The near-optimal feasible space of a renewable power system model

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ABSTRACT

Models for long-term investment planning of the power system typically return a single optimal solution per set of cost assumptions. However, typically there are many near-optimal alternatives that stand out due to other attractive properties like social acceptance. Understanding features that persist across many cost-efficient alternatives enhances policy advice and acknowledges structural model uncertainties. We apply the modeling-to-generate-alternatives (MGA) methodology to systematically explore the near-optimal feasible space of a completely renewable European electricity system model. While accounting for complex spatio-temporal patterns, we allow simultaneous capacity expansion of generation, storage and transmission infrastructure subject to linearized multi-period optimal power flow. Many similarly costly, but technologically diverse solutions exist. Already a cost deviation of 0.5% offers a large range of possible investments. However, either offshore or onshore wind energy along with some hydrogen storage and transmission network reinforcement appear essential to keep costs within 10% of the optimum.

1. Introduction

As governments across the world are planning to increase the share of renewables, energy system modeling has become a pivotal instrument for finding cost-efficient future energy system layouts. Energy system models formulate a cost minimization problem and typically return a single optimal solution per set of input parameters (e.g. cost assumptions).

However, feasible but sub-optimal solutions may be preferable for reasons that are not captured by model formulations because they are difficult to quantify [1]. Public acceptance of large infrastructure projects, such as many onshore wind turbines or transmission network expansion, ease of implementation, land-use conflicts, and regional inequality in terms of power supply are prime examples of considerations which are exogenous to most energy system models. Bypassing such issues to enable a swift decarbonization of the energy system may justify a limited cost increase.

Thus, providing just a singular optimal solution per scenario underplays the degree of freedom in designing cost-efficient future energy systems. Instead, presenting multiple alternative solutions and pointing out features that persist across many near-optimal solutions can remedy the lack of certainty in energy system models [2,3]. Communicating model results as a set of alternatives helps to identify *must-haves* (investment decisions common to all near-optimal solutions) and *must-avoids* (investment decisions not part of any near-optimal solution) [4].

The resulting boundary conditions can then inform political debate and support consensus building.

A common technique for determining multiple near-optimal solutions is called Modeling to Generate Alternatives (MGA) which uses the optimal solution as an anchor point to explore the surrounding decision space for maximally different solutions [1]. Other methods, such as scenario analysis, global sensitivity analysis, Monte Carlo analysis and stochastic programing, that likewise address uncertainty in energy system modeling, concern *parametric* uncertainty, i.e. how investment choices change as cost assumptions are varied [3,5–7]. Conversely, MGA explores investment flexibility for a single set of input parameters, by which it accounts for *structural* uncertainty and simplifications of model equations. In consequence, MGA is a complement rather than a substitute for methods sweeping across the parameter space.

Evidence from previous work suggests many technologically diverse solutions exist that result in similar total system costs for a sustainable European power system [15,16]. These two studies research the sensitivity of cost input parameters or the relevance of transmission network expansion for low-cost power system layouts considering 30 regions.

Previous studies that applied MGA to long-term energy system planning problems or retrospective analyses are reviewed in Table 1. This work is the first to apply a variant of MGA to a European pancontinental electricity system model which includes an adequate number of regions and operating conditions to reflect the complex

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Table 1
Literature review: studies applying MGA to energy system models.

Source	Main Sector	Region	Nodes	Snapshots	Pathway	Max. GHG Reduction	MGA Objective	Cost Deviation	Near-optimal Solutions	LOPF
Price et al. [8]	coupled (IAM)	global	16	>1	yes	50%	energy	<10%	30	no
DeCarolis et al. [9]	electricity	US	1	1	no	85%	capacity	<25%	9	no
DeCarolis et al. [1]	electricity	US	1	1	yes	80%	energy	<10%	28	no
Li et al. [10]	electricity	UK	1	>1	yes	80%	any	<15%	800	no
Sasse et al. [11]	electricity	CH	2258	1	no	none	energy	<20%	2000	no
Trutnevyte et al. [12]	electricity	UK	1	3	no	none	any	<23%	250,500	no
Berntsen et al. [13]	electricity	CH	1	386	no	none	any	N/A	520	no
Nacken et al. [14]	coupled	DE	1	8760	no	95%	capacity	<10%	1025	no
Hennen et al. [4]	urban energy	generic	1	>1	no	none	capacity	<10%	384	no
This study	electricity	Europe	100	4380	no	100%	capacity	<10%	1968	yes

IAM–Integrated Assessment Model, GHG–greenhouse-gas, MGA–Modeling to Generate Alternatives, LOPF–Linear Optimal Power Flow, UK–United Kingdom, CH–Switzerland, US–United States of America, DE–Germany

spatio-temporal patterns shaping cost-efficient investment strategies in a fully renewable system. Furthermore, the co-optimization of generation, storage and transmission infrastructure subject to linear optimal power flow (LOPF) constraints is unique for MGA applications.

The goal of this work is to systematically explore the wide array of similarly costly but diverse technology mixes for the European power system, and derive a set of rules that must be satisfied to keep costs within pre-defined ranges. Additionally, we investigate how the extent of investment flexibility changes as we apply more ambitious greenhouse gas (GHG) emission reduction targets up to a complete decarbonization and allow varying levels of relative cost increases.

