Causal Inference in Engineering Applications

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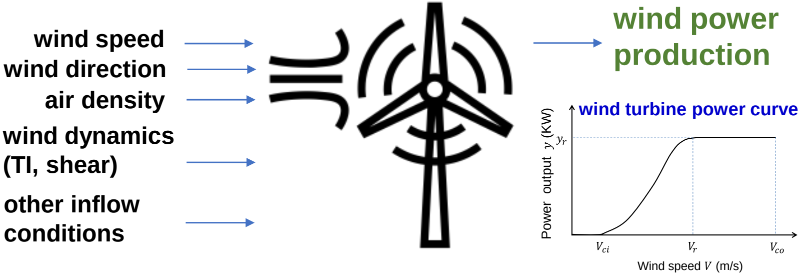
Natural experiments and causal inference

- Natural experiments "*are observational studies and are not controlled in the traditional sense of a randomized experiment*." (source: Wikipedia)
- Causal inference aims at
  - determining which factors have a genuine cause-and-effect relationship with the response
  - quantifying the effect on the response due to the action taken.
- Huge impact in economics and social sciences.
- In some engineering applications, conducting controlled experiment is either too costly or infeasible. Then, causal inference becomes relevant.

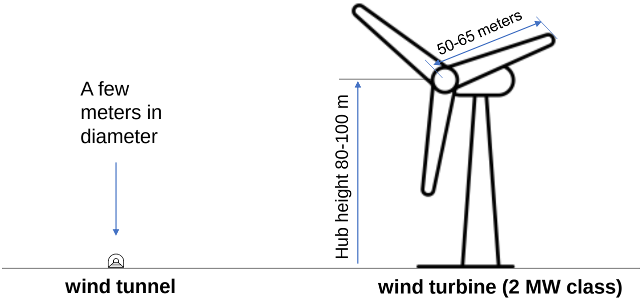
Wind energy application

- Wind energy (the same for solar) is known as *variable* renewable energy.
- Its fuel input is not controllable. Nor are other environmental conditions, which affect the wind power production, too.



Size matters

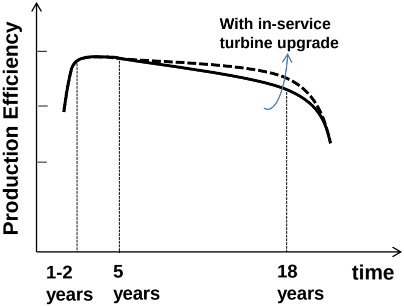
- Typical wind tunnels are an order of magnitude smaller than the size of commercial turbines.



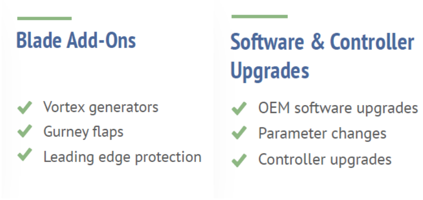
- Controlled experiments can be done on lab-scaled small turbines, but extrapolating to the commercial setting causes huge inaccuracy.

Where does causal inference help?

- Both aims are relevant, but the second aim, i.e., the effect quantification, is particularly so.
- To counter a turbine's fast deterioration, a popular solution is to retrofit wind turbine, especially the blades. Such retrofit is known as **turbine upgrade**, meant to be **performance enhancement**.



Service providers sell all kinds of performance enhancement options.



Staffell and Green (2014). "How does wind farm performance decline with age?" *Renewable Energy*, **66**:775–786.

Tasker, Bechant, Post, "Are Power Curve Upgrades Worth It? Measuring the ROI of Turbine Upgrades" *American Wind Energy Association* Seminar, Sept 15, 2020.

- Take vortex generators for example (picture courtesy of SMART BLADE® GmbH).
- Installing VGs on one turbine costs about \$10K, so for a 200-turbine farm, the total cost is \$2M.
- The key question is how soon can the wind farm operator pay back the expense?
- Depends on the increase in AEP after VG installation.

AEP = Annual Energy Production

Causal inference for effect quantification

- If confirmed 1.5% – 3% improvement, as EDF advised, it makes a difference!

  3% improvement in AEP = \$1.2 million revenue increase

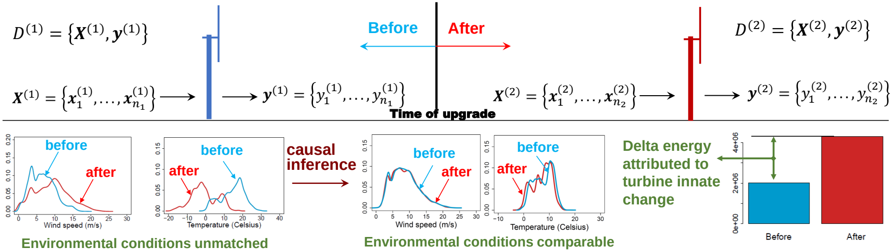
  (for a wind farm with 200 2MW-class turbines at 6 cents/kWh price)

- The general consensus is that the VG benefit in commercial settings is moderate, producing likely 1% – 5% increase in AEP.

