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Impacts of power sector model features on optimal capacity expansion: A comparative study

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ABSTRACT

The transition towards decarbonized energy systems requires the expansion of renewable and flexibility technologies in power sectors. Many powerful tools exist to find optimal capacity expansion. In a stylized comparison of six models, we evaluate the capacity expansion results of basic power sector technologies. The technologies under investigation include base- and peak load power plants, electricity storage, and transmission. We define four highly simplified and harmonized test cases that focus on the expansion of only one or two specific technologies to isolate their effects on model results. We find that deviating assumptions on limited availability factors of technologies cause technology-specific deviations between optimal capacity expansion in models in almost all test cases. Fixed energy-to-power ratios of storage can entirely change optimal expansion outcomes, especially shifting the ratio between short- and long-duration storage. Fixed initial and final-period storage levels can affect the seasonal use of long-duration storage. Models with a pre-ordered dispatch structure substantially deviate from linear optimization models, as missing foresight and limited flexibility can lead to higher capacity investments. A simplified net transfer capacity approach underestimates the need for grid infrastructure compared to a more detailed direct current load flow approach. We further find deviations in model results of optimal storage and transmission capacity expansion between regions, and link them to variable renewable energy generation and demand characteristics. We expect that the general effects identified in our stylized setting also hold in more detailed model applications, although they may be less visible there.

1. Introduction

1.1. Background and motivation

The 2020 European Climate Law as part of the European Green Deal sets greenhouse gas (GHG) emission reduction targets of 55% until 2030, compared to 1990 levels, and targets climate neutrality for 2050 [1]. However, only 18% of the European gross energy consumption were covered by renewable energy sources in 2018 [2]. The use of renewable energy is a main strategy for decarbonizing not only the power sector, but also the heat provision and mobility sectors via sector coupling. Therefore, decarbonizing the power sector by expanding renewable generation capacities is one of the main challenges when combating climate change. Most variable renewable energy (VRE) sources such as photovoltaics (PV) and wind power generally have low costs and high expansion potentials. Yet they require additional system flexibility [3] beyond what base load power plants are able to provide. Short- and long-duration storage as well as the transmission grid facilitate a temporal and spatial smoothing of VRE, complemented with flexible

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List of abbreviations

CHP	combined heat power
DCLF	direct current load flow
E2P	energy-to-power
EES	electric energy storage
FLH	full load hours
GHG	greenhouse gas
LP	linear programming
NTC	net transfer capacity
PV	photovoltaics
TPP	thermal power plants
TYNDP	Ten-Year Network Development Plan
VRE	variable renewable energy

thermal power plants (TPP) [4,5].

Capacity expansion models are a subset of energy system models used to investigate possible future system designs. Their main objective is to find optimal capacity expansion of generation and flexibility technologies. These models are per definition simplified representations of the real world, in most cases minimizing total system costs. The abstraction from reality leads to a variety of different modeling approaches that may lead to diverging results, e.g. concerning the optimal expansion of generation and flexibility technologies in energy systems with VRE.

1.2. State of research

A wide range of scientific publications deals with comparative analysis of energy system models. In Table 1 the categorization of existing literature shows that many studies mainly focus on the theoretical comparison of certain aspects of existing models. Gacitua et al. [21] for instance discuss policy instruments of 21 capacity expansion models for the power sector. Dagoumas and Koltsaklis [18] categorize capacity expansion planning models in three groups in order to evaluate usability. Fewer studies in the literature not only compare the features, but also the outcomes of capacity expansion models in the scope of a structured and parallel application. Bistline et al. [10], Huntington et al. [11], and Sugiyama et al. [17] all compare different model outcomes from a scenario based application. However, the results between models are often very different because all three studies neglect to use fully harmonized input data. This makes it difficult to identify modeling differences that drive differences in model outcomes. In contrast, Gils et al. [19] conduct a harmonized model comparison of four power sector models, including the coupling of multiple sectors. Three fully harmonized scenario variations are used to find deviations in model outcomes. Furthermore, Siala et al. [12] compare capacity expansion of five power market models in a harmonized setting. The impact of specific features like model type, planning horizon, and resolution on model outcomes is evaluated in detail. Both studies highlight the importance of harmonizing input data for understanding result deviations in comparative scenario analyses. However, the complexity of the conducted scenarios impede the identification of drivers of individual differences. As the complexity in those studies particularly results from sector coupling, focusing on the power sector is a helpful approach when looking at technology detail (see Table 1). In addition, to gain a deeper understanding of the underlying effects and drivers of capacity expansion model outcomes from different models, simplified scenarios can be useful [7].

Table 1
Categorization of existing peer-reviewed literature on structured comparison of energy system models. The categories are **a)** theoretical comparison of features, **b)** scenario based comparison, **c)** power sector only, **d)** capacity expansion considered, and **e)** fully harmonized input data.

Reference	Year	a)	b)	c)	d)	e)
Giarola et al. [6]	2021		✓	✓	✓	
Gils et al. [7]	2021		✓			✓
Gils et al. [8]	2021		✓		✓	✓
Klemm and Vennemann [9]	2021	✓				
Bistline et al. [10]	2020		✓	✓	✓	
Huntington et al. [11]	2020		✓		✓	
Siala et al. [12]	2020		✓	✓	✓	✓
Prina et al. [13]	2020	✓				
Ridha et al. [14]	2020	✓				
Fattahi et al. [15]	2020	✓				
Priesmann et al. [16]	2019	✓		✓		
Sugiyama et al. [17]	2019		✓		✓	
Dagoumas and Koltsaklis [18]	2019	✓				
Gils et al. [19]	2019		✓	✓	✓	✓
Savvidis et al. [20]	2019	✓				
Gacitua et al. [21]	2018	✓		✓		
Ringkjøb et al. [22]	2018	✓		✓		
Koltsaklis and Dagoumas [23]	2018	✓				
Cebulla and Fichter [24]	2017	✓		✓		
Hall and Buckley [25]	2016	✓				
Mahmud and Town [26]	2016	✓				
Després et al. [27]	2015	✓				
Pfenninger et al. [28]	2014	✓				

1.3. Contribution of this paper

This paper contributes to the energy modeling literature by exploring the drivers for differences in the outcomes of capacity expansion models. To this end, technology expansion outcomes of six power sector models are compared. Many studies focusing on model comparison use complex scenarios which makes it difficult to isolate effects of single modeling features. Therefore, and in contrast to existing literature, we focus on detecting the influence of single features of expansion models on outcomes. This is achieved by analyzing simplified systems that allow for the elimination of any overlaying effects that could potentially occur from various model differences. We consider highly simplified test cases to separately examine the expansion of simple combinations of power generation, storage, or transmission technologies. This approach addresses the challenge of data harmonization [12], substantially reduces complexity regarding model outcomes, and enables the association of outcome differences with model specifics. The selected scope of model approaches and technology modeling of the six contributing power sector models aims at covering a wide range of typical model features. Insights may also support policy makers when interpreting model-based policy recommendations. The simplicity of the defined test cases also allows us to trace back the influence of hourly VRE generation and demand profiles on model results.

2. Materials and methods

Section 2.1 and 2.2 introduce the set-up and input data of the model comparison. Section 2.3 briefly presents contributing models and their properties. Section 2.4 highlights key differences between these models that are relevant to the discussion of results. Finally, Section 2.5 describes the procedure of the model comparison and result analysis.

2.1. Definition of test cases

The model comparison comprises four abstract test cases of a future Central European energy system with regional demand and VRE generation potential profiles (see Fig. 1). The geographical scope includes the countries of Austria, Belgium, the Czech Republic, Denmark, France, Germany, Italy, Luxembourg, the Netherlands, Poland, and Switzerland. All of the simplified systems consist of the same hourly power demand time series and hourly generation potentials of three VRE technologies including PV, wind onshore, and wind offshore.

