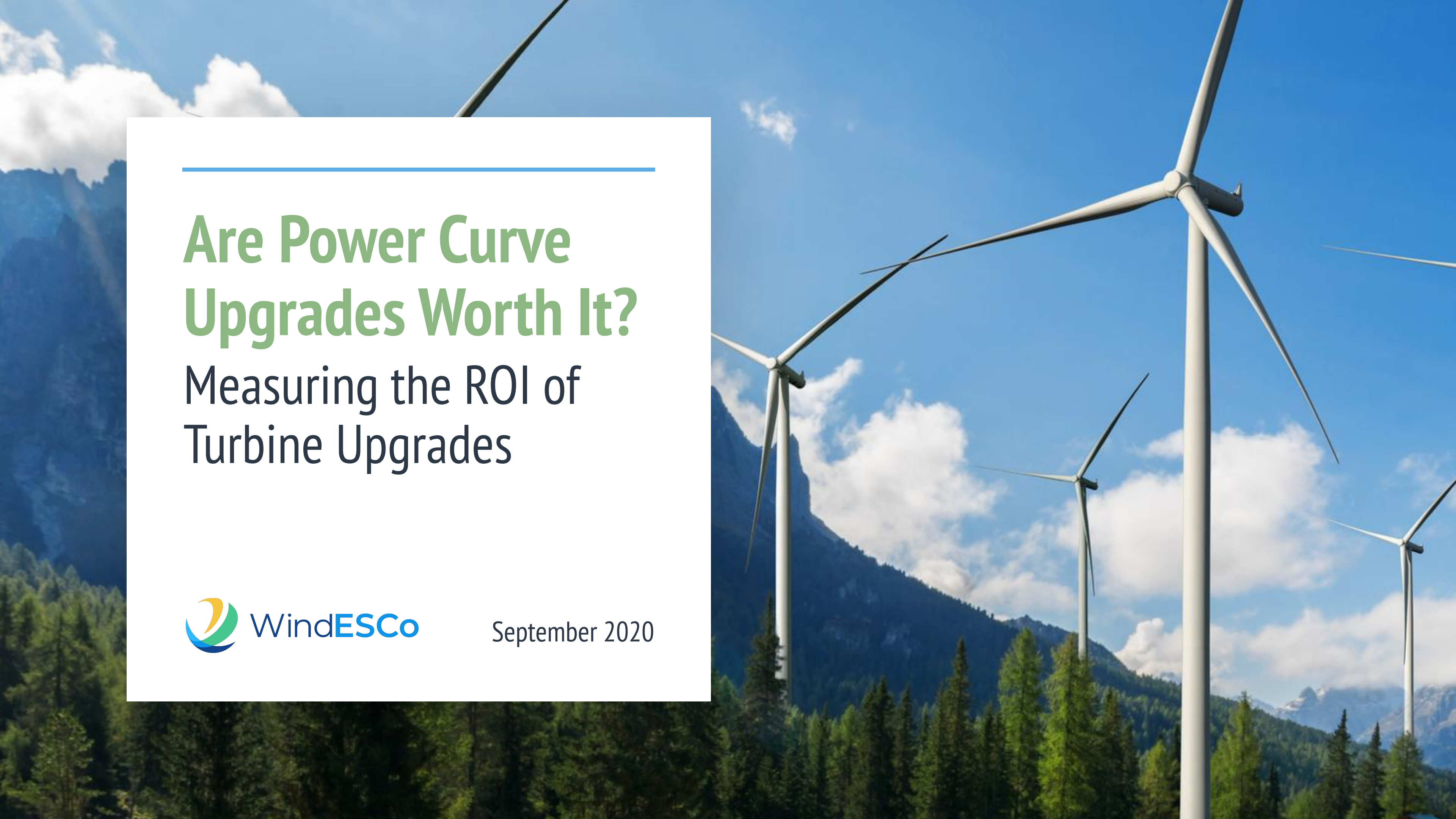

Are Power Curve Upgrades Worth It?

Measuring the ROI of Turbine Upgrades

WindESCo

September 2020

WindESCo

Upgrading Your Turbines for Better Performance

You want your plant operating as efficiently as possible. There are many types of upgrades available that will impact your AEP:

OEM Upgrades

- PowerUp by GE
- PowerPlus by Vestas
- Energy Thrust by SGRE

Blade Add-Ons

- Vortex generators
- Gurney flaps
- Leading edge protection

Software & Controller Upgrades

- OEM software upgrades
- Parameter changes
- Controller upgrades

All of these available upgrades have the same goal: **increased energy production**. Unfortunately, the business evaluation for such features can be complicated to manage.

