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Aggregation of intermittent renewables in energy market models

Capturing correlations and extreme events

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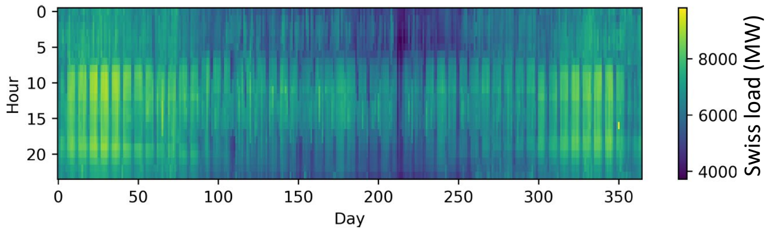
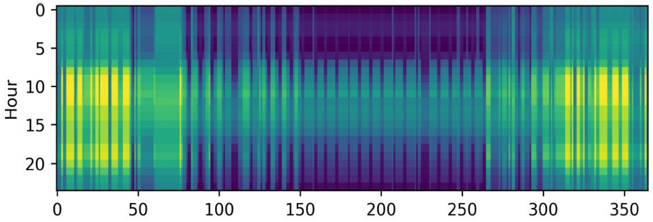
Energy time series aggregation

- Why time series aggregation? → Numerical tractability of energy system models
- Majority of works (and ours): Aggregation on criteria “inside” input data (Hoffman,2020)
  - Minority: “Energy system structure” aggregation: Pöstges & Weber, 2019; Teichgräber et al., 2019; Wogrin, 2022
- Frequently used are clustering method: K-means, k-medoids, hierarchical clustering, with vector-norm of differences, e.g. $\sqrt{\sum_i (x_i - y_i)^2}$

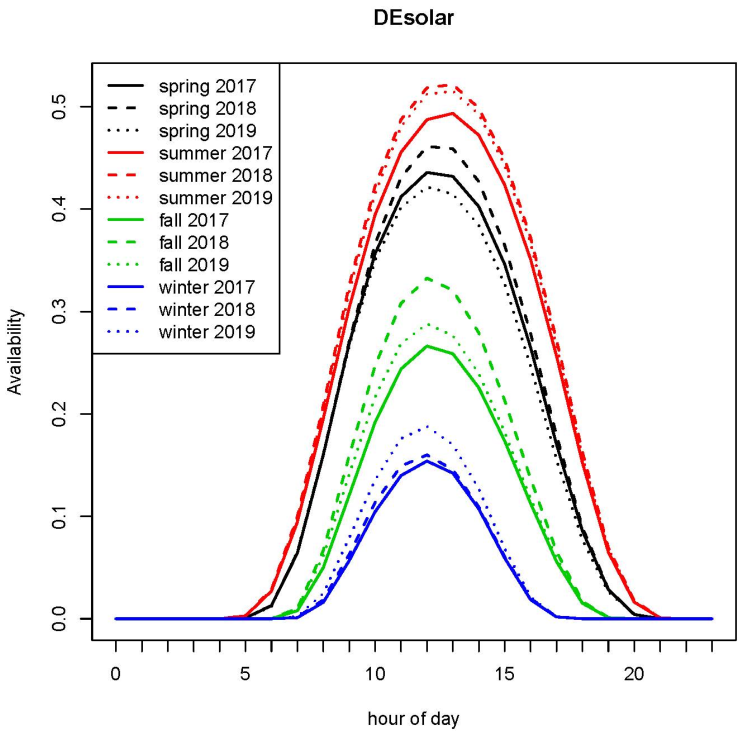


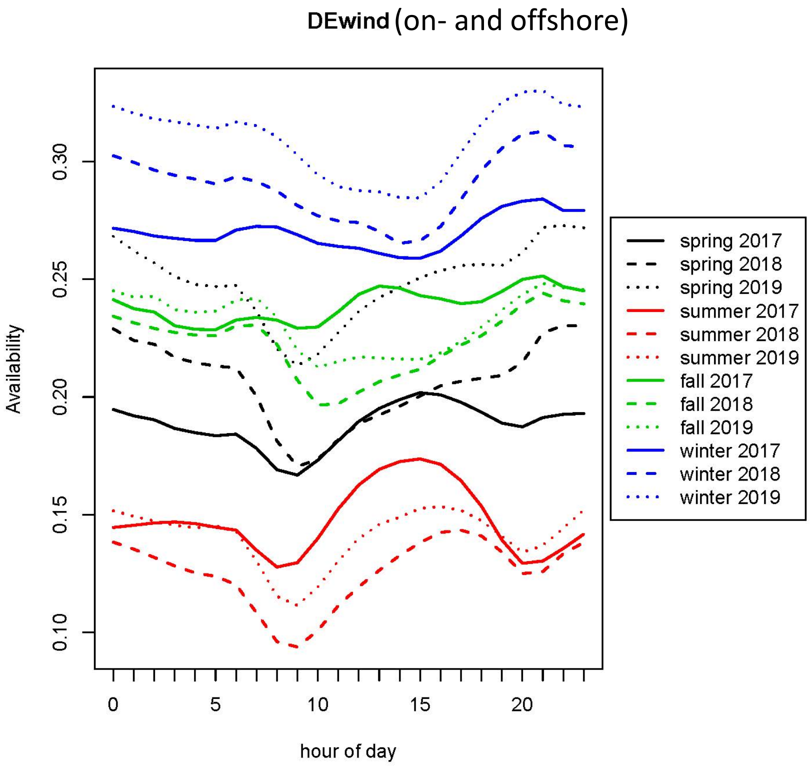


Boddu, S. (2021): (PSI MSc Thesis)

