Highlights

Inverse methods: How feasible are spatially low-resolved capacity expansion modeling results when dis-aggregated at high resolution?
Martha Maria Frysztacki, Veit Hagenmeyer, Tom Brown

- Methodology to dis-aggregate spatially low-resolved capacity expansion model results into higher or original resolution
- Evaluating the feasibility of spatially low-resolved capacity expansion model results with respect to higher spatial detail
- Modeling results of a one-node-per-country model of Europe are not fit for detailed investment decisions
- Results derived from 100 – 200 node models of Europe using state-of-the-art spatial aggregation methods lead to load-shedding of 3-7% of electricity demand, depending on the exact model resolution and dis-aggregation methodology
Inverse methods: How feasible are spatially low-resolved capacity expansion modeling results when dis-aggregated at high resolution?*

Martha Maria Frysztacki\textsuperscript{a,b}, Veit Hagenmeyer\textsuperscript{a} and Tom Brown\textsuperscript{b}

\textsuperscript{a}Institute for Automation and Applied Informatics, Karlsruhe Institute of Technology, 76344 Eggenstein-Leopoldshafen, Germany
\textsuperscript{b}Institute of Energy Technology, Technical University Berlin, Einsteinufer 25, 10587 Berlin

\textbf{ARTICLE INFO}

\textbf{Keywords:}
- Electricity System Optimisation
- Renewable Energy
- Investment Planning
- Spatial Clustering
- Inverse Methods
- Dis-Aggregation Methods

\textbf{ABSTRACT}

Spatially highly-resolved capacity expansion models are computationally intensive. As a result, models are often simplified to a lower spatial resolution by clustering multiple regions to a smaller number of representatives. However, when capacity expansion is modeled for electricity systems at a coarse resolution, the aggregation mixes sites with different renewable features while removing transmission lines that can cause congestion. As a consequence, the modeling results may represent an infeasible electricity system when the capacities are fed back into higher spatial detail. Thus far there has been no detailed investigation of how best to dis-aggregate the capacity expansion results into its original resolution and whether the spatially highly-resolved dis-aggregated model is technically feasible. This is a challenge since there is no unique or obvious way to invert the clustering.

In this paper we proceed in two stages. First, we propose three methods to dis-aggregate spatially low-resolved model results into higher resolution: (a) uniformly distribute the regionalised results across their original set of regions, (b) re-optimising each clustered region separately at high resolution (c) a novel approach that minimises the custom “excess electricity” function. Second, we investigate the resulting highly-resolved models’ feasibility by running an operational dispatch. While re-optimising yields the lowest amounts of load-shedding and curtailment, our novel inverse-method provides comparable results for considerably less computational effort. Feasibility-wise, our results strengthen previously published research that modeling every country by a single region is insufficient. Beyond that, we find that results obtained from state-of-the-art reduced models with 100-200 regions for Europe still yield 3-7% of load-shedding, depending on the model resolution and inverse method.

\section{1. Introduction}

Capacity expansion models have gained recognition over the past years as their results are often taken as a reference to formulate road maps or to make investment decisions to achieve intended carbon emission targets. They are used by non-governmental organizations, political institutions, transmission system operators and large companies. Latest trends in model utilisation are analysed by Lopion, Markewitz, Robinis\textsuperscript{2} and Stolten (2018), who outline that today’s models must accurately portray renewable potentials and thus capture the weather-driven variability of wind and solar photovoltaic generation in order to provide reliable investment recommendations for renewable generator, storage and transmission installations.

A variety of recent literature has identified that a high spatial resolution is required for the modeling to produce an accurate representation of renewable generation. Schlachberger, Brown, Schramm and Greiner (2017) found that modeling a large geographical area at the scale of Europe allows the model to exploit very good continental renewable potentials and strongly impacts the composition of the generation and storage fleet of individual regions. However, Aryanpur, O’Gallachoir, Dai, Chen and Glynn (2021) stress that for models that include heterogeneous regions, a high spatial granularity is relevant. This particularly includes models with a high share of renewable generation. Martínez-Gordón, Morales-España, Sijm and Faaij (2021) describe that the necessity for the models to include a higher spatial resolution is essential to detect bottlenecks in the transmission grid, assess renewable potentials based on local weather conditions and to identify regional variations in electricity demand. The granularity of this data-driven information significantly improves the design and composition of the electricity mix and the routing of new grid infrastructure predicted by the model. Frysztacki, Hörsch, Hagenmeyer and Brown (2021) further disentangle the effects of sourcing renewable generation versus routing the electricity to locations of high demand, revealing that routing dominates the system effects and forces the model to build renewable assets closer to demand centers at potentially worse capacity factors when the model has a high spatial resolution.

The downside of higher resolution is that processing large data volumes inevitably results in a computational burden that arises from solving the associated mathematical formulation in the model. In order for the spatially aggregated models to better represent the highly-resolved system, more effective clustering methods have been developed. Findings by Scaramuzzino, Garegnani and Zambelli (2019) and Siala and Mahfouz (2019) show that aggregating based on political zones and borders is not suited to accurately portray the electricity system because there is per se no correlation between the distribution of solar radiation, wind speed, elec-
trical load on the one hand and the administrative divisions on the other hand. Instead, they suggest to aggregate regions based on their similarities in renewable feed-in or demand patterns, such as load density distribution and solar and wind potentials. Another approach by Biener and Garcia Rosas (2020) suggests to cluster regions with high electrical connectivity to minimize load flow deviations after the aggregation. A recent survey by Frysztacki, Recht and Brown (2022) improves previous methods and suggests which of them is most suitable for which modeling scenario. The overall consensus of most studies is to model the European electricity system that scatters across an area of 10 million square kilometers and contains more than 5000 substations at and above 220kV at a spatial model resolution of 100 – 200 nodes. An exact recommendation however depends on the model configuration, i.e. the technology-mix or the amount of transmission grid expansion. It is therefore subject to an individual analysis of the set-up of the model.

