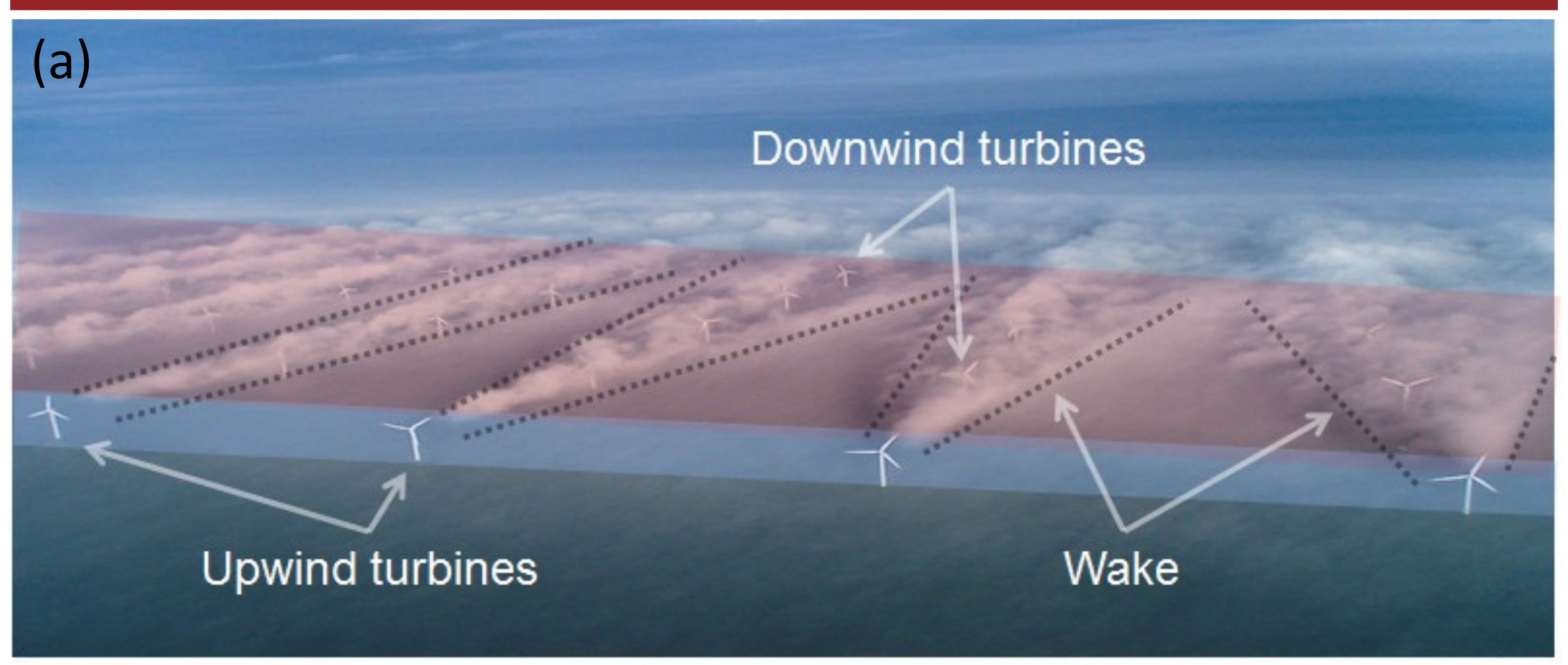
Wake Effect Calibration in Wind Power Systems with Adaptive Sampling based Optimization

NC STATE UNIVERSITY
Edward P. Fitts Department of Industrial and Systems Engineering