- Clustering ensures that amounts (energy, availabilities, etc.) are similar “on average”
- What about the correlations between hours of day, and to other time series (esp. wind & solar)?
- In this talk: **Capturing correlations of wind & solar availability per seasons**

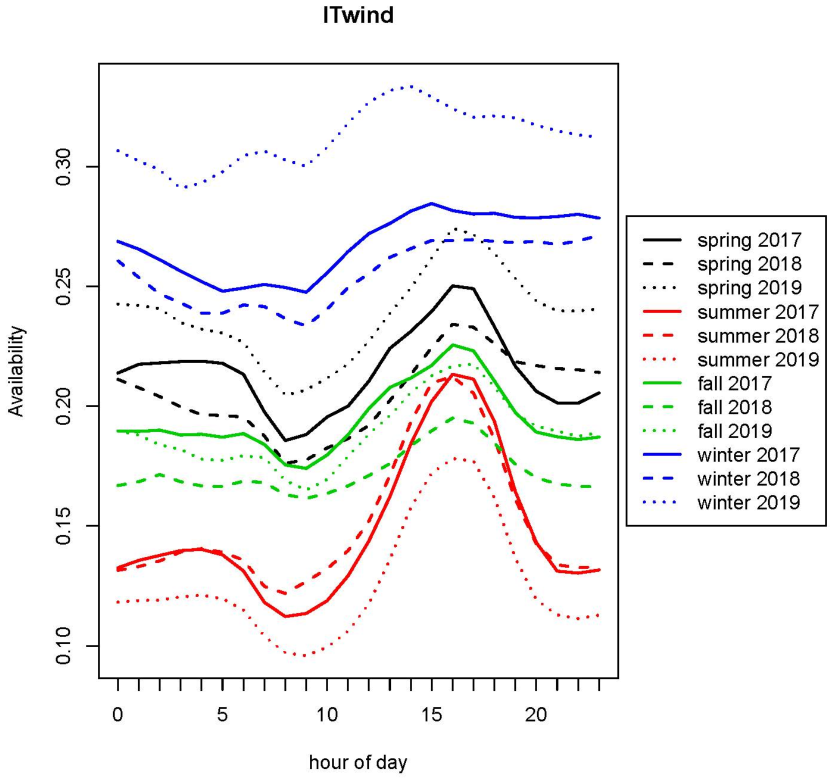
Wind & solar availability: Average days per season





- Solar-wind correlation

Different wind pattern: Example Italy



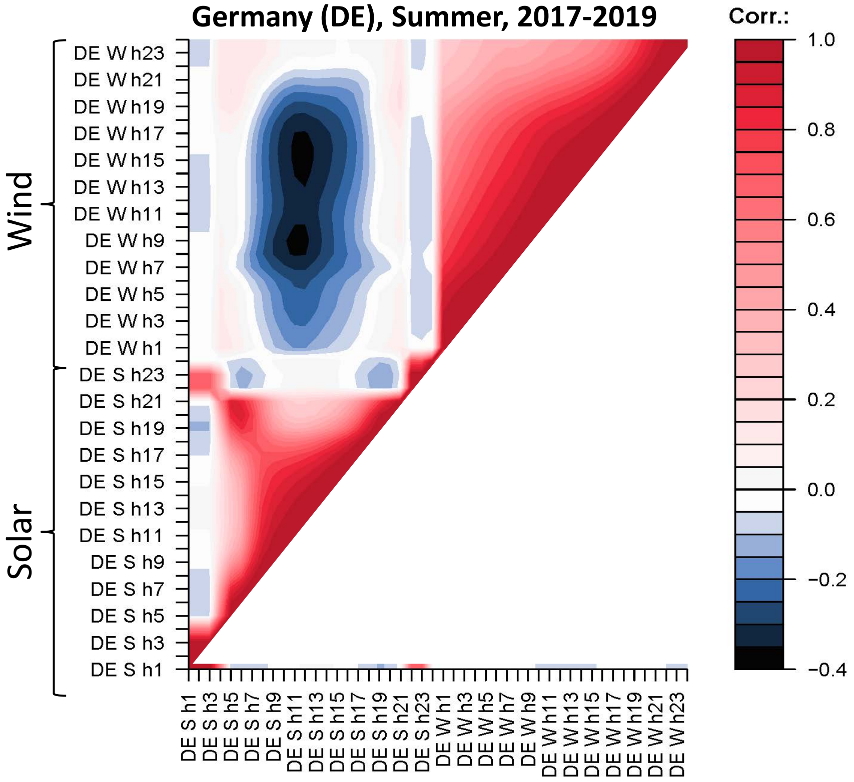
Correlation: Hourly wind & solar PV availability

