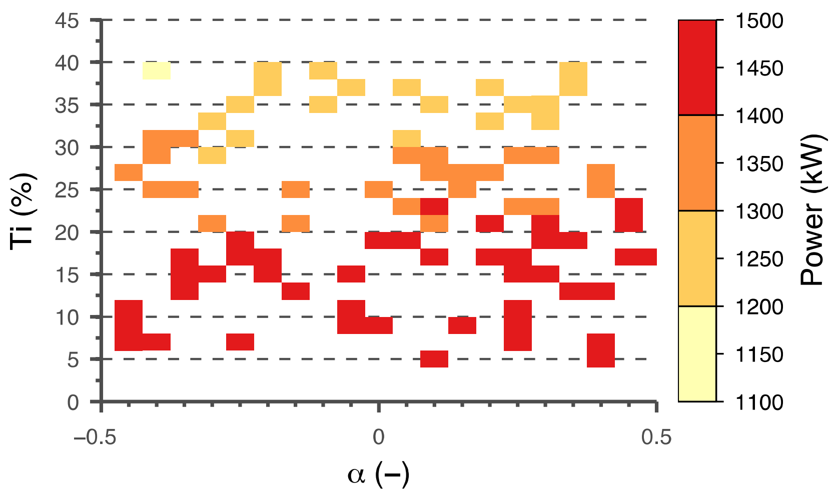
7-8 m s^{-1}



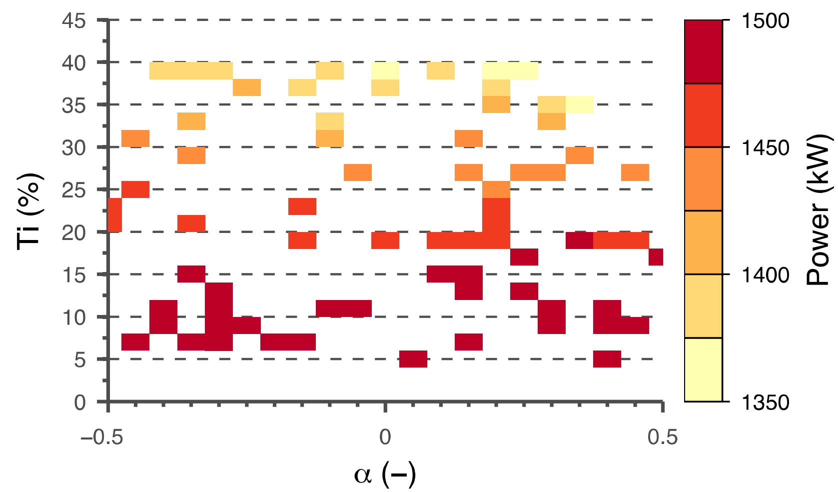
Power output depends on region

- Below rated (Region II, U < 11.5)
  - *Ti* increases power
  - Shear increases power
- Above rated (Region III)
  - *Ti* decreases power
  - Shear less important than *Ti*
- Is this actionable?

12-13 m s^{-1} (rated = 11.5 m s^{-1})



