Optimization of Regionally Resolved Energy Systems by Spatial Aggregation and Disaggregation

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Abstract: Regionally resolved energy system models are a valuable tool to support decision makers in long-term strategy planning. The optimal synthesis of energy systems requires high spatial resolution to account for local constraints such as grid limitations and local fluctuations of renewable energy. However, the required high spatial resolution leads to large-scale optimization problems, which are computationally challenging. Therefore, these optimization problems are typically simplified to be solved. However, solutions based on simplifications might not be feasible for the original energy problem.

To provide feasible solutions for regionally resolved energy systems, we present the SpArta method for Spatial Aggregation and disaggregation. SpArta initially also simplifies the optimization problem by aggregation but then decomposes the aggregated solution to find a feasible solution to the original problem. For this purpose, we first spatially aggregate the regionally resolved system into clusters. For the aggregated energy system, we simultaneously optimize design and operation. The design optimization considers all energy converters and the grid that connects the clusters. In the disaggregation step, the resulting design and grid flows serve as constraints for the design optimization of each cluster at the original spatial resolution. In the last step, the designs of the single clusters are combined to form a design for the original problem.

Based on a study of the German energy system, we show that SpArta leads to feasible results at high solution quality while significantly reducing solving time compared to the original optimization problem. Thereby, SpArta enables the design of large energy systems with high spatial resolution.

Keywords: Design optimization, Decomposition, Spatial resolution, National energy systems, Synthesis

1 Introduction

Renewable energy supply varies strongly spatially. Thus, models of large energy systems with renewable energy supply require high spatial resolution. E.g., Heuberger et al. (2020) find that insufficient spatial resolution can lead to an overestimation of the CO_2 reduction potential and an underestimation of energy storage needs.

However, high spatial resolution increases problem size and thereby the computational complexity. Thus, the maximal calculation time often limits the spatial resolution of energy system models (Ringkjøb et al. 2018). The resolution of national energy models therefore ranges from a single node (e.g. Henning and Palzer (2015)) to several thousand nodes (e.g. Robinius et al. (2017)). The impact of spatial resolution is increasingly analyzed. Hörsch and Brown (2017) compare multiple aggregation levels of the European energy system under a 95% greenhouse gas emission reduction scenario. The authors stress the importance of a joint optimization of energy systems design and grid extension, which is enabled by high spatial resolution. Further, Frew and Jacobson (2016) explore temporal and spatial aggregation in a model of the US power system. Their run time scales quadratically with increasing problem size. Their study shows that computational complexity results in a tradeoff between spatial and temporal detail.

For the temporal resolution, the trade-off between temporal detail and computational complexity has been intensely studied using time-series-aggregation methods, e.g. by Teichgräber et al. (2019), Kotzur et al. (2018) and Bahl et al. (2017). Aggregation leads to a loss of information and thus, the aggregated solution is not necessarily a solution for the full-scale problem. For time-series aggregation, this problem has been overcome by the RiSES3 method which reduces complexity while yielding a solution of the full-size problem (Bahl et al. (2018); Baumgärtner et al. (2019)). For this purpose, RiSES3 exploits the two-stage character of the optimization problem: the design optimization is performed with an aggregated time series, whereas the validation of the system employs the full time series. Such approaches are currently missing for the spatial dimension. Therefore the computational complexity can currently only be reduced at the expense of undefined losses of spatial information, which leads to suboptimal and possibly infeasible solutions for the original problem.

In this work, we propose the method SpArta for the optimization of regionally resolved energy systems by spatial aggregation and disaggregation. We bridge the gap between complexity reduction and feasibility for the original problem. SpArta reduces problem size of the design optimizations and thus reduces computational times by aggregation. Subsequently, we decompose the aggregated results to get a feasible solution of the original problem at high spatial resolution.

In Section 2, we introduce the four steps of the SpArta method. As an example for a regionally resolved energy systems model, we use the optimization model SecMOD, which is introduced in Section 3. Results for the application of the SpArta method in SecMOD using Germany as a case study are shown in Section 4. Finally, Section 5 provides conclusions.