The remainder of the paper is structured as follows: Section 2 guides through the problem formulation, the employed variant of MGA, sources of model input data, and the experimental setup. The results are presented and discussed from different perspectives in Section 3 and critically appraised in Section 4. The work is concluded in Section 5.

2. Methodology

2.1. Problem formulation for long-term power system planning

The objective of long-term power system planning is to minimize the total annual system costs, comprising annualised[1] capital costs c_* for investments at locations i in generator capacity $G_{i,r}$ of technology r, storage capacity $H_{i,s}$ of technology s, and transmission line capacities F_ℓ, as well as the variable operating costs o_* for generator dispatch $g_{i,r,t}$:

$$\min_{G,H,F,g} f(G, H, F, g)$$

$$= \min_{G,H,F,g} \left[\sum_{i,r} c_{i,r} \cdot G_{i,r} + \sum_{i,s} c_{i,s} \cdot H_{i,s} + \sum_{\ell} c_\ell \cdot F_\ell + \sum_{i,r,t} w_t \cdot o_{i,r} \cdot g_{i,r,t} \right] \quad (1)$$

where representative time snapshots t are weighted by duration w_t such that their total duration adds up to one year; $\sum_{t=1}^{T} w_t = 365 \cdot 24$ h= 8760h. The objective function is subject to a set of linear constraints, including multi-period linear optimal power flow (LOPF) equations, resulting in a convex linear program (LP).

The capacities of generation, storage and transmission infrastructure are constrained above by their installable potentials and below by any existing infrastructure:

$$\underline{G}_{i,r} \leq G_{i,r} \leq \overline{G}_{i,r} \quad \forall i, r \quad (2)$$

$$\underline{H}_{i,s} \leq H_{i,s} \leq \overline{H}_{i,s} \quad \forall i, s \quad (3)$$

$$\underline{F}_\ell \leq F_\ell \leq \overline{F}_\ell \quad \forall \ell \quad (4)$$

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[1] The annuity factor $\frac{1-(1+\tau)^{-n}}{\tau}$ converts the overnight investment of an asset to annual payments considering its lifetime n and cost of capital τ.

The dispatch of a generator may not only be constrained by its rated capacity but also by the availability of variable renewable energy, which is derived from reanalysis weather data. This can be expressed as a time- and location-dependent availability factor $\overline{g}_{i,r,t}$, given in per-unit of the generator's capacity:

$$0 \leq g_{i,r,t} \leq \overline{g}_{i,r,t} G_{i,r} \quad \forall i, r, t \quad (5)$$

The dispatch of storage units is split into two positive variables; one each for charging $h_{i,s,t}^+$ and discharging $h_{i,s,t}^-$. Both are limited by the power rating $H_{i,s}$ of the storage units.

$$0 \leq h_{i,s,t}^+ \leq H_{i,s} \quad \forall i, s, t \quad (6)$$

$$0 \leq h_{i,s,t}^- \leq H_{i,s} \quad \forall i, s, t \quad (7)$$

This formulation does not prevent simultaneous charging and discharging, in order to maintain the computational benefit of a convex feasible space. The energy levels $e_{i,s,t}$ of all storage units have to be consistent with the dispatch in all hours.

$$e_{i,s,t} = \eta_{i,s,0}^{w_t} \cdot e_{i,s,t-1} + w_t \cdot h_{i,s,t}^{\text{inflow}} - w_t \cdot h_{i,s,t}^{\text{spillage}} \quad \forall i, s, t$$
$$+ \eta_{i,s,+} \cdot w_t \cdot h_{i,s,t}^+ - \eta_{i,s,-}^{-1} \cdot w_t \cdot h_{i,s,t}^- \quad (8)$$

Storage units can have a standing loss $\eta_{i,s,0}$, a charging efficiency $\eta_{i,s,+}$, a discharging efficiency $\eta_{i,s,-}$, natural inflow $h_{i,s,t}^{\text{inflow}}$ and spillage $h_{i,s,t}^{\text{spillage}}$. The storage energy levels are assumed to be cyclic

$$e_{i,s,0} = e_{i,s,T} \quad \forall i, s \quad (9)$$

and are constrained by their energy capacity

$$0 \leq e_{i,s,t} \leq \overline{T}_s \cdot H_{i,s} \quad \forall i, s, t. \quad (10)$$

To reduce the number of decision variables, we tie the energy storage volume to power ratings using a technology-specific parameter $\overline{T}_s$ that describes the maximum duration a storage unit can discharge at full power rating.

Kirchhoff's Current Law (KCL) requires local generators and storage units as well as incoming or outgoing flows $f_{\ell,t}$ of incident transmission lines ℓ to balance the inelastic electricity demand $d_{i,t}$ at each location i and snapshot t

$$\sum_r g_{i,r,t} + \sum_s h_{i,s,t} + \sum_\ell K_{i\ell} f_{\ell,t} = d_{i,t} \quad \forall i, t \quad (11)$$

where $K_{i\ell}$ is the incidence matrix of the network.

Kirchhoff's Voltage Law (KVL) imposes further constraints on the flow of passive AC lines. Using linearized load flow assumptions, the voltage angle difference around every closed cycle in the network must add up to zero. This constraint can be formulated using a cycle basis of the network graph where the independent cycles c that span the cycle space are expressed as directed linear combinations of lines ℓ in a cycle incidence matrix $C_{\ell c}$ [17]. This leads to the constraint

$$\sum_\ell C_{\ell c} \cdot x_\ell \cdot f_{\ell,t} = 0 \qquad \forall\, c,\, t \tag{12}$$

where x_ℓ is the series inductive reactance of line ℓ. The controllable HVDC links are not affected by this constraint.

