Why the Weather matters

The Coaction of meteorological and techno-economical parameters in numerical power system models

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EnergieSys-AI workshop

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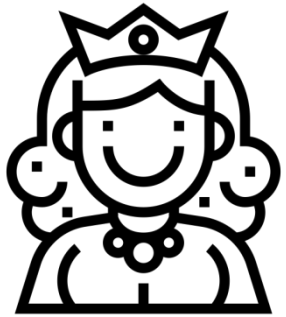
DLR Institute of Networked Energy Systems

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?



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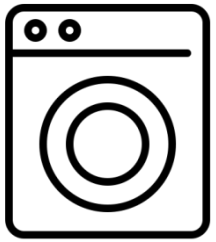
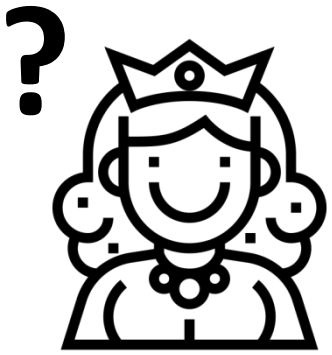


All icons from the Noun Project



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- 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?

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A model!

$$minimise\ Investment\ costs + Operation\ costs$$

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 fulfils 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

$$f(x) = investment\ cost + operation\ cost = f(\overline{g}, g, l)$$

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

Model Parameters

Information	Parameter	Source
Weather-related potential generation from variable renewable resources	Capacity factors	Wind speed, irradiance, temperature
What's the demand for electricity?	load	Historical data from ENTSO-E[1]
Which technologies are available?	Energy carrier	Own choice
What are the specific characteristics of the technologies?	Costs, efficiencies, emissions, …	Various, here PyPSA-Eur[2]

[1] https://data.open-power-system-data.org/time_series/

[2] 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.

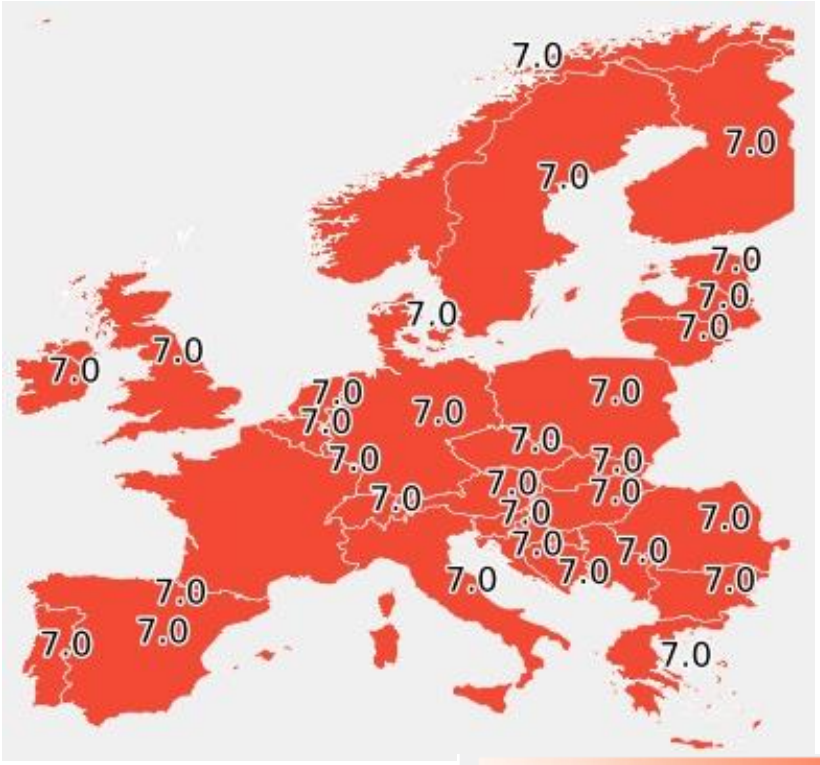
Uncertainty in the definition of the cost of capital

or

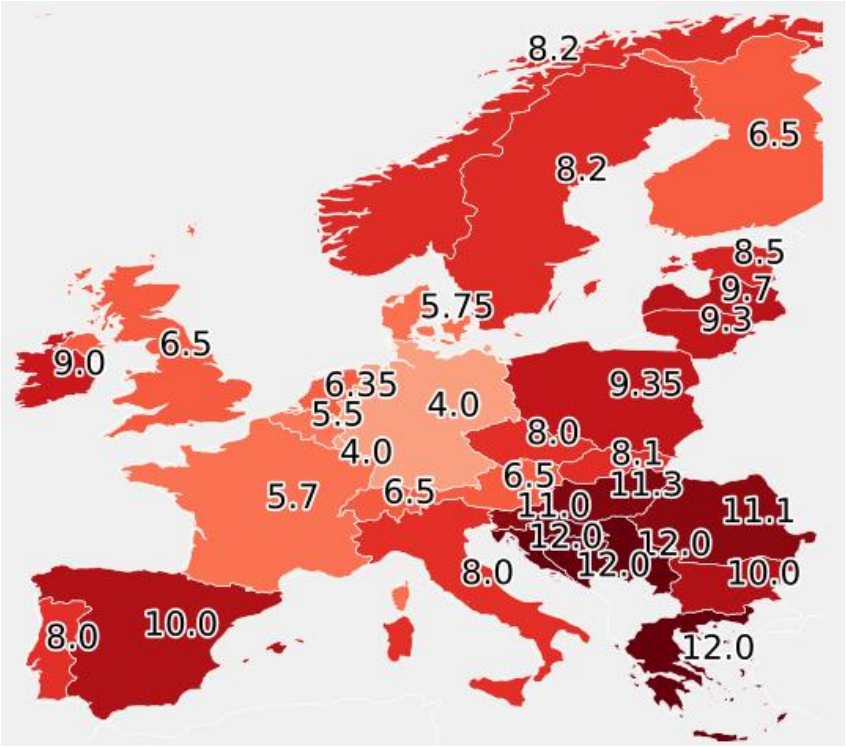
How do regional differences in the cost of capital influence the cost-optimal system design?

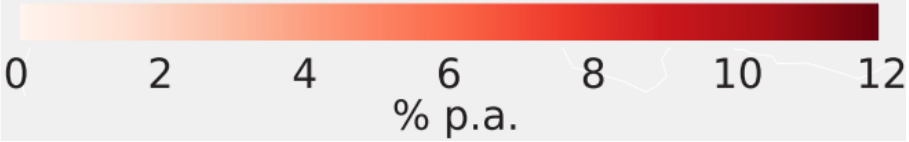
Regional differences in the cost of capital

Reference



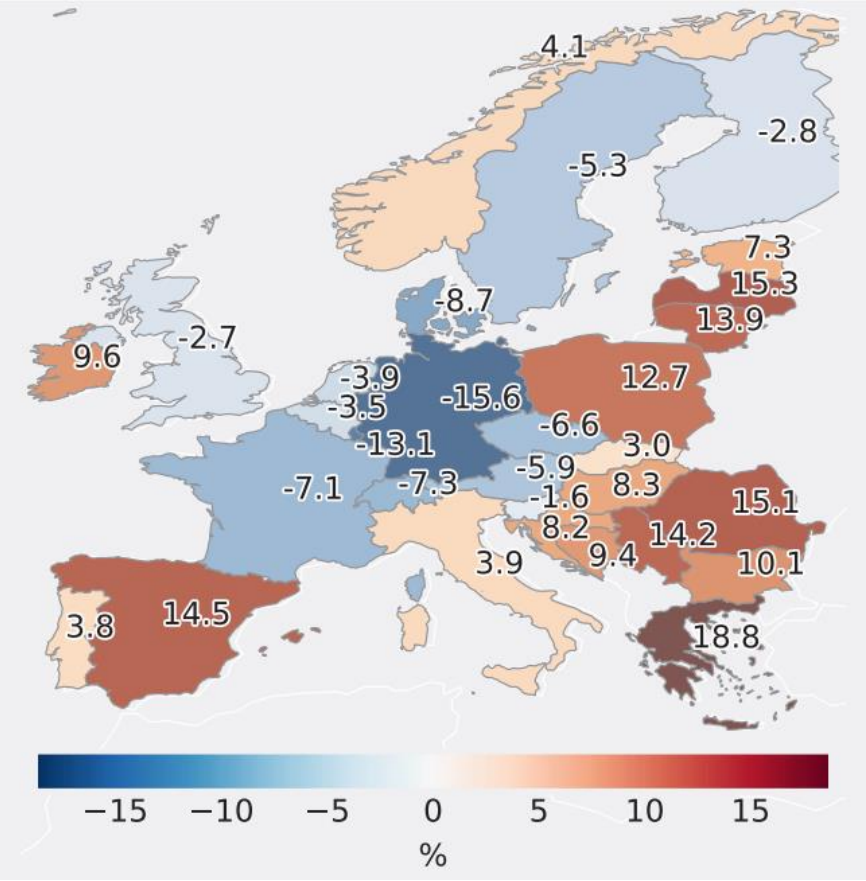
Diacore project





Weighted average cost of Capital (WACC) in European countries, adopted from Noothout et al. [2016]

Implications on the optimal system design



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

- 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

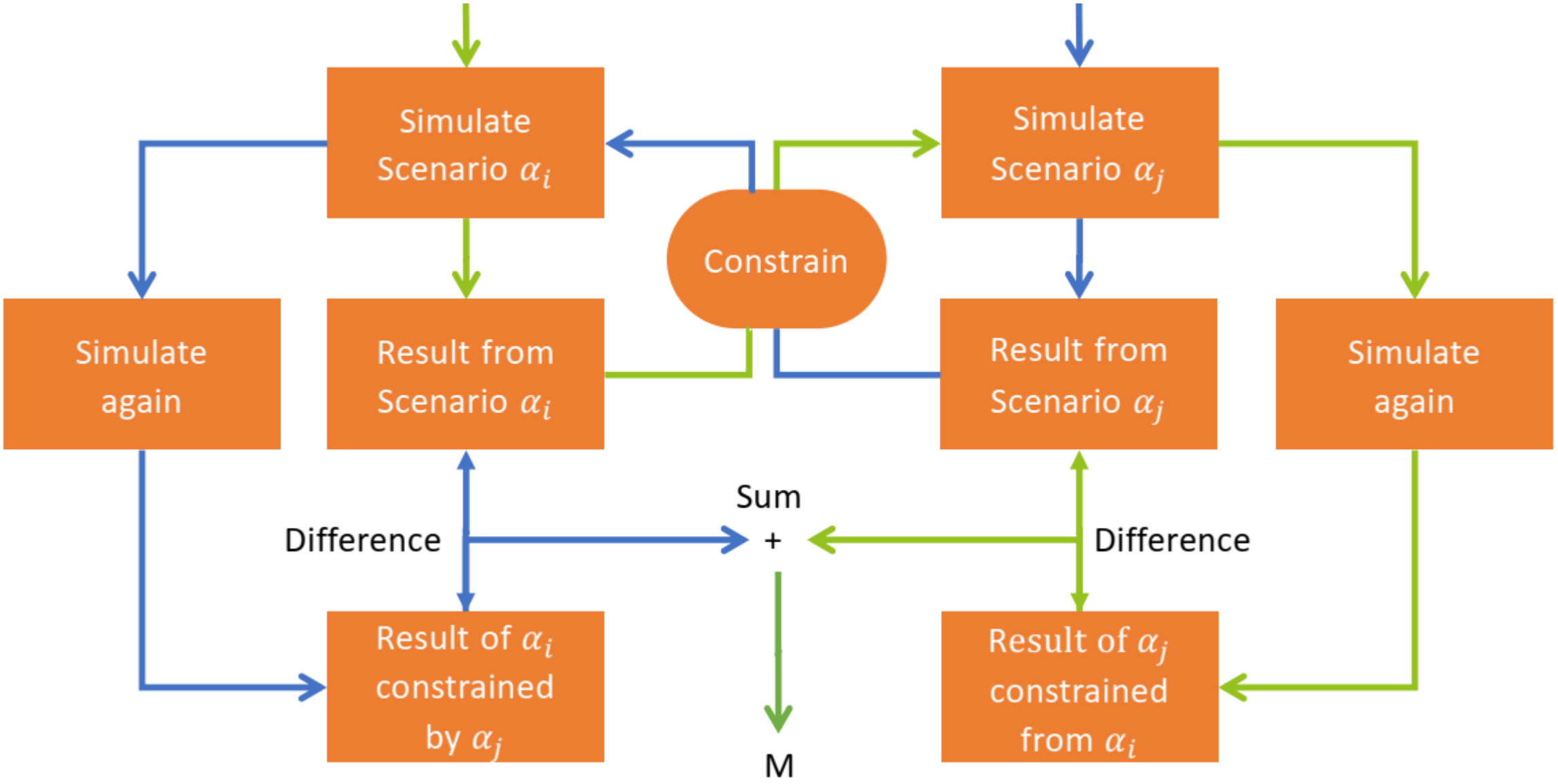
Schyska and Kies (2020), preprint on arxiv

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.


