Decision Support for Large Offshore Wind Farms via Bayesian Optimisation

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NCL PGR Conference
8th July, 2021

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- Important logistic considerations:
    - How many spare parts of different types does the operator purchase?
    - Where to store spare parts?
- Stochastic modelling, decision analysis and expert judgement can help to answer these questions

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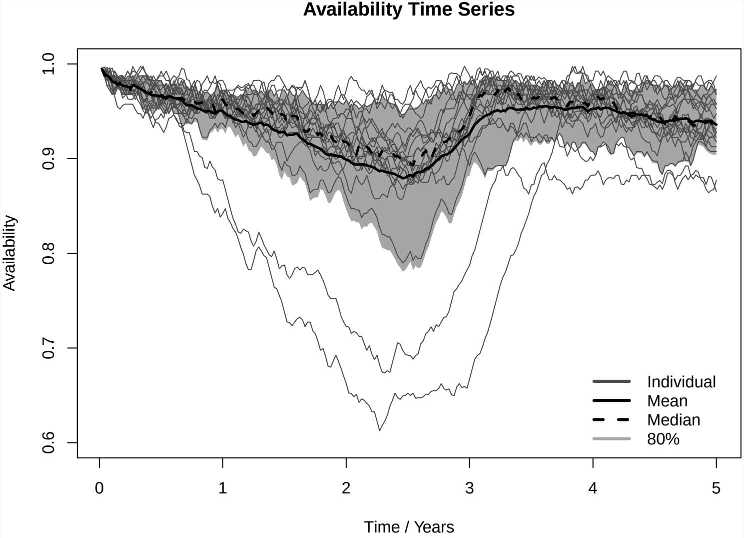
Athena Trajectories



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- $U(\boldsymbol{x}) = \mathrm{E}\{u(\boldsymbol{x})\}$ is 'actual utility' – expresses DM's preference for $\boldsymbol{x}$
- The Bayes' Optimal Decision is the decision $\boldsymbol{x}^*$ such that

$$\boldsymbol{x}^* = \arg\max_{\boldsymbol{x} \in \mathcal{X}} U(\boldsymbol{x})$$

- Eliciting $u(\cdot)$ performed in terms of gambles over consequences (and hence probabilities) therefore useful to keep $u(\boldsymbol{x}) \in [0, 1]$

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- Also want to optimise the policy for which describes how/when we buy in more spare components
- We buy in more components of type j when $s_j(t) < p_j S_j$
- Want to find:
    - Best warehouse
    - How to fill with spares
    - When to buy in more spares

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For each choice of warehouse (k) will solve:

$$\text{maximise } U(\boldsymbol{x}) \text{ subject to } \sum_{i=1}^{9} x_i = C_k$$

$$u(\boldsymbol{x}) = a_A u_A(\boldsymbol{x}) + a_W u_W(\boldsymbol{x}) + a_S u_S(\boldsymbol{x})$$

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$$\begin{pmatrix} y \\ u(\boldsymbol{x}_{new}) \end{pmatrix} \sim N\left\{\begin{pmatrix} \mu(\boldsymbol{x}) \\ \mu(\boldsymbol{x}_{new}) \end{pmatrix}, \begin{pmatrix} \Sigma_{\boldsymbol{x},\boldsymbol{x}} + \lambda^2 I & \Sigma_{\boldsymbol{x},\boldsymbol{x}_{new}} \\ \Sigma_{\boldsymbol{x}_{new},\boldsymbol{x}} & \Sigma_{\boldsymbol{x}_{new},\boldsymbol{x}_{new}} \end{pmatrix}\right\}$$

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- Posterior $\pi_n(U(\boldsymbol{x}_{new}))$ is also Gaussian with linearly adjusted mean $\mu_n(\boldsymbol{x}_{new})$ and variance $\sigma_n^2(\boldsymbol{x}_{new}))$

Bayesian Optimisation

- An *acquisition function* (sequential design rule) tells us which value of $\boldsymbol{x}$ to next run the computer model at
- $\boldsymbol{x}_{n+1} = \arg\max_{\boldsymbol{x} \in \mathcal{X}} \alpha \left\{ \pi_n[U(\boldsymbol{x})] \right\}$