All line flows $f_{\ell,t}$ are also limited by their capacities F_ℓ

$$|f_{\ell,t}| \le \overline{f}_\ell F_\ell \qquad \forall\, \ell,\, t, \tag{13}$$

where $\overline{f}_\ell$ acts as a per-unit security margin on the line capacity.

Finally, total CO_2 emissions may not exceed a target level Γ_{CO_2}. The emissions are determined from the time-weighted generator dispatch $w_t \cdot g_{i,\,r,\,t}$ using the specific emissions ρ_r of fuel r and the generator efficiencies $\eta_{i,r}$:

$$\sum_{i,r,t} \rho_r \cdot \eta_{i,r}^{-1} \cdot w_t \cdot g_{i,r,t} \le \Gamma_{CO_2}. \tag{14}$$

Note, that this formulation does not include pathway optimization (i.e. no sequences of investments), but searches for a cost-optimal layout corresponding to a given GHG emission reduction level. For capacity expansion planning, it assumes perfect foresight for the reference year based on which capacities are optimized. Additional aspects such as reserve power, system stability, or robust scheduling have not been considered. The optimization problem is implemented in the open-source modeling framework PyPSA [18].

2.2. Modeling to generate alternatives (MGA)

As shown in Fig. 1, following a run of the original model, the objective function is encoded as a constraint such that the original feasible space is limited by the optimal objective value f^* plus some acceptable relative cost increase ϵ.

$$f(G, H, F, g) \le (1 + \epsilon) \cdot f^* \tag{15}$$

Other than preceding studies, this paper pursues a more structured approach to MGA to span the near-optimal feasible space. The search directions are not determined by the Hop-Skip-Jump (HSJ) algorithm that seeks to minimize the weighted sum of variables of previous solutions [5], but by pre-defined groups of investment variables. Consequently, the new objective function becomes to variously minimize and maximize sums of subsets of generation, storage and transmission capacity expansion variables given the ϵ-cost constraint.

The groups can be formed by region and by technology. Examples for thought-provoking search directions are to minimize the sum of onshore wind capacity in Germany or the total volume of transmission expansion (cf. Section 2.4).

This process yields boundaries within which all near-optimal solutions are contained and can be interpreted as a set of rules that must be followed to become nearly cost-optimal.

In fact, by arguments of convexity, it can be shown that near-optimal solutions exist for all values of a group's total capacity between
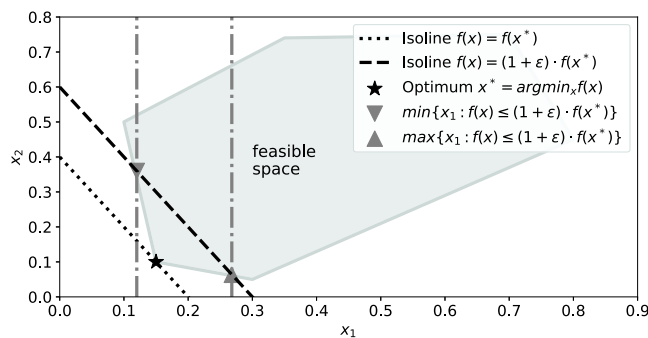
their corresponding minima and maxima. The original problem is convex as it classifies as a linear program. Neither adding the linear ϵ-cost constraint nor introducing an auxiliary variable z that represents the mentioned sum of the group of variables alter this characteristic. Hence, for any total $z \in [z_{min}, z_{max}]$ a near-optimal solution exists, however not for any combination of its composites leading to this total.

2.3. Model input data

The exploration of the near-optimal feasible space is executed for the open model dataset PyPSA-Eur of the European power system with a spatial resolution of 100 nodes and a temporal resolution of 4380 snapshots (two-hourly for a full year) [23]. The chosen levels of geographical and temporal aggregation reflect, at the upper end, the computational limits to calculate a large ensemble of near-optimal solutions and, at the lower end, the minimal requirements to expose transmission bottlenecks and account for spatially and temporally varying renewable potentials with passable detail [24,25].

Following a greenfield approach (with the exception of the transmission grid and hydropower installations), we allow simultaneous capacity expansion of transmission lines, HVDC links and various types of storage units and generators: solar photovoltaics, onshore wind turbines, offshore wind turbines with AC or DC grid connections, battery storage, hydrogen storage and, ultimately, open- and combined cycle gas turbines (OCGT/CCGT) as sole fossil-fueled plants.

Run-of-river and pumped-hydro capacities are not extendable due to assumed geographical constraints. All other generators and storage units can be built at any location up to their geographical potentials. The corridors for new HVDC links, limited to 30 GW, are taken from the TYNDP 2018 [26]. Individual AC transmission line capacities may be expanded continuously up to four times their current capacity, but not reduced. We further assume that the annual electricity demand for the power sector does not deviate substantially from today's levels. Given the densely meshed and spatially aggregated transmission system, we do not add new expansion corridors but constrain options to reinforcement via parallel AC lines. To approximate $N-1$ security, the effective transfer capacity of transmission lines is restricted to 70% of their nominal rating [23]. The dependence of line capacity expansion on line impedance is addressed in a sequential linear programing approach [27]. This relaxation is justified as it removes the excessive computational burden of integer programming, while yielding equally accurate solutions given tolerated optimality gaps in discrete problems and other more decisive model condensations (e.g. network clustering) [27]. Full details on the workflow of PyPSA-Eur and processing the underlying datasets can be found in [23]. Cost assumptions and further techno-economic input parameters are listed in Table 2.