Correlation wind vs. solar over all hours a year

Region	2017	2018	2019
Austria	-0.12	-0.14	-0.17
Switzerland	-0.16	-0.05	-0.12
Germany (on- and offshore)	-0.17	-0.24	-0.22
Germany offshore	-0.15	-0.21	-0.16
France	-0.15	-0.21	-0.16
Italy	-0.07	-0.09	-0.10

- Negative correlation can be higher in certain hours, up to: -0.4
- Positive correlation at
  - late-evening solar
  - late-evening wind

Correlation for each hour

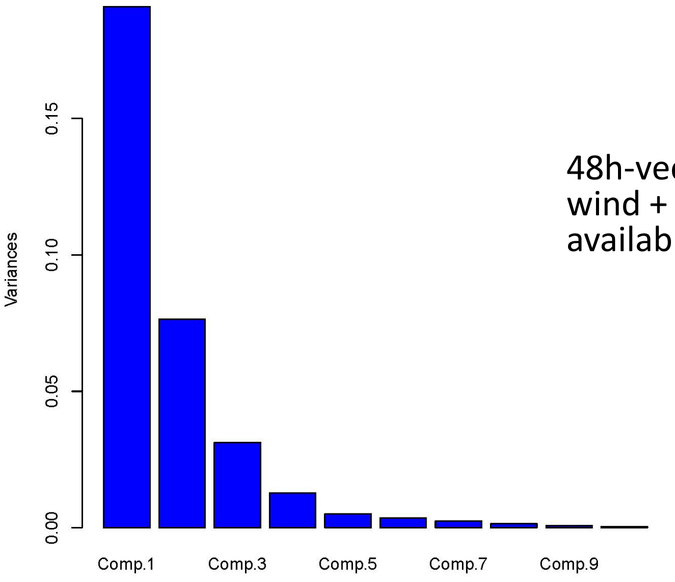


(wind: on + offshore)

Principal Component Analysis (PCA)

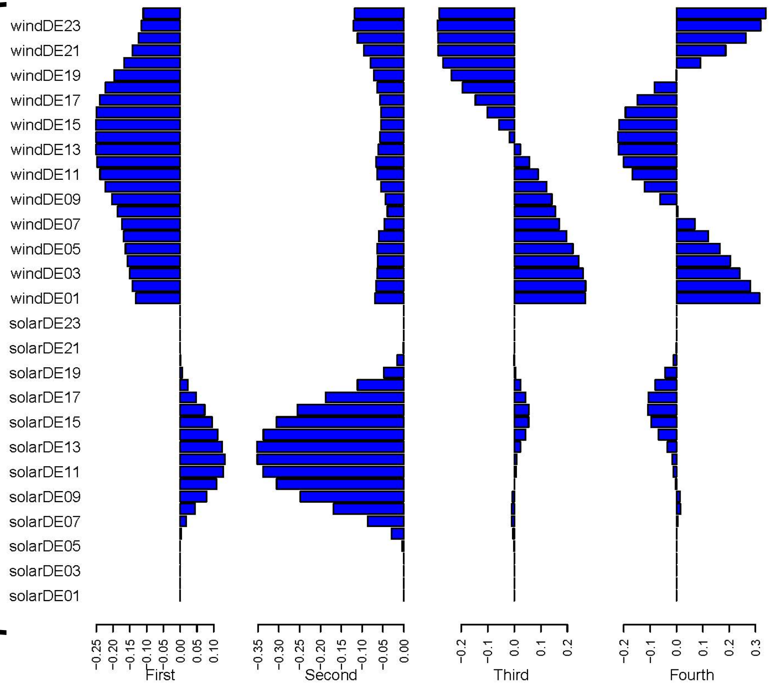
- PCA decomposes the covariances, PCA yields uncorrelated loadings