Simulate Scenario α_i
Simulate Scenario α_j
Constrain
Simulate again
Result from Scenario α_i
Result from Scenario α_j
Simulate again
Sum
Difference
+
Difference
Result of α_i constrained by α_j
Result of α_j constrained from α_i
M

Computing the Metric: Cost of Capital Example

Levelized Cost of Electricity: $\mathrm{LCOE} = \frac{Cost\ for\ Investment\ and\ Operation}{Demand\ met}$

	Reference	Diacore
LCOE unconst. [EUR / MWh]	72,2	70.8
LCOE constr. [EUR / MWh]	74,7	72,8
Difference	2,5	2,0

M = 4.5 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:
  - Historical (HIS): 1970 – 1976
  - Begin of century (BOC): 2000 – 2006
  - Mid of century (MOC): 2038 – 2044
  - End of century (EOC): 2094 - 2101

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

- PyPSA-Eur (one node per country)

- Including:
  - Load time series
  - Renewable potentials
  - Cost
  - Technologies

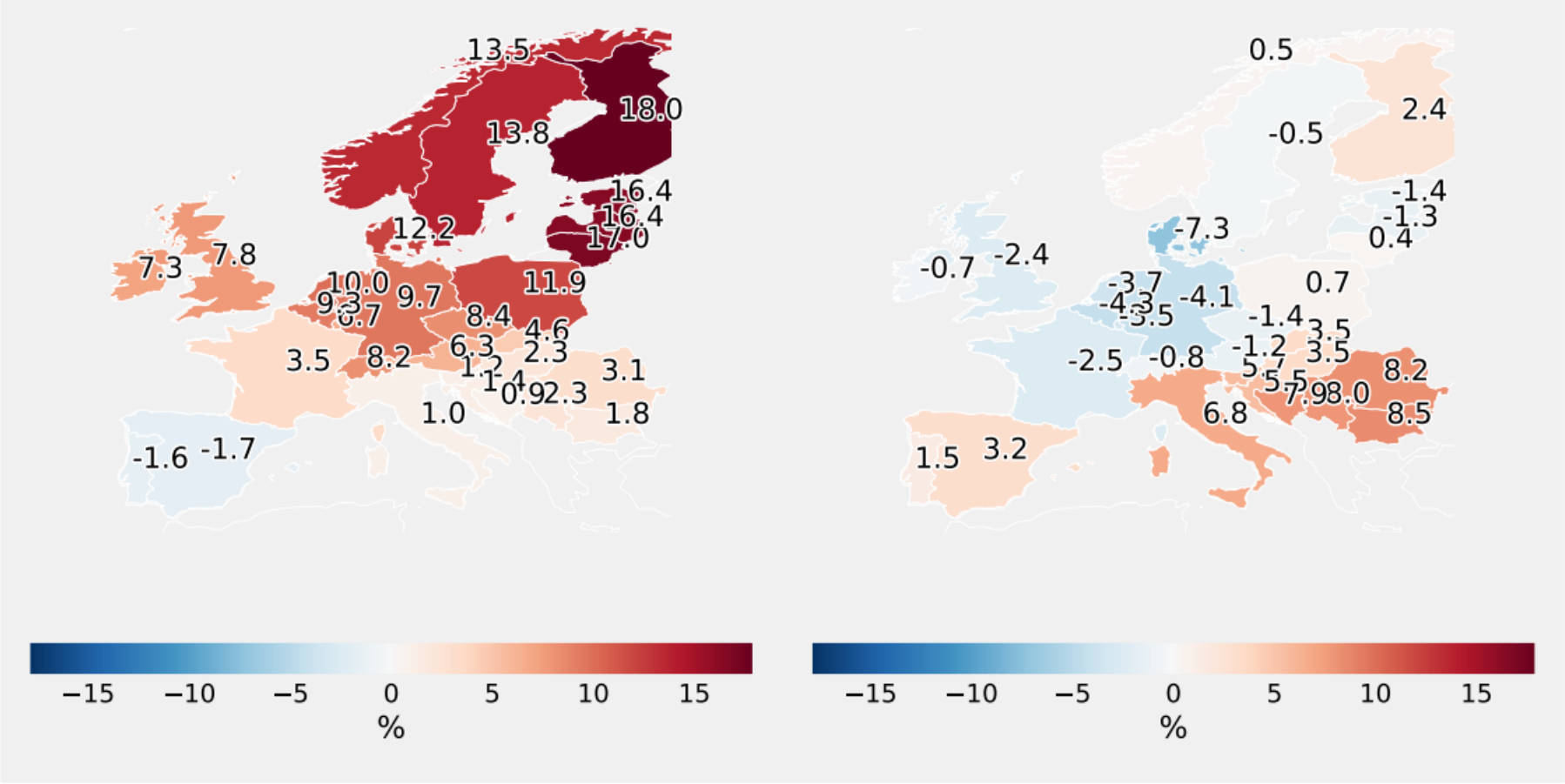
- Onshore + offshore wind, solar PV, OCGT, hydro, batteries, hydrogen storage

- 95% CO_2 reduction scenario

Hörsch et al. (2018), Energy Strategy Reviews, arxiv preprint

Capacity Factor Changes towards the End of the Century

Solar PV

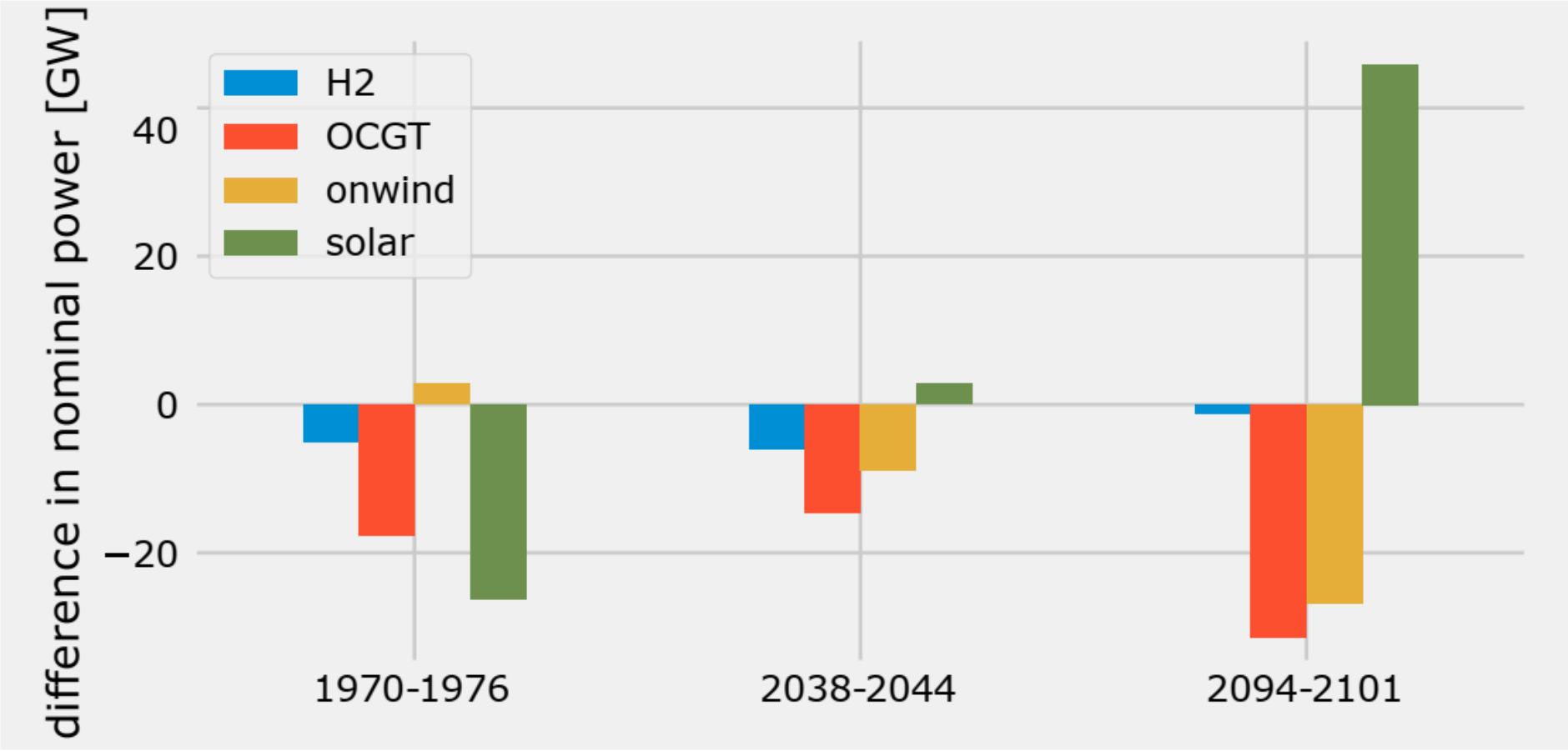


Onshore wind

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

Schyska et al., submitted, preprint on arxiv

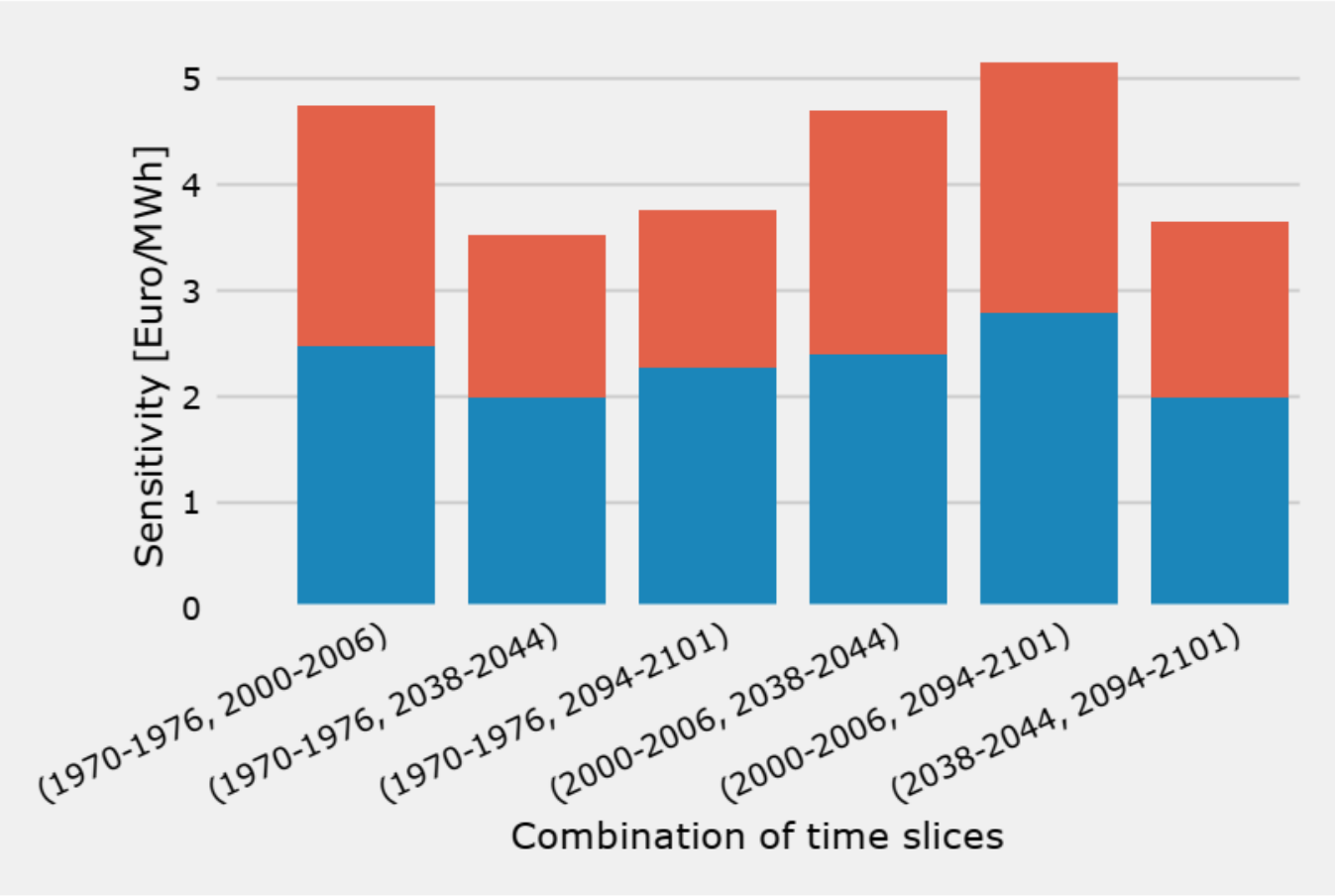
Differences in optimal Capacity Expansion