2.4. Experimental setup

The MGA analysis is run within a parallelized workflow for different deviations $\epsilon \in \{0.5\%, 1\%, 2\%, 3\%, 4\%, 5\%, 7.5\%, 10\%\}$ from the cost-optimal solution and for system-wide greenhouse-gas emission reduction targets of 80%, 95% and 100% compared to emission levels in 1990. This allows to follow the propagation of investment flexibility for increasing optimality tolerances and more ambitious climate protection plans. The alternative objectives are to minimize and maximize the generation capacity of all (i) wind turbines, (ii) onshore wind turbines, (iii) offshore wind turbines, (iv) solar panels, and (v) natural gas turbines. Moreover, we search for the minimal and maximal deployment of (vi) hydrogen storage, (vii) battery storage, and (viii) power transmission infrastructure. This setup yields 384 near-optimal solutions. On average, each problem required 6.5 h and 31 GB of memory to solve with the Gurobi solver.

For slacks $\epsilon \in \{1\%, 5\%, 10\%\}$ and a 95% emission reduction target a 3-hourly resolved model is run for country-wise minima and maxima of the investment groups above, resulting in additional 1584 near-optimal

Fig. 1. Illustration of the near-optimal feasible space and the modeling to generate alternatives (MGA) methodology for a two-dimensional problem for the search-directions relating to dimension x_1.

Table 2
Assumptions for techno-economic input parameters.

Technology[e]	Investment [€/kW]	Fixed O&M [€/kW/a]	Marginal [€/MWh]	Lifetime [a]	Efficiency [-]	Investment [€/kWh]	$\bar{T}$[f] [h]	Source
Onshore Wind	1330	33	2.3	25	1			DEA [19]
Offshore Wind (AC)	1890	44	2.7	25	1			DEA [19]
Offshore Wind (DC)	2040	47	2.7	25	1			DEA [19]
Solar	600	25	0.01	25	1			Schröder et al. [20]
Run of River	3000	60	0	80	0.9			Schröder et al. [20]
OCGT[a]	400	15	58.4[b]	30	0.39			Schröder et al. [20]
CCGT[a]	800	20	47.2[b]	30	0.5			Schröder et al. [20]
Hydrogen	689	24	0	20	$0.8 \cdot 0.58$[c]	8.4	168	Budischak et al. [21]
Battery	310	9	0	20	$0.81 \cdot 0.81$[c]	144.6	6	Budischak et al. [21]
Pumped Hydro	2000	20	0	80	0.75	N/A[d]	6	Schröder et al. [20]
Hydro Reservoir	2000	20	0	80	0.9	N/A[d]	fixed	Schröder et al. [20]
Transmission (submarine)	2000 €/MWkm	2%	0	40	1			Hagspiel et al. [22]
Transmission (overhead)	400 € /MWkm	2%	0	40	1			Hagspiel et al. [22]

[a] Gas turbines have a CO_2 emission intensity of 0.19 t/MW_{th}.

[b] This includes fuel costs of 21.6 € /MWh_{th}.

[c] The storage round-trip efficiency consists of charging and discharging efficiencies $\eta_+ \cdot \eta_-$.

[d] The installed facilities are not expanded in this model and are considered to be amortized.

[e] For all technologies a discount rate of 4% is assumed.

[f] This relates a storage unit's energy capacity to its power capacity; it is the maximum duration the storage unit can discharge at full power capacity.

solutions. On average, each problem required 3.5 h and 22 GB of memory to solve.

3. Results and discussion

3.1. Optimal solutions

Before delving into near-optimal solutions, we first outline the characteristics of the optimal solutions for different emission reduction levels (cf. Table 3). A system optimized for a 100% emission reduction is strongly dominated by wind energy. More than half of the electricity is supplied by offshore wind installations. Onshore wind turbines provide another quarter. In contrast, photovoltaics account for only 16% of electricity generation. Strikingly, a system targeting a 95% reduction in greenhouse gases uses significantly less onshore wind generators but more solar energy in comparison to a completely decarbonized system, while keeping the share of offshore wind generation constant. Thus, for the last mile from 95% to 100% more onshore wind generation is preferred to phase out the last remaining natural-gas-fired power plants. The total system costs scale nonlinearly with more tight emission caps. Achieving an emission reduction of 95% is roughly a quarter more expensive than a reduction by 80%, while a zero-emission system is almost 50% more expensive.

