

Data-driven characterization of performance trends in ageing wind turbines

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Context

- Ageing wind turbines can experience **performance decay** (e.g. due to wear) or **improvement** (e.g. due to control optimization)
 - Performance is influenced by multiple factors:
 - ageing
 - maintenance
 - operative mode
 - environmental conditions
 - seasonality
- } Factors not influencing long-term performance



Motivation and Goal

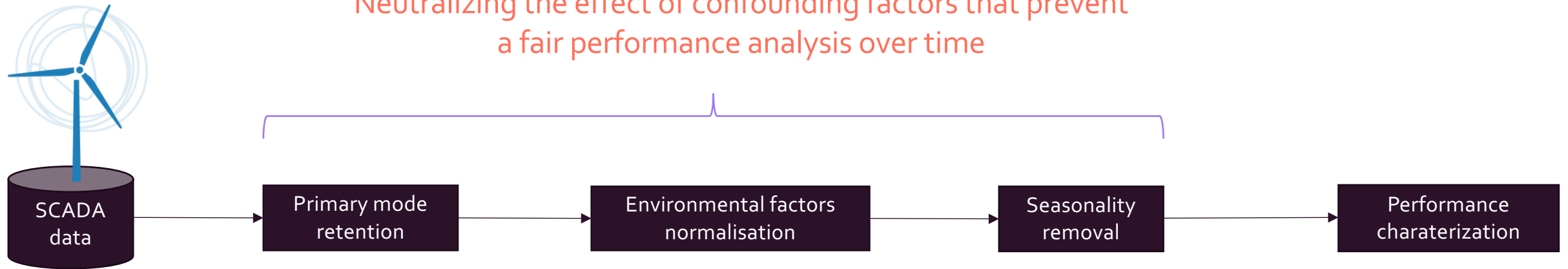
- Monitoring and quantifying the **long-term performance** is required to evaluate the return on investment
 - ➔ Isolating the impact of **ageing** on turbine performance is fundamental to make informed decision on turbine lifetime extension
- Due to the complex dynamics in which the turbine operates, there is no knowledge-based model able to describe the effect of ageing on performance
 - ➔ data-driven model are a viable solution for analyzing the aging effect

Goal: Develop a data-driven model to characterize the performance trend of a turbine **due to aging**

Methodology

Workflow

Neutralizing the effect of confounding factors that prevent
a fair performance analysis over time



Primary mode retention

Turbines can operate in multiple operating modes

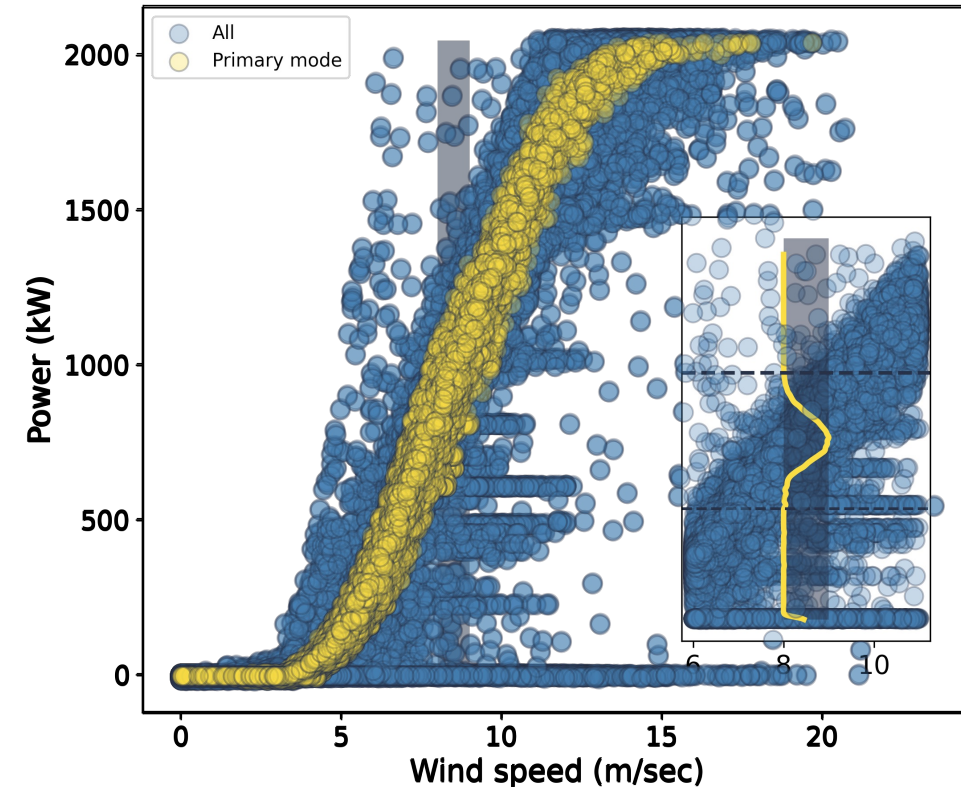
- Primary mode: the turbine can extract the maximum possible energy
- Secondary modes: the turbine extracts energy in a suboptimal way (e.g. due to curtailment, failures)

