Quantifying uncertainty in energy system simulators

Amy Wilson

Durham University

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Energy system simulators

A large part of the study of energy systems involves the building of simulators (deterministic or stochastic) to represent particular aspects of an energy system. A simulator:

- takes a set of inputs (known, uncertain, control parameters)
- produces a set of outputs from these inputs
- is an approximation of a system.

Simulators can be thought of as a function f, with

$$\mathbf{y} = f(\mathbf{x}).$$

where inputs= $\mathbf{x}$, outputs= $\mathbf{y}$.

All models are wrong

George Box: ‘Essentially, all models are wrong, but some are useful’

To determine how useful a simulator is, need to quantify how much it reduces our uncertainty.

Types of uncertainty

- **Input uncertainty:** uncertainty about the appropriate input parameters ($\mathbf{x}$) to use.
  - E.g. demand forecasts, investor risk level, weather data.
- **Structural uncertainty:** how the simulator itself (f) relates to the real-world process it is modelling
  - E.g. is this process really Normally distributed? what effect does this simplifying assumption have on the results?
- **Function uncertainty:** what the output of the simulator, $f(\mathbf{x})$ is at untested $\mathbf{x}$.

Problem: it is hard to quantify uncertainty when simulators are computationally expensive.

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Emulation - general idea

- Many simulators take a long time to run - so standard Monte Carlo simulation methods for investigating uncertainty are infeasible,
- Instead build statistical model of underlying energy system simulator, based on a small number of simulator evaluations (an emulator).
- At inputs for which simulator hasn't been evaluated, don't know what simulator output is (i.e. function uncertainty).
- Emulator gives a distribution for the output at each input.

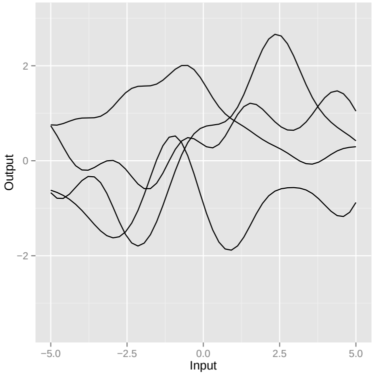
Model

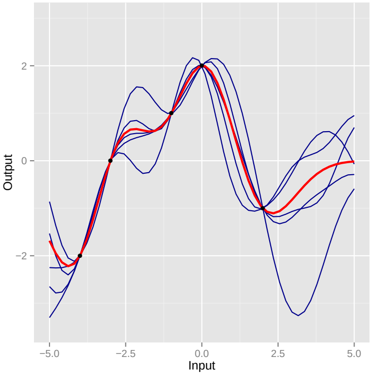
- Can model simulator output as:

$$f(\mathbf{x}) = \sum_{i=1}^{p} \beta_i h_i(\mathbf{x}) + \epsilon(\mathbf{x}),$$

  with β_i a set of constants, $h_i(\mathbf{x})$ a set of basis functions and $\epsilon(\mathbf{x})$ a stochastic process.
- Common choice for $\epsilon(\mathbf{x})$ is a Gaussian Process - for m different input vectors, $\mathbf{x}_1, \ldots, \mathbf{x}_m$, the joint distribution of $\epsilon(\mathbf{x}_1), \ldots, \epsilon(\mathbf{x}_m)$ follows a multivariate Normal distribution.
- Set prior distributions for β_i, variance of $\epsilon(\mathbf{x})$ and set a prior correlation function for the Gaussian Process (e.g. Gaussian, Matérn).
- Use data D to update beliefs about these parameters.

Example





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The Dynamic Dispatch Model (DDM)

- Large planning simulator of the future energy market (e.g. simulates future energy prices, mix of generators, emissions),
- Built by LCP (consulting firm),
- Used by DECC, National Grid and others for making evidence-based policy decisions.

Strike price analysis

- As part of Electricity Market Reform, government planned to hold auctions for support for renewable technologies (replacing Renewables Obligation).
- Renewable generation would be guaranteed a fixed price for power (known as a strike price).
- Individual generators can make bids, but the price awarded is subject to an 'administrative strike price' or a maximum set by the government for each future year.
- First auction was held in late 2014, with results in February 2015.

Decision problem

- In 2013, DDM was used to help determine the parameters of the auction.
- Aimed to find administrative strike prices that would result in:
  - a total cost in 2020 of less than £7.6bn,
  - a proportion of renewable generation greater than 30% in 2020,
  - emissions of less than 100 gC02/kWh in 2030.
- Also wanted to test sensitivity of these outputs to changes in inputs, and to assess overall uncertainty.

Scenarios

- Takes around 1 hour to run the DDM for the strike price analysis,
- In 2013, approach was to use different scenarios to assess uncertainty/ sensitivity,
- But only possible to test around 20 scenarios - so no idea of model output between scenarios (in very large input space),
- Difficult to find strike prices that will meet constraints with a high probability with so few model runs.
- Could emulation resolve these issues?