Example: Germany, summer, 2017-19



Variance of PCs ordered by variance

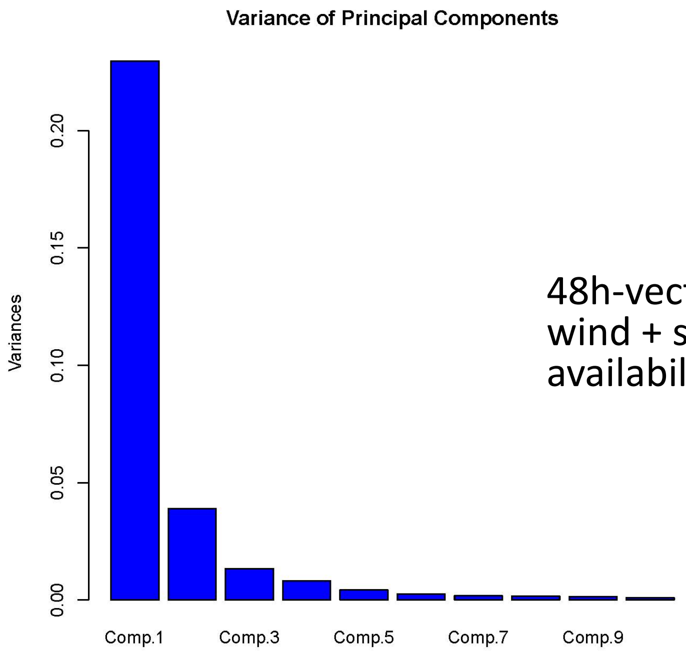
48h-vector wind + solar availability



Loadings of the ordered PCs

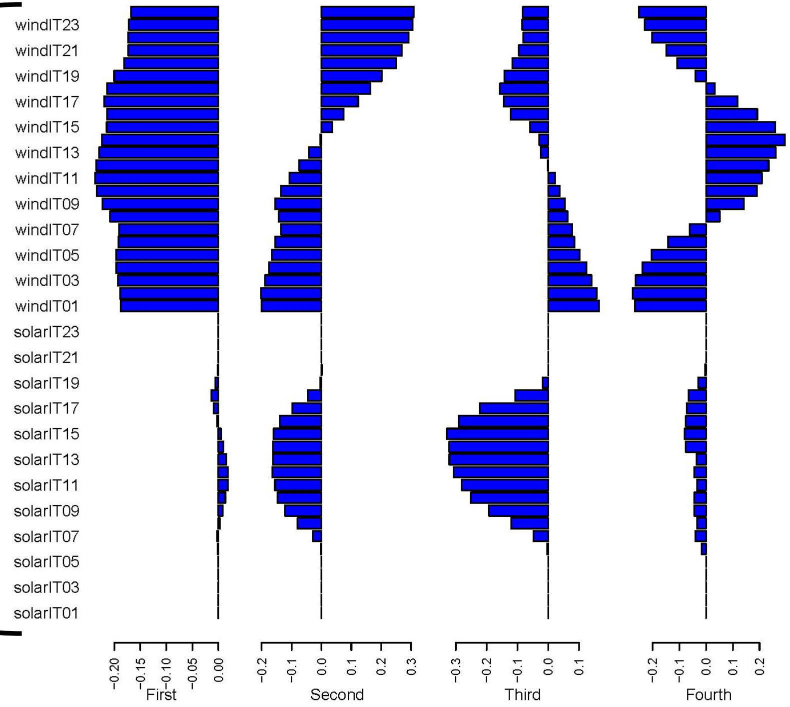
Italy: PCA of hourly wind & solar

Again: Summer, 2017-19



Variance of PCs ordered by variance

48h-vector wind + solar availability



Loadings of the ordered PCs

Scenario generation: Factor model given by PCA

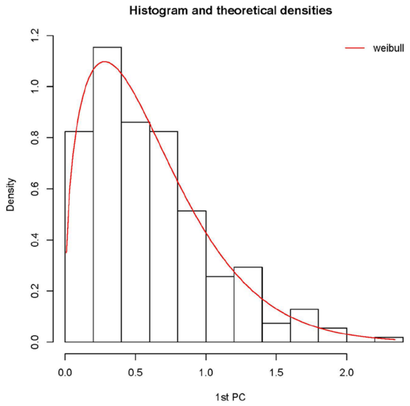
- PCA approximates covariance matrix of X by sum of uncorrelated loadings:

$$X \approx \sum_{i=1}^{k} P_i u_i, \qquad k < n$$

  - $X \in \mathbb{R}^n$: original random vector with values in n-dimensional space (n = 48),
  - $P_i \in \mathbb{R}$: random variable, i^{th} PC,
  - $u_i \in \mathbb{R}^n$: loadings of PC (deterministic vector)

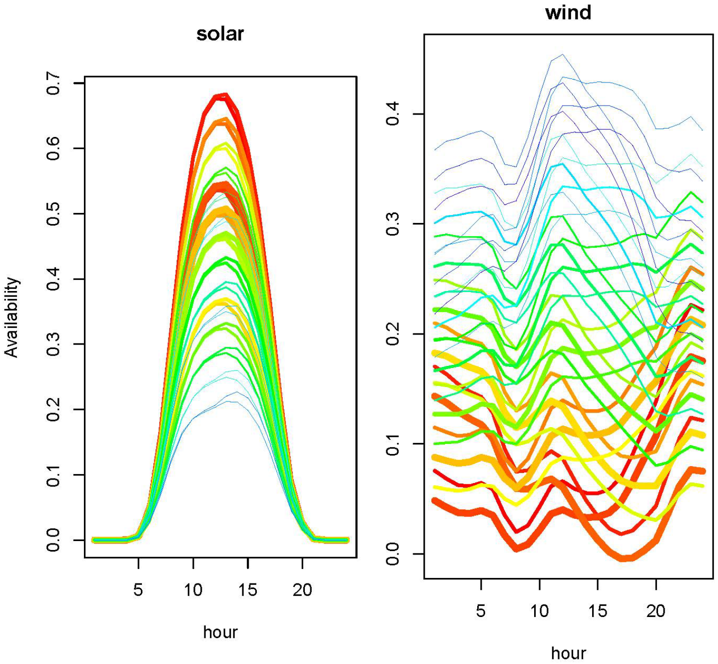
- **Factor model:** $X = UF + \varepsilon$
  - $F = (P_1, \dots, P_k)^T \in \mathbb{R}^k$: lower-dimensional factor,
  - $U = (u_1, \dots, u_n)$
  - Distribution of factors P_i are fitted by continuous distributions and then discretized:

