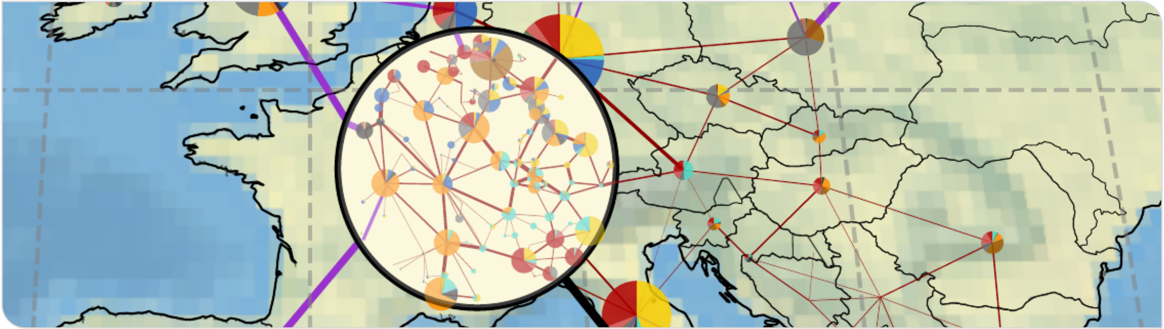
Open
Energy
Transition
from the creators of PyPSA meets Earth

PyPSA

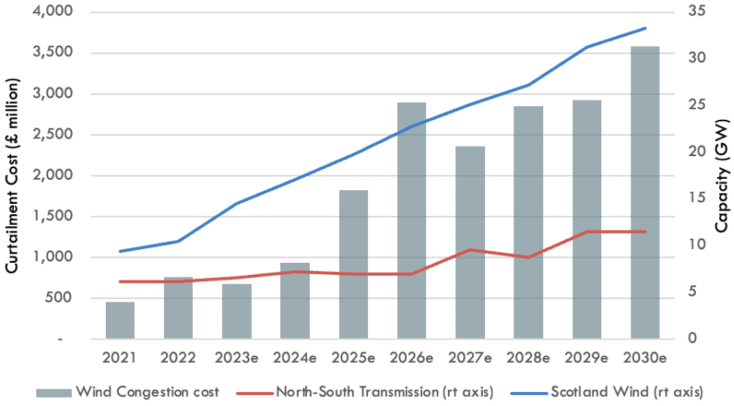
The Impact of Spatial Scale on Offshore Expansion

Turning the Tide: Optimising Europe's Offshore Energy Future with Holistic Planning and Engagement

Dr. Martha Maria Frysztacki | April, 25th 2024



Challenge I: Unresolved Grid Bottlenecks cause Grid Congestion



Britain wastes enough wind generation to power 1 million homes [1]

"Optimal" Investments made using spatially low-resolved models

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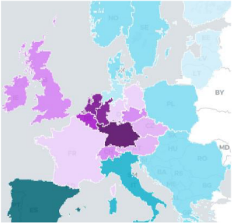
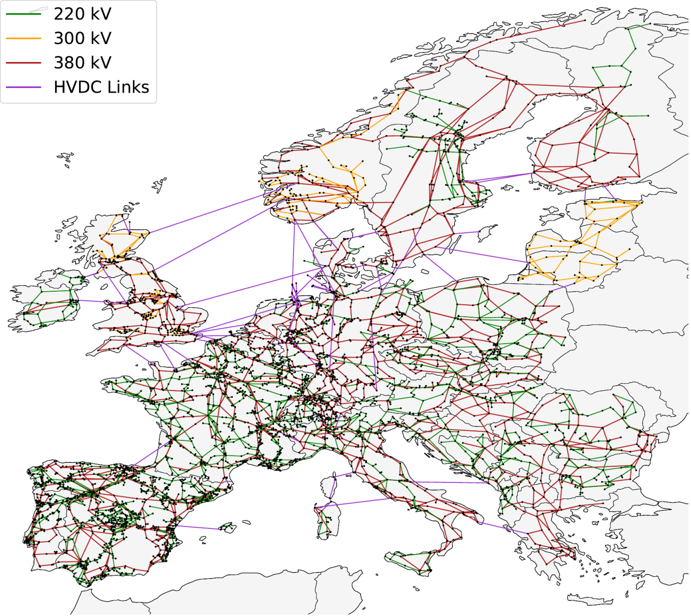


- **"Langfristszenarien"** [2]
  commissioned by BMWK; Model: Enertile v5 (1 node per country, except 6 nodes for Germany)
- **"Deutschland auf dem Weg zur Klimaneutralität 2045"** [3]
  commissioned by BMBF; comparing 4 models REMIND (1 node for Germany), energyANTS (high spatial coverage for technologies), REMod (Germany, "multi-node" possible) & TIMES PanEU (EU27+3, 1 node for Germany)

The ENTSO-E Transmission Grid Map



[4]

Challenge II: Conflicts between Resource & Transmission Planners

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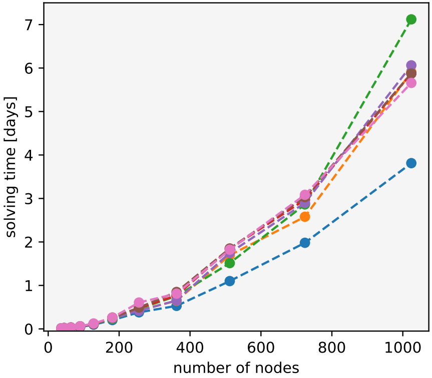
Source: Telos Energy, Presentation uploaded to LinkedIn

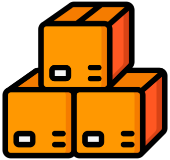
Challenge III: Limited Computational Resources for Combined Planning

Experimental resource requirements to solve the European **Grid and Resource** Model using Gurobi [5], [6].



How to Make Investment Decisions for Renewable Technologies?

&



How much?

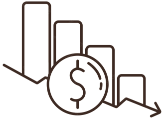
&

What does it cost?

Investment Decisions using Electricity System Models

Objective: minimise the total system cost that consist of

- investment costs in new generation projects
- investment costs in new storage capacity
- investment costs in new transmission line projects
- variable costs, such as costs for fuels or maintenance



$$\min_{\substack{G_{v,s},\, H_{v,r} \\ g_{v,s,t},\, h^{\pm}_{v,r,t} \\ f_{(v,w),t}}} \left[\sum_{v\in\mathcal{V},\, s\in\mathcal{S}} \left(c_{v,s} G_{v,s} + \sum_{v\in\mathcal{V},\, r\in\mathcal{R}} c_{v,r} H_{v,r} + \sum_{(v,w)\in E} c_{(v,w)} F_{(v,w)} + \sum_{t\in\mathcal{T}} w_t o_{v,s} g_{v,s,t} \right) \right]$$

[7], [8]

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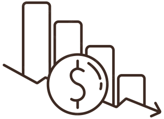

$$\min_{\substack{G_{v,s},\, H_{v,r} \\ g_{v,s,t},\, h^{\pm}_{v,r,t} \\ f_{(v,w),t}}} \Bigg[\sum_{v\in\mathcal{V},\, s\in\mathcal{S}} \Bigg(c_{v,s} G_{v,s} + \sum_{v\in\mathcal{V},\, r\in\mathcal{R}} c_{v,r} H_{v,r} + \sum_{(v,w)\in E} c_{(v,w)} F_{(v,w)} + \sum_{t\in\mathcal{T}} w_t o_{v,s} g_{v,s,t} \Bigg) \Bigg]$$

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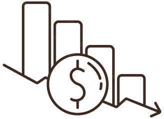

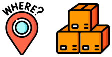

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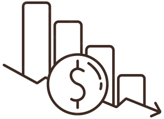

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[7], [8]

Solution: Reduce the Representation of the Model?

How to reduce the size of the network?

temporal scale → average over certain Δt (here $\Delta t \leq 3h$) [9], [10]

spatial scale

Research Questions

Section	Research Questions	Answers
Effects of Spatial Resolution		
Methods to Improve Clustering		
Disaggregation & Feasibility		

Research Questions

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Effects of Spatial Resolution	1. How does spatial resolution impact modeling investments? 2. What are the driving forces for the differences?	
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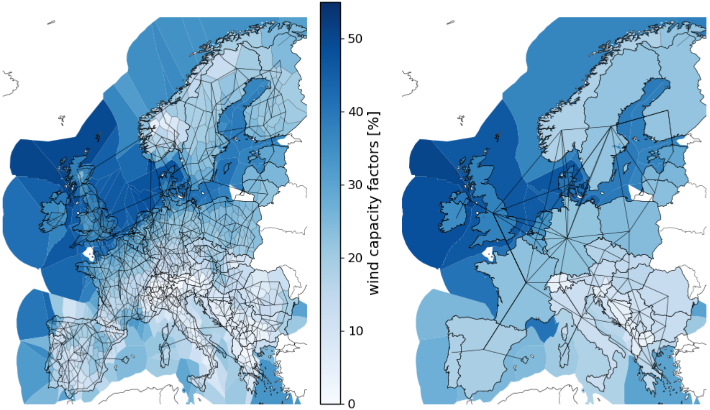
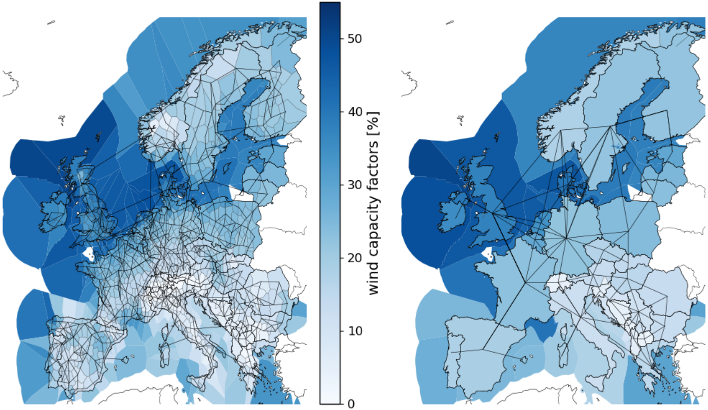
Disaggregation & Feasibility	5. Do the different results impact an inverted spatially highly-resolved model ?	


wind capacity factors [%]
50
40
30
20
10
0

TC: $270 \cdot 10^9$ €



TC: $248 \cdot 10^9$ €

Spatial Resolution Impacts Optimal Solution of the Model

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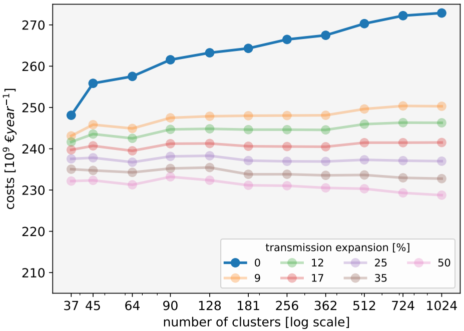