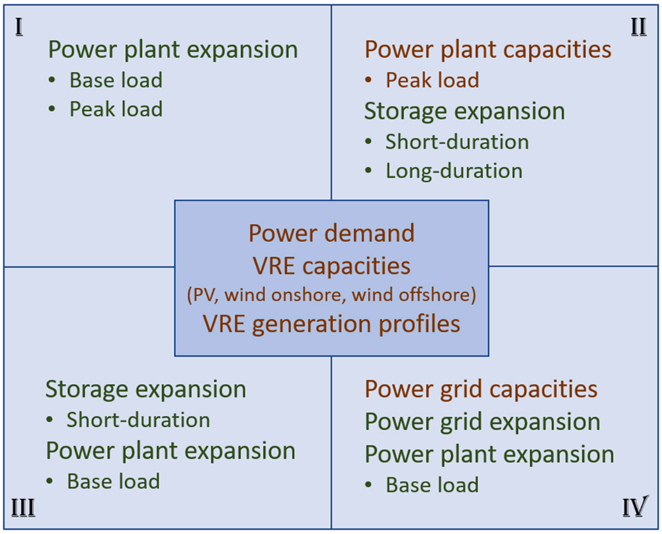


Fig. 1. Test cases considered in the model comparison. Endogenous capacity optimization is indicated by "expansion" (green), exogenously defined capacities by "capacities" (orange). The capacities in the center are identical for all test cases.

The demand and VRE generation profiles determine the temporal occurrence of surplus and deficit situations. This makes them a key driver for investment decisions in balancing technologies. To evaluate the dependency of the result deviations on the hourly demand and VRE power generation, we consider the profiles of three different historic years. For the VRE technologies, these differ in both annual full load hours (FLH) and hourly output (see Table 2).

Further, pre-installed and expandable technology capacities are individually defined for all test cases. Fig. 1 gives an overview of the available technologies and endogenous or exogenous capacity choices in the different test cases. All test cases are optimized in an hourly temporal resolution for a full year.

Test case I focuses on the capacity optimization of dispatchable power plants. We include nuclear power plants as an example for a base load generation technology with high investment costs and low variable costs, and gas turbines as sample peak load technology with lower investment costs but higher variable costs. Test case II investigates the capacity optimization of electric energy storage (EES), with lithium-ion batteries as short-duration storage option and hydrogen caverns with electrolyzers and hydrogen turbines for long-duration storage. To avoid a lack of supply, peak load turbines with a capacity matching the region-specific residual load peak are also included in test case II. The competition between dispatchable generation and storage is addressed in test case III, where the capacities of base load power plants and short-duration EES are optimized. Finally, test case IV evaluates the interaction in the capacity expansion of power transmission lines and base load power plants. Power exchange across model regions is only possible in test case IV. Existing and currently planned transmission capacities are considered according to ENTSO-E's Ten-Year Network Development Plan (TYNDP) [29]. Further, an endogenous expansion of those capacities is allowed. Across all test cases, input data is fully harmonized, including techno-economic parameters, VRE capacities, and annual demand as well as the corresponding time series. The reference to the full input data set is provided in the data availablilty section of this article. The highly simplified design of the test cases enables linking the differences in models outcomes to model specifics, and does not intend to realistically represent the future European energy system.

2.2. Data characteristics

The profiles for VRE generation and power demand show an individual pattern per region. To highlight such regional characteristics we define a PV-to-demand-ratio ($\rho_{PV,demand,r}$) (1), wind-to-demand-ratio ($\rho_{wind,demand,r}$) (2), summer-demand-share ($\rho_{summer,demand,r}$) (3), and winter-demand-share ($\rho_{winter,demand,r}$) (4). In this context, summer is defined from 21st of March until 20th of September and winter from 21st of September until 20th of March.

$$\rho_{PV,demand,r} = \frac{1}{T}\sum_{t=1}^{T}\frac{C_{PV,r} \times c_{PV,r}(t)}{d_r(t)} \quad \forall r \in \{Regions\} \tag{1}$$

$$\rho_{wind,demand,r} = \frac{1}{T}\sum_{t=1}^{T}\frac{C_{Wind,r} \times c_{Wind,r}(t)}{d_r(t)} \quad \forall r \in \{Regions\} \tag{2}$$

$$\rho_{summer,demand,r} = \frac{\sum_{21.Mar}^{20.Sep} d_r(t)}{\sum_{01.\ Jan}^{31.\ Dec} d_r(t)} \quad \forall r \in \{Regions\} \tag{3}$$

$$\rho_{winter,demand,r} = 1 - \rho_{summer,demand,r} \quad \forall r \in \{Regions\} \tag{4}$$

where C is the power plant capacity, c is the capacity factor for VRE units, and d is the demand.

By using a variety of model regions with different characteristics, we aim at strengthening the data foundation and robustness of our analysis. Further, this gives us the opportunity to analyze the effects of region-specific settings on the expansion of technologies.

Fig. 2 illustrates the calculated values for all characteristics (1–3), which vary strongly across the considered regions. Poland and Denmark have the highest wind-to-demand-ratios, followed by Germany, Czech Republic, France, and the Netherlands. In contrast, the PV-to-demand-ratio is especially high in Luxembourg, Belgium, Switzerland, and Italy. While in France energy consumption in summer is 13% lower than in winter, demand in Italy is similar for both seasons.

It is important to emphasize that the regional characteristics used here are highly stylized, as they for example neglect hydro power. They should thus not be used for deriving real-world policy conclusions. Yet, their simplified structure allows for meaningful comparisons and insights in the context of this model comparison exercise.

2.3. Contributing models

Six power sector models with maintainers from different research institutions across Germany contribute to the model comparison (Table 3). A well-balanced mixture of criteria is the foundation of selecting appropriate models for the model comparison. This includes, that models show a high scientific visibility through publications and that they are well established and documented. Moreover, factors like open source availability, reliability of maintainers, or novelty of concept are partly taken into account. With our selection, we further aim for a high model comparability despite specific modeling differences. All of the models feature an hourly time resolution, a multi-regional setting

Table 2
Indexing and characterization of weather years used in the analysis. All FLH are capacity-weighted average values across the 11 considered regions.

Index	Application	Characteristic	FLH_{avg} PV	FLH_{avg} onshore	FLH_{avg} offshore
Year A	Base analysis	Low VRE	1065 h	2015 h	3721 h
Year B	Sensitivity 1	Medium VRE	1049 h	2267 h	3725 h
Year C	Sensitivity 2	High VRE	1062 h	2300 h	4330 h