Example: Germany, summer, P_1



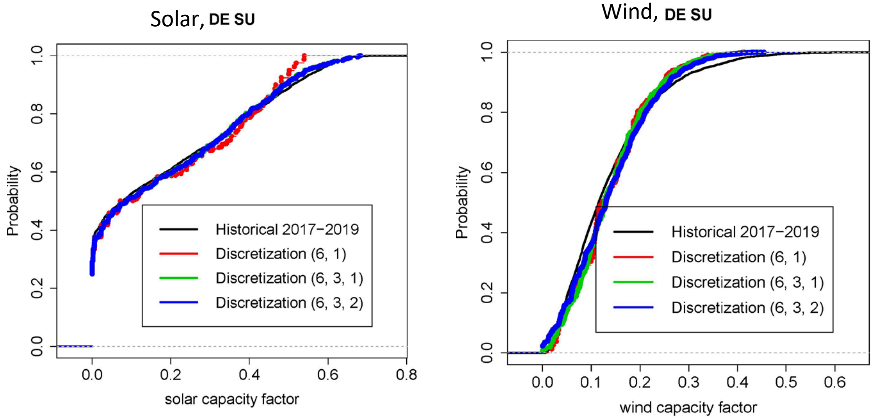
Scenarios; Quality

Example: Germany, summer; 36 scenarios;
line width = probability weight



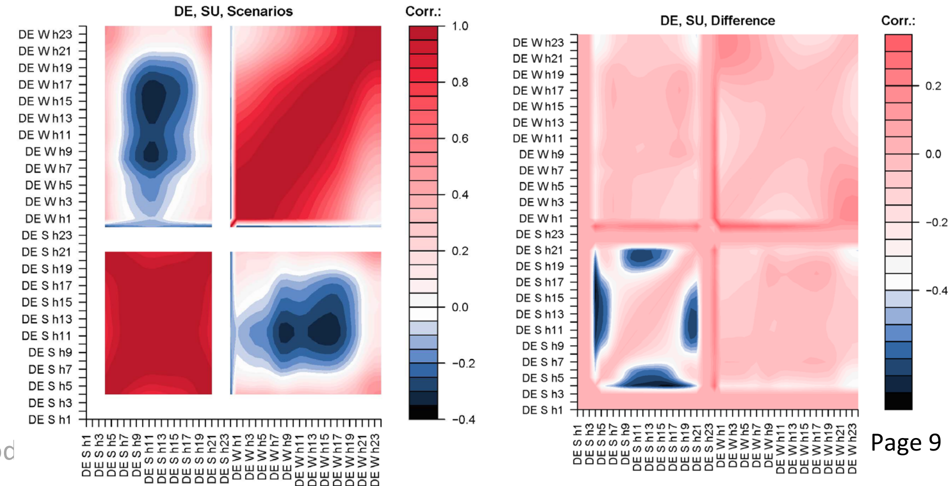
- number of components and discretizations:
  1st, 2nd, 3rd PC = 6, 3, 2