Pranav Jain, Dr. Sara Shashaani, North Carolina State University,

Dr. Eunshin Byon, University of Michigan, Ann Arbor

Problem



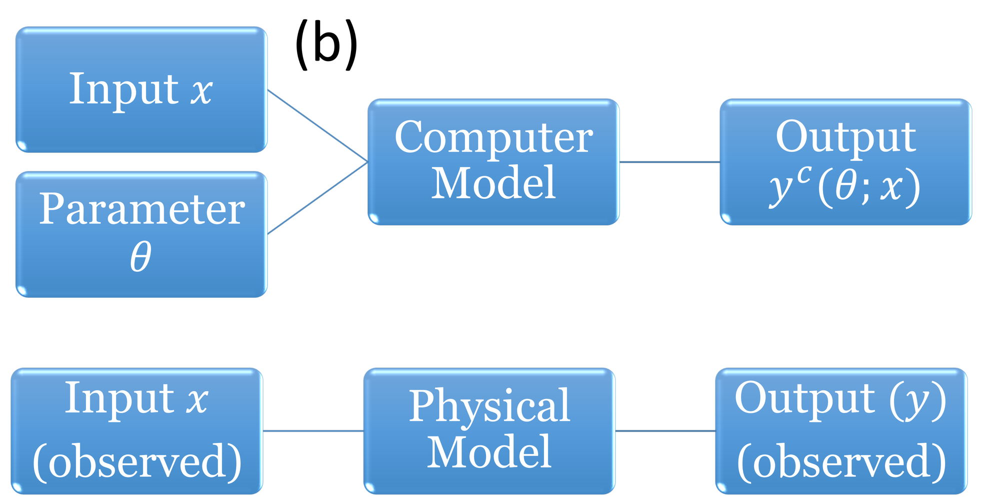


Fig 1: (a) In the wind farms, downstream turbines' efficiency is lower due to the **wake effect**.

(b) Computer model parameter calibration aims to find a parameter value, well-informed by data uncertainty.

We aim to cast calibration for this problem (with **big data**) with stochastic optimization; Bayesian calibration has limitations with that.

Data-driven Stochastic Optimization

Suppose we have $< x_j, y_j > j = 1, \dots, n$ data points, where x_j is wind speed and y_j is the generated power from the turbines. We seek

$$\min_{\theta \in [\theta_{\min}, \theta_{\max}]} f(\theta) := \mathbb{E}_{X,Y}[\ell(y^c(\theta; X), Y)].$$

The loss function is the mean absolute error of prediction residuals. Estimated objective at a solution θ with the sample set $\mathcal{S}(\theta)$ is

$$F(\theta, \mathcal{S}(\theta)) = \frac{1}{|\mathcal{S}(\theta)|} \sum_{<x_j, y_j> \in \mathcal{S}(\theta)} \ell(y^c(\theta; x_j), y_j).$$

Optimization is **derivative-free** with the main assumptions:

- $F(\theta, \mathcal{S}(\theta)) \xrightarrow[n\to\infty]{} f(\theta)$ almost surely for all θ.
- $f(\theta)$ has a minimum and its rate of change stays below a threshold.
- The parameter θ is the same for all wind speeds.

Methodology

We use **Trust-region** as our search engine, which iteratively approximates $f(\theta)$ with a local model and suggests the next best solution in a neighborhood around the current best solution.

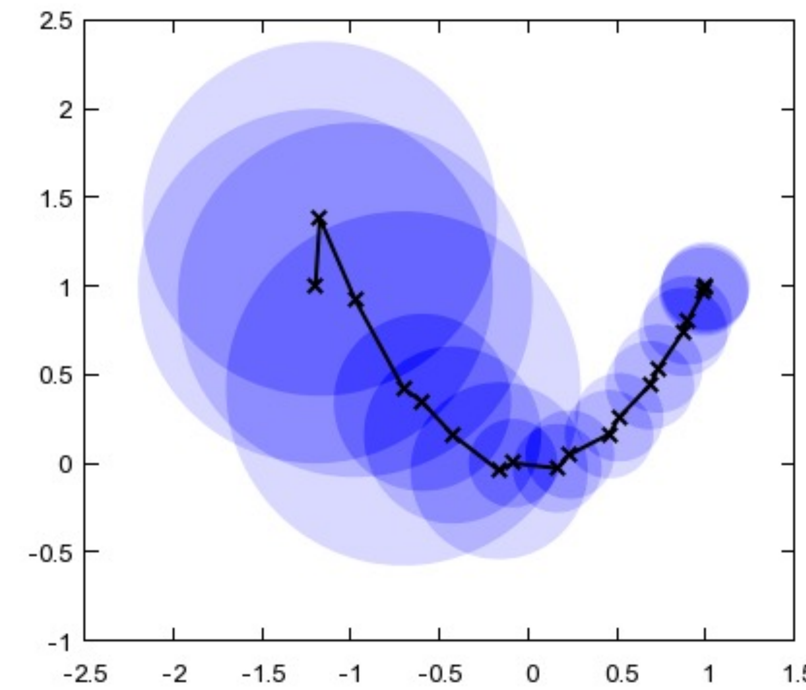


Fig 2: Trust-region optimization in $\mathbb{R}^2$.

