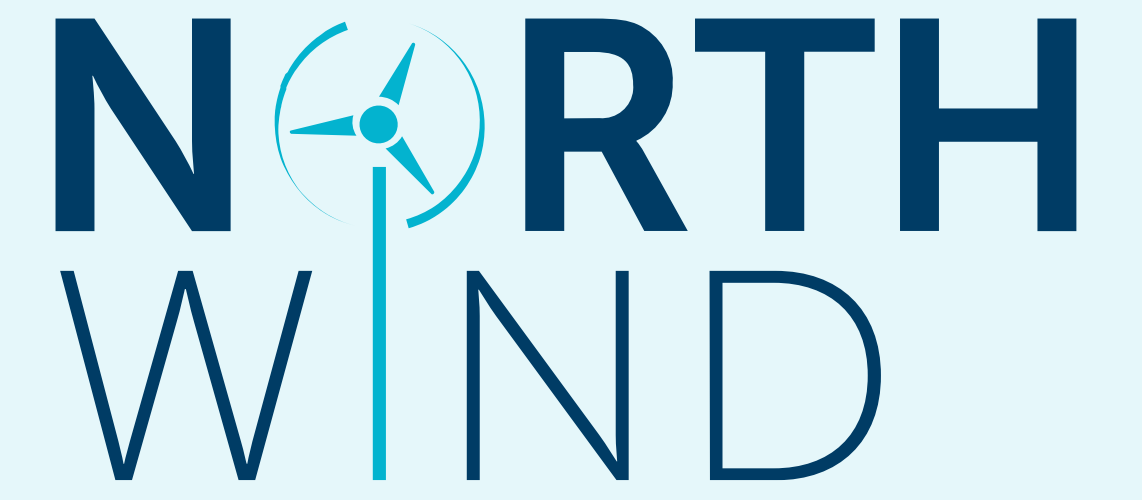


Machine Learning is in the Wind: Bayesian Optimisation for Offshore Wind



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Motivation

We want to use Bayesian optimisation to **plan the layout of offshore wind parks**.

The motivations are:

- Better layouts, giving more power generation, and
- Faster optimisation, so more areas and layouts can be evaluated

We formulate layout planning as an optimisation problem, maximising the electric power generation. Other objectives or objective combinations are also possible.