Duration curves



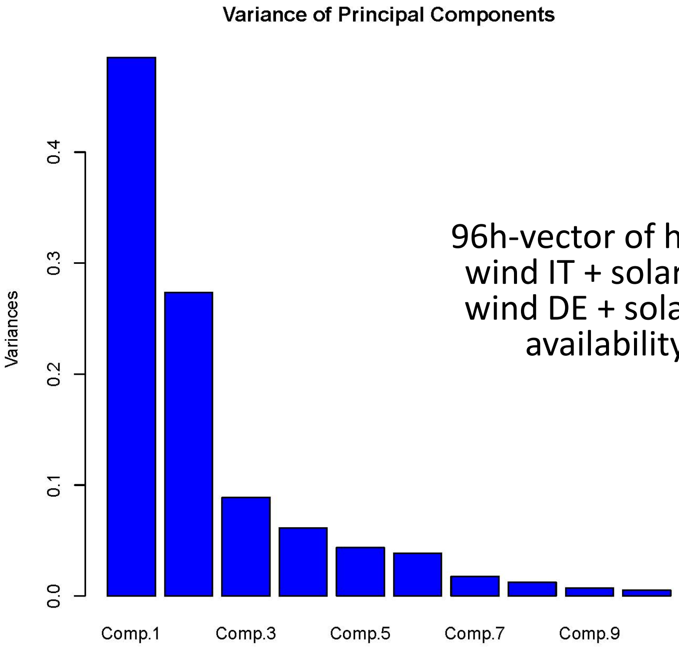
Correlation of scenarios

Correlation: error



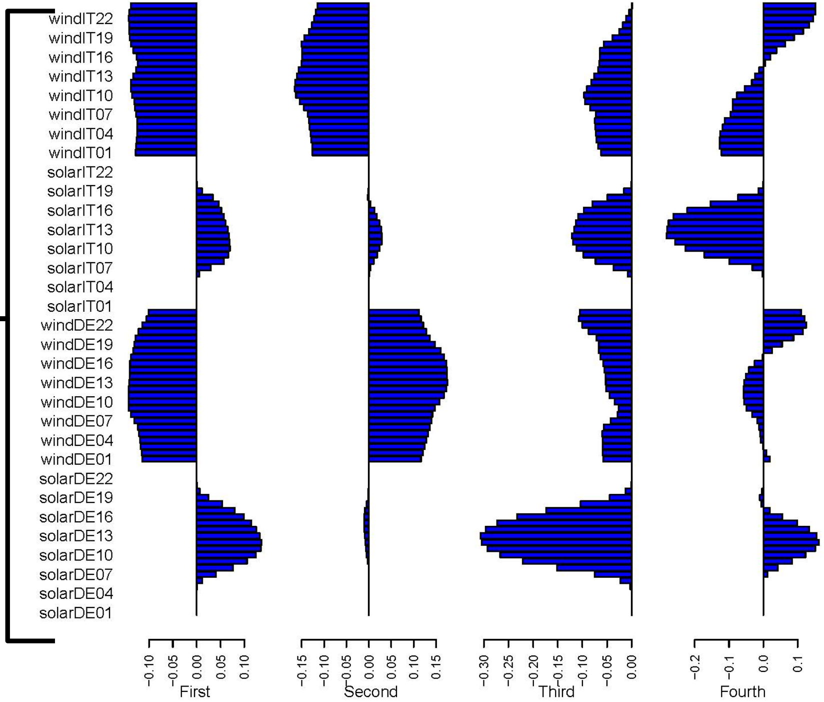
Several countries: PCA over two countries?