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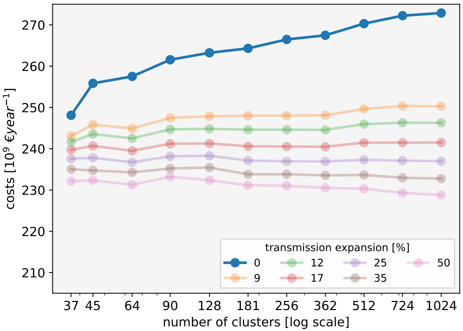

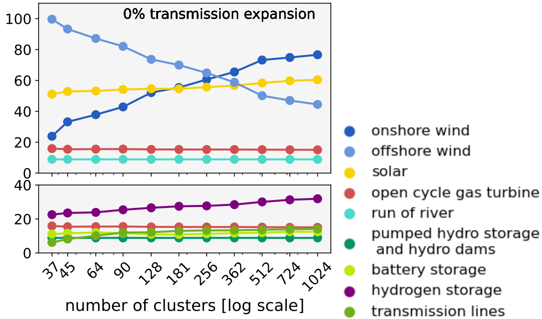

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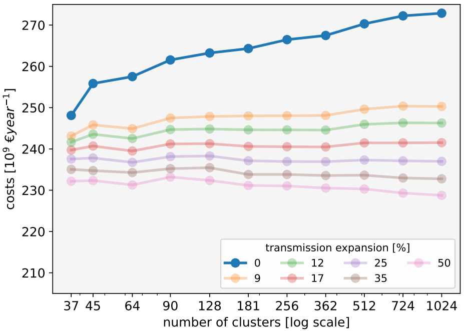

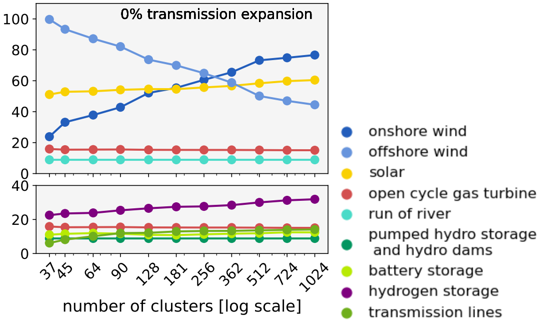

What modeling effects drive these results?

Methods and Experimental Setup to Disentangle Effects of Spatial Resolution

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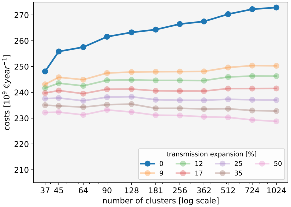
	Simultaneous	Generation	Transmission
Total Costs			
Effect dominated by	 offshore → onshore, solar & flexibility ↑↑		

contents of this Chapter are based on [6] Martha Maria Frysztacki, Jonas Hörsch, Veit Hagenmeyer, et al. "The strong effect of network resolution on electricity system models with high shares of wind and solar". In: *Applied Energy* 291 (2021), p. 116726. ISSN: 0306-2619. DOI: doi.org/10.1016/j.apenergy.2021.116726

Disentangle Spatial Representation of Renewables and Transmission Grid

How to reduce the size of the network?

temporal scale

spatial scale

k-means

Disentangle Spatial Representation of Renewables and Transmission Grid

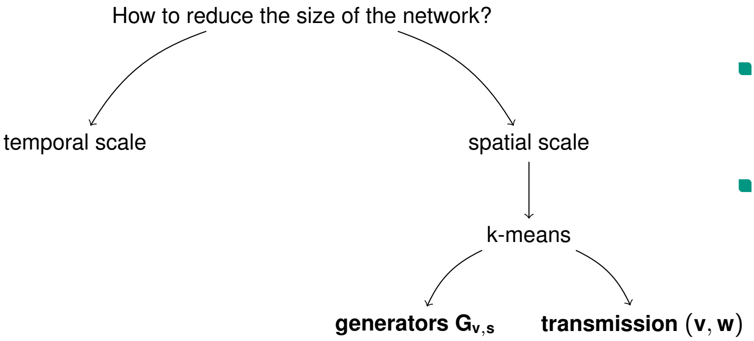
How to reduce the size of the network?

- temporal scale
- spatial scale → k-means → **generators $\mathbf{G_{v,s}}$**

- renewable generation:

$$\bar{g}_{v,\mathbf{s}} G_{v,\mathbf{s}} \leftrightarrow \mathbf{s} \in \mathcal{S}^{\text{re}}$$

Disentangle Spatial Representation of Renewables and Transmission Grid



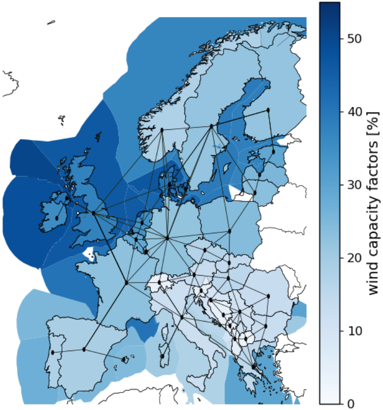
- renewable generation:

$$\bar{g}_{v,\mathbf{s}} G_{v,\mathbf{s}} \leftrightarrow \mathbf{s} \in \mathcal{S}^{\text{re}}$$

- transmission grid:

$$F_{(v,w)} \leftrightarrow (\mathbf{v}, \mathbf{w}) \in \mathbf{E};\ v, w \in \mathcal{V}$$

TC: $248 \cdot 10^9$ €



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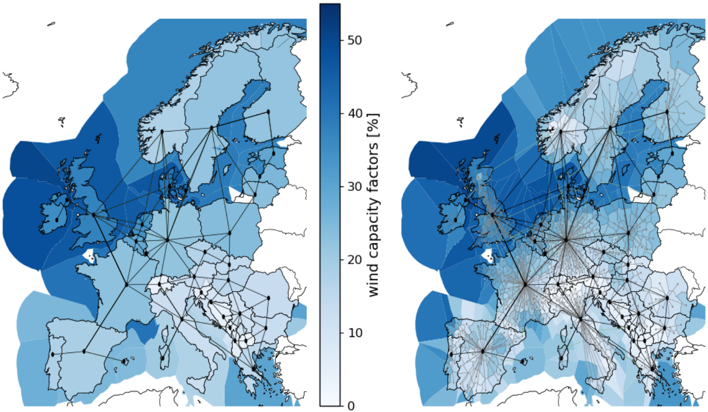
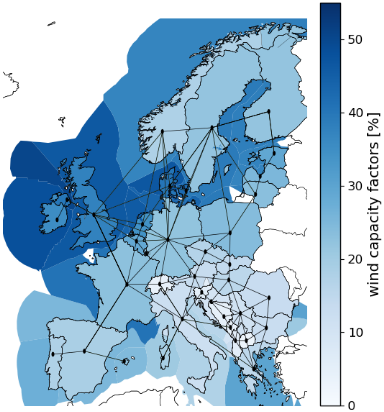
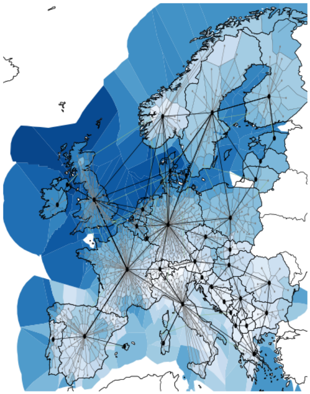


TC: $224 \cdot 10^9$ €

TC: $248 \cdot 10^9$ €





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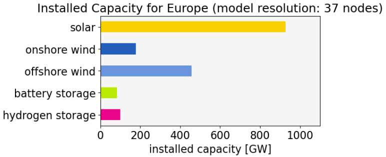
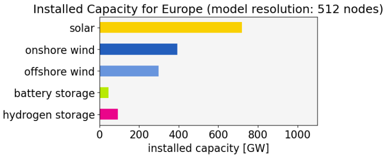
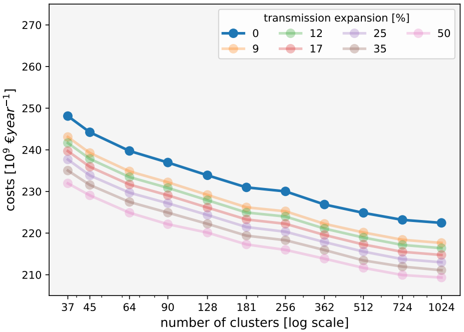




Spatially Highly-Resolved Renewable Generation Drives Down System Costs by 10%



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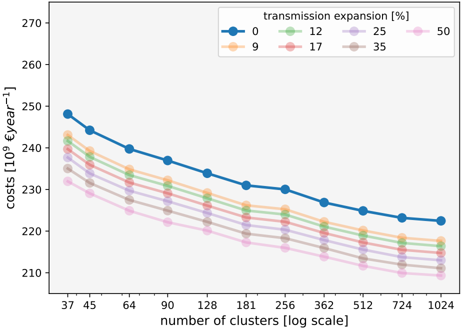

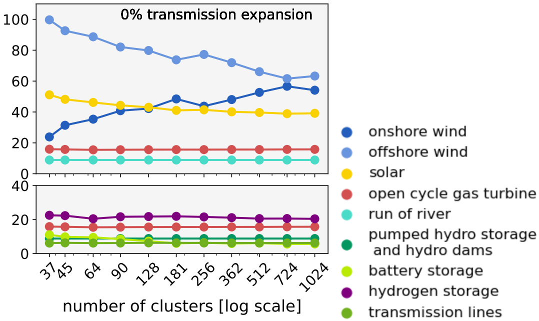

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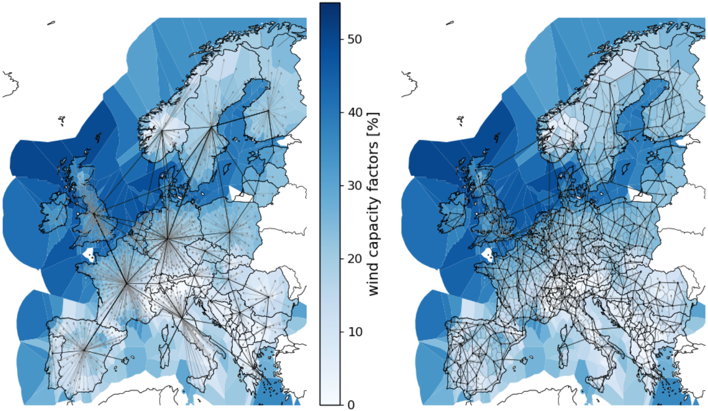