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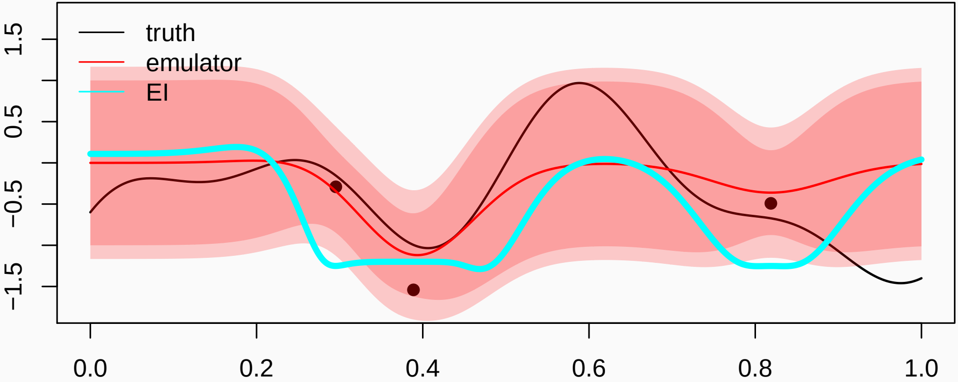
- examples:
  - $\mathrm{PI}(\boldsymbol{x}) = P_{\pi_n}(U(\boldsymbol{x}) > y_n^*)$
  - $\mathrm{EI}(\boldsymbol{x}) = \mathrm{E}_{\pi_n}\{\max(0, U(\boldsymbol{x}) - y_n^*)\}$
  - $\mathrm{UCB}(\boldsymbol{x}) = \mu_n(\boldsymbol{x}) + \gamma_n^2 \sigma_n(\boldsymbol{x})$

Bayesian Optimisation

No uncertainty in final answer considered in BayesOpt $\longrightarrow$ decision support

$$Z(x) = \frac{\mathrm{E}[U(x^*) - U(x)]}{\sqrt{\mathrm{Var}[U(x^*) - U(x)]}}$$



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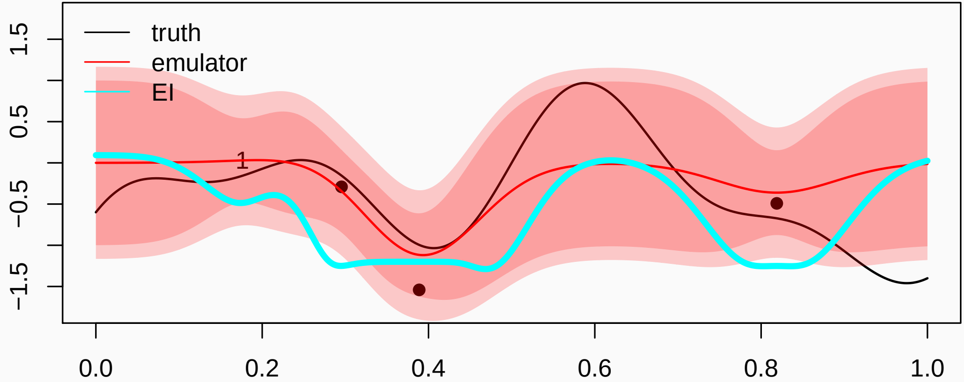
$$I(x) = \frac{E[U(x^*) - U(x)]}{\sqrt{Var[U(x^*) - U(x)]}}$$



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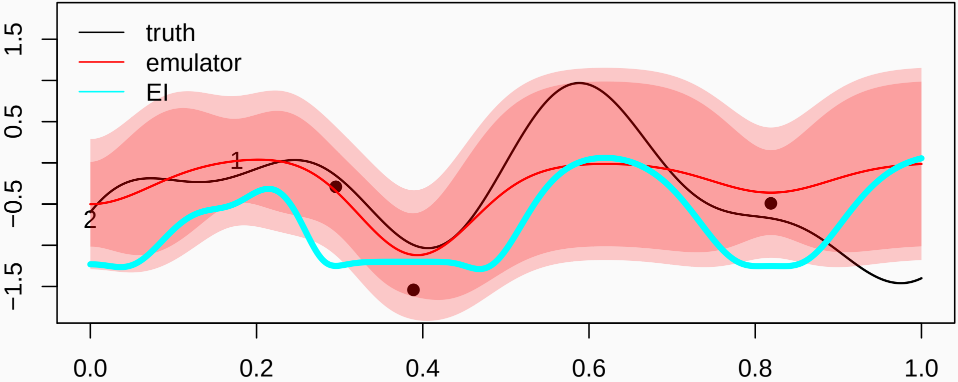