→ The operating mode needs to be fixed to analyze performance trend

The operating mode is often not recorded by the SCADA system

Goal: Filter raw sensor data to retain only data points in the primary mode

Power curve



Environmental factors normalization

To evaluate a turbine's performance, the following factors need to be considered:

- active power
- environmental conditions

Once the environmental conditions are fixed, the turbine performance is described as **efficiency**:

$$efficiency = \frac{actual\ active\ power}{expected\ active\ power}$$

The expected active power is computed using a machine learning model

Goal: Factor out environmental factors from turbine performance

Seasonality removal

Turbine performance can present a seasonal variability:

- Not all seasonal factors are known or tracked (e.g. icing)

Seasonality is removed via two state-of-the-art methods:

- Year-over-Year degradation detection (YoY) [1]
- Seasonal and Trend decomposition using Loess (STL) [2]

Goal: Factor out the seasonal component from turbine performance



Picture taken from: The conceptual design of a safety system: For the 5MW Deepwind offshore floating vertical-axis wind turbine

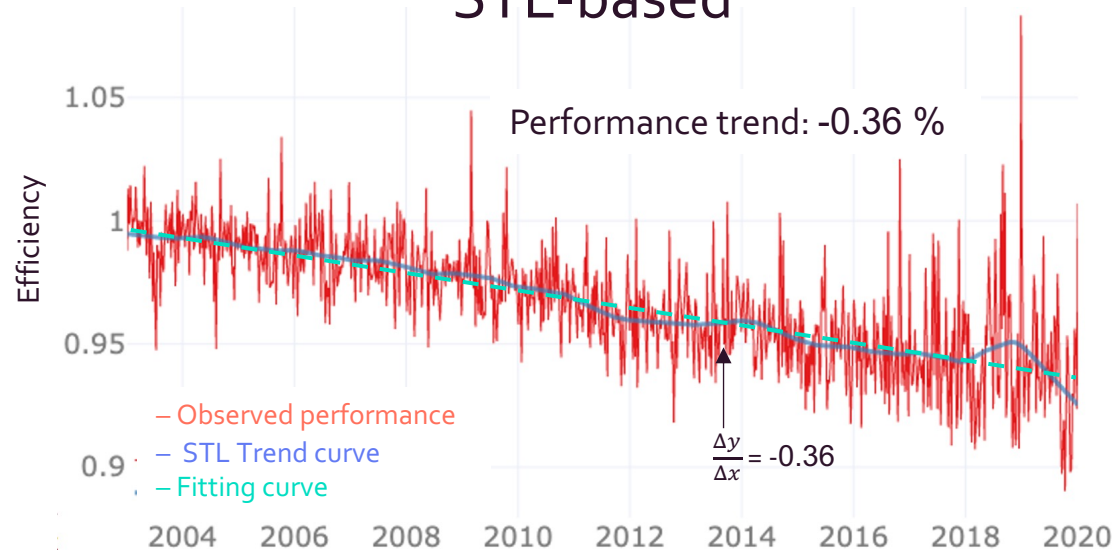
[1] Validation of the PV Life model using 3 million module-years of live site data. Hasselbrink, E.F. et al., 2013

[2] Cleveland, R.B., Cleveland, W.S., McRae, J.E., and Terpenning, I. (1990). STL: A seasonal-trend decomposition. Journal of Official Statistics 6, 3–73