TC: $264 \cdot 10^9$ €

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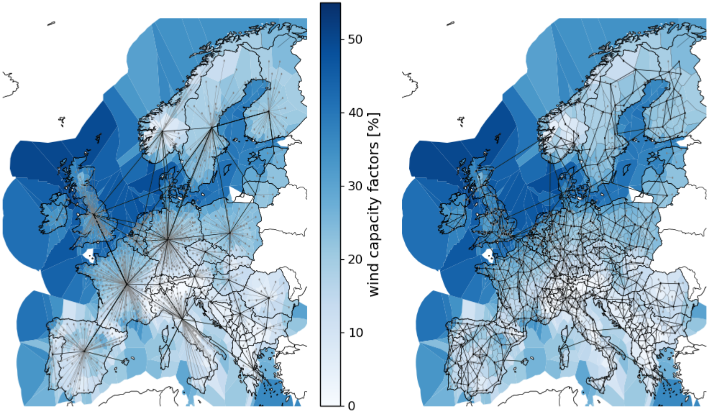

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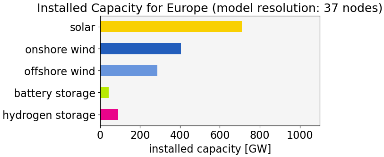
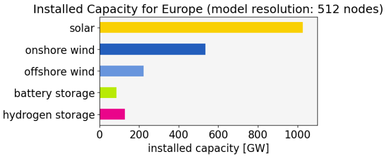
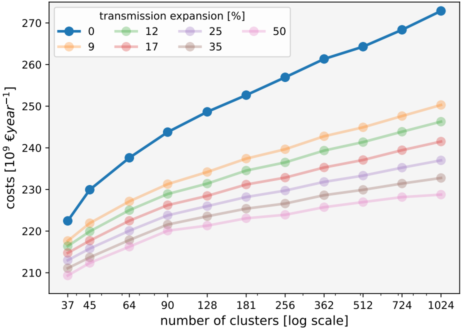




Low Network Resolution Ignores Congestion and Underestimates Costs by 23%



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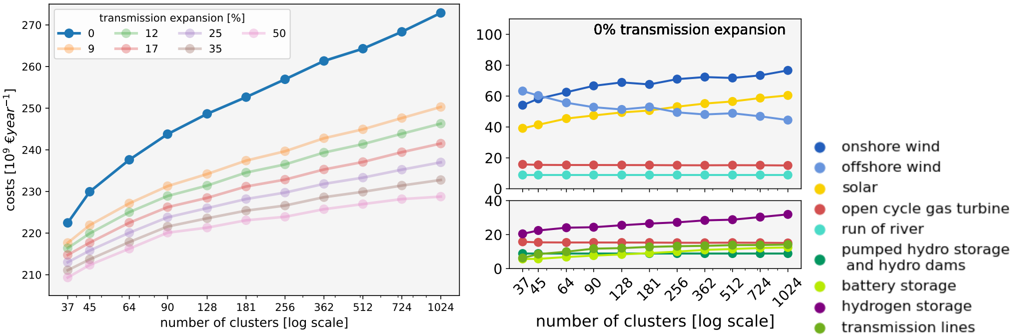
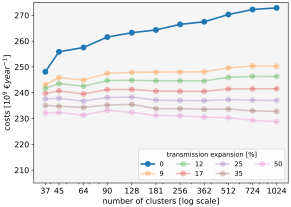
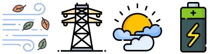


Summary: Spatial Effects of Renewable Resources and Transmission Grid Counteract!

	Simultaneous	Generation	Transmission
Total Costs			
Effect dominated by	 offshore $\longrightarrow$ onshore, solar & flexibility $\uparrow\uparrow$		

methods contributed to the open-source model PyPSA-EUR [8] `https://github.com/PyPSA/pypsa-eur` (licence: MIT)

data published: Martha Frysztacki, Jonas Hörsch, Veit Hagenmeyer, et al. *Clustering Dataset*. DOI: `doi.org/10.5281/zenodo.3965780` (license: CC BY 4.0)

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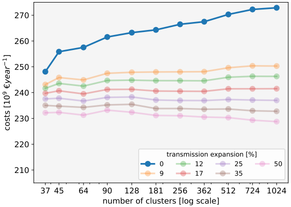
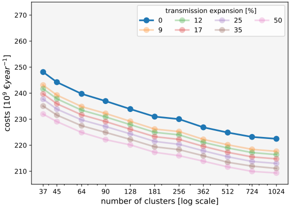
<tr><td>Total Costs</td><td>
</td><td>
</td><td></td></tr>
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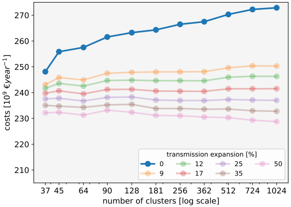
<td>
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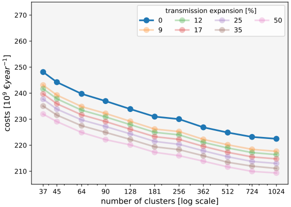
<td>
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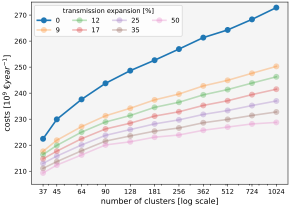
<td>
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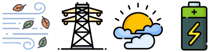
<td>
offshore → onshore,
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Can Other Spatial Clustering Methods Improve Results?

How to reduce the size of the network?

- temporal scale
- **spatial scale**
  - **k-means**

contents based on [6] Martha Maria Frysztacki, Gereon Recht, and Tom Brown. "A comparison of clustering methods for the spatial reduction of renewable electricity optimisation models of Europe". In: *Energy Informatics* 5.4 (2022). ISSN: 2520-8942. DOI: doi.org/10.1186/s42162-022-00187-7

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hierarchical clustering, f^{cap}, f^{time} (renewable properties)

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  - **k-means**
  - **modularity maximisation**, Q (connectivity of the grid)

---

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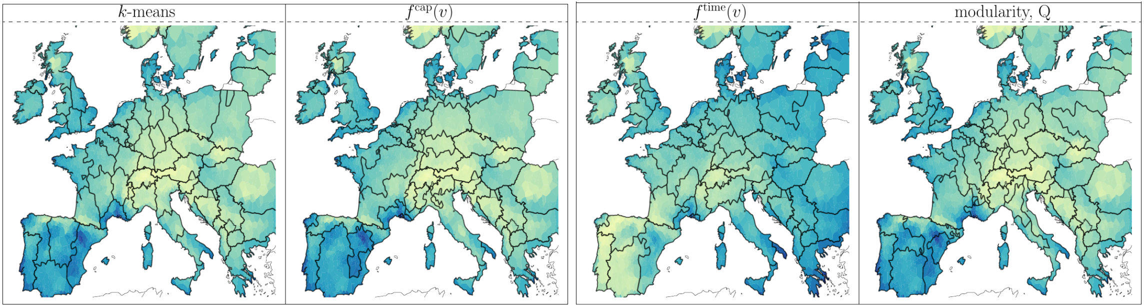
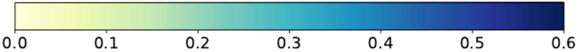
Resulting Regions Using 4 Different Clustering Methods

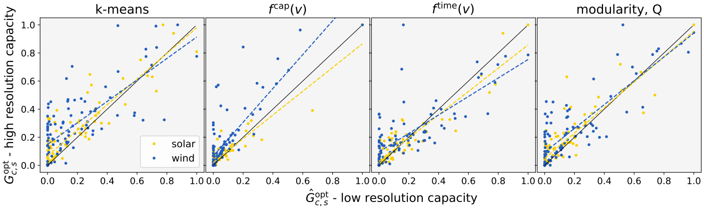
Example: 64 regions



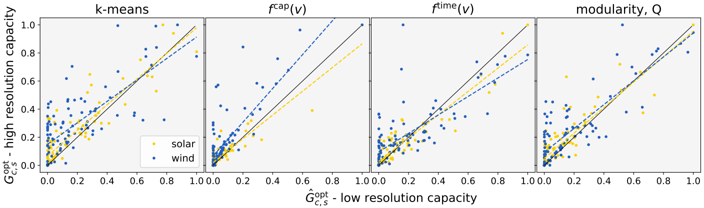
avg. annual capacity factors (wind and solar combined), avg. at 8 o'clock for f^{time}



Choice of Regions Strongly Impacts Optimal Solution



Choice of Regions Strongly Impacts Optimal Solution



CO_2 reduction	100%	
MSE	**wind**	**solar**
k-means	3.8	1.3
$f^{\text{cap}}(v)$	2.2	0.3
$f^{\text{time}}(v)$	2.5	0.6
Q	2.3	1.0

Hierarchical Methods allow accurate representation of Grid Connectivity & Wind Potentials

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- compared to the presented methods, **k-means performs worst**: no grid & no resource representation
- HAC methods are best: aggregate only regions ...
  - ... connected by a **transmission** line (possible to include a weighting)
  - ... that are homogeneous in terms of load, on- and offshore profiles

---

methods contributed to open-source python packages PyPSA [7] `https://pypsa.org/`(license: MIT) and NetworkX `https://networkx.org/` (license: 3-clause BSD), and the open-source model PyPSA-EUR [8] `github.com/PyPSA/pypsa-eur` (license: MIT)

Inverse Methods: Disaggregate Spatially Low-Resolved Optimisation Results

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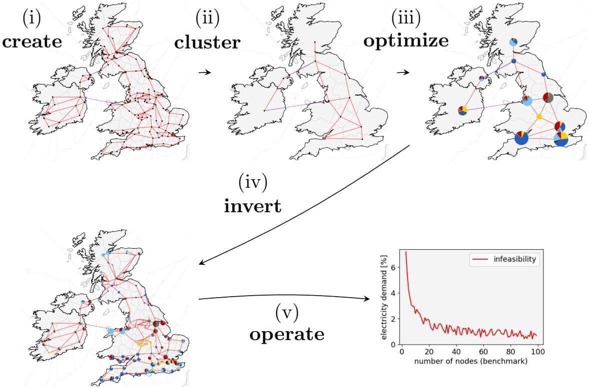
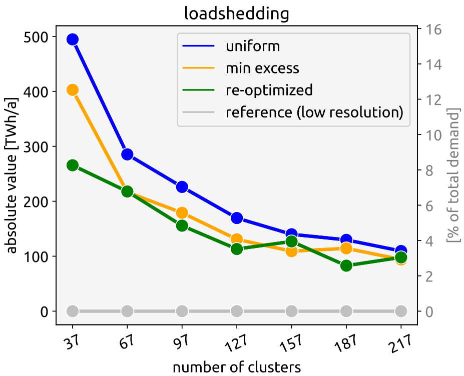
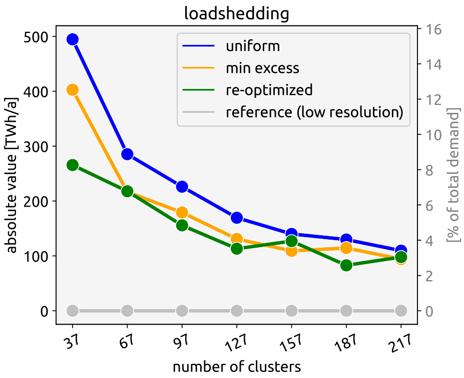


contents based on [13] Martha Maria Frysztacki, Veit Hagenmeyer, and Tom Brown. "Inverse methods: How feasible are spatially low-resolved capacity expansion modeling results when dis-aggregated at high resolution?" In: *submitted to Energy (under review)* (2023). DOI: doi.org/10.48550/arXiv.2209.02364

Spatially Low-Resolved Models cause Lost Loads!