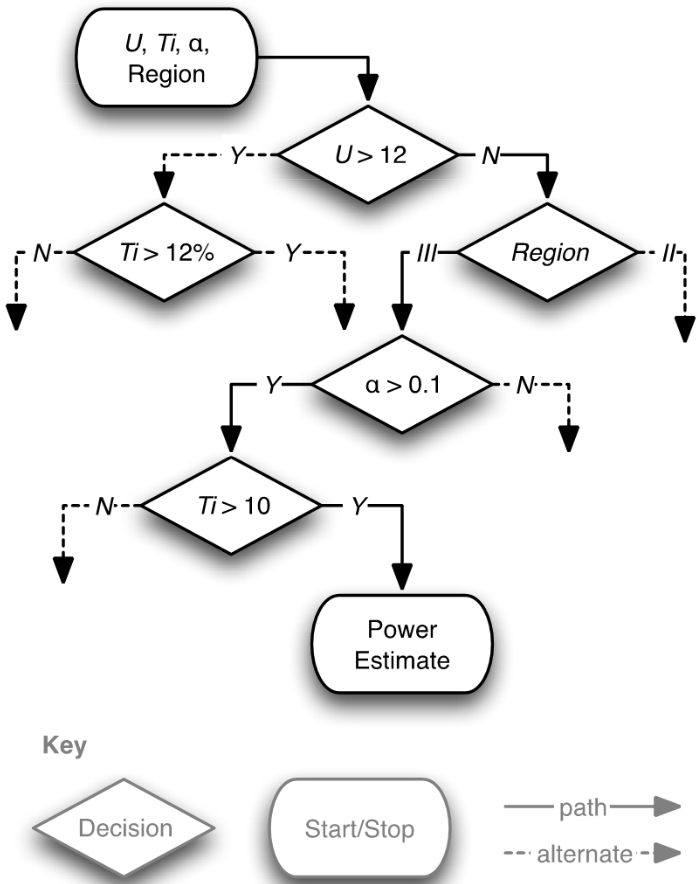
16-17 m s^{-1}



Modeling power output

- **Need continuous predictions of power**
- **Must be 'trainable' using observations**
  - o Simulations
  - o Field testing
- **Limited inputs**
  - o Wind speed & operating region
  - o Rotor-disk shear
  - o Turbulence intensity
- **One output**
  - o 10-minute power

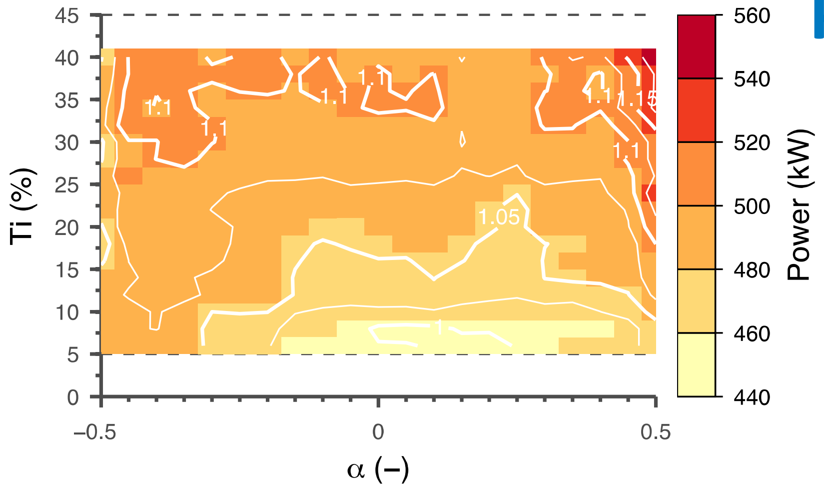
'Classification and Regression Tree'