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You Can't Manage What You Don't Measure

Accurate measurement is the most critical part of making turbine upgrades. Unfortunately, it has been historically difficult to find a measurement method that works.

The Problem

01 No standardized energy improvement methodology means everyone gets different results

02 Providers, owners, and independent consultants all get different results

03 Margin of error too high so you can't detect small changes

Challenges of Measurement

With so many options for turbine upgrades, we need to measure their effectiveness—but simply comparing output before and after upgrades is not an effective assessment method. Wind is complex, which makes changes difficult to measure:

01 Turbine output is affected by many factors:

- Wind speed
- Wind direction
- Wind flow characteristics
- Turbine state
- Number and position of operational neighboring turbines

02 Relationships of variables with turbine output are complex and not always well-defined

03 Continuously varying conditions

Therefore, we need an analysis approach that can evaluate change in performance while accounting for differences in conditions from one period to the next.

Elements of an Effective Energy Improvement Assessment

Cost-Effective

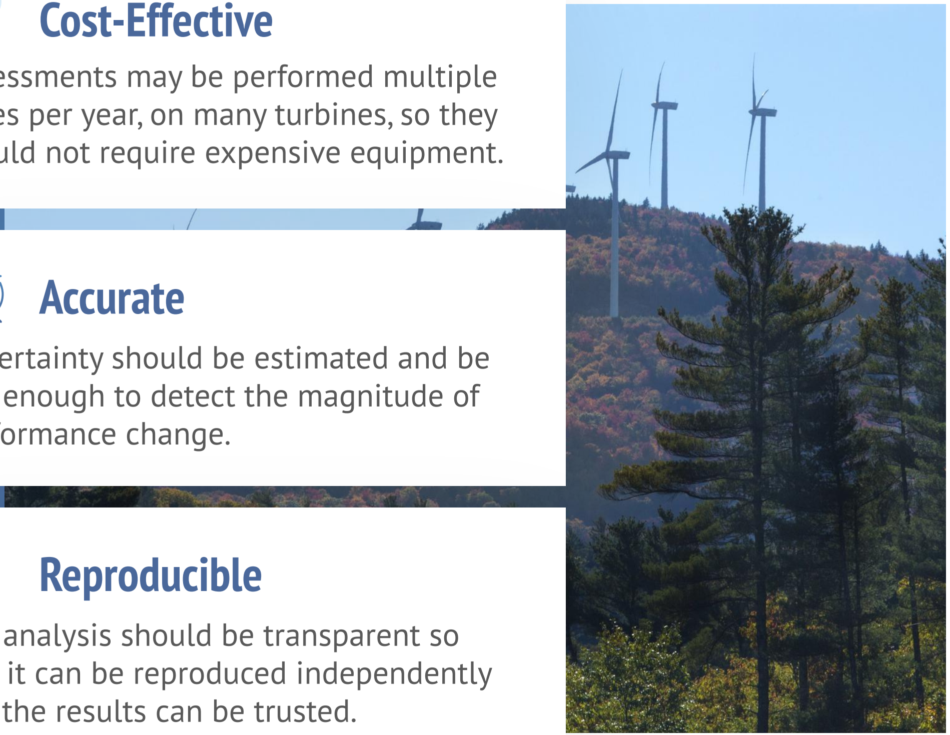
Assessments may be performed multiple times per year, on many turbines, so they should not require expensive equipment.

Accurate

Uncertainty should be estimated and be low enough to detect the magnitude of performance change.

Reproducible

The analysis should be transparent so that it can be reproduced independently and the results can be trusted.



