Why the Weather matters
The Coaction of meteorological and techno-economical parameters in numerical power system models

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Content

- Part I: Parameter co-action in numerical power system models

- Part II: What aspect(s) of the meteorological time series affect to simulation result in a significant manner?
• How could this be achieved? What’s the optimal system design?

• What does it cost and who should pay how much for the electricity he/she consumes?

• How does everything depend on the weather and how does all this change with a changing climate?

• What kind of storage do we need?

• How do all the system’s components interact?

• What would be a good price for CO$_2$?
A model!

On condition that

- The demand is met at any point in space and time.
- Local electricity generation from VRES is only as high as there is generation capacity available.
- The flow of electricity fulfills the laws of physics.
- Emissions are below a certain threshold X.
Power System Expansion Models

1. Numerical models for planning and operating power systems

2. Bi-level optimisation problems with linearized load flow (LP or MILP)

\[ \min_x f(x) \]

with

\[ f(x) = \text{investment cost} + \text{operation cost} = f(\bar{g}, g, l) \]

1. Decision variables: nominal capacity \( \bar{g} \), generation \( g \), load flow \( l \)
2. Power systems are approximated via a limited number of nodes and lines and finite, discrete time series
3. Limited (small) choice of technologies for generation, storage and transmission
## Model Parameters

<table>
<thead>
<tr>
<th>Information</th>
<th>Parameter</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weather-related potential generation from variable renewable resources</td>
<td>Capacity factors</td>
<td>Wind speed, irradiance, temperature</td>
</tr>
<tr>
<td>What's the demand for electricity?</td>
<td>load</td>
<td>Historical data from ENTSO-E&lt;sup&gt;1&lt;/sup&gt;</td>
</tr>
<tr>
<td>Which technologies are available?</td>
<td>Energy carrier</td>
<td>Own choice</td>
</tr>
<tr>
<td>What are the specific characteristics of the technologies?</td>
<td>Costs, efficiencies, emissions, …</td>
<td>Various, here PyPSA-Eur&lt;sup&gt;2&lt;/sup&gt;</td>
</tr>
</tbody>
</table>

<sup>1</sup> [https://data.open-power-system-data.org/time_series/](https://data.open-power-system-data.org/time_series/)

<sup>2</sup> Hörsch et al., 2017
Parameter Uncertainty

- Parameters are derived from various data sources.

- Often, parameters are projections for future times (e.g. costs for 2030).

- Power systems are planned based on historical data.

- Two different kind of uncertainty:
  1. Uncertainty about the choice of the data sources (see presentation of Mariia Bilousova)
  2. Uncertainty of the data source itself

- Uncertainties propagate in the model results.
Uncertainty in the definition of the cost of capital

or

How do regional differences in the cost of capital influence the cost-optimal system design?
Regional differences in the cost of capital

Weighted average cost of Capital (WACC) in European countries, adopted from Noothout et al. [2016]
Implications on the optimal system design

- Accumulation of generation capacity in countries with favourable financing conditions

- Higher share of wind power (esp. onshore)

- Lower share of solar PV and gas

- Overall lower levelized cost of electricity

- Increasing inequality in the expenditures for electricity from the centre to the periphery

Relative change of average prices for electricity in the diacore scenario compared to the reference

Schyska and Kies (2020), preprint on arxiv
Defining a Sensitivity Metric

Systematic description of the impacts of different parameter choice on the simulation results -> measure the sensitivity

Define a metric, which

• quantitatively describes the sensitivity of power system models,

• allows to compare a great number of scenarios,

• is symmetric to the choice of the scenario and

• is greater equal zero.
Computing the Metric: Cost of Capital Example

Levelized Cost of Electricity: \( \text{LCOE} = \frac{\text{Cost for Investment and Operation}}{\text{Demand met}} \)