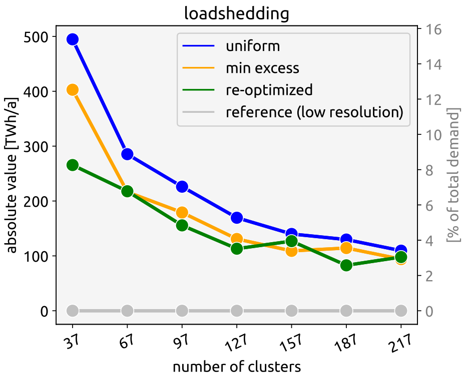


Spatially Low-Resolved Models cause Lost Loads!



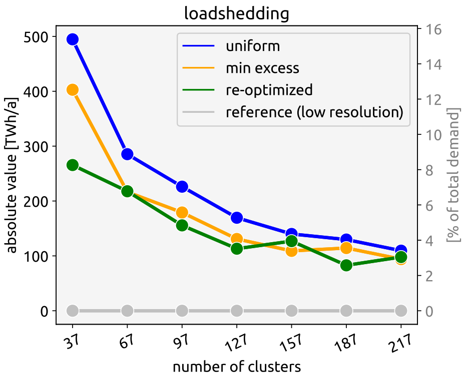
- (substantial) differences in disaggregation methods

Spatially Low-Resolved Models cause Lost Loads!



- (substantial) differences in disaggregation methods
- **37 nodes**: 8 – 15% of demand can not be met by renewable generation

Spatially Low-Resolved Models cause Lost Loads!



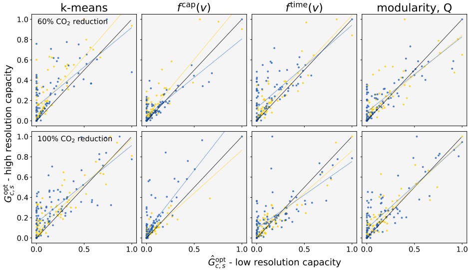
- (substantial) differences in disaggregation methods
- **37 nodes**: 8 – 15% of demand can not be met by renewable generation
- **127 nodes or more**: 3 – 6% of demand can not be met by renewable generation, thereafter improvement is lower

Conclusions

Spatial Clustering Methods Have a Strong Impact on Grid and Resource Planning

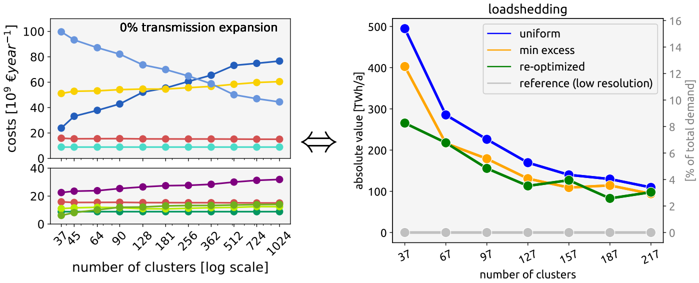
→ in contrast to *k*-means, **hierarchical clustering** accounts for network topology ⇒ better solution

→ depending on allowed carbon emissions in the model, use e.g. **modularity** or **renewable feed-in** as similarity measure for clustering



Low-Resolved Model Results Are Inaccurate and Infeasible

- Spatially **low-resolved model solutions deviate significantly** from highly-resolved solutions
- **Deviations** lead to system configurations that are **infeasible at high resolution** due to **transmission bottlenecks**



Research Questions

Effects of Spatial Resolution	1. How does spatial resolution impact modeling investments? 2. What are the driving forces for the differences?	1. Large impact on technology ratio **Offshore : Onshore** 2. Counteracting transmission & generation constraints
Methods to Improve Clustering	3. Are there better ways to cluster the model? 4. Which methods are best for offshore planning?	3. Yes, e.g. hierarchical clustering 4. Accurate representation of on- **and** offshore potentials
Disaggregation & Feasibility	5. Do the differences impact an inverted spatially highly-resolved model?	5. "in-feasibility" or "lost load" depends on reference resolution.

Literature I

Open Energy Transition
from the creators of PyPSA meets Earth

[1] *Britain wastes enough wind generation to power 1 million homes*. 2020. URL: https://carbontracker.org/britain-wastes-enough-wind-generation-to-power-1-million-homes/.

[2] *Langfristszenarien und Strategien für den Ausbau der Erneuerbaren Energien in Deutschland unter besonderer Berücksichtigung der nachhaltigen Entwicklung sowie regionaler Aspekte*. Tech. rep. Nov. 2022.

[3] G. Luderer, C. Kost, and D. Sörgel. *Deutschland auf dem Weg zur Klimaneutralität 2045 - Szenarien und Pfade im Modellvergleich*. Tech. rep. 2021. DOI: doi.org/10.48485/pik.2021.006.

[4] European association for the cooperation of transmission system operators (TSOs) for electricity. *Transmission System Map*. 2018. URL: www.entsoe.eu/data/map/.

[5] Gurobi Optimzation. URL: https://www.gurobi.com/.

Literature II

[6] Martha Maria Frysztacki, Jonas Hörsch, Veit Hagenmeyer, et al. "The strong effect of network resolution on electricity system models with high shares of wind and solar". In: *Applied Energy* 291 (2021), p. 116726. ISSN: 0306-2619. DOI: doi.org/10.1016/j.apenergy.2021.116726.

[7] Tom Brown, Jonas Hörsch, and David Schlachtberger. "PyPSA: Python for Power System Analysis". In: *Journal of Open Research Software* 6 (2018), p. 4. DOI: https://doi.org/10.5334/jors.188.

[8] Jonas Hörsch, Fabian Hofmann, David Schlachtberger, et al. "PyPSA-Eur: An Open Optimisation Model of the European Transmission System". In: *Energy Strategy Reviews* 22.v3 (2018), pp. 207–215. DOI: doi.org/10.1016/j.esr.2018.08.012.

[9] Leander Kotzur, Peter Markewitz, Martin Robinius, et al. "Impact of different time series aggregation methods on optimal energy system design". In: *Renewable Energy* 117 (2018), pp. 474–487. ISSN: 0960-1481. DOI: 10.1016/j.renene.2017.10.017.

Literature III

[10] D.P. Schlachtberger, T. Brown, M. Schäfer, et al. "Cost optimal scenarios of a future highly renewable European electricity system: Exploring the influence of weather data, cost parameters and policy constraints". In: *Energy* 163 (2018), pp. 100–114. ISSN: 0360-5442. DOI: https://doi.org/10.1016/j.energy.2018.08.070. URL: https://www.sciencedirect.com/science/article/pii/S0360544218316025.

[11] Martha Frysztacki, Jonas Hörsch, Veit Hagenmeyer, et al. *Clustering Dataset*. DOI: doi.org/10.5281/zenodo.3965780.

[12] Martha Maria Frysztacki, Gereon Recht, and Tom Brown. "A comparison of clustering methods for the spatial reduction of renewable electricity optimisation models of Europe". In: *Energy Informatics* 5.4 (2022). ISSN: 2520-8942. DOI: doi.org/10.1186/s42162-022-00187-7.

Literature IV

[13] Martha Maria Frysztacki, Veit Hagenmeyer, and Tom Brown. "Inverse methods: How feasible are spatially low-resolved capacity expansion modeling results when dis-aggregated at high resolution?" In: *submitted to Energy (under review)* (2023). DOI: doi.org/10.48550/arXiv.2209.02364.

[14] Deutsche Energie-Agentur. *DENA-GEBÄUDEREPORT 2022. Zahlen, Daten, Fakten.* Tech. rep. 2022.

[15] Martha Frysztacki and Tom Brown. "Modeling Curtailment in Germany: How Spatial Resolution Impacts Line Congestion". In: *2020 17th International Conference on the European Energy Market (EEM)*. 2020, pp. 1–7. DOI: https://doi.org/10.1109/EEM49802.2020.9221886.

[16] J. A. Hartigan and M. A. Wong. "Algorithm AS 136: A K-means clustering algorithm". In: *Applied Statistics* 28.1 (1979), pp. 100–108. DOI: https://doi.org/10.2307/2346830.

[17] Joe H. Ward Jr. "Hierarchical Grouping to Optimize an Objective Function". In: *Journal of the American Statistical Association* 58.301 (1963), pp. 236–244. DOI: doi.org/10.1080/01621459.1963.10500845.

Literature V

[18] Aaron Clauset, M. E. J. Newman, and Cristopher Moore. “Finding community structure in very large networks”. In: *Physical Review E* 70 (6 2004), p. 066111. DOI: doi.org/10.1103/PhysRevE.70.066111.