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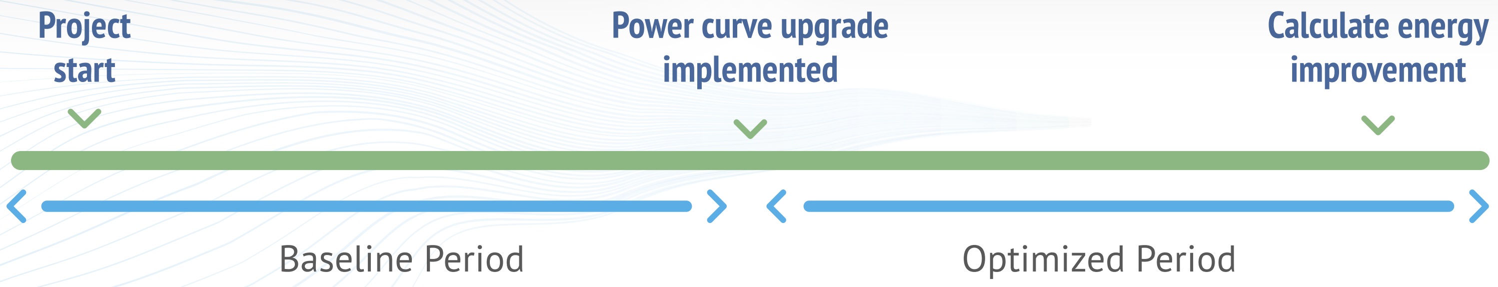
Baseline and Optimized Periods

Baseline Period:

In order to see if a turbine changed, we first need to collect a dataset to evaluate the turbine performance prior to the change being implemented. This is the **baseline period**.

Optimized Period:

A change is implemented, after which we continue to record data for a second period of time. We call this the **optimized period**. At the end of this time, we will assess the energy improvement.



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Common Approaches for Energy Improvement Assessment

01 Nacelle Power Curves

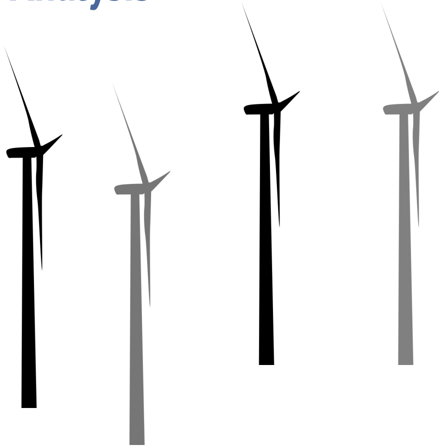
Nacelle anemometer

02 Hardware-Based Power Curves

Met tower, LiDAR

03 SCADA Data-Based Side-by-Side Analysis

Test and Control turbines



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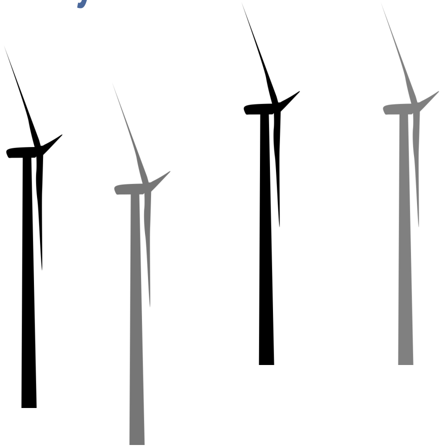