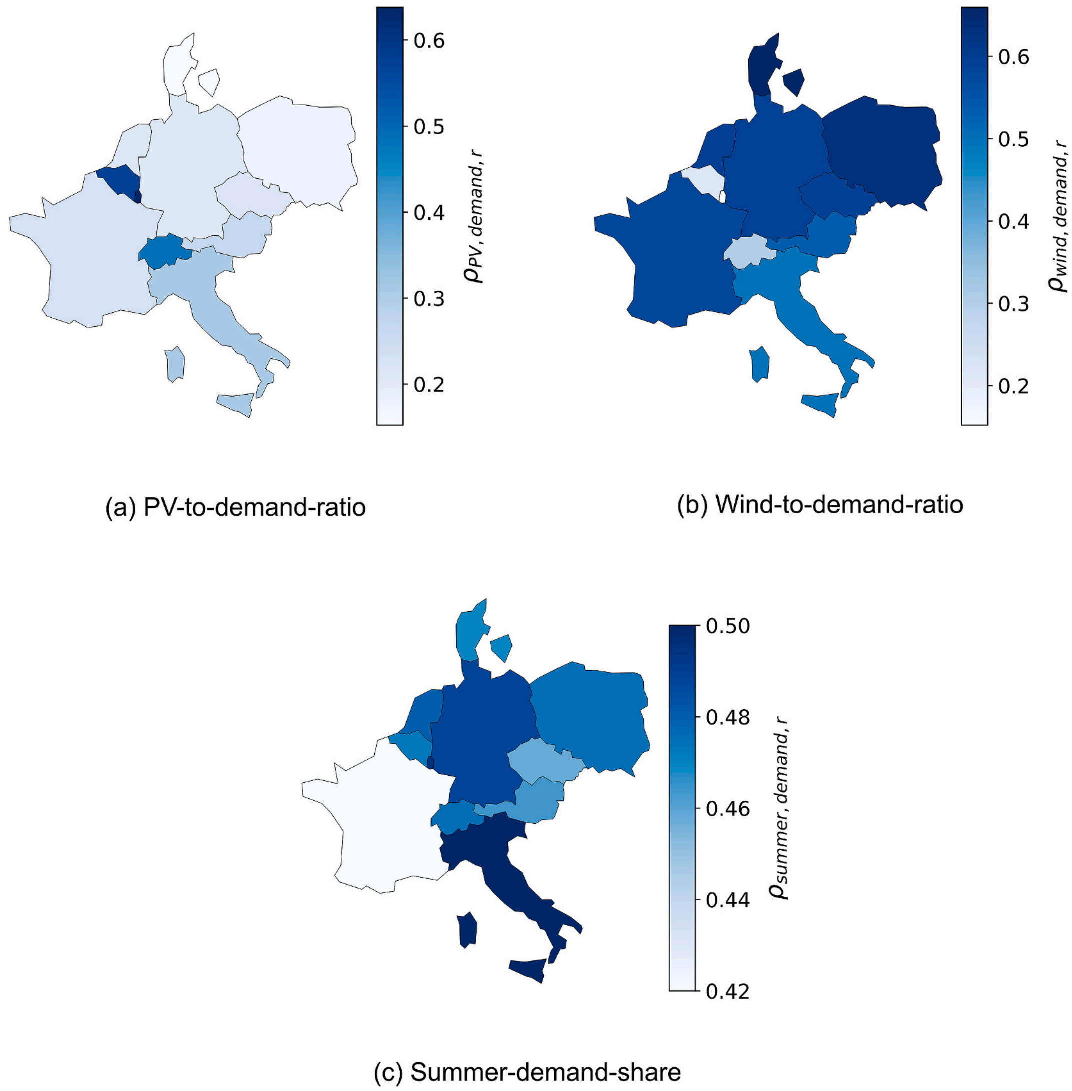


Fig. 2. Regional VRE and demand characteristics for the 11 considered regions.

Table 3
Overview of the six contributing models and their properties in the versions used for this model comparison.

	DIETER	E2M2	GENESYS-2	ISAaR	oemof	REMix
Programming language	GAMS	GAMS	C++	MATLAB/PostgreSQL	Python	GAMS
Modeling approach	LP	LP	Population based heuristic	LP	LP	LP
Foresight in hours	8760	8760	None	8760	8760	8760
Documentation	[30–32]	[33,34]	[35,36]	[37–39]	[40–42]	[43,44]

Table 4
Overview of technology modeling details and features that apply to the model version used for this comparison.

Feature	DIETER	E2M2	GENESYS-2	ISAaR	oemof	REMix
Limited technology availability	Constant factor	Constant factor	Not considered	Not considered	Not considered	Constant factor
Power plant flexibility	Simple load change costs	No load change costs	No load change costs	No load change costs	No load change costs	Simple load change costs
Storage levels	Start: 50%, End: 50%	Start: Optim., End: equal	Start: 0%, End: optim.	Start: 0%, End: optim.	Start: Optim., End: equal	Start: Optim., End: equal
Storage E2P ratio	Variable	Fixed	Variable	Variable	Variable	Variable
Charging to discharging cap. ratio for long-duration storage	Variable	Fixed	Variable	Variable	Variable	Variable
Capacity expansion transmission	With expansion NTC-based		With expansion NTC-based		Without expansion NTC-based	With expansion DCLF-based

with grid interconnection, and an optimized capacity expansion of generation, balancing, and transmission technologies. They differ in modeling language, programming approach, and level of foresight. GENESYS-2 follows a different approach than the other linear programming (LP) models by building on a population-based heuristic to find the optimal solution. Additionally, the underlying dispatch structure sets a fixed rule-based dispatch hierarchy for all generation and storage technologies as well as transmission. For this reason, the model has no foresight beyond the actual hour of operation. Another feature of the dispatch structure is that it drives local use of energy and short-distance energy distribution. More information on these models can be found in this issue (Gils et al. [7]).

2.4. Key modeling differences

The contributing models differ with respect to technology representation and model features (Table 4). Typical features, however, usually coincide across at least three models and only differ for some of the models. This allows us to isolate the impacts of different implementations on model outcomes. For instance, in contrast to all other models, GENESYS-2, oemof, and ISAaR do not consider a limited power plant and storage availability, which requires less generation and storage capacity for supplying peak load. Differences in power plant operation can result from the consideration of simplified load change costs, as implemented in DIETER and REMix. Regarding electricity storage, the DIETER model version used here requires initial and final-period storage levels to equal 50% of the endogenous energy storage capacity, which potentially affects the seasonal operation of long-duration storage. In E2M2, both the energy-to-power (E2P) ratio and the ratio between charging and discharging capacity of storage units are exogenously fixed, resulting in more limited flexibility when expanding such technologies. Furthermore, the models have fundamentally different approaches for power transmission modeling. While REMix uses a detailed direct current load flow (DCLF) approach, all other models use a simplified transport model based on net transfer capacities (NTC) for grid representation. The NTC-based approach used in GENESYS-2, however, differs from the other models. It is embedded in the predefined dispatch order, ensuring that transmission is only possible when there is a regional surplus from VRE or a shortage in local generation. In case a region requires import or export via transmission, the transmission model favors exchange with neighboring regions over regions that are more distant.

Note that many of these characteristics solely apply to the particular model version used for this comparison exercise, and do not represent the full capabilities of the models. Many of these simplifications are, among others, a result of the data harmonization process.

2.5. Procedure of the model comparison

Not every model participates in each test case (Table 5). This is because some models cannot use the harmonized input data, or some model features do not allow for modeling certain test cases. It is important to note that oemof participates in test case IV but without modeling capacity expansion of transmission lines. However, due to the brownfield approach of test case IV, including pre-installed transmission capacities, oemof functions as a benchmark for the other models that allow for transmission expansion.

Table 5
Overview of model participation in the defined test cases.

	Test case I	Test case II	Test case III	Test case IV
DIETER	✓	✓	✓	✓
E2M2	✓	✓	✓	
GENESYS-2	✓	✓	✓	✓
ISAaR			✓	
Oemof	✓	✓	✓	(✓)
REMix	✓	✓	✓	✓

The model comparison follows four steps that, at the same time, represent the flow of data. First, the input data files of the defined test cases are provided to all modelers in a standardized data format. All model maintainers convert this unified data-set into their model-specific input format by implementing model-specific interfaces. Then, each test case is optimized individually by all participating models for all three weather years (see Table 2). Subsequently, relevant model outcomes are converted back into a standardized format, which is designed to allow for easy and automated comparison. Relevant outcomes include annual and hourly values for endogenous capacity expansion, generation, transmission and storage use, VRE curtailment, or costs. We develop and apply a visualization tool to create standardized plots. This procedure allows for a systematic analysis of result deviations and provides the foundation to associate them with model differences.

