Quantifying uncertainty in energy system simulators - examples

Amy Wilson

Durham University

May 2016

The Dynamic Dispatch Model

- 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.

GB capacity market auction

- Auction to secure future GB electricity security,
- Generators bid to provide capacity rather than power (so can receive payment even if not required to generate power),
- First auction was in December 2014 for capacity in 2018/2019,
- UK government needed to know how much capacity to procure through this auction,
- National Grid used DDM to estimate this.
- Results: $\sim$ 50 GW capacity procured at a cost of $\sim$ £1bn

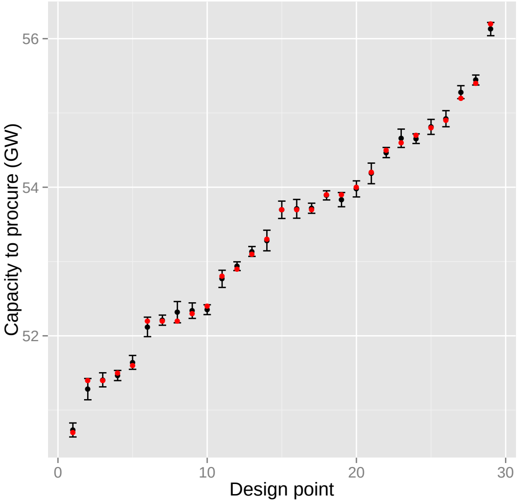
Statistical study

- Investigated impact of uncertainty on DDM outputs.
- 121 inputs listed in National Grid report. Focused on 6 of these (all 2018/2019 predictions):
  - inputs (all 2018): annual demand, peak demand, interconnector flow, CCGT availability, wind level (normal/low), weather conditions (cold/normal/warm).
  - output: capacity to procure in 2018 UK capacity market auction.
- 30 DDM evaluations to use (no ability to perform further DDM evaluations).

Model

- Modelled DDM output as
$$f(\mathbf{x}) = \mathbf{h}(\mathbf{x})^T \beta + \epsilon(\mathbf{x})$$
with $\epsilon(\mathbf{x})$ a Gaussian Process.
- Set
$$\mathbf{h}(\mathbf{x})^T = (1, x_2, x_3, x_4, x_5, x_6, x_7, x_2^2, \frac{x_2}{x_1}),$$
x_1 =annual demand, x_2 =peak demand, x_3 =interconnector, x_4 =CCGT, x_5 =low wind, x_6 =warm weather, x_7 = cold weather.
- Used Gaussian correlation function, so that
$$\mathrm{Cov}(f(\mathbf{x}), f(\mathbf{x}') \mid \sigma^2) = \sigma^2 \exp[-(\mathbf{x} - \mathbf{x}')^T D(\mathbf{x} - \mathbf{x}')],$$
with D diagonal.
- Weak prior used for β, σ^2: $\pi(\beta, \sigma^2) \propto \sigma^{-2}$.

Example - DDM



Input parameters

- Considered parametric uncertainty due to: peak demand, annual demand, interconnector flow, CCGT availability,
- Assumed normal weather conditions and normal wind conditions,
- Distribution of input parameters:

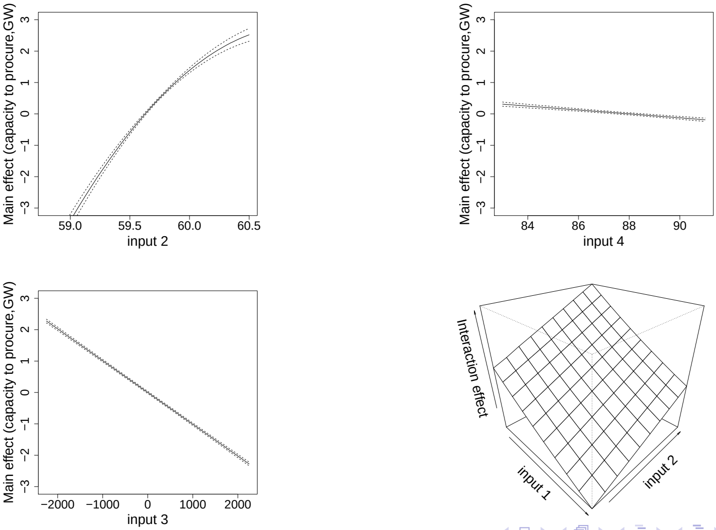
$$X \sim N\left(\begin{pmatrix} 343 \\ 59.7 \\ 0 \\ 88 \end{pmatrix}, \begin{pmatrix} 7.5625 & c & 0 & 0 \\ c & 0.180625 & 0 & 0 \\ 0 & 0 & 1265625 & 0 \\ 0 & 0 & 0 & 4 \end{pmatrix}\right),$$

- Covariance unknown - investigated different correlations between annual and peak demand.