Difference in optimal capacity expansion compared to BOC [GW]

Schyska et al., submitted, preprint on arxiv

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

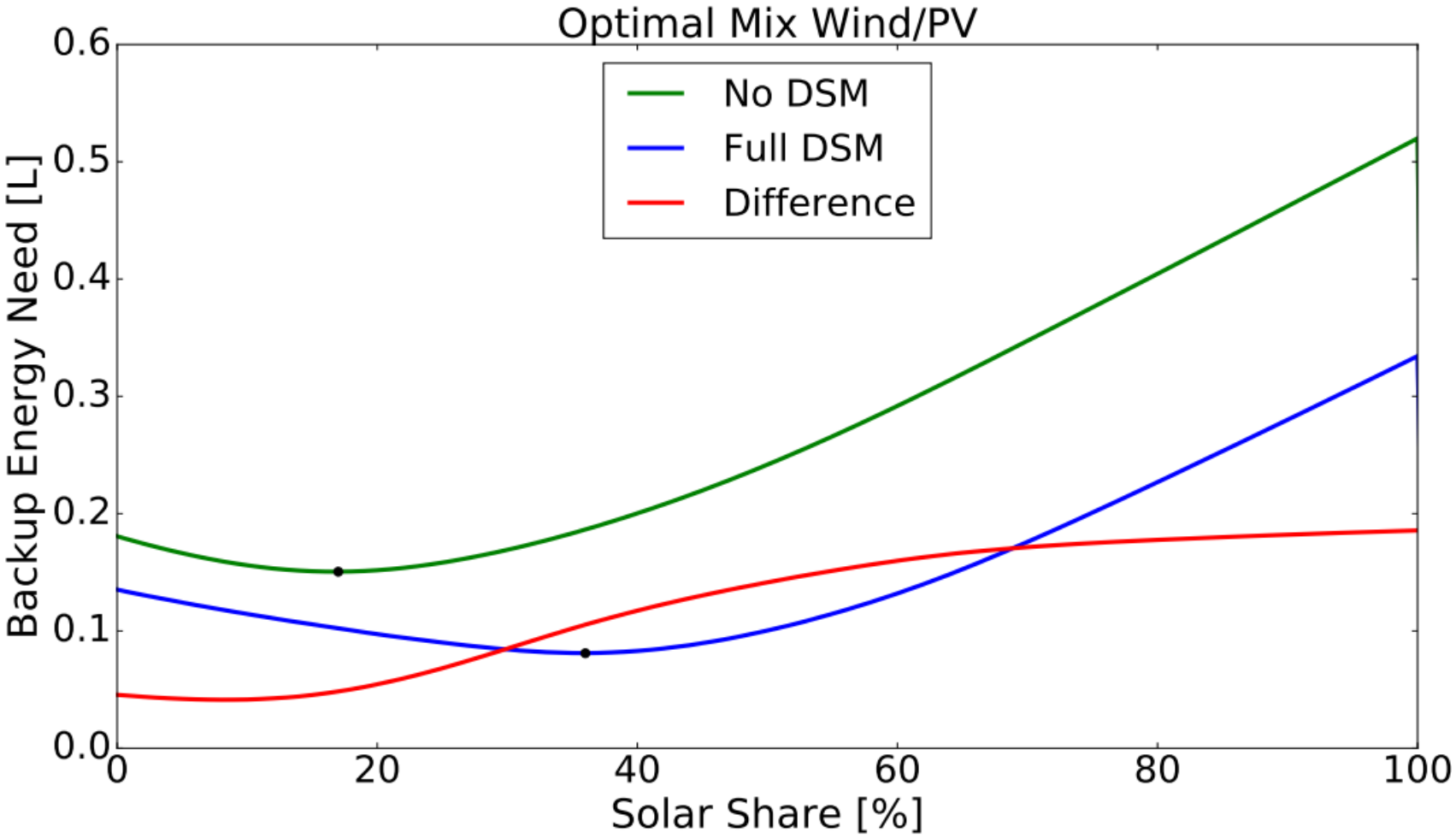
Schyska et al., submitted, preprint on arxiv

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

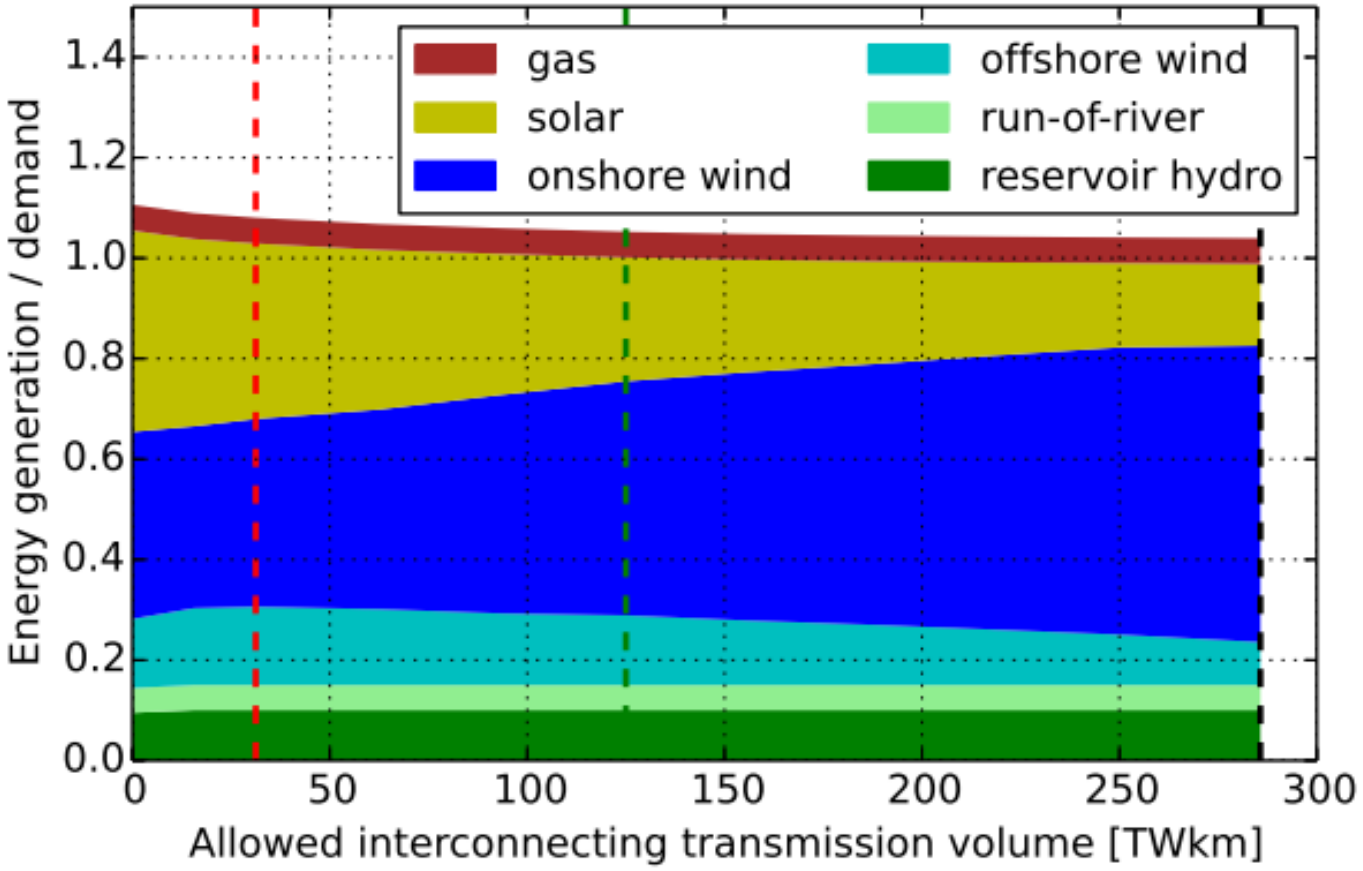
The presence of demand side management options increases the optimal share of solar power from 19 to 37%.



[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.

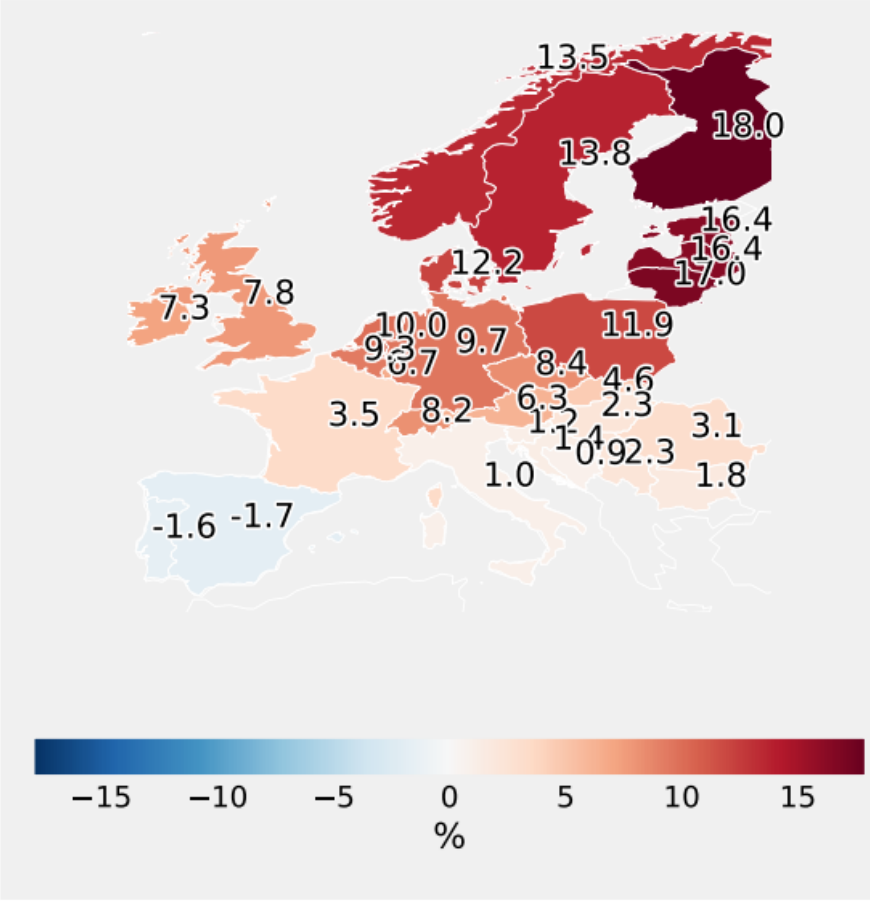
What characteristic(s) of the capacity factor time series ‘drive’ the model results?