<table>
<thead>
<tr>
<th></th>
<th>Reference</th>
<th>Diacore</th>
</tr>
</thead>
<tbody>
<tr>
<td>LCOE unconst. [EUR / MWh]</td>
<td>72.2</td>
<td>70.8</td>
</tr>
<tr>
<td>LCOE constr. [EUR / MWh]</td>
<td>74.7</td>
<td>72.8</td>
</tr>
<tr>
<td>Difference</td>
<td>2.5</td>
<td>2.0</td>
</tr>
</tbody>
</table>

\( M = 4.5 \text{ EUR/MWh} \)

Schyska et al., submitted, preprint on arxiv
The Sensitivity to Meteorological Parameters: Data

- RCP 8.5 climate projections from the CNRM-CERFACS-CNRM-CM5
- Scaled down within EURO-CORDEX

- Near-surface wind speed extrapolated to hub-height (90m) using the logarithmic wind profile
- Surface downwelling shortwave radiation and near-surface air temperature for solar PV
- Total runoff for hydro power

- 5 time slices:
  - Mid of century (MOC): 2038 – 2044
  - End of century (EOC): 2094 - 2101

- PyPSA-Eur (one node per country)
- Including:
  - Load time series
  - Renewable potentials
  - Cost
  - Technologies

- Onshore + offshore wind, solar PV, OCGT, hydro, batteries, hydrogen storage

- 95% CO$_2$ reduction scenario

Schlott et al. (2018), Applied Energy, preprint on arxiv

Hörsch et al. (2018), Energy Strategy Reviews, arxiv preprint
Capacity Factor Changes towards the End of the Century

Relative change in 2094-2101 compared to 2000-2006 [%]

Schyska et al., submitted, preprint on arxiv
Differences in optimal Capacity Expansion

Difference in optimal capacity expansion compared to BOC [GW]

Schyska et al., submitted, preprint on arxiv
The Sensitivity to the Capacity Factor Time Series

- Same order of magnitude as sensitivity to cost of capital
- Combinations with 2000 – 2006 exhibit highest sensitivities, e.g. higher as HIS + EOC
- 2000-2006 leads to *extraordinary* solution -> not representative
- Comparably low sensitivity on scenarios HIS, MOC and EOC

Schyska et al., submitted, preprint on [arxiv](https://arxiv.org/)
Parameter Coaction

• Sensitivity expresses the co-action of the model parameters.

• All model parameters co-act, together they determine the optimal system design.

• The higher the sensitivity, the higher the action of the parameter.

• Examples:
  
  − Regional differences in the cost of capital favour the deployment of wind power
  
  − Climate change increases the optimal solar share
Parameter Coaction: Examples

The presence of demand side management options increases the optimal share of solar power from 19 to 37%.

[Graph showing the optimal mix of wind and PV with and without demand side management (DSM).]

[Kies et al., 2016]
Parameter Coaction: Examples

Strong grid enforcements in Europe foster the deployment of wind power and hydro power, while weaker grids are dominated by solar power and storage facilities.

[Schlachtberger et al., 2017]
Summary Part I

• Parameters co-act.

• Choosing the ‘right’ weather data is as important as choosing the ‘right’ cost data.

• Better do not choose the period 2000-2006.
Motivation Part II

• The meteorological data has a significant action on the model results.

• The period 2000-2006 is special.

What characteristic(s) of the capacity factor time series ‘drive’ the model results?
Capacity Factor Characteristics

- Capacity factors are spatio-temporal data sets.

- Characteristics:
  - Mean
  - Spread
  - Extremes
  - Increment statistics
  - (Co-)Variance
  - Single events
Capacity Factor Changes towards the End of the Century

Solar PV

Onshore wind

Relative change in 2094-2101 compared to 2000-2006 [%]

Schyska et al., submitted, preprint on arxiv
Differences in optimal Capacity Expansion

Difference in optimal capacity expansion compared to BOC [GW]

Schyska et al., submitted, preprint on arxiv
Investigating the Effect of changing Capacity Factor Means

1. Scale the capacity factor time series for each generator of the HIS, MOC and EOC time series, such that the average equals the average of the BOC period.
2. Compare differences in optimal system design.
Investigating the Effect of changing Capacity Factor Means (reverse)

1. Scale the capacity factor time series for each generator of the BOC time series, such that the average equals the average of the HIS, MOC and EOC period, respectively.
2. Compare differences in optimal system design.
Capacity Factor Characteristics

• Capacity factors are spatio-temporal data sets.

