Efficient quantification of the impact of demand and weather uncertainty in energy system models

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Uncertainty on time series inputs leads to demand and weather uncertainty on model outputs
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**INPUTS**

Demand & weather data at different locations on the grid
- Demand levels
- Wind speeds
- Solar irradiances
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- Installed capacities of different technologies
- Hourly generation levels of different technologies
- Total system cost
- Total carbon emissions
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Uncertain inputs → *Demand and weather uncertainty on outputs*
Natural climate variability can lead to large uncertainty on energy system model outputs.
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- Spread in model outputs across uncertain demand and weather can be large: risk in “picking wrong year”
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Can we quantify this *demand* and *weather uncertainty*?
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Traditional Monte Carlo methods are inefficient in data and computation

Obtain 100 years of data
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Obtain 100 years of data

- Year 1
- Year 2
- Year 3
- ...
- Year 98
- Year 99
- Year 100
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- Year 1
- Year 2
- Year 3
  ...
- Year 98
- Year 99
- Year 100

Obtain 100 years of data ➔ run model
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Obtain 100 years of data

- Year 1
- Year 2
- Year 3
- ...
- Year 98
- Year 99
- Year 100

run model

Model output
Traditional Monte Carlo methods are inefficient in data and computation

- Obtain 100 years of data
- Year 1
- Year 2
- Year 3
- ...
- Year 98
- Year 99
- Year 100

run model

Inefficient in
- data: 100 years of demand and weather data
- computation: 100 1-year simulations
New method resamples data into shorter subsamples to calculate uncertainty intervals more efficiently
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Obtain 5 years of data.
New method resamples data into shorter subsamples to calculate uncertainty intervals more efficiently

- Short sample 1
- Short sample 2
- Short sample 3
- ...
- Short sample 98
- Short sample 99
- Short sample 100
New method resamples data into shorter subsamples to calculate uncertainty intervals more efficiently.

- Obtain 5 years of data
  - Resample
  - Short sample 1
  - Short sample 2
  - Short sample 3
  - ... (to 98)
  - Short sample 99
  - Short sample 100

*Resample weeks from seasons*

  e.g. one week from winter, spring, summer, autumn
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- Short sample 98
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- Short sample 100

Resample weeks from seasons

- e.g. one week from winter, spring, summer, autumn

Rescale model output
New method resamples data into shorter subsamples to calculate uncertainty intervals more efficiently

Obtain 5 years of data

- Short sample 1
- Short sample 2
- Short sample 3
- ...
- Short sample 98
- Short sample 99
- Short sample 100

Resample weeks from seasons

  e.g. one week from winter, spring, summer, autumn

Resample

... run model

rescale

Model output

\[
\text{short sample length} = \sqrt{\text{full sample length (1yr)}}
\]
New method resamples data into shorter subsamples to calculate uncertainty intervals more efficiently.

Obtain 5 years of data
resample

- Short sample 1
- Short sample 2
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  ...
- Short sample 98
- Short sample 99
- Short sample 100

run model

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e.g. one week from winter, spring, summer, autumn

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Efficient in
- data: 5 years of demand and weather data
- computation: 100 1-year short simulations
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• Approach, based on $m$ out of $n$ bootstrap, resamples shorter datasets, reducing computing cost and removes need for any additional data.
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