2 SpArta method

The SpArta method enhances regionally resolved energy systems optimization while spatial information is maintained. Regionally resolved energy system models typically consist of multiple nodes, which are connected by a grid. The design optimization is computationally challenging, since the design of both grid and energy technologies is optimized at each node for each time step. The systems are typically strongly coupled and can thus not be decomposed easily because of time coupling due to investments and storage and spatial coupling due to the investments in the grid. As a result, the design problems cannot be solved independently for each node and time step but require the solution of one large-scale optimization problem.

In SpArta, we decompose the design of energy converters and the design of the grid into two design optimizations. Thereby, we reduce the problem size of each single design optimization and therefore the solving time of the problem. Figure 1 shows the four steps of the SpArta method which are explained in the following.

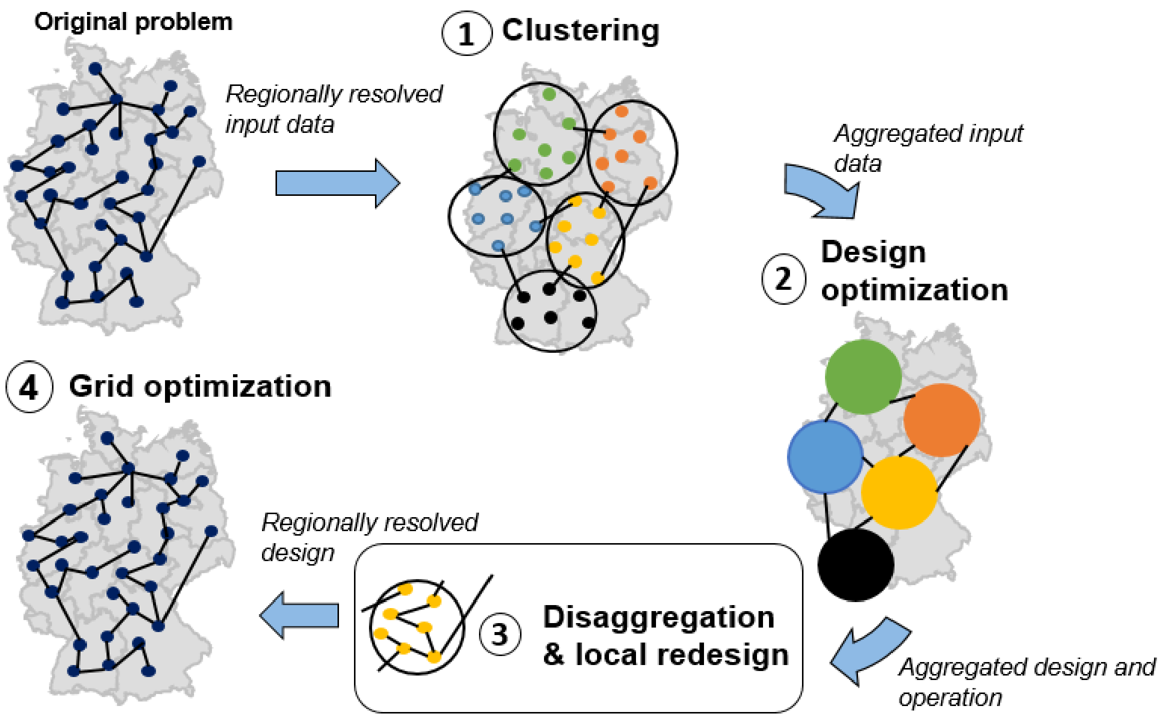

Figure 1: The four steps of the SpArta method illustrated for a regionally resolved grid.

2.1 Clustering: Spatial aggregation (Step ①)

In step 1, we aggregate the energy system to a predefined number of clusters. For this purpose, we sum up all energy demands and existing energy converters. We maintain grid elements connecting the clusters, but neglect grid limitations within each cluster.

The power output of fluctuating renewables (e.g. solar) $Power_{solar}(n,t)$ depends on the capacity utilization rate $solar(n,t)$ and the installed capacity $Cap_{solar}(n)$.

$$Power_{solar}(n,t) = solar(n,t) \cdot Cap_{solar}(n) \text{ , } \forall \text{ n} \in \text{N}, \ \forall \text{ t} \in \text{T}$$

The capacity utilization rate is spatially and temporally dependent. Thus, to get the capacity utilization rate for each cluster c, the capacity utilization rates at each node in the cluster ($n \in N_c$) are weighted. As weighting metric, we chose the maximal potential capacity (here $Cap_{solar}^{max}(n)$).

$$Solar(c,t) = \frac{\sum_{n \in N_c}(Cap_{solar}^{max}(n) \cdot Solar(n,t))}{\sum_{n \in N_c} Cap_{solar}^{max}(n)}, \forall \, c \in C, \; \forall \, t \in T$$

Thus, a node with a high maximal potential capacity will have a higher weighting factor than a node where only few wind or solar capacities can be built.