Capacity Factor Characteristics

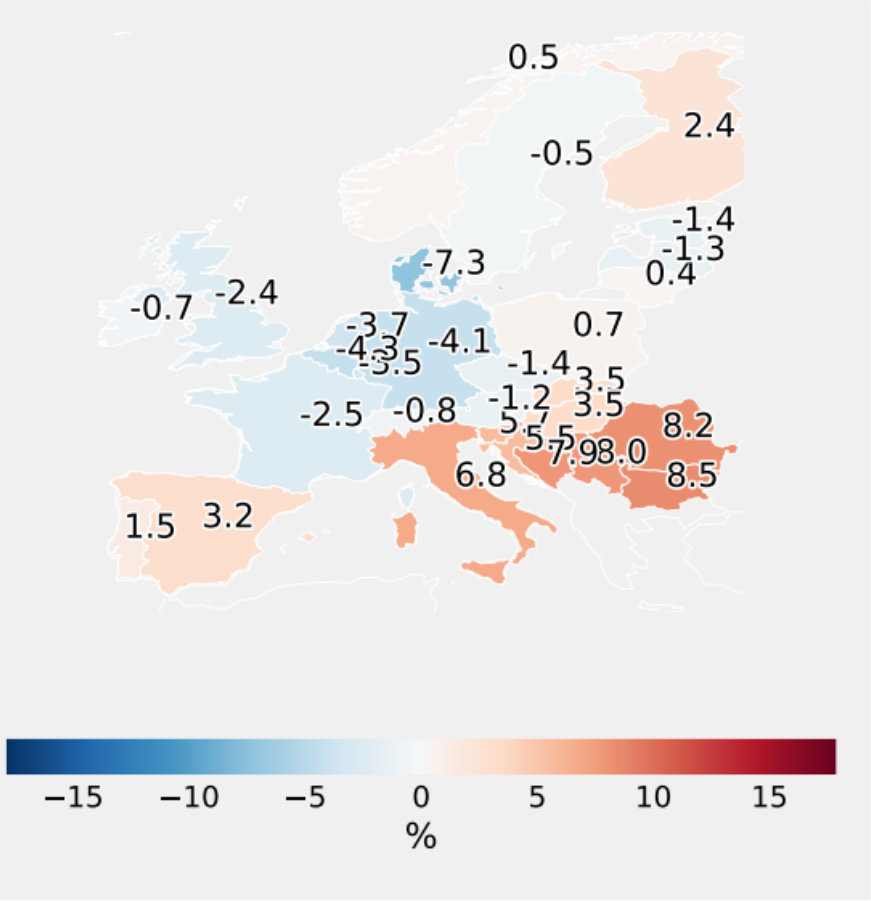
- Capacity factors are spatio-temporal data sets.
- Characteristics:
  - Mean
  - Spread
  - Extremes
  - Increment statistics
  - (Co-)Variance
  - Single events

Capacity Factor Changes towards the End of the Century

Solar PV



Onshore wind

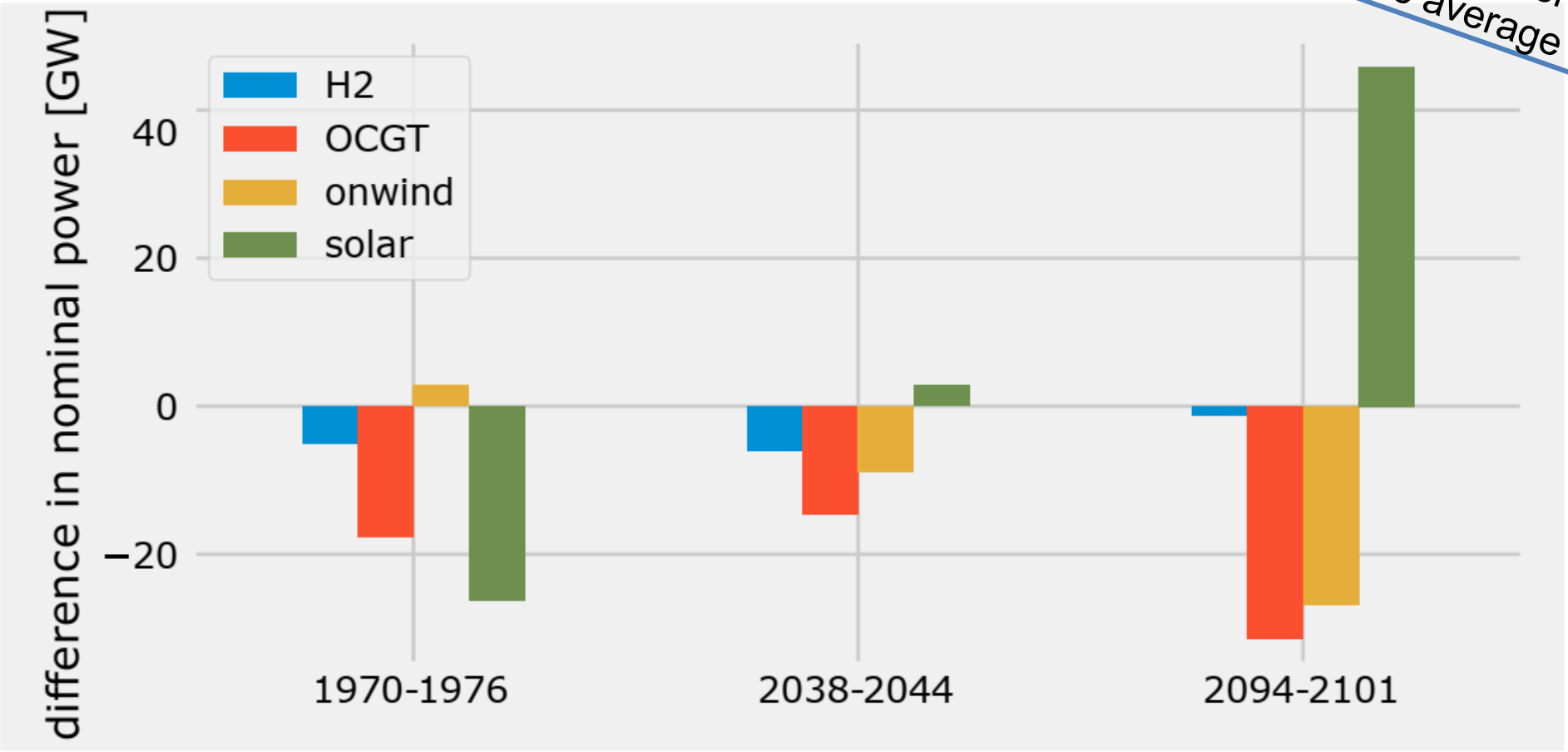


Relative change in 2094-2101 compared to 2000-2006 [%]

Schyska et al., submitted, preprint on arxiv

Differences in optimal Capacity Expansion

How much of this difference can be related to changes in the average capacity factor?

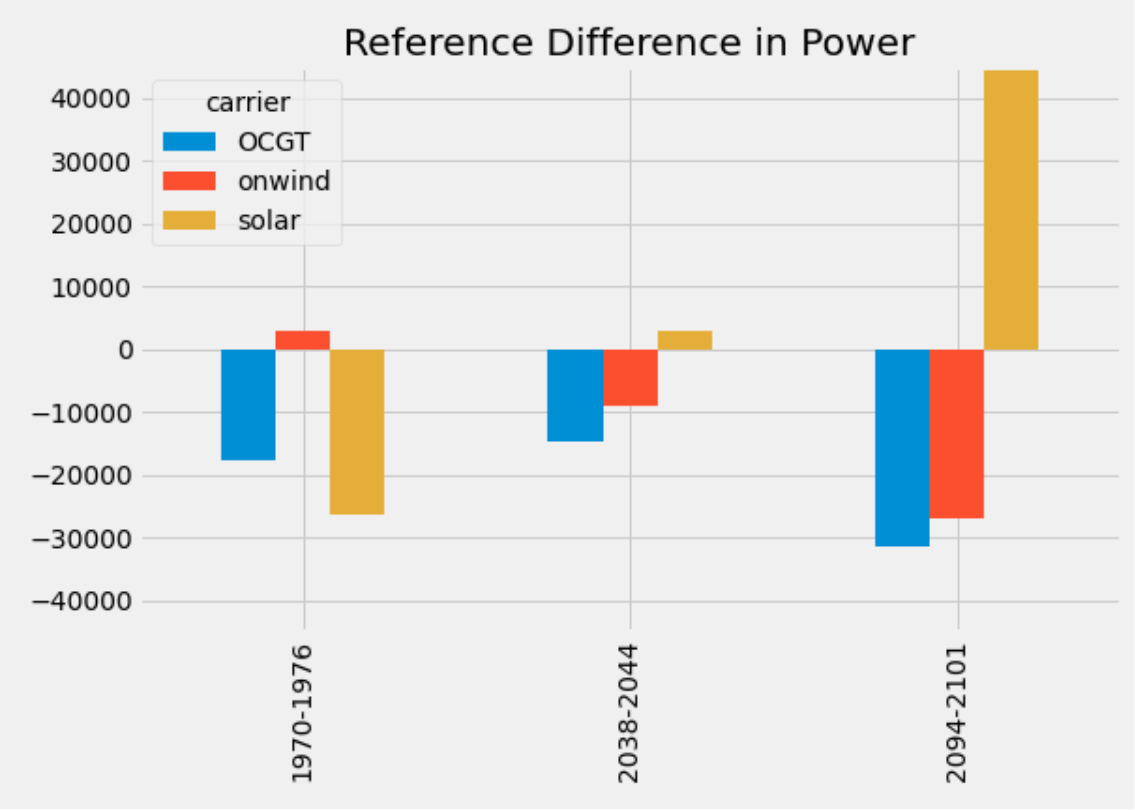


Difference in optimal capacity expansion compared to BOC [GW]

Schyska et al., submitted, preprint on arxiv

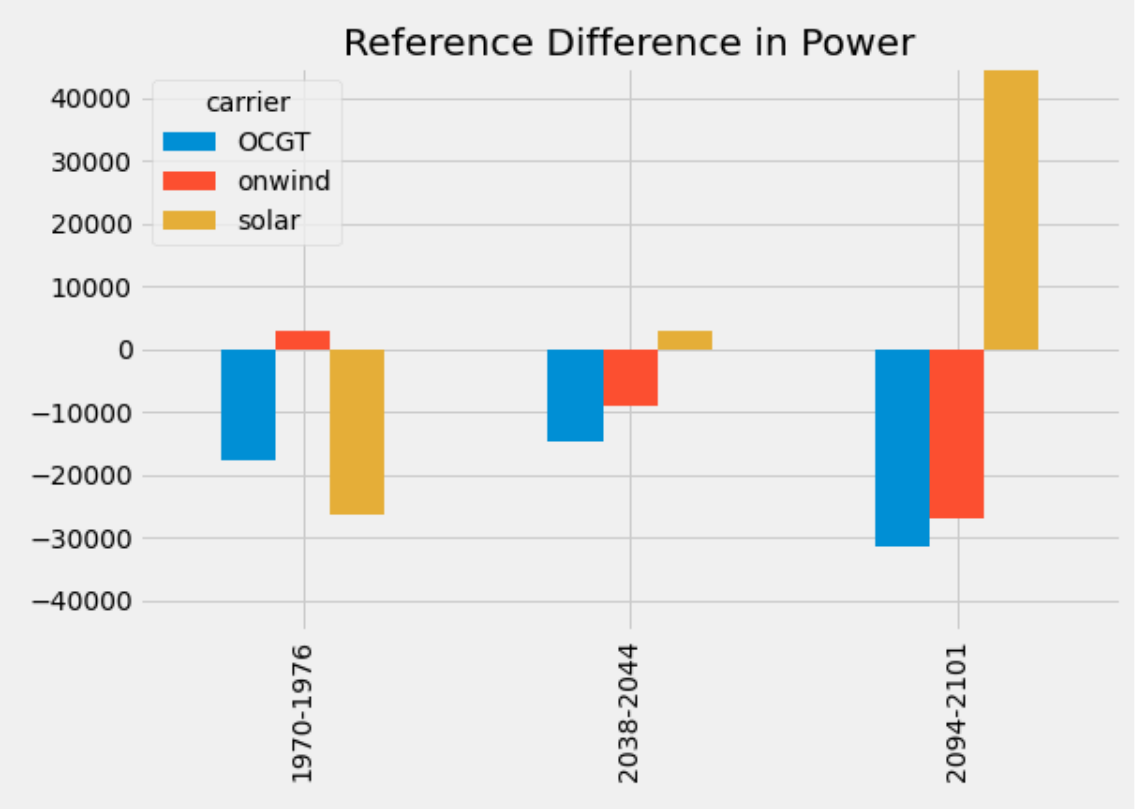
Investigating the Effect of changing Capacity Factor Means

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.



