Project Proposal: Multi-fidelity BO for Wind Farm Layout Optimization

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Wind farms are among the cleanest sources of energy, given their low greenhouse gas emissions and minimal water consumption [3]. One practical challenge with constructing and deploying wind turbines in practice, however, comes from the fact that turbines placed in nearby locations will affect each others' performance by altering the strength and turbulence of the wind. After wind passes through a turbine, it becomes weaker and more turbulent, which can lead to less power generation and higher fatigue on downwind turbines [6]. The zone after a turbine in which the wind flow is disrupted is known as the *wake*. Optimizing the layout of turbines given their wakes, then, is essential to the feasibility and performance of wind farm energy generation in practice.

There are a variety of strategies to calculate or simulate the wake pattern and power performance of a wind farm given the layout of its turbines. The gold standard for wake prediction arises from an expensive computational fluid dynamics technique known as large-eddy simulation (LES) [9]. Given the cost of running such simulations, many authors have proposed cheaper, analytical approximations. One commonly used strategy is the Jensen model [7], for example. But as described in [2], even one run of the cheaper Jensen model calculation may take up to 15 seconds on a CPU.

The high computational cost of even the cheap analytic approximations has made wind farm layout optimization a suitable candidate for Bayesian Optimization (BO). In [3], for example, the authors introduce a set-valued Gaussian Process surrogate model and apply expected hypervolume improvement to learn layout configurations along the performance/cost Pareto frontier. More recent papers [1] [8] incorporate the higher-fidelity expensive LES model into optimization routines, but focusing primarily on the related problem of optimizing the *angles* of turbines in fixed locations.

In this project, I propose a BO approach that takes into account multiple approximation schemes along with the expensive LES procedure. Specifically, I aim to apply asynchronous multi-fidelity batch Bayesian optimization, as described in [5], to the wind farm layout optimization problem. The setup of that paper is as follows.

Multi-fidelity optimization is conceptually simple. Assume we have $1, \ldots, M$ auxiliary functions $f^{(m)}$ that approximate the function we care about, f, with varying fidelities. Each auxiliary function has a fixed known evaluation cost, $C^{(m)}$. Either using independent GP surrogates or one joint multi-output GP (MOGP), we learn a model of the objective values which we then use in BO. At each step of the optimization procedure, then, we simply select an input location x and a fidelity m to obtain an observation $f^{(m)}(x)$.

In [5], the authors note that higher fidelity observations may take *far longer* to obtain. We may want to continue querying from lower-fidelity observations *while* we wait for the higher fidelity observation.

They posit a fixed computational bandwidth Λ, and assign each fidelity a batch space parameter $\lambda^{(m)}$ that indicates how much of the compute bandwidth is taken up at one time. At each timestep, then, we may obtain values from the previous timestep with cheaper observations, or many timesteps before, in the case of more expensive observations. To solve this problem, they apply Thompson Sampling to perform batch BO, and use either an upper confidence bound variant or the expected information gain to select the fidelity of the following observation.

In the context of the wind farm problem, I propose to use two auxiliary functions. The Jensen approximate analytical model as the low-fidelity auxiliary, and the Winc3D large-eddy simulation as the expensive, high-fidelity auxiliary [4], following [8]. The input space will be "configuration sets", following [3], which are a collection of coordinate locations for the turbines in a layout.

References

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