

Chair of

EE Energy Economics

Energy Systems &

RUHR-UNIVERSITÄT BOCHUM

ROBUST PLANNING OF A
EUROPEAN ENERGY SYSTEM
UNDER CLIMATE UNCERTAINTY
USING IMPORTANCE SUBSAMPLING

OR Karlsruhe 2022, Leonie Sara Plaga, Valentin Bertsch

Overview

- Motivation
- Description of case study
- 3 Importance Subsampling
- 4 Conclusion and outlook





Overview

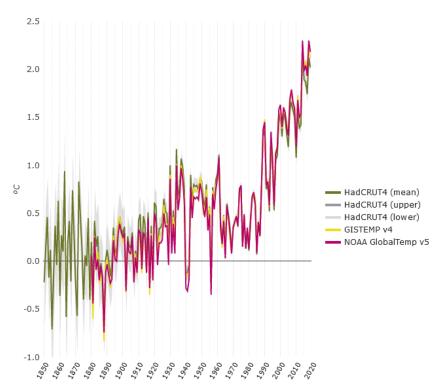
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- Climate change impacts already visible
- Energy systems depend on climate variables
- Climate projections are highly uncertain
- Many different models for many different years

European average temperature anomaly



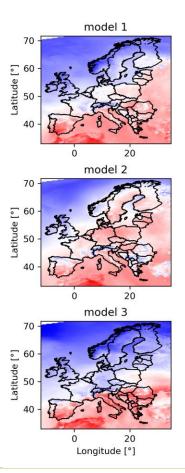
Source: https://www.eea.europa.eu/data-and-maps/indicators/global-and-european-temperature-10/assessment

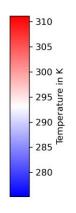






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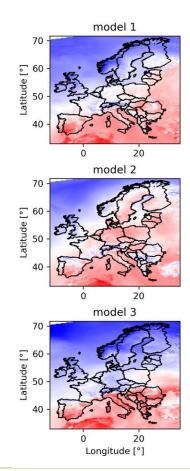


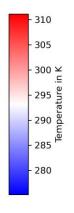






- How can one incorporate the different projections into energy system planning?
- How can we reduce the input data to incorporate large numbers of years and models?



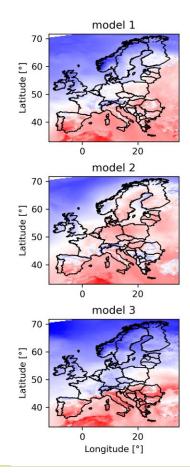


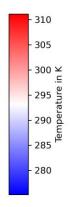






- How can one incorporate the different projections into energy system planning?
- How can we reduce the input data to incorporate large numbers of years and models?
- → Importance Subsampling











Overview

- My PhD Project
- Description of case study
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Description of case study

Overview

- Optimization of the European electricity sector for target year 2050
- No coal, oil or gas power plants
- Investment in nuclear power, wind, PV, batteries and hydrogen storage







Description of case study

Data and software

- Analysis in energy system model backbone¹
- Most power system data from pypsa-eur²
- Climate projections from Euro-Cordex
 - >5 different climate models
 - All years from 2006 to 2100









¹ Helistö et. al, 2019, doi.org/10.3390/en12173388

² Hörsch et. al, 2018, doi.org/10.1016/j.esr.2018.08.012

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Original Method

- Introduced by Hilbers et. al (2019)*
- Aim: represent a large dataset with a small number of timesteps

* 10.1016/j.apenergy.2019.04.110

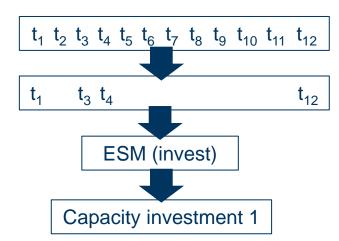






Original Method

- Methodology:
 - 1. Randomly sample *N* timesteps from dataset.
 - 2. Estimate capacity investments based on these datasets.



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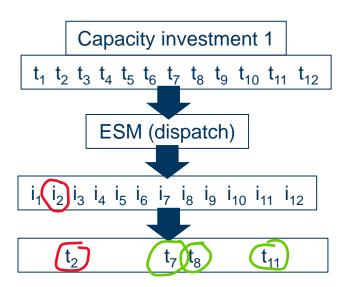






Original Method

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 - 1. Randomly sample *N* timesteps from dataset.
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 - Estimate importance of each dataset based on capacity investment 1.
 - 4. Construct a dataset of length N consisting of N_i important timesteps and N_r random timesteps.