One branch of a regression tree

Regression tree model results

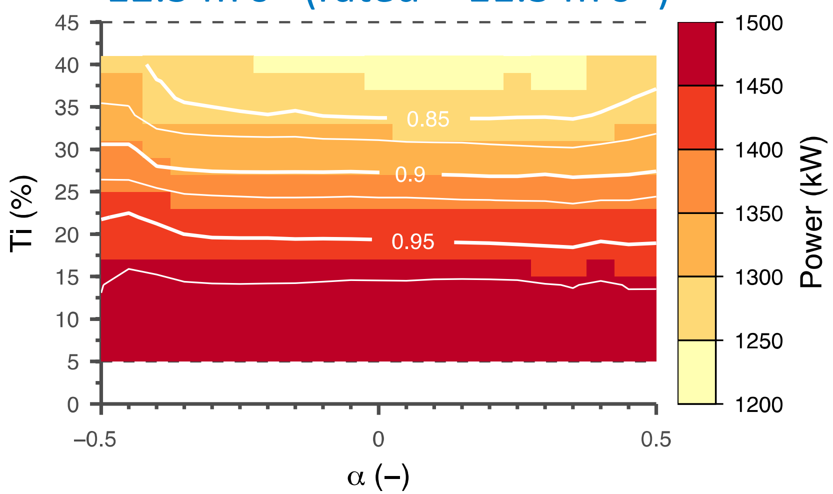
7.5 m s^{-1}



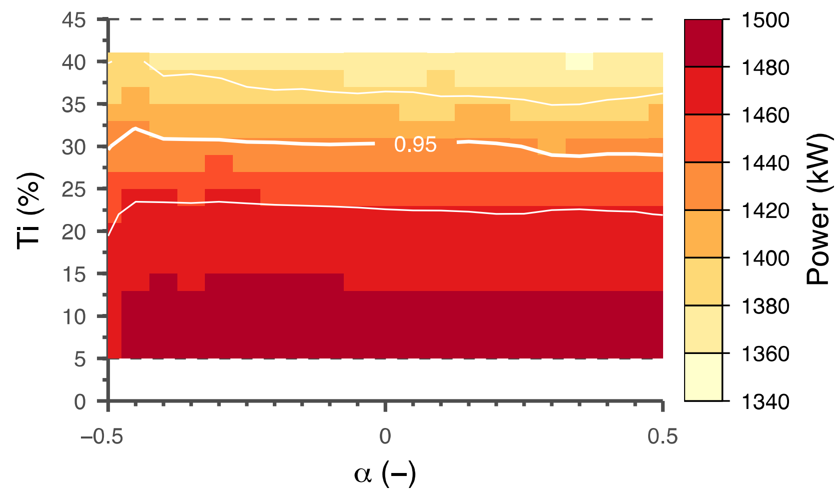
Power output is a function of region, Ti and shear

- What were the conditions where the turbine was tested?
- What are the conditions at the new site?

12.5 m s^{-1} (rated = 11.5 m s^{-1})