+ Adaptive sampling

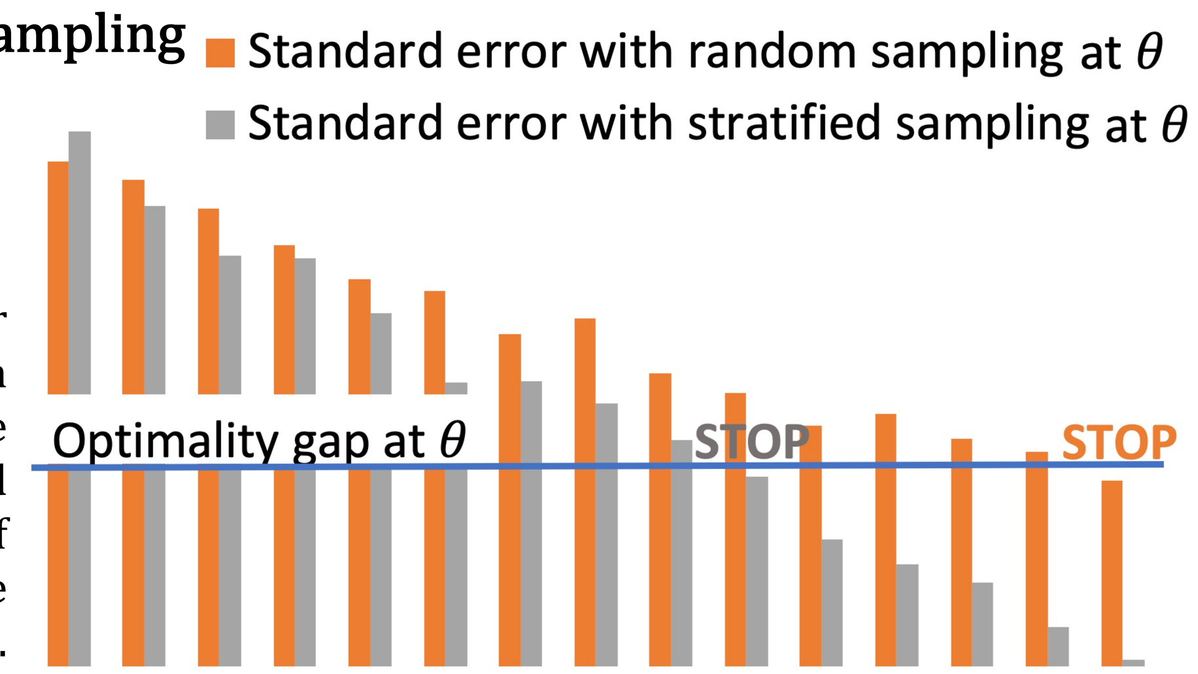


Fig 3: Error changes with sample size increase and stopping of adaptive sampling.

+ Stratified sampling

- Sample size of each stratum is determined by the ratio of population in that stratum and the variance of response in that stratum.

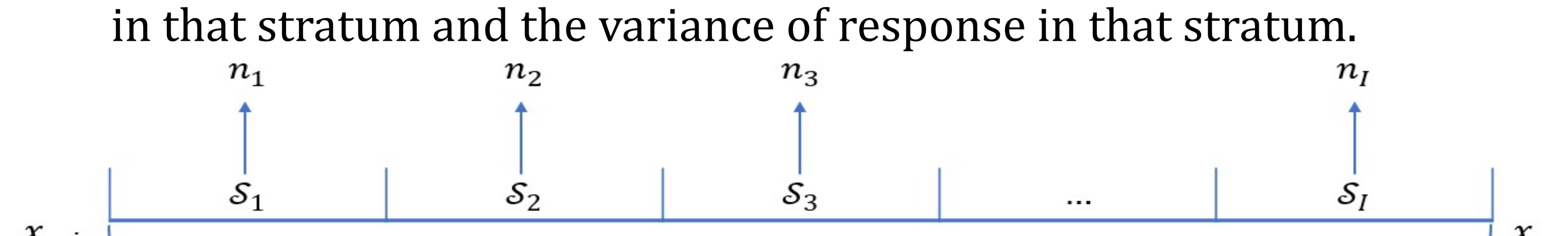


Fig 4: Stratified sampling using a one-dimensional variable.