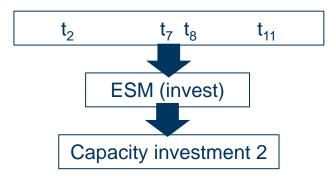






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 - 5. Estimate capacity investment based on this dataset.

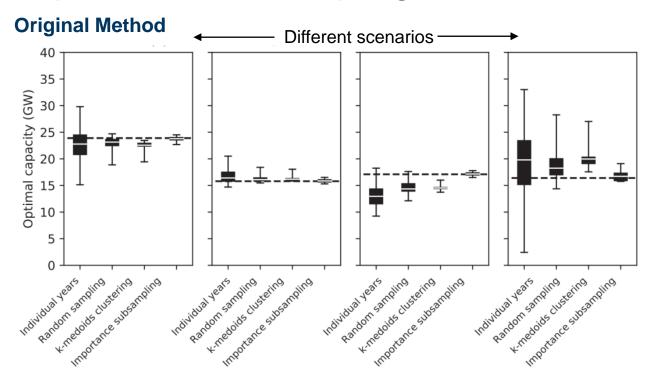










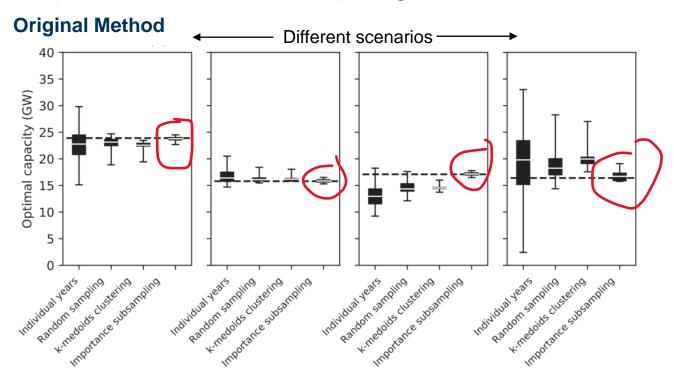


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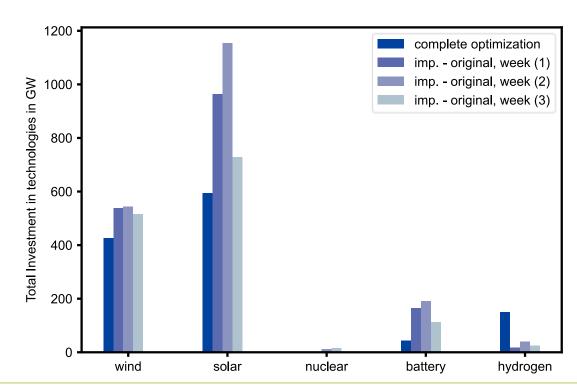


Adaptions for our model

- Length of subsamples at least 24 hours → 1 week (168 h)
- 1 year of data
- N = 6 and $N_i = 2$