Also, the map in Fig. 2-(i) shows the optimal regional distribution of the capacities of power system components for a fully renewable European power system. Generation hubs tend to form along the coasts of North, Baltic and Mediterranean Sea, whereas inland regions produce

little electricity. Expectedly, solar energy is the dominant carrier in the South, while wind energy prevails close to the coasts of the North Sea and the Baltic Sea. Most grid expansion can be found in Germany, France and the United Kingdom and individual HVDC links are built with capacities of up to 30 GW. The routes and capacities of HVDC links are well correlated with the placement of wind farms.
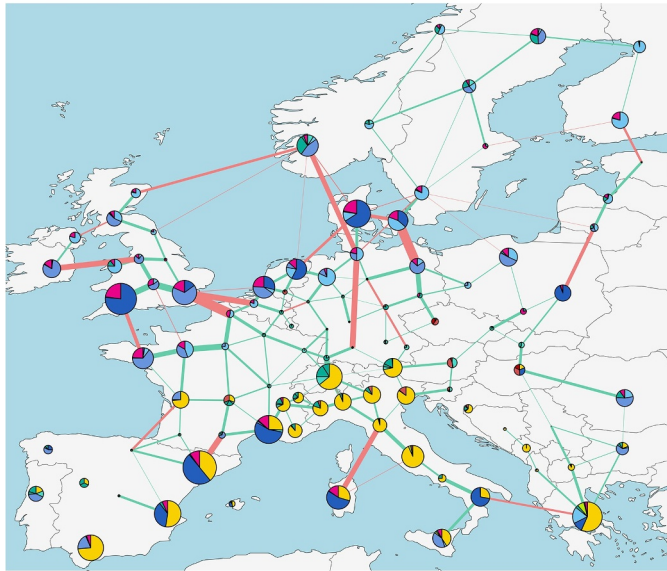
3.2. The near-optimal feasible space

In this section we extremise different groups of investments in generation, storage and transmission infrastructure. As an example, Fig. 2-(ii) depicts a system that seeks to deviate from the optimum by minimizing the volume of transmission network expansion up to a total cost increase of 10%, for instance as a concession to better social acceptance. With the results particularly the Suedlink HVDC link connecting Northern and Southern Germany manifests as a no-regret investment decision up to a capacity of 15 GW in the context of full decarbonization. It is one of the few persistent expansion routes. All other transmission expansion corridors are (to a significant extent) not compulsory. Missing transmission capacities can be compensated by adding storage capacity and more regionally dispersed power generation. Nevertheless, some transmission network reinforcement is indispensable to remain within the given cost bounds. These results are also broadly aligned with findings in [15,24].

Beyond this example, the MGA results offer insights about the structure of the near-optimal space. The intent is to portray a set of technology-specific rules that must be satisfied to keep costs within predefined ranges ε. Note, that the discontinuity created by ε restricts the accuracy of the solution space.

Fig. 3 reveals that wind generation, either onshore or offshore, is essential to set up a cost-efficient European power system for all three evaluated emission reduction levels. Whilst already a small cost increase of 0.5% yields investment flexibilities in the range of ± 100 GW, even a 10% more costly solution would still require more than 500 GW of wind generation capacity for a fully renewable system: two-thirds of the optimal system layout. However, even for a zero-emission system a cost increase of just 4% enables abstaining from onshore wind power, and a 7.5% more expensive alternative can function without offshore wind farms.

The investment flexibility develops nonlinearly with increasing slack levels ε. Even a minor deviation from the cost optimum by 0.5% creates room for maneuver in the range of ± 200 GW for onshore and ± 150 GW offshore wind installations, which indicates a weak

Table 3
Statistics on optimal solutions for different GHG emission reduction levels.

GHG Emissions	−100%	−95%	−80%
Generation [TWh]			
- Onshore Wind	750 (24%)	421 (14%)	423 (15%)
- Offshore Wind (AC)	886 (28%)	568 (19%)	297 (10%)
- Offshore Wind (DC)	873 (27%)	1032 (34%)	769 (27%)
- Solar	502 (16%)	605 (20%)	381 (13%)
- Run of River	150 (5%)	153 (6%)	154 (5%)
- CCGT (natural gas)	0 (0%)	171 (6%)	761 (26%)
- OCGT (natural gas)	0 (0%)	41 (1%)	105 (4%)
Transmission [TWkm]	504 (+71%)	458 (+55%)	368 (+25%)
Load [TWh]	3138	3138	3138
Total Cost [bn € /a]	246	207	165
Total Cost [€ /MWh]	78.4	66.1	52.6

(i) Optimal transmission network expansion (ε=0% / GHG -100%)

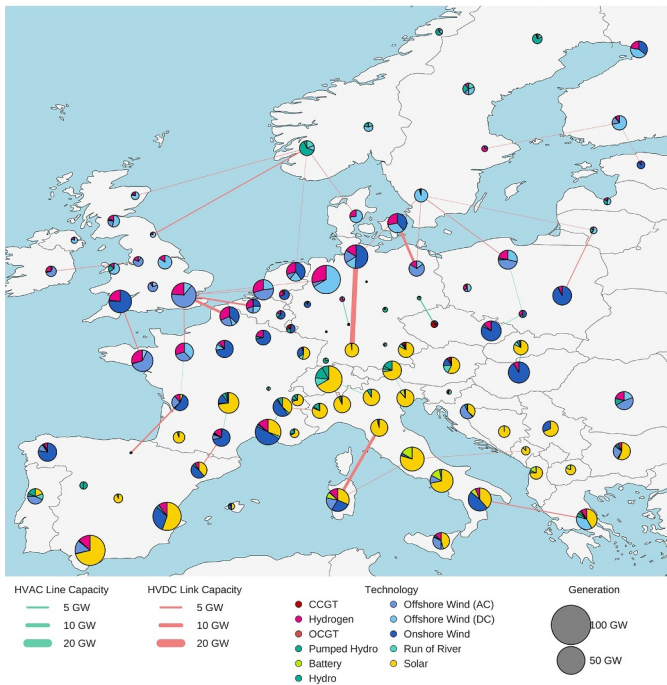## (ii) Minimize transmission network expansion (ε=10% / GHG -100%)

Fig. 2. Maps of transmission line expansion and regional generator and storage capacities for a 100% renewable power system for the (i) optimal solution and (ii) minimal transmission volume within a 10% cost increase.