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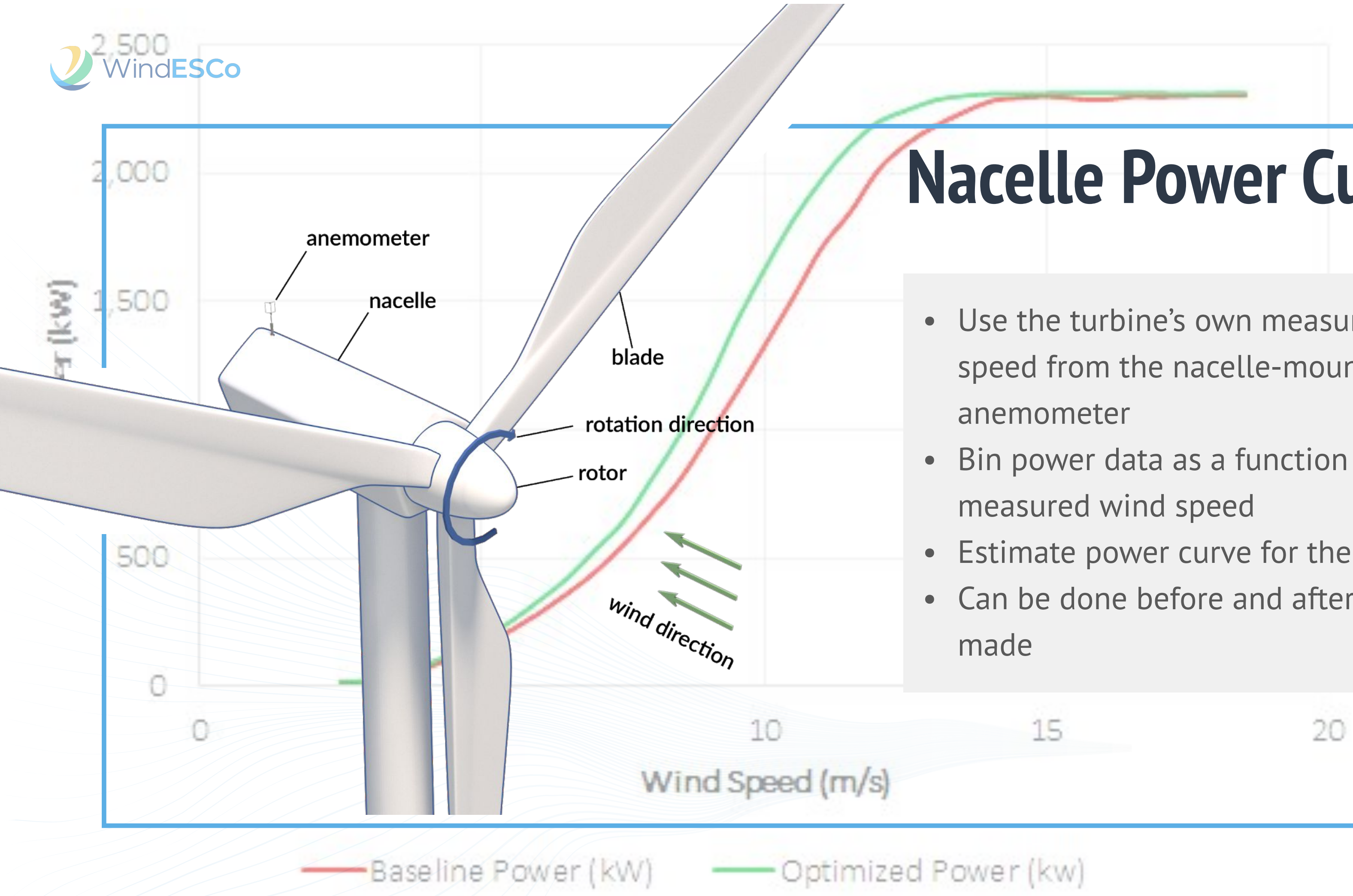
Nacelle Power Curves



- Use the turbine’s own measurement of wind speed from the nacelle-mounted anemometer
- Bin power data as a function of the measured wind speed
- Estimate power curve for the turbine
- Can be done before and after a change is made

✔ PROS

- Simplest approach
- No additional equipment or hardware required
- Requires only one turbine and data that is already being collected

✖ CONS

- Change in performance leads to change in the flow behind the rotor—where the nacelle anemometer sits
- Anemometer measures wind speed ad a single point, so it cannot measure turbulence intensity, shear, veer, etc.
- If wind conditions are different in baseline and optimized periods, nacelle power curves are not comparable

Conclusion:

Using a nacelle power curve, we may be able to detect if something changes, but we will not be able to accurately determine the magnitude of the change—or even whether the turbine performance got better or worse.

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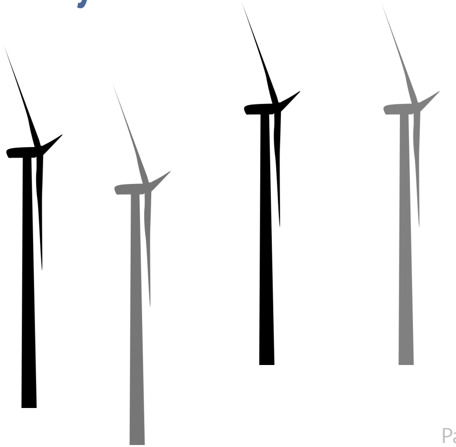

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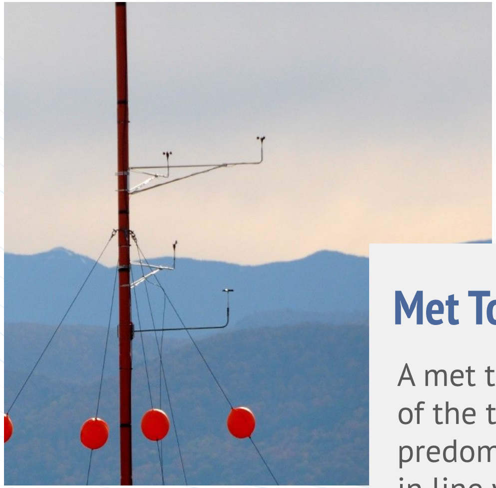
Hardware-Based Methods



Source: NRG Systems

Met Tower

A met tower is installed upwind of the turbine in the predominant wind direction or in line with a row of turbines. Care needs to be taken to filter out only data where both the met tower and the turbine are not impacted by wakes of other turbines or obstructions.