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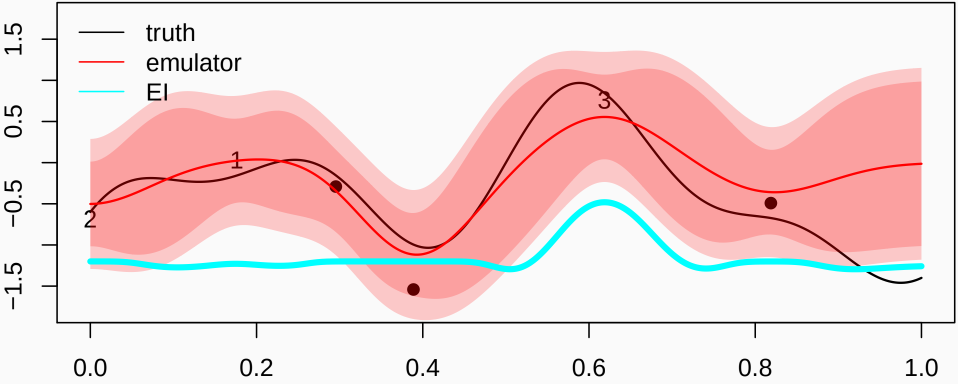

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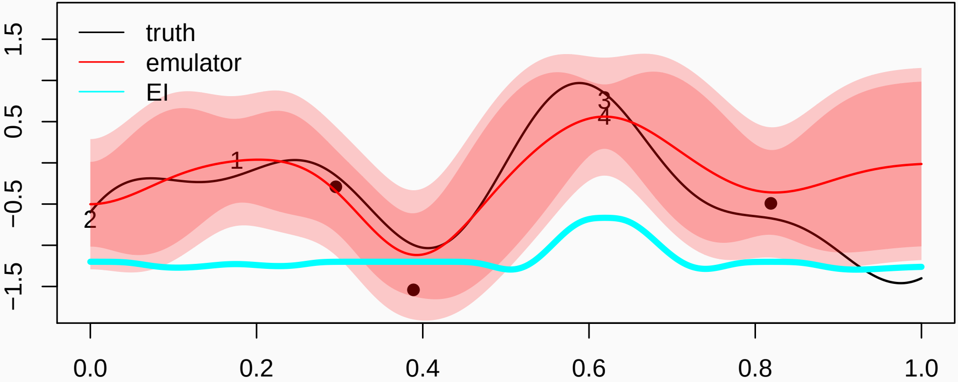

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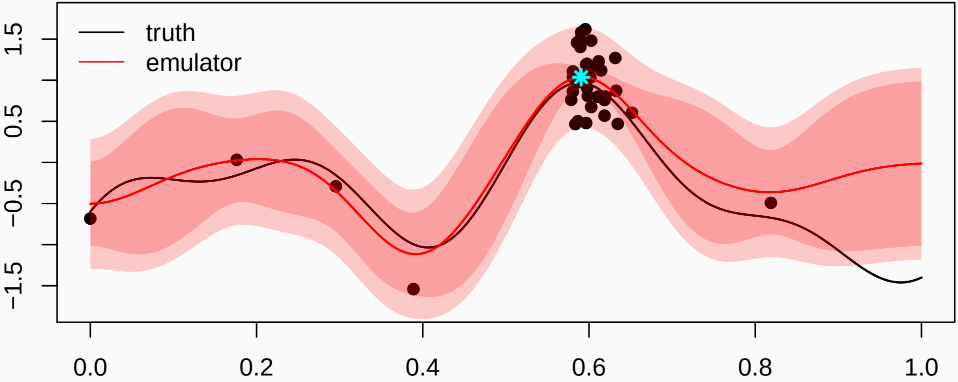
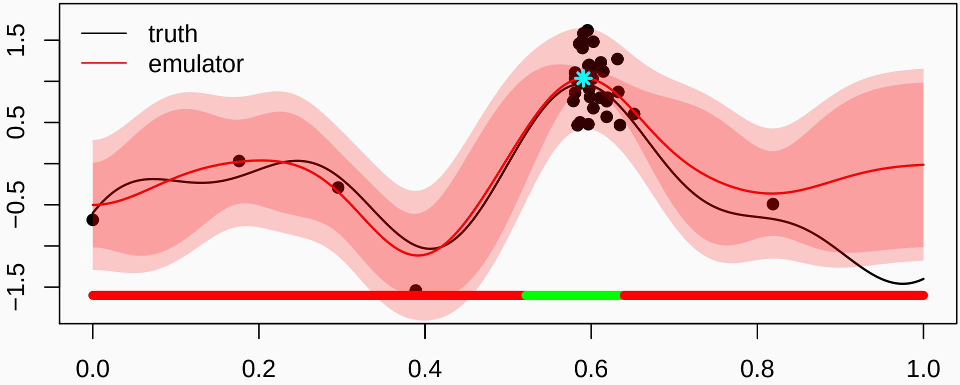