Example: Italy + Germany



Variance of the PCs having highest variance

96h-vector of hourly wind IT + solar IT + wind DE + solar DE availability

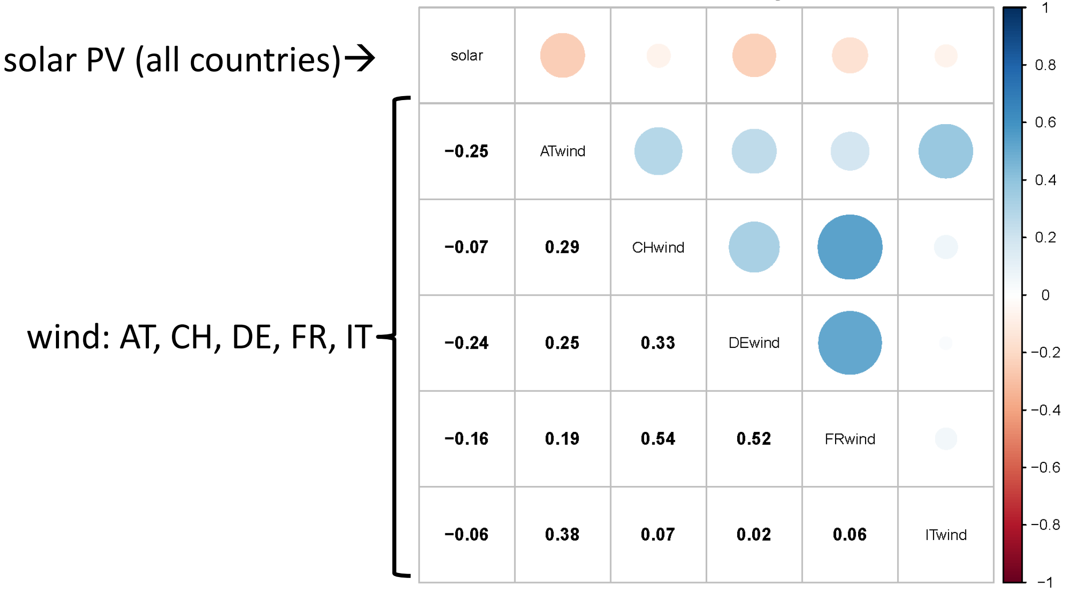


Loadings of the ordered PCs

Across regions: Daily wind & solar availability

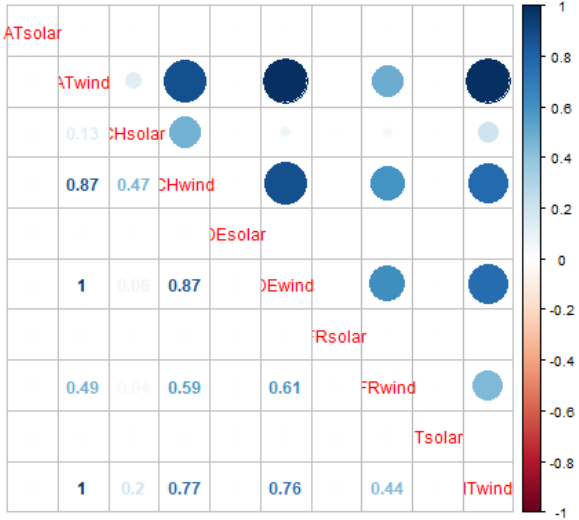
- Regions: Switzerland and surrounding countries: CH, AT, DE, FR, IT
- Keep dimension low (i): Cross-regional correlation between daily availability (avg. of hourly)
- Keep dimension low (ii): By statistical analysis: If sun is shining, then usually in all countries

Correlation matrix daily wind and solar



Tail-dependence of wind & solar across regions

- Tail dependence := Probability of joint, extremely-high values (or extremely low values)
- Daily wind & solar availability across regions: High tail-dependence = 0; Low tail-dependence =



Within a day:

- Likely: Joint calms across regions
- Unlikely: Joint storms, or dark- & calmness

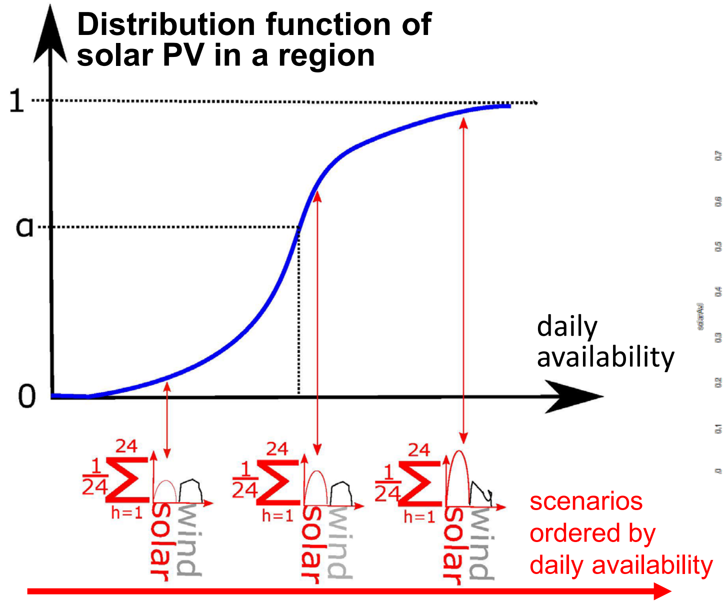
- Scenario generation: Random sampling from multivariate distribution of the variables
- Estimation of distribution? Gaussian has tail-dependences = 0. We use: t-distribution

Random sampling of copula of t-distribution

- Copulas in spatial energy time series: see e.g. Zhan et al. (2019), Camal et al. (2019)
- A random sample of a copula are quantiles of its marginal distributions. Two steps:
  (i) Sample quantile α for daily wind, solar, for each region (-> daily values across regions)
  (ii) Identify with hourly scenario having closest quantile α (ordered by daily values)

(i) Random sample of copula for solar in region

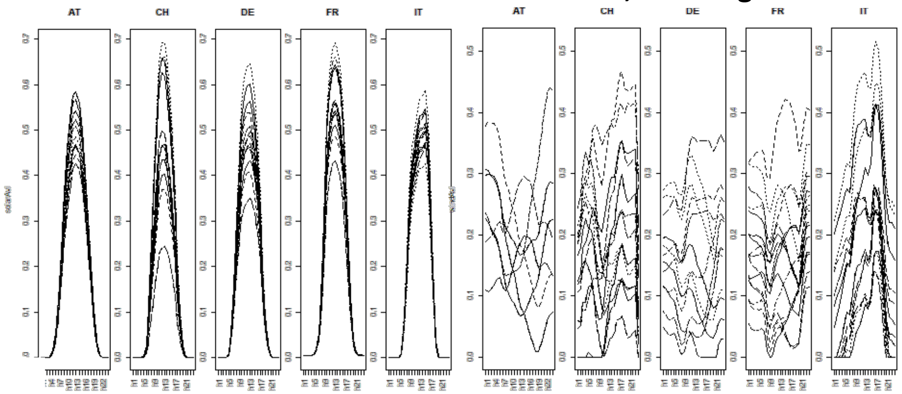
(ii) Identification with hourly scenario in region



