Data-efficient optimisation of wind farms providing secondary frequency regulation with Bayesian optimisation

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Motivation

- Advanced model predictive controllers for wind farm control can be beneficial as it allows for constraints and multi-objective control objectives.
- However, tuning the resulting predictive controller is hard in practice as the closed-loop solution is usually not known or cannot be analytically derived [1].
- Recent advances in Bayesian optimisation show promise as an efficient black-box optimisation tool for even high-dimensional optimisation problems [2].

- **Given these premises we propose a controller auto-tuning strategy based on**
  1. Data-efficient Bayesian optimisation for single- and multi-objective optimisation of closed-loop controllers.
  2. Leveraging high-dimensional Bayesian optimisation for handling many tuning parameters in wind farm controllers that provide secondary frequency regulation.

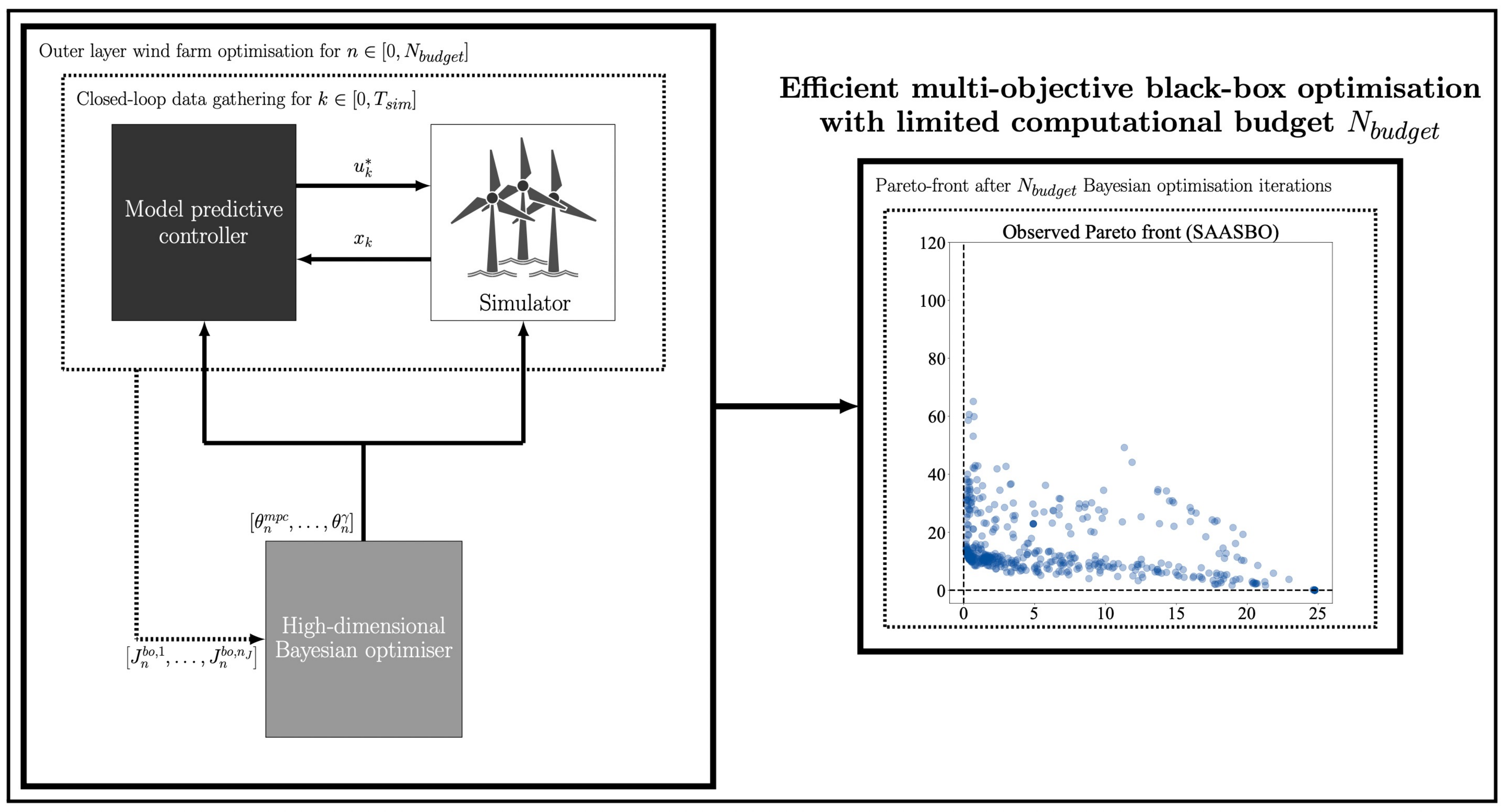

*Fig. 1: A schematic of the proposed method for optimising constrained closed-loop wind farm systems providing secondary frequency regulation with model predictive control. By collecting limited samples of the closed-loop costs **J** for the current choice of closed-loop system specific parameters θ, Pareto-optimal θ can be approximated despite limited computational budget.*

Idea: Bayesian optimisation for data-efficient auto-tuning of controllers

1. Run closed-loop experiments with a given controller design/configuration θ to gather closed-loop performance measures *y*, for example tracking or dynamic loading.