Technology Cost Assumptions I

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Table: Technology investment costs.

asset	cost	unit
onshore wind	1110	€/kW
offshore wind	1640	€/kW
solar PV utility	425	€/kW
solar PV rooftop	725	€/kW
open cycle gas turbine	400	€/kW
run of river	3000	€/kW
HVAC overhead transmission	400	€/(MWkm)
HVAC underground transmission	1342	€/(MWkm)
HVAC subsea transmission	2685	€/(MWkm)
HVDC underground transmission	1000	€/(MWkm)
HVDC subsea transmission	2000	€/(MWkm)

Technology Cost Assumptions II

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Table: Technology investment costs with 1\$ = 0.7532€.

asset	cost	unit
pumped hydro storage	2000	€/kW
hydro storage	2000	€/kW
battery storage	192	\$/kWh
battery power conversion	411	$\$/kW_{el}$
hydrogen storage	11.3	\$/kWh
hydrogen power conversion	689	$€/kW_{el}$

Notation I

Abbrev.	Description
	general abbreviations
r	technology type (storage)
$\mathcal{R}$	set of all storage technologies
s	technology type (generators)
$\mathcal{S}$	set of all generating technologies
$\mathcal{S}^{\mathrm{re}}$	subset of renewable technologies, $\mathcal{S}^{\mathrm{re}} \subseteq \mathcal{S}$
t	time discretization
$\mathcal{T}$	set of all time-steps t
$\mathcal{V}$	set of all original nodes in the network graph $\mathcal{G}$
(v, w)	(highly-resolved) line connecting nodes $v, w \in \mathcal{V}$
E	set of all original lines in the network graph $\mathcal{G}$
$\mathcal{G}$	original, fully-resolved network graph, $\mathcal{G} = (\mathcal{V}, E)$

Notation II

K	number of clusters
c, d	clusters, or (low-resolved) nodes
$\mathcal{V}_c$	set of nodes $v \in \mathcal{V}$, aggregated to form cluster c
	line attributes
$r_{(v,w)}$	resistance of transmission line (v, w)
$x_{(v,w)}$	reactance of transmission line (v, w)
$c_{(v,w)}$	capital costs of line (v, w)
$F_{(v,w)}$	capacity of transmission line (v, w)
$f_{(v,w),t}$	electricity flow of transmission line (v, w) at time t

Notation III

	nodal attributes
x_v, y_v	coordinates of node v
$G_{v,s}$	cost-optimal capacity of technology s in node v
$H_{v,r}$	cost-optimal capacity of technology r in node v
$c_{v,s}$	capital costs of technology s in node v
$c_{v,r}$	capital costs of technology r in node v
$o_{v,s,t}$	variable costs of technology s in node v and time t
$\bar{g}_{v,s,t}$	capacity factor for renewable technology s in time t
$g_{v,s,t}$	dispatch in node v of generator s in time t
	graph related attributes
$\mathcal{A}_{v,w}$	(weighted) adjacency matrix of the network graph $\mathcal{G}$
k_v	(weighted) degree of node $v \in \mathcal{V}$

Aggregation rules I

attribute	aggregated attribute	mapping	values or units
latitude & longitude	$(x_c, y_c)^T$	$\frac{1}{\lvert\mathcal{V}_c\rvert} \sum_{v \in \mathcal{V}_c} (x_v, y_v)^T$	$\mathbb{R}^2$
power capacity	$G_{c,s}$	$\sum_{v \in \mathcal{V}_c} G_{v,s}$	MW
installable potential	$G_{c,s}^{\max}$	$\sum_{v \in \mathcal{V}_c} G_{v,s}^{\max}$	MW

Aggregation rules II

attribute	agg. attribute	mapping	values or units
length	$l_{(c,d)}$	$\min_{(v,w)\in E_{(c,d)}} l_{(v,w)}$	km
power capacity	$F_{(c,d)}$	$\sum_{(v,w)\in E_{(c,d)}} F_{(v,w)}$	MVA
length underwater	$u_{(c,d)}$	$\frac{1}{l_{(c,d)}} \sum_{(v,w)\in E_{(c,d)}} (l \cdot u)_{(v,w)}$	p.u.

Aggregation rules III

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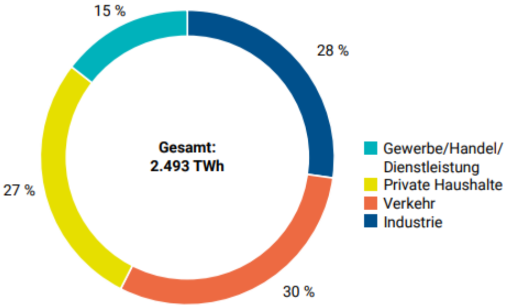
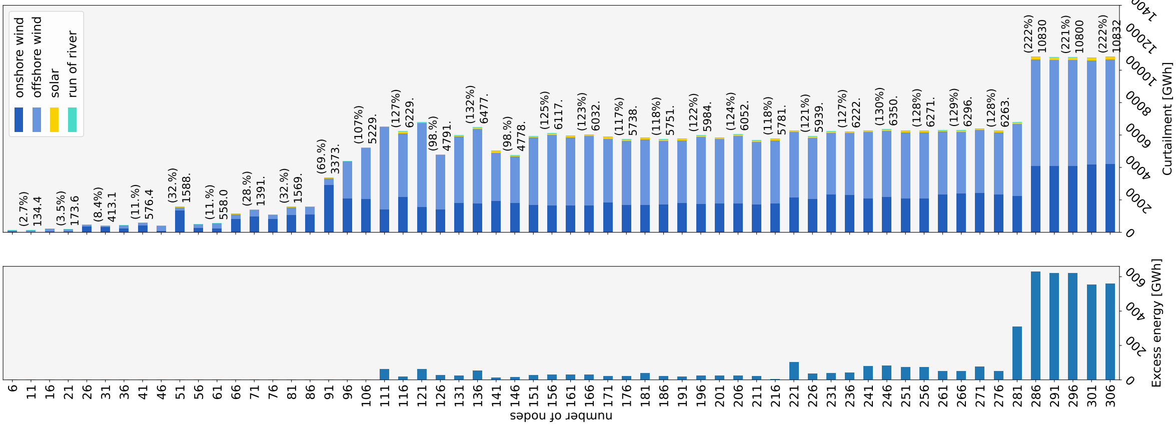
attribute	agg. attribute	mapping	values or units
power capacity	$s^{\text{nom}}_{(c,d)}$	$\sum_{(v,w)\in E_{(c,d)}} s^{\text{nom}}_{(v,w)}$	*MVA*
power capacity maximum	$s^{\text{min}}_{(c,d)}$	$\sum_{(v,w)\in E_{(c,d)}} s^{\text{min}}_{(v,w)}$	*MVA*
power capacity minimum	$s^{\text{max}}_{(c,d)}$	$\sum_{(v,w)\in E_{(c,d)}} s^{\text{max}}_{(v,w)}$	*MVA*
number of parallel lines	$n^{\text{parallel}}_{(c,d)}$	$\sum_{(v,w)\in E_{(c,d)}} n^{\text{parallel}}_{(v,w)}$	$\mathbb{R}$
terrain factor for capital costs	$\text{t}_{(c,d)}$	$\lvert E_{(c,d)}\rvert^{-1} \sum_{(v,w)\in E_{(c,d)}} \text{t}_{(v,w)}$	p.u.

Final Energy Consumption by Sector



[14]



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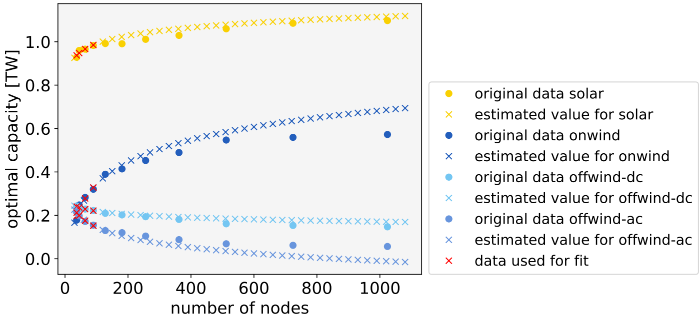
Lessons Learned to Adapt Calibration Methods



Fit a function to, for example:

$$\mathbf{a} \cdot \log(\mathbf{b} \cdot x) + \mathbf{c}$$

& pass constraints to optimisation:

$$\mathbf{G_{v,s}}^{\min} \leq G_{v,s} \leq \mathbf{G_{v,s}}^{\max}$$

Technology Variables are Subject to Expansion Limits & Restricted Amount of CO_2 (Equivalents)

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Expansion of Generators and Storages is subject to upper and lower bounds:

$$G^{\min}_{v,s} \leq G_{v,s} \leq G^{\max}_{v,s} \quad \forall v \in \mathcal{V},\ s \in \mathcal{S}^{\mathrm{re}}$$

$$H^{\min}_{v,r} \leq H_{v,r} \leq H^{\max}_{v,r} \quad \forall v \in \mathcal{V},\ r \in \mathcal{R}.$$

Transmission lines can not be expanded (in the presented results):

$$F^{\min}_{(v,w)} = F_{(v,w)} \qquad \forall (v,w) \in E\,.$$

Carbon emissions from fuels are constrained by a cap

$$\sum_{v\in\mathcal{V},\, s\in\mathcal{S},\, t\in\mathcal{T}} \frac{1}{\eta_{v,s}} \rho_s w_t g_{v,s,t} \leq \Gamma_{\mathrm{CO}_2} \cdot \sum_{z\in\mathcal{Z}} \gamma_z .$$

Transmission Variables are Subject to Expansion Limits

Expansion of Transmission Lines is subject to a lower bound:

$$F^{\min}_{(v,w)} \leq F_{(v,w)} \quad \forall (v,w) \in E\,.$$

The upper bound is given as a cumulative cap (measured in *MWkm*)

$$\sum_{(v,w)\in E} l_{(v,w)} F_{(v,w)} \leq \left(1 + \bar{F}^{\max}\right) \sum_{(v,w)\in E} l_{(v,w)} \cdot F^{\min}_{(v,w)}$$

Generation Variables are Subject to Generation Limits

Generation of conventional generators is bound by their installed capacity

$$0 \leq g_{v,s,t} \leq G_{v,s} \quad \forall v \in \mathcal{V},\ s \in \mathcal{S}^{\text{con.}},\ t \in \mathcal{T}.$$

Generation of renewable generators is bound by a weather-related fraction of their installed capacity

$$0 \leq g_{v,s,t} \leq \bar{g}_{v,s,t} G_{v,s} \quad \forall v \in \mathcal{V},\ s \in \mathcal{S}^{\text{re}},\ t \in \mathcal{T}.$$

State of charge is bound by the capacity of the storage unit

$$0 \leq e_{v,r,t} \leq T_r H_{v,r,t} \quad \forall v \in \mathcal{V},\ r \in \mathcal{R},\ t \in \mathcal{T}.$$

State of Charge (Storage) Must be Consistent

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(Dis)charging of storage units is constraint by their thermal ratings

$$0 \leq h^{+}_{v,r,t},\ h^{-}_{v,r,t} \leq H_{v,r} \quad \forall v \in \mathcal{V},\ r \in \mathcal{R},\ t \in \mathcal{T}\,. \tag{1}$$

... and must be consistent with its earlier state of charge and operational behaviour while accounting for all efficiencies (charge, discharge, standing, spillage, ...)

$$\begin{aligned} e_{v,r,t} = {} & w_t \cdot \left(\eta_{v,r,+} \cdot h^{+}_{v,r,t} - \eta^{-1}_{v,r,-} \cdot h^{-}_{v,r,t}\right) \\ & + w_t \cdot \left(h^{\text{inflow}}_{v,r,t} - h^{\text{spill}}_{v,r,t}\right) + \eta^{w_t}_{v,r,0} \cdot e_{v,r,t-1} \\ & \forall v \in \mathcal{V},\ r \in \mathcal{R},\ t \in \mathcal{T} \setminus \{0\} \end{aligned}$$

Additionally, we require reservoirs to be filled by the end of the year to the same level as they were at the beginning of the year.

$$e_{v,r,0} = e_{v,r,|\mathcal{T}|} \quad \forall v \in \mathcal{V},\ r \in \mathcal{R}.$$