The comparison of model results requires a harmonized definition of system costs (K_{system}), which are minimized in all models. The equation in (5) defines the composition of total system costs. They consist of annualized investment costs $K_{Invest,annuity}$ as well as fixed ($K_{OPEX,fix}$) and variable ($K_{OPEX,variable}$) operational expenditures. The latter is the sum of fuel costs, CO_2 emission costs, costs of uncovered load (implemented as a slack variable in the models to ensure mathematical feasibility), and power plant specific variable costs. The annualized investment costs and fixed operational expenditures solely include costs for endogenous capacity expansion and are summarized as expansion costs K_{exp}.

$$K_{system} = K_{Invest,annuity} + K_{OPEX,fix} + K_{OPEX,variable} = K_{exp} + K_{OPEX,variable} \quad (5)$$

3. Results and discussion

3.1. Optimal capacity expansion costs

The comparison of optimal expansion costs K_{exp} can be used to identify substantial result variations originating from different modeling approaches. With the design of the simplified test cases, it is possible to isolate the effects of the expansion of different technologies. In this way, for every expansion technology, we can analyze the resulting expansion cost deviations.

Fig. 3 illustrates the expansion costs for all test cases and models.

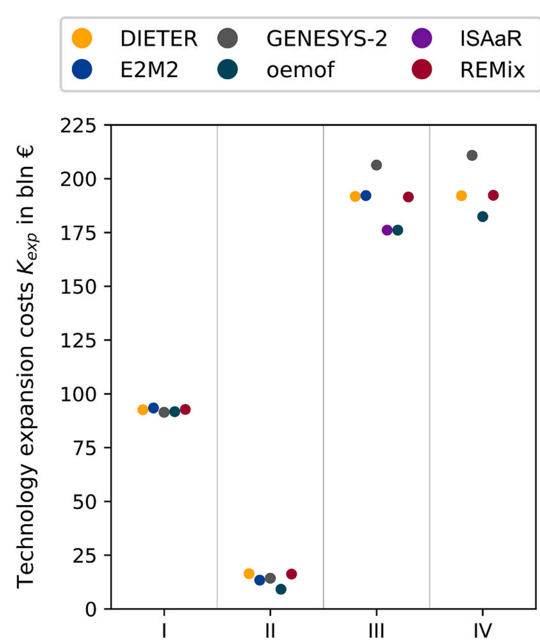


Fig. 3. Optimal expansion costs K_{exp} for all test cases (I-IV) and participating models, for weather year A.

These costs differ substantially in their absolute values. The lowest costs by far result in test case II. This is linked to the exogenous installation of peak load capacities, which considerably reduces the investment requirement for balancing technologies. In contrast, in test cases III and IV, extensive capacities of base load power plants must be added endogenously to ensure load coverage. The possibility of adding peak load power plants in test case I reduces the costs substantially, as these are much more favorable in terms of investment costs.

While expansion costs hardly vary across all models for test cases I and II, they deviate more substantially for test cases III and IV. This is driven by relatively similar expansion decisions for test cases I and II, and substantially different expansion decisions for test cases III and IV. In contrast to test cases I and II, in which we expand capacities of the same technology group (base/peak load power plants or storage), in test cases III and IV entirely different technologies (base/peak load power plants, storage, or transmission) compete against and interact with each other for optimal expansion, causing larger deviations.

In test cases III and IV, expansion costs in oemof and ISAaR are lower compared to other models. One main driver for this behavior is that both models usually contain fewer restrictions from features than other LP models, like no limitations on availabilities of technologies (Table 4). In contrast, GENESYS-2 clearly exceeds the expansion costs of the other models in test cases III and IV. This implicates that the substantially different modeling approach in GENESYS-2 has an overall influence on expansion decisions.

3.2. Test case I: expansion of thermal power plants

Fig. 4 shows the optimal capacity expansion and power generation for base load and peak load generators accumulated across all regions. We find two groups of model results with similar optimal capacity expansion. Optimal peak load generation capacity in the first group (DIETER, E2M2, REMix) exceeds the results in the second group (GENESYS-2, oemof) on average by 10%, while optimal base load capacity is almost identical for both groups with a maximum deviation of 1%. For generation the effects are the opposite (Fig. 4). Models in the first group show 6% less generation from base load, and 18% more generation from peak load power plants. This is because models use a different availability ratio of peak load over base load power plants. Models in the first group apply a constant limitation of available generation capacity to account for planned and unplanned outages. The assumed availability is 94.8% for peak load power plants and 91.2% for base load power plants, which results in an availability ratio of roughly 1.04. Models in the second group assume perfect availability with an availability ratio of 1.00. Consequently, each unit of installed base load capacity can generate more electricity than peak load capacity in models of the second group compared to those of the first. Additionally, an availability ratio of 1.00 requires less expansion to supply peak loads. Since the specific investment costs of peak load power plants are substantially lower than those of base load plants, the capacity effect is more pronounced for optimal peak load capacity (Fig. 4). In contrast, the generation effect is rather similar for both technologies. This is because the difference in variable costs of both technologies is lower compared to investment costs. The analyzed effects, however, only cause small variations in expansion costs between the models (Fig. 3).

Overall, the results indicate that even a subtle model feature such as technology availability may cause substantial distortions of model outcomes. At the same time, the expansion values indicate that mainly peak load power plants are affected by this, despite a higher availability. In contrast, the dispatch approach of GENESYS-2 has no impact on model outcomes in this stylized setting, as the results are very similar to oemof. This is because the dispatch hierarchy of GENESYS-2 only depends on the marginal costs of generation units, and this is what matters in this test case without storage and transmission technologies.

3.3. Test case II: expansion of storage technologies

The optimal capacity expansion and discharged energy for short-duration and long-duration storage vary broadly across the models (Fig. 5). In contrast to all other models, E2M2 almost exclusively invests into short-duration storage. The preference towards short-duration storage in E2M2 originates from the fixed E2P ratio (4 h for batteries, 400 h for long-duration storage) and the fixed ratio between charging and discharging capacity for long-duration storage units. For the charging unit of long-duration storage, the exogenous E2P ratio in E2M2 is much higher than the endogenous E2P ratios determined by the other models, with a maximum of 197 h. For the discharging unit, the optimized values range between 236 h and 1573 h with an average of 620 h. This leads to long-duration storage being a more expensive technology to expand in E2M2 than in the other models, which causes a shift from long-duration storage to short-duration storage.

For GENESYS-2, the investments into both short- and long-duration storage are generally lower compared to other models. Due to the missing foresight in GENESYS-2, less energy can be used and stored from VRE generation. For this reason, the capacity expansion of electricity storage is generally lower in models with a pre-determined dispatch order such as GENESYS-2. Generation from peak load power plants compensates for the resulting decrease in storage discharge in peak periods.