Statistical study

- 14 inputs considered: 6 parameters associated with strike prices (for onshore, offshore and solar), demand, fuel prices (coal, gas), technology costs, hurdle rates (onshore and offshore) and load factors (onshore and offshore).
- Three outputs: spend (2020), proportion of renewables (2020) and emissions (2030).
- Three sets of model evaluations completed:
  - Wave one - 40 runs.
  - Wave two - 16 runs.
  - Wave three - 24 runs.
- Built a separate emulator for each of the three outputs.

Choice of design

- Very few DDM evaluations possible,
- To maximise use of every run, developed criteria (evaluated over a grid) to select design for third wave:

$$\tilde{\mathbb{E}}\left[\sum_j \left(\mathrm{Var}^*(\mathbb{E}_Z[f_s(\theta^{(j)},\mathbf{z})]) + \mathrm{Var}^*(\mathbb{E}_Z[f_r(\theta^{(j)},\mathbf{z})]) + \mathrm{Var}^*(\mathbb{E}_Z[f_e(\theta^{(j)},\mathbf{z})])\right)\right] \times$$

$$P(f_r(\theta^{(j)},\mathbf{z}) + \epsilon_r > 0.3,\ f_e(\theta^{(j)},\mathbf{z}) + \epsilon_e < 100,\ f_s(\theta^{(j)},\mathbf{z}) + \epsilon_s < 7.6)$$

- Criteria seeks to reduce the function uncertainty (the emulator variance) but focussing on the region of the space where the three criteria are met with a high probability (after integrating over other parametric uncertainties).

Basis functions

- Basis functions selected by testing different regression models and making a subjective assessment of which parameters might be influential:
- All three emulators included linear terms for: strike price rate of decay (offshore), starting strike price (offshore), starting strike price (onshore), gas price, technology costs, hurdle rate (offshore), load factor (offshore). In addition,
  - Renewables emulator - linear terms: demand, hurdle rate (onshore), load factor (onshore). Four interaction terms.
  - Emissions emulator - linear terms: demand, coal price. Six interaction terms.
  - Spend emulator - linear terms: load factor (onshore). Eight interaction terms.

Problem

Coefficient (Renewables emulator)	Low (coeff 3)	High (coeff 3)
1. Constant	-0.07	0.02
2. Strike price rate of decay (offshore)	-0.13	-0.13
3. Starting strike price (offshore)	0.33	0.40
4. Starting strike price (onshore)	0.03	0.08
5. Demand	-0.49	-0.54
6. Gas price	0.06	0.05
7. Technology cost	-0.31	-0.37
8. Hurdle rate (offshore)	-0.14	-0.19
9. Hurdle rate (onshore)	-0.02	-0.08
10. Load factor (offshore)	0.58	0.75
11. Load factor (onshore)	0.23	0.23
12. Interaction:3*7*10	0.16	0.07
13. Interaction:3*7	0.01	-0.06
14. Interaction:3*10	0.18	0.00
15. Interaction:3*10	-0.11	-0.03

Model

- Outputs of big computer models can be very different in different regions of the input space.
- Can fit emulator in waves, with each wave focussing on a subset of the previous wave (throwing away information from previous waves).
- Have very limited data so this approach is not a good one!
- Instead allow the parameters governing the global response of the model to vary in different areas of the input space.

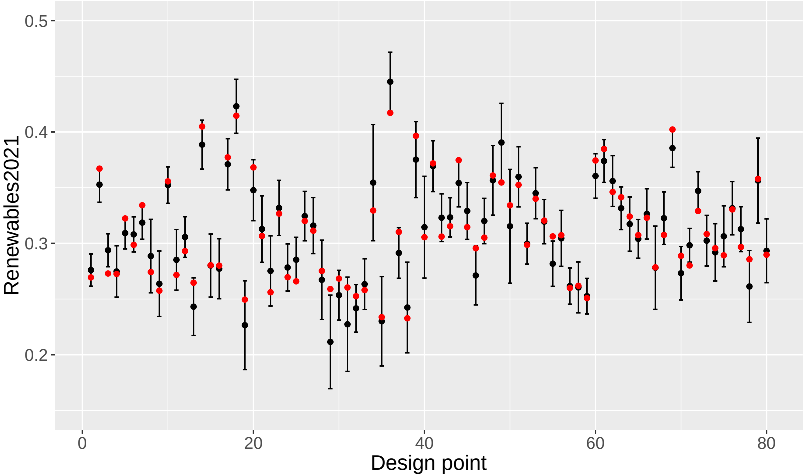
Model

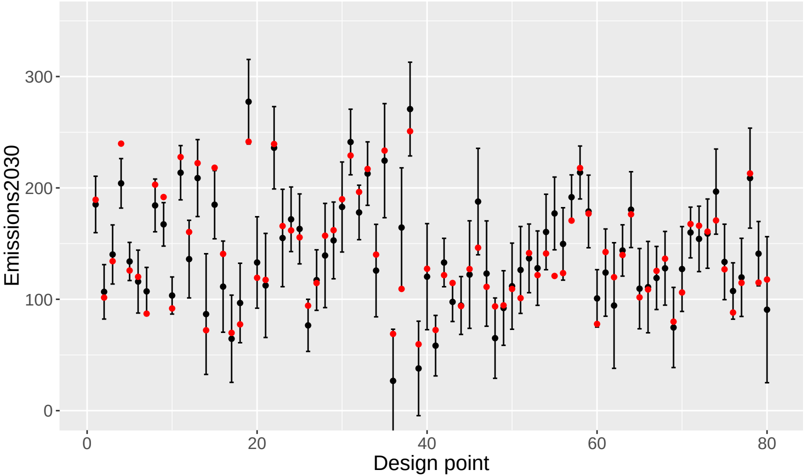
- Proposed model:

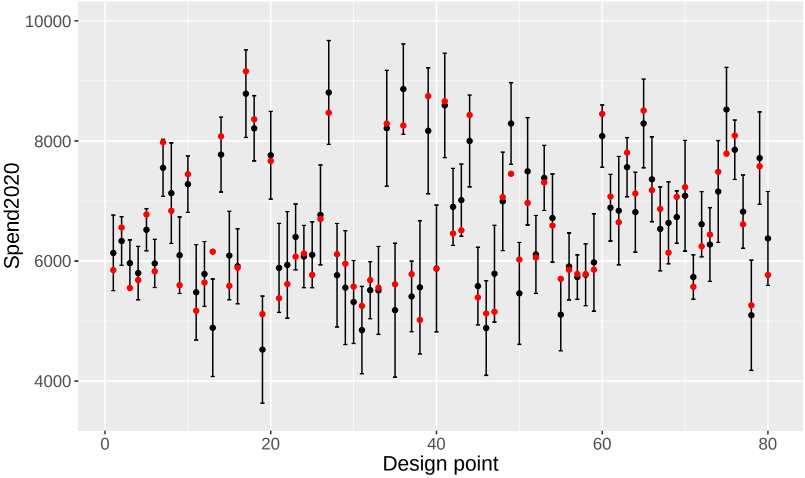
$$f(\mathbf{x}) = \sum_i \beta_i h_i(\mathbf{x}) + \sum_i \epsilon_{\beta_i}(\mathbf{x}) h_i(\mathbf{x}),$$

  where $\epsilon_{\beta_i}(\mathbf{x})$ are stochastic processes, β_i are constants and $h_i(\mathbf{x})$ are basis functions.
- For comparison, the model described earlier was:

$$f(\mathbf{x}) = \sum_i \beta_i h_i(\mathbf{x}) + \epsilon(\mathbf{x}).$$


Renewables2021
0.5
0.4
0.3
0.2
0
20
40
60
80
Design point


Emissions2030
300
200
100
0
0
20
40
60
80
Design point


10000
8000
6000
4000
Spend2020
0
20
40
60
80
Design point

Modelling uncertainty

- Want to find strike prices which meet the three criteria (renewables$>$30%, emissions$<$100gCO2/kWh and cost$<$£7.6bn) with a high probability, given parametric uncertainty, structural discrepancy and function uncertainty.
- Set parametric uncertainty using ranges and means in NG and DECC scenarios (multivariate Normal distribution). Set (coal, gas) correlation to 0.4 and (coal, demand) and (gas, demand) correlation to 0.2.
- No historical data - set structural discrepancy to around 10% to investigate impact on probability of meeting criteria.
- Used emulators with MC simulation to estimate probability of meeting all three criteria and hence to select potential strike prices.

Results

Five strike price choices (scaled by mean and sd) with highest expected probability of meeting criteria:

Prob	Rate of decay Offshore	Start price Offshore	Rate of decay Solar	Start price Solar	Rate of decay Onshore	Start price Onshore
11.3%	-1.20	0.77	-1.16	-0.23	1.58	-1.68
11.1%	-0.98	1.07	1.10	-0.83	0.39	-1.66
10.7%	-1.28	0.76	-0.99	1.26	-1.76	-1.45
10.5%	-1.00	0.92	-1.35	-1.66	-1.48	-1.51
10.4%	-1.02	1.30	-1.43	0.40	-0.71	-1.50

Results

Strike price choice with highest expected probability of meeting criteria (11.3%):

	Parametric uncertainty	
	Expectation (sd)	Std deviation (sd)
% Renewables	0.32 (0.00)	0.02 (0.00)
Emissions (gCO2/kWh)	122.22 (1.14)	25.85 (0.83)
Cost (£m)	6991.44 (26.86)	578.12 (20.22)

Results

- Emulators are much faster to run than the DDM - would be difficult to quantify uncertainty in this much detail without emulation.
- Able to give policy-makers a much better idea of risk than with traditional scenario analysis.
- Could use these results to choose further DDM evaluations. Emulation can give an idea of which model evaluations are likely to meet criteria, without having to do a time consuming search.

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Conclusion

- Important to consider uncertainties when modelling - parametric, structural and functional.
- Without assessing uncertainties, it is not normally possible to use a simulator to say anything about the 'real-world'.
- Emulation can be a useful tool for quantifying function uncertainty
- Combining emulation with a model for structural uncertainty and with distributions over model inputs allow structural and parametric uncertainties to be assessed even in simulators that are slow to run.

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