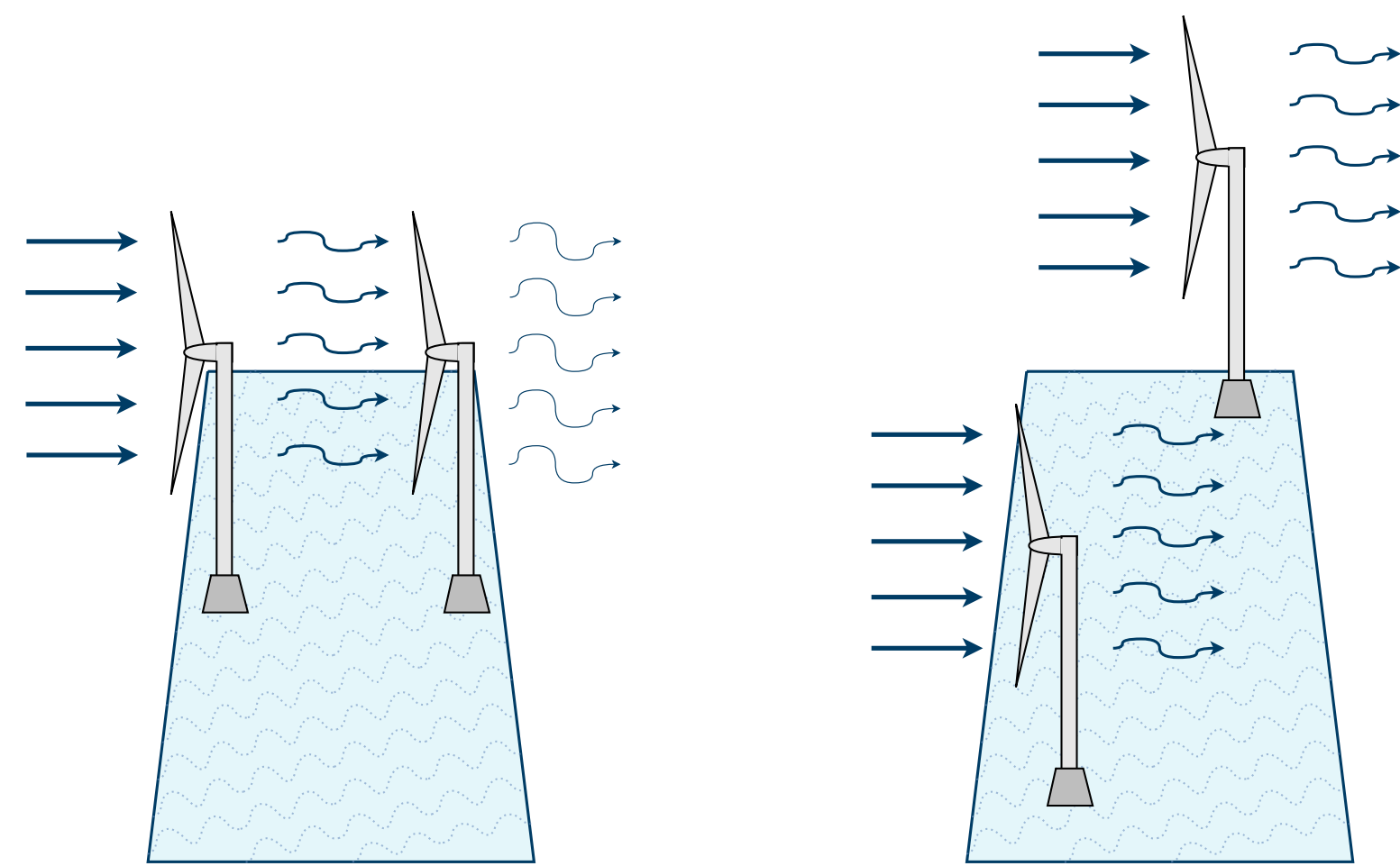
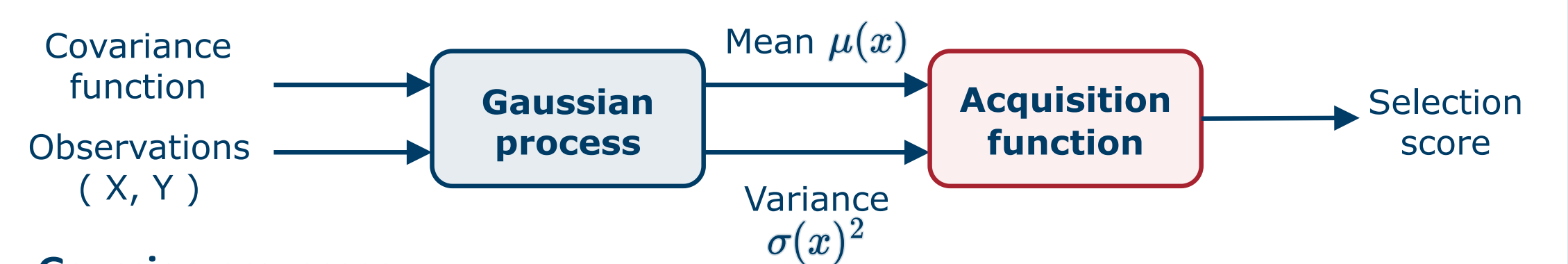


Fig 1. Some layouts are preferable because passing through a turbine makes wind weaker and more turbulent.

Bayesian optimisation building blocks



Gaussian processes

Probabilistic machine learning models that use historical data and assumptions about covariance structures to make predictions. Also called kriging.

