Plan: Multi-fidelity BO for Wind Farm Layout Optimization
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1 Setup

1.1 Notation

Say we have a function $f_{\text{LES}}^{(T)}(X, \theta, v, \phi)$ to simulate the power output from an N-turbine wind farm over a T-minute duration, taking parameters:

- $X \in \mathbb{R}^{N\times 2}$, a set of coordinate pairs representing the turbine locations,
- $\theta \in \mathbb{R}^N$, a set of angles representing the orientations of each turbine, in an appropriately defined coordinate system,
- $v \in \mathbb{R}_{>0}$, the incoming wind speed to the site,
- $\phi \in \mathbb{R}$, the incoming wind angle to the site, again defined in an appropriate coordinate system.

Following [1], we'll assume that temporal windows larger than 2 hours, or $T \geq 120$, simply return to us the true power performance. Write this "true" power performance as f_{LES}, so

$$f_{\text{LES}} \coloneqq f_{\text{LES}}^{(T)}, \quad \text{for } \ T \geq 120.$$

Since evaluations of f_{LES} are expensive, we also have access to a variety of cheap analytic approximations, $f_{\text{approx}}^{(m)}$, for $m = 1, \ldots, M$. We'd like to place minimal assumptions on the correctness of these low-fidelity observations.

Finally, we might also be interested in obtaining observations that are higher-quality than $f_{\text{approx}}^{(m)}$ but cheaper than f_{LES}. To get these, we can run shorter simulations $f_{\text{LES}}^{(T)}$ for smaller T. It seems reasonable to model these fidelities as unbiased relative to f_{LES}, but with noise levels dependent on T.

1.2 Wind Farm Optimization

In the most common case, we want to maximize average-case performance under some historical distribution of wind speeds and directions, $p(v, \phi)$:

$$\begin{aligned} \text{maximize}_{X,\theta} \quad & \mathbb{E}_{p(v,\phi)}[f_{\text{LES}}(X, \theta, v, \phi)] \\ \text{s.t.} \quad & g(X) > c, \end{aligned}$$

where $g(X) > c$ is a feasibility constraint, bounding below by c the distance between each turbine in configuration X.

We might also consider fixing a condition (v, ϕ) ahead of time and optimizing for that condition only. This condition might represent a best or worst-case scenario.

2 Methodology

2.1 Large Eddy Simulations

There are several open-source large eddy simulation software packages available online.

The package `WInc3D` [2] has been used in [1, 4]. A newer package, `TOSCA` [7], was released four years later in 2024, with more of a focus on modeling "gravity waves." It does seem like `WInc3D` is the smart choice here, though, since both BO papers I've looked at use it.

2.2 Analytic Wake Models

Analytic wake models are often implemented in the open-source package `FLORIS` [5].

The Gauss-curl hybrid (GCH) model [6] seems to be the standard model for this application, being used in [4, 1].

2.3 Optimization Procedure

Asynchronous batch BO with multiple fidelities: [3]. This paper would work for everything, except anything about constituent evaluations.

3 Experiments

3.1 Proof of Concept

3.2 Horns Rev

This is a large offshore wind farm, consisting of 80 turbines in an 8x10 grid with a spacing between each turbine of $7D$.

In [4], the authors optimized the yaw angles of each row of turbines. They used the following configurations:

- LES configuration:
  - Uniform grid of size $74D \times 500m \times 7D$.
  - Grid spacing of $D/10$ in each spatial direction.
  - Power output averaged over 2hrs, timestep of 0.2 seconds.
  - Third-order Adams-Bashforth time advancement.
  - Grid scale filter coefficient of $\alpha_{\text{filter}} = 0.49$.
  - ABL parameters:
    * Friction velocity $u^* = 0.442m/s$
    * Boundary layer height of $\delta = 504m$
    * Roughness length $z_0 = 0.05m$
- BO configuration:
  - Latin hypercube sampling with 100 low-fidelity and 12 high-fidelity configurations.
  - UCB acquisition function
  - Multi-fidelity GP using "NARGP" models.

I have essentially four novel-ish ideas or contributions. Here's a draft motivation.

The cost of wind farm energy depends on the annual energy production (AEP) metric, which necessitates studying wind farm performance in a variety of wind speed and direction conditions, not just the optimal environment. Calculating the performance of a given wind farm layout in multiple conditions, however, requires re-running the expensive large eddy simulations for each wind speed and direction. Optimizing wind farm configurations for a variety of wind farm conditions, then, is computationally prohibitive.

In this paper, we take advantage of the "grey-box" Bayesian optimization literature on "constituent evaluations" to address this problem and allow for the optimization of wind farm configurations with average-case performance as an objective.

To further reduce the computational burden of running multiple high-fidelity LESs, we introduce a novel (to our knowledge) multiple-fidelity formulation of a large-eddy simulation that allows an optimization routine to adaptively select the temporal window over which wind farm power production is averaged and calculated. This gives the routine the option of obtaining cheaper, noisier evaluations from a large eddy simulation; such an option may be desirable, especially when trying to quickly understand the average-case performance of a given configuration, if more precision than an analytical wake model approximation is required.

We expect the benefits of considering average-case performance to be most noticeable when we are jointly optimization wind farm layout and orientation, since the performance of a wake-steered wind farm is likely highly dependent on the incoming wind direction. To simplify the computational burden of the higher-dimensional optimization problem, we'll use trust regions.

3.3 Extension of [4]

In [4], the authors solve the wake-steering problem in a multi-fidelity manner. They use a GCH model as low-fidelity option, and a `WInc3D` simulation as the high-fidelity option.

Questions relative to this paper:

- Is the NARGP prior really necessary?
- Do we save any computation by using a shorter temporal averaging window?
- Do we lose any performance in doing so?

3.4 Compare to [1]

3.5 Whole Boy

Jointly solving wake steering and micro-siting.

References

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