LiDAR

LiDAR systems can be ground-based and provide data similar to the met tower, or they can be nacelle-mounted and always measure the wind speed upwind of the turbine regardless of the wind direction.

Source: Windar Photonics

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PROS

- Continuous monitoring of wind flow characteristics upwind of turbine
- Some ability to measure wind shear and veer

CONS

- Measure wind at a distance from the rotor, making them unable to capture all the characteristics of the wind
- Very expensive
- Time-consuming
- High uncertainty
- Requires periodic maintenance

Conclusion:

Hardware-based methods address some of the problems with nacelle power curves, but they do not meet our criteria of being reliable, cost-effective, and reproducible. They are useful for R&D, but not as a scalable option.

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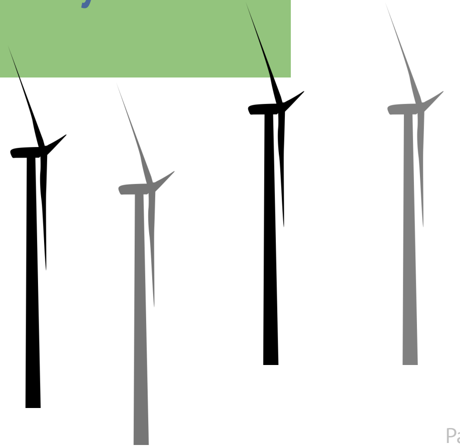
Test and Control turbines



SCADA Data-Based Approaches

The most reliable signal available is the behavior of neighboring unchanged (control) turbines, which can be measured with existing SCADA data.

Let's test available SCADA-based approaches with a sample dataset.

Mean power ratio	01
Power ratio binned by power	02
Power delta binned by power	03
Power delta binned by power and wind direction	04
Machine learning	05

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Validation Case

Test 1: Null Hypothesis

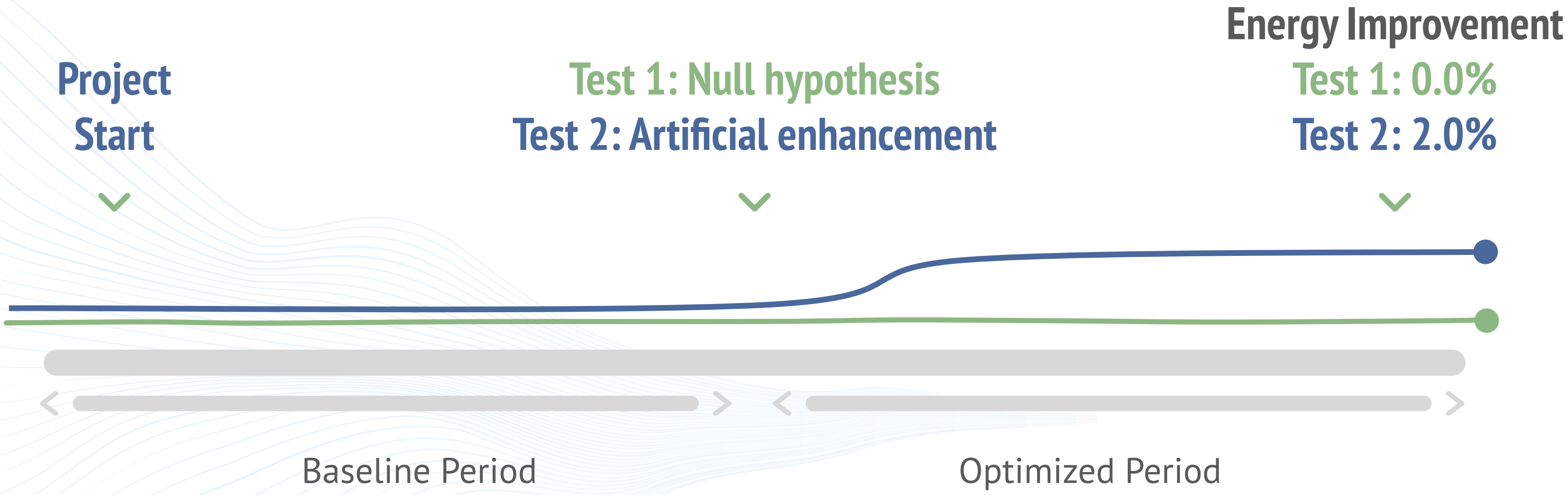
We set up a validation case using a dataset where no turbines were modified. We expect that if we split the data into baseline and optimized periods, the performance should be the same in both.