Power Flows Must Obey Line Limits and Kirchhoff's Laws

Power flows are constrained by the transmission line capacities minus a 30% security margin

$$\left|f_{(v,w),t}\right| \leq 0.7 \cdot F_{(v,w)} \quad \forall (v,w) \in E,\ t \in \mathcal{T}.$$

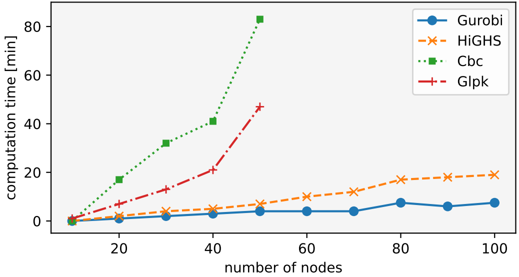
... and subject to Kirchhoff's first (current or junction) and second (voltage, loop) law.

$$\sum_{w \in \mathcal{V}\colon (v,w) \in E} \mathcal{K}_{v,(v,w)} f_{(v,w),t} = d_{v,t} + \sum_{r \in \mathcal{R}} \left(h^{+}_{v,r,t} - h^{-}_{v,r,t}\right) - \sum_{s \in \mathcal{S}} g_{v,s,t} \quad \forall v \in \mathcal{V},\ t \in \mathcal{T}$$

$$\sum_{(v,w) \in c} \mathcal{L}_{(v,w),c} x_{(v,w)} f_{(v,w),t} = 0 \quad \forall t \in \mathcal{T},\ c \in \mathcal{C}.$$

Optimisation Model: Computational Resource Requirements

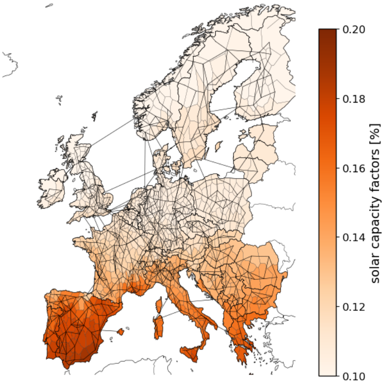
Currently, there does not exist an acceptable open-source solver for such large scale modeling.
A promising benchmark of 3 open-source and the commercial solver Gurobi on small PyPSA models:

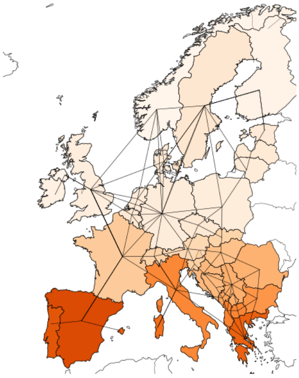


European Electricity Model: implementation in HiGHS unacceptably slow relative to Gurobi. For example:

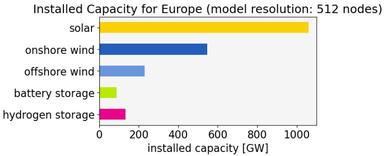
$\lvert\mathcal{V}\rvert$	$\lvert\mathcal{T}\rvert$	ratio [s]
5	240	4:21
100	240	521:1148
5	8760	180:11363

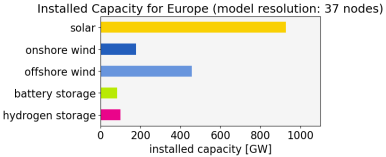
TC: $270 \cdot 10^9$ €





TC: $248 \cdot 10^9$ €





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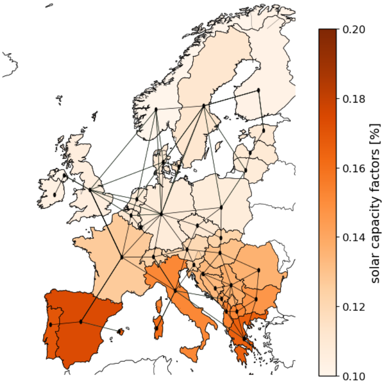
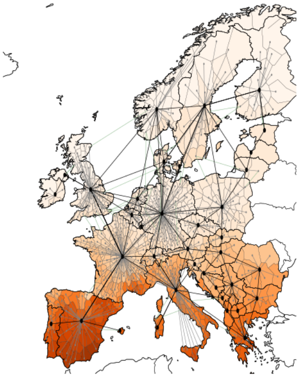
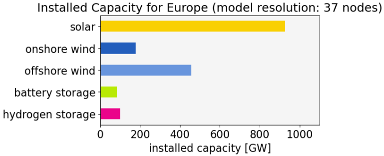
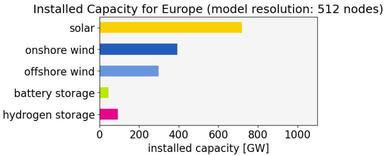