Fig. 3. Solution space of renewable generation infrastructure by technology for different levels of slack ϵ and emission reduction targets.

tradeoff between onshore and offshore wind capacities very close to the optimum. Nonetheless, dispensing with both is not viable. Furthermore, 10% of total system costs must be spent to rule out solar panels, but already a slack of 1% allows to reduce the solar capacity by a third.

Price et al. observed in their model that investment flexibility in generation infrastructure decreased as more tight caps on carbon-di-oxide emissions were imposed [8]. While it is reproduced in this contribution that more ambitions climate protection plans incur more must-haves (i.e. minimum requirements of capacity), for the case-study at hand the viable ranges of marginally inferior solutions increase as more total capacity is built.

As Fig. 4 exhibits, even for a complete decarbonization of the European power system building battery storage is not essential, although they are deployed in response to e.g. minimizing network
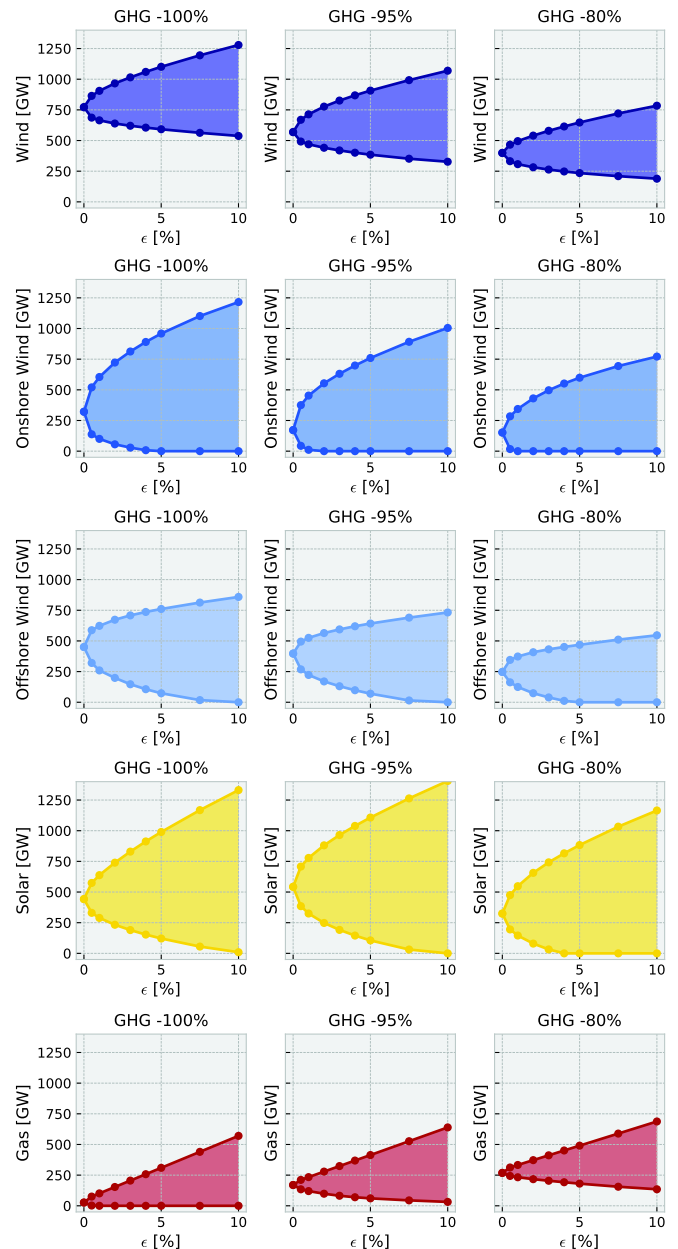
reinforcement. Conversely, once weather-independent dispatch flexibility from natural-gas-fired power plants is unavailable, it becomes imperative to counter-balance with long-term hydrogen storage. The cutback of hydrogen infrastructure under these circumstances goes along with building additional generation capacities and multiplied amounts of curtailment.

The reinforcement of the transmission network becomes more pivotal the more the power system is based on renewables. Aiming for an emission reduction by 80% a 2% more expensive variant can get by without any grid reinforcement. Reducing emissions by 100% still requires some additional power transmission capacity at a 10% cost deviation. However, within this range, the transmission volume can deviate from almost double of today's network capacities to merely a marginal reinforcement (cf. Fig. 2).