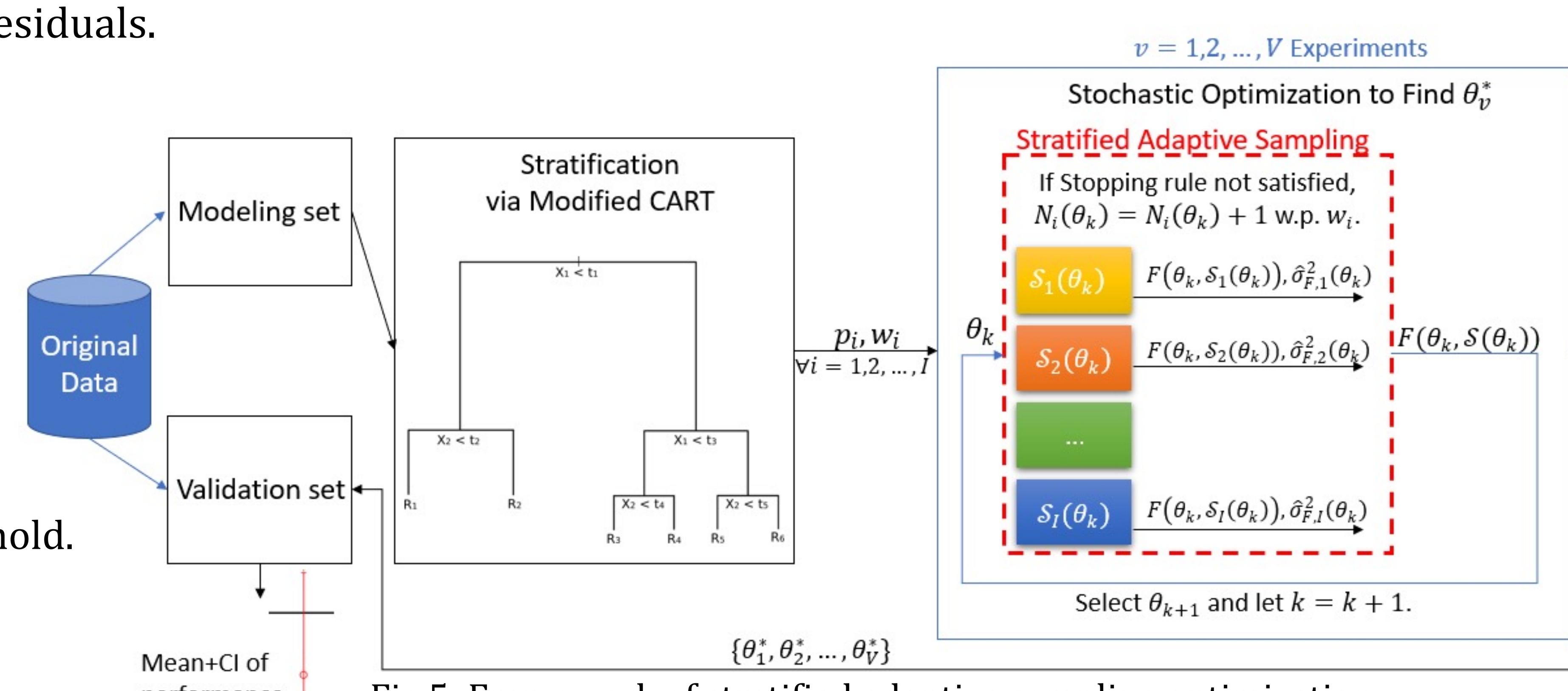


Fig 5: Framework of stratified adaptive sampling optimization.