Test 2: Artificial Enhancement

After the initial test, we applied an artificial enhancement to the test turbine power signals so we could compute the exact energy added, and then test the ability of each method to measure this enhancement, which came out to 2%.

Validation Case

Test 1: Null Hypothesis   Test 2: Artificial Enhancement



Validation Dataset

Dataset description: **12 turbines** from a row in a **145 MW** plant.

- 4 turbines used as test turbines.
- 5 turbines used as control turbines.
- 3 turbines excluded from the row due to significant downtime.

Data period
7 months

Baseline period
4.5 months

Optimized period
2.5 months

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Method 1:
Power Ratio

First, we'll try averaging the power for test and control turbines at each point in time and calculate their ratio.

$$\left(\frac{P_{\text{test}}}{P_{\text{control}}}\right)_{\text{optimized}} \Big/ \left(\frac{P_{\text{test}}}{P_{\text{control}}}\right)_{\text{baseline}}$$

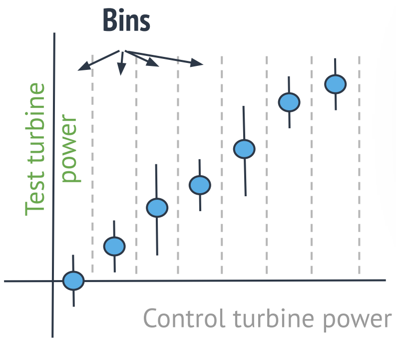
Test	Expected Result	Actual Result
Null Hypothesis	0%	−2.1%±0.5%
Artificial Enhancement	2%	−0.3%±0.5%

Conclusion:

Power ratio fails to capture changes in ambient conditions that make it look like the test turbines underperformed. This is not captured in the uncertainty.

Method 2:
Binning by Power

Next, we'll look at this ratio in bins of the control turbine power. This will give us some degree of resolution to account for times when both test and control turbines are at rated power.



Test	Expected Result	Actual Result Binned Power Ratio	Actual Result Binned Power Delta
Null Hypothesis	0%	−1.5%±0.4%	−1.6%±0.4%
Artificial Enhancement	2%	−0.5%±0.4%	−0.3%±0.4%

Conclusion:

We've reduced uncertainty, but still fail to predict the correct results.

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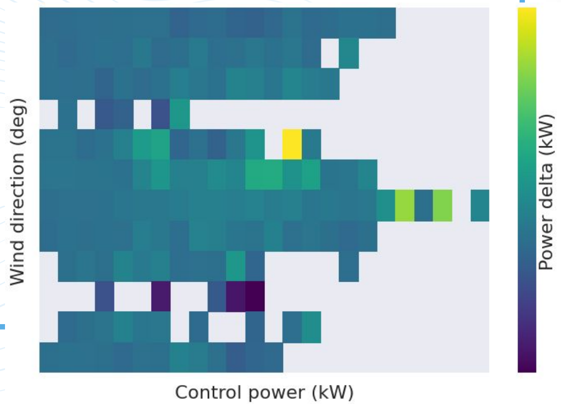
Method 3:
Binning by Power and Wind Direction

We can try including more independent variables, but this increases the number of bins, reducing the number of data points in each bin. This is called **the curse of dimensionality**.



Test	Expected Result	Actual Result
Null Hypothesis	0%	−2.1%±0.4%
Artificial Enhancement	2%	−0.2%±0.4%

Conclusion:

Even with added feature dimensions, the binned approach fails to capture the correct result and retains high uncertainty.