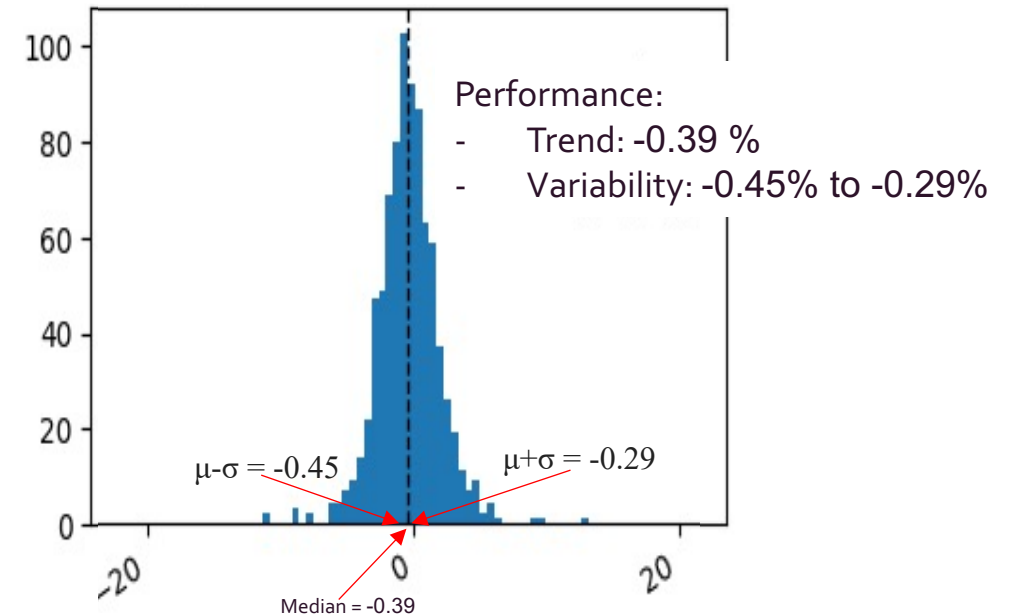
Performance characterization

- Performance is reported in terms of **trend** and **variability**

STL-based



YoY-based



Goal: Summarize actionable information from the evolution of turbine performance in terms of performance trend and performance variability per year

Results

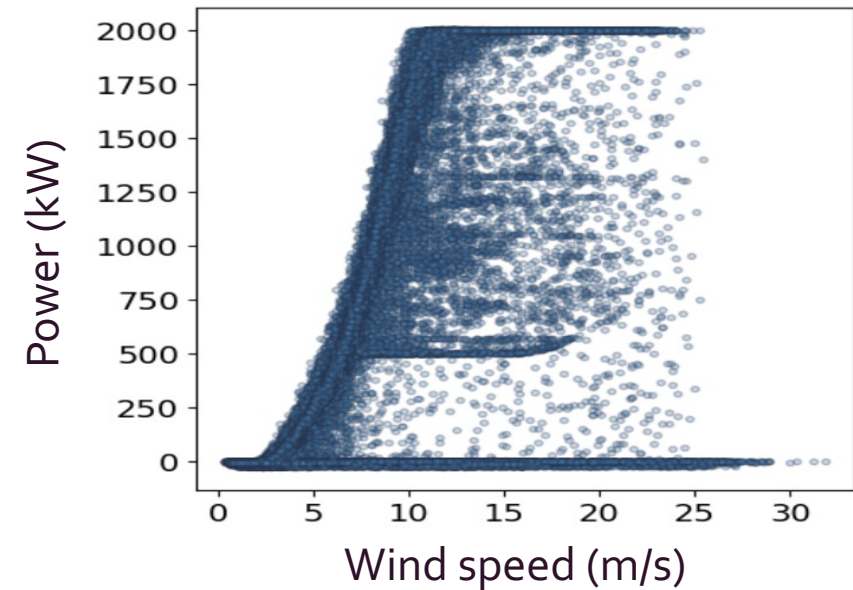
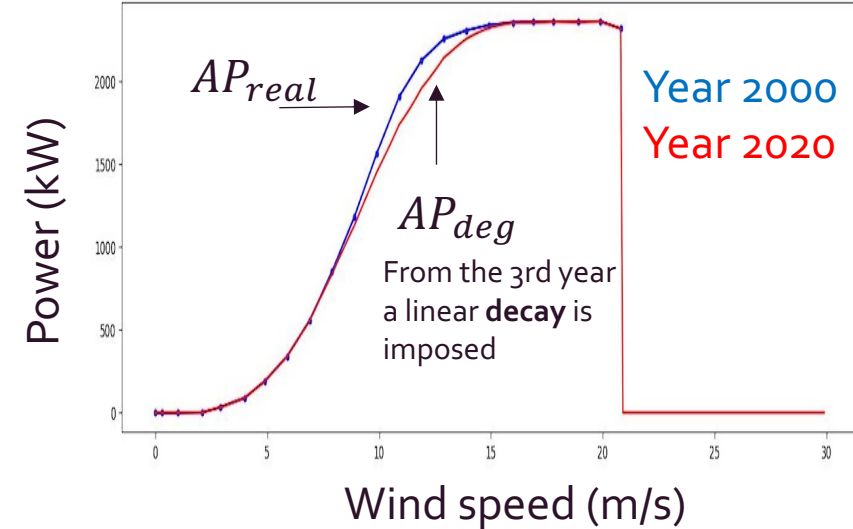
Dataset