Aggregating the inputs simplifies the problem to an aggregated system at lower spatial resolution. This aggregated input data is used in step ②.

2.2 Design optimization: Optimization of the aggregated system: (Step ②)

SpArta performs the design optimization of the aggregated system in a two-stage synthesis problem that simultaneously optimizes design and operation (Lin et al. 2016). From the design optimization, we obtain results for both the design and operation of the aggregated system. The aggregated design consists of the resulting energy converters and the grid extension between the clusters. The operational results are both the optimal operation strategy of all energy converters and the power flows between the clusters.

2.3 Disaggregation & local re-design: Optimal regional distribution of energy converters: (Step ③)

In step 3, we disaggregate the aggregated design. For each cluster, we fix parts of the design and the power flows. Subsequently, each cluster is re-designed independently. Thereby, we reduce the degrees of freedom and enhance computational time compared to the original problem.

For each cluster, we distribute the resulting energy converters from step ② to the nodes within the cluster. To distribute the capacity of energy converters within the cluster, we fix the energy converter capacity for each technology in the design optimization, using the results from step ② as a constraint. In addition, we also fix the power flows at the border of the cluster using the power flow results from the optimal operation strategy of step ②. The grid within each cluster is considered in the re-design optimization. With the optimal distribution of the energy converters while regarding local grid limitations and extensions, we obtain a regionally resolved design for each cluster element.

2.4 Design optimization of the grid: (Step ④)

The target of the SpArta method is to obtain a regionally resolved design and an optimal operation strategy, which is feasible for the full-scale problem. Hence, we combine the regionally resolved designs of all single clusters from step ③ to obtain an overall design for the original problem. Since we fixed the power flows between the clusters in step ③, the operation strategy and grid design are not optimal for the combined infrastructure yet.

Therefore, in a last design optimization, we optimize the full grid while maintaining the regionally resolved energy converter infrastructure from step ③. We optimize both the design of the grid and the operation of all energy converters, obtaining a feasible design and operation strategy of the original problem.

3 Energy systems optimization model SecMOD

In this Section, we introduce the regionally resolved energy systems optimization model SecMOD for the case study of Germany. SecMOD is a linear long-term energy systems optimization model to optimize the design and operation of the German electricity, heat and transport sector. SecMOD is fully described by (Baumgärtner et al. 2020) and based on the electricity dispatch optimization ELMOD-DE (Egerer 2016).

SecMOD accounts for regional fluctuations of energy supply and demand by a spatial resolution of 416 nodes. A grid connects the nodes: power flows between the nodes are possible within the limits of grid infrastructure. SecMOD designs the energy converter and grid infrastructure using a least-cost optimization. Further, SecMOD constrains the greenhouse gas emissions according to national emission targets.

The power grid is modeled using a direct current load flow (DCLF) approach, neglecting transmission losses (van den Bergh et al. 2014). Both switching to a higher voltage level and building new power lines can extend the grid.

In this case study, we optimize the infrastructure of year 2030. SecMOD considers 14 types of energy converters for electricity generation, 3 storage technologies, 6 heating technologies and 6 vehicle types. These types of infrastructure can be employed to expand previously existing infrastructure in Germany. For this purpose, we determine the existing infrastructure in SecMOD for the year 2025 according to the current national emission targets (Figure 2). In addition, the existing infrastructure comprises storage capacities. The existing infrastructure can be extended during the design optimization. During the design optimization, we simultaneously optimize the design and operation for all time steps.