• Characteristics:
  − Mean  
  − Spread
  − Extremes
  − Increment statistics
  − (Co-)Variance
  − Single events

limited effect
Complementarity

From the review of Jakub Jurasz et al. [2020]:

• “a relationship or situation in which two or more different things improve or emphasize each other’s qualities” [Oxford dictionary]

• Spatial, temporal and spatio-temporal complementarity

• Various indices to assess the complementarity exist (see Jurasz et al. [2020] for an overview).

• Easiest is the correlation.
Complementarity

A, CC = 1, phase: 0

B, CC = 0.5, phase: π/6

No complementarity

Increasing complementarity

[Jurasz et al., 2020]
Complementarity

[A, CC = 1, phase: 0]

[C, CC = 0, phase: π/4]

No complementarity

Increasing complementarity

[Jurasz et al., 2020]
Complementarity

A, CC = 1, phase: 0

D, CC = -0.5, phase: π/3

[Jurasz et al., 2020]

No complementarity

Increasing complementarity
Complementarity

A, CC = 1, phase: 0

E, CC = -1, phase: π/2

[Jurasz et al., 2020]

No complementarity

Perfect complementarity
Measuring the Complementarity

- Measure complementarity of resource $s$ at node $n$ as the average correlation across all generators, that can be reached via maximum $r$ lines in the network

$$C_{n,s} (r) = \langle q(x_{n,s}, x_{m,s}) \rangle_{m \in \Omega_r}$$

- Compute complementarity separately for the seasonal, trend and residual component of the capacity factor time series, i.e. after decomposing the time series (here STL [Cleveland et al., 1990]).
Differences in the Complementarity

- Normalised difference in % of BOC
- Trend component
- $r = 3$
- Onshore wind power
Differences in the Complementarity

- Normalised difference in % of BOC
- Seasonal component
- $r = 3$
- Onshore wind power
Differences in the Complementarity

- Normalised difference in % of BOC
- Residual component
- $r = 3$
- Onshore wind power
Capacity Factor Characteristics

- Capacity factors are spatio-temporal data sets.

- Characteristics:
  - Mean: limited effect
  - Spread
  - Extremes
  - Increment statistics
  - (Co-)Variance: potentially, need for further research
  - Single events
Investigating the Effect of single Events

1. Run model over one year (instead of 5).
2. Move the considered period with steps of 4 weeks.
3. Plot the difference of the optimal system design compared to the full period.
Capacity Factor Characteristics

• Capacity factors are spatio-temporal data sets.

• Characteristics:
  – Mean: limited effect
  – Spread
  – Extremes
  – Increment statistics
  – (Co-)Variance: potentially, need for further research
  – Single events: set the requirements for the backup system, indirect effects on other resources
Summary Part I + II

• Parameters co-act.

• Choosing the ‘right’ weather data is as important as choosing the ‘right’ cost data.

• Better do not choose the period 2000-2006.

• Average capacity factors have a limited effect on the optimal system design.

• Complementarity of the resources appears to have a higher impact.

• Single (extreme) events define the optimal capacities of the backup system.

• Further research is needed (mail: bruno.schyska@dlr.de)

Thank you for your attention!
Parameter Coaction: Examples

The presence of demand side management options increases the optimal share of solar power from 19 to 37% [Kies et al., 2016].

• Strong grid enforcements in Europe foster the deployment of wind power and hydro power, while weaker grids are dominated by solar power and storage facilities [Schlachtberger et al., 2017]

• The sensitivity of the power system to meteorological drivers increases with the share of variable renewable resources [Bloomfield et al., 2018].