MGA iterations were also applied from a country-wise perspective. Remarkably, any one country could completely forego any one generation or storage technology and remain within 5% of the cost
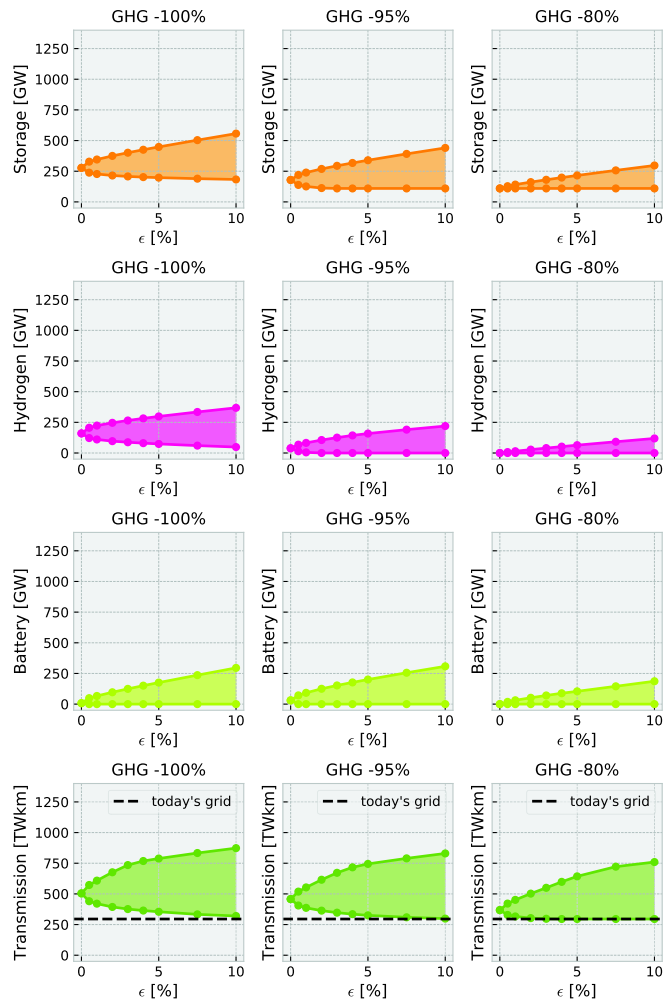
Fig. 4. Solution space of storage and transmission infrastructure by technology for different levels of slack ϵ and emission reduction targets.

optimum when targeting a 95% reduction in greenhouse gas emissions. In this case, neighboring countries offset the absence of this technology.

3.3. Correlations

So far, the study of the near-optimal feasible space did not capture the interdependence between different system components apart from the envelopes the analysis provided for each technology. Shifting to the extremes of one technology will diminish the investment flexibility of other carriers. Fig. 5 demonstrates how diversity in capacity mixes rises if more leeway is given in terms of system costs. The striking variety in capacity totals is largely attributable to the lower capacity factors of solar compared to wind energy.

Hennen et al. suggested to present the intertwining of technologies through Pearson's correlation coefficient across all near-optimal solutions [4]. Fig. 6 confirms many of the previously noted connections. Hydrogen storage substitutes natural gas turbines and is positively correlated with onshore and offshore wind capacity, while battery deployment rather matches with solar installations. Likewise, transmission expansion occurs in unison with onshore and offshore wind deployment. Thereby, hydrogen storage and transmission become complements for high renewable energy scenarios. It should be noted with caution that CCGT and OCGT as well as AC- and DC-connected offshore wind installations have high correlations because they are grouped in the MGA iterations.
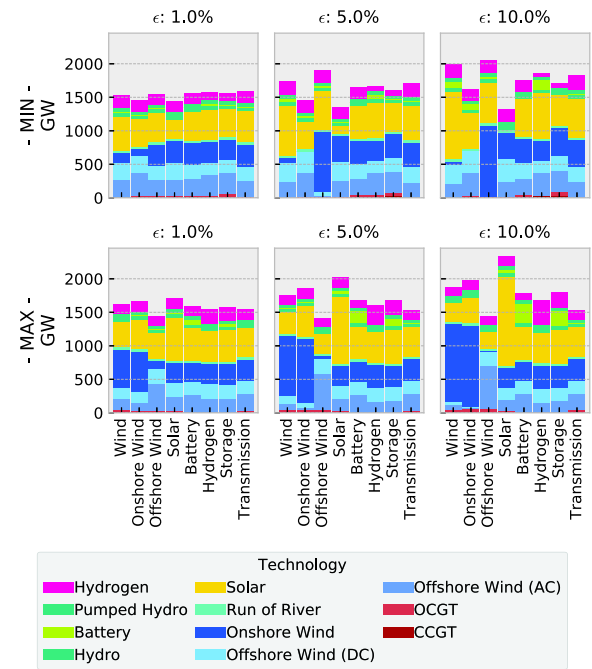

Fig. 5. Composition of generation and storage capacities for various near-optimal solutions with 100% renewables. Each subplot corresponds to a slack level ϵ and an optimization sense. The labels of the bar charts indicate which group of investment variables is included in the objective.
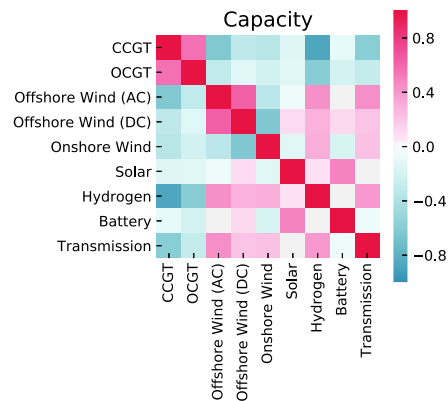

Fig. 6. Correlations of capacities across all near-optimal solutions.