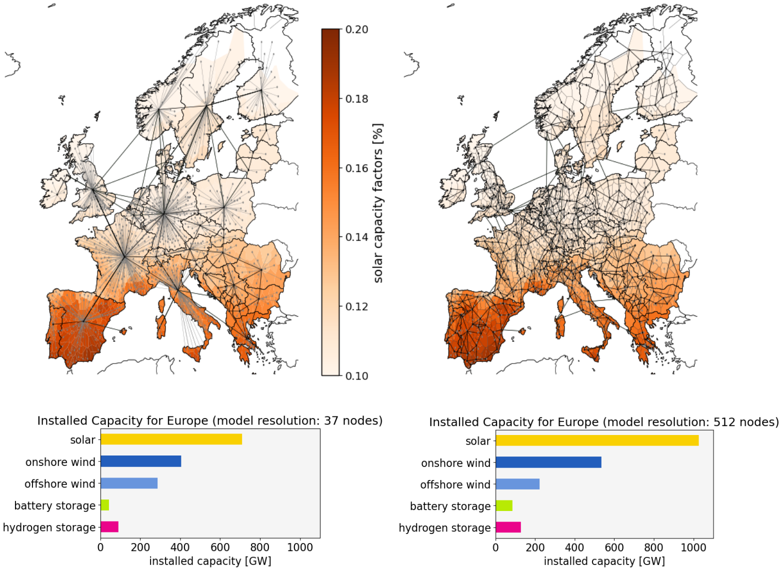


TC: $224 \cdot 10^9$ €



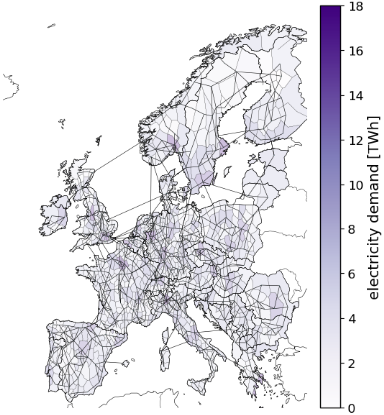


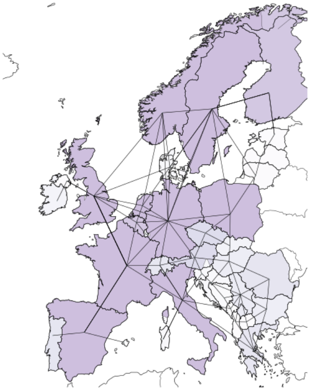
TC: $224 \cdot 10^9$ €



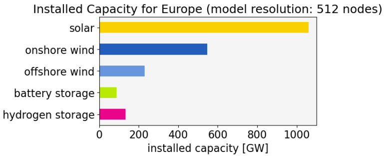
TC: $264 \cdot 10^9$ €

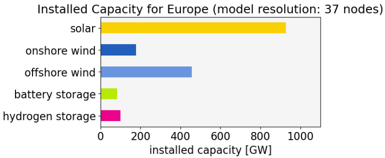
TC: $270 \cdot 10^9$ €



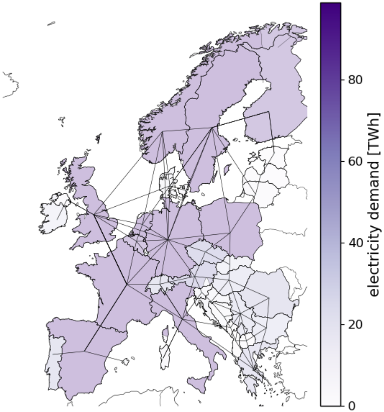


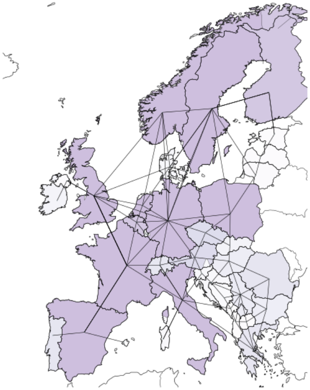
TC: $248 \cdot 10^9$ €



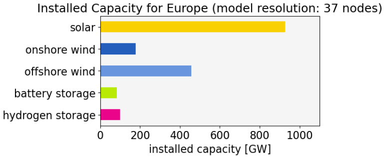


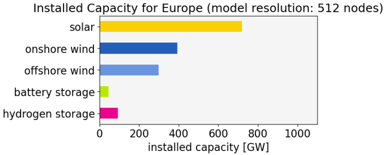
TC: $248 \cdot 10^9$ €



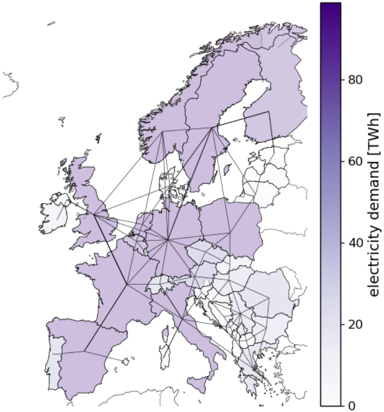


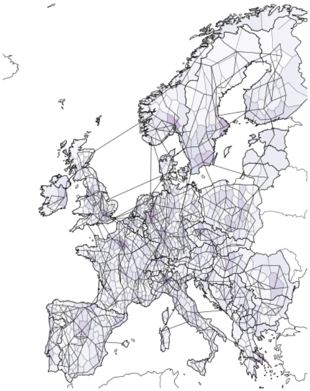
TC: $224 \cdot 10^9$ €



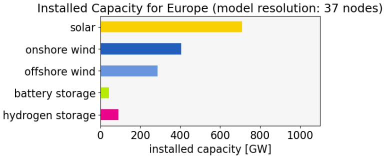


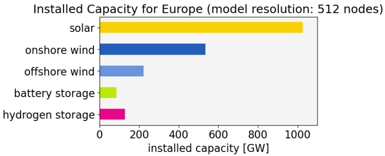
TC: 224 · 10^9 €



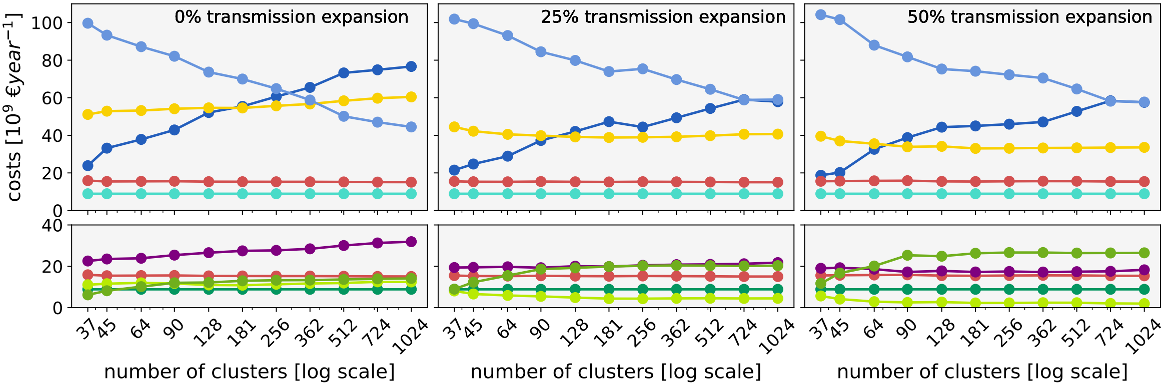


TC: 264 · 10^9 €

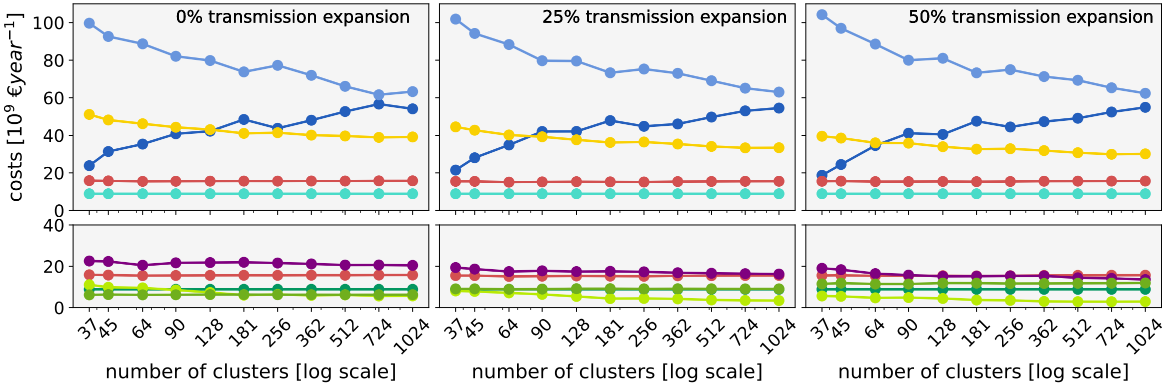


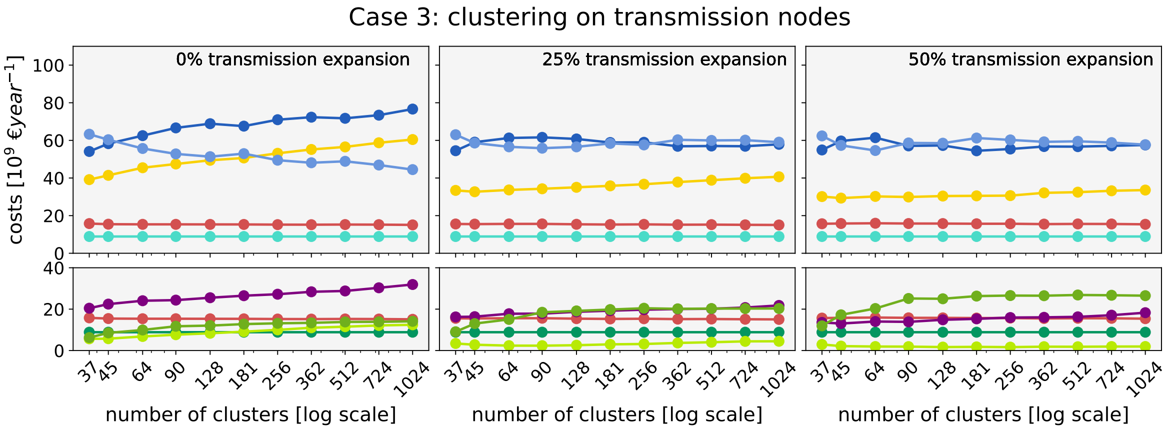


Case 1: simultaneous clustering



Case 2: clustering on siting resolution

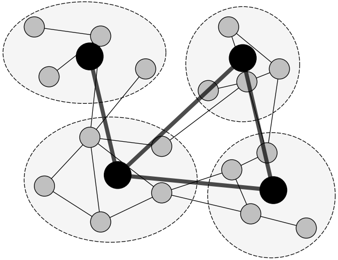




Case 3: clustering on transmission nodes
0% transmission expansion
25% transmission expansion
50% transmission expansion
costs [10^9 €$year^{-1}$]
number of clusters [log scale]

k-means [16]

Problem with *k*-means: does not see **renewable generation** or connectivity of the **transmission grid**



$$\min_{(x_c, y_c)^T \in \mathbb{R}^2} \sum_{c=1}^{k} \sum_{v \in \mathcal{V}_c} w_v \| (x_c, y_c)^T - (x_v, y_v)^T \|_2$$

Hierarchical Agglomerative Clustering: Ward's Method [17]

Open Energy Transition
from the creators of PyPSA meets Earth

- bottom-up
- initially: each node is its own singleton *cluster*
- iteration: aggregate two adjacent clusters with most similar feature $f : \mathcal{V} \mapsto \mathbb{R}^n$ (greedy)
- $\Rightarrow$ **Freedom to choose**: "feature" f; ideally incorporating *renewable resource availability*

Our choice:

$$f^{\text{cap}}(v) := \bar{g}_{v,s} = \begin{pmatrix} \bar{g}_{v,\text{ solar}} \\ \bar{g}_{v,\text{ wind}} \end{pmatrix} \qquad f^{\text{time}}(v) := \bar{g}_{v,s,t} = \begin{pmatrix} \bar{g}_{v,\text{ solar},\ t_1} \\ \bar{g}_{v,\text{ solar},\ t_2} \\ \dots \\ \bar{g}_{v,\text{ solar},\ t_{|\mathcal{T}|}} \\ \bar{g}_{v,\text{ wind},\ t_1} \\ \bar{g}_{v,\text{ wind},\ t_2} \\ \dots \\ \bar{g}_{v,\text{ wind},\ t_{|\mathcal{T}|}} \end{pmatrix}$$

Clauset-Newman-Moore Greedy Modularity Maximisation [18]

- aim: find community structures in (large) networks
- initially: each node is its own sigleton cluster
- iteration: aggregate adjacent clusters that maximise modularity Q most

$$Q = \frac{1}{2m} \sum_{v,w \in \mathcal{V}} \left(\mathcal{A}_{v,w} - \frac{k_v k_w}{2m} \right) \delta(c_v, c_w)\,,$$

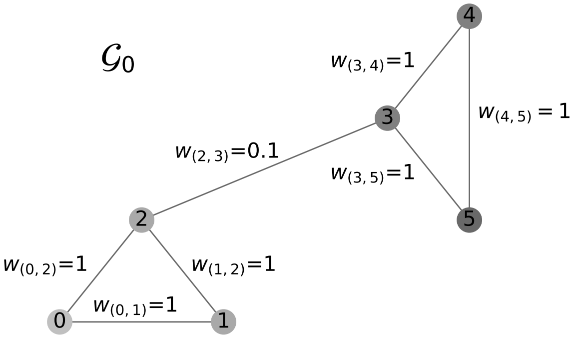
where

$$\underbrace{\mathcal{A}_{v,w} := \begin{cases} w_{(v,w)} & \text{if } (v,w) \in E \\ 0 & \text{otherwise} \end{cases},}_{\textit{weighted adjacency matrix}} \quad \underbrace{m := \frac{1}{2} \sum_{v,w} \mathcal{A}_{v,w},}_{\textit{sum of all weights}} \quad \underbrace{k_v := \sum_{w} \mathcal{A}_{v,w},}_{\textit{weighted degree of node } v} \quad \underbrace{\delta(c_v, c_w) := \begin{cases} 1 & \text{if } \quad c_v = c_w \\ 0 & \text{otherwise} \end{cases}}_{\textit{Kronecker-Delta}}$$

and $w_{(v,w)} := \frac{1}{|z_{(v,w)}|}$ (inverse impedance)

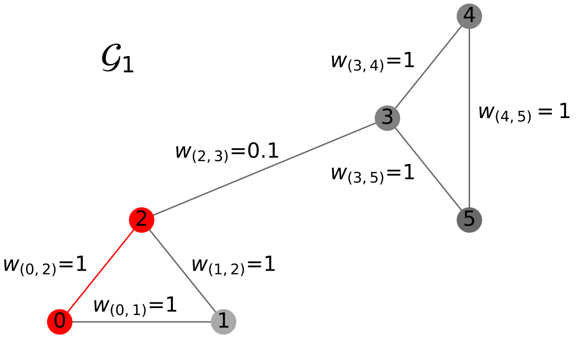
Modularity: Examples of Good and Bad Communities

$$\Delta Q(v, w) \sim \mathcal{A}_{v,w} - \frac{k_v k_w}{2m}$$



Modularity: Examples of Good and Bad Communities

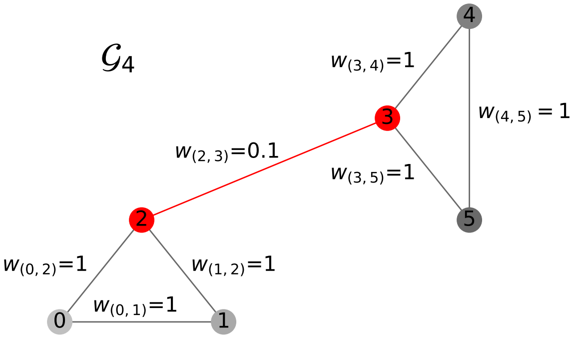
$$\Delta Q(v, w) \sim \mathcal{A}_{v,w} - \frac{k_v k_w}{2m}$$



$$\mathcal{A}_{\mathbf{0,2}} = \mathbf{1} > \frac{\mathbf{k_0 k_2}}{\mathbf{2m}} \approx \mathbf{0.17}$$