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  - Mean limited effect
  - Spread
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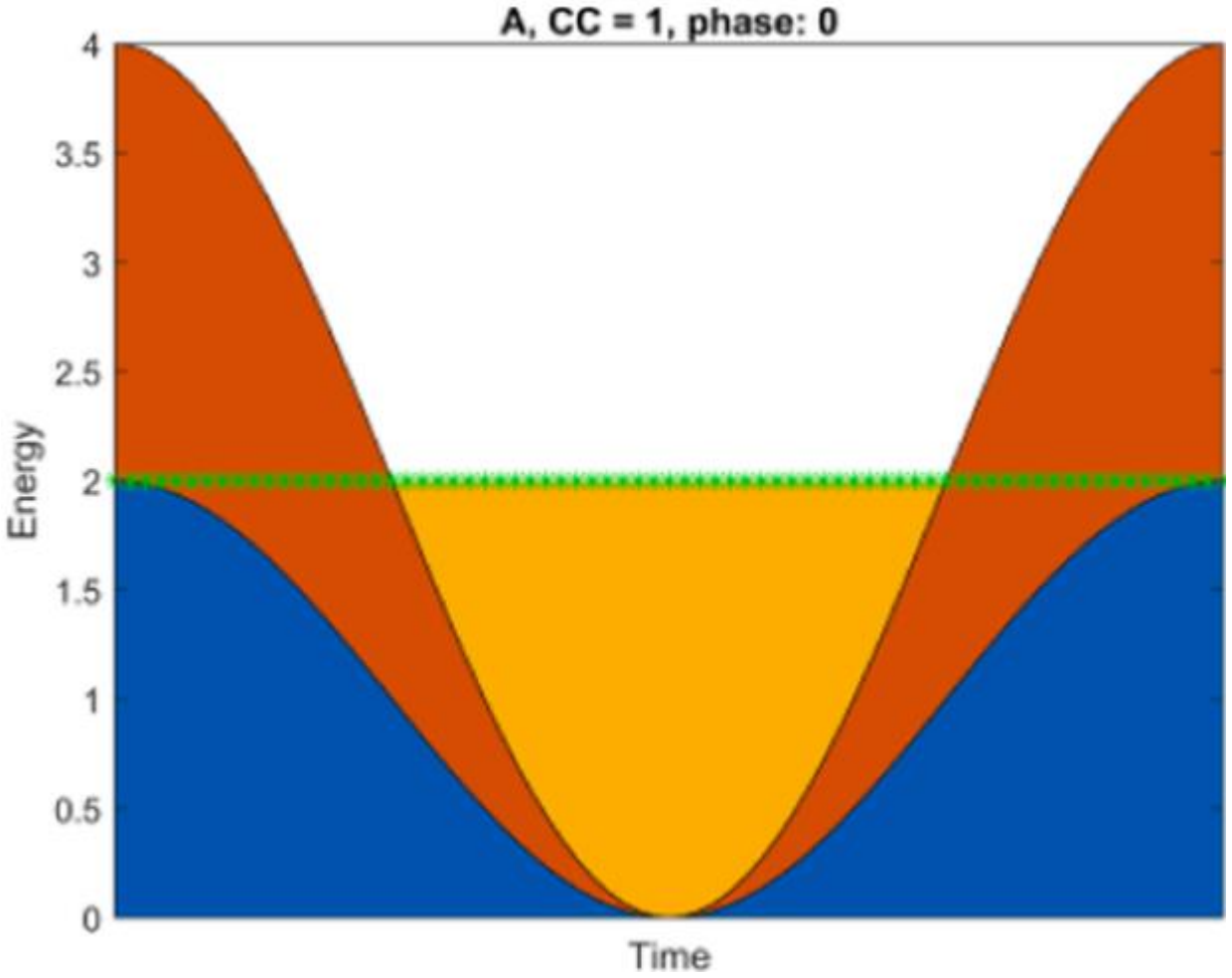
  - Single events