Nevertheless, previous literature did not provide insight whether the spatial resolution of the models impacts only the optimal found solution, or whether these spatially simplified modeling results are feasible with respect to the original, spatially highly-resolved model. Moreover, approaches to dis-aggregate the simplified modeling results back into its original high-resolution set-up are not well represented in previous research. There exist only a few publications, such as from Müller, Schachler, Scharf, Bunke, Günther, Bartels and Pleßmann (2019) who dis-aggregate simplified modeling results into higher spatial detail. But this approach was conducted only as means to distribute capacity from transmission level down to distribution level, and did not analyse the overall feasibility at a higher spatial resolution at transmission level and considers only Germany. Thus, neither the assumptions on the dis-aggregation, or the resulting highly-resolved systems were analysed in detail with respect to their plausibility. Another dis-aggregation method is presented by Reinert, Söhler, Baumgärtner and Bardow (2020), who propose an iterative dis-aggregation process and allow transmission grid expansion in the final iteration, such that the the highly-resolved model becomes feasible. Here it remains unclear how feasible the dis-aggregated model is when omitting transmission grid expansion. Finally, Grochowicz, van Greevenbroek, Benth and Zeyringer (2022) propose three dis-aggregation methods. However, in their case-study they generate highly-resolved results that are aggregated and again dis-aggregated, such that they are designed to be feasible.

In this contribution, we present the first comparison of different dis-aggregation methods in a continent-scale model. Furthermore we provide new algorithms for dis-aggregation options in section 2. We start by presenting the model used for this study and a detailed description of three methods to dis-aggregate coarse model results. Two of the dis-aggregations are improved methods that were proposed in earlier research, and one of them is completely novel. Results from the dis-aggregation are presented in section 3, where we test if the dis-aggregated highly-resolved models are feasible from a technical point of view. This analysis is completely novel to the author’s knowledge, as none of the dis-aggregation methods was previously analysed with respect to model feasibility. Conclusions are drawn in section 4. Finally, we discuss limitations of this study in section 5.

2. Data and Methods

In this section we present the underlying data used for the modeling problem. The overall modeling process is described in 2.1, where we also highlight the novelty of this study. A selection of the most important data and methods of the model employed for this study are presented in section 2.2. The three newly proposed inverse methods on how spatially low-resolved capacity expansion model results can be dis-aggregated back into higher spatial detail are presented in sections 2.3-2.5 and are summarised Table 1. The treatment of inter-cluster powerflows is discussed in section 2.6. The study design and evaluation of results are presented in section 2.7.

2.1. Modelling Overview

Figure 1 displays the overall approach of electricity system modelling. It typically executes in the following order: (i) Creating the model. This includes collecting data of the system to be analyzed, for example the network topology of the transmission system, capacities of generators that are to be included in the model, land-use constraints, time-series of electricity demand, wind speeds, solar radiation, etc. and assigning the data to the correct locations. (ii) Clustering the spatially highly-resolved network down to a smaller approximation to gain computational advantages. (iii) Formulating a set of mathematical equations associated with the problem.
and solving it.

Here, we introduce an additional fourth and fifth step to this queue: (iv) Dis-aggregating the low-resolution results (i.e. the resulting renewable capacities \(G_{n,s,t}\)) back into high spatial resolution. But as the clustering \(f: \mathbb{R}^m \rightarrow \mathbb{R}^n\) reduces the (spatial) dimension of the data \((n < m, \text{in many cases even } n \ll m)\), the mapping is surjective but not injective, hence not bijective. Therefore, finding an inverse that maps the results back into high dimension \(f^{-1}: \mathbb{R}^n \rightarrow \mathbb{R}^m\) is a challenging task and the inverse is not unique. We therefore propose three different approaches to tackle the dis-aggregation of the generation and storage capacities for each technology from the low-resolution model to the high-resolution model and suggest adequate inverse methods. The proposed methods are summarised in Table 1 and are explained in detail in the following three sections. (v) Running an optimisation with fixed capacity that is derived from step (iii). This is also referred to as operational optimisation. It allows to gain insight into the dynamics of the electricity system, and particularly analyse its feasibility.

2.2. Model and Input Data

For this study, we employ the openly available European Electricity System Model at transmission substation level, PyPSA-Eur. It is described in detail in its original publication by Hörsch, Hofmann, Schlachtberger and Brown (2018), so we only summarize its major functionality. The mathematical model formulation and solving is based on the python package PyPSA, originally developed by Brown, Hörsch and Schlachtberger (2018). In the following, we focus on features that are relevant in our specific use-case.

The full model covers 33 European countries with a full spatial resolution of 5323 nodes (3609 substations), 6640 transmission HVAC and HVDC lines at and above 360 kV.

Electricity demand is embedded from the Open Power System Data (OPSD) (2019) project. Historical weather data to account for the variability of renewable resources is provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) (2017) in the “ERA5 Reanalysis” dataset, and by Pfiefroth, Kothe, Müller, Trentmann, Hollmann, Fuchs and Werscheck (2017) in the second edition of the “Surface Radiation Data Set (SARAH-2)”. This raw data containing for example solar radiation, wind-speeds or temperature is processed using the open source software “atlite”, developed by Hofmann, Hampp, Neumann, Brown and Hörsch (2021), to translate it into capacity factors.