The remaining models DIETER, oemof, and REMix show a very similar short-duration storage expansion and discharge, with deviations of less than 2% between the models. For long-duration storage investments, however, DIETER exceeds oemof and REMix by about 15% and shows the highest expansion of all models. An analysis of the long-duration storage level over the full modeling period, accumulated for all regions, helps to understand this difference (Fig. 6). It can be seen that the storage level at the beginning and at the end of the year, which is determined endogenously in oemof and REMix (about 40%), is

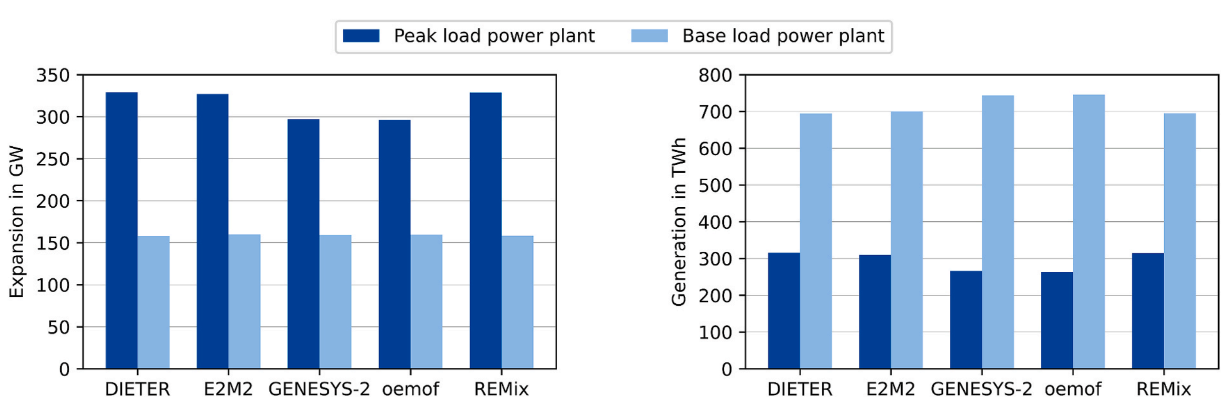


Fig. 4. Capacity expansion and generation of thermal power plants across all regions, for weather year A.

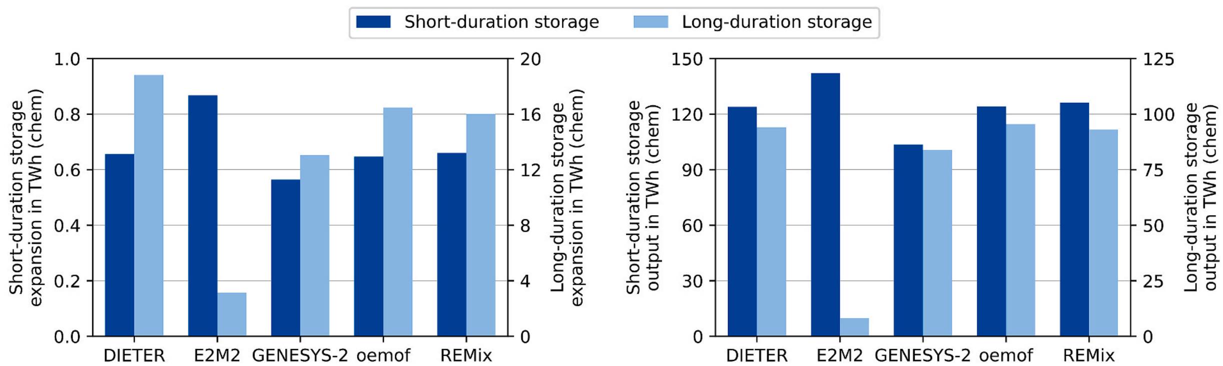


Fig. 5. Capacity expansion and discharged energy of short-duration and long-duration storage across all regions, for weather year A.

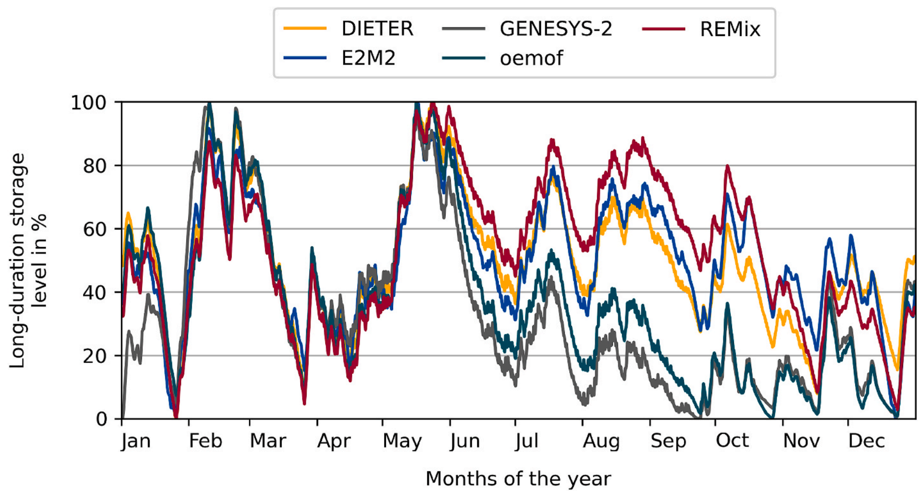


Fig. 6. Long-duration storage level accumulated across all regions, for weather year A.

substantially lower than the value of 50% specified in DIETER. Therefore, the storage level cannot drop as much as in the other models towards the end of the year. This goes along with an increased optimal storage capacity in DIETER. However, this is accompanied by low additional costs and hardly any higher capacities of the charging and discharging unit. Another effect can be observed for oemof. Despite a deviation of only 3% in the storage capacity, the filling level in oemof differs substantially from that in REMix. This can be explained by the different implementation of availability factors for storage technologies. While oemof assumes full availability, REMix models reduced availability for short-duration (98%) and long-duration storage (95%). When expanding both technologies this leads to a different ratio of short-to-long-duration storage in both models, with oemof investing slightly more into long-duration storage power and energy capacity. Therefore, long-duration storage in oemof can be discharged with higher rates such that the storage level drops quicker in the second half of the year.

Despite the substantial difference in storage capacity between DIETER, REMix, and oemof, withdrawal from long-duration storage differs only by about 2%. This supports the interpretation that the higher storage capacity in DIETER is essentially caused by the default start level.

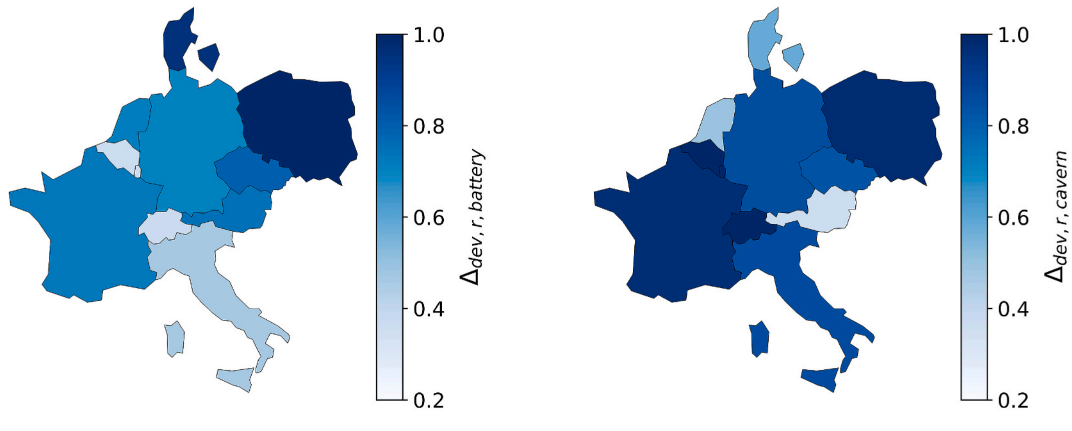
In the next step, we also examine the distribution of deviations in storage expansion results on a regional level. The scenario set-up contains 11 regions and thus allows for a detailed analysis of results for individual regions. Section 2.2 highlights important characteristics of the input time series data in each region. Such characteristics include maximum available VRE generation shares and seasonal demand variations. These temporal variations have an influence on the optimal use of storage. To quantify the deviating regional patterns, we define the deviation $\Delta_{dev,r,s}$ within the results of one region (r), and for the expansion C_{exp} of either short- or long-duration storage (s), according to the following measure:

$$\Delta_{dev,r,s} = \frac{\max\left(C_{exp,r,s,i}\right) - \min\left(C_{exp,r,s,i}\right)}{\max\left(C_{exp,r,s,i}\right)} \quad \forall i \in \{Models\}, \forall s \in \{Storage\ technologies\}, \forall r \in \{Regions\} \tag{6}$$

Fig. 7 shows the deviation of optimal short-duration and long-duration storage capacity for all considered regions.