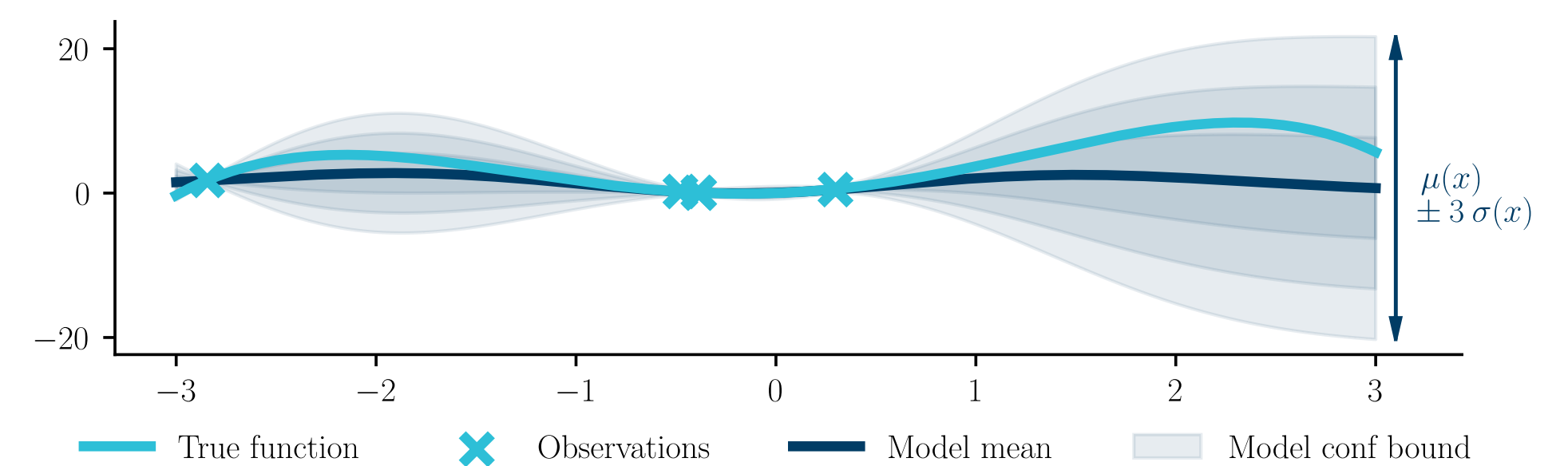


Fig 3. Example fitting a Gaussian process to five observations of a function.

Acquisition functions

Used to choose what input to evaluate or simulate next.

- Simple: **Upper Confidence Bound (UCB)**: $a(x; \beta) = \mu(x) + \beta\sigma(x)$
- Popular: Expected improvement over f' : $a(x) = \mathbb{E}[\max(0, f(x) - f')]$

What is Bayesian optimisation?

Bayesian optimisation [1] is a **machine learning (ML)** method for optimisation. It relies on a **probabilistic** model of the function we are optimising, together with an **acquisition function** which chooses what input to try next. The model is usually a **Gaussian process (GP)**. We retune our model whenever we have new evaluations.