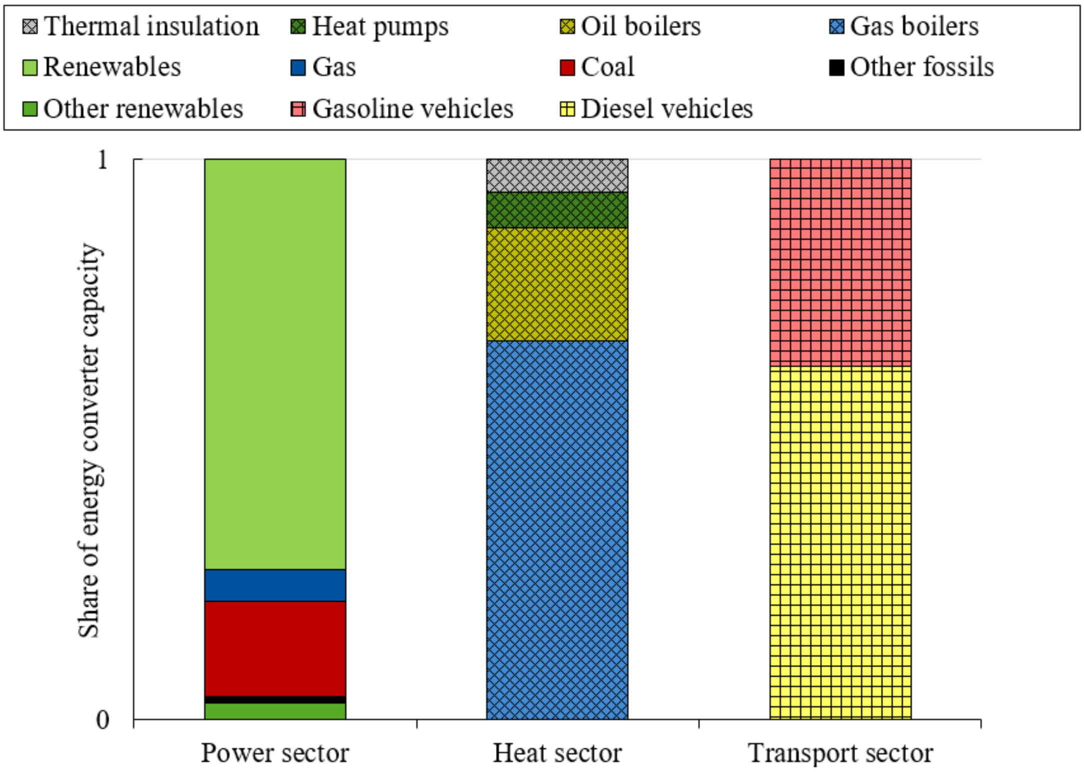

Figure 2: Existing infrastructure in year 2025 in Germany, calculated by the SecMOD model according to national greenhouse gas emission targets.

4 Results for computational time and solution quality

The SpArta method is applied to the model SecMOD for the German energy system. As benchmark, we consider using the full spatial resolution. In addition, we also consider the aggregated system corresponding to steps 1 and 2 of SpArta but without the disaggregation steps 3 and 4.

To be able to compare SpArta to the full resolution benchmark, we choose a problem size where we can find a solution for both SpArta and the benchmark. A fixed time series is used with 7 time periods, subdivided in 7 segments employing the time-series aggregation method from (Bahl et al. 2018). The time segments within each time period are interconnected to enable storage within a time period. With a total of 49 time steps per optimization, the benchmark can be solved within our solving time limit of 250,000 seconds. All calculations are performed using 4 Intel-Xeon CPUs with 3.0 GHz and 64 GB RAM with CPLEX 12.6.3.0.We compare the total system cost and the calculation time of SpArta to the benchmark and the aggregated system.

For the spatial aggregation, we vary the predefined number of nodes between 1 and 18. For the aggregation in step 1 of SpArta, we use the k-medoids algorithm.

The cost differs by up to 3.6 % between the solution of the aggregated system (without disaggregation) and the benchmark. Generally, the cost difference decreases when more nodes are added: for 6 or more nodes, the cost difference between the benchmark and the aggregated system is below 1 %. However, since the aggregated solution is not necessarily a feasible solution for the original problem, the costs are only comparable to a limited extent.

Using the full SpArta method (with disaggregation), the system cost differ by less than 0.7 % for all aggregation levels in our case study. For 6 and more nodes, the cost difference between SpArta and the benchmark is less than 0.3 %.