Synthetic dataset

- 20 years data
- Variables
 - Wind Speed
 - Wind direction
 - Air Density
 - Active Power (AP_{real})
 - Active Power_degraded (AP_{deg})
 - Active Power_expected (AP_{exp})

Real-world dataset

- 7 turbines
- 11 years of data
- In 2018 the controller was modified

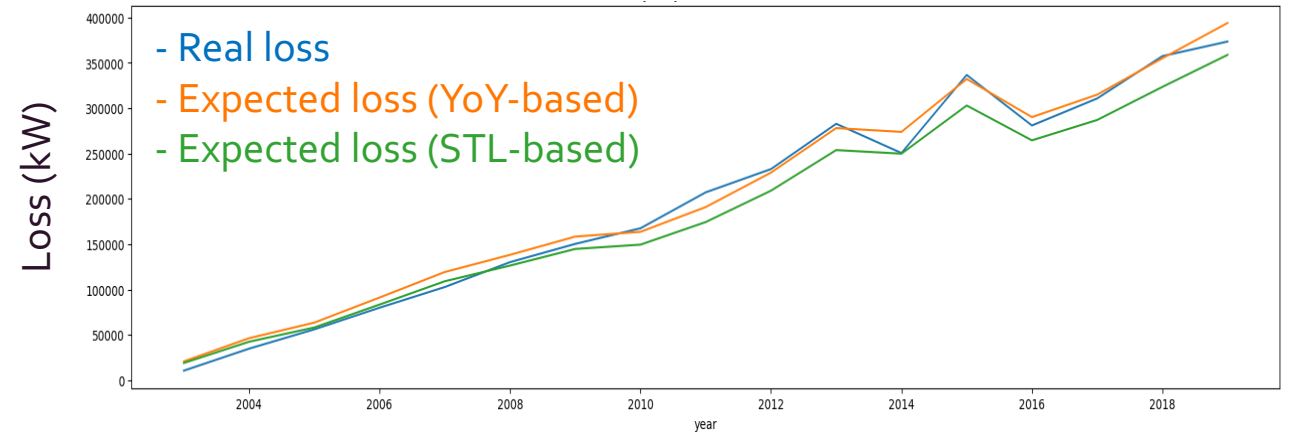


Results

SYNTHETIC DATASET

- Performance Trend (PT):
 - 0.0039 (YoY)
 - 0.0036 (STL)
 - Real loss: $AP_{real} - AP_{deg}$
 - Expected loss: $AP_{exp} - AP_{deg}$
- $AP_{deg} \left(\frac{PT * \# \text{ years}}{1 - PT * \# \text{ years}} \right)$

Yearly loss evolution



R^2 between real and expected loss is:

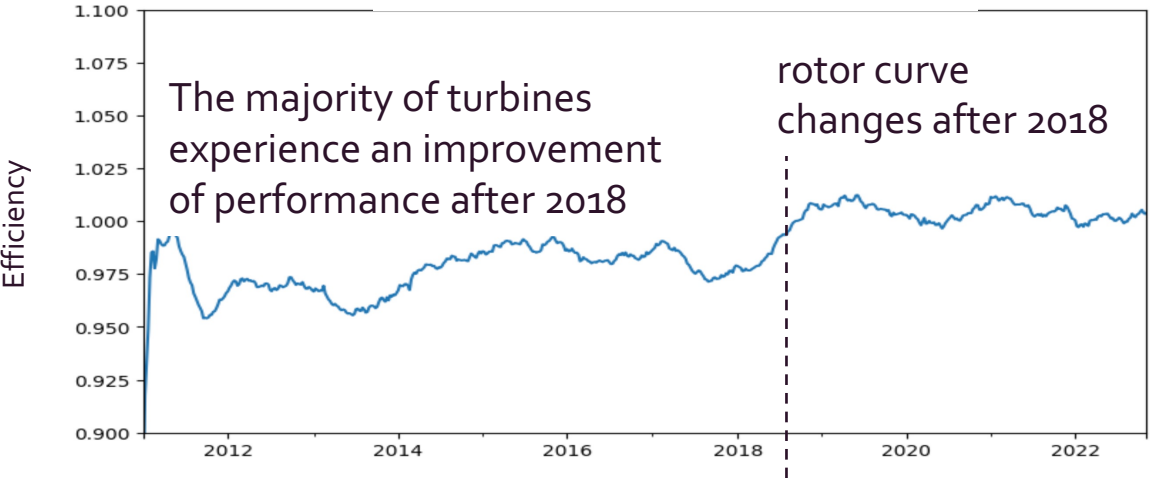
- 0.97 (STL) - 0.99 (YoY)

The methodology provides a good estimation of the real loss, i.e. it correctly estimates the induced performance decay

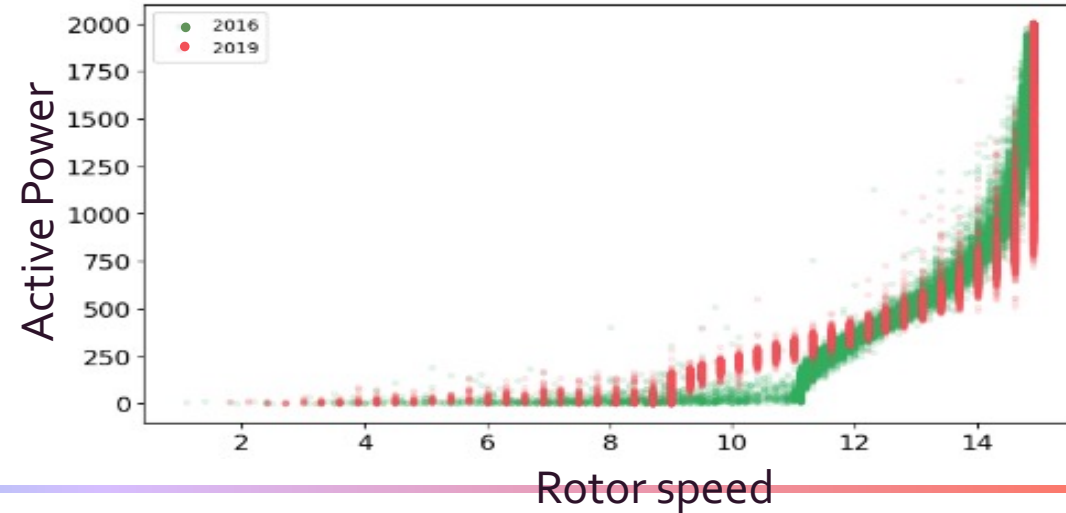
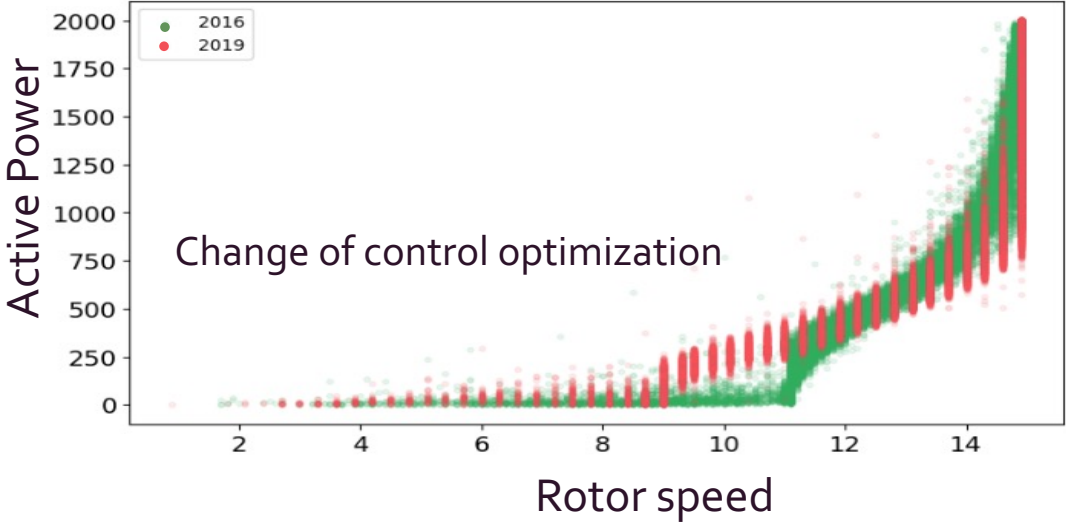
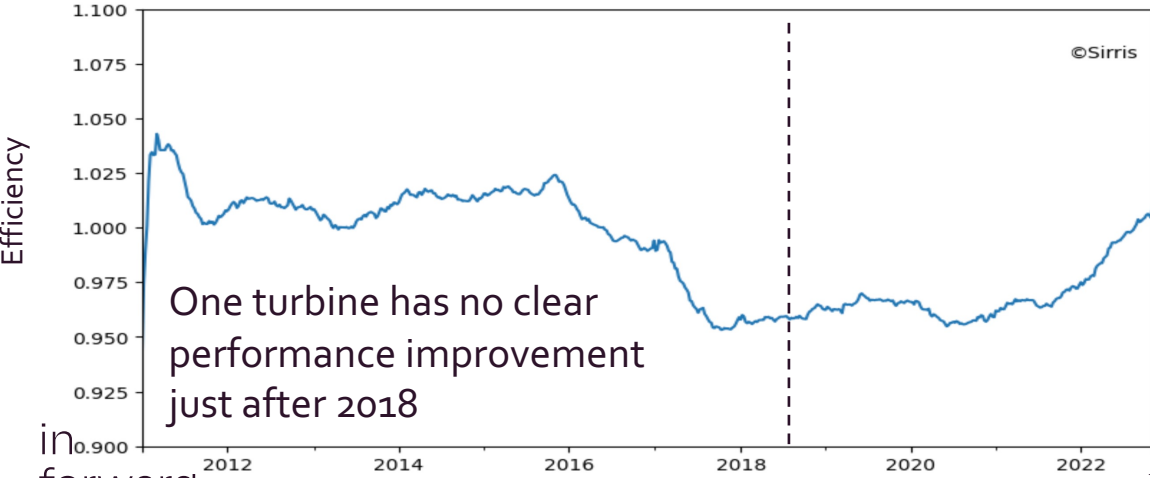
Results