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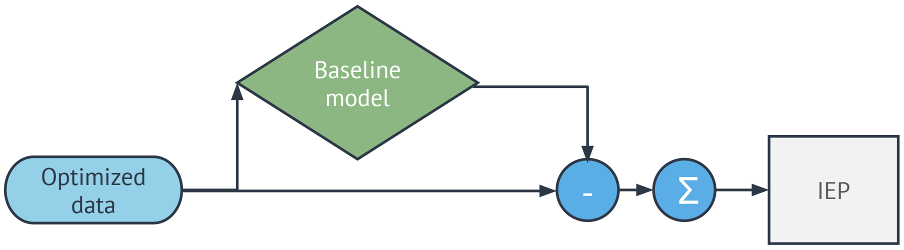
Method 4:
Machine Learning

Finally, we'll try using machine learning to model the relationship between test and control turbine behavior.

When we build one of these models and apply it to our validation case, we are able to successfully calculate both the null hypothesis and artificial enhancement, with uncertainties half that of the binning approaches.



Test	Expected Result	Actual Result
Null Hypothesis	0%	0.0%±0.2%
Artificial Enhancement	2%	2.0%±0.2%

Conclusion:

The machine learning model was able to accurately predict the behavior of the farm with the lowest uncertainty of all methods.

Summary of Results

Method	Null Hypothesis Expected result = 0%	Artificial Enhancement Expected result = 2%
Mean power ratio	−2.2%±0.5%	−0.3%±0.5%
Power ratio binned by power	−1.5%±0.4%	0.5%±0.4%
Power delta binned by power	−1.6%±0.4%	0.3%±0.4%
Power delta binned by power and wind direction	−2.1%±0.4%	−0.2%±0.4%
Machine learning	**0.0%±0.2%**	**2.0%±0.2%**

Conclusion:

A machine learning algorithm can accurately predict the power production of the test turbines as a function of the control turbines accounting for variation in ambient conditions—providing an accurate improvement measurement.

A word of caution

Machine learning can be a powerful tool for assessing the energy improvement from wind turbine upgrades.

However, a model applied incorrectly will produce an incorrect result, so wind domain expertise is critical.

WindESCo assists our customers by performing this analysis in a transparent way so that they can be confident in the results.

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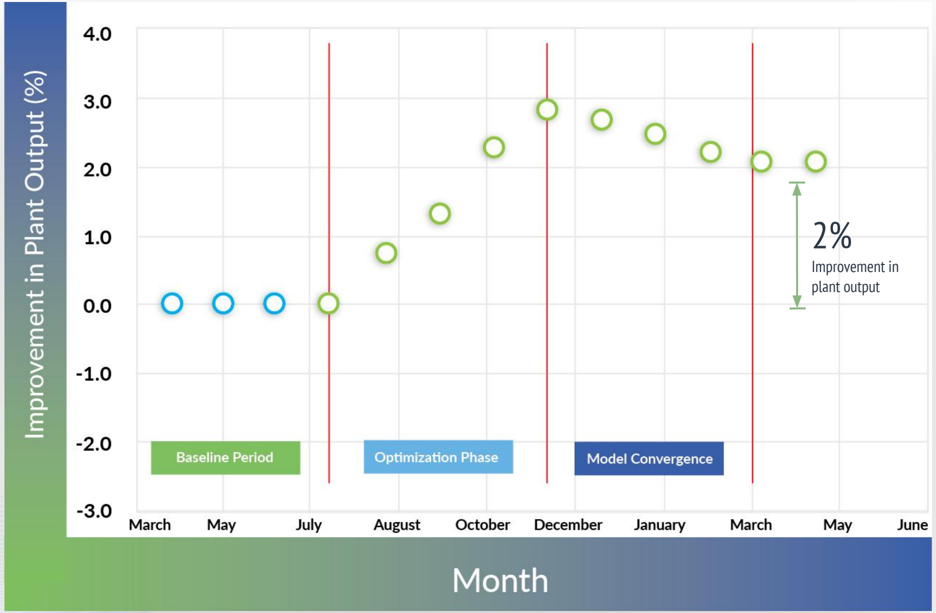
WeBoost Basic Case Study