- Detecting this small improvement and attributing its effect to VG installation is where causal inference can help with.

Covariate matching—A classical causal inference method

- Basic idea (Rubin 1973[†]): carefully select data points for making the environmental conditions probabilistically comparable BEFORE and AFTER.
- Specific techniques (Shin et al. 2018[††]):
  1. Hierarchical subgrouping
  2. Controlling for unmeasured factors
  3. One-to-one matching with replacement
  4. Robustness check on the order of matching

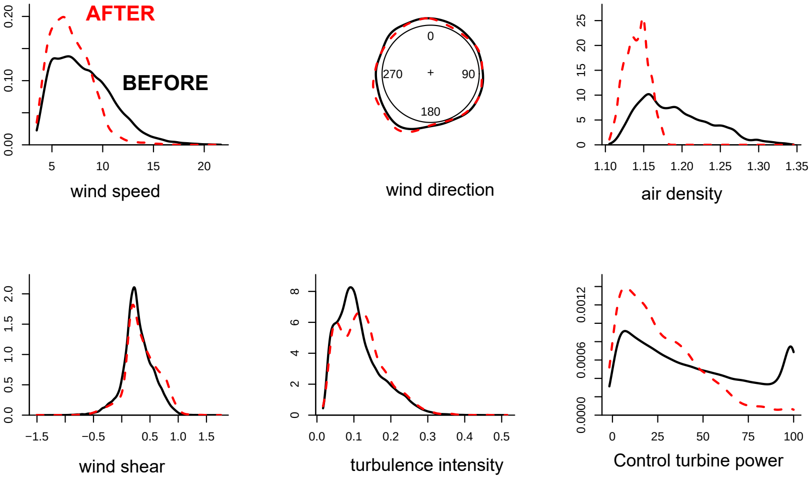


[†] Rubin (1973). “Matching to remove bias in observational studies.” *Biometrics*, **29**: 159-183.

[††] Shin, Ding, and Huang (2018). "Covariate matching methods for testing and quantifying wind turbine upgrades," *Annals of Applied Statistics*, **12**: 1271-1292.

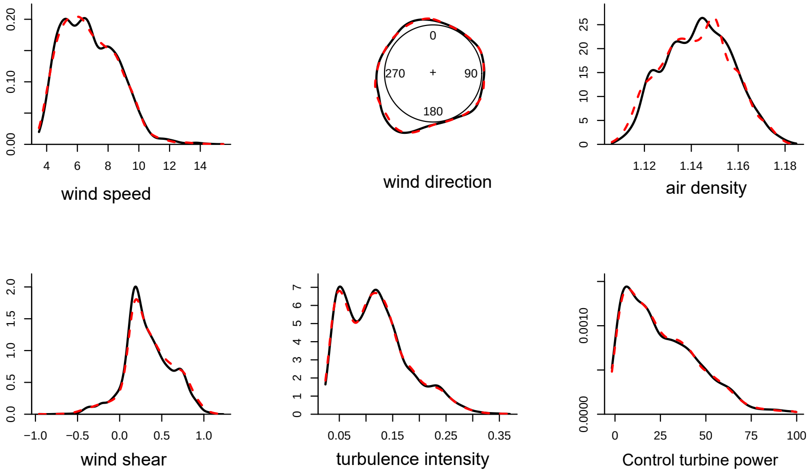
Matching results

- Two turbines are involved: a test turbine and a control turbine
- Before matching, the change in environmental conditions **confounds** the effect of a turbine upgrade



Matching results

- Two turbines are involved: a test turbine and a control turbine
- After matching, the density curves are probabilistically comparable.



Further need for bias-reduction

- Even though a visual inspection shows reasonable alignment, there may still be a few percentage difference between two functional curves, large enough if compared with the anticipated upgrade effect.
- We explored a number of advanced options for covariate matching but those do not help and some even makes the bias worse.
- Bias reduction is still a pressingly needed.

Causal Inference Nested in a Three-Step Procedure

- Three methodological components.

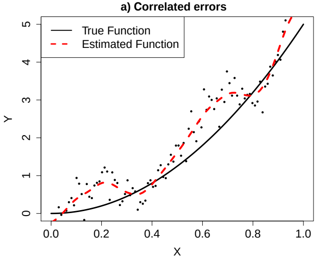
Which input variables to use?	Which data subsets to use?	How to compare nonparametric functions?
J. of Am. Stat. Assoc. (2015), Technometrics (2022, online)	Annals of Applied Stat. (2018)	Technometrics (2022)
↓	↓	↓
Nonparametric regression Temporal overfitting	Casual inference for natural experiments	Nonparametric comparison & uncertainty quantification

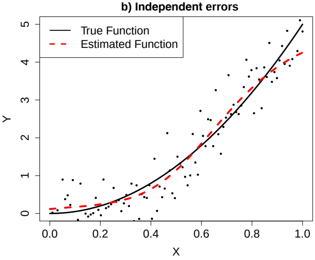
- The solution procedure† is implemented in both `R` and `Python` packages, named "DSWE".