REAL-WORLD DATASET

Performance evolution – **Turbine 07**



Performance evolution – **Turbine 01**



Results

REAL-WORLD DATASET

Turbine performance during 2011-2022

Wind Turbine	YoY-based performance trend	YoY-based performance variability	STL-based performance trend
T01	0.02	[-0.26; 0.20]	-0.38
T02	-0.04	[-0.53; 0.31]	0.00
T03	0.10	[-0.30; 0.61]	0.11
T04	-0.20	[-0.52; -0.01]	0.06
T05	-0.04	[-0.53; 0.31]	0.15
T06	-0.18	[-0.43; 0.06]	0.10
T07	0.42	[0.08; 0.60]	0.52



YoY-based and STL-based performance trends are generally aligned

Results

REAL-WORLD DATASET

Turbine performance during 2011-2022

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T02	-0.04	$[-0.53; 0.31]$	0.00
T03	0.10	$[-0.30; 0.61]$	0.11
T04	-0.20	$[-0.52; -0.01]$	0.06
T05	-0.04	$[-0.53; 0.31]$	0.15
T06	-0.18	$[-0.43; 0.06]$	0.10
T07	0.42	$[0.08; 0.60]$	0.52

Results

REAL-WORLD DATASET

Turbine performance

2011-2022

2016 vs 2019

Wind Turbine	YoY-based performance trend	YoY-based performance trend
T01	0.02	-1.92
T02	-0.04	1.44
T03	0.10	2.74
T04	-0.20	-0.05
T05	-0.04	0.45
T06	-0.18	1.01
T07	0.42	1.07

In the short-term, maintenance activity clearly improves performance

Conclusions

- We presented a methodology to characterize turbine **performance** in the **long-** and **short-term**
 - The methodology can factor out confounding effects that can affect turbine performance (e.g. weather, operative mode)
- On a synthetic dataset, the methodology identified the induced performance decay
- On a real-case dataset, the methodology provided insights in performance evolution in the long- and short-term
 - Control optimization may not always have a positive effect on turbine performance
 - Turbine performances tend to be rather stable over the years