16.5 m s^{-1}

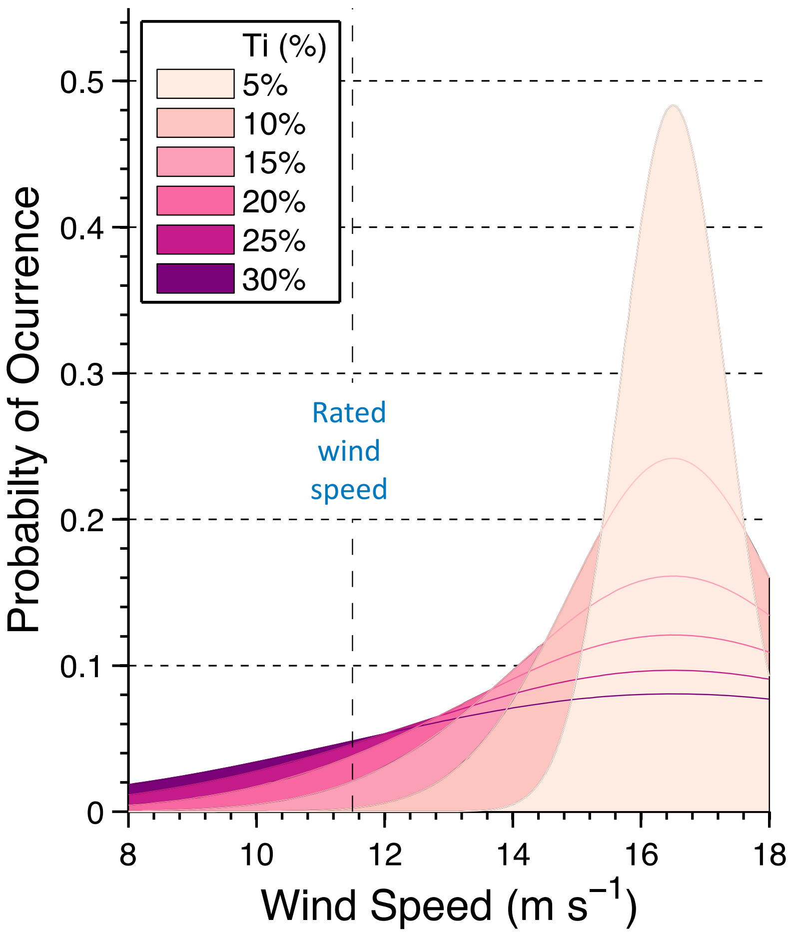


Contour lines show power normalized by zero-turbulence case

A note on high turbulence intensities

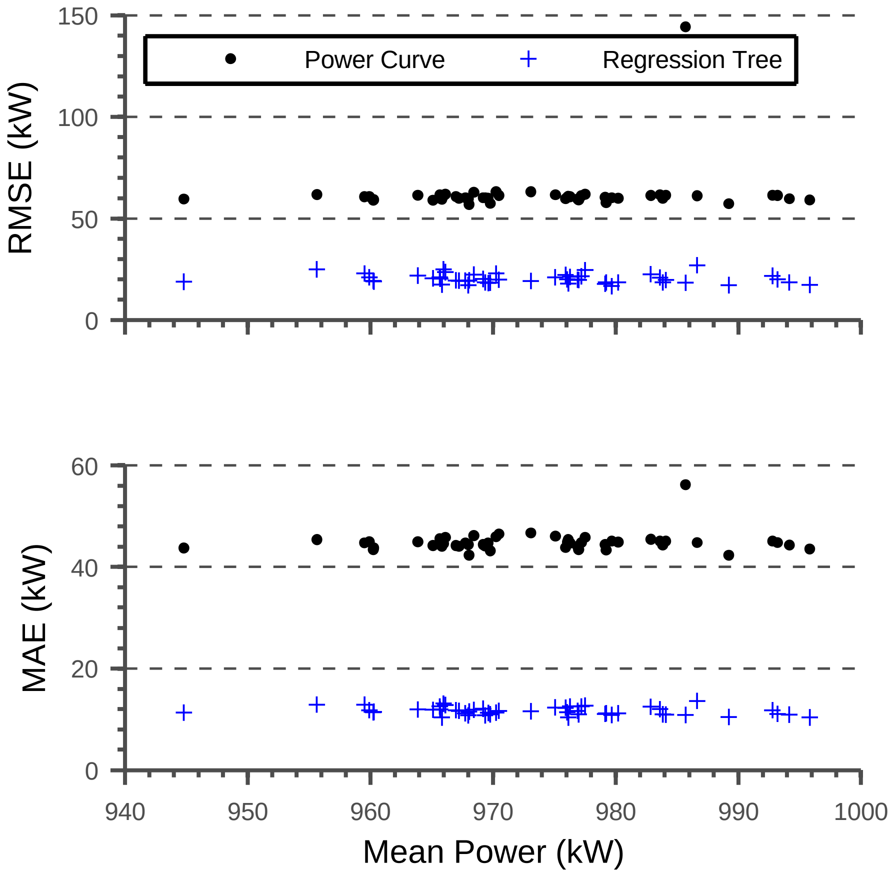
- **Assume u is normally distributed***
  - 15.8 % of observations will be less than U-σ(u)
  - 2.2 % of observations will be less than U-2σ(u)
  - All nicely defined by the normal distribution
- **Even at high mean wind speeds, wind speeds can be below rated if Ti is high enough**
  - Chance of wind speeds below rated if Ti > 10% at 16.5 m s^{-1}
  - Compare with plots of power versus shear and Ti on previous page