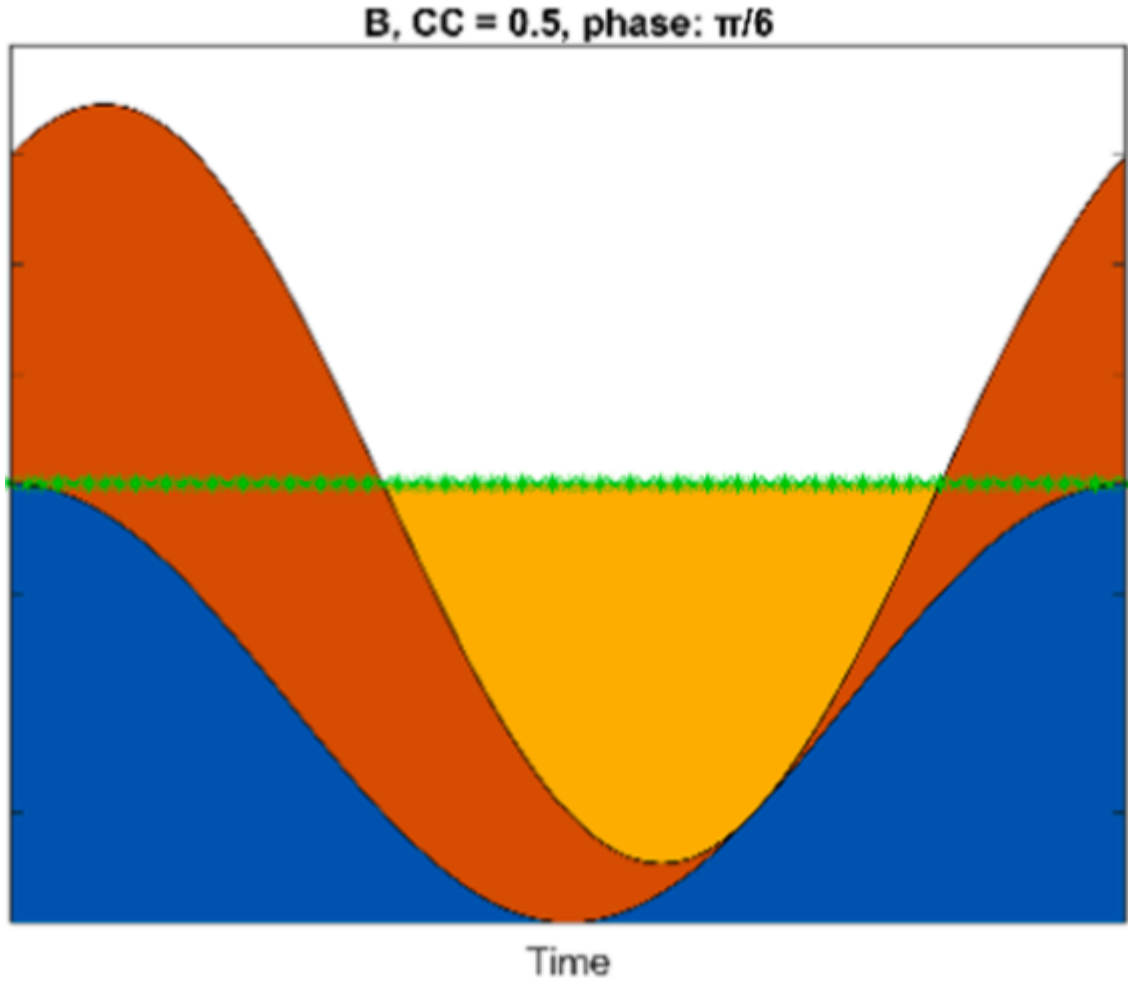
Complementarity

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



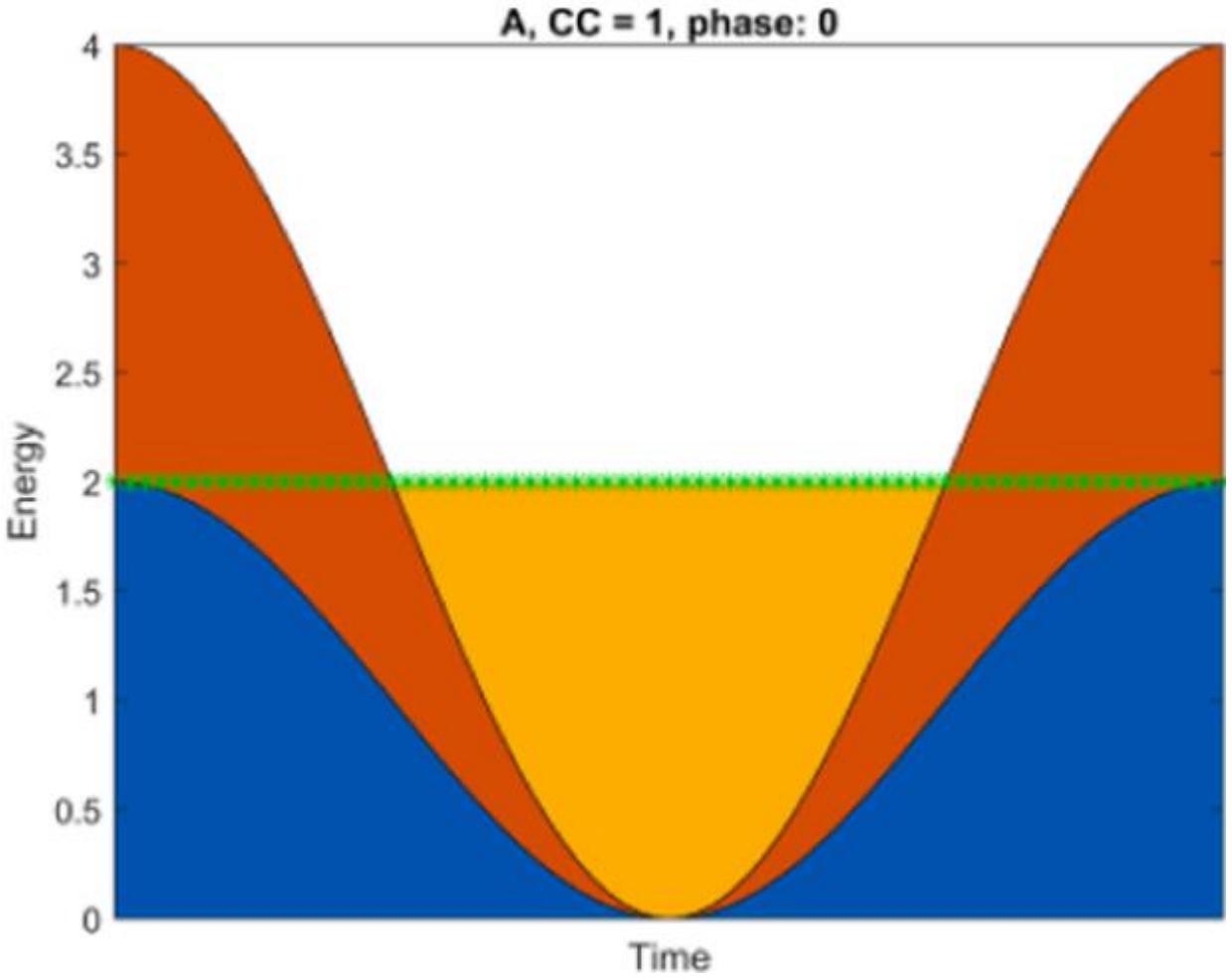


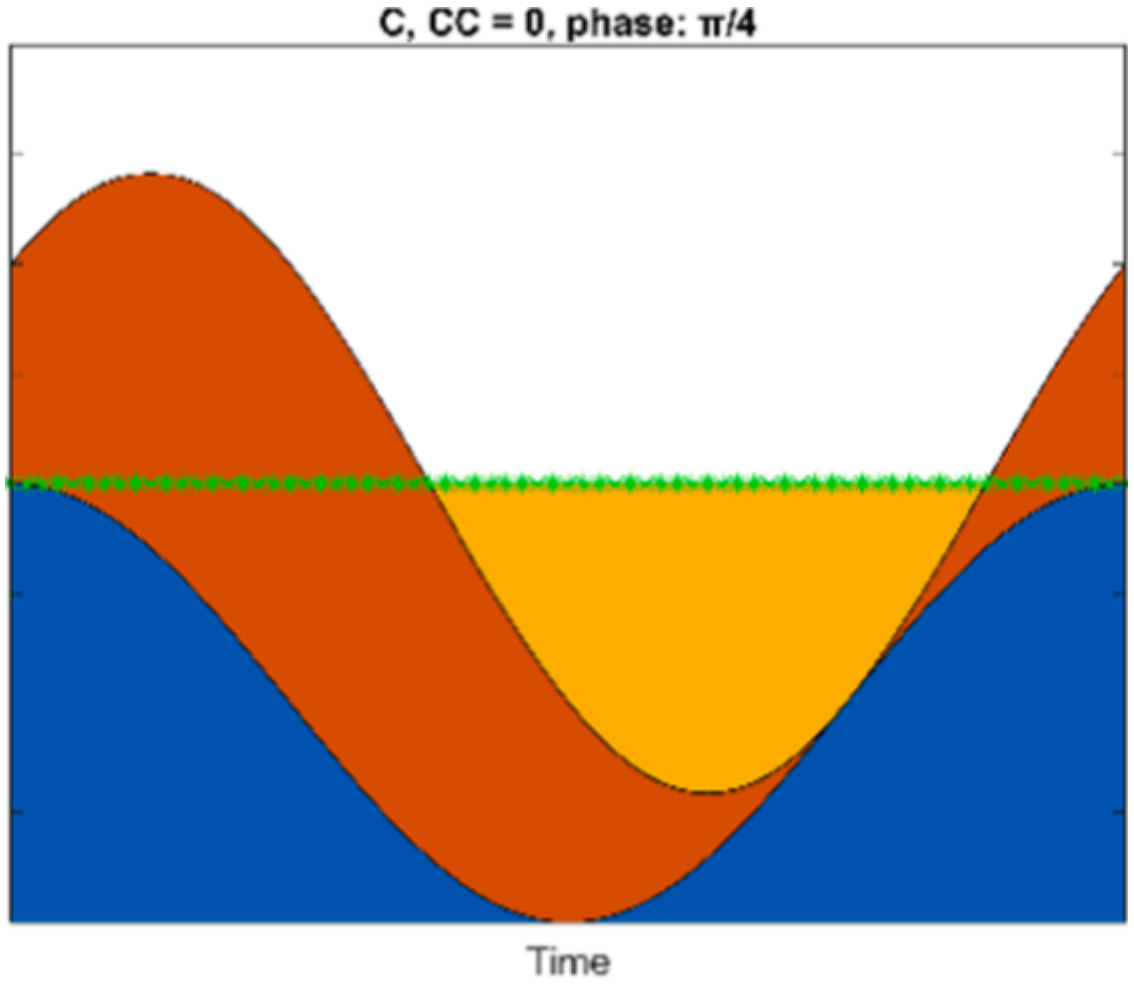
[Jurasz et al., 2020]

No complementarity

Increasing complementarity

Complementarity





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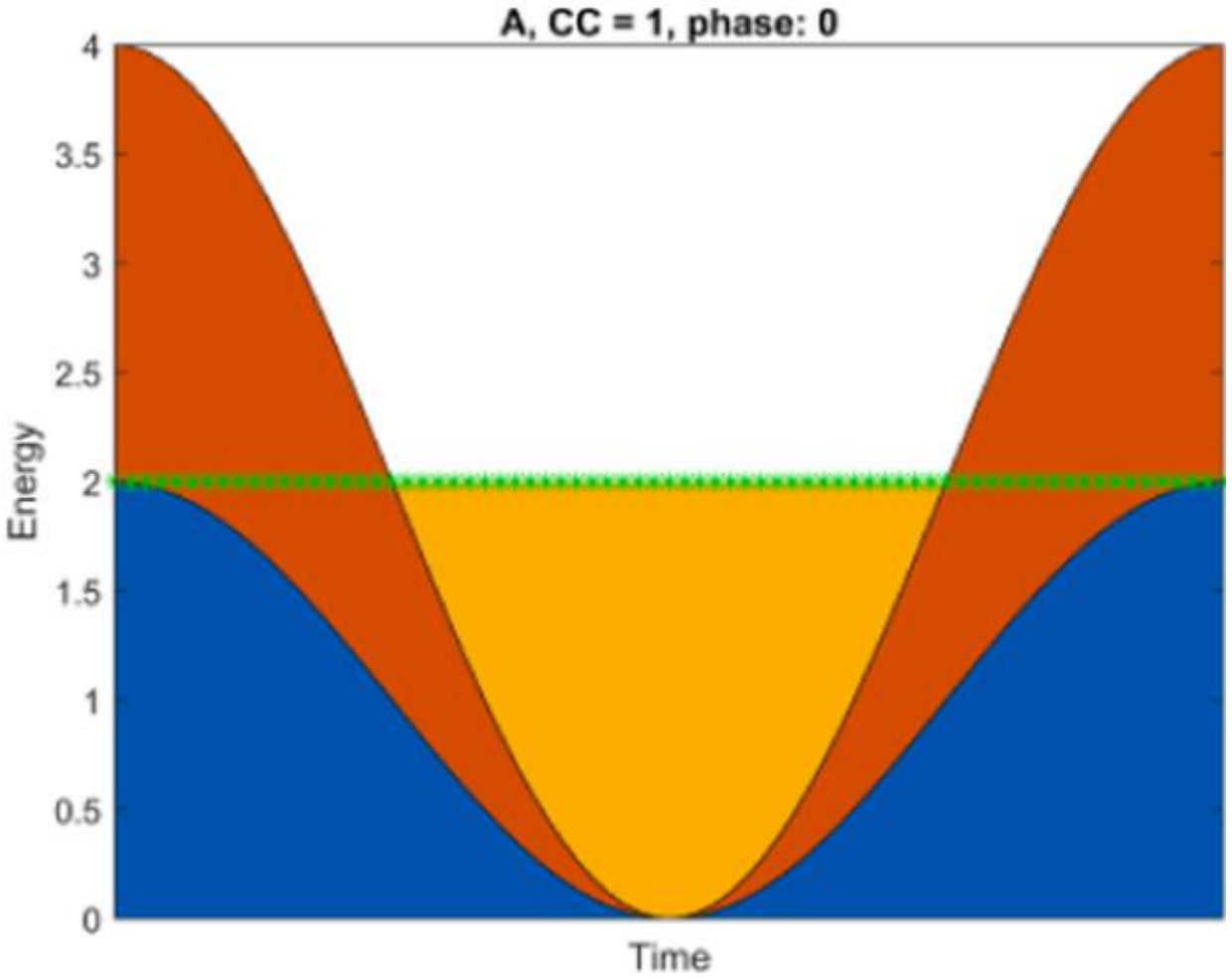
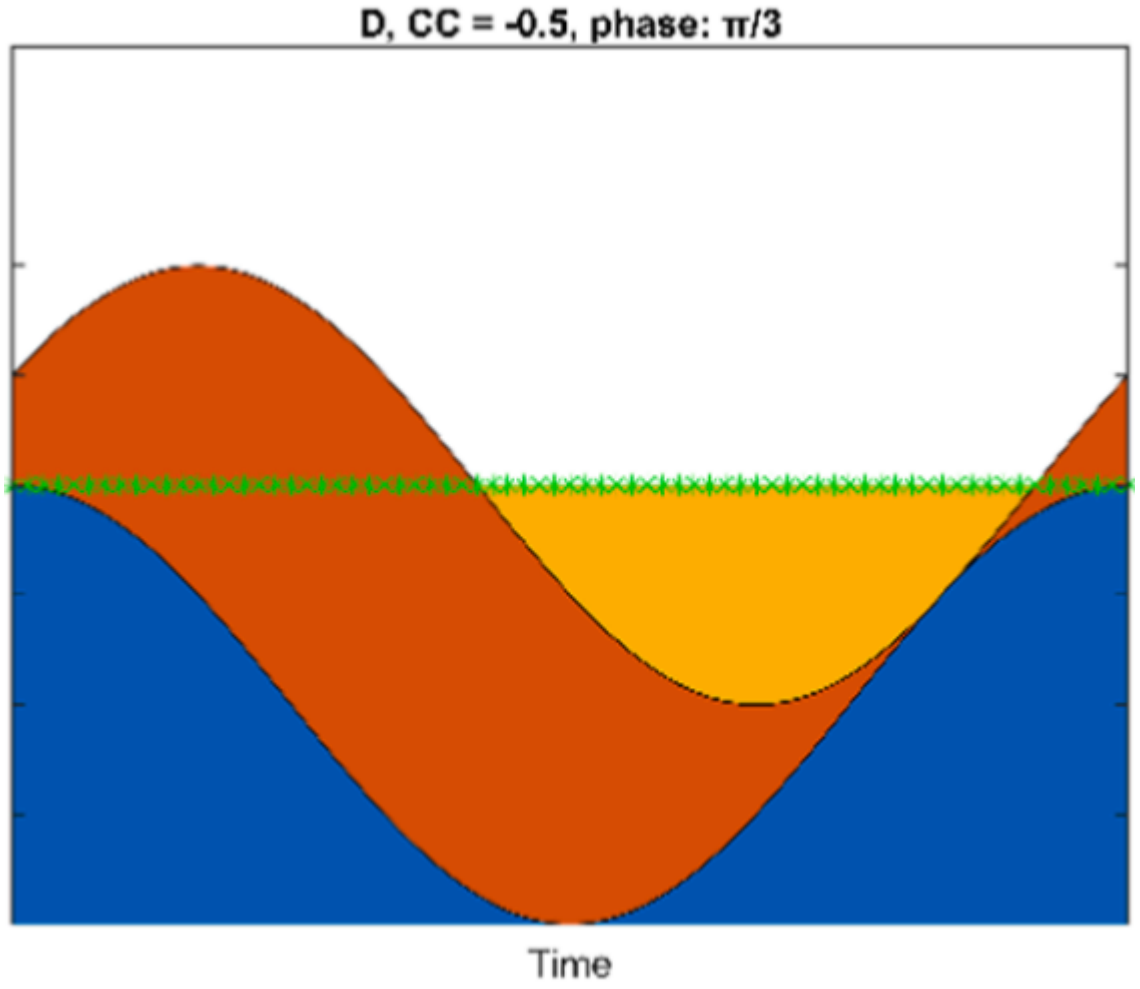
Increasing complementarity