The main objective of the optimisation model is to minimise the annual system costs that consist of the sum of all investments in new capacity \(G_{c,s}\) at each node \(v\) of every technology \(s\), as well as the variable costs related to the dispatch of the generators \(g_{c,s,t}\) at each time \(t\). The weight \(w_j\) relates to the duration of dispatch and is fixed to 2 in our application, i.e. \(w_j = 2\). Mathematically, this can be formulated as

\[
\min_{G_{c,s}, g_{c,s,t}, f_{c,s,t}} \left( \sum_{v \in V} \sum_{s \in S} \left( c_{c,s} G_{c,s} + \frac{1}{|V_c|} \sum_{t \in T} w_j \rho_{c,s,t} g_{c,s,t} \right) \right),
\]

with additional constraints to guarantee network security, to cover demand at all times and places, and to account for the system to be physically plausible including Kirchhoff’s circuit laws and upper and lower bounds for generator dispatch.

All variables appearing in this article are explained in the Glossary, section 7, Table 4. Cost assumptions are based on suggestions by the Danish Energy Agency [dea (2019)] for wind technologies, Schröder, Kunz, Meiss, Mendeleitich and von Hirschhausen (2013) in case of open cycle gas turbines, pumped hydro storage, hydro, run-of-river, Budischak, Sewell, Thomson, Mach, Veron and Kempton (2013) for storage technologies and Vartiainen, Masson and Breyer (2017) for solar. We present them in the Appendix, A.1.

To enable computational feasibility, the whole model with more than 5000 nodes must be reduced to a computationally tractable size by spatially clustering the nodes. Then, the reduced optimisation problem (1), now with a smaller set of nodes \(V\), can be solved. There exist many approaches to spatially reduce the size of such model. Latest research from Biener and Garcia Rosas (2020) and Frysztacki et al. (2022), motivated by insights from Siala and Mahfouz (2019), have demonstrated that the best suited clustering method for capacity expansion models with highly renewable scenarios are of hierarchical nature. Therefore, for this study, we have chosen a hierarchical agglomerative clustering for the spatial scale. It is a bottom-up approach, where each node is treated as a singleton cluster. Then, in every iteration, two clusters that have the highest similarity and that are connected by a transmission line are aggregated. We use the same similarity measure as previously analysed. It is defined such that the aggregated nodes have the most similar renewable timeseries \(g_{c,s,t}\) throughout the whole year, i.e.

\[
g_{c,s,t}^{\text{agg}} \in V_c, s \in \{\text{solar, wind}\}, t \in T \rightarrow \{0, 1\}^{2|T|}.
\]

In terms of temporal scale, we aggregate every two consecutive hours. This approach has shown to yield good results compared to full temporal resolution while reducing the model size by a factor of 2 [Schlachtberger, Brown, Schäfer, Schramm and Greiner (2018)].

2.3. Uniform Distribution

The first approach to dis-aggregate low-resolution modeling results is simple and computationally inexpensive. For each generation and storage technology, we distribute the capacity retrieved from the coarse model within every cluster uniformly across all high-resolution nodes:

\[
G_{c,s} \rightarrow \frac{1}{|V_c|} \begin{pmatrix}
G_{c,s} \\
G_{c,s} \\
... \\
G_{c,s}
\end{pmatrix} \in \mathbb{R}^{|V_c|}.
\]

An additional constraint is formulated to account for land-use constraints. This upper limit is formally defined as

\[
G_{v,s} \leq G_{v,s}^{\text{max}} \quad \forall v \in V_c
\]

and is enforced by selecting the generators where (4) is not satisfied and uniformly distributing the residual capacity over
The remaining nodes within the cluster, i.e. across the following set of generators:

\[
\{ G_{v,s} : v \in \mathcal{V}_c \land G_{v,s} < G_{\text{max}} \}.
\]

The last step is repeated until all nodes satisfy constraint (4).

### 2.4. Regional Re-Optimisation

The second considered method may be computationally challenging. Within each cluster, we re-optimise at high-resolution the original objective (1) with all associated mathematical constraints. Additionally, we impose another set of constraints to incorporate the low-resolution model results:

\[
\sum_{v \in \mathcal{V}_c} G_{v,s} = G_{c,s} \quad \forall s \in S.
\]

This set of constraints ensures that the amount of installed capacity is the same for every technology in every region.

Depending on the size of the cluster, the dis-aggregation may blow up the problem beyond the computational capacity of the machine and can result in an even larger problem than the clustered one. On the positive side, the re-optimisations for each cluster can be run in parallel.

### 2.5. Minimal Excess Electricity

Our third Ansatz for dis-aggregation is motivated by finding a compromise in terms of computational resources. It is not evident that solving the full optimisation problem is necessary to distribute renewable capacity. Instead, we define a simpler new objective function that minimizes (renewable) excess electricity. It is designed to spatially align renewable generation with demand and possible flexibility options inside the cluster:

\[
\min_{G_{v,s}} \sum_{v \in \mathcal{V}_c, s,t} \left[ \tilde{g}_{v,s} G_{v,s} - d_{v,t} - 0.7 \sum_{l \in \mathcal{L} : t \in E} F_{(v,w)} \right]^+.
\]

The bracket \([x]^+ := \max\{0,x\}\) yields the positive part of the sum. Compared to the regional re-optimisation introduced in section 2.4, the set of additional constraints to the optimisation problem is much smaller. We only impose equations (4) and (6). The choice of this objective function is motivated by prior research carried out by Frysztacki and Brown (2020) where equation (7) was invoked as a measure to balance the spatial resolution of the model and accurate modeling results. Similarly to the previous methods, this dis-aggregation method can be run in parallel for each cluster.