Results

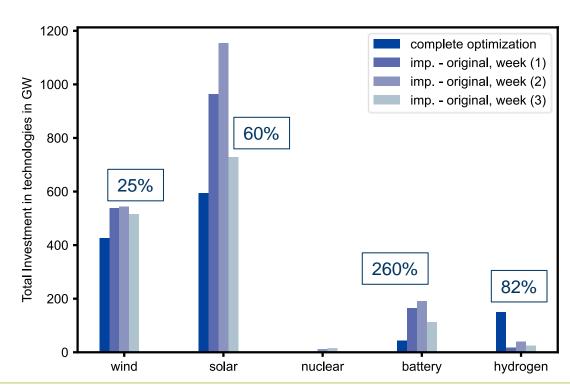








Results



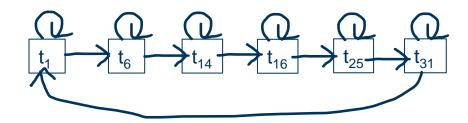






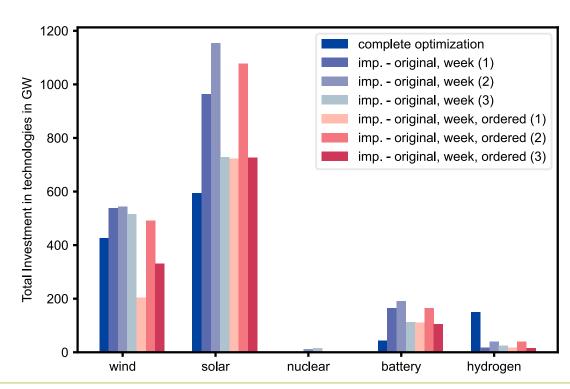
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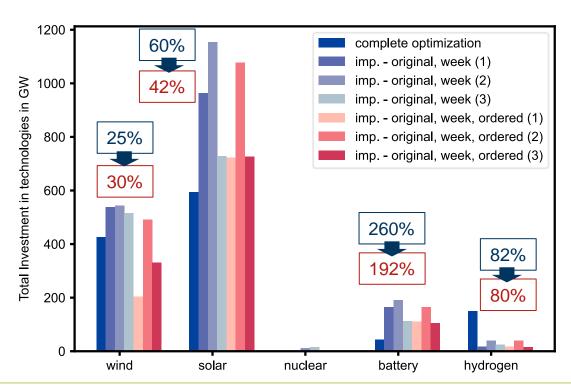








Results







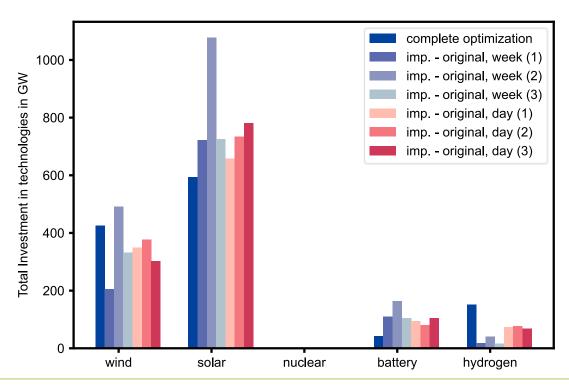


Adaptions for our model

- Length of subsamples at least 24 hours → 1 week (168 h)
- 1 year of data
- N = 6 and $N_i = 2$
- Is it important to keep the temporal order of the subsamples?
- What influence has the length of the subsample?
 - Length: 24 h
 - N = 42 and $N_i = 14$
 - Same total length as weekly dataset



Results

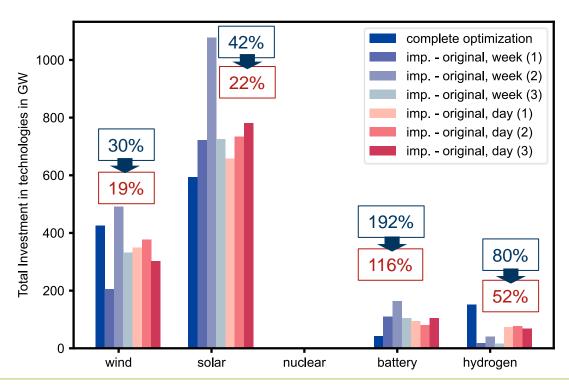








Results



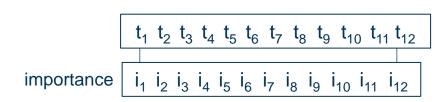






Adaptions for our model

- Deviations still high
- Improve keeping temporal order of timesteps
- Cluster all subsamples into clusters of variable length
- Choose length of clusters aiming to minimize the maximal difference from cluster average

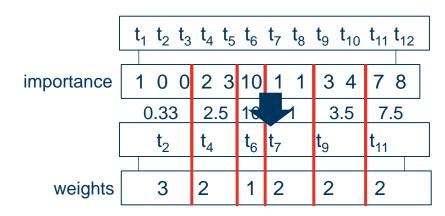






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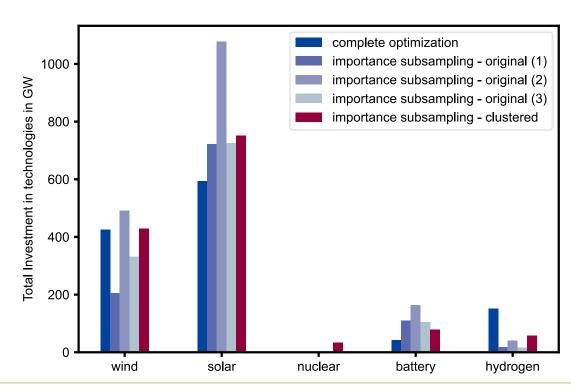
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Results after clustering