Complementarity





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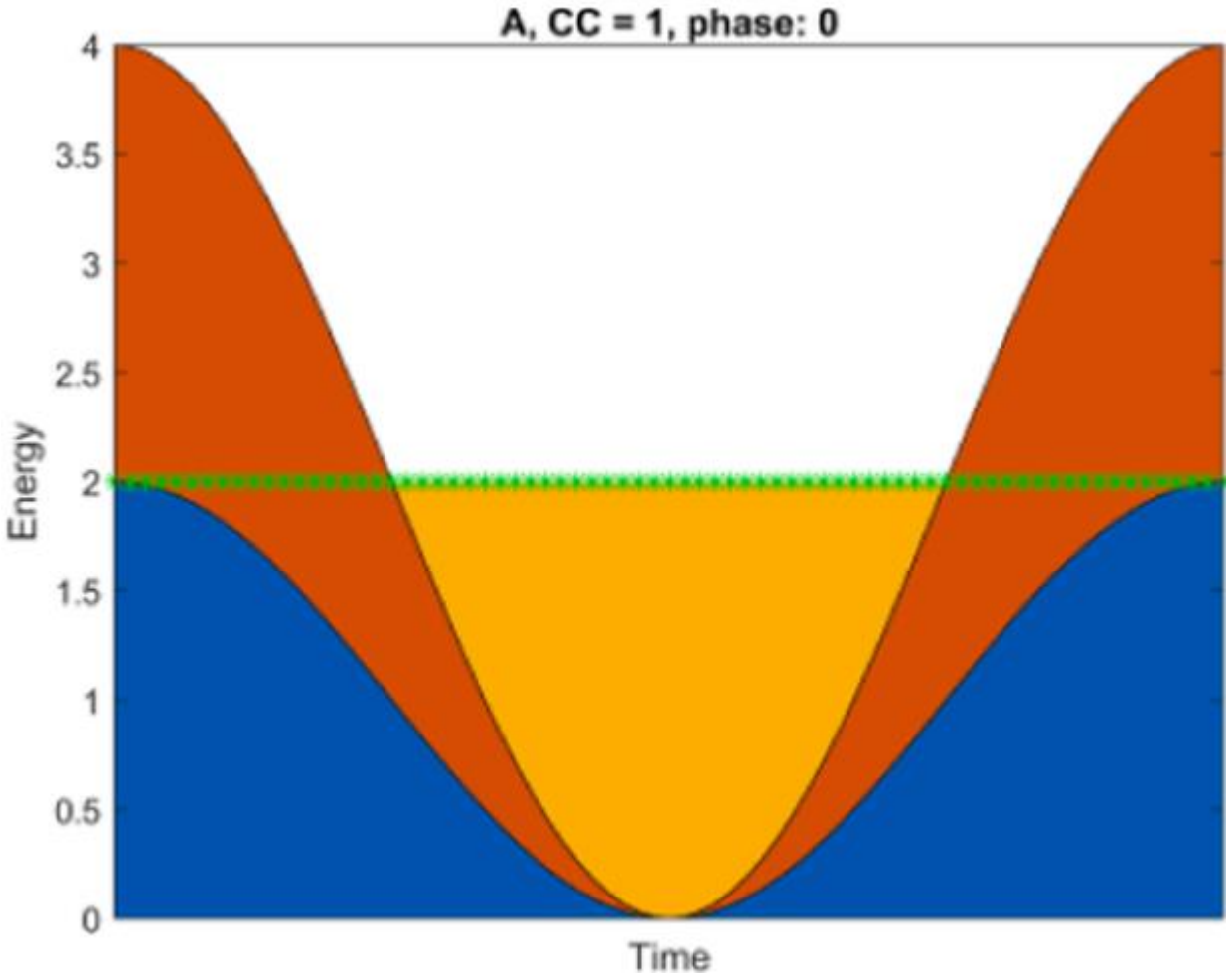
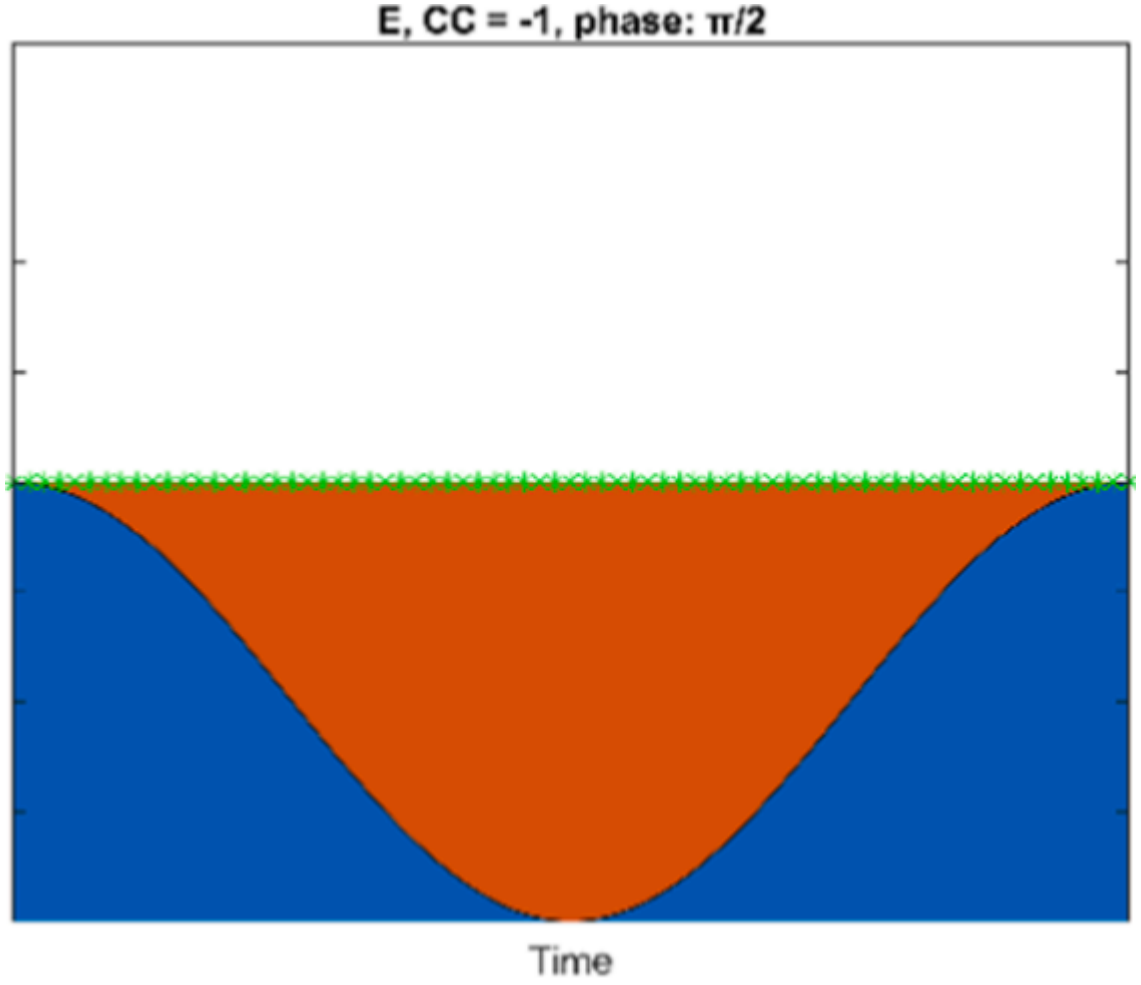




[Jurasz et al., 2020]

No complementarity

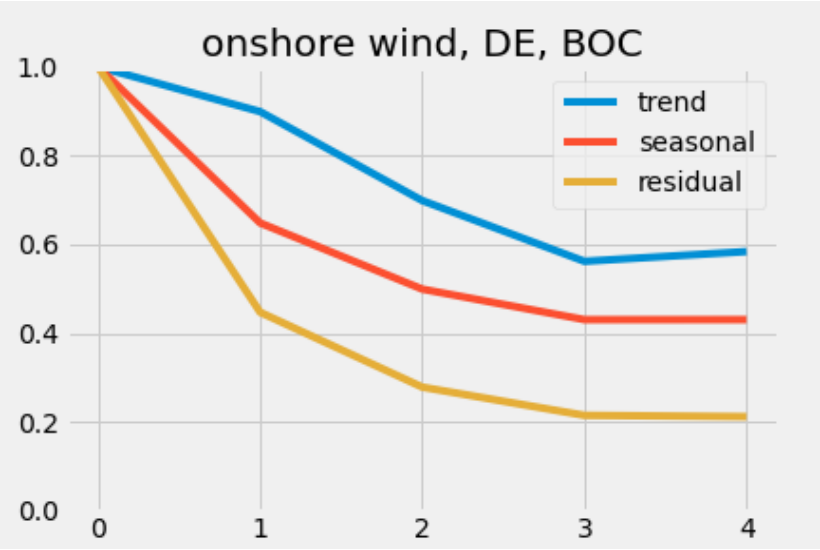
Perfect complementarity

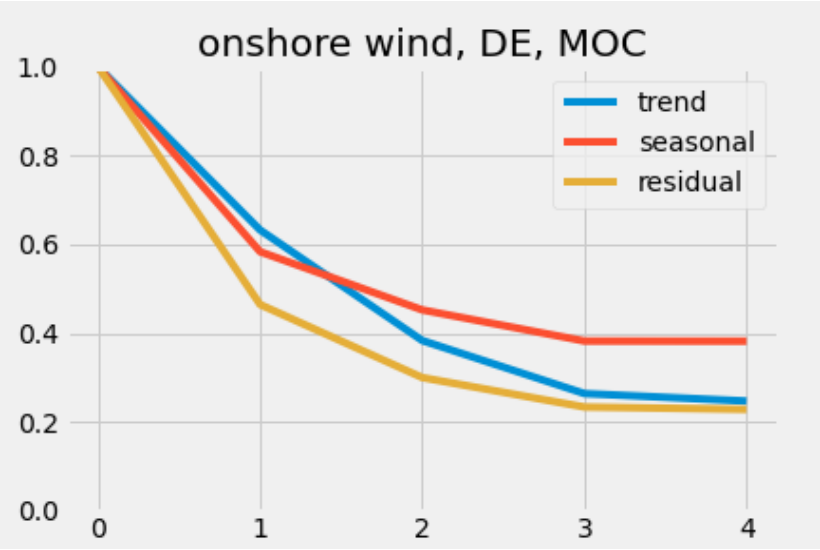
Measuring the Complementarity

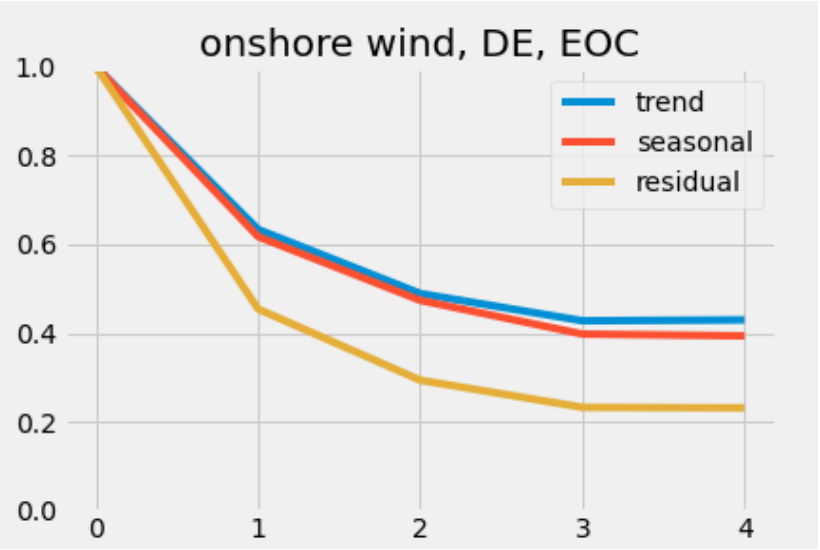
- Measure complementarity of resource *s* at node *n* as the average correlation across all generators, that can be reached via maximum *r* lines in the network

$$C_{n,s}\,(r) = \left\langle \varrho\left(x_{n,s}, x_{m,s}\right)\right\rangle_{\mathrm{m}\in\Omega_r}$$

- 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]).