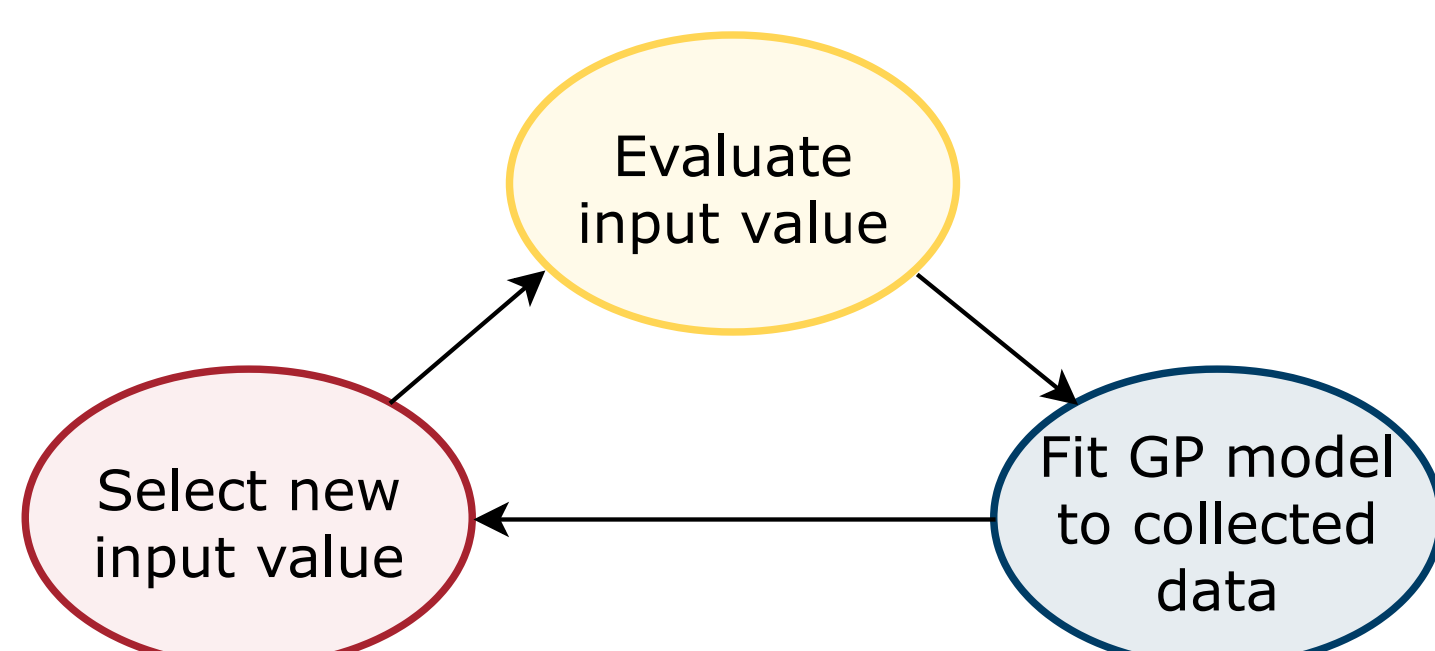


Fig 2. Internal steps of Bayesian optimisation for choosing each new input to evaluate.

Bayesian optimisation is well suited to problems that:

- Have a complex or unknown structure
- Are expensive or slow to evaluate
- Require identifying extrema

Strengths:

- Less samples needed
- Does not need gradients
- Can learn from optimising other tasks

Weaknesses:

- More computation between samples
- Does not scale directly to many evaluations. *Approximations exist*
- Requires design choices
 - Acquisition function
 - Covariance function

Common applications

Bayesian optimisation is popular for optimising the hyperparameters of other machine learning models, e.g. neural networks.

It has seen applications related to **wind turbines**: for optimal control, e.g. [2], and layout planning, e.g. [3], who also published a benchmark for this application.