Uncertainty analysis

Uncertainty measure	Capacity to procure (GW)		
	Correlation= 0	0.25	0.85
Expected value:	53.59	53.59	53.58
Variance (emulation):	0.00030	0.00031	0.00031
Variance (parameter):	8.64	6.95	2.77
Variance of variance (emulation):	0.30	0.17	0.02

Sensitivity analysis



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, National Grid used the DDM 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 optimal strike prices with so few model runs.
- Using emulation to resolve these issues.

Statistical study

- Focussed on 14 inputs: 6 parameters associated with strike prices (for onshore, offshore and solar), demand, fuel prices (coal, oil, 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).
- Two waves of the analysis completed so far - one to go.
- Wave one - 40 runs of the DDM.
- Wave two - 16 runs of the DDM.
- Wave three - will be 16 further runs.

Choice of design

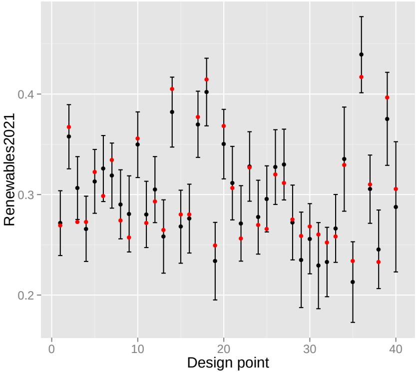
- Very few DDM evaluations possible,
- To maximise use of every run, developed criteria to select design for third wave:

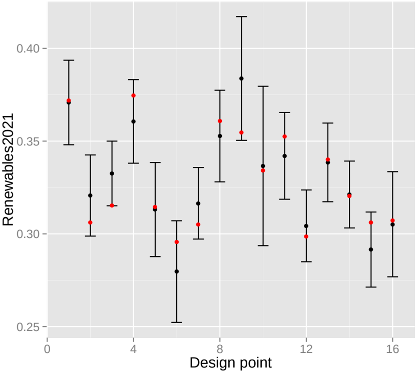
$$\tilde{\mathbb{E}}\left[\sum_j \Big(\mathrm{Var}^*(\mathbb{E}_Z[f_s(\theta^{(j)},\mathbf{z})]) + \mathrm{Var}^*(\mathbb{E}_Z[f_r(\theta^{(j)},\mathbf{z})]) + \mathrm{Var}^*(\mathbb{E}_Z[f_e(\theta^{(j)},\mathbf{z})])\Big) \times \right.$$

$$\left. P(f_r(\theta^{(j)},\mathbf{z}) + \epsilon_r > 0.3,\, f_e(\theta^{(j)},\mathbf{z}) + \epsilon_e < 100,\, f_s(\theta^{(j)},\mathbf{z}) + \epsilon_s < 7)\right]$$

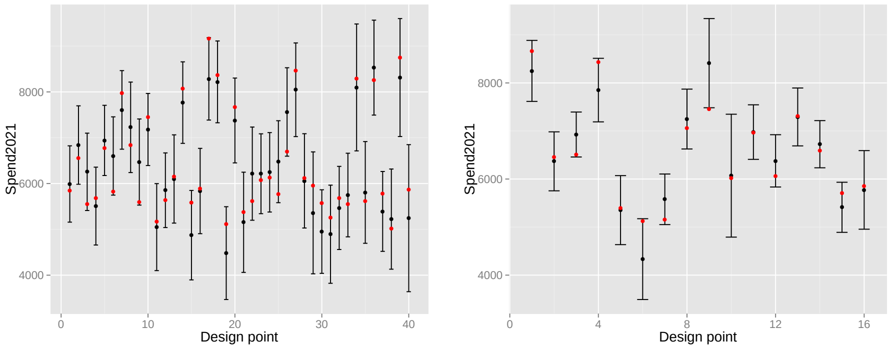
- Idea is to minimise function uncertainty where we care most about it - i.e. when we are in the region where the spend is low, renewables are high and emissions are low (and we want to minimise function uncertainty after integrating over our parametric uncertainty).