3.4. Distributional equity

Surveys suggest that an equal distribution of power supply is preferred among the population and may increase their willingness to participate in the energy system transformation process [28]. Sasse et al. and Drechsler et al. investigate the trade-offs between least-cost and regionally equitable solutions in Switzerland and Germany by using concepts of the Lorenz curves and the Gini coefficients as equity measures [11,28].

In the context of power, the Lorenz curve can relate the cumulative share of electricity generation of regions to their cumulative share of electricity demand as shown in Fig. 7. For more ambitious emission reduction targets, less equitable solutions are favored from a cost-perspective, however, they may not be in line with the public attitude.

The Gini coefficient is the corresponding scalar measure of uniformity and is determined by multiplying the area between the Lorenz curve and the identity line by two. A Gini coefficient of 1 represents the most unequal distribution, while 0 corresponds to the situation where every region produces, on average, as much electricity as they consume.
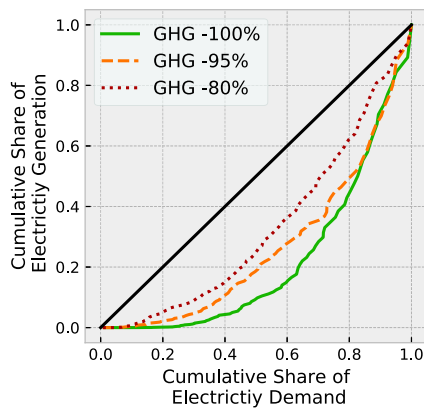
Fig. 7. Lorenz curves for the optimal solutions at different emission reduction levels relating the cumulative share of electricity generation to the cumulative share of demand in the 100 regions of the European power system model.
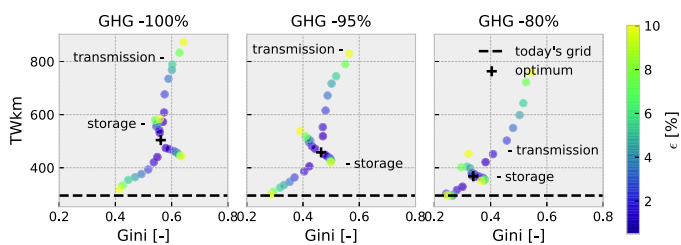

Fig. 8. Development equitable power generation measured by the Gini coefficient in relation to the capacity of the power transmission network measured in TWkm. The four plotted search directions are minimization and maximization of each, total transmission volume and storage capacity.

Preceding studies have, in general, noted that the focus on wind power tends to be detrimental to a regionally balanced distribution of electricity generation [28], whereas photovoltaic power supply is a key factor for an even distribution of the power supply [11]. This observation is consistent with the results of the European power system at hand. But as we consider the transmission grid and energy storage options, we can further extend on these findings. In Fig. 8 we track the equity of solutions in relation to the transmission network volume as we approach the boundaries of either technology category. Substantially more regionally equitable solutions are attainable for a limited cost-increase when diverting attention away from transmission network expansion. Utilizing less energy storage rather discourages equitable generation patterns; in the opposite direction, this is not the case for a zero-emission system. Note that the equity measures are only an observed side-effect and not the objective of a particular search direction of the MGA method. There is no guarantee that no more equitable solutions exist within the near-optimal feasible space.

4. Critical appraisal

This paper covers the electricity sector only. Brown et al. suggested that with an increasing coupling of energy sectors the benefit of the transmission system decreases [29]. It is not far-fetched, that the near-optimal feasible space might look very different with a tightened sectoral integration.

Within the computational constraints, it is moreover desirable to further enhance the spatial and temporal resolution to better reflect curtailment caused by transmission bottlenecks and factor in extreme weather events [24].

This work further neglects parametric uncertainty. Coupling this paper's variant of MGA with a parameter sweeping method (such as Monte Carlo simulation [10]) would allow to derive a more sophisticated version of Figs. 3 and 4 with fuzzy boundaries that represent the

probability with which the respective capacities of system components are contained within the near-optimal feasible space.

5. Summary and conclusions

This work sheds light on the flatness of the near-optimal feasible decision space of a power system model with European scope for ambitious climate protection targets.

An understanding of alternatives beyond the least-cost solutions is indispensable to develop robust, credible and comprehensible policy guidelines. Therefore, we derived a set of technology-specific boundary conditions that must be satisfied to keep costs within pre-defined ranges using an adapted modeling-to-generate-alternatives methodology. These rules permit well-informed discussions around social constraints to the exploitation of renewable resources or the extent to which the power transmission network can be reinforced, given large degrees of freedom.

Indeed, we observed high variance in the deployment of individual system components, even for a fully renewable system. Already a minor cost deviation of 0.5% offers a multitude of technologically diverse alternatives. It is possible to dispense with onshore wind for a cost increase of 4%, and to forego solar for 10%. Nevertheless, either offshore or onshore wind energy plus at least some hydrogen storage and grid reinforcement are essential to keep costs within 10% of the optimum.

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.

Supplementary Material

For supplementary material and reading the reader is referred to the source code repository on Github (https://github.com/pypsa/pypsa-eur-mga) and the documentations of PyPSA (https://pypsa.readthedocs.io, [18]) and PyPSA-Eur (https://pypsa-eur.readthedocs.io, [23]).

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