Optimal short-duration storage sizing largely coincides between models in Belgium, Italy, Luxembourg, and Switzerland. In Denmark and Poland, two countries with a high share of wind generation (Fig. 2), the deviation is more than 80% (Fig. 7a). More generally, results show that deviations of optimal short-duration storage expansion increase with relatively high generation from wind power. In regions with a high PV share, short-duration storage capacity expansion takes place in all models. In those regions, there are only small deviations between models, and optimal short-duration storage capacity is comparatively large in relation to the peak load capacity. In regions with a higher importance of wind power, which fluctuates in less regular patterns than PV, even small model differences, like availability assumptions in DIETER, have a much stronger impact on optimal investments. Therefore, regional characteristics in combination with small differences in technology modeling can substantially affect the optimal use and investment decisions of short-duration storage.

For long-duration storage, deviations on a regional level are higher than for short-duration storage (Fig. 7b). One reason are higher total investment costs for this technology that is mainly used to shift large amounts of energy from summer to winter (Fig. 6). The differences



(a) Short-duration storage (b) Long-duration storage

Fig. 7. Maximum deviation $\Delta_{dev,r,s}$ of optimal storage capacity expansion for weather year A. A value of zero implies that capacities are identical across all models, whereas the deviations between the models increase for higher values.

between models are particularly pronounced in Belgium, France, Luxembourg, Poland, and Switzerland with deviations up to almost 100%. In Belgium, Luxembourg, and Switzerland the gap between base and maximum peak demand is small compared to other regions. At the same time, expanded capacities for long-duration storage are comparatively small with respect to maximum peak loads. Consequently, we conclude that there is potentially less demand for long-duration storage in those regions having the effect that, because of small modeling differences, E2M2 and GENESYS-2 decide against expanding. The other models (DIETER, oemof, and REMix), on the contrary, decide to expand which leads to a high deviation between the two groups of models. However, in France the difference between base and maximum peak demand is the largest of all regions, and the summer-demand-share is the lowest of all regions (Fig. 2c), which leads to higher demands for long-duration storage expansion. On the contrary, the implementation of a fixed E2P ratio and a charge-to-discharge ratio for long-duration storage in E2M2 increases the costs for expanding this technology. For this reason, E2M2 builds 96% less capacity compared to the average of all other models that invest heavily in this technology. The same applies to Poland with the difference that the main cause is the comparatively high expansion of long-duration storage towards base demand.

3.4. Test case III: expansion of thermal power plants and storage technologies

Fig. 8 shows optimal energy capacity of short-duration storage and generation capacity of base load power plants. Additionally, the discharge of short-duration storage and generation of base load power plants is shown. The optimal capacity results highlight that DIETER, E2M2, and REMix, as well as ISAaR and oemof, show very similar expansion for base load power plants. Comparing the two groups of results, the capacity expansion in ISAaR and oemof is 9% lower. This difference occurs because DIETER, E2M2, and REMix, in contrast to ISAaR and oemof, consider limited availability factors (Section 3.2). Therefore, less expansion is required in models with full availability of components. For the expansion of short-duration storage, the same conclusion applies. However, the limited availability of short-duration storage is at 98% such that the differences between the models are only minor. The higher short-duration storage capacities in DIETER and REMix compared to E2M2 result from considering simplified load change costs of power plants.

Standing out from all other models, GENESYS-2 only invests into base load power plants, and no short-duration storage capacity is built. This is because of a missing foresight window of the pre-defined dispatch approach. If installed, the available energy in the short-duration storage unit would not always suffice to meet the hourly peak demand in every time step (in combination with the base load generation capacity), because the decisions to fill up the storage would have to be made in past time steps. Instead, the optimal base load generation technology increases, which is assumed to be fully available at any given time, in order to meet peak residual load. We conclude that models with a predetermined dispatch order per design are not suitable for simplified test cases focusing on choices between a fully dispatchable generation technology and electricity storage. However, such a limited technology portfolio is unlikely to be applied beyond the model comparison conducted here.

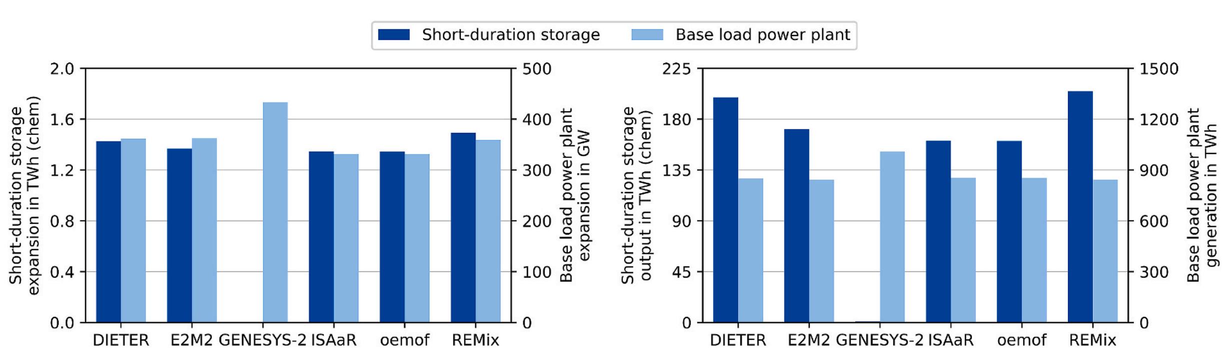


Fig. 8. Capacity expansion and generation of short-duration storage and base load power plants across all regions, for weather year A.

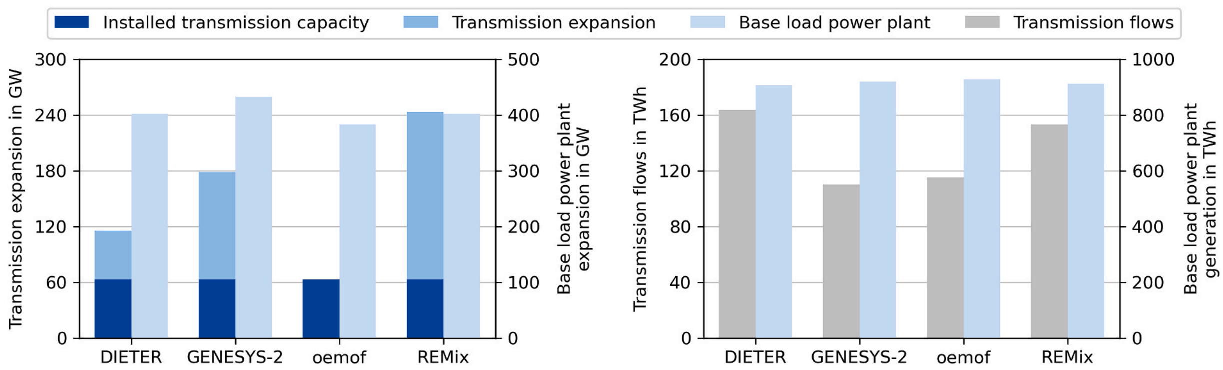


Fig. 9. Capacity expansion of transmission lines and base load power plants (left) and transmission flows and generation of base load power plants (right) across all regions, for weather year A.