### 2.6. Modeling Power Flows between Clusters

For two of the three proposed dis-aggregation methods (‘re-optimize’ and ‘min excess’), we add additional boundary constraints on the inter-cluster transmission lines to simulate electricity im- and exports. This can be done by extracting the optimal power flows of the low-resolution network \(f_{(c,d)},t\) and distributing them proportional to the capacitivities of the inter-cluster high-resolution transmission lines \(F_{(v,w)}\) following

\[
f_{(c,d),t} = \frac{F_{(c,d)}}{F_{(c,d)},t} \in \left( -F_{(c,d)}, F_{(c,d)} \right) \quad \forall (v, w) \in E : v \in \mathcal{V}_c, w \in \mathcal{V}_d \land c \neq d.
\]

The resulting fine power flow \(f_{(c,d),t}\) is modeled as additional demand imposed on all nodes \(v \in \mathcal{V}_c\) and \(w \in \mathcal{V}_d\) that are connected by a transmission line \((v, w) \in E\), with \(c \neq d\), i.e.

\[
d_{v,t} \mapsto d_{v,t} + f_{(c,d),t} \quad \forall v \in \mathcal{V}_c,
\]

\[
d_{w,t} \mapsto d_{w,t} - f_{(c,d),t} \quad \forall w \in \mathcal{V}_d \quad (c \neq d),
\]

where positive power flows represent electricity imports and negative ones electricity exports. These results do not deviate strongly from those where each region is treated as an island, meaning that no powerflows retrieved from the coarse model are considered in the dis-aggregation. However it is plausible to include them when inverting modeling results, therefore in this article we focus on this approach. Islanded results can be found in the Appendix, see A.2.

### 2.7. Study Design

To investigate the quality of the proposed dis-aggregation methods, the model is solved as a pure operational problem, where no further capacity can be built. This is equivalent to solving equation (1) with its associated constraints, however the technology capacities \(G_{c,s}\) are removed from the set of optimisation variables and replaced by a fixed number. Load-shedding generators with high but non-extendable capacity are added to the network to guarantee physical feasibility. The operational problem is computationally less extensive to solve because the inter-temporal capacity expansion has been removed from the problem. Therefore, solving a spatially highly-resolved model becomes feasible.
Investigated intra-cluster scenarios for each of the dis-aggregation methods. This means we additionally formulate constraints on the transmission lines within each cluster.

| Short name | Scenario description |
|------------|----------------------|
| regular    | ... no further adaptations are made. |
| copperplate| ... the intra-cluster transmission capacity is infinitely high. Note, that the inter-cluster transmission capacity is still bound. |

As main quality measures the amount of load-shedding in the high-resolution network with the dis-aggregated results and the amount of renewable curtailment are considered. Curtailment describes how much abundant electricity the low-resolved model chooses to generate which, when highly resolved, cannot be transported to locations with high electricity demand. This is mostly due to an inaccurate choice of siting capacity due to missing information about possible transmission bottlenecks in the low-resolved model. Load-shedding is chosen because it indicates how much capacity is underestimated by the low-resolved model due to averaging capacity factors and removing grid bottlenecks from the network. Load-shedding could stem from different reasons: i) the dis-aggregation of solar and wind capacities to multiple sites with different capacity factors could result in a lower overall yield compared to the aggregated site, or ii) the grid bottlenecks inside the clusters could cause congestion, such that power generated at locations with surplus of electricity can not be transported to locations with high net load.

As load-shedding is a greater risk in terms of energy security, we design a test to better understand its origin. To rule out reason ii), we run a second operational scenario (which we refer to as “copper-plate”), where the capacity of all transmission lines that have vanished in the low-resolution network due to aggregation are set to \( \infty \), i.e.

\[
F_{(v,w)} \to \infty \quad \forall (v,w) \in V_c, \forall c .
\]

This modification is only applied to solve the operational problem, not for the dis-aggregation of results.

The results presented here are derived from the “regular” set-up, meaning with no adjustment to the intra-cluster grid capacities in the high resolved optimisation model (see Table 2). The resulting amounts of load-shedding and curtailment are presented in Figure 2.

For any of the three proposed dis-aggregation methods it can be seen that the amounts of both curtailment and load-shedding decrease as the resolution of the underlying low-resolution model increases. However, there are substantial differences in the performance of the dis-aggregation methods.

3.1. Feasibility Considerations

3.1.1. Regular Intra-Cluster Transmission Capacity

The results presented here are derived from the “regular” set-up, meaning with no adjustment to the intra-cluster grid capacities in the high resolved optimisation model (see Table 2). The results presented in Figure 2.

For any of the three proposed dis-aggregation methods it can be seen that the amounts of both curtailment and load-shedding decrease as the resolution of the underlying low-resolution model increases. However, there are substantial differences in the performance of the dis-aggregation methods.

Curtailment rates of the different methods deviate by 1–3% from one another on average, depending on the reference resolution. Distributing coarse investment variables across the spatially highly-resolved operational model results following the ‘min excess’ approach yields the highest curtailment rates of 11%–22% of annual electricity demand, depending on the coarse reference resolution and the dis-aggregation method. The lowest reference resolution has the highest curtailment. Uniformly distributing results performs similar to the ‘min excess’ method at a very low reference resolution of 37 nodes (one node per country), resulting in 22% of curtailed electricity. The ‘re-optimize’ method performs better in this regard, resulting only in 19% of curtailed electricity. But the curtailment rates decrease to approximately 14.5% (‘min excess’), 13% (‘uniform’) and 11% (‘re-optimized’) of annual electricity demand, as the reference model resolution increases. Re-optimizing the local problem yields the lowest curtailment for every reference model resolution, which is approximately 2–3% lower compared to the referenced resolution.
Inverse methods: How feasible are low-resolved modeling results?

to the results of the ‘uniform’ approach.