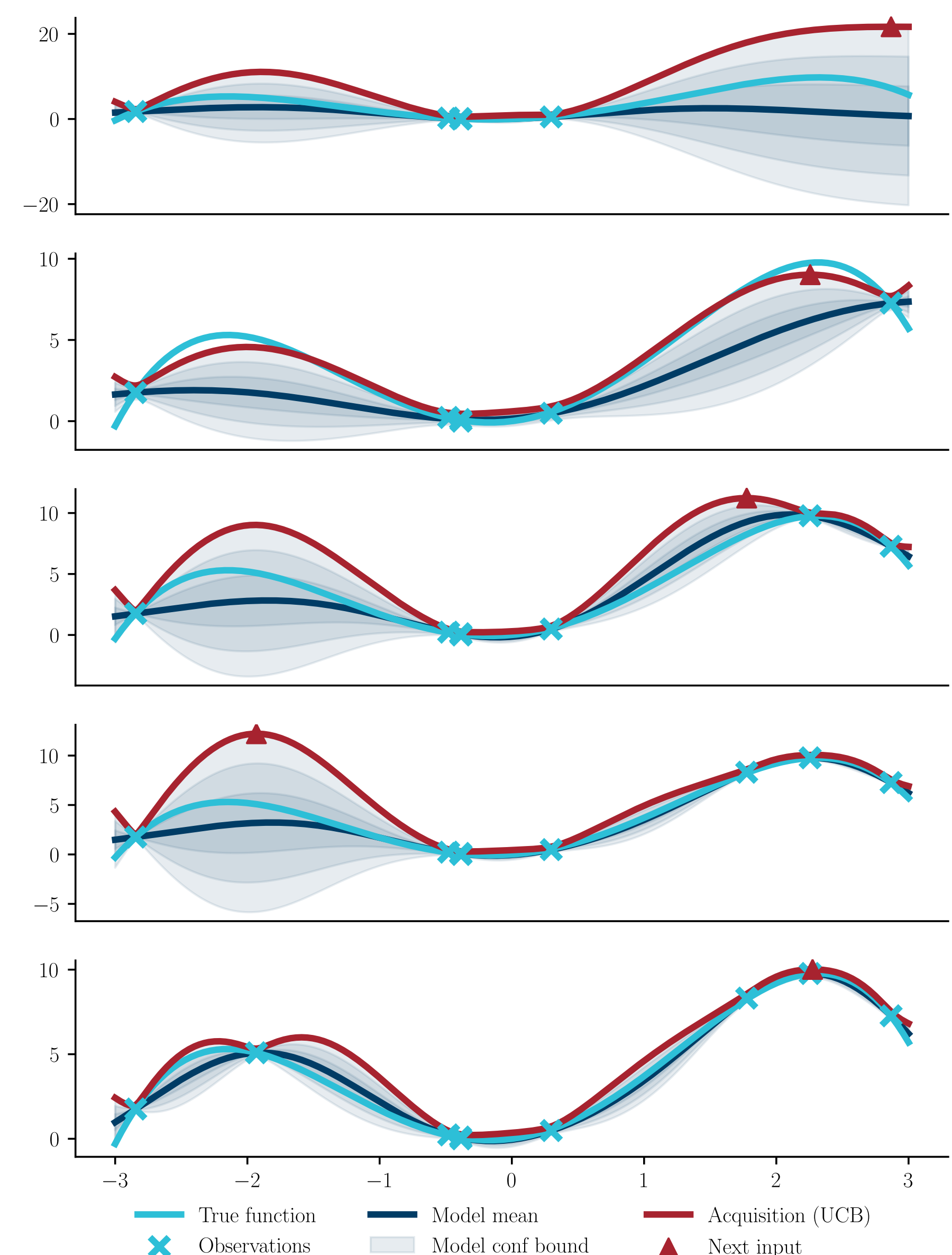
[1] Garnett. Bayesian optimization. Cambridge University Press, 2023.

[2] Park & Law. "Bayesian ascent: A data-driven optimization scheme for real-time control with application to wind farm power maximization." *IEEE Transactions on Control Systems Technology* (2016).

[3] Bliet et al. "Benchmarking surrogate-based optimisation algorithms on expensive black-box functions." *Applied Soft Computing* (2023).

Example optimisation

We apply Bayesian optimisation to an **unknown function**. The **acquisition function** chooses what input to evaluate next. At each step, we fit a **probabilistic model**.



Norwegian Centre for Environment-friendly Energy Research

FME NorthWind is financed by the Norwegian government through the Norwegian Research Council's Centres for Environment-friendly Energy Research program.

Paper