Wind speeds during a 10-minute interval
Mean wind speed = 16.5 m s^{-1}



*this is an approximation, used to show the possible effects of *Ti*

Higher-fidelity model is more accurate

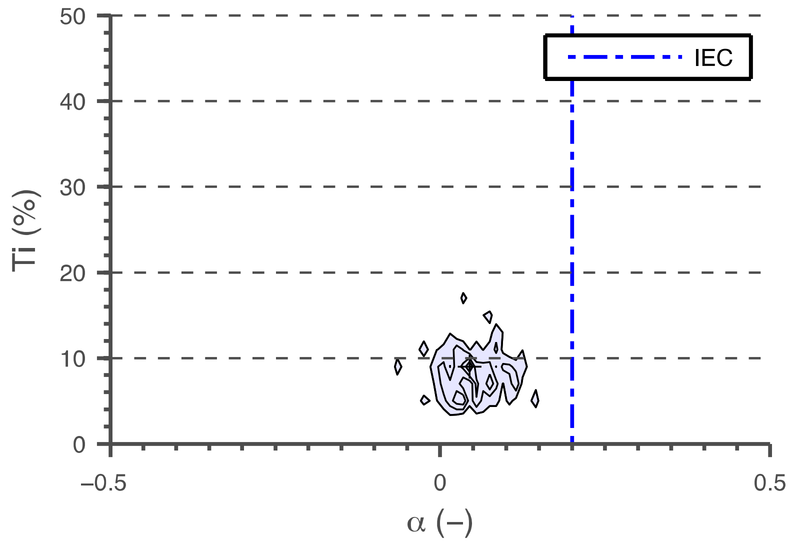


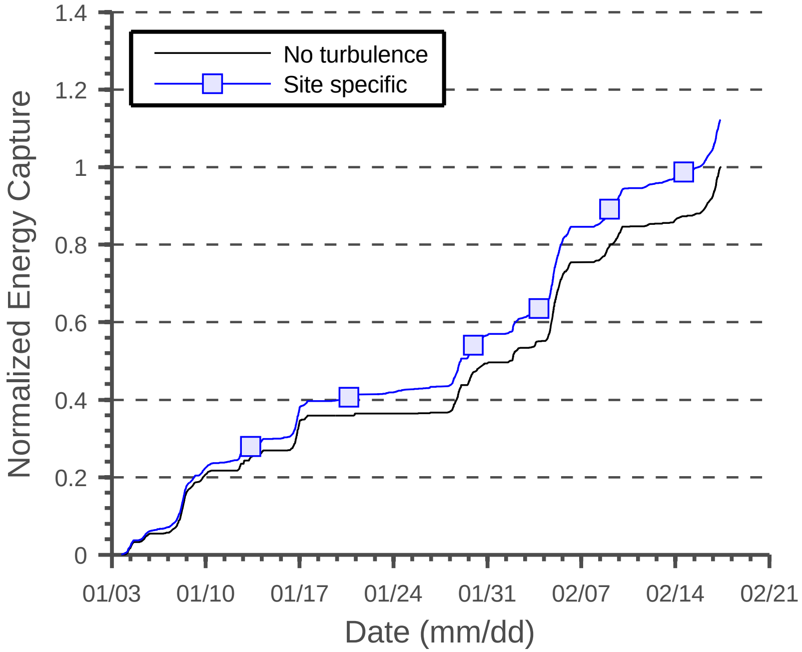
Randomly split simulations into training and test data sets

- 898 random data points each (50% of simulations)
- Predict 10-minute mean power
  - Power curve
  - Regression tree
- Quantify error
  - Root-mean-squared-error
  - Mean absolute error
- Repeat 50 times

Creating a site-specific power estimate

- **Use time series of wind speed, shear and Ti**
  - Plug numbers in to the regression tree
  - Get power estimate
  - Easy to do with a time series…
  - …needs some thought on how to do it with a wind rose.





Plots are preliminary and for illustration only. From: Clifton, A., Daniels, M. H., and Lehning, M. *Causes of mountain pass winds and their effects on wind turbines.* Wind Energy. In revision, 2/2013

What I learned about Machine-Learning

Pros

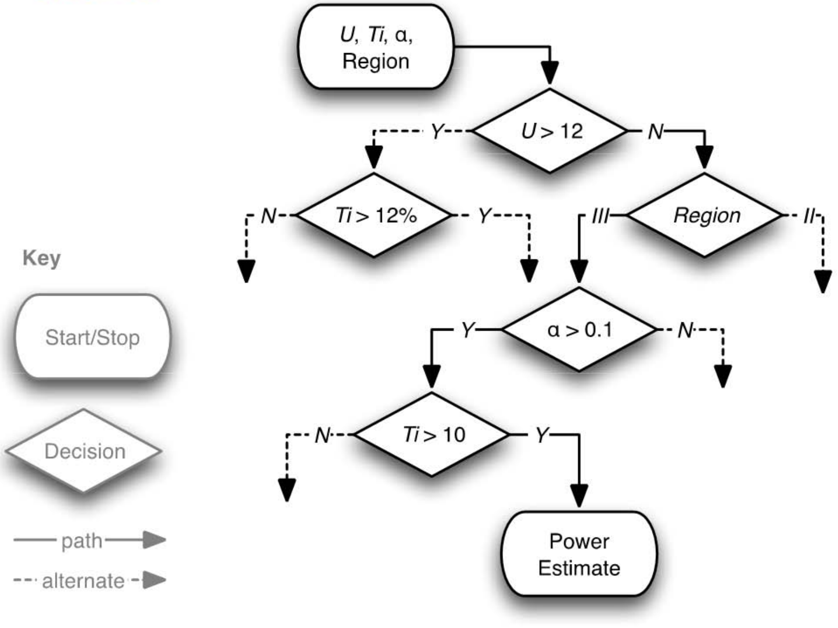
- Doesn’t require you to know all of the physics
- Lets you use a lot more of the data you have
  - Wind speed, shear, Ti, region
  - Could add veer
  - Could divide shear into top and bottom of rotor
  - Could use rotor-equivalent wind speed
- Can be very fast
- Can give you site-specific power estimate