Regarding load-shedding, for a low-resolution network where every country is represented by a single node (37 clusters in Figure 2), ‘re-optimize’ performs best as it results in the lowest load-shedding rates. Re-optimising yields approximately 265 TWh or 8.2% of the annual electricity demand that can not be covered by renewable generation. If this gap were filled with gas to satisfy electricity demand, annual carbon emissions would rise from 0% to 3.2% of 1990s levels. Compensating the unmet demand when dis-aggregating results with the ‘min excess’ method yields approximately 400 TWh of load-shedding, resulting in 4.8% of carbon emissions (1.6% more compared to ‘re-optimized’) if gas is dispatched for the load-shedding measure. When uniformly dis-aggregating renewable capacity within the clusters, the operational problem returns 500 TWh of load-shedding measures. Compensating with gas would result in 6% of carbon emissions of 1990, 1.2% more compared to ‘min excess’.

When increasing the reference model resolution, the amount of load-shedding decreases for all the dis-aggregation methods. It can be seen that at a model resolution of 67 or more nodes, the amount of load-shedding is in the same range for the methods ‘re-optimised’ and ‘min excess’ deviating by only 0.5% on average. When uniformly distributing the retrieved coarse capacities, load-shedding measures are higher than those of the competing dis-aggregation methods by initially 2.8% at a reference resolution of 37 nodes and linearly decreases as the resolution of the reference model increases. At around 187 nodes, the difference for all three methods is below 0.5% in terms of necessary load-shedding measures. At an underlying reference model resolution of 217 nodes, the amounts of load-shedding are all within the range 94 – 110 TWh, corresponding to 3 – 3.5% of annual electricity demand in Europe.

3.1.2. Localization of Load-Shedding and Curtailment

In this section we analyse where curtailment and load-shedding is spatially localized. Recall that the highly-resolved model yields load-shedding measures because of i) dis-aggregating capacity factors results in a different overall yield of renewable electricity or ii) grid bottlenecks that did not occur in the low-resolved model, as described in detail in section 2.7.

Figure 3 displays the regions of curtailment and load-shedding spatially distributed after running the operational highly-resolved 1250 node model for all three dis-aggregation methods for a reference model resolution of 97 nodes. In all three cases it can be seen that the load-shedding is scattered in central Europe such as southern Poland, central and southern Germany, Switzerland and Austria and thus far from coastal areas and southern locations, such as e.g. northern Germany and France, Italy and Spain. In the same time, these locations have high amounts of curtailment. Transmission lines connecting regions with high amounts of curtailment and regions with high load-shedding show high congestion rates. Thus, the resulting network suggests that the low-resolved model favours investments in wind turbines at locations with good wind conditions at coastal areas, and in solar panels in the southern regions with good solar radiation, while it is blind to transmission bottlenecks that prohibit transporting the electricity to demand centers.

3.1.3. Infinite Intra-Cluster Transmission Capacity

To verify why load-shedding measures are necessary as well as to better understand the high curtailment rates, we now consider a setting where within each cluster the transmission capacity is set to infinity, following the description provided in the beginning of section 2.7, see equations (9)-(10).
This means that in the high-resolution model, only the capacity between clusters is limited. Results on load-shedding and curtailment are presented in Figure 4.

It can be seen that the amounts of renewable curtailment deviate by less than 5% from the curtailment rates of the reference model. They can mainly be explained by varying capacity factors. In the highly-resolved models, larger deviations of capacity factors within each clustered region become available compared to the reference model.

As the reference resolution increases, the amount of curtailment also tends to increase slightly. This can be explained by the fact that more total capacity is installed for a higher resolved reference resolution.

Regarding load-shedding, the amount for uniformly dis-aggregating renewable capacity drops to 0 for a reference model resolution above 100 nodes. For a one-node-per-country reference model (37 nodes), there remains a relatively low amount of load-shedding of approximately 50 TWh, resembling about 1.5% of annual electricity demand. In case the ‘re-optimize’ dis-aggregation Ansatz is invoked, load-shedding decreases to 0% of annual electricity demand for every low-resolution reference model. ‘min excess’ yields less than 5 TWh (< 0.5%) of load-shedding measures for any reference low-resolution model. At peak (97 nodes) this amount of gas would emit around 800 kg of CO₂ (0.05% of 1990s emissions). We conclude that these results are consistent with the main cause of load-shedding being the transmission restrictions within the clusters.

3.2. Trade-Offs of the Dis-Aggregation Approaches

There are four main qualities that we consider when evaluating trade-offs of the different dis-aggregation methods. First, the quality of results: How well do the proposed methods solve the problem at hand? Second and third, we consider the computational efforts. These mainly focus on the question: Are the proposed methods computationally legitimate for the considered problem? This consideration includes not only the memory requirements needed to solve the problem, but also the time it takes to solve. Fourth, depending on the results of the methods or the problem formulation, it might also be worth considering the efforts to implement a solver.

For the proposed methods in this paper, a summary of these four qualities is provided in Table 3. The performance with respect to the quality of results of the proposed dis-aggregation methods was already discussed in section 3.1. Now, we analyse the performance of the proposed methods from a computational point of view. Rating the efforts of implementation is a subjective task, we therefore solely relate to the fact that uniformly distributing a number across a set of nodes does not involve mathematical optimisation. Therefore applying an uniform distribution is rated “easier” than formulating a mathematical constraint to an existing optimisation problem as proposed in ‘re-optimize’, or a whole optimisation problem including both objective function and associated constraints, as proposed in ‘min-excess’.