20 random samples from t-copula → 20 scenarios

solar, each region

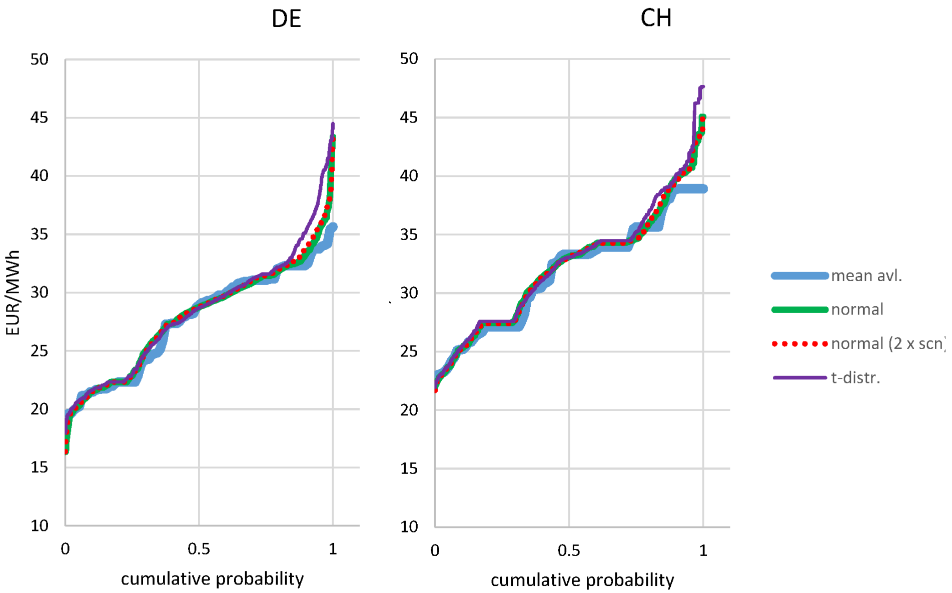
wind, each region



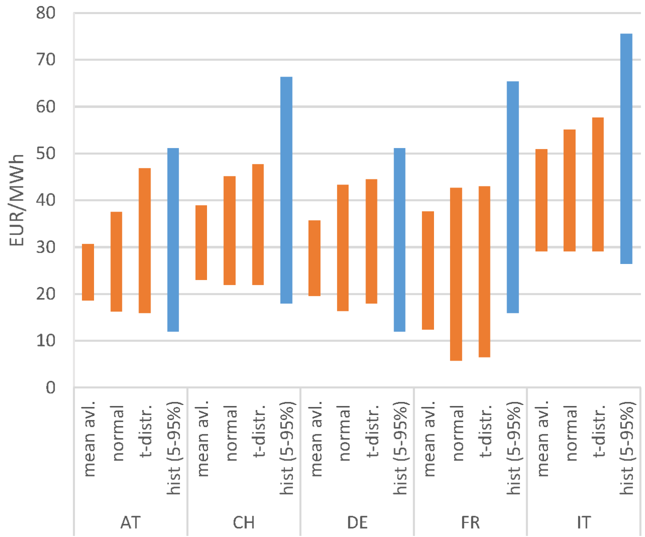
Results in an electricity market model

- BEM: Cross-border electricity market model: Switzerland and surrounding countries (Panos & Densing, 2019)
- BEM is run for this work in “basic” marginal-cost mode (price-peaks in model too low)

Price duration curves



Price ranges



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Conclusions

- To capture dependences between time series of renewable supply is difficult:
  - Correlation and extreme events can be captured with daily inter-regional resolution and hourly intra-regional resolution: Fat-tail copulas and PCA

- **Limitation:** To match correlations, we need several (statistical) representative days per season: Suitable for daily or seasonal storage, but not (yet) for consecutive days; dimension goes up!

- Why **not** use the original 8760h model?
  - Numerical intractability

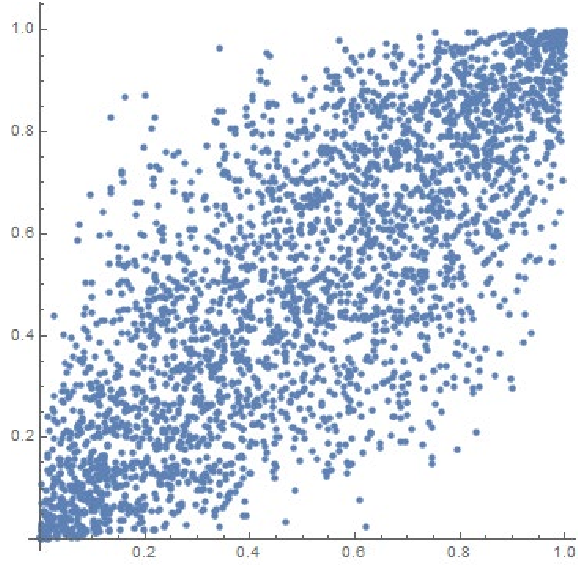
- Why use the original 8760h model?
  - Dependencies are trivially captured
  - Energy modelers are not meteorologists

- Densing & Wan, 2022. Low-dimensional scenario... *Applied Energy*. 10.1016/j.apenergy.2021.118075
- R-package: https://gitlab.psi.ch/energy-economics-group/representative-days.

Correlation is not enough

Copula: Multivariate random variable, values in [0,1], to capture only interdependencies

Random samples of
Bivariate **Gaussian (normal) copula**,
corr = 80%



Random samples of
Bivariate **t-copula**
corr=80%