Model fit

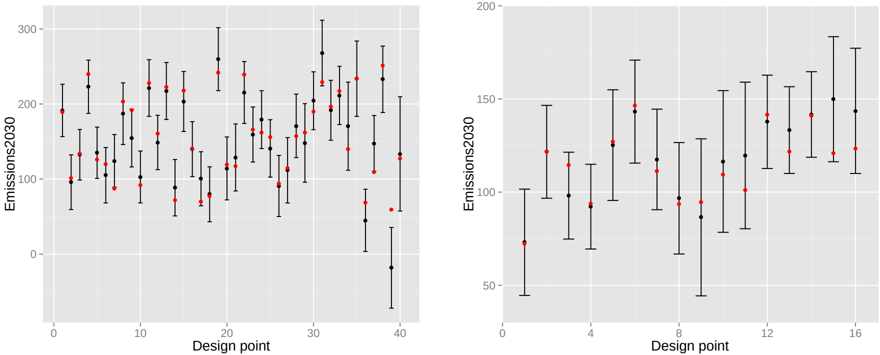

Renewables2021
0.2
0.3
0.4
0
10
20
30
40
Design point


Renewables2021
0.25
0.30
0.35
0.40
0
4
8
12
16
Design point

Model fit


Spend2021
8000
6000
4000
0
10
20
30
40
Design point
Spend2021
8000
6000
4000
0
4
8
12
16
Design point

Model fit


Emissions2030
300
200
100
0
0
10
20
30
40
Design point
Emissions2030
200
150
100
50
0
4
8
12
16
Design point

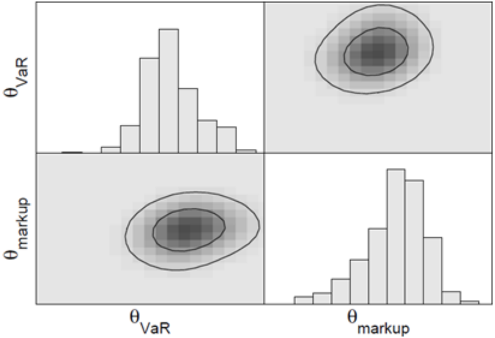
Initial results

- Function uncertainty very large!
- Hoping that the third wave will reduce some of this uncertainty, but likely that we will still have substantial uncertainty,
- Demonstrates size of uncertainty when performing a limited scenario analysis.

Generation investment model

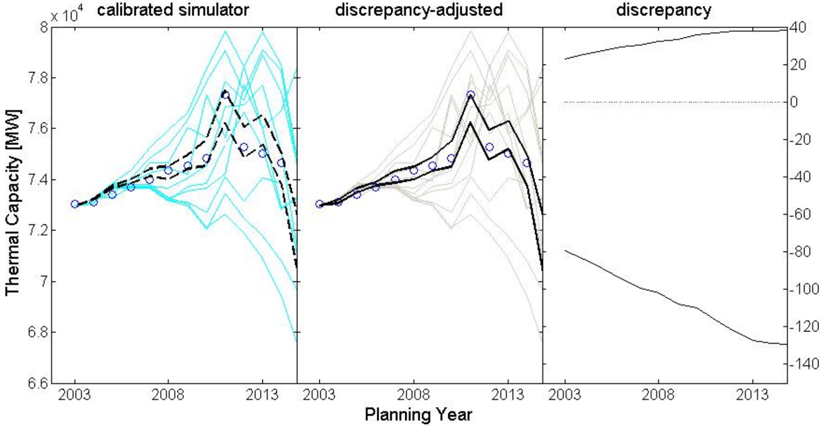
- Long-term generation investment model developed by Eager, Bialek and Hobbs
- Analysis done by Meng Xu, Durham University.
- inputs: attitude to risk, price mark-up
- output: annual installed thermal generation capacity
- 12 evaluations
- Structural discrepancy modelled using sum of three Normal kernels
- Aim: calibration

Generation investment model



Posterior distributions of calibrated parameters - prior distribution was uniform.

Example - generation investment



Conclusions

- Important to consider uncertainties when modelling - parametric, structural and function.
- 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 and can allow us to quantify uncertainties for complex simulators where it would not normally be possible to do a traditional Monte Carlo analysis.