Computational resources and solving times for dis-aggregating low-resolution model results back into high spatial resolution are presented in Figure 5 for every proposed method.

Resource-wise, re-optimising the local model consumes up to 13 times (1.7 times in average) the amount of resources compared to minimising a simpler objective in “min excess”, and up to 26 times (2.7 times in average) compared to uniformly distributing the capacity obtained from the low-resolution model (“uniform”). In absolute numbers, the method “re-optimize” consumes up to 22.2GB RAM at peak, compared to 2.2GB RAM for “min excess” and only 1.5GB RAM in case of “uniform”. Today’s average state-of-the-art personal computers are able to solve both the “uniform” and “min excess” problem formulations for any model resolutions, while solving the “re-optimize” approach needs more computational power and, therefore, requires a more advanced machine or even a high-computational cluster access. All local dis-aggregation runs were carried out in parallel.

Considering the computational times, these trade-offs are

---

**Table 3**

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

---

**Figure 5**: Memory resource requirements (left) and solving times (right) for executing the proposed dis-aggregation methods for individual regions. Possible memory consumption and solving times are marked by the corresponding color shades, depending on the cluster size. The memory resource requirement and solving time for the largest and smallest local problem can be taken from the edges of the marked area. Median requirements are displayed with a dotted line. The black dotted line denotes the requirements of the underlying low-resolution network for reference. Note that for ‘min excess’ and ‘uniform’, the median values coincide with the lower bounds, and are thus hidden in the plot. Moreover, for ‘uniform’, there upper and lower bounds collapse, thus no distribution is visible.
similar. The method “uniform” is up to 4000 times faster at peak than “min excess” and 70 times faster in average. In turn, “min excess” is up to 20 times faster than “re-optimize” and 11 times faster in average. Note that computational times might change when allowing a lower accuracy of the results. Here, we choose a barrier convergence tolerance of $10^{-9}$ and a feasibility tolerance of $10^{-6}$, which is not necessarily required. A tolerance of $10^{-3}$ might suffice in most applications. However, lowering the tolerance of the solver reduces solving times, but the memory consumption persists.

All experiments presented in this article were carried out on a high-computational cluster with 5 nodes, each having an allocatable capacity of 48 cpu's and 256 GB memory.

4. Conclusions

From these results, we can draw conclusions on the methodology of the dis-aggregation methods as well as on the insights of dis-aggregating coarse modeling results into a higher spatial detail.

The presented methods to dis-aggregate optimal infrastructure investment of renewable generation technologies and flexibility options have significant differences in their quality of results, simplicity of implementation and computational resource consumption. We have shown that it is not necessary to locally solve the full optimization problem to dis-aggregate coarse results into higher spatial detail, as it was conducted in previous research. Instead, it can be sufficient to formulate a suitable alternative objective which reduces computational cost and is able to preserve the quality of the dis-aggregation. In this paper, we suggest a function “min excess” that performs just as well, for lower computational burden. Further inverse functions could be considered in future research.

Regarding the insights of the dis-aggregated results, we formulate only conclusions retrieved from the best method that performs best as the presented dis-aggregation methods have deviations in their quantitative results. The “best” method is considered the one which yields the lowest amount of load-shedding. From the findings presented in this paper, we can stress that modeling Europe at a resolution of one node per country is insufficient to retrieve reliable capacity expansion suggestions. Moreover, results retrieved from models clustered to a spatial resolution of around 100-200 nodes using state-of-the-art evaluated aggregation methods fail to cover approximately 100 TWh of Europe’s electricity demand, approximating 3 – 5% of its annual consumption. Instead of consuming the excess electricity, curtailment rates rise by approximately the shed amount, additional to what would have been expected for an economic optimum. Our analysis reveals that the electricity shortage is due to local transmission constraints. Spatially low-resolved models assume that power can be transferred without limit to all locations that are represented within a single node. Therefore, intra-nodal transmission constraints are ignored in the constraints of the aggregated model. Thus, dis-aggregated results into higher spatial detail are confronted with power flow restrictions, resulting in transmission congestion and imply necessary load-shedding measures, making the investment decisions retrieved from a coarse model technically infeasible. However, the insight from studies dealing with spatial clustering and dis-aggregation provide insights that might help improve modeling results by developing methods to calibrate the low-resolution models.

5. Limitations of this Study

Removing the set of optimisation variables that accounts for the capacity expansion allows solving an operational dispatch model at a higher model resolution. Nevertheless, the presented operational model results are based on model runs retrieved from a model resolution of 1250 nodes, i.e. approximately 25% of the original network size, due to a persisting computational burden. The results presented in this paper are likely to intensify if the operational model was spatially highly-resolved and, thus, strengthen our main argument.

While we have analyzed methods to dis-aggregate the suggested optimal generation fleet, this study did not investigate methods to dis-aggregate transmission capacity expansion modeling results, or how additional transfer capacity obtained from a transmission expansion problem could improve the overall results. Such an analysis could build on our presented methods and extend them on an additional optimization variable. Moreover, all results presented in this paper carried out for a fully self-sufficient and fully renewable Europe. Lowering the carbon emission target could relax the findings and would not make as strong implications. Therefore, in a future study, different carbon emission targets could be analyzed more carefully.

Results of this study are all based on the MIT-licensed models PyPSA v0.18.0 and PyPSA-EUR v0.3.0. Therefore, nearly all of the limitations that apply for this version of the model also apply for this study. These include for example retrieving optimal capacities that rely on weather data from a single weather year, applying only a linearized power flow model or neglecting dynamic line rating. Some of these simplifications might improve in the future.

6. Data Availability

All code is or will be publicly available on github under an open source license.

7. Glossary

Abbreviations and variables are documented in Table 4.