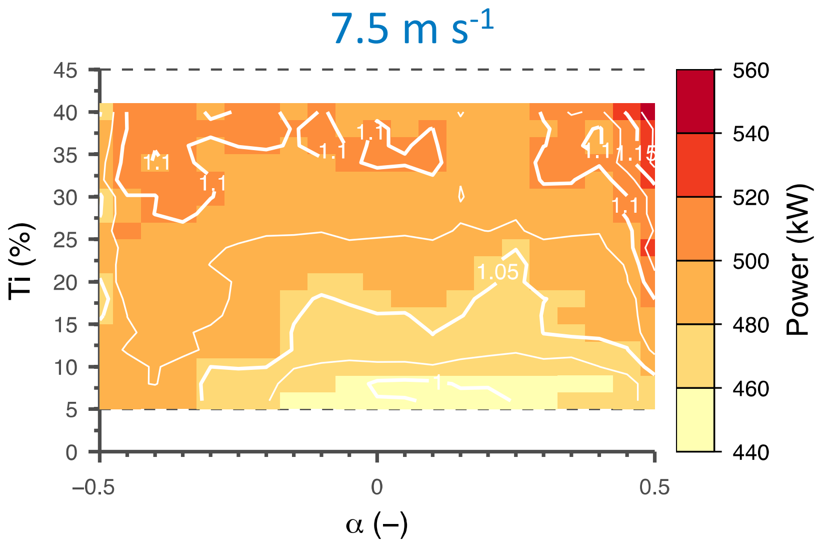
Cons

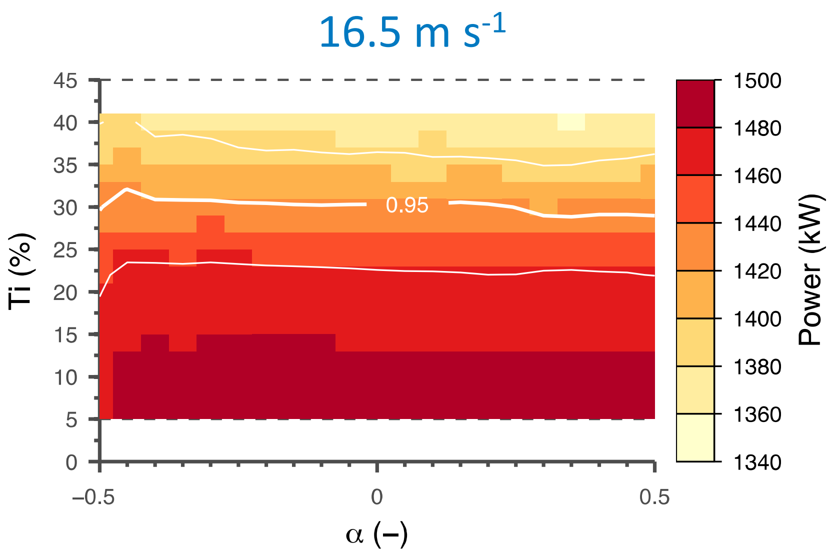
- Needs a good data set to train the model
- Training conditions should bracket site conditions

Conclusion: multivariate power curves are possible

- **Simulations show strong sensitivity to *Ti***
- **Regression trees offer lower error**
- **Needs testing with more data**







References

Clifton, A., Kilcher, L., Lundquist, J., and Fleming, P.
Using machine learning to predict wind turbine power output.
Environmental Research Letters. Accepted 3/2013

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Causes of mountain pass winds and their effects on wind turbines.
Wind Energy. In revision.