2. Based on previous data, train a Gaussian process for each performance measure to model the closed-loop interactions between current controller and system.
3. Iteratively, based on the trained Gaussian process, compute the posterior to derive the next search space based on an acquisition function.

1

$$\dot{x}(t) = f\left(x(t), u^*\left(x(t), P^{\mathrm{ref}}, \theta^{\mathrm{MPC}}\right), p(t), w(t), \theta^{\mathrm{WF}}\right) \mathrm{d}t$$

1. Based on a simulator or real-life setup, apply the controller with some current design parameters θ.
   - θ can encompass both controller tuning constants but also binary decisions such as whether to use a model predictive controller or PID.
2. Collect closed-loop performance measure y.
   - When using model predictive controller, plant/model mismatch is common. The resulting input is thus sub-optimal and the closed-loop consequence of applying the controller is different from the open-loop calculations.

2

$$y = J^{\mathrm{cl}}\left(z^{cl}(\theta, \mathcal{W})\right) + \epsilon \sim \mathrm{GP}\left(m(\theta), k(\theta, \theta'), \psi\right)$$

- Based on each performance measure *y*, train a probabilistic surrogate model (commonly a Gaussian process).

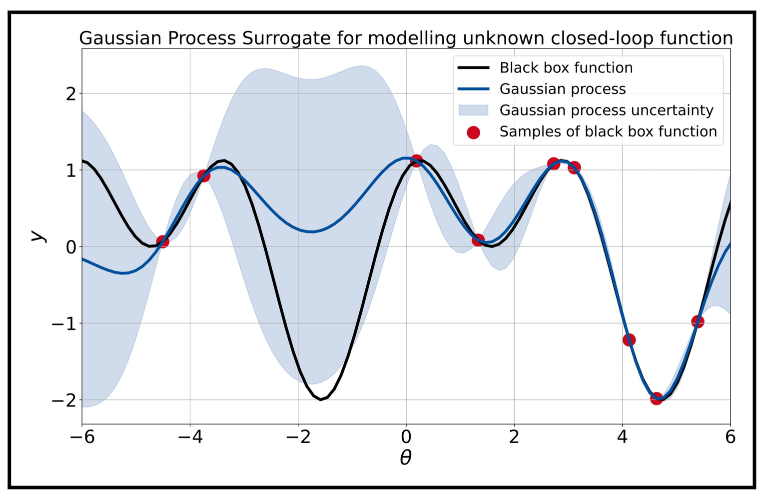

Fig. 2: Example 1d Gaussian model of y given some samples of θ.

3

$$\theta^{*,\mathrm{pareto}} = \arg\min_{\theta} J^{\mathrm{cl}}\left(z^{cl}(\theta, \mathcal{W})\right)$$

- Leverage the posterior of the probabilistic surrogate model to estimate the next θ untill the optimal θ is estimated with an acquisition function for balancing exploitation vs exploration.