8. Acknowledgements

MF and VH acknowledge funding from the Helmholtz Association under the program “Energy System Design”, MF and TB acknowledge funding from the Helmholtz Association under Grant No. VH-NG-1352.
Table 4
Glossary. Variables and their description.

| Abbrev. | Description                      |
|---------|----------------------------------|
| $\mathcal{V}$ | Set of all nodes contained in the model. |
| $E$     | Set of all edges representing transmission lines contained in the model. |
| $v, w$  | Representative names for high-resolution nodes. |
| $c, d$  | Representative names for clustered nodes. |
| $\mathcal{V}_c$ | Set of highly-resolved nodes that are aggregated to node $c$. |
| $(v, w)$ | a HVAC or HVDC line connecting nodes $v$ and $w$. |
| $S$     | Set of available technologies in the model, for example wind generator or battery storage. |
| $s$     | Generator or storage technology. |
| $T$     | Set of snapshots in the model. |
| $t$     | Snapshot, typically covering a duration of 2 hours. |
| $G_{v,s}$ | Capacity in node $v$ of generators of type $s$. |
| $g_{v,s,t}$ | Dispatch in node $v$ of technology type $s$ at time $t$. |
| $\hat{g}_{v,s,t}$ | Capacity factor at node $v$ for technology $s$ at time $t$. |
| $w_t$   | Weighting for time, here $w_t \equiv 2 \forall t \in T$, representing a 2-hourly model run. |
| $\mathcal{L}$ | Set of transmission lines in the model. |
| $F_{(v,w)}$ | Capacity of the transmission line connecting nodes $v$ and $w$. |
| $f_{(v,w)\ell}$ | Power flow from node $v$ to node $w$ at time $t$. |
| $d_{v,t}$ | Electricity demand in node $v$ at time $t$. |
| $r_{v,s}$ | Capital costs at node $v$ of technology $s$. |
| $\alpha_{v,s,t}$ | Operational costs at node $v$ for technology $s$ at time $t$. |
| $\gamma_v(t)$, $\gamma_c(t)$ | Curtailment of the high-resolution model ($V$) or the clustered model ($C$) at time $t$. |
| $\Delta_v(t)$, $\Delta_c(t)$ | Load-shedding measure of the high-resolution model ($V$) or the clustered model ($C$) at time $t$. |

9. Declaration of Interests
The authors declare that they have no competing financial interests.

A. Appendix

A.1. Cost Assumptions
Cost assumptions used for the clustered reference models to make cost-optimal investment decisions can be taken from Table 5.

A.2. Results of Island-ed Dis-Aggregation Method
In this setting each cluster is treated as an island, meaning that no electricity trade between other clusters is considered for the dis-aggregation. Results on load-shedding and curtailment for this scenario are displayed in Figure 6.

Figure 6: Results as displayed in Figure 2 of an island model, meaning that no inter-cluster electricity imports or exports are considered for the dis-aggregation.

The overall trend of the results is similar to the simulations where inter-cluster power flows were considered in the simulations. However, there are minor differences mainly affecting the “re-optimize” results. These result in an overall higher curtailment of 2–3%, and lower load-shedding of 1–2%.

Figure 7: Results as displayed in Figure 7 of an island model, meaning that no inter-cluster electricity imports or exports are considered for the dis-aggregation.
A.3. Analysing the Source for Load-Shedding

Figure 8 additionally displays if load-shedding measures occur at times where the curtailment of the high-resolution model is higher compared to the lower resolved reference model, see equations (11)-(12).

\[
\delta t \left( t = 0 \right) \left( T_V - T_C \right) \cdot \left( T_V - T_C \right) (t) \leq 0.5 \cdot \Delta V (t) \quad (11)
\]

\[
\delta t \left( t = 0 \right) \left( T_C - T_V \right) (t) \leq 0.5 \cdot \Delta V (t) \quad (12)
\]

where \( \Delta V (t) \) represents the amount of load-shedding measures in the high-resolution dis-aggregated model at snapshot \( t \), and \( T_V (t) := \sum_{s \in S} \left( g_{t,s} \cdot G_{t,s} \right) - \Delta g_{t,s} \) the amount of curtailment in the high-resolution dis-aggregated model at snapshot \( t \). Accordingly, \( T_C (t) \) represents the amount of curtailment in the lower resolved reference model.

It can be seen that, as the reference model resolution increases, there are more and more times \( t \) where the hypothesis is wrong. The amount of curtailed electricity is higher than load-shedding in 85% of the times on average for all of the three dis-aggregation methods for a very low-resolved reference model of 37 nodes. As the reference model resolution increases to 217 nodes, the statement is only true in average for 65% of the times for all three dis-aggregation methods. This indicates that transmission resolution is starting to saturate, however is still the major bottleneck preventing to feed-in the extra green electricity that is being curtailed.

CRediT authorship contribution statement

Martha Maria Frysztacki: Conceptualization, Methodology, Software, Formal Analysis, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization.
Veit Hagenmeyer: Writing - Review & Editing, Funding Acquisition. Tom Brown: Conceptualization, Writing - Review & Editing, Project Administration, Funding Acquisition.

References

Aryanpur, V., O’Gallachoir, B., Dai, H., Chen, W., Glynn, J., 2021. A review of spatial resolution and regionalisation in national-scale energy systems optimisation models. Energy Strategy Reviews 37, 100702. URL: https://www.sciencedirect.com/science/article/pii/S2211467X21000882, doi:https://doi.org/10.1016/j.esr.2021.100702.

Biener, W., García Rosas, K.R., 2020. Grid reduction for energy system analysis. Electric Power Systems Research 185, 106349. URL: https://doi.org/10.1016/j.ener.2020.106349.