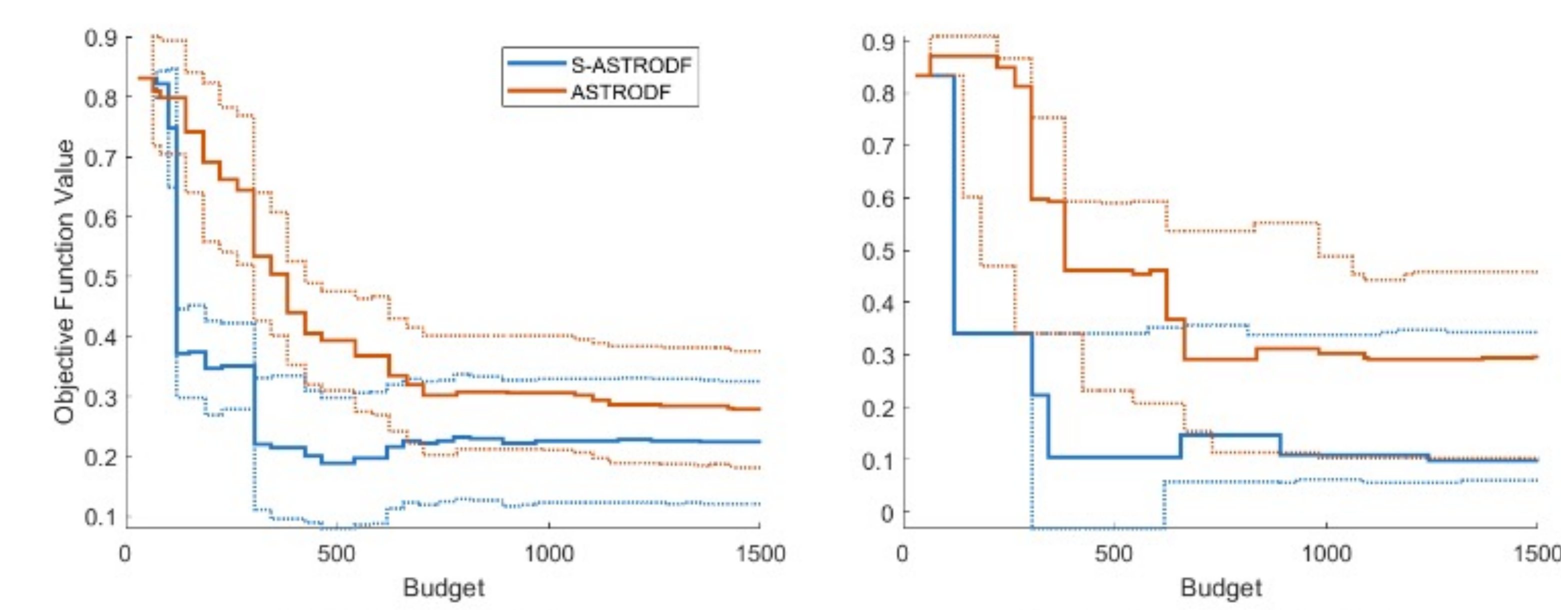
Experimental Results

Table 1: Summary of the numerical examples used for comparison

	Input	Computer Model	Noise
Example 1	1-D	Perfect	Homogeneous
Example 2	1-D	Imperfect	Homogeneous
Example 3	1-D	Perfect	Heterogeneous
Example 4	2-D	Perfect	Homogeneous

Table 2: The proposed algorithm (S-ASTRODF) finds better calibrated parameter values than Bayesian calibration and its original counterpart (ASTRODF).

Method	Example 1	Example 2	Example 3	Example 4
Bayesian-1	-1.42	-0.26	1.93	0.14
Bayesian-2	2.95	1.08	2.87	0.23
ASTRODF	-1.08	-0.04	1.99	0.11
S-ASTRODF	-1.01	-0.18	2.03	0.11
True value	-1.00	N/A	2.00	0.10



(a) Mean-CI plots. (b) Median-Quantile plots.

Fig 6: Convergence curves from 20 microreplication show that the proposed algorithm (S-ASTRODF) outperforms the original algorithm (ASTRODF), that lacks the stratification, for wake effect calibration in a wind farm case study.

Conclusions

- Compared to Bayesian approach, trust-region approach can capture the local variations better, leading to effective parameter calibration.
- Combination of adaptive and stratified sampling gives better solutions with **lower variability, i.e., higher reliability.**

References

- Bingjie Liu, Matthew Plumlee, and Eunshin Byon. Data-driven parameter calibration in wake models. In 2018 Wind Energy Symposium, 2018.
- Sara Shashaani, Fatemeh S Hashemi, and Raghu Pasupathy. ASTRO-DF: A class of adaptive sampling trust-region algorithms for derivative-free stochastic optimization. SIAM Journal on Optimization, 28(4):3145–3176, 2018.