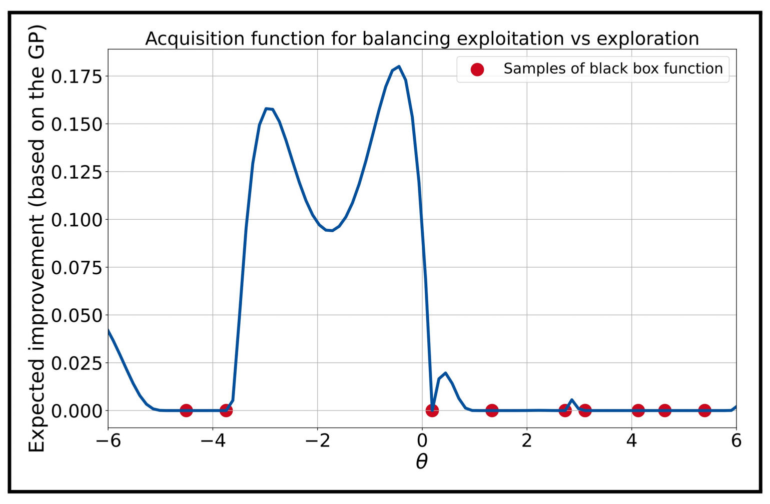

Fig. 3: Example plot of 1d acquisition function (given the GP from Fig.2.)

High-dimensional Multi-objective case study – tracking and dynamic loading

- Based on a model predictive controller from [3] with 28 tuneable parameters, the proposed method is validated in simulations using WFsim [4].
- The performance measures that is considered is **tracking** and **dynamic loading** with a computational budget for Bayesian optimisation of 100 with 5 replicates.
- From closed-loop experiments, Pareto fronts can be estimated to help some operator to decide on the optimal controller parameterisation with no prior knowledge.
- Utilising sparse-axis aligned subspaces (SAAS) priors improve the results with the notion of **automatic relevance** (deciding the importance on the go from data).
- Higher relevance results in lower values in the lengthscales ψ in the Gaussian process.
- Results in an improved Pareto front.

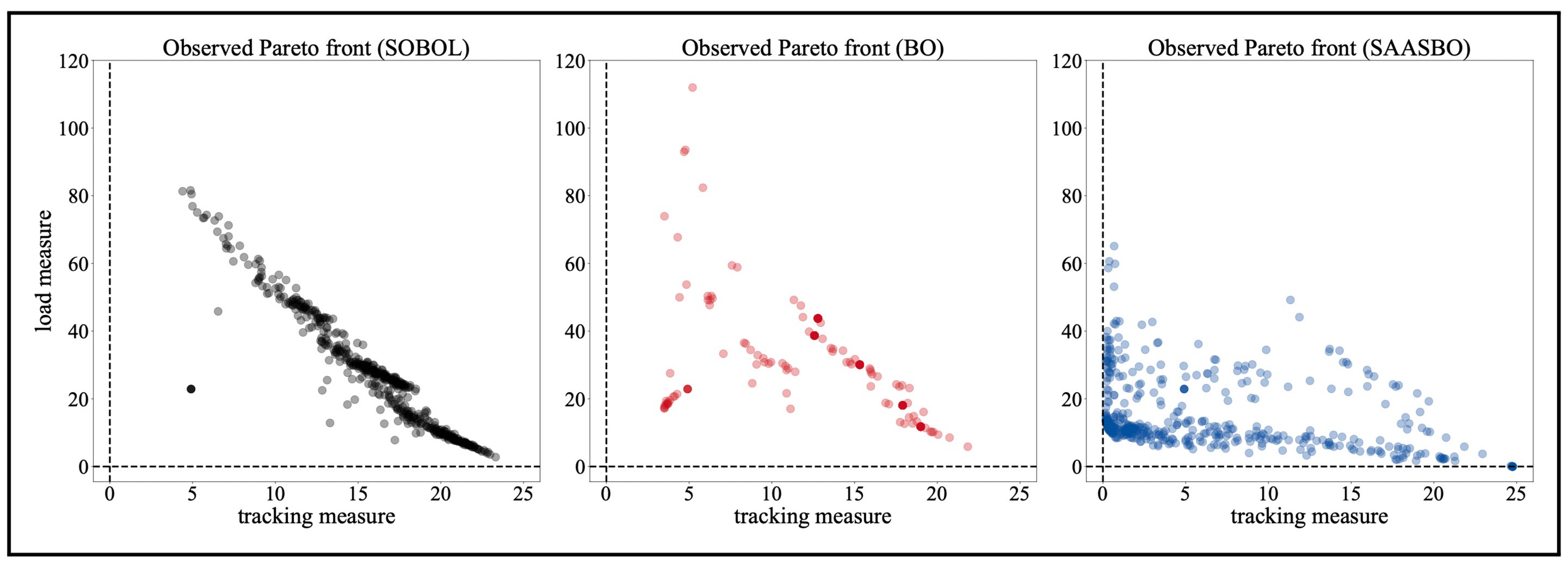

Fig. 4: Scatterplots of the resulting Pareto-front for optimising cumulative tracking and dynamic load.