Bayesian Optimisation

No uncertainty in final answer considered in BayesOpt $\implies$ decision support

$$\mathcal{I}(\boldsymbol{x}) = \frac{\mathrm{E}\{U(\hat{\boldsymbol{x}}^*) - U(\boldsymbol{x})\}}{\sqrt{\mathrm{Var}\{U(\hat{\boldsymbol{x}}^*) - U(\boldsymbol{x})\}}}$$



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\alpha_{EI}(\boldsymbol{x}) &= \int_{\theta_n(\boldsymbol{x})}^{\infty} \operatorname{expit}\left\{\mu_n(\boldsymbol{x}) + \sigma_n(\boldsymbol{x})z\right\}\phi(z)\,\mathrm{d}z \\
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Back to Wind Farms

- Run EI and UCB ($\gamma_n^2 = 3$) scheme for the decision problem
- An independent scheme run for each sub-problem (warehouse) until $\min\{1000 \text{ runs}, 2 \text{ days}\}$ elapsed
- Utility stochastic $\implies$ ran 20 replicates at each design point
- Assumed $u(\cdot) \sim Beta(a(\cdot), b(\cdot))$
- GP hyperparameters updated every 30 iterations after an initial 40 'warm up' iterations
- Decision support:
    - $\mathcal{I}(\boldsymbol{x}) > 3 \implies$ ruled out
    - $\mathcal{I}(\boldsymbol{x}) \leq 3 \implies$ NROY

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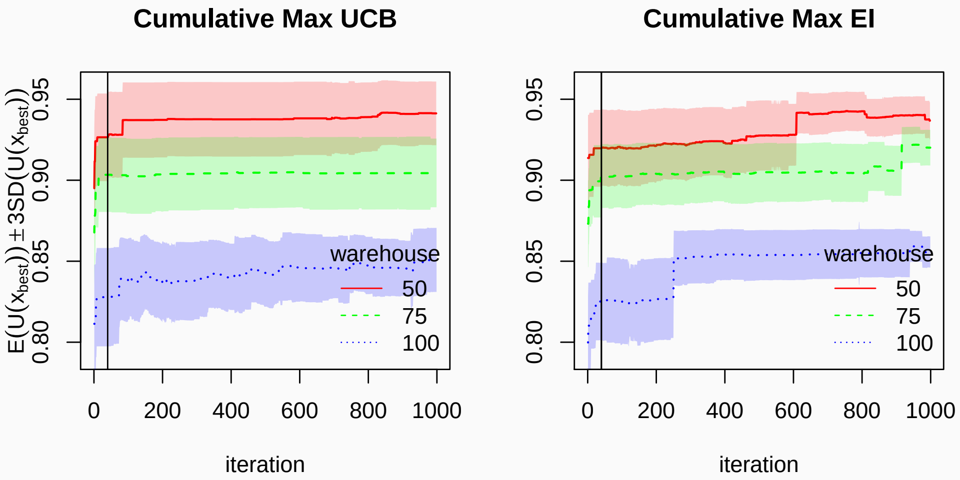

Back to Wind Farms

Conclusions

- Presented method for BayesOpt of utility functions which leverages problem structure
- EI seems to be better at minimising uncertainty; UCB ($\gamma_n = 3$) better at exploration
- Unification of decision support and optimisation - sequential design also helps with messy decision space
- Managed to rule out largest warehouse. For middle warehouse $\min \mathcal{I}(\boldsymbol{x}) \approx 1 < 3$

Further Work

- Better choice of kernel than squared exponential for discrete simplex like space?
- Incorporate notion of model discrepancy
- Perform another ‘wave’ of emulation/optimisation to try get decision space down to one warehouse

Thanks!

References

Frazier, P. I. (2018), 'A tutorial on Bayesian optimization', *arXiv preprint arXiv:1807.02811* .

Lawson, A., Goldstein, M. & Dent, C. (2016), 'Bayesian framework for power network planning under uncertainty', *Sustainable Energy, Grids and Networks* **7**, 47 – 57.
URL: *http://www.sciencedirect.com/science/article/pii/S2352467716300133*

Pukelsheim, F. (1994), 'The three sigma rule', *The American Statistician* **48**(2), 88–91.

Vernon, I., Goldstein, M., Bower, R. G. et al. (2010), 'Galaxy formation: a Bayesian uncertainty analysis', *Bayesian Analysis* **5**(4), 619–669.

Zitrou, A., Bedford, T. & Walls, L. (2016), 'A model for availability growth with application to new generation offshore wind farms', *Reliability Engineering and System Safety* **152**(C), 83–94.

Zitrou, A., Bedford, T., Walls, L., Wilson, K. & Bell, K. (2013), Availability growth and state-of-knowledge uncertainty simulation for offshore wind farms, *in* '22nd ESREL conference 2013'.
URL: *https://strathprints.strath.ac.uk/45377/*