Increase in energy	2%
Revenue Increase	$450,000 /Yr
Revenue Increase	$5,700 /MW/Yr



www.windesco.com/wind-plant-increases-yearly-revenue-by-5700-mw

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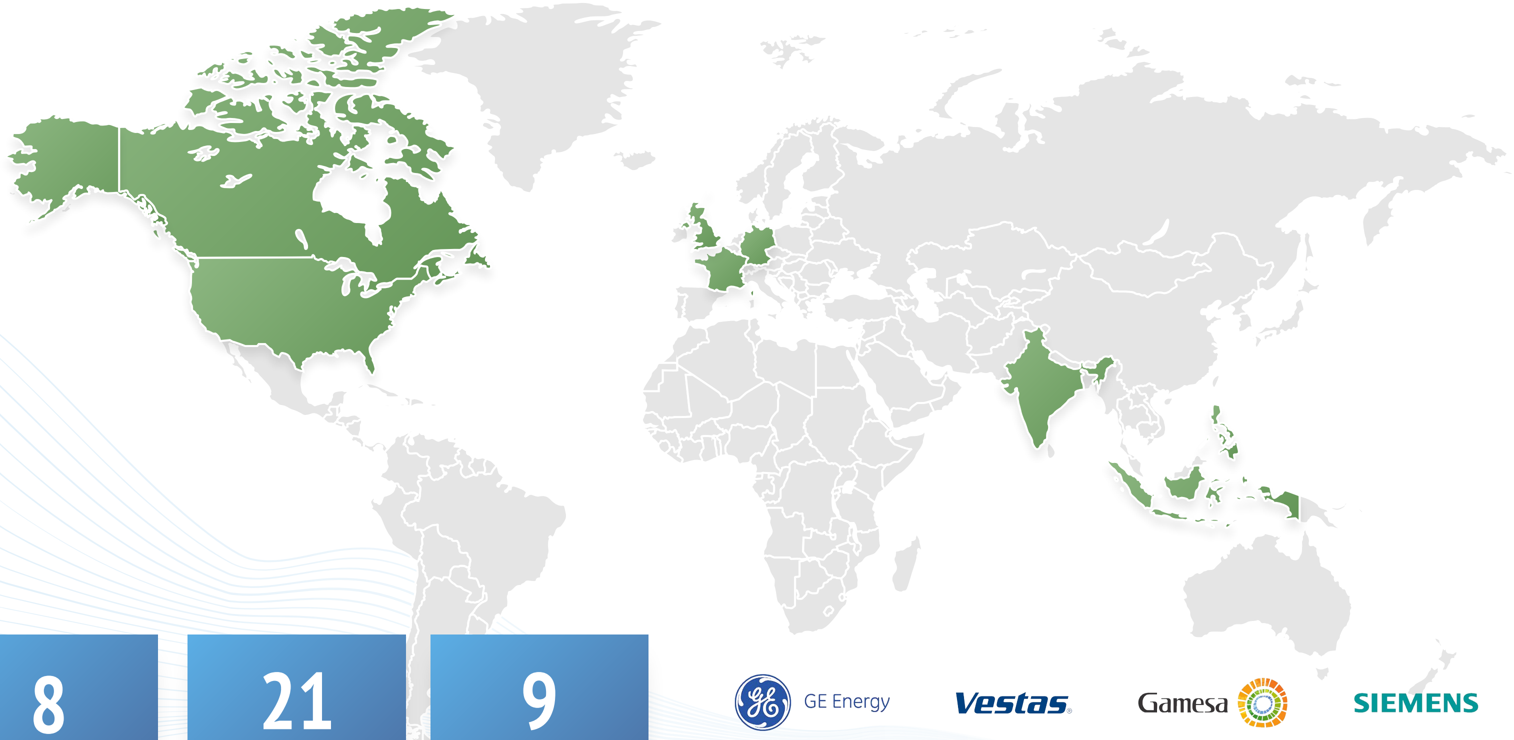

8
Country

21
Customers

9
OEMs

GE Energy
Vestas
Gamesa
SIEMENS
SUZLON POWERING A GREENER TOMORROW
NORDEX
SENVION wind energy solutions
Clipper
MITSUBISHI

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longroad ENERGY

Acknowledgements

Thanks to our customer Longroad Energy for allowing us to use their wind plant data for the example analysis.

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Watch the Webinar

Want to hear more from the experts at WindESCo? Access the webinar recording:

- ✓ Recording: Are Power Curve Upgrades Worth It?

Additional resources:

- ✓ Wind Ed
- ✓ Case study: Increase your wind plant revenue

How to contact us

Sam Tasker,
VP North America Sales
617-510-0816
sam@windesco.com

www.windesco.com