† Ding, Kumar, Prakash, Kio, Liu, Liu, and Li (2021) "A case study of space-time performance comparison of wind turbines on a wind farm," *Renewable Energy*, **171**: 735-746.

Step 1. Build a model that avoids temporal overfitting

- Cause-and-effect of certain variables is unmistakeable, like wind speed, while conditional cause-and-effect of other variables are not so clear.
- When data are autocorrelated, deciding the conditional causal effect becomes tricky. Regular cross-validation tends to select an overfitting model.
- Our method, tempGP, is meant to extract the genuine effect despite the autocorrelation in data.





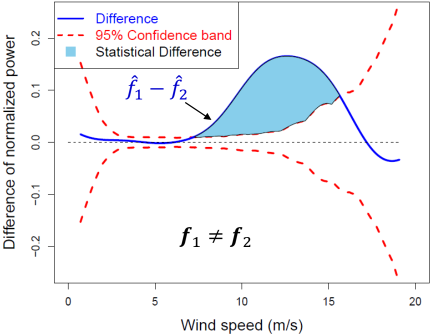
Prakash, Tuo, and Ding (2022) "The temporal overfitting problem with applications in wind power curve modeling," *Technometrics*, online published.

Step 3. Inference and UQ of difference in nonparametric functions

Let $f_1(\cdot)$ and $f_2(\cdot)$ be two nonparametric functions, representing the performances of two turbines of the same period, or two periods of the same turbine.

$$H_0 : f_1(\boldsymbol{x}) = f_2(\boldsymbol{x}) \quad \forall \quad \boldsymbol{x} \in \mathcal{X}$$
$$H_1 : f_1(\boldsymbol{x}) \neq f_2(\boldsymbol{x}) \quad \exists \quad \boldsymbol{x} \in \mathcal{X}.$$

1. The functional estimates, $\hat{f}_1(\cdot)$ and $\hat{f}_2(\cdot)$, are used, as $f_1(\cdot)$ and $f_2(\cdot)$ are unknown.
2. Gaussian Process modeling provides foundation for uncertainty quantification.
3. Karhunen Loève (KL) expansion makes computation feasible.



Prakash, Tuo, and Ding (2022) "Gaussian process aided function comparison using noisy scattered data," *Technometrics*, **64**: 92-102.

A simulated study

The power in the test period is multiplied by a factor of $1 + r$ for those corresponding to wind speed greater than 9 m/s.

r	2%	3%	4%	5%	6%	7%	8%	9%
r'	1.25%	1.87%	2.49%	3.11%	3.74%	4.36%	4.98%	5.60%
Δ in Ding et al. (2021)	1.12%	1.77%	2.73%	3.43%	3.69%	4.69%	5.16%	5.59%
Δ/r'	0.90	0.95	1.10	1.10	0.99	1.08	1.04	1.00
UPG in Shin et al. (2018)	1.74%	2.21%	2.68%	3.16%	3.63%	4.11%	4.58%	5.05%
UPG/r'	1.39	1.18	1.08	1.02	0.97	0.94	0.92	0.90
DIFF in Lee et al. (2015)	1.97%	2.56%	3.15%	3.73%	4.30%	4.86%	5.42%	5.97%
DIFF/r'	1.58	1.37	1.27	1.20	1.15	1.11	1.09	1.07

- Ding et al. (2021): functional fitting + covariate matching + UQ.
- Shin et al. (2018): covariate matching only.
- Lee et al. (2015): functional fitting only.

Industrial case studies

- 2014, a blind study, with EDPR North America. [ASME TurboExpo Conference Proceedings, GT 2015, Montreal, Canada, June 15-19.]
- 2015-2016, with SMART BLADE® GmbH (Germany). [*Renewable Energy*, 2017, volume 113, pp. 1589–1597.]
- 2017-2018, with EDP Renewables (Spain/US). [A specialized `R` package named `gainML`].

  The above studies focused on VG installation.

- 2019-2020, with Goldwind (China). Evaluation of software and control logic options. [*Renewable Energy*, 2021, volume 171, pp. 735–746].
- 2020-2021, with Wind Energy Institute of Canada (WEICan). Evaluation of leading-edge protection options on blades. [*Wind Energy* , 2022, volume 25, pp. 1203–1221].

Takeaways

- Causal inference to wind engineering: simple idea, real impact.
- For the aim of effect quantification, both bias reduction and uncertainty quantification are still challenging problems.
- Data characteristics deviating from standard iid assumptions raises new needs in causal inference.
- **Other applications**. Brian Denton recently published a perspective paper in *IISE Transactions*, entitled "*Frontiers of medical decision-making in the modern age of data analytics*". The whole Section 2 is dedicated to the discussion of leveraging observational data to build IE/OR models.