3.5. *Test case IV: expansion of transmission capacities*

Fig. 9 illustrates the optimal expansion of transmission capacities and base load power plants. The existing transmission capacity sums up to about 63 GW across all lines. The model oemof does not allow for transmission expansion. Its underlying transmission grid is limited to the exogenous endowment.

The expansion results show that REMix determines the highest optimal transmission capacity expansion, followed by GENESYS-2 and DIETER. The deviation between DIETER and GENESYS-2 is driven by differences in underlying modeling approaches. In GENESYS-2, the dispatch model favors the regional use of energy, which leads to lower transmission flows compared to DIETER. Domestic load is balanced with neighboring regions first. Only if this is not possible, balancing with regions that are more distant becomes available. In contrast, DIETER allows for spatial energy exchange without any regional preferences. Grid use across all regions is more evenly and efficiently distributed, which reduces investment costs into transmission infrastructure compared to GENESYS-2. The less efficient use of transmission capacity in GENESYS-2 leads to higher investments into base load power plants and higher generation from such in comparison with all other models. Consequently, the high investment costs for base load power plants are the main driver for the increased expansion costs in GENESYS-2 in test case IV (Fig. 3).

Standing out from the other models, REMix uses a DCLF grid representation, also accounting for the impact of regional grid use on the entire grid. A margin of the available transfer capacity of one line is used due to flows on other lines. Consequently, optimal transfer capacities increase compared to GENESYS-2 and DIETER, and accumulated transmission flows are lower than in DIETER. This shows that in this stylized setting with a very limited set of available flexibility options, the simplified NTC approach is likely to underestimate the true need for grid infrastructure. Despite this, the investment costs in REMix are lower than in GENESYS-2, and on the same level as DIETER (Fig. 3). The high costs for expansion of base load capacity, which are very similar in REMix and DIETER, make up the largest share of total investment costs such that differences in transmission expansion have only a minor effect.

Without the capability of expanding transmission capacities, the expansion of base load capacity is the only option to cover demand in oemof. Nevertheless, oemof shows lower expansion in comparison with DIETER and REMix, because those two models account for reduced availability of base load power plants (91.2%) (Section 3.2). This way, oemof requires about 5% less base load capacity and can generate more electricity from one unit than the other models. Considering the relatively high investment costs for base load power plants compared to transmission capacity, it becomes clear why oemof has the lowest overall investment costs in this test case (Fig. 3). Furthermore, oemof shows efficient use of its comparably small pre-installed grid capacity transmission. This is indicated by higher overall transmission flows than in GENESYS-2, and more than three quarter of the flows in REMix and DIETER. However, the low grid capacity leads to higher curtailment than in GENESYS-2, which induces a higher generation from base load power plants.

On a region level, the results also differ because of different transmission modeling approaches. This is illustrated in Fig. 10 with the geographical distribution of transmission expansion.

DIETER and REMix find a very similar optimal distribution of transmission expansion, yet with a level shift driven by the difference between NTC and DCLF representations. In contrast, GENESYS-2 only expands selected regional lines. This effect result from the dispatch hierarchy in GENESYS-2 that favors the exchange of energy with regional neighbors rather than with distant regions.

Focusing on the details, all models show a higher expansion from Poland and France to one or more neighboring countries. In Poland, comparably high available wind generation (Fig. 2) is one factor that increases the possibility of exports. In addition, Poland only connects to two other countries, which aggregates necessary grid exchange to only two transmission lines. Those characteristics cause a strong capacity expansion between Poland and the Czech Republic of more than 40 GW in GENESYS-2. France combines a high wind generation availability with a relatively low summer-demand-share (Fig. 2). Regions including high available PV generation and a higher summer-demand-share, like Austria, Belgium, and Switzerland (Fig. 2), can be a supplement to France by balancing out generation and demand between the regions. This drives the stronger grid expansion between France and such countries.

3.6. *Dependency of the result deviations on VRE and demand profiles*

Optimal capacity expansion costs for all three weather years, test cases, and participating models are depicted in Fig. 11.

The sensitivity analysis reveals that the results are mostly robust against a change in the weather year, as there are only minor differences in the cost ratios between most models. This implies that the effects observed in all four test cases also hold for different demand and VRE generation profiles. However, small deviations for some models indicate that analyzed effects can be more or less pronounced in different weather years. Understanding the different patterns in some models requires a closer view at the overall trends between weather years. The increase in VRE generation potential from year A to C has a visible impact on overall results in test cases I, III, and IV, but only a minor impact on test case II.

With increasing generation from VRE, optimal thermal power plant expansion costs in test case I generally decrease to the same extent for all models, except for GENESYS-2 and oemof. Both models do not consider reduced availability factors. Weather year B and C require less base load and more peak load power plants, which reduces the effect of neglecting the availability factor.

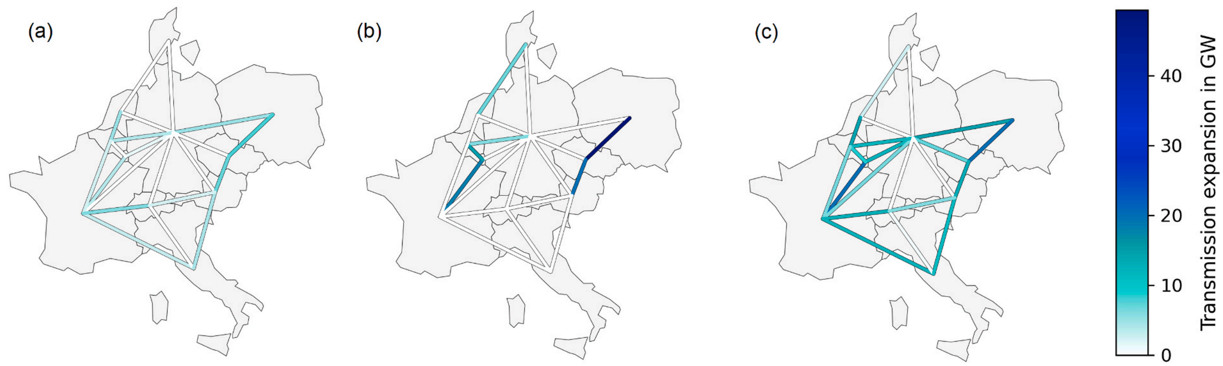


Fig. 10. Geographical distribution of capacity expansion of transmission lines in (a) DIETER, (b) GENESYS-2, and (c) REMix, for weather year A.