Brown, T., Hörch, J., Slachthuber, D., 2018. PyPSA: Python for Power System Analysis. Journal of Open Research Software 6, 4. doi:10.5334/jors.186.

Budischak, C., Sewell, D., Thomson, H., Mach, L., Veron, D.E., Kempton, W., 2013. Cost-minimized simulations of wind, power, solar power and electrochemical storage, powering the grid up to 99.9% of the time. Journal of Power Sources 225, 60 – 74. URL: https://doi.org/10.1016/j.jpowsour.2012.09.054.

European Centre for Medium-Range WeatherForecasts (ECMWF), 2017. ERA5 Reanalysis. https://software.ecmwf.int/wiki/display/CKB/ERA5+data+documentation.

Frysztacki, M., Recht, G., Brown, T., 2022. A comparison of clustering methods for the spatial reduction of renewable electricity optimisation models of europe. Energy Informatics 5. URL: https://doi.org/10.1186/s42162-022-00187-7.

Frysztacki, M.M., Brown, T., 2020. Modeling curtailment in Germany: How spatial resolution impacts line congestion, in: Proceedings of 17th International Conference on the European Energy Market (EEM 2020). URL: https://doi.org/10.1109/EEM49802.2020.9221886.

Hörsch, J., Hofmann, F., Slachthuber, D., Brown, T., 2018. PyPSA-Eur: An Open Optimisation Model of the European Transmission System. Energy Strategy Reviews 22, 207–215. URL: https://doi.org/10.1016/j.esr.2018.08.012, doi:10.1016/j.esr.2018.08.012.

Lopion, P., Markewitz, P., Robinius, M., Stolten, D., 2018. A review of current challenges and trends in energy systems modelling. Renewable and Sustainable Energy Reviews 96, 156–166. URL: https://www.sciencedirect.com/science/article/pii/S1364032118305537, doi:https://doi.org/10.1016/j.rser.2018.07.045.

Martínez-Gordón, R., Morales-Espaňa, G., Sijm, J., Faaì, A., 2021. A review of the role of spatial resolution in energy systems modelling: Lessons learned and applicability to the North Sea region. Renewable and Sustainable Energy Reviews 141, 110857. URL: https://www.sciencedirect.com/science/article/pii/S1364032121001519, doi:https://doi.org/10.1016/j.rser.2021.110857.

Müller, U.P., Schachler, B., Scharf, M., Bunke, W.D., Günther, S., Bartels,
Inverse methods: How feasible are low-resolved modeling results?

J. Pleßmann, G., 2019. Integrated Techno-Economic Power System Planning of Transmission and Distribution Grids. Energies 12. URL: https://www.mdpi.com/1996-1073/12/11/2091, doi:10.3390/en12112091.

Open Power System Data (OPSD), 2019. Load in hourly resolution. http://www.open-power-system-data.org/, doi:10.25832/time_series/2019-06-05.

Pfeifroth, U., Kothe, S., Müller, R., Trentmann, J., Hollmann, R., Fuchs, P., Werscheck, M., 2017. Surface Radiation Data Set - Heliosat (SARAH) - Edition 2. URL: https://doi.org/10.5676/EUM_SAF_CM/SARAH/V002, doi:10.5676/EUM_SAF_CM/SARAH/V002.

Reinert, C., Söhler, T., Baumgärtner, N.J., Bardow, A., 2020. Optimization of Regionally Resolved Energy Systems by Spatial Aggregation and Disaggregation, in: Proceedings of the 16th Symposium Energieinnovation (EnInnov). URL: https://www.tugraz.at/events/eninnov2020/nachlese/download-beitraege/stream-c/.

Scaramuzzino, C., Garegnani, G., Zambelli, P., 2019. Integrated approach for the identification of spatial patterns related to renewable energy potential in European territories. Renewable and Sustainable Energy Reviews 101, 1–13. URL: https://www.sciencedirect.com/science/article/pii/S1364032118307275, doi:https://doi.org/10.1016/j.rser.2018.10.024.

Schlachtberger, D., Brown, T., Schramm, S., Greiner, M., 2017. The benefits of cooperation in a highly renewable European electricity network. Energy 134, 469–481. URL: https://doi.org/10.1016/j.energy.2017.06.004, doi:10.1016/j.energy.2017.06.004.

Schlachtberger, D., Brown, T., Schäfer, M., Schramm, S., Greiner, M., 2018. Cost optimal scenarios of a future highly renewable European electricity system: Exploring the influence of weather data, cost parameters and policy constraints. Energy 163, 100–114. URL: https://www.sciencedirect.com/science/article/pii/S0360544218316025, doi:https://doi.org/10.1016/j.energy.2018.08.070.

Schröder, A., Kunz, F., Meiss, J., Mendelevitch, R., von Hirschhausen, C., 2013. Current and prospective costs of electricity generation until 2050. Data Documentation, DIW 68. Deutsches Institut für Wirtschaftsforschung (DIW). Berlin. URL: http://hdl.handle.net/10419/80348.

Siala, K., Mahfouz, M.Y., 2019. Impact of the choice of regions on energy system models. Energy Strategy Reviews 25, 75–85. URL: https://doi.org/10.1016/j.esr.2019.100362, doi:10.1016/j.esr.2019.100362.

Vartiainen, E., Masson, G., Breyer, C., 2017. The True Competitiveness of Solar PV: A European Case Study. Technical Report. European Technology and Innovation Platform for Photovoltaics. URL: http://www.etip-pv.eu/fileadmin/Documents/ETIP_PV_Publications_2017-2018/LCOE_Report_March_2017.pdf.