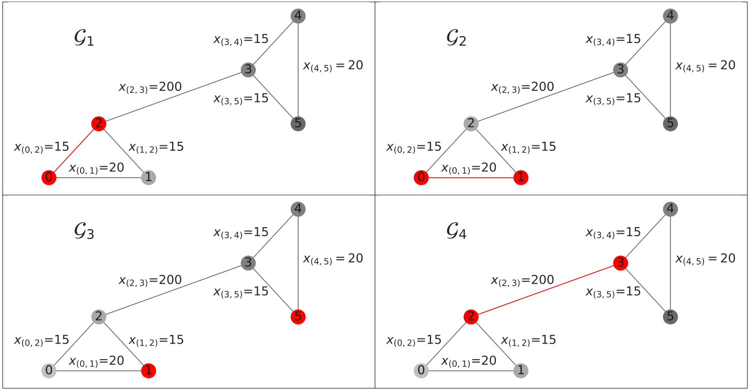
Modularity: Examples of Good and Bad Communities

$$\Delta Q(v, w) \sim \mathcal{A}_{v,w} - \frac{k_v k_w}{2m}$$



$$\mathcal{A}_{2,3} = 0.1 < \frac{k_2 k_3}{2m} \approx 0.18$$

Modularity: Examples of Good and Bad Communities



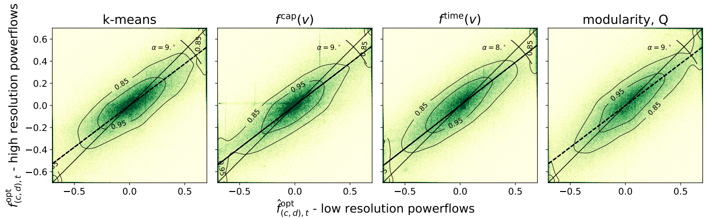
$$\mathcal{G}_1 : \mathcal{A}_{0,2} \approx \mathbf{0.067} > \frac{\mathbf{k_0 k_2}}{\mathbf{2m}} \approx \mathbf{0.006}$$

$$\mathcal{G}_2 : \mathcal{A}_{0,1} = 0.05 > \frac{k_0 k_1}{2m} \approx 0.010$$

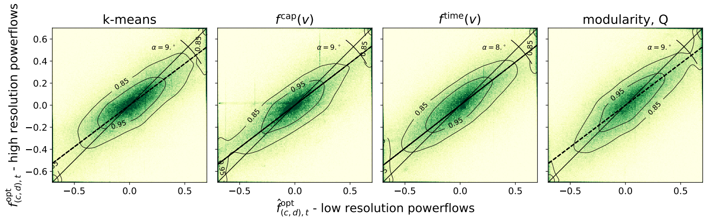
$$\mathcal{G}_3 : \mathcal{A}_{1,5} = 0 < \frac{k_1 k_5}{2m} \approx 0.010$$

$$\mathcal{G}_4 : \mathcal{A}_{2,3} = 0.005 < \frac{k_2 k_3}{2m} \approx 0.007$$

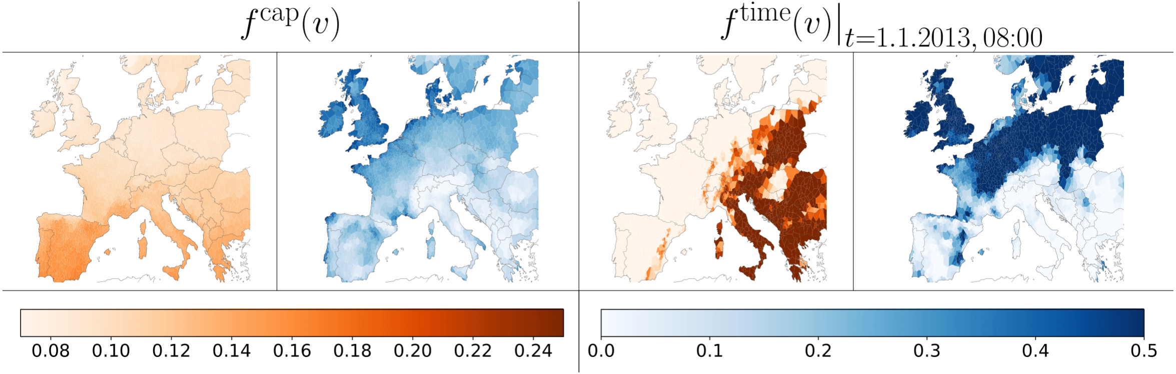
Choice of Regions Strongly Impacts Optimal Power Flows



Choice of Regions Strongly Impacts Optimal Power Flows



CO_2 reduction	100%
	ρ
k-means	0.75
$f^{cap}(v)$	0.76
$f^{time}(v)$	0.78
Q	0.75


$f^{\text{cap}}(v)$
$f^{\text{time}}(v)\big|_{t=1.1.2013,\,08:00}$
0.08 0.10 0.12 0.14 0.16 0.18 0.20 0.22 0.24
0.0 0.1 0.2 0.3 0.4 0.5

Choice of Regions Strongly Impacts Optimal Solution: 67

Open Energy Transition
from the creators of PyPSA meets Earth

CO_2 reduction	60%		100%	
technology	wind	solar	wind	solar
k-means	$0.33 + 2.65$	$0.01 + 2.34$	$0.22 + 2.43$	$0.25 + 0.71$
$f^{\text{cap}}(v)$	$0.23 + 0.79$	$0.05 + 0.31$	$0.14 + 1.12$	$0.05 + 0.12$
$f^{\text{time}}(v)$	$0.02 + 2.26$	$0.07 + 0.99$	$0.51 + 1.63$	$0.06 + 0.24$
Q	$0.42 + 1.45$	$0.16 + 0.71$	$0.61 + 1.76$	$0.07 + 0.48$

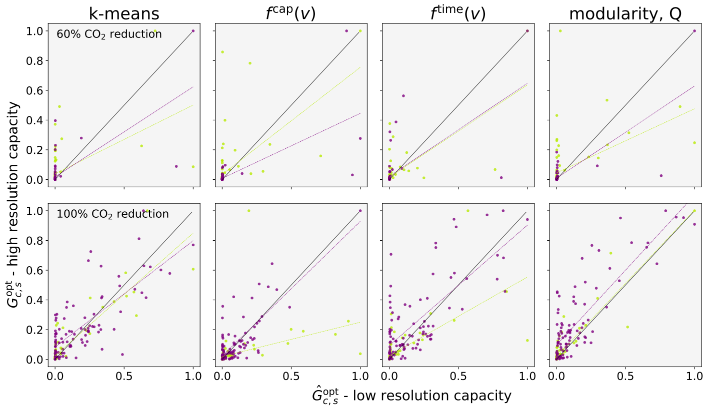
Choice of Regions Strongly Impacts Optimal Solution: 97

CO_2 reduction	60%		100%	
MSE	wind	solar	wind	solar
k-means	$0.37 + 3.82$	$0.01 + 2.80$	$0.51 + 3.33$	$0.12 + 1.23$
$f^{\text{cap}}(v)$	$0.21 + 0.60$	$0.03 + 1.00$	$0.01 + 2.22$	$0.11 + 0.15$
$f^{\text{time}}(v)$	$0.04 + 3.17$	$0.08 + 0.79$	$0.55 + 1.94$	$0.26 + 0.28$
Q	$0.36 + 1.31$	$0.47 + 1.17$	$0.25 + 1.98$	$0.17 + 0.78$

Choice of Regions Strongly Impacts Optimal Solution: 127

CO_2 reduction	60%		100%	
technology	wind	solar	wind	solar
k-means	$0.42 + 5.34$	$0.06 + 2.17$	$0.51 + 2.22$	$0.21 + 1.03$
$f^{\text{cap}}(v)$	$0.79 + 0.86$	$0.02 + 0.82$	$0.2 + 1.14$	$0.11 + 0.15$
$f^{\text{time}}(v)$	$0.81 + 2.74$	$0.02 + 1.45$	$0.14 + 2.38$	$0.24 + 0.75$
Q	$0.36 + 1.31$	$0.47 + 1.17$	$0.24 + 2.2$	$0.36 + 1.07$

Choice of Regions Strongly Impacts Optimal Solution



MSE	hydrogen	battery
CO_2 reduction	**60%**	
k-means	$0.6 + 0.2$	$1.0 + 0.7$
$f^{cap}(v)$	$1.3 + 0.0$	$0.4 + 1.3$
$f^{time}(v)$	$0.6 + 0.5$	$0.5 + 0.2$
Q	$0.5 + 0.0$	$0.8 + 1.4$
CO_2 reduction	**100%**	
k-means	$0.7 + 1.5$	$0.2 + 0.3$
$f^{cap}(v)$	$0.2 + 0.6$	$2.2 + 0.6$
$f^{time}(v)$	$0.5 + 2.7$	$0.9 + 0.3$
Q	$0.0 + 2.8$	$0.0 + 0.2$

Choice of Regions Strongly Impacts Optimal Power Flows: 67

CO_2 reduction	60%		100%	
	ρ	r_2	ρ	r_2
k-means	0.704	0.188	0.725	0.195
$f^{\text{cap}}(v)$	0.754	0.174	0.759	0.187
$f^{\text{time}}(v)$	0.749	0.173	0.765	0.181
Q	0.739	0.173	0.740	0.187

Choice of Regions Strongly Impacts Optimal Power Flows: 97

CO_2 reduction	60%		100%	
	ρ	r_2	ρ	r_2
k-means	0.746	0.165	0.755	0.175
$f^{\text{cap}}(v)$	0.769	0.160	0.768	0.173
$f^{\text{time}}(v)$	0.767	0.160	0.781	0.169
Q	0.757	0.164	0.757	0.179

Choice of Regions Strongly Impacts Optimal Power Flows: 127

CO_2 reduction	60%		100%	
	ρ	r_2	ρ	r_2
k-means	0.735	0.164	0.772	0.166
$f^{\mathrm{cap}}(v)$	0.802	0.144	0.786	0.163
$f^{\mathrm{time}}(v)$	0.782	0.147	0.808	0.152
Q	0.789	0.152	0.792	0.165

Disaggregation is Not Unique: 3 Approaches

Short name	Method description	Formula
	Optimal low-resolved capacities are distributed ...	
uniform	... uniformly across all nodes within a cluster	$G_{c,s} \mapsto \frac{1}{\lvert\mathcal{V}_c\rvert}\begin{pmatrix} G_{c,s} \\ \cdots \\ G_{c,s}\end{pmatrix} \in \mathbb{R}^{\lvert\mathcal{V}_c\rvert}$
re-optimize	... anew by re-optimising capacities within each cluster & enforcing build-out capacity totals per technology and region	objective + constraints + $\sum_{v\in\mathcal{V}_c} G_{v,s} = G_{c,s}$
min excess	... according to the objective to concentrate generation at nodes with higher demand and grid capacity	$\min_{G_{v,s}} \sum_{v\in\mathcal{V}_c,\ s\in\mathcal{S},\ t\in\mathcal{T}} \left[\bar{g}_{v,s,t}G_{v,s} - d_{v,t} - 0.7\sum_{l_{(v,w)}\in E:\ v=c\lor w=c} F_{(v,w)}\right]^+$

Accuracy of Disaggregation Balances Computational Requirements

	Implementation	Solving Time	Memory (RAM)	Results Quality
uniform	✓	✓	✓	✗
min excess	✗	✓	✓	✓
re-optimize	✗	✗	✗	✓