Figure 3 compares the benchmark solution (benchmark), the first aggregated solution with a cost difference below 1 % using 6 nodes and the SpArta solution also using 6 nodes. The aggregated system underestimates the amount of new power lines and voltage switches strongly, thus underestimating the need for transmission expansion. SpArta retains the regional resolution and thus increases grid infrastructure compared to the aggregated system. Compared to the benchmark, the capacity extension of the grid is only slightly smaller.

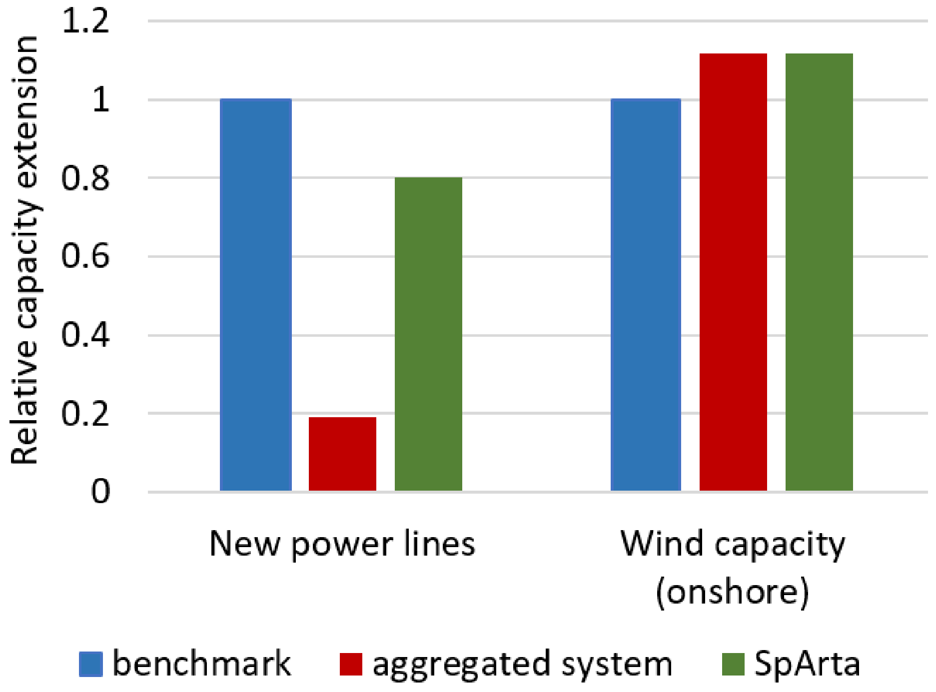

Figure 3: Capacity extensions for the grid and wind onshore from solutions of the benchmark system, the aggregated system using 6 nodes and the system solved using SpArta using also using 6 nodes.

Deviations to the benchmark are inherent in the SpArta method: the separation of the design optimizations of energy technologies and the grid influences the technology preference. The SpArta method thus obtains a different design than the benchmark using the full spatial resolution.

The difference in technology preference is also observed for energy converters. The largest difference is found for onshore wind power as shown in Figure 3: the aggregated system extends onshore wind capacity more strongly than benchmark. The aggregation of fluctuating renewable energies based on their technical potential favors the extension of renewable energy converters. This increased wind capacity is inherited by the SpArta design. However, since the SpArta design is feasible and its cost is within 0.3% of the benchmark, the results are practically of similar quality.

At the same time, the separate design of the energy technologies and the grid significantly reduces computational time at large problem sizes. In Figure 4, we vary the problem size: while the spatial resolution of 416 nodes of the full problem and spatial aggregation to 6 nodes in step 1 of SpArta remain constant, we vary the number of time steps. At small problem sizes, the benchmark solves faster than the SpArta method. However, at large problem sizes, here starting at 25 time steps, the SpArta method is faster than the benchmark. Lopion et al. (2018) show that there is a trend from models using typical periods to models with flexible or hourly time steps. Typical problems in energy systems optimization therefore contain more than 49 time steps.