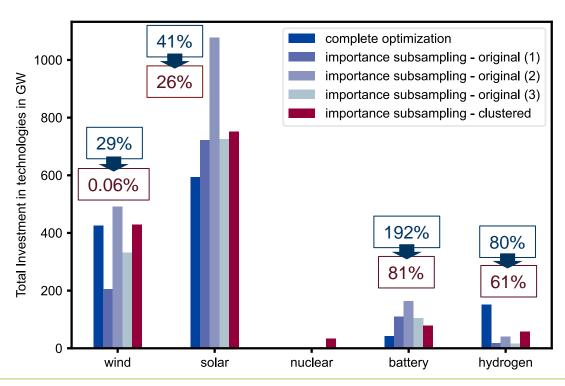








Results after clustering









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Conclusion and outlook

Conclusion

- Adaption of importance subsampling for more complicated systems → challenging
- Original method show differences in invest decisions especially for storages
- Choice of appropriate length for subsample necessary
- Clustering all timesteps based on their importance enhances results, but:
 - Leads to higher computational times
 - Deviations still quite high





Conclusion and outlook

Outlook

- Combine daily subsamples with cluster algorithms
- Compare importance subsampling results to other sampling methods
- Use reduced dataset as input in robust optimization





Thank you for your attention!

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- Demand
- Hydro power
- Wind power
- Solar power
- Efficiency of thermal power plants

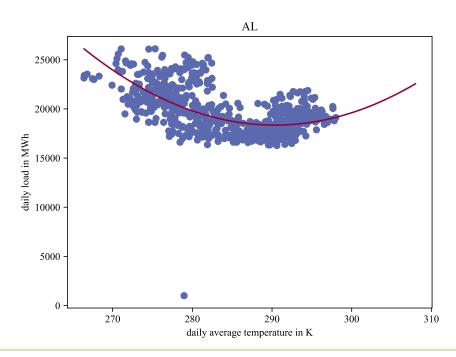




- Demand
 - Temperature influences heating and cooling demand
 - Country-specific regression







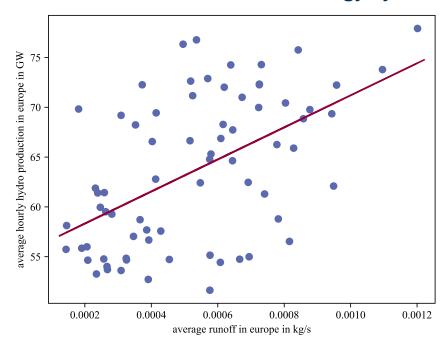




- Hydro power
 - River-runoff determines production
 - Site-specific evaluation very costly
 - Europe-wide regression
 - Estimating country-specific hydro production based on European trend











- Hydro power
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- Wind power
 - Interpolate wind speed to hub height
 - Use standardized production functions
- Solar power
 - Output depends on solar irradiation
 - Rising temperature decreases cell efficiency
 - Temperature of cell rises with outside temperature and irradiation





- Efficiency of thermal power plants
 - Cooling system is depending on temperature
 - Once-through cooling more vulnerable than closed-loop cooling
 - In this study: only closed-loop





Influence of climate variables on energy systems

- Wind power
 - Climate models report wind speeds
 - Interpolate to hub height:

$$v(h) = v(h_0) \cdot \left(\frac{h}{h_0}\right)^{1/7}$$

Calculate capacity factor:

$$c_{\rm f} = \begin{cases} 0, & v < v_{\rm in} \\ \frac{v^3 - v_{\rm in}^3}{v_{\rm r}^3 - v_{\rm in}^3}, & v_{\rm in} \le v < v_{\rm r} \\ 1, & v_{\rm r} \le v < v_{\rm out} \\ 0, & v > v_{\rm out} \end{cases}$$



Influence of climate variables on energy systems

- Solar power
 - Rising temperature decreases cell efficiency:

$$\eta = \eta_{\rm STC} (1 - \beta (T_{\rm cell} - T_{\rm STC}))$$

Temperature of cell rises with outside temperature and irradiation:

$$T_{\text{cell}} = T_{\text{am}} + c \cdot G$$



- Efficiency of thermal power plants
 - Cooling system is depending on temperature
 - Once-through cooling more vulnerable than closed-loop cooling
 - In this study, only closed-loop:

$$\eta = \begin{cases} \eta_0, & T \le T_{\text{health}} \\ \eta_0 (1 - \rho (T - T_{\text{health}})), & T > T_{\text{health}} \end{cases}$$