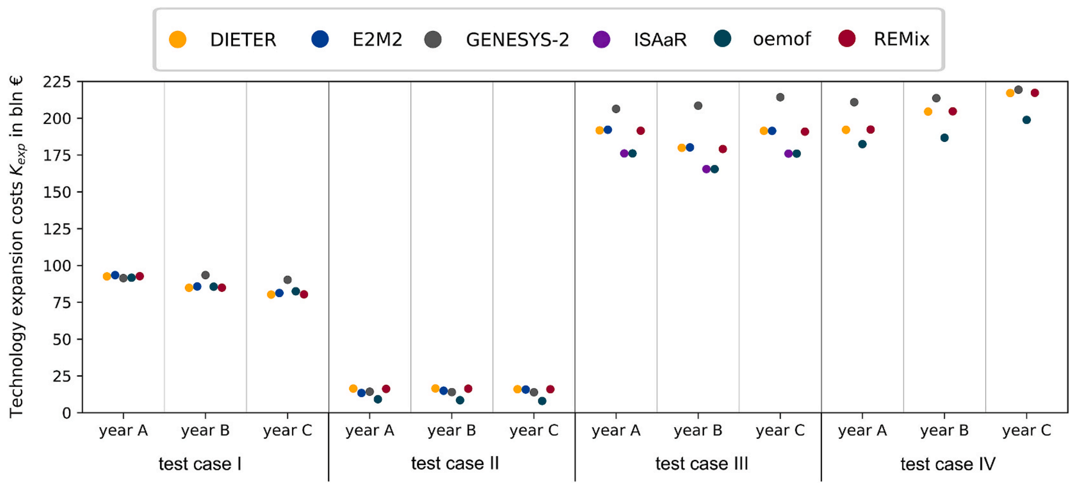


Fig. 11. Optimal expansion costs K_{exp} for all weather years (A–C), all test cases (I-IV), and participating models.

In test case II, optimal expansion costs are almost on the same level for all weather years and models. However, for E2M2 a relative increase in costs can be observed. The reason for this behavior is the fixed E2P-ratios and charge-to-discharge ratios for storage in E2M2, which are less suited for the demand and VRE generation profiles considered in year B and especially year C.

In test case III, all models except GENESYS-2 obtain very similar costs for years A and C. Instead, the demand and VRE generation profiles in year B allow for a reduction in power plant capacity and thus costs in these models. There is no visible change in the cost ratios. In GENESYS-2, reduced flexibility caused by the pre-defined dispatch order prevents investments into short-duration storage (see Fig. 8). Therefore, less generation from VRE can be utilized and increased expansion of base load power plants is required. One main factor for the reduction in all other models in year B is the reduced solar potential (see Table 2) that, at the same time, reduces the need for short-duration storage. In years A and C, however, solar potential is at a very similar level.

The optimal investments into transmission infrastructure in test case VI increase with increasing VRE generation, driving a growing gap between DIETER and REMix on the one hand, and oemof on the other. At the same time, a saturation effect can be observed in GENESYS-2 because the possibility of regional exchange tends to get smaller with higher VRE generation potentials. This is influenced by the fact that the share of demand per region supplied by VRE generation increases, and less energy needs to be distributed by the grid.

4. Summary and conclusion

We compare six capacity expansion models for the power sector, drawing on four simplified test cases. These allow separating the effects from expanding different technologies by covering individual building blocks of a future energy system. In all test cases, we identify deviations in expansion results and link them to modeling differences, taking into account overlapping effects. A comparison of expansion costs shows that deviations are highest when combining expansion of storage and base load power plants.

We do not observe fundamental modeling differences regarding the expansion of power plants in the contributing LP models. Most relevant is the endogenous consideration of power plant outages using a constant availability factor. We find that this drives a divergent investment behavior, increasing the required capacity especially for peak load power plants and less for base load power plants.

Reduced flexibility in storage design caused by a fixed E2P ratio and identical charging and discharging units leads to substantially deviating results, especially underestimating the system benefit of long-duration storage. On a region level, we observe that for short-duration storage the biggest differences in results occur in regions with a high potential of wind power generation. In contrast, the highest deviations for long-duration storage are observed when the gap between annual base and peak load is smallest, because the need for expensive long-duration storage decreases. Therefore, we generally conclude that between regions, different levels of generation from VRE and demand characteristics can increase the likelihood of deviations between model results. Modelers should generally be aware of this dependency.

The usage of a simplified DCLF approach causes a substantial underestimation of the grid demand, compared to a NTC approach. However, the geographic distribution of transmission expansion is not affected. Here, we observe that models focusing on regional energy supply in a pre-ordered dispatch structure show a divergent investment behavior.

The observed model differences affecting the flexibility of the operation of power plants and storage have a minor impact on investment behavior. However, we find that exogenous assumptions on initial and final-period storage levels can have an impact on the operation of long-duration storage. Regarding the design of future energy systems, it can be concluded that power plant availability needs to be considered exogenously, if not endogenously determined in the model, to ensure that capacities are sufficient for meeting demand in all hours. For the appropriate determination of required storage capacities, it is important to consider a flexible design of charging, discharging, and storage capacity, as the expansion strongly depends on the present VRE generation and demand profiles. In this regard, different weather years should be considered to produce more robust results. Moreover, using an NTC approach underestimates the transmission capacity that is required in a real system application.

Other deviations in capacity expansion result from differences in modeling approaches. Embedding a pre-ordered dispatch structure in a model generally leads to slightly lower capacity expansion of flexibility technologies like storage and transmission, but higher expansion of base or peak load power plants, due to missing foresight and flexibility of energy supply. At the same time, this causes higher investment costs in comparison with LP-models. In test case III, we show that models with a pre-ordered dispatch structure in a stylized setting with few flexibilities can generate entirely different optimal expansion solutions. Nevertheless, we expect that these effects would be less pronounced in more detailed test cases with a larger technology portfolio.

A sensitivity analysis reveals that most of the results obtained from all four test cases show high robustness towards variations in demand and VRE generation profiles. Despite three different weather years, most models show similar result patterns. The main differences are caused by using a pre-defined dispatch order. Despite small variations, the observed effects for all use cases and models are still valid, but are more or less pronounced.

Despite the simplicity of our test cases, we expect that the general effects identified in our stylized setting also hold in more detailed model applications, although they may be less visible there. However, it will then be more difficult to isolate the effects, as they overlap or interfere with each other. This challenge is further addressed in this issue (Gils et al. [8]), taking into consideration the insights from the stylized setting used here.

Additionally, with our analysis, we exclusively cover the power sector and exclude other sectors such as heat, gas, and mobility, because our main intention is to demonstrate our approach relying on simplified test cases in a less complex setting. Future work may focus on applying our approach to other sectors of the energy system and the interactions between sectors. However, this potentially leads to increasing model complexity related to sector coupling and may complicate the analysis and comparison of different model results. This includes the modeling of more complex components for sector coupling, like combined heat power (CHP) and heat pumps, that can be modeled very differently and thus require additional harmonization effort for model comparison. To isolate effects from different sector coupling modeling approaches, we propose to apply our simplified approach in respective future model comparisons. Furthermore, our findings highlight that regional differences have substantial impacts on result deviations and individual factors are difficult to separate. Therefore, these correlations should be investigated further in a more realistic scenario setting.

Author contribution

Jonas van Ouwerkerk: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing - Original draft preparation, Writing - Review & Editing, Visualization **Hans-Christian Gils:** Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - Original draft preparation, Writing - Review & Editing, Visualization, Supervision, Project administration, Funding acquisition **Hedda Gardian:** Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - Original draft preparation, Visualization **Martin Kittel:** Methodology, Software, Validation, Formal analysis, Investigation, Writing - Original draft preparation, Writing - Review & Editing **Wolf-Peter Schill:** Software, Investigation, Writing - Review & Editing, Funding acquisition **Alexander Zerrahn:** Methodology, Software, Validation, Formal analysis, Investigation **Alexander Murmann:** Methodology, Software, Validation, Formal analysis, Investigation, Writing Original draft preparation, Writing - Review & Editing **Jann Launer:** Methodology, Software, Validation, Formal analysis, Investigation, Writing - Original draft preparation, Writing - Review & Editing **Laura Torralba-Díaz:** Methodology, Software, Validation, Formal analysis, Investigation, Writing - Original draft preparation, Writing - Review & Editing **Christian Bußar:** Writing Review & Editing, Software, Funding acquisition.

Data availability

The data template and input data used are available on https://zenodo.org/record/5802178.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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