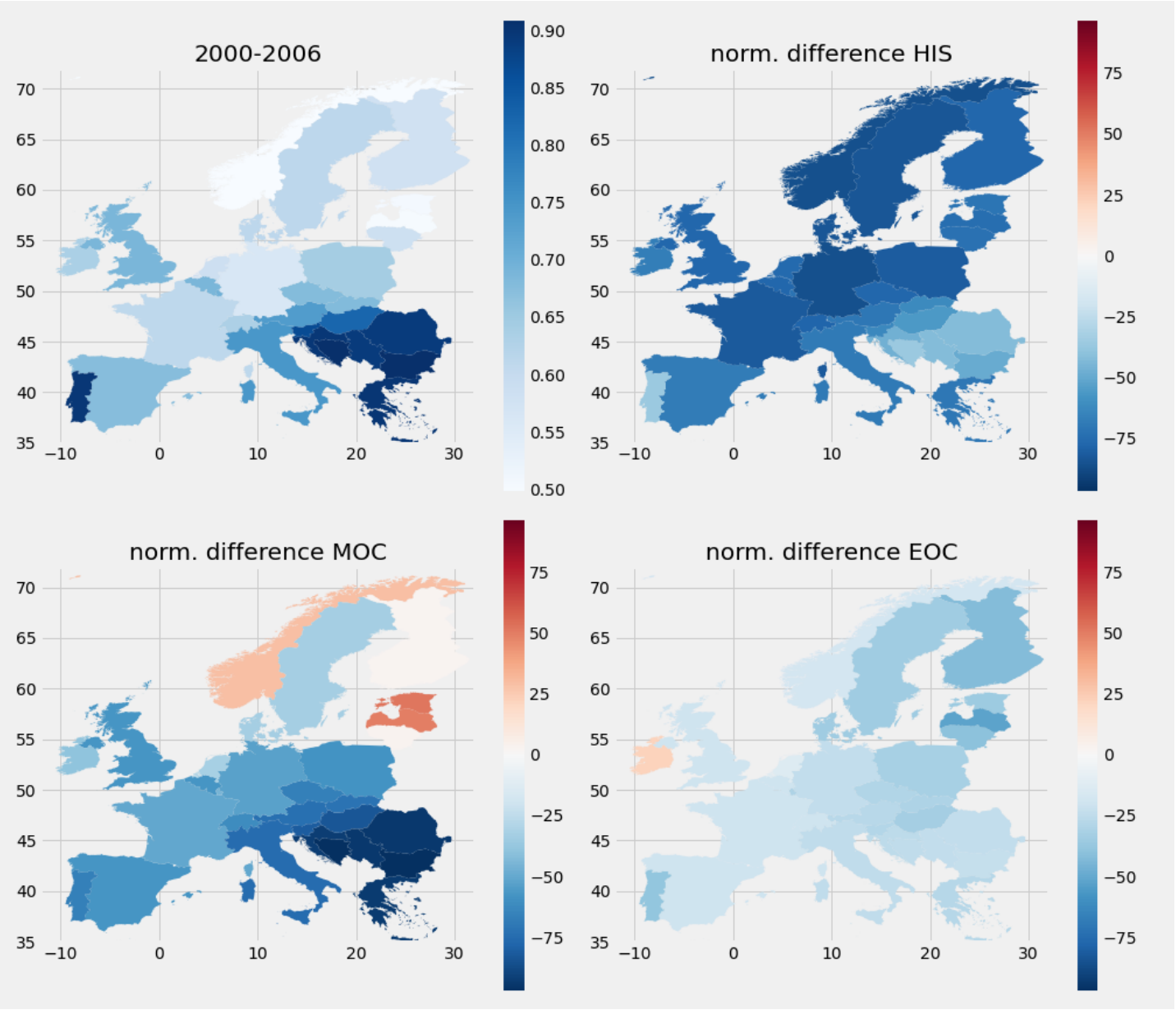






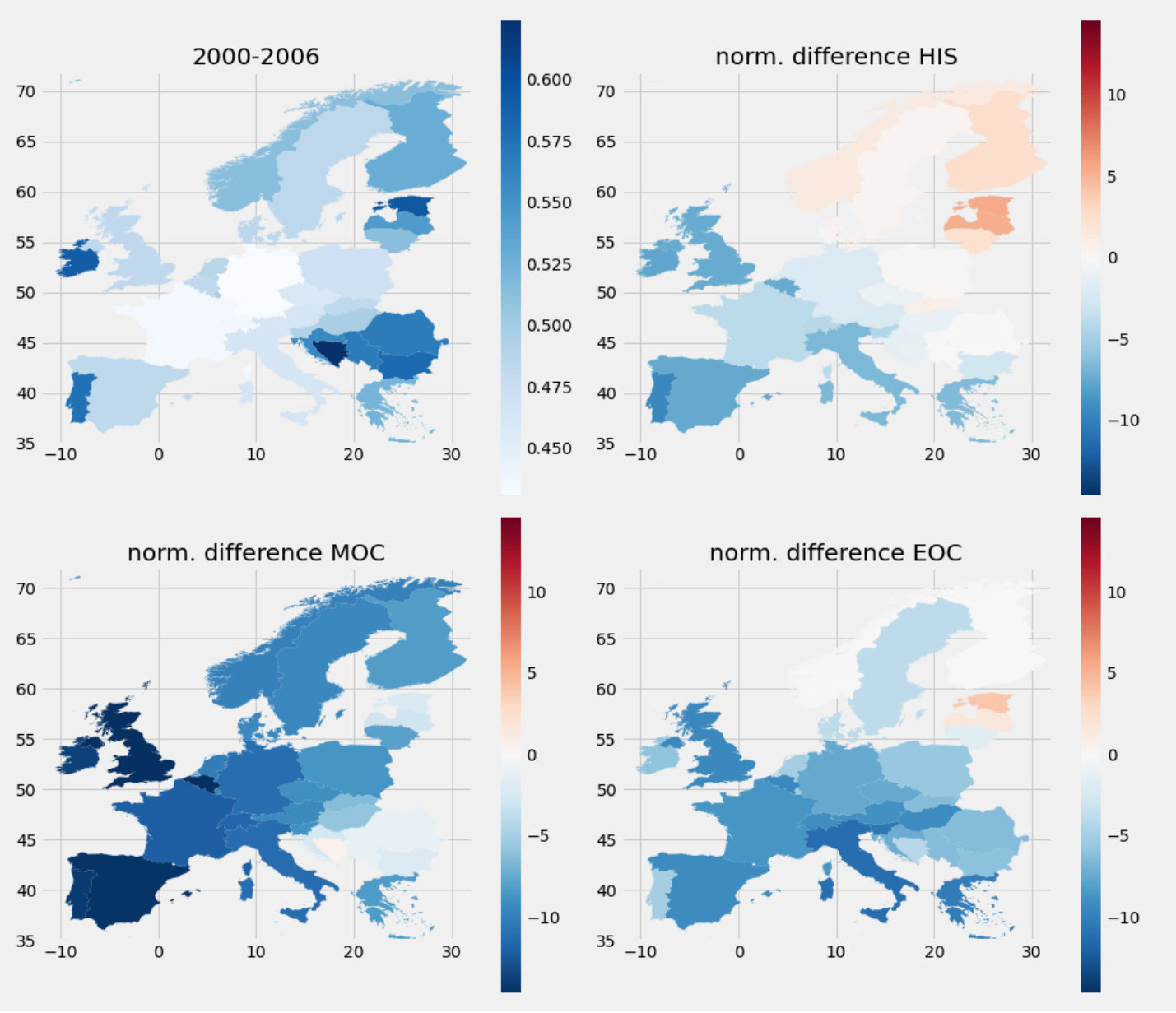
Differences in the Complementarity

- Normalised difference in % of BOC
- Trend component
- r = 3
- Onshore wind power



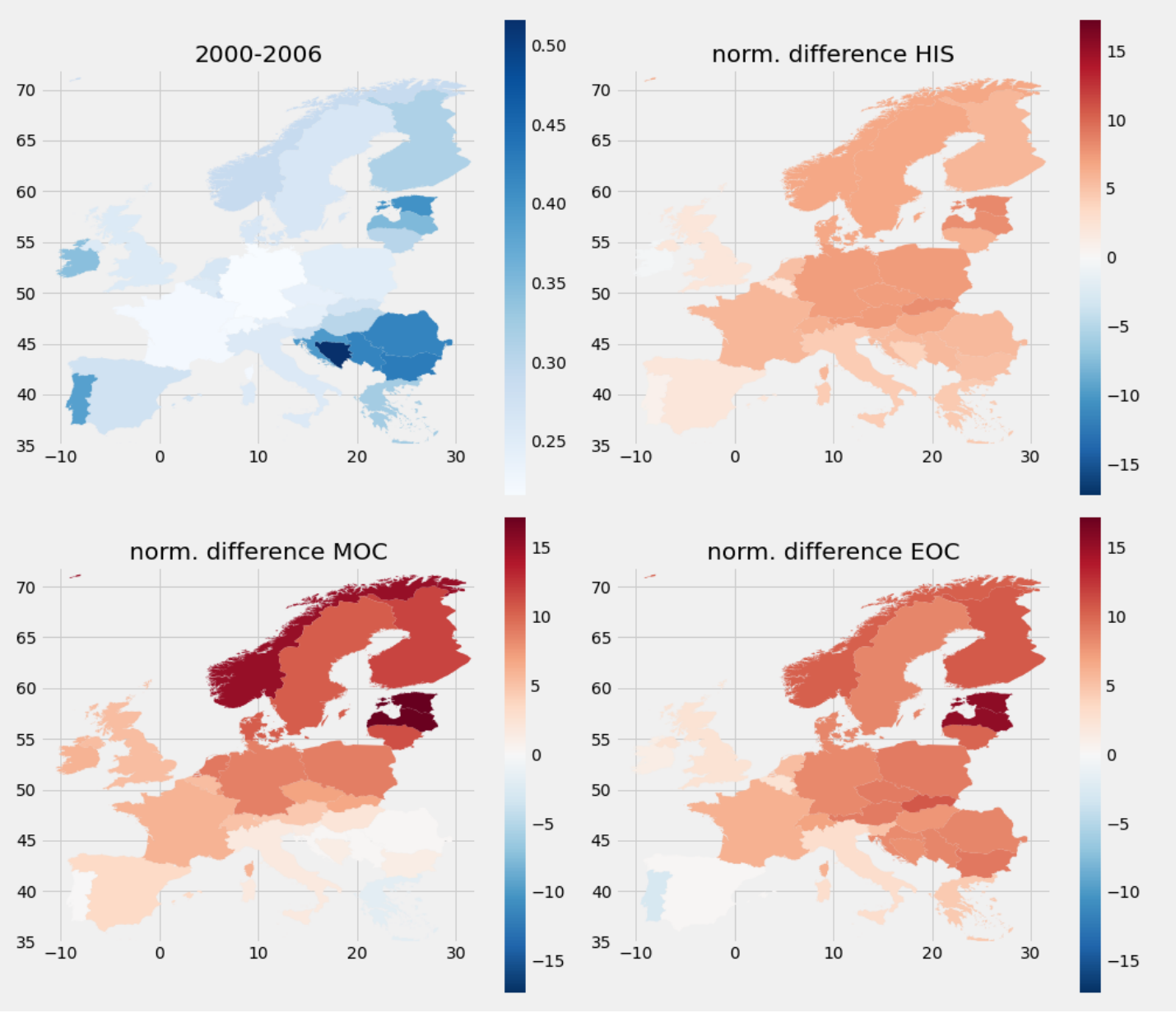
Differences in the Complementarity

- 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

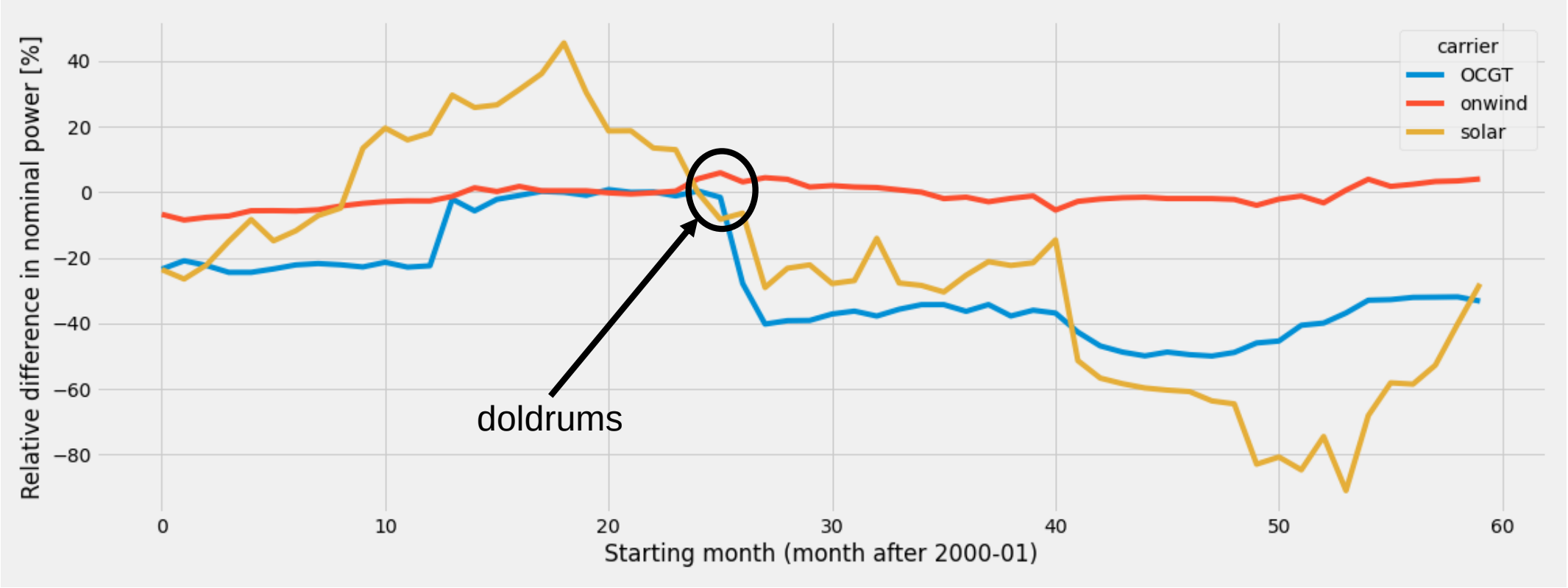


Capacity Factor Characteristics

- 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.



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- 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].

Technology

Technology/Cost/ societal

Meteorology