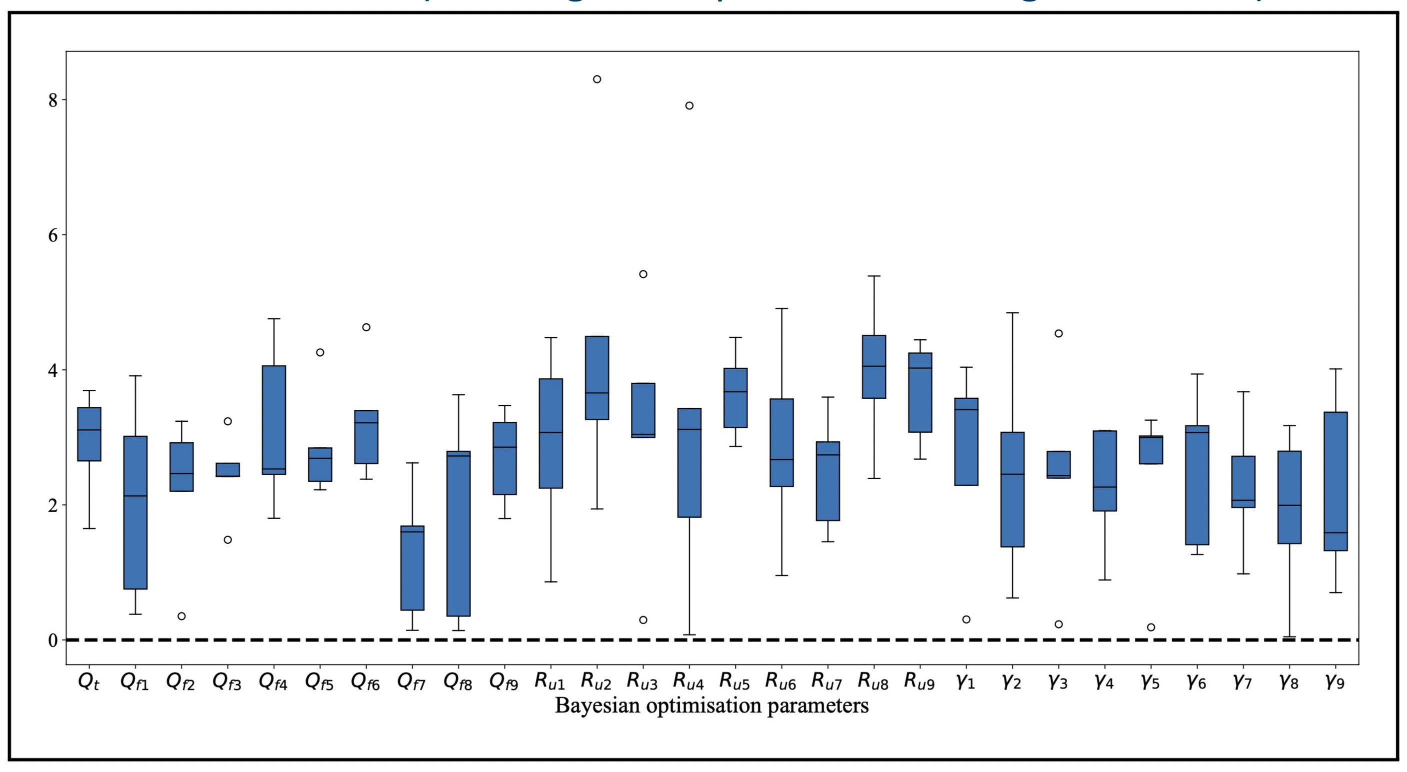

Fig. 5: Boxplots of the resulting lengthscales in the SAAS priors for deriving automatic relevance .

References

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