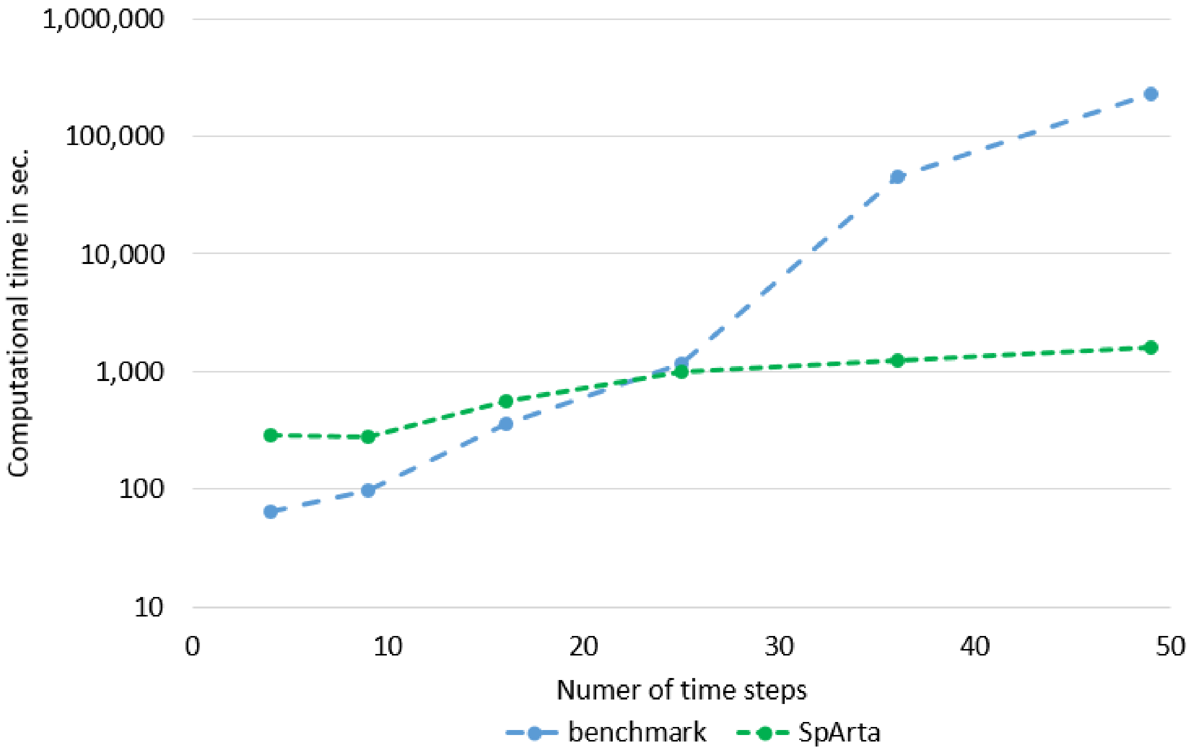

Figure 4: Computational time of the benchmark and the SpArta method at differing numbers of time steps. The spatial resolution of the benchmark is 416 nodes, which are aggregated to 6 nodes in step 1 of SpArta.

For 49 time steps and an aggregation to 6 nodes in step 1, Sparta reduces computational time by a factor 143, from 231,915 seconds (benchmark) to 1,616 seconds (SpArta).

Here, we limited the problem size to be able to compute the benchmark solution. The results show that SpArta could also find solutions when the benchmark becomes computationally prohibitive due to memory or time limits.

5 Conclusions

High spatial resolution is necessary for energy models with high shares of renewable energies, but increases computational complexity. The SpArta method for spatial aggregation and disaggregation can reduce computational time while maintaining full spatial resolution using decomposition. In SpArta, we initially aggregate the optimization problem but then decompose the aggregated solution to subproblems. These subproblems are then recombined to find a feasible solution to the original problem.

Applying SpArta to regionally resolved energy system optimizations can thus reduce computational time while maintaining high solution quality. For a problem with 416 nodes and 49 time steps, we demonstrate a reduction of computational time by a factor 143, when the system is aggregated to 6 nodes. At the same time, the total system costs between the full resolution benchmark system and SpArta differ by less than 0.3 %.

An increasingly interconnected world requires energy systems of increasing size and complexity. The SpArta method enables the feasible design of such systems.

6 Acknowledgements

Christiane Reinert thanks the Ministry of Economics, Innovation, Digitalization and Energy of North-Rhine Westphalia (Grant number: EFO 0001G). The support is gratefully acknowledged.

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